Housing Discrimination Study Innovative Methodology Project

Final Comprehensive Report

U.S. Department of Housing and Urban Development | Office of Policy Development and Research

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November 29, 2024

Prepared for:
U.S. Department of Housing and Urban Development
Office of Policy Development and Research

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ABOUT THIS REPORT

This Comprehensive Report includes case studies of three innovative methodologies that measure different forms of housing discrimination. Three different academic research teams developed case studies and conducted feasibility tests of the methods under a subcontract with 2M Research. The report describes the process by which innovative methods for measuring housing discrimination were identified, how HUD selected the three methods to test, and the results of these feasibility tests. The report concludes by discussing the benefits of these selected methods to housing discrimination research and the challenges/limitations HUD may face in their future application.

DISCLAIMER

Acknowledgments

The preparers of this report gratefully acknowledge our partners at the U.S. Department of Housing and Urban Development's (HUD's) Office of Policy Development and Research (PD&R). We owe particular thanks to the Contracting Officer's Representative, Nathan Bossie, for his guidance and support throughout all phases of the study.

The preparers thank the academic teams that authored each of the three case studies. The authors of Discrimination in Refinance Appraisals (Chapter 2) include Brent Ambrose, James Conklin, N. Edward Coulson, Mousa Diop, and Luis Lopez. The authors of Selective Advertising in the Rental Housing Market (Chapter 3) include Daniel Gold, Lu Han, and Christopher Timmins. The authors of Discriminatory Lending Practices (Chapter 4) include Sheri Smith, Cheryl Toombs, and Errol Williams.

The preparers also thank the numerous experts and researchers that supported this study in various ways. These include

- The expert panelists, Claudia Aranda, Fred Freiberg, Martha Galvez, and Peter Hull, who helped to review the innovative methodologies received by 2M Research and supported the development of recommendations for feasibility tests.
- The Housing Discrimination Study (HDS) conference panelists, Mackenzie Allston, Peter Bergman, Fred Freiberg, Peter Hull, and Stepen Ross, who presented their housing discrimination research to the public and discussed their thoughts on directions of future research to inspire additional work in the field.
- Our subject matter expert, Christopher Timmins, who provided invaluable input at the beginning of the study and moderated the HDS conference before transitioning to a role on one of the academic research teams conducting feasibility tests.
- Our subject matter expert, Peter Christensen, who offered invaluable input throughout the study, moderated the HDS conference, reviewed methodologies, and supported development of this report.

Two researchers at PD&R were also instrumental in this project. Stephanie Hawke provided analytical support to the Discrimination in Refinance Appraisals team. Michael Craig provided data cleaning and merging support to the Discriminatory Lending Practices team. These PD&R researchers facilitated the use of data that is otherwise not available to researchers outside of HUD. Without their support, the researchers would have faced significant challenges in obtaining the necessary data and conducting the feasibility test.

Finally, we are grateful to the many people at 2M—in addition to the named preparers—who contributed to this study. Neel Chakraborti and Lara Milavickas provided technical quality oversight and managerial input, which greatly improved this work. Lan Hu and Dennis Okyere supported review of innovative methodologies. Kowther Elqutob supported outreach to the research community to identify innovative housing discrimination research methodologies.

Foreword

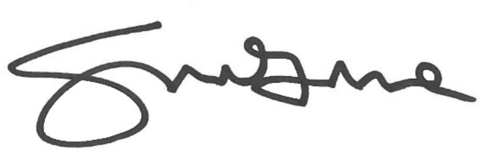
Since the passage of the Fair Housing Act in 1968, HUD has been committed to advancing policies and programs to ensure that all individuals and families have equal access to housing opportunities, free from discrimination based on race, color, national origin, religion, sex, familial status, or disability. As part of this commitment, HUD has a long history of conducting research that has been designed to assess and monitor the prevalence and extent of discrimination in housing markets across the country. These studies have gathered empirical evidence on the state of fair housing in the country to guide policymaking, enforcement, and public education efforts.

The body of evidence that has been established over the past decades related to the prevalence of housing discrimination underscore that while overt discrimination on the basis of race and ethnicity of home seekers in both rental and sales markets has declined over time, subtle forms of discrimination are becoming more prevalent. Additionally, recent studies have questioned whether the primary methods used for measuring housing discrimination can address the more subtle discriminatory practices some landlords, lenders, sellers and other actors involved in housing transactions have adopted to evade detection, particularly with the evolution of technology in the marketplace.

In response to these concerns, HUD launched the Housing Discrimination Study Innovative Methodology Project in 2021 to identify and test new methodologies that could augment and enhance housing discrimination research. Following a nationwide search, HUD selected three innovative methods to test. This final report presents the case studies of the three feasibility tests, each of which demonstrate how these new approaches complement existing housing discrimination research and have the ability to uncover forms of discrimination that earlier methods may have missed.

While these case studies are feasibility tests, each of the tests suggest that discrimination exists in different stages of the housing process that prior housing discrimination research has not focused on. This exploration into innovative methods also demonstrates the significant promise in building evidence of discrimination in areas that prior housing discrimination work has not emphasized through the exploration and testing of new research methods.

It is worth emphasizing that the research methods used in these case studies are exploratory and experimental. The research teams recognize the limitations of the data and their methods in their contributions to this report, as does the concluding chapter written by 2M, HUD's primary contractor and the preparer of this report. HUD is encouraged that investing in innovative methods of studying housing discrimination can help us detect, describe and address previously understudied forms of discrimination. But we also recognize that we still have a long way to go, not only to improve and scale these methods, but also to realize the promise of the Fair Housing Act of 1968: a housing marketplace in which everyone has equal access to housing, free from discrimination.



Solomon J. Greene
Principal Deputy Assistant Secretary for Policy Development and Research
U.S. Department of Housing and Urban Development

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Chapter 1. Introduction

In September 2021, the U.S. Department of Housing and Urban Development (HUD) Office of Policy Development and Research (PD&R) contracted with 2M Research (2M), a policy research and evaluation firm, to identify and test new and existing methodologies that augment and enhance housing discrimination research. HUD initiated this contract in response to concerns raised in *Cityscape* journal articles, which argued that housing discrimination studies using paired testing[1] might underreport the prevalence of discrimination under certain circumstances (Turner and James, 2015).

Organization of Report

The report begins with this introductory chapter that outlines the history and significance of the Fair Housing Act and provides an overview of HUD's prior Housing Discrimination Studies (HDS). This chapter examines stages in the housing rental and home-buying processes where discrimination may occur, highlighting areas that previous HDS focused on and identifying gaps that call for innovative methodologies. Additionally, this chapter discusses 2M's outreach efforts to identify innovative methodologies and provides summaries of the three research methodologies tested in this study. The chapter concludes by discussing the three methodologies' potential to advance housing discrimination research.

Chapters 2 through 4 present detailed case studies of the three methodologies, demonstrating how these approaches complement existing housing discrimination research and uncover forms of discrimination that previous HDS may have missed. Chapter 5 concludes by reflecting on key findings, lessons learned, and implications for future research.

The Fair Housing Act of 1968

The Fair Housing Act, enacted as Title VIII of the Civil Rights Act of 1968, serves as a cornerstone in the fight against housing discrimination in the United States. The Fair Housing Act was designed to ensure that individuals and families have equal access to housing opportunities, free from discrimination based on race, color, national origin, religion, sex, familial status, or disability (U.S. Department of Justice, 2023). Initially, the Fair Housing Act targeted racial discrimination and segregation in the housing market, addressing issues such as redlining, exclusionary zoning, and discriminatory practices by landlords, real estate agents, and mortgage lenders. By prohibiting practices such as refusing to sell or rent property to certain groups, steering individuals to specific neighborhoods, and misrepresenting the availability of housing, the Fair Housing Act established the foundation for more equitable housing policies.

Over time, the Fair Housing Act has been expanded through amendments to enhance its protections and respond to evolving societal needs. In 1974, the Act was amended to prohibit discrimination on the basis of sex, recognizing the systemic barriers that women faced in accessing housing and credit. In 1988, the Fair Housing Amendments Act expanded protection to include familial status and disability. This amendment also strengthened enforcement

[1] In paired testing, two individuals who are matched on social and economic characteristics but who differ on one characteristic that is the subject of the test will assume the role of applicants for housing (Evidence Matters, 2014). Evidence of discrimination is shown when one tester is treated differently than the paired tester by the housing provider (ibid.).

mechanisms, allowing for the imposition of civil penalties for violations and granting HUD the authority to more effectively investigate and resolve complaints. The 1988 amendments also required newly constructed multifamily housing units to include accessible housing design, enabling individuals with disabilities to live more independently. Together, these amendments reflect the Act's adaptability to evolving societal needs and its ongoing role in addressing the diverse and complex forms of housing discrimination that still persist in the United States.

Previous Housing Discrimination Studies (HDS)

Since the 1970s, HUD has conducted four national studies to assess and monitor the prevalence and extent of discrimination in housing markets across the country based on race and ethnicity, and has sponsored several smaller-scale pilot tests measuring housing discrimination on the basis of other protected characteristics under the Fair Housing Act and amendments such as family status and disability. These studies have gathered empirical evidence on the state of fair housing in the country to guide policymaking, enforcement, and public education efforts.

Key Studies and Methodology

HUD's HDS have primarily employed a "paired testing" methodology, in which two testers—one from a minority group and one from a control group (usually White)—pose as equally qualified home seekers. Each tester interacts with housing providers, such as real estate agents or landlords, to observe any differential treatment. This method is considered one of the most reliable ways to detect discrimination because it controls for variables like income, employment, and other observable characteristics. Through this method, these studies capture various discriminatory practices against minority groups such as differential treatment in relation to unit availability, appointments for property viewings, the number of units shown, and rental terms offered.

The methodologies and findings of HUD's four national studies to date are described below:

1. **Housing Market Practices Survey (HMPS) – 1977**
    - ***Groups Studied*:** Black renters and buyers.
    - ***Scale and Method*:** 3,264 tests in 40 metropolitan areas, primarily using newspaper ads to find rental and sales units.
    - ***Findings*:** Black testers were systematically disadvantaged in both rental and sales markets, with rental tests usually having Black testers contact landlords first and White testers being prioritized in sales tests.
2. **Housing Discrimination Study (HDS1989)**
    - ***Groups Studied**:* Black and Hispanic renters and buyers.
    - ***Scale and Method:*** 3,800 tests in 25 metropolitan areas, using specific advertised units for anchoring.
    - ***Key Advancement:*** First to measure racial and ethnic "steering," where minority testers were often directed away from certain neighborhoods.
    - ***Findings:*** Showed significant discrimination in terms of units shown and the quality of service provided, with minority testers generally shown fewer properties.
3. **Housing Discrimination Study (HDS2000)**
    - ***Groups Studied:*** Black, Hispanic, Asian, and Native American testers.
    - ***Scale and Method:*** 4,600 tests across 23 metropolitan areas, with additional geographic oversampling.

- ***Key Changes:*** This study included testers' actual characteristics (e.g., income and education) and randomly ordered initial contact calls. Testers requested specific advertised units and similar properties.
- ***Findings:*** Minorities often received fewer options and less favorable terms compared to White testers. Additionally, minority testers were sometimes quoted higher prices or rental rates.

4. **Housing Discrimination Study (HDS2012)**
    - ***Groups Studied:*** Black, Hispanic, and Asian renters and buyers.
    - ***Scale and Method:*** 8,047 tests in 28 metropolitan areas. Contact was randomized via phone or email to secure appointments, and testers assessed unit availability and explored additional options in person.
    - ***Findings:*** Discrimination has evolved to be subtler but remains prevalent. White testers were more likely to be informed about available units and were often shown more properties than their minority counterparts.

The four national HDS underscore that while overt discrimination on the basis of race and ethnicity of home seekers in both rental and sales markets has declined over time, subtle forms of discrimination are still prevalent. In additional to the national studies, HUD has also funded pilot studies to measure discrimination against people who are deaf or who use wheelchairs (Levy et al., 2015); families with children (Aron et al., 2016); renters with mental disabilities (Hammel et al., 2017); renters with housing choice vouchers (Cunningham et al., 2018); and lesbian, gay, and transgender renters (Levy et al., 2017).

Challenges and Gaps in Current Methodology

While paired testing is an effective tool for conducting housing discrimination studies, it has some key limitations. Early versions of this method relied on in-person interactions, which were labor intensive and costly, limiting the method's widespread use. More recently, studies have used correspondence testing, which reduces costs by utilizing communication methods such as emails, phone calls, or online inquiries to assess responses. This approach eliminates the need for in-person visits, which reduces costs and allows researchers to test a larger sample size more efficiently.

Recent studies have questioned whether paired testing can address the more subtle discriminatory practices some landlords have adopted to evade detection (Freiberg and Squires, 2015). For instance, the Fair Housing Justice Center reported that certain housing providers take steps to reduce contact with undesired groups by avoiding public advertisements or targeting ads to select audiences. Since discrimination research based on paired testing often depends on advertised listings to develop a sample pool, these advertising practices make it difficult to capture this subset of housing and these types of discriminatory practices. Further, housing providers may initially appear to follow non-discriminatory practices, yet discriminatory behaviors can become evident later in the housing search process (and are thus not captured in research). Typically, paired testing research captures only a single interaction early in the housing search process, potentially underreporting discrimination that occurs at later stages of ongoing interactions (Freiberg and Squires, 2015). The evolution of discriminatory practices, especially in rental and sales markets, calls for continued monitoring and more nuanced testing approaches.

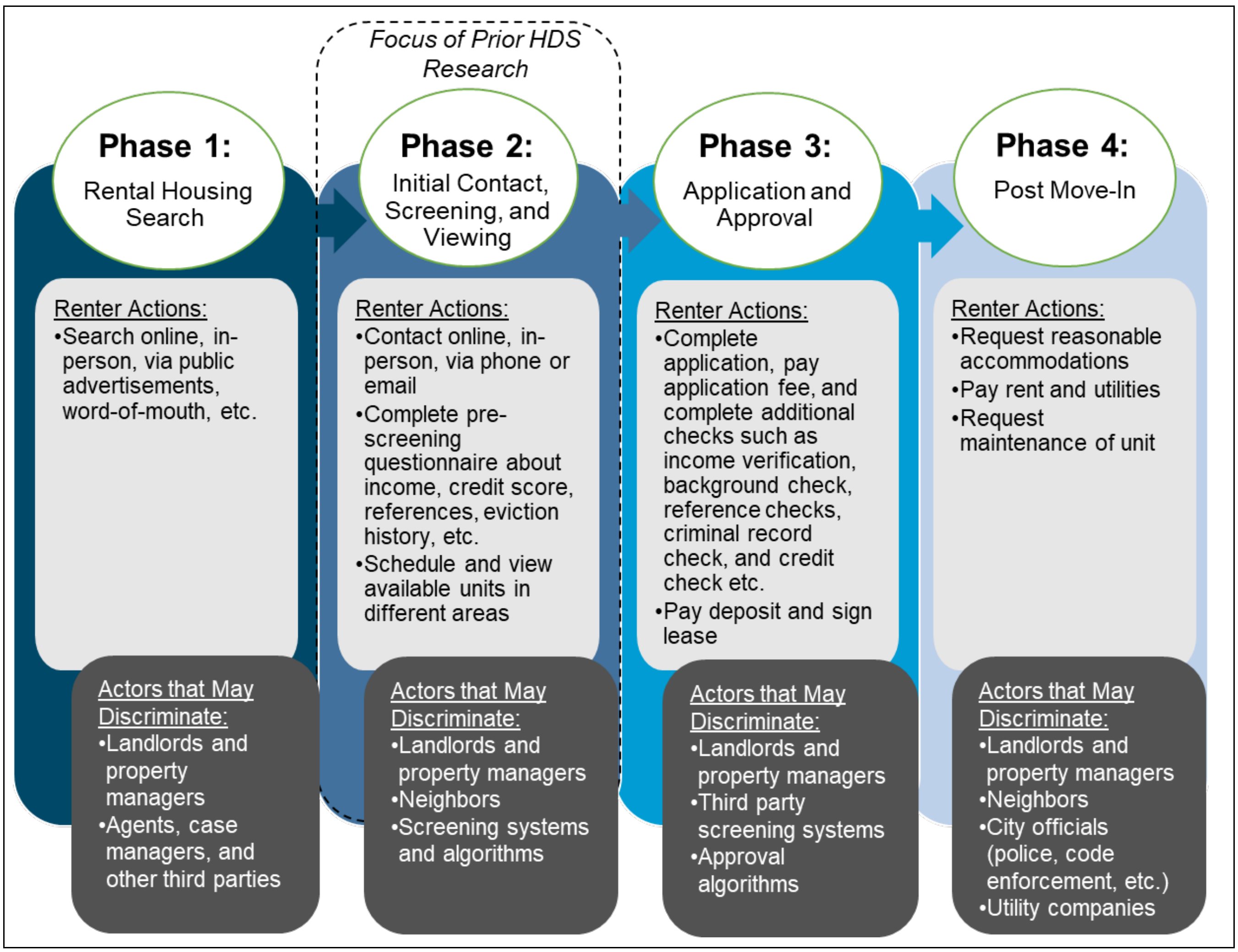
Examining Discrimination Across the Housing Journey

In light of these critiques, HUD commissioned this study to identify and test new approaches to test for housing discrimination beyond the traditional narrow focus on the initial phase of the housing search process. Housing discrimination can occur at multiple stages of rental and home-buying processes, involving various actors. Given the complexity of rental and home-buying processes, it is crucial to examine the stages individuals must navigate to identify where discrimination may occur, determine the key actors involved, and uncover gaps in existing methodologies. This section outlines the stages of both renting and home buying, identifies the key actors at each stage, and highlights the points where existing methodologies are typically applied, providing a foundation to address existing limitations.

Stages of the Rental Leasing Process

The rental leasing process typically involves several key stages (see **Exhibit 1.1**), each requiring interaction among various individuals.

Exhibit 1.1 | The Rental Leasing Process



Notes: Exhibit 1.1 is not meant to be an exhaustive description of all actions and actors involved in the rental housing process. It shows at a high level the general process involved in the market and how prior HDS focused on specific phases of the process, highlighting the need for additional discrimination research methodologies that examine other phases.

Opportunities for Discrimination in the Rental Housing Process

Exhibit 1.1 outlines the various points during rental leasing process at which discriminatory decisions or actions could occur, emphasizing the need to consider each phase of the process, as well as the various actors who may be encountered during each phase, when studying housing discrimination in the rental market. For example, discrimination can occur at the following stages:

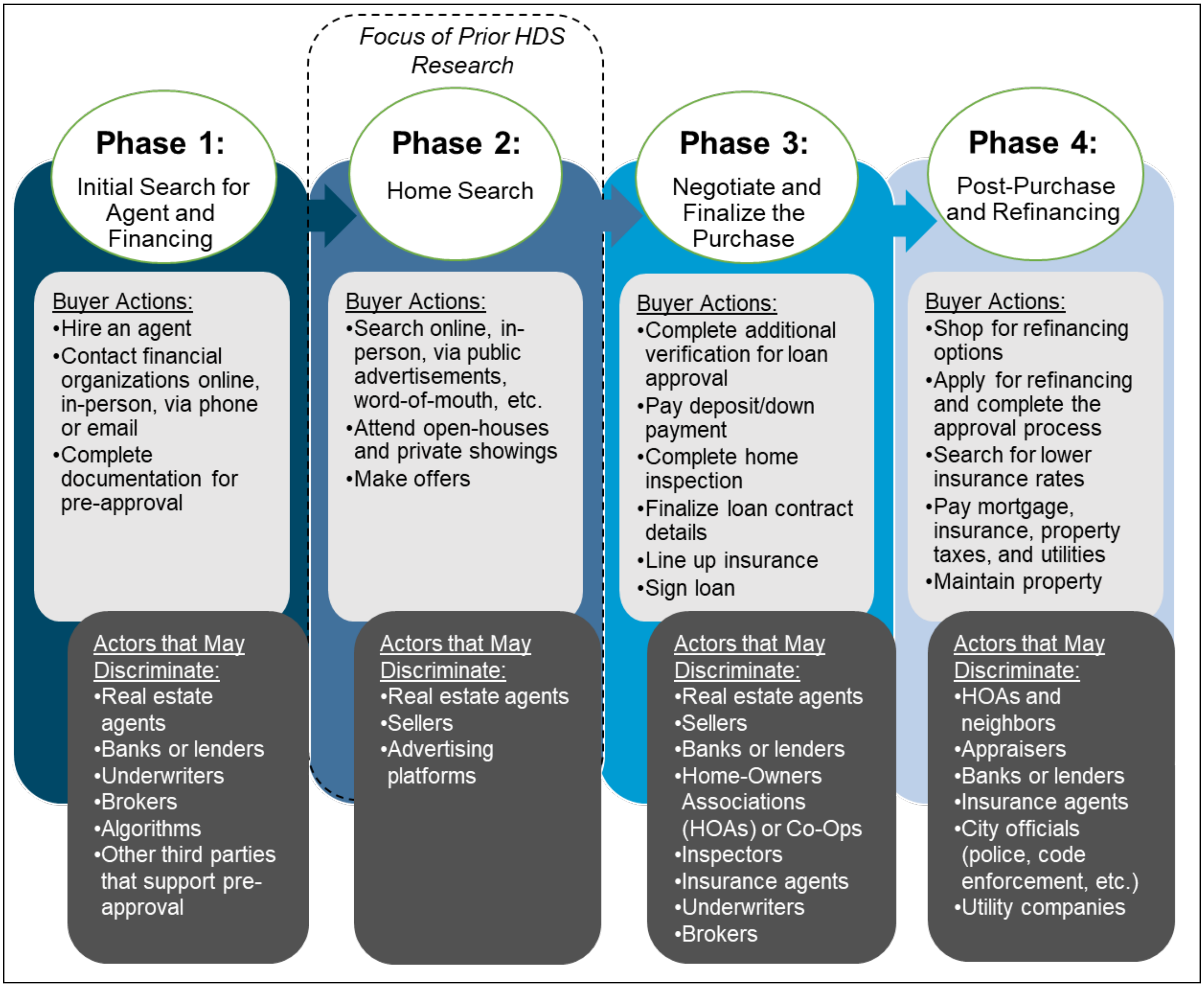
- **At the initial apartment search stage**, some units or properties may not be advertised publicly to avoid attracting undesired renters. Landlords, property managers, rental agencies, or housing search platforms may also introduce bias by selectively presenting housing options or crafting ads that target certain groups. Even when potential tenants reach out to inquire about a property, they may be ignored or dismissed before a conversation begins.
- **During the contact stage,** commonly studied in HUD's paired testing research, landlords may falsely claim that units are unavailable, steer potential tenants toward specific neighborhoods, or provide unequal levels of service.
- **During the application and approval stage,** landlords may impose different fees, rents, or qualification standards based on a potential tenant's characteristics.
- **During the move-in, tenancy, and move-out stage,** tenants may face discriminatory practices such as extra fees or high security deposits, denials of reasonable accommodation requests, segregation from other tenants, restricted amenities, or harassment from landlords or property managers with the intention to force certain groups of renters out.

These various forms of housing discrimination are prohibited under the Fair Housing Act. Prior HDS have focused mostly on the initial contact, screening, and viewing stage (outlined in Exhibit 1.1), but some forms of discrimination remain underexamined due to the limitations of current research methodologies.

Stages of the Home-Buying Process

Like the rental leasing process, the home-buying process typically involves several key stages requiring interaction among various individuals and organizations. Exhibit 1.2 below illustrates how these stages involve multiple interactions between homebuyers, real estate professionals, lenders, and other stakeholders.

Exhibit 1.2 | The Home-Buying Process



Notes: Exhibit 1.2 is not meant to be an exhaustive description of all actions and actors involved in the home-buying process. It shows at a high level the general process involved in the market and how prior HDS have focused on specific phases of the process, highlighting the need for additional discrimination research methodologies that examine other phases.

Opportunities for Discrimination in the Home-Buying Process

Similar to the rental leasing process, the various stages of the home-buying process present opportunities for discriminatory practices, highlighting the need to consider each phase of the process, as well as the various actors that may be encountered during each phase, when studying discrimination in the home buying market. For example, discrimination can occur at the following stages:

- **During mortgage pre-approval:** Lenders may impose stricter requirements, such as higher credit score thresholds or additional documentation for income, for certain groups.

- **During the property search**: Real estate agents may engage in steering by showing homes only in specific neighborhoods based on a buyer's race or ethnicity.
- **During the offer and negotiation phase**: Sellers or their agents may reject offers from minority buyers due to biases or preferences for buyers with certain characteristics.
- **During inspection and appraisal:** Appraisers may undervalue properties in predominantly minority neighborhoods or homes owned by minorities, limiting financing options. Additionally, the closing process may take longer.
- **Post-purchase:** Homeowners may face discriminatory practices in refinancing or when seeking home equity loans, such as higher fees or unequal treatment based on neighborhood demographics.

As with the rental process, studying housing discrimination in the home-buying process requires examining these interactions in detail to capture subtle and overt discriminatory behaviors. HUD's prior HDS have focused mostly on the initial contact, screening, and viewing stages (outlined in Exhibit 1.2), but some forms of discrimination remain underexamined due to the limitations of current research methodologies.

Given the complexity of both rental and home-buying processes, it is essential to study discrimination which occurs outside of the housing search process phases which have been studied previously. To do so, researchers will likely need to employ methodologies other than in-person paired-testing. As discussed above, discrimination can occur at multiple points throughout these journeys, involving various actors and interactions that are not adequately captured by existing methodologies. To address these gaps, a comprehensive approach is needed to pinpoint where and how discriminatory practices emerge, uncover overlooked stages of the process, and develop innovative strategies for measuring and mitigating housing discrimination. This study sought to identify innovative new strategies for measuring housing discrimination at various phases of the housing search process.

Process to Identify Innovative Methodologies for Housing Discrimination Research

To identify new methods with the potential to augment paired-testing, 2M conducted outreach and engagement with over 650 individual experts and other stakeholders in organizations involved in discrimination-related research or with practical testing experience of discrimination from a range of fields such as economics, sociology, and psychology. The outreach included an email and phone call campaign, a virtual conference featuring five presentations from researchers implementing innovative discrimination methodologies that attracted over 300 attendees, and a follow-on moderated panel discussion. 2M designed and hosted a website (https://hdsstudy.com), which includes information on the project and a page (now closed) for the submission of new methodologies. From this outreach, 2M received 11 submitted methodologies shown in **Exhibit 1.3.**

Exhibit 1.3 | Housing Discrimination Research Methodologies Received and Reviewed by 2M

#	Title	Description
1	***Testing for Discrimination in Menus***	The methodology detects lender discrimination in mortgage pricing by comparing the prices (i.e., rates and upfront fees) of originated loans of minority borrowers to observationally similar White borrowers. The authors planned to measure mortgage pricing discrimination by assessing “the proportion of Black and Hispanic borrowers that would prefer to switch mortgage terms with White borrowers who went to the same lender, at the same time, in the same county, and have similar credit scores, loan-to-value ratio, and loan amount as them, as well as the amount that they would pay to switch.” As a result, both the proportion of the population that would prefer to switch and the amount that they would pay to switch would represent the measures of mortgage pricing discrimination.
2	***Appraisal Bias in Automated Valuation Models: A Quasi-Experimental Approach***	The methodology measures racial discrimination in automated valuation methods (AVM) using a two-step, quasi-experimental design. The first part of the approach uses a propensity score matching model that pairs homebuyers that differ only by the race. The second part of the approach computes differences in model-predicted home prices between each pair of matched homebuyers to identify the extent to which Black and White homebuyers receive different home AVM appraisals. The authors planned to impute the predicted race and ethnicity of homebuyers using a Bayesian algorithm.
3	***Exposing Housing Discrimination in the U.S.: A Mixed-Methods Approach***	The method measures discrimination that takes place before and after interactions between housing seekers and providers (e.g., microaggressions, guiding/steering) with the use of a mixed methods sequential design comprising three phases: quantitative analysis on historical redlining (phase 1); qualitative interviews with housing providers and seekers (phase 2); and data analysis and validation of findings (phase 3). In phase 1, the authors planned to map the historical redlining data constructed in the 1930s by the Home Owners’ Loan Corporation onto the 2020 census tracts from the Mapping Inequality Project to identify the geographic areas most impacted by historical redlining practices. In phase 2, the authors planned to conduct interviews and focus groups with housing providers and housing seekers in the areas identified in phase 1 to understand housing providers’ business practices and thought processes when screening housing applicants as well as housing seekers’ discriminatory experiences as manifested in historically redlined regions. In phase 3, the authors planned to develop themes from the qualitative data and triangulate findings with existing literature to “validate the findings and ensure that the results accurately reflect the experiences of Black and Brown homeowners and the practices of lending institutions.”
4	***Discriminatory Lending Practices***	The authors defined closing costs and time to close indices to support research on discrimination in mortgage lending. The closing costs index is normalized and indexed as a percentage of the total cost. A higher index indicates a higher acquisition cost. Time to close is represented as the number of days between the loan application date and closing date. The methodology uses the indices as dependent variables in regression models that statistically test for associations between the race of the borrower and higher closing costs and longer time to close.
5	***Methodology (untitled)***	The methodology seeks to identify one specific aspect of algorithmic bias: Do online real estate markets systematically exclude disfavored groups because of (potentially neutral) market design decisions in how to rank and display search results? The authors planned to exploit Facebook’s advertising platform—which allows for algorithmic optimization of housing ads—to test whether online platforms’ algorithms lead to disparities in which listings are shown to prospective renters. As in audit studies, the methodology involves creating accounts for prospective renters who differ only by a proxy for a protected trait. To test for bias in the system, the methodology also involves creating accounts for prospective housing providers. The housing provider accounts will create a series of apartment listings. The methodology would measure which simulated renters get shown a listing when a proxy for a protected trait is varied experimentally. Second, it would assess how Facebook’s algorithmic ad optimization process makes any of these disparities worse or better. Third, using Facebook’s ad library (which lists every real estate ad in a geographic area), the researchers would assess observationally whether there are any differences in which renter accounts see real estate housing provider listings.

#	*Title*	Description
6	***Selective Advertising in the Rental Housing Market***	The methodology detects "landlords' discrimination against minorities through selective advertising" by leveraging data on public rental listings and data on rental units that turnover to new renters, regardless of whether the units are publicly listed or not, and then examining whether minority renters are more likely to move into units that were listed publicly than White renters. The authors then planned to use findings from the analysis to understand the extent to which minority renters' choice sets are constrained by selective advertising and how this limits their access to better neighborhood amenities.
7	***Methodology (untitled)***	The methodology combines traditional testing approaches to identify rental agents who appear to treat minority renters differentially yet have taken minimal or no effort to conceal this behavior; survey techniques to document the self-reported practices and attitudes and priorities of agents; and experimental field studies using randomization to test whether sharing information on responses that correlate strongly with realized racial differences in treatment reduce racial differences in follow-up testing. While some agents consciously discriminate against minorities and actively work to avoid detection by local testing organizations, this methodology focuses on identifying factors that can explain the likely much larger number of agents who may be less aware of how their behavior creates racial differences. According to the authors, these factors likely drive the persistent racial differences in access to rental housing identified in traditional testing studies, and examining the identification of such factors could be used to reduce these persistent and widespread racial differences.
8	***Using Behavioral Interventions to Mitigate Racial and Gender Discrimination in the Rental Housing Market***	This methodology uses a correspondence test for discrimination in combination with an experiment that tests the impact of behavioral interventions referred to as "nudges" and "boosts." First, researchers create a set of fake names indicating the gender and ethnic origin of fake applicants. Inquiries about houses with these names would then be sent to landlords through emails. The fake names are also randomly allocated into three groups – a control group, a boost treatment group, and a nudge treatment group. Inquiries from the nudge treatment group end with a social media hashtag, which reminds rental agents to adhere to social trends. Inquiries in the boost treatment group contain positive information about employment, hinting that the applicant has a stable or well-paid job. Inquiries from the control group would not contain either type of information. The prevalence of housing discrimination and the impact of the nudges and boosts could then be estimated by comparing the positive response rates to the inquires between females and males and among different racial groups.
9	***Intracity Homelessness Methodology for Housing Discrimination***	The methodology involves spatial analysis and a survey of the population experiencing homelessness to measure housing discrimination. For the spatial analysis step, the author planned to calculate a racial residential segregation index and identify census tracts by their segregation levels within a city. Next, the author planned to collect information on multifamily rental housing in all census tracts of the selected city, including racial composition of tenants, occupancy or vacancy rates, and rental costs and sizes. In the second step, the author planned to randomly select a sample of individuals experiencing homelessness from all emergency shelters and transitional housing in the selected city and develop a survey that would include questions about respondents' prior addresses and their experience of housing discrimination and residential segregation. Using results from the above steps, the author planned to measure aspects of housing discrimination by comparing survey results and spatial data between White and Black respondents based on their prior addresses.

#	*Title*	Description
10	***Methodology (untitled)***	The author developed a mechanism to reduce discrimination by establishing a centralized federal housing rental unit registry for tenants and landlords. Under this system, landlords and tenants are transparent in their relationships. The author included 10 recommendations: 1. Create a federal standardized website where landlords can register their properties and tenants can search for rental units. 2. Design a standardized application like form 1003, including demographic information. 3. Require landlords to submit a demographic report like the Home Mortgage Disclosure Act (HMDA). 4. Allow prospective tenants to complete online applications and upload their information. 5. Establish affordable landlord rental insurance like FHA mortgage insurance premiums (MIPs). This insurance protects the landlord against loss of rent for six months. 6. Establish lead abatement insurance for landlords like MIP. 7. Provide annual housing discrimination training for landlords. 8. Provide training certifications for tenants in maintaining the housing units and adhering to the lease agreement. 9. Create rating systems for tenants and landlords. Both ratings include property upkeep. 10. Pay the tenant's application fee not exceeding $150 once the application is approved. The author planned a survey of 1,000 landlords to gather their reactions to the recommended rental unit registry.
11	***Discrimination in Refinance Appraisals***	The methodology measures racial discrimination in the appraisal process by "comparing the appraised value of the collateral obtained during a refinance to a benchmark value of the collateral based on an automatic valuation estimate (AVM)." The authors planned to compare the appraisal-to-estimated value ratio across the race of homeowners and the race of appraisers.

2M reviewers used the set of criteria in Appendix **Exhibit A1.1** to review the methodologies. Two SMEs and the expert panel also independently reviewed the methodologies. Based on these reviews, 2M drafted a memo to HUD recommending five methods to be selected for feasibility testing, of which HUD selected three methods for feasibility testing.

Three Innovative Methodologies Selected by HUD

Exhibit 1.4. provides information on the methodologies and the design of the three feasibility tests selected by HUD for implementation.

Exhibit 1.4 | Three Methodologies Selected for Feasibility Tests

Title	Authors	Design of the Feasibility Test
Discrimination in Refinance Appraisals	▪ **Brent W. Ambrose**, Smeal College of Business, The Pennsylvania State University ▪ **James N. Conklin**, Terry College of Business, University of Georgia ▪ **N. Edward Coulson**, Paul Merage School of Business, University of California, Irvine ▪ **Moussa Diop**, Sol Price School of Public Policy, University of Southern California ▪ **Luis A. Lopez**, College of Business Administration, University of Illinois at Chicago	The researchers use Federal Housing Administration (FHA) mortgage refinance data to test whether the race of the borrower or appraiser affects the difference between the appraised value of the home and an estimate of the home value based on Automated Valuation Models.
Selective Advertising in	▪ **Daniel E. Gold**, Department of Economics, University of Wisconsin-Madison	The researchers use data from Dwellsy, a rental listing platform, to identify properties that contain

Title	Authors	Design of the Feasibility Test
the Rental Housing Market	▪ **Lu Han**, Wisconsin School of Business, University of Wisconsin-Madison ▪ **Christopher Timmins**, Wisconsin School of Business, University of Wisconsin-Madison	listed and selectively unlisted units. The researchers link this information with data from InfoUSA to determine the race of individuals that move into listed and unlisted units that turned over in the past year. Next, the researchers use statistical models to test whether race affects the likelihood of moving into a listed or unlisted rental unit. Finally, the researchers measure the degree to which this form of discrimination steers minority renters into neighborhoods with lower-quality amenities.
Discriminatory Lending Practices	▪ **Sheri L. Smith**, Texas Southern University Foundation ▪ **Cheryl L. Toombs**, Texas Southern University Foundation ▪ **Errol Williams**, Texas Southern University Foundation	The researchers use mortgage data from the Multiple Listing Service (MLS) and Home Mortgage Disclosure Act (HMDA) to test whether the race of the borrower affects the time to close and cost to close on mortgage loans and discuss how this form of discrimination exists in Houston area.

Potential Contributions of the Three Selected Feasibility Tests to Existing Research

The three methods selected—*Discrimination in Refinance Appraisals*, *Selective Advertising in the Rental Housing Market*, and *Discriminatory Lending Practices*—highlight distinct but interconnected mechanisms of discrimination in the rental leasing and home-buying processes. Each method illuminates specific stages where systemic biases limit opportunities for minority households to access, afford, or sustain housing, perpetuating socioeconomic disparities.

Discrimination in Refinance Appraisals

Recent articles have reported that minority homeowners, particularly African Americans, are receiving unexpectedly low home appraisal values when attempting to refinance their mortgages (Williamson and Palim, 2022; Ambrose et al., 2024). Following these reports, and a widespread call to address the concern of appraisal bias, the White House created the Interagency Task Force on Property Appraisal and Valuation Equity (PAVE). However, there is limited research on this form of discrimination. Recent studies examining racial disparities in home appraisals between 2000 and 2024 finds significant evidence of systemic bias in the U.S. housing market affecting Black and Hispanic homeowners and neighborhoods. Freddie Mac's research (2021, 2022) found that below-contract-price appraisals occurred twice as frequently in minority neighborhoods compared to White neighborhoods, while Williamson and Palim (2022) documented that Black-owned homes were undervalued by 0.68 to 2.42 percent compared to White-owned homes in refinancing situations. Jean and Blustein (2021) revealed that Black borrowers were twice as likely to have mortgage applications denied due to low appraisals, and Ambrose et al. (2024) found that Black-owned homes were systematically undervalued by 0.6 to 4 percent compared to similar White-owned properties, regardless of the appraiser's race, demonstrating a persistent pattern of racial bias in home valuations across the conventional mortgage market.

The undervaluation of minority appraisals not only increases the cost of borrowing for minority homeowners but also impacts their long-term wealth accumulation. This appraisal bias stands out in refinancing because, unlike during purchase applications, there is no transaction price to anchor the appraisal: while the appraiser has access to the transaction price when producing an appraisal for a purchase mortgage application, the appraisal is often the only estimate of value used in underwriting mortgage refinancing applications. This leaves room for subjective judgments to perpetuate inequities. This methodology provides a baseline for further research into appraisal bias stemming from the contrast between appraisal information for purchase mortgage applications versus refinancing mortgage applications and presents a viable way for PD&R to continue to research the topic as additional FHA data becomes available.

Selective Advertising in the Rental Housing Market

Housing discrimination can occur in different stages of the housing process. One of the most persistent forms of discrimination is "discriminatory steering," where minority households are guided toward minority neighborhoods during the search stage (Dymski, 2006; Galster and Godfrey, 2005; Yinger, 1995). This research highlights selective advertising as a subtle yet impactful form of discrimination that occurs before potential minority renters or buyers begin their housing search. This discriminatory practice is particularly concerning as it can preemptively limit minorities' access to better neighborhoods and amenities, restricting opportunities before they can even participate in the housing market.

Traditional methods for measuring housing discrimination such as paired testing rely on publicly available advertisements to select a sample for testing. As a result, they may fail to detect discrimination by housing providers who may intentionally avoid or limit public advertising to exclude minorities and other potential renters or buyers (Freiberg and Squires 2015; Pitingolo and Ross 2015). Although selective advertising is a known discrimination tactic, its prevalence and impact remain understudied. More robust detection mechanisms and deeper research are required to address how selective advertising practices reinforce segregation and restrict minorities' access to neighborhoods with better schools, services, and opportunities. This method provides a way to identify selectively unlisted rental units, revealing how landlords may manipulate advertisements to exclude minorities.

Discriminatory Lending Practices

Discrimination in mortgage lending persists at multiple stages of the process, from initial meetings with loan officers to finalizing terms. While explicit bias has diminished due to legal protections, structural and institutional racism continues to shape outcomes for minority borrowers. Some housing providers may change their behavior in meetings with housing applicants after the initial interaction, suggesting discrimination in the mortgage lending process is not visible in the initial interactions that prior HDS work has focused on (Freiberg and Squires 2015). Unequal treatment manifests in higher interest rates, increased closing costs, and delays in loan approvals, often driven by implicit bias or discriminatory algorithms in automated underwriting. Factors such as yield spread premiums and differences in service quality exacerbate these disparities, as minority borrowers face higher costs and fewer favorable terms compared to their White counterparts.

Despite advancements in understanding discrimination mechanisms in home lending, significant knowledge gaps persist. The interplay of factors such as credit scores, credit history, closing costs, yield spread premiums, and level of service creates a complex landscape that contributes to unequal outcomes in the mortgage process. These factors, influenced by structural and institutional racism, involve both demand-side and supply-side variables that perpetuate discriminatory lending practices that disproportionately burden minority buyers and widen the racial wealth gap. The complexity of these interactions makes them difficult to detect through surface-level investigations, necessitating a more nuanced analysis of time-to-close metrics and transaction costs. Further research is needed to explore these dynamics in greater depth, particularly regarding the role of automated underwriting and the continuing influence of implicit bias in the lending process. By analyzing time to close and closing costs, this method helps to identify delays and cost increases faced by minority borrowers that may go undetected in initial interaction paired testing research. Addressing these complex, interconnected issues will be crucial to advancing equity and fairness in mortgage lending.

Feasibility Case Studies

The next three chapters present the case studies for each methodology. Each case study was written as a stand-alone document, and the authors were given freedom to develop the case study using a structure they felt best presented their methodology and the associated feasibility test. As a result, there are differences in the sections of each case study; however, each chapter provides a comprehensive understanding of the innovative methodology.

Chapter 2. Case Study: Discrimination in Refinance Appraisals

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Abstract

This study presents a methodology to identify racial disparities in appraisals of owner-occupied residences that are being used as collateral for Federal Housing Administration (FHA) refinanced mortgages. The method involves comparing the appraised value of each property to an estimated value, generated using an Automatic Valuation Model. Hedonic pricing techniques are employed to isolate the impact of the borrower's and appraiser's race. Using information from the Integrated Database (IDB-1) Data Mart and the Computerized Homes Underwriting Management System (CHUMS) dataset linked with an internal roster of FHA appraisers, this study shows that Black and Hispanic owned homes are valued 1.3 and 0.8 percentage points lower than comparable White owned homes, respectively. The race of the appraiser does not influence the results; however, racial disparities are greater in locations where population density or the market share of FHA financing is low, suggesting a fruitful avenue for future research.

Executive Summary

Several recent press articles report that minority homeowners, primarily African Americans, received surprisingly low home appraisal values when seeking to refinance their mortgages. Based on these reports, one could conclude that relatively low appraisal valuations are a reoccurring phenomenon. As a result, there have been mounting calls for the government to investigate and rein in this potential problem that could further impede minorities' ability to accumulate needed wealth through homeownership and improve their communities and lives. Given the seriousness of widespread allegations of racial bias in appraisals, the White House put together an interagency task force to examine the issue.[2]

This project seeks to shed more light on the issue of appraisal fairness by presenting a methodology to assess racial bias in appraisals for mortgage refinancing. The method involves creating a ratio that benchmarks appraised values against independent property value estimates generated from an automated valuation model (AVM).[3] If the appraisal-to-AVM ratio is systematically lower for homes owned by minorities (Blacks and Hispanics) than White-owned homes, then the method suggests that there is a racial bias against minority households. The method (1) incorporates the appraiser's race into the analysis to understand whether homophily affects racial bias, and (2) accounts for the possibility that the AVM contains errors that may be associated with race.

We apply our method to appraisals associated with Federal Housing Administration (FHA)-insured mortgage refinancings. The FHA mortgage refinancing data provides a unique setting since the FHA Integrated Database (IDB-1) Data Mart, which includes every insured mortgage lien within the FHA's portfolio, provides detailed information about the mortgage including the borrower, lender, property, and location. Specifically, the database reports the borrower's race/ethnicity, gender, and number of dependents as well as information about the mortgage (including the closing date, loan purpose, cash-out indicator, loan-to-value, original loan amount, mortgage term, and debt-to-income). Crucial for this project, the database includes the property appraised value and the id number of the appraiser, which are critical elements necessary to implement the method. The final sample consists of 584,366 refinance mortgages (from 2019 to 2023) with minority appraisers accounting for about seven percent of appraisals while minority borrowers account for 38 percent of the sample.[4] The average FHA refinance loan has an appraised value of $294,000 with an AVM of $288,000. The average appraisal-to-AVM estimate is 1.04, which indicates that valuations are about four percent higher than algorithmic value estimates, on average.

We first apply the method to the appraisal-to-AVM ratio without considering the impact of appraiser race. The results show that Black-owned homes are valued 0.4 to 0.5 percentage points lower than comparable White-owned homes. However, we find no evidence that Hispanic-owned homes are undervalued compared to White-owned homes. We then apply a correction to address concerns that AVMs may miss important unobservable property characteristics that also affect

[2] For more information, see: https://pave.hud.gov/actionplan.

[3] Our measure of bias is continuous. It measures the distance between price (as projected onto AVM) and the appraisal. An alternative metric would be to create a discrete measure based on whether the appraisal is inside the AVM confidence interval. However, such a measure would not take into account the bias in the AVM itself, or the degree of bias when the appraisal is outside the confidence interval. As a result, we leave to future research issues regarding the appropriateness of alternative measures of bias.

[4] A minor number of loans originated in 2018, which account for about 1.6% of the refinance sample.

property values. When using the improved valuation benchmark, the results show that, on average, all Black- and Hispanic-owned homes are valued 1.3 and 0.8 percentage points lower than comparable White-owned homes, respectively. The mean property value is approximately $290,000, so these coefficients translate into sizeable average minority valuation discounts of between $2,320 and $3,770. In turn, affected borrowers have less access to equity in their own homes.

For example, the most common type of refinance loan is the cash-out refinance, in which borrowers take out a sufficiently large loan to pay off the existing loan and obtain a cash amount.[5] If the lender’s required loan-to-value ratio is 80%, then the racial bias would cause the cash out component of the loan to be reduced by an average amount of about $3,000 (80% x $3,770) for a Black borrower when compared to a similarly qualified White borrower. These are funds that the borrower could have used for home improvements, debt consolidation, investment, a dependent’s college education, and so on. Additionally, in the traditional refinance scenario, such racial appraisal bias could increase the likelihood that a loan application is rejected for affected Black and Hispanic borrowers.

We next include appraiser race in the statistical model and find two key results. First, minority borrowers receive lower valuations, consistent with the first analysis. Second, within any given borrower race category, valuation does not appear to vary with appraiser race. For example, White-owned homes appraised by Black and Hispanic appraisers are not valued significantly differently from White-owned homes appraised by White appraisers. Also, the Black discount when the appraiser is White is virtually identical to the Black discount when the appraiser is Black (1.4 percentage points versus 1.2 percentage points). Similarly, Hispanic owners receive the same discount (0.7 percentage points) whether the appraiser is White or Hispanic. Thus, the analysis provides no evidence of homophily in valuations.

Lastly, we provide a cross-sectional analysis on racial bias. We examine the effect of the borrower’s race, considering various neighborhood characteristics including the tract-level racial composition, median house value, population density, and FHA market share of loan originations. We find racial bias is most sensitive to the population density and FHA market share but not necessarily the median house value or racial composition.

Our analysis demonstrates the feasibility of detecting racial and ethnic bias in home appraisals using a large sample of mortgage refinance applications that include information on the property, the appraisal, and the appraiser. The findings are consistent with the application of standard appraisal rules and procedures followed by all appraisers, which results in minority homeowners tending to receive lower valuations on average, as opposed to individual appraisers specifically using race as a factor in determining the value of an individual property. While our analysis does not specify the impact on individual borrowers or quantify the number of impacted borrowers, one could create a distribution of predicted price-to-appraisal ratios, devise a cutoff level of “harm”, and count the number of households beyond that threshold. Since such analysis is beyond the scope of this paper, we leave it to future research. However, regardless of the source of the observed differences, the implication is that minority homeowners, on average, had less access to their home equity than similar White homeowners.

[5] Cash-out refinance loans comprise 76% of the FHA refinance mortgages in the sample (see **Exhibit 2.2**).

Introduction

The Fair Housing Act of 1968, enforced by the Department of Housing and Urban Development (HUD), protects individuals buying or renting a home, seeking housing assistance, or getting a mortgage from discrimination based on race, color, religion, sex, family status, disability, and national origin. In addition to prohibiting all forms of discrimination in lending, the fair lending component of the law specifically provides protection from discrimination in property appraisal. Despite these protections against discrimination granted by the law, several studies have documented evidence of entrenched discrimination in housing and other related markets (e.g., real estate brokerage, property tax assessments, and mortgage lending).[6]

More recently, a flurry of press articles report of minority homeowners, primarily African Americans, receiving surprisingly low home appraisal values when seeking to refinance their mortgages.[7] Based on these reports, relatively low appraisal valuations appear to be a reoccurring phenomenon experienced in many states, and likely not restricted to mortgage refinancing as these reports may suggest. As a result, there have been mounting calls for the government to investigate and rein in this potential problem that could further impede minorities' ability to accumulate needed wealth through homeownership and improve their communities and lives. Given the seriousness of widespread allegations of racial bias in appraisal, the White House put together an interagency task force on Property Appraisal and Valuation Equity (PAVE) to examine racial discrimination in home appraisals. The PAVE task force has issued recommendations aimed at advancing the goal of equitable valuation across the United States. As part of this effort, HUD has recently reached an agreement with the Appraisal Foundation, the nation's foremost authority on the valuation profession, to improve racial diversity in the industry.

This project seeks to shed more light on the issue of appraisal fairness by presenting a methodology to assess racial bias in appraisals for mortgage refinancing. The methodology is designed to tease out the incidence and magnitude of appraisal bias in situations where the appraiser has less access to other value estimates that could serve as valuation benchmarks. For example, in producing an appraisal to support a purchase mortgage application, the appraiser has access to the transaction price, which serves as an anchor for the appraisal valuation. As a result, such appraisals are rarely lower than the contract price, which limits the incidence and magnitude of potential appraisal bias. By contrast, the appraisal is often the only estimate of value used in underwriting mortgage refinancing applications, which may explain why most of the anecdotal evidence of racial appraisal bias reported in the press concerns refinancing mortgages, making them the ideal test case for observing potential incidents of appraisal bias.

Another important reason why our methodology focuses on refinance mortgages is the need to ensure that the appraiser effectively knows the race of the borrower. For refinance mortgages, the borrower usually occupies the home and interacts with the appraiser during the property inspection. Therefore, the appraiser is more likely to observe the race of the borrower for refinance loans than with purchase mortgage applications, where the appraiser is more likely to interact with

[6] For example, Ondrich, Ross and Yinger (2003) and Zhao, Ondrich, and Yinger (2006) show evidence of raced-based disparate treatment by real estate agents, whereas Munnell et al. (1996) and Ambrose, Conklin, and Lopez (2021) show evidence of racial pricing disparities in the cost of mortgage credit. Meanwhile, Howell and Korver-Glenn (2018) and Avenancio-Leon and Howard (2022) demonstrate similar patterns of racial disparities in property tax assessments.

[7] For example, see Haythorn (2020) and Malagón (2020).

the seller. Consequently, refinancing mortgages are a more appropriate focus than purchase mortgages when examining the question of racial bias in home appraisals.

Our method involves benchmarking appraised values against independent property value estimates generated from an automated valuation model (AVM). This method allows us to thoroughly test whether the owner's race impacts the appraiser's evaluation by examining racial differences in appraisal (A)-to-AVM ratios. If the A-to-AVM is systematically lower for homes owned by minorities (Blacks and Hispanics) than White-owned homes, that would suggest that there is a racial bias against minority households. It is important to note that our analysis will identify racial disparities at the appraiser level, because we observe the identity of the appraiser and compare valuation differences by the same appraiser of equivalent minority- and White-owned properties.

AVM estimates may miss important unobservable property characteristics that also drive property values. To address this potential source of bias in our estimates based on AVMs, we use a methodology developed by Ambrose et al. (2024) to generate more accurate value estimates from purchase mortgage data that includes both property prices and AVMs.

However, examining whether the A-to-AVM is affected by the appraiser's race is also critical. If the A-to-AVM is lower for minority groups but the effect weakens when the appraiser and borrower share the same race, the results would suggest a possible mechanism to even the playing field. Understanding the sensitivity of race-based effects is important from a policy perspective because it enables guidance on how to address such injustice in minorities' homeownership experience. We again borrow methods from Ambrose et al. (2024) to address this issue.

Overview of Literature on Appraisal Bias

We present a chronological overview of various studies that have explored racial disparities in home valuations. An early study by LaCour-Little and Green (1998) shows that Black loan applicants in the 1990s were more likely to receive low appraisal values, even after accounting for differences in the property's neighborhood and mortgage loan contract. This study, which relies on a relatively small sample of purchase mortgages in Massachusetts, does not quantify the magnitude of appraisal bias suffered by Black loan applicants. In a more recent Brookings study that uses the American Community Survey data and home prices from Zillow, Perry, Rothwell, and Harshbarger (2018) report an undervaluation of homes in Black-majority neighborhoods of about 22 to 23 percent after accounting for differences in neighborhood quality and property quality. This study was influential in drawing attention to racial disparities in home valuations and was featured in testimony to the U.S. House of Representatives Committee on Financial Services Subcommittee on Housing, Community Development, and Insurance, on "What's Your Home Worth? A Review of the Appraisal Industry." However, the Perry, Rothwell, and Harshbarger (2018) study does not speak directly to racial bias in home valuation by appraisers because it relies on information provided by either homeowners (via the U.S. Census Bureau American Community Survey) and sellers or real estate agents (via list prices). Moreover, this work, along with the work by Freddie Mac discussed below, has been scrutinized by the American Enterprise Institute for other errors and omissions.

The investigative press reports of widespread undervaluation of Black-owned homes noted earlier have brought the issue of fairness in home appraisals to the fore, forcing the two dominant home mortgage market makers, Freddie Mac and Fannie Mae, to take a close look at the question. A set of studies by Freddie Mac (Freddie Mac, 2021, 2022) of appraisals for purchase loans of single-family homes from 2015 to 2020 document significant disparities and the greater propensity for appraised value to fall below the contract price of the property when the purchaser is a minority. At the neighborhood level, the Freddie Mac studies find that below-contract-price-appraisals occur in 15.4 percent of purchase mortgages in Hispanic neighborhoods, 12.5 percent in Black neighborhoods, but only 7.4 percent in White neighborhoods. This sizable racial gap in below-price appraisals suggests that home purchases requiring mortgage financing are less likely to close due to collateral shortfall in Black and Hispanic neighborhoods and for Black and Hispanic borrowers more generally. Instead of examining purchase mortgages as in the Freddie Mac study, Williamson and Palim (2022) examine more than 1.8 million refinance applications from 2019 to 2020 obtained from Fannie Mae's Desktop Underwriter system. They report that the median appraisal for Black-owned homes falls by as much as 0.58 percent below estimates provided by AVMs, whereas those of White-owned homes reach up to 1.84 percent above AVM estimates. Their findings imply that in today's conventional mortgage loan market, Black-owned homes are undervalued by about 0.68 percent to 2.42 percent, limiting equity for Black (and possibly Hispanic) borrowers by about $2,669 to $4,527 when compared to White borrowers who are seeking to refinance their homes. Together, these studies provide evidence of significant racial bias in home appraisals in the conforming mortgage market.

In a study commissioned by the Illinois Realtors, Jean and Blustein (2021) examine reasons for loan application denial using the Home Mortgage Disclosure Act (HMDA) public data from 2007 to 2020. They find that Black and Hispanic home buyers are more likely than their White counterparts to have their mortgage applications denied due to collateral (i.e., a low appraisal). More specifically, this study finds that purchase mortgage applications by Black borrowers are twice as likely (8.7 percent vs 3.5 percent) to be denied by lenders because of low appraisal of the property than similar applications from White borrowers.[8]

A more recent study by Ambrose et al. (2024), which pioneered the methodology used in this feasibility study, tests for racial disparities in home appraisals on refinance mortgages originated between 2000 and 2007 by New Century Financial Corporation, a defunct major subprime lender. Unlike the case of a home purchase appraisal, where the appraiser may not know the race of the borrower, the appraiser is likely to know the race of the borrower for a refinance mortgage because the appraiser meets the homeowner, who is also the borrower. Although their data came from a single lender, it includes home valuations by more than 61,000 unique appraisers nationwide, of whom approximately 40 percent are still active. The study finds that Black-owned homes were undervalued by 0.6 percent to 4 percent when compared to similar White-owned homes appraised by the same appraiser after accounting for differences in location and property characteristics. Moreover, the documented appraisal racial gap appears to be systemic and not necessarily driven by a few bad apples. However, the study finds no evidence that the appraisal gap varies with the race of the appraiser, implying White appraisers are not the only culprits.

[8] On the positive side, a below-purchase price appraisal can trigger renegotiation for a lower purchase price, which protects buyers from overpaying and lowers their property taxes, while also mitigating mortgage fraud.

Feasibility Test Methodology

We test whether minority-owned homes are valued differently than similar White-owned homes in appraisals associated with FHA-insured mortgage refinancings. As noted earlier, appraisals associated with mortgage refinancings are better suited for examining racial bias than appraisals associated with purchase mortgages for several reasons. First, we observe the borrower's race in the FHA mortgage data, and the appraiser is also likely to observe the borrower's race on a refinance mortgage because the appraiser typically meets with the owner, who is also the borrower. In purchase mortgages, by contrast, the appraiser typically meets with the current owner (the seller) or the real estate agent, and we do not observe seller or agent race in our data. Second, whereas lenders on purchase mortgages have at least two estimates of market value, the appraisal and the sales contract price, for refinance mortgages there is no contract price, making the appraisal crucial for determining mortgage terms. Finally, appraisers usually see the sales contract on appraisals associated with purchase mortgages, which can bias their valuation toward the contract price (price anchoring), leaving less room for subjective bias. Refinance appraisals, without a clear target value, allow for more subjective judgment.

We follow the approach developed in Ambrose et al. (2024) and focus on the variation in the ratio of the appraised value (A) of a property to its estimated value (V):

$$\frac{\boldsymbol{A_i}}{\boldsymbol{V_i}} = \delta_1 Black_i + \delta_2 Hispanic_i + X_i\beta + Appraiser_i + \mathrm{Tract_i} + \mathrm{Time_i} + \varepsilon_i \qquad (1)$$

where $\frac{\boldsymbol{A_i}}{\boldsymbol{V_i}}$ is the ratio between the appraised value and a benchmark property valuation; X_i includes a set of borrower controls (number of dependents; years at job; whether borrower is self-employed; income in the natural log form, gender) and mortgage characteristics (high debt-to-income ratio indicator; low credit score indicator; loan term less than 30 years indicator; and cash-out refinance indicator); $\mathrm{Tract_i}$ and $\mathrm{Time_i}$ represent the census tract and origination year-month fixed effects, respectively, that account for time-invariant spatial factors and temporal changes in national economic conditions that impact valuations; and ε_i is an error term.

$Black_i$ and $Hispanic_i$ are indicator variables denoting whether the property owner is non-Hispanic Black and Hispanic, respectively. Homes owned by non-Hispanic White borrowers are the reference group. δ_1 and δ_2 are the key coefficients to be estimated.

To control for differences in valuations by individual appraisers, we include appraiser fixed effects, $Appraiser_i$, which help account for appraiser-specific heterogeneity. This approach is similar to methodologies used in paired-audit experiments, which aim to isolate the impact of certain variables, such as race, on outcomes. The estimates for the δ parameters are derived from variation in property valuations and owner race among appraisers who have conducted valuations for both White and minority property owners. The null hypothesis states that, after adjusting for potential confounding factors, the race of the property owner does not influence the appraiser's valuation ($\delta_1 = \delta_2 = 0$).

We use two different valuation benchmarks ($\boldsymbol{V_i}$) in our analysis. The first benchmark is an AVM estimate. To be precise, an AVM is a statistical model that generates value estimates for individual properties by incorporating data on the property's features (such as the number of bedrooms and bathrooms, square footage, etc.) and time-varying local real estate market information. While the specific model used is proprietary, automated valuations typically rely on data from public records and local market transactions, including sold, active, and off-market prices, as well as property listing details and their respective characteristics (Jensen and Reifler, 2010). We use an AVM estimate provided in FHA's Computerized Homes Underwriting Management System (CHUMS).

AVM estimates may not be the best valuation benchmark for appraisals, as they rely on potentially outdated or incomplete data based as they are on publicly available information. AVMs therefore may not consider value-relevant property characteristics that are not captured in publicly available datasets, but are observed by appraisers (e.g., property condition and uniqueness). In our context, this could lead to systematic over- or under-valuation of minority-owned homes if these characteristics are correlated with race. We introduce a second value benchmark, $\widehat{\boldsymbol{V_i}}$, which combines AVM estimates with proxies for other-value relevant characteristics that are not captured by AVMs. The model used to create this valuation benchmark is based on a sample of purchase mortgages where the market value (sales price) is observed. This is appropriate because the goal of an appraisal is to estimate said market value.

We use a two-stage procedure to obtain $\widehat{\boldsymbol{V_i}}$. We begin by calibrating a valuation model using a sample of properties purchased with an FHA insured loan. We project the log sales price (market value) onto AVM value estimates and other controls with the following model:

$$\boldsymbol{ln}(\boldsymbol{P_i}) = \rho \ln(AVM_i) + \delta_1 Black_i + \delta_2 Hispanic_i + X_i\beta + \mathrm{Tract_i} + \mathrm{Time_i} + \varepsilon_i \qquad (2)$$

The control variables proxy for value-relevant factors that are not captured by the AVM. For example, borrower income likely serves as a proxy for property quality not captured by the AVM estimates (see **Exhibit 3.2** for a list of additional control variables).[9] Next, we use the coefficient estimates from Equation 2, calibrated on the purchase sample, to predict out-of-sample log market values ($\widehat{ln(P_i)}$) for properties in our refinance sample. The estimated market value, in levels, for the refinance sample can be estimated as:

$$\widehat{\boldsymbol{V_i}} = \exp\{\widehat{ln(P_i)} + \hat{\sigma}^2\}. \qquad (3)$$

In summary, to implement this procedure, we first estimate Equation 2 using a sample of purchase mortgage applications, where the market value (purchase price) is observed. We use the coefficient estimates to predict out-of-sample market values of the properties in the refinance mortgage sample. We then estimate the baseline regression, Equation 1, using the refinance sample but with the "predicted" property values serving as the valuation benchmark for the appraisal ($\frac{A_i}{\hat{V}_i}$).

We also examine whether racial disparities in appraisal vary with appraiser race. In particular, we explore if minority-owned properties receive more favorable valuations when the appraiser shares the same race as the owner (homophily). Ambrose et al. (2024) conduct a similar exercise, inferring appraiser race from appraiser names. A key difference in our study is that we observe appraiser race rather than infer it. Appraisals for FHA-insured mortgages must be completed by appraisers on

[9] Note that the control variables in Equation (2) include the same ones as in Equation (1) except for the cash-out refinance indicator since it is always 0 in the purchase sample.

the FHA Appraiser Roster. As part of the registration process, appraisers disclose race and ethnicity, which we use in our analysis.

Data

Our analysis uses Federal Housing Administration (FHA) mortgages from the Integrated Database (IDB-1) Data Mart, which includes every insured mortgage lien within FHA's portfolio. The IDB-1 dataset provides information about the mortgage including the borrower, lender, property, and location. We collect from this database the borrower's race/ethnicity, gender, and number of dependents. Additionally, we collect mortgage characteristics including the closing date, loan purpose, cash-out indicator, loan-to-value, original loan amount, and mortgage term. Property characteristics include a condo indicator, county, ZIP code, and the exact property address and geo location. This dataset also includes the property appraised value and the id number of the appraiser, which are critical elements.

We merge these data with information from the Computerized Homes Underwriting Management System (CHUMS) dataset using the mortgage case number. The CHUMS is an automated system used for processing appraisal documentation for single family mortgage insurance applications and loan applications. The CHUMS data contains AVM estimates and information about the appraisals. The AVM comes from the Electronic Appraisal Delivery system. Effectively, the AVM uses the same information that is available to the appraiser in developing an assessment. It also has information on borrower underwriting: high debt-to-income flag, low/missing FICO credit score flags, and self-employed flag.

We link these data to an internal roster of FHA appraisers using unique appraiser identification numbers. This allows us to observe the race and ethnicity of the appraiser. Additionally, we link information about neighborhoods from the 2019 American Community Survey, 5-year Estimates to each observation. The final sample excludes properties that are missing the appraiser ID and other critical variables in the analysis. Moreover, we limit the analysis to FHA loans that are FHA standard mortgages (203B), Improvements mortgages (203K), and Condominium mortgages (234C) that were originated from 2019 to 2023, excluding HECM (255) and HOPE For Homeowners (257) mortgages.[10] Furthermore, to establish adequate comparison groups, we limit the sample to observations where the borrower is either Black, Hispanic, or White and the appraiser is either Black, Hispanic, or White. The sample excludes observations mapped to more than one race. The final sample consists of 584,366 refinance mortgages and 2,204,047 purchase mortgages.

Exhibit 2.1 reports a matrix exhibiting the match between borrowers and appraisers by race for refinance mortgages in Panel A and purchase mortgages in Panel B.

Exhibit 2.1 | Race Tabulation

Panel A: Refinance				
Borrower Race	Black Appraiser	Hispanic Appraiser	White Appraiser	Total
Black	6,972	3,894	73,353	84,219
Hispanic	2,454	9,165	65,226	76,845
White	9,590	12,171	401,541	423,302
Total	19,016	25,230	540,120	584,366
Panel B: Purchase				
Borrower Race	Black Appraiser	Hispanic Appraiser	White Appraiser	Total
Black	18,924	15,291	356,698	390,913
Hispanic	12,136	58,083	446,876	517,095
White	17,065	34,220	1,244,754	1,296,039
Total	48,125	107,594	2,048,328	2,204,047

[10] Less than 2% of the sample includes loans originated in 2018.

Minority appraisers account for about seven percent of appraisals while minority borrowers account for 38 percent of FHA mortgages in the sample. These statistics are consistent with the racial distribution of appraisers reported by the Appraisal Foundation and Appraisal Institute, which report that Black and Hispanic appraisers make up less than 10 percent of all appraisers.[11]

Exhibit 2.2 reports summary statistics by mortgage type. The average FHA refinance loan has an appraised value of $294,000 with an AVM of $288,000, whereas the average FHA purchase loan has an appraised value of $256,000 with an AVM of $250,000. Both types of mortgages have an average A-to-AVM ratio of 1.03, which indicates that valuations are about three percent higher than algorithmic value estimates, on average. The A-to-$\widehat{V}_i$ is 1.04 and 1.02 for refinance and purchase mortgages, respectively.

Exhibit 2.2 | Summary Statistics of FHA Mortgages

Variable	Refinance Mean	Refinance SD	Purchase Mean	Purchase SD
Appraisal-to-AVM Ratio	1.03	0.14	1.03	0.14
Appraisal-to-$\widehat{V}$ Ratio	1.04	0.15	1.02	0.12
Property Appraisal Value ($)	294,465	143,160	256,123	119,881
AVM Estimate ($)	288,348	138,515	250,178	118,135
Dependents Count	0.64	1.19	0.93	1.30
Borrower's Employment Years	7.75	8.18	4.81	5.67
Self-Employment Flag	0.00	0.03	0.03	0.17
Total Annual Effective Income ($)	81,665	42,006	76,985	39,377
Gender: Male	0.57	0.50	0.55	0.50
Gender: Female	0.41	0.49	0.42	0.49
Gender: Other	0.02	0.12	0.02	0.15
Gender: Not Reported	0.00	0.02	0.00	0.01
Debt-to-Income: High	0.12	0.33	0.14	0.34
Debt-to-Income: Low	0.16	0.37	0.16	0.36
Debt-to-Income: Not Available	0.00	0.03	0.01	0.07
Mortgage Term (Months)	349.65	38.73	359.56	7.88
Mortgage Term Less than 30 Years Flag	0.08	0.27	0.00	0.06
Adjustable Rate Mortgage Flag	0.00	0.05	0.00	0.02
Cash-Out Mortgage Flag	0.76	0.43	0.00	0.00
Observations	584,366		2,204,047	

The typical FHA borrower has roughly $80,000 in total annual effective income, with five to seven years of employment history at origination. Virtually all FHA mortgages in the sample have fixed interest rates and a term of 30 years with monthly payments (only eight percent of refinance mortgages have a shorter term). Among the refinance mortgages, about 76 percent are cash-out refinances, in which the borrower obtains cash from the lender upon getting a new loan with modified contract terms. This suggests that a low appraisal valuation would reduce the available equity that a homeowner may extract from his or her primary residence.

Feasibility Test Results

Exhibit 2.3 reports coefficient estimates from Equation 1 using appraisals associated with FHA-insured refinance mortgages. To maintain brevity, we only report the race coefficients in all models in Exhibit 2.3.

[11] For more information, see: https://www.appraisalinstitute.org/.

Exhibit 2.3 | Appraised Value to AVM

VARIABLES	(1)	(2)	(3)	(4)
Black Borrower	-0.005***	-0.002***	-0.005***	-0.004***
	(-8.136)	(-3.673)	(-7.790)	(-6.519)
Hispanic Borrower	-0.000	-0.001**	0.005***	0.004***
	(-0.566)	(-2.499)	(8.457)	(6.803)
Observations	584,366	584,205	576,761	573,241
Adjusted R-squared	0.000	0.017	0.099	0.131
Constant	✓	✓	✓	✓
Controls		✓	✓	✓
Census Tract FE			✓	✓
Appraiser FE				✓
Year-Month FE		✓	✓	✓

Notes: *The stars ***, **, * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level. In parentheses are t-statistics, based on standard errors clustered by census tract.*

Column 1 controls only for borrower race so the coefficients can be interpreted as unconditional differences in appraisal to AVM ratio (A-to-AVM) ratio relative White-owned homes. The Black borrower coefficient is significant at the one percent level of confidence and suggests that Black-owned homes are valued 0.5 percentage points lower, on average, than White-owned homes. The Hispanic coefficient is not distinguishable from zero. Column 2 adds controls for borrower and mortgage characteristics, as described above, as well as year by month fixed effects. The Black coefficient remains negative and significant, but the absolute magnitude of the coefficient declines. The Hispanic coefficient is negative and small, but now significantly different from zero at the five percent level of confidence. Introducing location (census tract) fixed effects in column 3 has a significant impact on the coefficients. Black owned homes are valued at 0.5 percentage points less than White owned homes, but Hispanic owned homes are valued 0.5 percentage points higher. Assuming a well specified model, the results imply that appraisals are discounted for Blacks, but Hispanics receive more favorable valuations than Whites. Column 5 adds individual appraiser fixed effects to account for appraiser heterogeneity, with the absolute magnitude of both race coefficients declining slightly.

In **Exhibit 2.4** we turn to our second valuation benchmark. Column 1 shows coefficient estimates from our valuation model using appraisals associated with home purchases, where we project the log purchase price on log AVM value, race, and the other control variables that proxy for unobserved value relevant property attributes. Only the race and log AVM coefficients are reported for brevity. The adjusted R-squared is 0.820 in column 1 of Exhibit 2.4, suggesting the model does a good job of explaining variation in sales prices. As we would expect, there is a strong positive conditional correlation between Ln(AVM) and log purchase price. Note that conditional on Ln(AVM) and our other controls, both the Black and Hispanic coefficients are positive and significant at the one percent level in column 1, implying that the AVM may systematically undervalue minority-owned homes. Note that the race coefficients in column 1 are meant to proxy for differences between minority- and White-owned homes that are not captured by the AVM or the other control variables. Next, we apply the coefficient estimates from the valuation model in column 1 to the observations in the refinance sample to obtain our second valuation benchmark, $\widehat{V_i}$ from Equation 3.

Exhibit 2.4 | Appraised Value to Predicted Value

	(1)	(2)	(3)
	First Stage	**Second Stage (V_1)**	**Second Stage (V_2)**
Sample	Purchase	Refi	Refi
Dep. Var.:	Ln(Purch Price)	App-to-$\hat{V}$	1[Appraisal $\leq \hat{V}$]
Ln(AVM)	0.841***		
	(2,112.448)		
Black Borrower	0.012***	-0.013***	0.043***
	(44.546)	(-20.652)	(17.213)
Hispanic Borrower	0.011***	-0.008***	0.037***
	(45.347)	(-14.457)	(15.285)
Observations	2,203,437	572,361	572,361
Adjusted R-squared	0.820	0.202	0.109
Constant	✓	✓	✓
Controls	✓	✓	✓
Year-Month FE	✓	✓	✓
Census Tract FE	✓	✓	✓
Appraiser FE	X	✓	✓

Notes: *The stars ***, **, * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level. In parentheses are t-statistics, based on standard errors clustered by census tract.*

Column 2 reports coefficient estimates from a regression model where the dependent variable is the appraised value divided by $\hat{V}_i$, which we will refer to as A-to-$\hat{V}_i$. The coefficients on Black and Hispanic are negative and significant at the one percent level of confidence. Black- and Hispanic-owned homes are valued 1.3 and 0.8 percentage points lower than comparable White-owned homes, respectively. The mean property value in our refinance sample is approximately $290,000, so these coefficients translate into sizeable average minority valuation discounts between $2,320 and $3,770.

Although the results in column 2 show average differences in valuation, a related but distinct question is whether minorities are *more likely* to receive low valuations. Our measure of a low valuation is a binary variable indicating whether the appraised value is less than the valuation benchmark. Thus, we estimate a linear probability model using the low valuation indicator as the dependent variable and report the results in column 3 of Exhibit 2.4, with all other control variables the same as in column 2. Black-owned properties are 4.3 percentage points more likely to receive a low valuation relative to White-owned properties; however, Hispanic owned properties are 3.7 percentage points more likely to receive a valuation below the benchmark value. Taken together, the results in columns 2 and 3 suggest that both Black- and Hispanic-owned properties are more likely to receive lower valuations than comparable White-owned properties.

Next, we examine whether valuation discounts vary with appraiser race. We are interested in whether minority valuation discounts are reduced when the borrower and the appraiser share the same race (homophily). We create a series of mutually exclusive indicator variables capturing the different appraiser and borrower race combinations. Because minority borrowers tend to work with either White appraisers or appraisers that share the same race, we exclude observations where both the borrower and appraiser are minorities, but of different races (e.g., Hispanic borrower /

Black appraiser).[12] Because appraiser race does not vary within appraiser, we exclude appraiser fixed effects from our models in **Exhibit 2.5**.

Exhibit 2.5 | Appraised Value to Predicted Value by Race Groups

VARIABLES	(1) App-to-$\hat{V}$	(2) App-to-$\hat{V}$	(3) App-to-$\hat{V}$
Black Borrower	-0.014***		
	(-22.197)		
Hispanic Borrower	-0.007***		
	(-13.028)		
Black Appraiser		-0.000	
		(-0.041)	
Hispanic Appraiser		0.000	
		(0.260)	
White Borrower/Black Appraiser			-0.000
			(-0.126)
White Borrower/Hispanic Appraiser			-0.000
			(-0.110)
Black Borrower/White Appraiser			-0.014***
			(-21.440)
Black Borrower/Black Appraiser			-0.012***
			(-6.762)
Hispanic Borrower/White Appraiser			-0.007***
			(-12.112)
Hispanic Borrower/Hispanic Appraiser			-0.007***
			(-5.304)
Observations	575,873	575,873	569,546
Adjusted R-squared	0.170	0.170	0.170
Constant	✓	✓	✓
Controls	✓	✓	✓
Year-Month FE	✓	✓	✓
Census Tract FE	✓	✓	✓
Appraiser FE	X	X	X

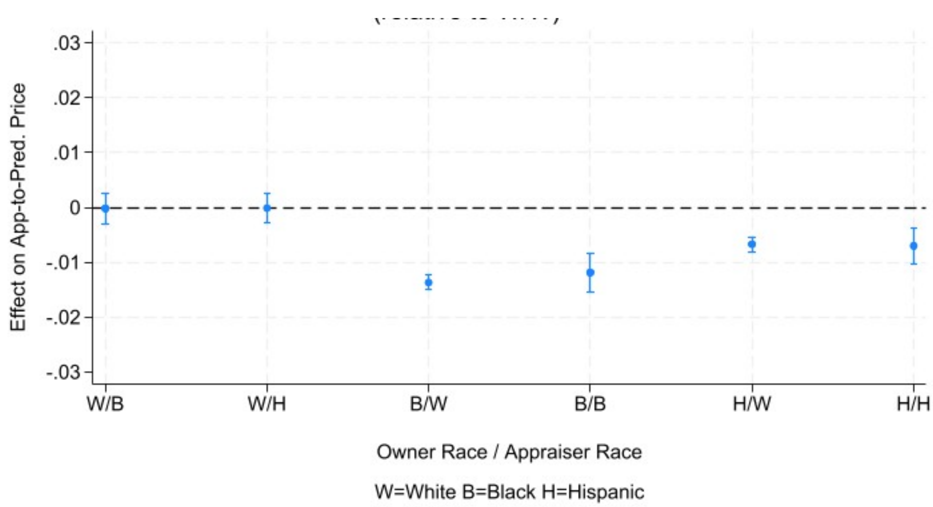
Notes: *The stars ***, **, * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level. In parentheses are t-statistics, based on standard errors clustered by census tract.*

Column 1 serves as a baseline to show that excluding appraisal fixed effects should not be problematic, as the results in column 1 are nearly identical to the results when appraiser fixed effects are included in column 2 of Exhibit 2.4. Column 2 of Exhibit 2.5 indicates that there are no systemic valuation differences in the A-to-$\hat{V}_i$ ratio across all mortgages that can be linked to the race of the appraiser. Lastly, the model in column 3 of Exhibit 2.5 regresses A-to-$\hat{V}_i$ on the borrower race/appraiser race indicators, with White-owned homes appraised by White appraisers (White borrower / White appraiser) as the omitted category. Thus, coefficient estimates should be interpreted as average differences relative to White-owned properties appraised by White appraisers. To facilitate comparisons across borrower race, we plot the coefficient estimates and 95 percent confidence intervals from Exhibit 2.5 column 3 in **Exhibit 2.6** below.

[12] In Exhibit A2.1, reported in the Technical Appendix, we provide an alternative estimation approach where all observations are kept but the main model (Equation 1) is estimated by appraiser race. The results provide supporting conclusions.

Exhibit 2.6 | Marginal Effect on App to Predicted Price

(relative to W/W)



Two key results emerge from Exhibit 2.6. First, minority borrowers receive lower valuations, consistent with our earlier evidence. Second, within any given borrower race category, valuation does not appear to vary with appraiser race. For example, White-owned homes appraised by Black and Hispanic appraisers (W/B and W/H in the exhibit) are not valued significantly differently from White-owned homes appraised by White appraisers (W/W—the omitted category). Also, the Black discount when the appraiser is White is virtually identical to the Black discount when the appraiser is Black (1.4 percentage points versus 1.2 percentage points). A Wald test fails to reject the null hypothesis that these coefficients are equal (B/W = B/B; Prob > F = 0.3021). Similarly, Hispanic owners receive the same discount (0.7 percentage points) relative to W/W whether the appraiser is White (H/W) or Hispanic (H/H). To summarize, the results in Exhibit 2.5 and Exhibit 2.6 provide no evidence of homophily in valuations.

Next, we provide several cross-section analyses. First, in **Exhibit 2.7** we examine whether racial disparities in valuation vary with population density (measured as the number of people per square mile in a census tract, *ppsqmi*). Our measure of population comes from the 2019 American Community Survey (ACS), 5-year estimates. Valuation may involve greater uncertainty in areas that are sparsely populated, leaving more room for valuation subjectivity, which in turn could lead to larger racial disparities in valuation. Hence, we subdivide the sample as follows: below the 10^{th} percentile (44 *ppsqmi*), below the 25^{th} percentile (321 *ppsqmi*), between the 25^{th} and 75^{th} percentile (321 to 5,413 *ppsqmi*), above the 75^{th} percentile (5,413 *ppsqmi*), and above the 90^{th} percentile (11,189 *ppsqmi*). Exhibit 2.7 reports results from models estimated separately by population density. The Black coefficient is negative and significant across all models. The Hispanic coefficient is negative and different from zero in the first four models. Consistent with our hypothesis, both the Black and Hispanic discounts are largest in areas with low population density.

Exhibit 2.7 | Appraised Value to Predicted Value by Neighborhood Density Measured as People Per Square Mile

VARIABLES	(1) Density < 44	(2) Density < 321	(3) 321 ≤ Density < 5,413	(4) Density ≥ 5,413	(5) Density ≥ 11,189
Black Borrower	-0.048***	-0.029***	-0.010***	-0.013***	-0.009*
	(-3.767)	(-10.992)	(-13.880)	(-9.288)	(-1.649)
Hispanic Borrower	-0.034***	-0.013***	-0.007***	-0.008***	0.003
	(-3.916)	(-5.152)	(-10.222)	(-7.883)	(0.687)
Observations	18,489	117,670	358,232	84,941	11,829
Adjusted R-squared	0.205	0.173	0.183	0.270	0.258
Constant	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓
Census Tract FE	✓	✓	✓	✓	✓
Appraiser FE	✓	✓	✓	✓	✓

Notes: *The stars ***, **, * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level. In parentheses are t-statistics, based on standard errors clustered by census tract.*

Exhibit 2.8 estimates the models separately by average neighborhood price levels using information on the median home values reported in the 2019 ACS 5-year estimates at the tract-level. Columns 1 and 3 restrict the sample to where the median home value is less than the 10th percentile ($75,400) and greater than the 90th percentile ($546,800), respectively. The magnitude of the Black coefficient is similar across all models, but the statistical significance varies, likely due to the small sample sizes in columns 1 and 3. By contrast, the Hispanic discount's significance increases with average neighborhood property value.

Exhibit 2.8 | Appraised Value to Predicted Value by Neighborhood Median House Value

VARIABLES	(1) Value < $75,400	(2) $75,400 ≤ Value < $546,800	(3) Value ≥ $546,800
Black Borrower	-0.012	-0.012***	0.012*
	(-1.294)	(-20.208)	(-1.793)
Hispanic Borrower	0.012	-0.008***	0.016***
	(0.997)	(-14.335)	(-3.462)
Observations	8,021	552,499	6,207
Adjusted R-squared	0.213	0.192	0.419
Constant	✓	✓	✓
Controls	✓	✓	✓
Year-Month FE	✓	✓	✓
Census Tract FE	✓	✓	✓
Appraiser FE	✓	✓	✓

Notes: *The stars ***, **, * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level. In parentheses are t-statistics, based on standard errors clustered by census tract.*

In **Exhibit 2.9** we examine whether minority valuation disparities vary with neighborhood racial composition at the tract-level also obtained from 2019 ACS 5-year estimates data. Column 1 includes appraisals in neighborhoods where minorities constitute more than 80 percent of the population. Column 2 includes neighborhoods where more than 80 percent of the population is White. Column 3 includes all other neighborhood racial compositions. Minority-owned homes are valued lower than comparable White-owned properties regardless of the neighborhood's racial composition, with slight differences in the magnitude of the racial bias across these neighborhoods. In other words, even in neighborhoods where most of the population are minorities, minority-owned homes have lower valuations than comparable White-owned homes.

Exhibit 2.9 | Appraised Value to Predicted Value by Neighborhood Racial Composition

VARIABLES	(1) Minority Share > 80%	(2) White Share > 80%	(3) White Share ≤ 80% and Min Share ≤ 80%
Black Borrower	-0.015***	-0.014***	-0.012***
	(-4.823)	(-8.488)	(-17.827)
Hispanic Borrower	-0.006**	-0.011***	-.008***
	(-2.485)	(-6.459)	(-13.249)
Observations	34,641	224,117	304,809
Adjusted R-squared	0.276	0.180	0.210
Constant	✓	✓	✓
Controls	✓	✓	✓
Year-Month FE	✓	✓	✓
Census Tract FE	✓	✓	✓
Appraiser FE	✓	✓	✓

Notes: *The stars ***, **, * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level. In parentheses are t-statistics, based on standard errors clustered by census tract.*

Lastly, as the impact of borrower race on the A-to-$\widehat{V}_i$ appears to be most sensitive to information availability, we test the sensitivity of the racial effects across the proportion of purchase loan applications in the market reported in the Home Mortgage Disclosure Act dataset that are for the FHA program. Intuitively, in neighborhoods where most purchase loan applications are FHA, there may be a greater similarity among the properties available on the market that could act as sales comparison data for appraisers. **Exhibit 2.10** shows that the effects of Black and Hispanic borrower race are much greater when the FHA share is below five percent than when the FHA share is above 29%, suggesting that a lack of information may be a factor influencing racial disparities in appraisal valuations.

Exhibit 2.10 | Appraised Value to Predicted Value by FHA Share

VARIABLES	(1) FHA Share < 5%	(2) 5% ≤ FHA Share < 29%	(3) FHA Share ≥ 29%
Black Borrower	-0.024***	-0.014***	-0.010***
	(-4.393)	(-16.586)	(-10.956)
Hispanic Borrower	-0.011**	-0.009***	-0.007***
	(-2.341)	(10.746)	(-8.417)
Observations	23,153	324,251	199,816
Adjusted R-squared	0.301	0.195	0.196
Constant	✓	✓	✓
Controls	✓	✓	✓
Year-Month FE	✓	✓	✓
Census Tract FE	✓	✓	✓
Appraiser FE	✓	✓	✓

Notes: *The stars ***, **, * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level. In parentheses are t-statistics, based on standard errors clustered by census tract.*

The methods used in this section to detect racial valuation disparities can easily be implemented by HUD in the future. We provide Stata code to clean the data and implement our analysis. The code can be modified to examine valuation disparities across different dimensions, including different time periods, locations (e.g., states, regions), or area characteristics (e.g., area level of racial animus). Additionally, future research could enhance the models by adding additional variables considered important. For example, although the two-stage procedure we present is designed to account for possible error in the AVM estimates, future research could modify Equation 2 to include AVM confidence scores to improve the model's precision. Alternatively, the use of census tract fixed effects may be replaced with time-varying tract level demographic variables (e.g., from the U.S. Census) to capture neighborhood specific trends or relax implicit assumptions about the independence of government-created geographic boundaries and racial bias.

Conclusion

In this report we demonstrated the feasibility of detecting racial and ethnic bias in home appraisals using a large sample of mortgage refinance applications that include information on the property, the appraisal, and the appraiser. That feasibility is noteworthy given the large sample we have been able to leverage, the wide variety of factors we have been able to consider, and the care taken in balancing the investigations of the hypotheses of interest with the ability of the data to test them.

Our conclusions from this study include:

1. Property appraisals are systematically lower for refinance mortgage applicants who are Black and Hispanic, relative to an estimate of the market transaction price of those properties.
2. These lower appraisals are not dependent on the race or ethnicity of the appraiser.
3. The extent to which minority applicants receive lower appraisals does depend on neighborhood characteristics, particularly neighborhood density.

There are several distinct dimensions on which this research could be expanded. One dimension would be the characteristics of the appraiser. In this study, we have limited ourselves to accounting for the appraiser's race, but it would be of interest to account for their education and experience. For example, if the most egregious examples of racial bias were performed by appraisers with lower levels of experience in the field, this would provide a ready-made policy recommendation: appraisers would benefit from greater training.

Appendix

Exhibit A2.1 | Appraised Value to Predicted Value by Appraiser Race

VARIABLES	(1) All Appraisers Purchases ln(Price)	(2) All Appraisers Refi App-to-$\hat{V}$	(3) White Appraisers Refi App-to-$\hat{V}$	(4) Black Appraisers Refi App-to-$\hat{V}$	(5) Hispanic Appraisers Refi App-to-$\hat{V}$
Ln(AVM)	0.841***				
	(2,112.448)				
Black Borrower	0.012***	-0.013***	-0.013***	-0.010***	-0.013***
	(44.546)	(-20.652)	(-19.972)	(-2.843)	(-4.987)
Hispanic Borrower	0.011***	-0.008***	-0.008***	-0.007*	-0.009***
	(45.347)	(-14.457)	(-13.246)	(-1.727)	(-4.216)
Observations	2,203,437	572,361	528,240	12,668	18,370
Adjusted R-squared	0.820	0.202	0.197	0.217	0.294
Constant	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Year-Month FE	✓	✓	✓	✓	✓
Census Tract FE	✓	✓	✓	✓	✓
Appraiser FE	X	✓	✓	✓	✓

Notes: *The stars ***, **, * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level. In parentheses are t-statistics, based on standard errors clustered by census tract.*

Chapter 3. Case Study: Selective Advertising in the Rental Housing Market[13]

Authors: Daniel E. Gold, Department of Economics, University of Wisconsin-Madison; Lu Han, Wisconsin School of Business, University of Wisconsin-Madison; Christopher Timmins, Wisconsin School of Business, University of Wisconsin-Madison

Abstract

A growing body of literature has documented persistent racial discrimination in rental housing markets, often using experimental (audit or correspondence) studies where fictitious identities request to view a housing unit. These methods are not designed to capture a subtle form of discrimination where landlords choose not to advertise certain units, instead reserving them for prospective tenants after an initial screening or other process to select renters on certain attributes. These selectively unadvertised units will not appear in the sample for an experimental analysis, potentially biasing the results of these studies. In this paper, we introduce an innovative method for detecting selective advertising. Our approach uses a large marketing dataset to track property unit turnovers in 27 major U.S. metropolitan areas. We match this data with a rental listings dataset to identify turnover units that are not publicly advertised. By comparing the racial composition of occupants in listed versus "hidden" units and controlling for alternative factors that might account for racial sorting, we assess the extent of discrimination through selective advertising. We find that this form of discrimination against Black and Hispanic renters is particularly severe in neighborhoods with higher income, education levels, and rents; where other forms of discrimination are more restricted; and in neighborhoods nearing "tipping points" in racial composition.

[13] We would like to thank the participants in the UW Grainger summer research workshop for their helpful comments and insights. All remaining errors and omissions are our own. We are also grateful to Cody Sondgeroth for his outstanding research assistance.

"Apart from misrepresenting the availability of apartments to African American testers, the manager also confided to a White tester that the landlord does not advertise available apartments because 'if you run ads, you get all kinds of things.'" Freiberg and Squires (2015)

Introduction

Housing discrimination based on color and race is illegal according to the Fair Housing Act of 1968 and its 1988 amendments, but racial discrimination still takes place at various stages of housing transactions, including home search (Christensen and Timmins, 2022; Ewens et al., 2014; Hanson and Hawley, 2011), negotiation over prices or rent (Bayer et al., 2017), home appraisal (Ambrose et al., 2024), and mortgage lending (Aaronson et al., 2021; Ambrose et al., 2021; Zhao, Ondrich, and Yinger, 2006; Frame et al., 2021). Among these, one of the most persistent forms of discrimination has been "discriminatory steering" of minority households into minority neighborhoods during the housing search stage (Dymski, 2006; Galster and Godfrey, 2005; Yinger, 1995). The discrimination that occurs at the initial search stage is concerning because it could eliminate the possibility of a successful housing transaction for the minority home seeker before the rest of the process even has a chance to unfold. Experimental work using White and minority testers with similar characteristics posing as prospective home buyers or renters has sought to measure the extent of racial discrimination. However, there have been growing concerns that these experimental approaches may not be able to detect a particularly subtle form of discrimination that occurs during the housing search stage. More specifically, enforcement agents have found that landlords who have a preference for certain renters' characteristics may withhold advertising on units for which they wish to control tenant access. Instead, these landlords may rely on word-of-mouth, referrals from current tenants, or real estate agents to locate prospective renters who meet their standards. Some units might still be advertised to attract a pool of potential renters for initial screening, after which landlords may assign them to unlisted units if desired. This selective advertising approach is often cited as a reason why correspondence and audit studies may fail, as these practices are challenging to detect, posing significant obstacles for fair housing enforcement (Freiberg and Squires, 2015).

In this paper, we introduce an innovative method for detecting selective advertising in rental markets. A landlord is considered to be selectively advertising if they choose to list some units while leaving others unlisted, AND if those unlisted units are more likely to be occupied by White renters, even after accounting for other factors that might influence racial sorting. Compared with audit and correspondence studies, the alternative strategy that we propose takes a data-intensive approach to finding broad evidence of selective advertising and learning about the contexts in which it is more likely to take place.

We present our analysis in several steps. First, using granular rental listing data merged with corresponding turnover data, we demonstrate that, unlike in owner-occupied markets, choosing not to list some available units is a common practice in the rental markets we study. While unlisting on its own is not necessarily selective advertising, it creates opportunities for landlords to avoid listing certain units for discriminatory reasons.

We then show that, conditional upon knowing that the units in a building could have been listed (i.e., in the same building or by the same manager that has units that were listed), how the attributes of the residents who end up in the units that were listed differ from those who end up in the unlisted units. This is after controlling for key neighborhood attributes (e.g., neighborhood race percentages) that might influence the sort of people who seek out apartments in that neighborhood. We find evidence that, indeed, Black and Hispanic renters are more likely to end up in the listed units. This result is consistent with an intentional policy of a landlord or property manager to save unlisted units for White renters, as has been suggested by evidence from fair housing enforcement and which would be illegal. It might also be evidence of landlords or property managers relying on some non-listing strategy to fill unlisted units that, while not intentionally designed to steer renters of color away from those units, has a disparate impact in that direction. For example, a property manager might request a letter of reference from an existing tenant rather than posting the listing on a commercial website. This would create a network based on the pool of existing residents, which could preserve the building's racial demographics.[14] A practice resulting in a disparate impact may still be illegal under HUD's "Discriminatory Effects" Rule.[15] The evidence of selective advertising highlights a disparate impact and suggests a new direction for targeting enforcement resources.

We also demonstrate how the extent of selective advertising varies based on tenants' income, family status, the neighborhood-level proportion of White tenants, and the degree of landlords' callback discrimination. Finally, we analyze the extent to which this practice hinders minorities' access to better amenities and neighborhoods with better opportunities.

To measure the extent in which selective advertising may lead to racial discrimination in housing, we required a setting in which we could compare the racial composition of tenants who end up in properties that were advertised to those in properties that were not. To address this challenge, we constructed a new dataset by merging, for the first time, two large data sources:

(i) Individual level turnover data compiled by Data Axle (a.k.a. InfoUSA) Residential Historical Files, which track the residential locations of hundreds of millions of individuals between 2006–2023 and provide information on race/ethnicity, gender, age, address, renter/owner status (we provide more information in the Data section below); and

(ii) Rental listing data at the property unit level compiled by Dwellsy (www.dwellsy.com), which contain information on address, unit number, rent, listing time, and landlord or property manager between 2020–2023, with a focus on the class of professionally managed properties.

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[14] Note that our results are robust to the inclusion of tract-, building-, and manager-specific fixed effects. If one manager is more likely to use non-listing strategies to recruit tenants than other managers, this would be controlled for by including the manager fixed effects. Moreover, if word-of-mouth recommendations tend to come from tenants whom landlords "favor" and those tenants, in turn, recommend friends of the same race, we would expect to see the results we observe only if landlords disproportionately favored White tenants. This does not inherently indicate discriminatory intent on the part of landlords, but it suggests a possible avenue for racial bias, whether explicit or implicit. While intent is complex to demonstrate, our study highlights potential disparities in tenant selection that result from informal marketing practices. By examining this further, HUD could consider whether reliance on word-of-mouth recommendations alone aligns with fair housing principles, regardless of intent.

[15] For more information, see: https://www.hud.gov/press/press_releases_media_advisories/hud_no_23_054#:~:text=The%20Fair%20Housing%20Act%20prohibits,actions%20brought%20by%20private%20plaintiffs.

The merged dataset is unique in several aspects:

(i) The dataset includes never-before-linked building-unit and individual tenant-level information on tenure status, race, income, rents, property characteristics, and an indicator for if a property unit is publicly listed. This makes it possible for us to relate the racial characteristics of actual tenants to the landlords' advertising choice.

(ii) The dataset is large, containing more than 719,000 observations, covering a wide range of U.S. metropolitan areas between 2021–2023. This allows us to examine whether discrimination is widespread and statistically significant.

(iii) The data provides granularity at the property unit level, enabling us to examine each multifamily building operated by the same landlord, as well as units across different buildings under the same management. This facilitates the use of fixed effects to control for determinants of the demographic composition of buildings that are driven by other property manager strategies aside from selective advertising. We analyze this behavior in 27 of the cities that have been the focus of the U.S. Department of Housing and Urban Development (HUD) Housing Discrimination Studies (HDS).[16]

A unit is classified as unlisted if it undergoes tenant turnover without being listed beforehand. We restrict our sample, listed and unlisted, to properties (i.e., buildings) with at least one unit already listed on the Dwellsy platform. This ensures that any unlisted property is not due to the cost of adopting the Dwellsy software, as the fixed cost has already been incurred and the practical cost of listing additional units is minimal. Therefore, the decision not to advertise a unit on Dwellsy is likely strategic rather than unintentional. We expect that this will be a conservative approach for identifying unlisted units. For example, we will not identify instances where entire buildings are left unlisted, nor will we capture selective advertising in market segments that do not list on Dwellsy. In practice, this limits our analysis and conclusions to professionally managed properties. Exploring how results vary across other market segments is something that we hope to pursue in future research.

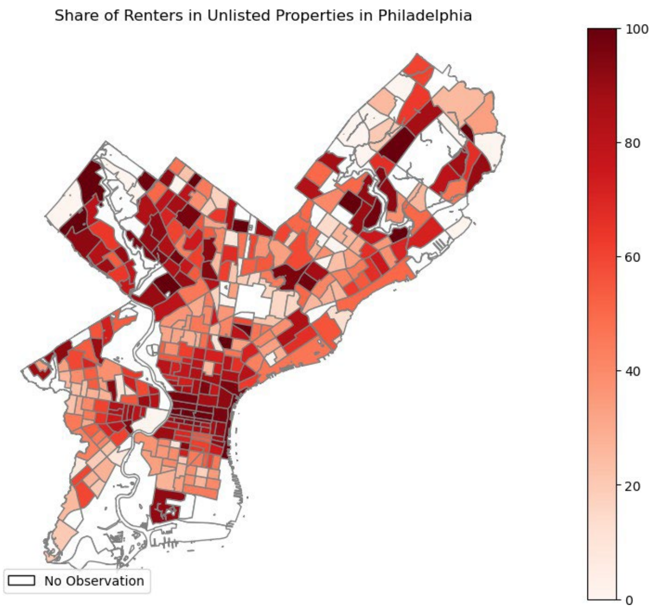
We start our analysis by examining the systematic difference in racial composition between listed and unlisted rental units. **Exhibit 3.1** (a) through (c) provides a heuristic introduction to this strategy using the city of Philadelphia as an example. **Exhibit 3.1** (a) and (b) show the spatial distribution of Black renters alongside the distribution of unlisted properties. In neighborhoods with more unlisted properties, there are fewer Black renters, suggesting that landlords might target White renters through informal networks or word of mouth. **Exhibit 3.1** (c) further shows that unlisted properties are more frequently found in areas with lower poverty rates, indicating that such selective (un)advertising is more likely to occur in neighborhoods with potentially better local amenities.

These patterns are not unique to Philadelphia. Across 27 major cities studied in the HDS, Black renters are, on average, 20 percent more likely than White renters to occupy listed apartments. Furthermore, unlisted units are disproportionately located in areas with lower poverty rates, higher

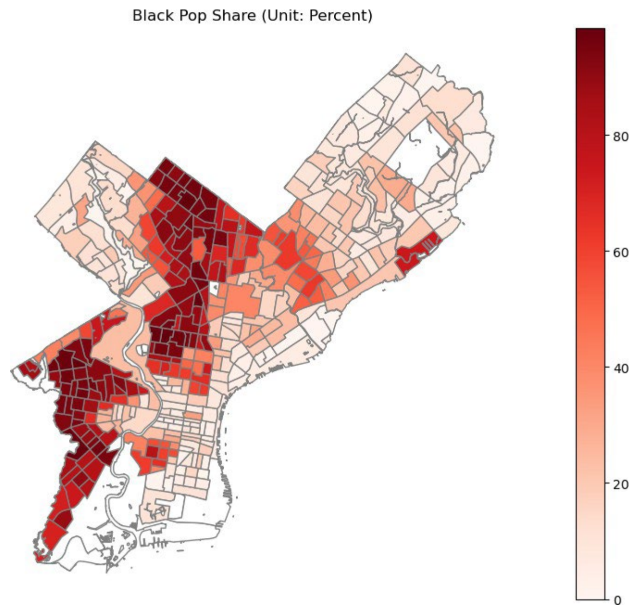
[16] HUD's Housing Discrimination Studies have used 27 cities chosen for the role that race plays in the local housing markets. We use these cities for our analysis, dropping Richmond, Virginia because of problems with missing data.

rent, more educated populations, and better environmental conditions. Although descriptive, this evidence suggests racial disparities in the local poverty rate—possibly related to the access to local amenities, potentially driven by selective advertising.

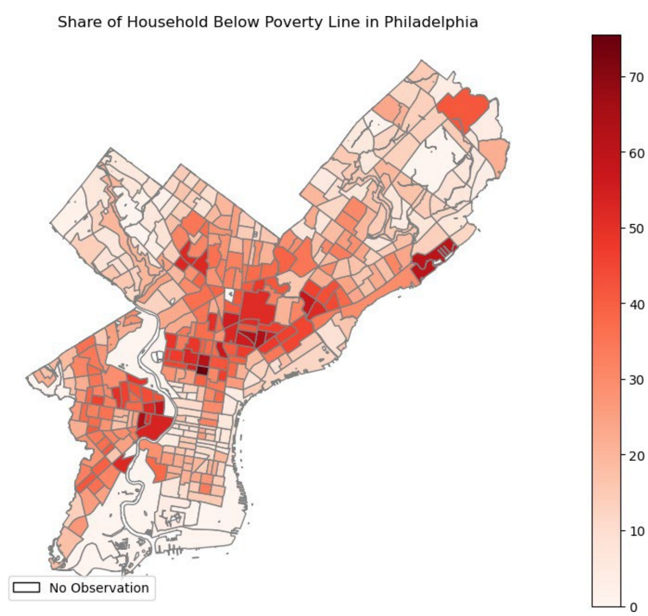
Exhibit 3.1 | Tract-Level Demographic Statistics for the City of Philadelphia



(a) Share of renters in unlisted units



(b) Black share of population



(c) Share of population in poverty

Motivated by this disparity, we aim to establish causal evidence and explore the consequences of selective advertising in rental markets. We begin by testing whether listed units are more likely to be rented to Black tenants, using a multinomial logit model. That model describes the outcome—

the race of the eventual resident of a rental unit, which can take one of five discrete values—as a function of whether or not that unit was listed along with controls for tract-level rent indices, the fraction of White renters, MSA fixed effects, and year fixed effects. We find that listed apartment units are 12.5 percent more likely to be occupied by Black tenants, 8.1 percent more likely by Hispanic tenants, and 40 percent less likely by Asian tenants compared to White tenants. These estimates remain robust to the inclusion of additional tract-level controls, suggesting that selective advertising is steering Black and Hispanic renters away from unlisted units. These results remain robust even with the inclusion of detailed neighborhood characteristics, such as the racial composition of renters, percentage of college graduates, local poverty rate, quality-adjusted Zillow rent indices, and local air quality—all of which help control for race-based sorting driven by non-discriminatory factors.

A legitimate concern is the possibility of non-selective unlisting. For instance, some landlords may not need to advertise a property if it is leased through corporate arrangements or subleased by an existing tenant. On this front, it is important to emphasize that evidence of selective advertising is not identified by the fraction of unlisted units, but rather by comparing the racial composition of listed and unlisted units within buildings already covered by Dwellsy. Unlisted units due to subleasing or corporate moves do not pose a threat to our strategy if these scenarios do not generate a systematic correlation between whether a property is listed and the racial composition of the tenants who subsequently occupy it. If they do—i.e., White tenants tend to sublease to other White tenants—then the question becomes to what extent are landlords using this as a tool to control the racial composition of their buildings.

Another potential concern is omitted variable bias. For instance, certain neighborhoods might experience higher turnover rates among specific racial groups due to factors such as immigration, company relocations, or college student turnover. In such cases, vacant units might be advertised internally rather than publicly. Alternatively, some managers may have relationships with alumni and/or corporate or community networks that could disproportionately attract tenants of a certain race, even without intentional steering.

To account for these unobserved factors, we estimate a linear probability model predicting a binary outcome—whether or not the eventual renter in a unit is Black. The advantage of the linear framework is that we can control for a rich set of fixed effects capturing unobservables at either the level of the census tract or the property manager (property managers may manage multiple buildings in different parts of the same MSA). This approach helps us mitigate bias from confounding factors at various levels, providing a cleaner identification strategy. For example, property manager fixed effects control for strategies used by the property manager that might have the inadvertent effect of steering more Black renters into these units. Tract fixed effects control for neighborhood characteristics that might induce more Black renters to seek apartments in places where there happen to be more listed units. Building fixed effects control for building characteristics that might attract a certain group of renters more than others. In our most demanding specification, we find that, all else equal, Black renters are 48 percent more likely to occupy listed units than non-Black households when controlling for unobservables at the tract and property manager level.

Exploring heterogeneity in our results, we find that selective advertising targets not only minorities but also families with children. Across nearly all racial groups (except for Asians), families with children are more likely to rent listed units than those without children. Black and Hispanic families face discrimination through selective advertising regardless of whether they have children, but the discrimination is significantly greater for those with children. Notably, the level of discrimination against White families with children is only slightly less than that experienced by minority families with children from the Black, Hispanic, or other racial groups.

We further explore the heterogeneity in the degree of selective advertising based on the percentage of the White population in a neighborhood. For Black renters, evidence of selective advertising becomes apparent when neighborhoods have a White population of approximately 60 to 80 percent (i.e., 20 to 40 percent minorities). This result is similar to that in Hanson and Hawley (2011), who find that rental discrimination, measured by landlords' response rates to email inquiries, is most severe in neighborhoods with a minority share between 5 to 20 percent, which corresponds to the tipping point range for White population outflows identified in Card, Mas, and Rothstein (2008).

Finally, we explore heterogeneity in the extent to which selective advertising varies with other documented forms of discrimination. In particular, we incorporate landlords' estimated call-back discrimination rates from a large-scale correspondence study of discrimination in rental markets in the 50 largest MSAs in the United States (Christensen, Sarmiento-Barbieri, and Timmins, 2021). Results suggest that selective advertising substitutes for more direct forms of discrimination (e.g., failing to respond to inquiries to view units from renters of color). This is important, as it suggests that a great deal of discriminatory activity may be missed by more traditional measurement approaches.

Why does selective advertising matter? It is important because when minorities and families with children are steered away from potential rental units during their search, they lose not just an apartment, but also the benefits associated with a particular location. Location is an asset: access to amenities and jobs provides a crucial context central to social inequality. We therefore explore the extent to which selective advertising may steer minorities away from neighborhoods with better amenities. We measure these amenities by income (poverty rates), education (percentage of the population with a college degree or higher), air quality (PM2.5), and a zip code-level quality-adjusted rent index.

We find that the detrimental steering effect on Black renters is mostly driven by neighborhoods with better amenities. Using quality-adjusted zip code-level ZORI rental indices as a proxy for local amenities, we find that listed apartment units are 37.4 percent more likely to be occupied by Black tenants compared to their White counterparts in neighborhoods where rents are above the average MSA level, and only 10.5 percent in neighborhoods where rents fall below the average MSA level. A closer investigation reveals that such steering is more likely to occur in neighborhoods with lower poverty rates, improved air quality, and more college graduates.

Thus, selective advertising not only limits Black renters' housing consumption options but also potentially restricts their access to better amenities. This is consistent with a report from the 2007 American Housing Survey, which shows that Black households are 30 percent more likely than White households to report safety concerns with their drinking water, 60 percent more likely to report a serious crime in their neighborhood, and twice as likely to report being dissatisfied with the neighborhood elementary school. Our results suggest that at least part of this disparity is due to discrimination against Black renters at the very beginning of the rental search process.

Compared to traditional forms of discrimination in rental markets, such as the number of houses shown and landlords' callback responses, discrimination through selective advertising is more subtle and harder to detect. Yet this form of discrimination is potentially more harmful, as it limits renters' housing choices at the very beginning stage of their rental search. We find that the degree of selective advertising is greater in areas where more blatant forms of discrimination (e.g., landlords' response rates to email inquiries) are more restricted. While recent HUD studies indicate a decline in some blatant forms of housing discrimination, our findings suggest that selective advertising may increasingly serve as a substitute for traditional forms of discrimination if it continues to go undetected.

Literature Review

Discriminatory Use of Information in Online Housing Markets

Our work is related to a literature that has explored the use of information in housing markets to achieve discriminatory outcomes. Prior to the Internet age, Galster, Freiberg, and Houk (1987) examined data on the listing behavior from a single large real estate company in Milwaukee, WI and found that sellers in Black neighborhoods receive less advertising activity (fewer/shorter ads and fewer open houses) compared to those in predominantly White neighborhoods. More recently, Boeing (2020) analyzed the over- versus under-representation of vacant units on Craigslist, and Adu and Delmelle (2022) examined the differential use of exclusionary language depending upon the racial makeup of the neighborhood where a unit is located. Kuk et al. (2021) focus on how advertisement language on Craigslist either emphasizes unit and neighborhood attributes or focuses on application criteria and logistics depending upon the neighborhood where the unit is located. Most directly related to our work, Humber and Matthews (2020) consider National Fair Housing Alliance v. Facebook, a case in which plaintiffs accused Facebook of allowing housing advertisers to target users based on protected characteristics such as age, sex, race, or zip code.

Experimental Approaches to Measuring Discrimination

Extensive research has been conducted on field experiment methods to reveal discrimination. Bertrand and Duflo (2017) offer a comprehensive overview, highlighting the differences between audit and correspondence studies. In an audit study, two testers —differing only by a specific characteristic like race—perform real-world tasks (such as inquiring about property availability) in person. These studies have been used to explore various markets, including bargaining at car dealerships (Ayres and Siegelman, 1995), gender discrimination in restaurant hiring (Neumark et al., 1996), and the combined effects of race and criminal records on employment (Pager, 2003). By contrast, correspondence studies involve fictitious applicants who interact solely via mail or online.

These methods were developed as alternatives to simple outcome studies, where discrimination is measured by regressing economic outcomes (e.g., wages) on productivity indicators and race. Such outcome studies may be biased by unobservable factors related to productivity and race. Audit and correspondence studies are designed to mitigate this issue.

Paired-Tester Audit Studies

A significant body of research has examined discrimination in the process of searching for rental and sales properties, especially at the stage when potential buyers or renters inquire about advertised units and receive recommendations or viewings. This phase is crucial as it helps shape the choice set available to the prospective tenant or buyer.

Historical data from HDS audits conducted in 1977, 1989, 2000, and 2012 shows a dramatic decrease in overt forms of housing discrimination, such as not showing an advertised property. However, it remains unclear whether more subtle forms of discrimination, like the number of properties shown, have also declined.

Research in this field often focuses on the likelihood that majority versus minority testers are given property viewings and opportunities to inspect. To understand the underlying mechanisms, studies typically test three hypotheses:

(i) Taste-based discrimination, where greater bias is expected from realtors with personal attributes that may make them more prejudiced;

(ii) Catering to White customers, where realtors may discriminate to avoid offending a prejudiced White clientele, especially in neighborhoods at risk of gentrification or where White customers have concerns about school integration; and

(iii) Statistical discrimination, where realtors base their behavior not on the individual characteristics of a minority customer but on the average attributes associated with that customer's race or class group.

Research in this area has largely focused on paired-tester audits, with notable studies including those conducted in Boston in 1981, as well as the HDS audits in 1989, 2000, and 2012. These studies share a common goal: measuring discrimination at the stage when realtors suggest rental units or homes for purchase and when customers are invited to inspect properties. However, they vary in their measures of discrimination and the minority groups they examine.

Yinger (1986), using data from the 1981 Boston audit, examined discrimination between White and Black testers. He advocated for the use of tester-pair fixed effects to account for unobservable factors specific to each audit pair (i.e., the two testers visiting a given realtor), a method that has since become standard in the field. Yinger's findings revealed that, on average, Black testers were informed of roughly 30 percent fewer rental units than their White counterparts, and White testers were invited to inspect 57 percent more apartments. Among the three hypotheses commonly explored in this literature, Yinger's study provided evidence supporting discrimination aimed at catering to a White customer base.

Page (1995) builds upon Yinger (1986) by using a Poisson model to account for the discrete and non-negative nature of the number of houses shown, as well as the heteroskedastic variance dependent on the total number of units available. Analyzing data from the 1989 HDS audit, Page finds that Black and Hispanic testers are shown 80 percent and 90 percent of the number of units shown to White testers, respectively. These results are consistent across both rental and sales properties, though the disparity is more pronounced in some cases. The findings are best explained by either White customer or statistical discrimination mechanisms, particularly for Black testers.

Analysis across HUD's Housing Discrimination Studies indicates that one of the most enduring forms of discrimination is the steering of minority households into minority neighborhoods during the search stage (Dymski, 2006; Galster and Godfrey, 2005; Yinger, 1995). Christensen and Timmins (2022) observe significant differences in neighborhood characteristics—such as pollution, crime, poverty, and the skill levels of local residents—of properties shown by realtors to White, African American, Hispanic, and Asian testers in the 2012 HDS. Further, Christensen and Timmins (2023) use a correspondence study, involving online interactions with racially distinct names to assess rental markets in five major cities. They find that discrimination results in average welfare costs—defined as an equivalent variation in income, or the amount of income that you would need to take away from individuals in the absence of discrimination to induce the same loss of welfare as caused by discriminatory constraints—of 3.5 to 4.4 percent of annual income for renters of color, with African American renters experiencing higher welfare costs as their incomes increase.

There is a literature describing the limitations of audit studies.[17] For example, it may be difficult to test for particular types of bias, such as bias against individuals with certain disabilities. It is also unlikely that testers will be identical in all respects except for the attribute of interest. Moreover, testers are aware of their role and may act in such a way as to try to sway the results toward or against finding evidence of discrimination. While sacrificing some richness in the portrayal of a racial identity, the investigator retains more control in a correspondence study where identities are typically conveyed by a name on an application or resume and can therefore be more easily controlled.

Correspondence Studies

Correspondence studies have been employed to examine labor market discrimination based on race and ethnicity. One of the most well-known studies used fictitious resumes sent in response to job advertisements in Boston and Chicago newspapers, varying only by the racialized names (Bertrand and Mullainathan, 2004). The findings revealed that resumes with White-sounding names received 50 percent more callbacks, and that stronger observable resume attributes mitigated the negative impact of Black names, indicating statistical discrimination. Following this, correspondence studies have explored discrimination in various other labor market contexts, including race and ethnicity (McGinnity et al., 2009; Baert et al., 2015; Booth et al., 2012; Maurer-Fazio, 2012; Galarza et al., 2014), gender (Carlsson, 2011; Booth and Leigh 2010), caste and religion (Banerjee et al., 2009; Wright et al. 2013), previous unemployment spells (Eriksson and Rooth, 2014; Ghayad, 2013), and sexual orientation and appearance (Ahmed et al., 2013; Patacchini et al., 2015; Bailey et al., 2013; Rooth, 2009).

In housing rental markets, correspondence studies have analyzed the role of race and ethnicity (Carlsson and Eriksson, 2014; Ahmed and Hammarstedt, 2008; Ahmed et al., 2010; Ewens et al., 2014; Hanson and Hawley, 2011; Carpusor and Loges, 2006), sexual orientation (Ahmed and Hammarstedt, 2009), and immigrant status (Baldini and Federici, 2011; Bosch et al., 2010).

One problem that might arise in both audit and correspondence studies, specific to the internet age, is the potential for those being audited to check the online profile of the tester or fictitious applicant. To address this problem, Acquisti and Fong (2015) develop an online presence for their fictitious applicants in a correspondence study of labor market discrimination. Similarly, Barto˘s et al. (2013) create websites for applicants and monitor their access rates. A separate set of problems may arise if those being audited actively pursue strategies to avoid detection.

[17] See, for example, Siegelman and Heckman (1993); Heckman (1998); Aranda (2015); Freiberg and Squires (2015).

Enforcement

Fair housing enforcement groups[18] have uncovered ample evidence that landlords and property managers are aware of the audit and correspondence studies described above and actively undertake strategies to avoid detection. Freiberg and Squires (2015) describe how property managers use word-of-mouth, referrals from existing tenants, real estate agents, and online platforms to find prospective applicants without listing vacant units. This allows them to screen applicants before making properties available. In one example, Freiberg and Squires (2015) note, “Although housing providers may have many reasons for using fewer public sources to reach prospective renters or buyers, discrimination is more likely to occur when providers restrict knowledge of, or access to, available housing by limiting advertising primarily to favored populations.” They go on to say that “Recent enforcement testing suggests that contacts by testers to housing providers, as part of initial visits by matched paired testers, may not always capture the housing provider’s practices in a way that adequately discloses or confirms whether fair and equal treatment is being provided.”

While enforcement groups have developed strategies to document this sort of discriminatory behavior, these approaches are time-consuming and labor-intensive. The alternative strategy that we describe below takes a data-intensive approach to finding broad evidence of selective advertising and to learning about the contexts in which it is most likely to take place.

Data

Our data is constructed primarily from two sources: Dwellsy and InfoUSA. Listings, including United States Postal Service (USPS)-verified address and (if applicable) unit number, asking rent, listing date, delisting date, and the name of listing company, come from Dwellsy. Dwellsy is a listing platform that contracts with listing software companies and does not charge per listing. Property managers who use a platform that contracts with Dwellsy may choose to advertise their unit without cost to potential renters on Dwellsy’s website.

Individual and household characteristics are from InfoUSA’s Residential Historical Database, which compiles information on a large panel of individuals from a variety of public and proprietary sources. InfoUSA developed the panel to be representative of the U.S. population. Variables included in the InfoUSA sample are USPS-verified address and a variety of imputed characteristics of the household, such as income and wealth, and characteristics of the individual, including imputed age, gender, and race/ethnicity.

Below, we provide more detail on the nature and coverage of the Dwellsy and InfoUSA data, respectively, and discuss the process of matching the two sources and identifying selective listings.

Dwellsy

Our data on rental listings come from Dwellsy, a rental listing platform. When a rental unit becomes available, the decision of whether to advertise it falls to the property manager, who may or may not also be the owner of the unit. The most common form of advertising is listing available properties on websites that aggregate listings across managers, such as Apartments.com and Dwellsy. Professional property managers tend to use management software both to track unit availability

[18] For example, see https://fairhousingjustice.org/about-fhjc/our-history/

internally and to efficiently list on multiple websites at once. The number of listing websites available depends on whether those websites have contracted with the company that provides the management software; so the property manager need not have adopted software that is specific to Dwellsy or even have had knowledge of Dwellsy prior to the listing decision to enter our sample.

Pricing for management software varies by firm as well as the array of services provided,[19] the number of units under management, and contract specifics such as whether billing is annual or monthly. In general, a per-unit fee is applied, but the fee is lower for plans that require a higher number of units. Thus, a unit is more likely to be in our sample if it is managed by a company with a higher number of units under management. However, while most listing websites charge a fee per listing, which may induce selective listing on the part of the property manager, Dwellsy does not charge a listing fee. We can therefore interpret an unlisted unit in a building whose manager has listed other units on Dwellsy within the same year to have been deliberately and selectively unlisted.

The Dwellsy data begin in January 2021 and ends at year-end 2023. Before matching to InfoUSA, 430,728 unique units were listed in our sample of 27 cities during the sample period. For each listing, a company name is provided. This variable provides the name of the account holder for the software and is usually the name of an LLC that appears to be a management company. Although some large management companies may operate in multiple markets, we identify managers within markets to avoid erroneously identifying common listing company names such as Midtown Management or Total Property Management (or, in some cases, simply just first names) as multi-market firms.

One of the key advantages of Dwellsy's data over other online platform listing data is its accuracy, which is evident in several ways. First, Dwellsy provides data feeds directly from professional managers, ensuring accurate reporting. In contrast, existing studies that rely on similar listing data from online platforms often must scrape the data, which inevitably introduces recording errors.

Second, on some online platforms, only the number of available apartment units by type (e.g., two-bedroom and one-bathroom) is advertised. Some units are listed as teaser units to keep the apartment building visible on the market, while other rental listings remain active long after being leased out. These practices pose significant challenges for identifying the true fraction of unlisted units and for matching tenant information with the listed units, both of which are important for our identification strategy. However, Dwellsy differentiates itself in the online rental market by requiring managers to truthfully report which apartment units are available in the buildings they manage and to diligently check and update these units' status.

Although Dwellsy's focus on professionally managed rental buildings limits its broader coverage, its accuracy in reporting and monitoring listings, ensured by professional managers, makes it an ideal dataset for our empirical analysis. To characterize the share of properties for which units may be advertised on Dwellsy, we use three additional sources of data: rental registry records from Seattle, building-level listing data from CoStar, and listing data scraped from 10 online rental platforms.

[19] Most management software provides services beyond the management and advertisement of listings, such as the facilitation of rent payments or submission of maintenance requests.

Comparison with Rental Registry Records: First, we obtained a file of all rental properties registered with the city of Seattle as of year-end 2023 from the Seattle Department of Construction and Inspections (SDCI). Seattle has required all rental properties to be registered with the SDCI since 2017.[20] In addition to reporting the address of the property, managers are required to report the number of rental units in the property, and the "contact" of the property is reported, often with the name of the management company.

Exhibit A3.1 displays Dwellsy's coverage of the Seattle rental market. While 19.3 percent of buildings registered as rentals in Seattle listed a unit on Dwellsy, these buildings accounted for nearly one-third of the city's registered rental units (31.4 percent). Similarly, 34.7 percent (43.3 percent) of buildings (units) registered as rentals have a property manager contact that was also the contact of a building that listed a unit in Dwellsy. Note that the rental registry data covers the entire rental stock, while Dwellsy data reflects the flow of rental units listed on their platform between 2001-2003. Considering Dwellsy's focus on professionally managed properties and the possibility that a fraction of rental units do not go back to the market during the sample period, the 31.4 percent coverage of rental units and 43.3 percent coverage of managers offers strong confidence in the representativeness of the Dwellsy data for the Seattle market.

Comparison with CoStar Listings: Second, we use all multifamily properties in July and August 2023 in eight cities taken from the sample of CoStar Group, a commercial real estate data company. Unlike the Seattle rental registration sample, these data include vacancy information for each building. CoStar acquires its information about the existence, unit counts, and unit availability of multifamily properties from a variety of sources, including its subsidiary rental listing service Apartments.com, its investment in Commercial Mortgage-Backed Securities (CMBS) pools, interviews with property managers, other public listing platforms, and public records. CoStar's data can therefore be viewed as representing the universe of available rental stock—whether listed or not—from the buildings it monitors.

For each city, we use the "market" designation from CoStar, which is larger than the city level but smaller than a metropolitan area. To ensure that we appropriately evaluate Dwellsy's coverage within this area, we attempt to match every observation from Dwellsy within the entire census metropolitan area and drop any unmatched observations. As with the Seattle data, we match on street address alone and consider a building covered by Dwellsy if any listing from 2023 matched to a CoStar property with a vacancy.

Exhibit A3.2 displays the coverage statistics. We see that Dwellsy covers between 11.47 percent and 32.19 percent of buildings included in CoStar with vacancies. In terms of units, these values range between 8.05 percent and 55.31 percent.

Note that CoStar's data includes all available rental stock, whether listed or not. By contrast, Dwellsy only reports the portion of the available rental stock that is listed on the Dwellsy platform, with a strict focus on professionally managed properties. Given this focus, Dwellsy's 20 percent average coverage across cities seems quite reasonable.

[20] All properties with at least 10 rental housing units were required to register beginning in July of 2014, with smaller rental properties being subject to registration requirements on a schedule that covered all units, with rare exceptions, by year-end 2016 (Seattle, Washington, Municipal Code §22.214.040).

Comparison with Scraped Listings: So far, we have compared Dwellsy data with the total rental stock from Seattle's Rental Registry and vacant rental stock from CoStar in selected cities. In both cases, Dwellsy rental listings represent a significant portion. To further verify whether this is indeed the case, we scraped rental listings from ten major online rental platforms between July and August 2023 in selected cities (Atlanta, Boston, DC, Minneapolis, Richmond, Seattle). These platforms include both popular well-known sites and other less well-known sites that target lower-income households. We collected data on the address, listing date, rent, and apartment characteristics for each listing, geocoded them, and compared them to Dwellsy listings from the same period, focusing only on buildings with at least one unit listed on Dwellsy. The goal was to see how many of these listings appeared on other rental websites but not on Dwellsy.

Exhibit A3.3 compares the number of units per building listed on Dwellsy versus the scraped websites. Panel A breaks this down by city. Across all six cities, the average number of units listed in Dwellsy buildings is generally close to that in the total scraped listings for almost all cities, with the exception of Washington, DC. The relatively large difference in Washington, DC is driven by one apartment building, which has 167 more units listed on a particular platform than on Dwellsy. A closer investigation reveals that this building was the result of a reporting error. To minimize the impact of outliers, the right panel shows the difference in listings per building between Dwellsy and the scraped sources. The difference is mostly zero at the 25th, 50th, and 75th percentiles across all cities, including Washington, DC. Panel B further breaks down the comparison by the source of the scraped data. When compared to each alternative rental platform, the number of units listed per building on Dwellsy is similar, with the difference again close to zero at the 25th, 50th, and 75th percentiles. On average, Dwellsy lists one unit fewer, likely due to its focus on professionally managed buildings and its diligent efforts to verify listings, avoid duplicates, and remove off-market listings.

Overall, this comparison gives us high confidence that Dwellsy's coverage of listings in Dwellsy-covered buildings is nearly universal. This aligns with the fact that Dwellsy does not charge per listing fees, allowing managers to advertise their listings at no additional cost once the initial software installation fee has been incurred.

InfoUSA

The InfoUSA Residential Historical Database is a large, annual panel of individuals and households owned by Data Axle. Information such as location, income, tenure status, age, and family composition are compiled from a set of both public (e.g., voter registration roles and land records) and private (e.g., marketing data sets) records. The coverage of the data is vast but non-universal; due to the relatively high quality of property ownership records and voter registration, unhoused and transient individuals are less likely to be included in the sample than homeowners and longtime residents.

The data also includes imputed racial and ethnic identity from the individual's full name and geography. Data Axle uses reference tables for ethnic backgrounds of names to infer an individual's identity beginning with their first name. When no unique inference is possible, the surname is used, then "expert rules" (e.g., all surnames ending with "oglu" are coded as Turkish), and middle names are used to break ties when two or more ethnic designations are possible. Demographics at the 9-digit zip code level are used to further resolve such ambiguities.

We aggregate the granular ethnicity variable into five exhaustive and mutually exclusive categories: Black, White, Hispanic, Asian, and Other.[21] Movers in the InfoUSA panel are identified by comparing their address (including unit number) in a given year with the prior year's address, or if InfoUSA indicates that they have lived in their unit for a year or less and they were most recently observed at their current address in the current year. Individuals are dropped from the InfoUSA sample if they lack an address, lack a unit number even though the address is known to be multi-unit, or lack an address in both the preceding two years.[22]

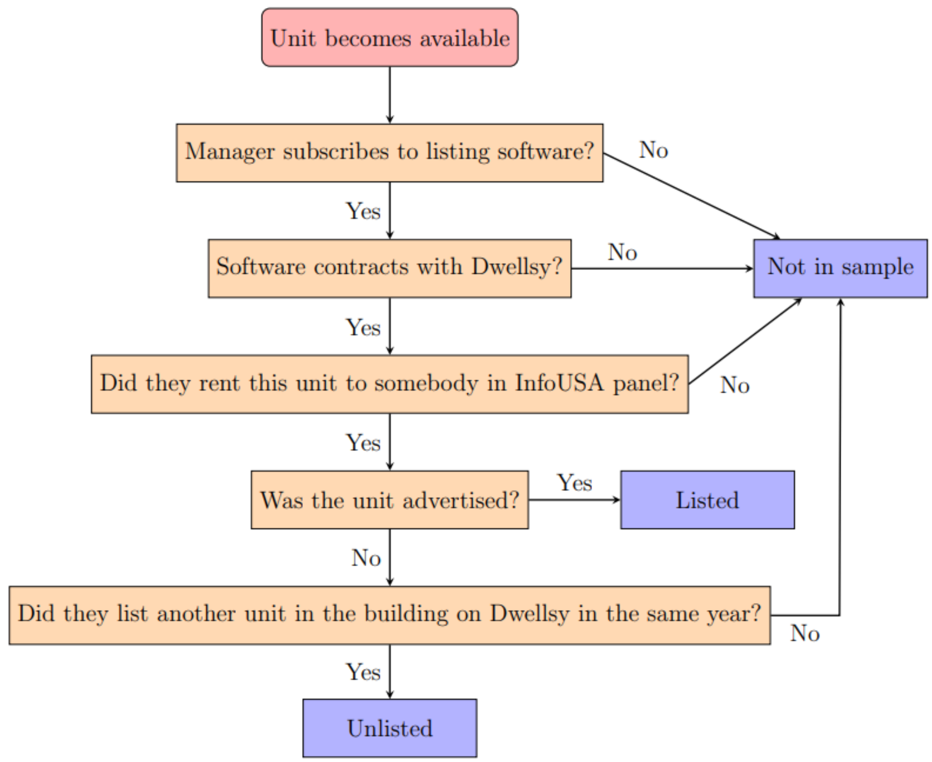
Identifying Listed and Unlisted Status of Turnover Units

We merge the Dwellsy and InfoUSA data on address to obtain a data set of renters in units that were either listed on Dwellsy or not. See **Exhibit 3.2** for a visual representation of how a unit that turns over during our sample period ends up in our sample and how it is categorized within our sample. Prior to a unit becoming available, the manager of the unit (which may or may not also be the landlord) decides whether to invest in a listing software. If they do not, or if they subscribe to a listing software that does not contract with Dwellsy, then the unit's eventual occupant is not in our sample, regardless of whether the unit is listed. If the unit manager does subscribe to a listing software that contracts with Dwellsy, then a necessary condition for the unit's eventual occupant being in our sample is that they are also included in the InfoUSA panel. If the unit rents to an individual in the InfoUSA panel, then the unit will be included in our panel in one of two cases: if the manager listed the unit on Dwellsy, then the unit is in our sample and coded as having been listed. If the manager did not list the unit on Dwellsy but within the same year listed other units, then the unit is included in our sample and coded as being unlisted.

[21] White includes ethnicities classified as Western European, Scandinavian, Australian, New Zealander, Mediterranean, Jewish, and European Hispanic (i.e., Spanish and Portuguese). Black includes only African American. Asian includes all East Asian, South Asian, and Pacific ethnicities. Hispanic includes all non-European Hispanic ethnicities and Brazilians. Other includes all other categories, which in practice includes ethnicities classified as Caucasian (i.e., central Asian), Surinamese, Arab, and African (but not African American). To account for the possibility that Africans and African Americans experience comparable discrimination in the rental market, we test a racial coding that includes Africans in the Black designation and re-generate our primary results. InfoUSA includes missing ethnicity observations. These individuals are dropped from the sample. In cases where an individual has multiple ethnic designations, InfoUSA uses both first and last name to assign ethnicity (e.g., Nguyen O'Brien is coded as Vietnamese).

[22] It is not uncommon for an individual to be absent from a single year of the InfoUSA data. If the individual lived in the same address both the following and prior year, the address is imputed to have been unchanged in the missing year. If their address was missing in the prior year but was not missing and different two years prior, they are assumed to have moved in the current year. These cases are noted so that they can be dropped as a robustness check.

Exhibit 3.2 | Process That Determines Whether a Turnover in a Unit is Included in the Sample and How it is Coded



We perform the merge by first subsetting each dataset by census metropolitan area, then merging on street address, zip code, and unit number (if one exists). Our sample comprises 27 cities across 25 metropolitan areas.[23] For units that were listed multiple times within the same calendar year, the most recent listing is retained.[24] Listings are presumed to have matched to a mover if they were deactivated in the year that InfoUSA observed the renter living in their current unit within a year after the initial listing date.

Given the nature of Dwellsy's data generating process—managers may advertise a unit on Dwellsy's platform without cost as long as the listing is created in their software—we identify the unit inhabited by a mover in the InfoUSA panel as being selectively unadvertised if it was not listed on Dwellsy but is in a building that had other units listed on Dwellsy in the same year.

American Community Survey

To explore how selective advertising behavior varies with neighborhood attributes and to control for the probability that potential tenants of a given racial category would apply for a given unit, we obtain tract-level sociodemographic characteristics from the five-year American Community

[23] The sample includes all observations from the cities and respective metropolitan areas of Albuquerque, Atlanta, Baltimore, Boston, Chicago, Cleveland, Columbia (South Carolina), Dallas, Washington (D.C.), Detroit, Fort Worth, Houston, Kansas City, Los Angeles, Miami, Minneapolis, Newark, New York, Philadelphia, Pittsburgh, Providence, Riverside, San Antonio, San Diego, San Jose, Seattle, and Tampa.
[24] These cases are overwhelmingly due to changes in listing details, with re-listings occurring subsequently in a short period of time. For example, a change in the asking price is registered in the data as a re-listing.

Survey (ACS). Although our data span 2022 and 2023, we use ACS data from the 2019 survey to avoid a five-year sample that includes the 2020 ACS data, which the U.S. Census Bureau chose not to release due to issues of potential non-response bias. In each tract, we retrieve the percentage of renters who are non-Hispanic White, Black, Hispanic (of any race), and Asian or Pacific Islander. We also obtain the percentage of households that are renters or have children and the percentage of the population that is in poverty or has a bachelor's degree or higher.

Sample Statistics

Exhibit 3.3 provides summary statistics at the neighborhood level for the merged Dwellsy-InfoUSA-ACS sample. The first six variables on listing status and tenant race are derived from individual-level unit and tenant information in the Dwellsy-InfoUSA sample. The remaining variables represent tract-level characteristics from the ACS.

Exhibit 3.3 | Summary Statistics for Variables Used in the Analysis

Individual-level variables	**Mean**	**SD**	**N**
Was the rental unit listed? (1=Yes)	0.177	0.382	411,895
Is the tenant White? (1=Yes)	0.610	0.488	411,895
Is the tenant Asian? (1=Yes)	0.109	0.311	411,895
Is the tenant Hispanic? (1=Yes)	0.145	0.353	411,895
Is the tenant Black? (1=Yes)	0.096	0.294	411,895
Is the tenant some other ethnicity? (1=Yes)	0.040	0.195	411,895
Census tract–level variables	**Mean**	**SD**	**N**
% of renters that are White	50.5	23.807	410,920
% of renters that are Black	16.9	21.664	410,920
% of renters that are Asian	10.3	10.253	410,920
% of renters that are Hispanic	19.8	19.342	410,920
% of renters from all other races/ethnicities	5.3	7.979	410,920
% Renters	64.3	20.762	410,920
% Households with children	36.7	13.262	410,920
% Bachelor's degree or higher	58.0	23.661	411,661
% Below poverty	14.6	10.566	410,921
PM 2.5	8.139	1.340	411,857
Toxic concentration (normalized)	0.026	0.742	411,857
Zip code–level variables	**Mean**	**SD**	**N**
ZORI Zip/Metro Index	106.13	22.136	399,808

Notes: *The tract shares by race/ethnicity do not sum to 100 due to the double-counting of non-White Hispanic renters. The Zillow Observed Rent Index (ZORI) is a repeat-rent index of rental rates provided by listing company Zillow.com, released at both the zip code and metro area level each month. We divide the zip code–level index by the MSA-level index and multiply by 100 such that a value of 100 implies that the average rent in the zip code is exactly equal to the average rent in the metro area in a given month. PM 2.5 is the concentration of PM 2.5 pollution in the census tract, and toxic concentration is measured using the EPA's Risk Screening Environmental Indicators (RSEI) data, which combines TRI data on the quantity of toxic chemicals released or transferred off site with information about the chemical's toxicity and its transport through the environment, to calculate a geographically precise measure of relative risk. We normalize toxic concentration by subtracting the MSA-wide mean and dividing by the MSA-wide standard deviation.*

Exhibit 3.4 further presents the sample means of neighborhood characteristics by race. The average percentage of college-educated residents at the neighborhood level is 38.66 percent for Black renters, 48.27 percent for Hispanic renters, but 62.15 percent for White renters. Similarly, the mean neighborhood poverty rate is 23.04 percent for Black renters, 15.55 percent for Hispanic renters, and only 13.08 percent for White renters. These sharp differences are accompanied by the fact that 27.99 percent of Black renters, 20.08 percent of Hispanic renters, but only 16.72 percent of White renters and 12.05 percent of Asian renters reside in listed apartments. A natural question is how neighborhood amenities are distributed between listed and unlisted units, which we turn to next.

Exhibit 3.4 | Covariate Means by Race

Variable	Asian	Black	Hispanic	Other	White
% of in-sample units that are listed	12.05	27.99	20.08	14.41	16.72
% of renters that are Black	11.90	55.86	14.86	15.68	12.32
% of renters that are White	51.92	26.01	41.34	51.02	56.24
% of renters that are Asian	16.51	4.68	9.07	11.66	10.27
% of renters that are Hispanic	16.95	11.83	32.63	19.08	18.56
% Population renters	68.62	64.55	62.93	65.01	63.71
% Households w/ children	33.84	40.23	39.73	36.41	35.93
% Bachelor's degree or higher	64.22	38.66	48.27	59.60	62.15
% in poverty	14.67	23.04	15.55	14.39	13.08
ZORI Zip Index (MSA Index = 100)	109.98	92.52	101.70	107.54	108.44
Toxic concentration (normalized)	0.12	0.04	-0.05	-0.02	0.03
PM 2.5	8.12	8.19	8.17	8.23	8.12

Notes: *Values display the correlation between the variable named in the first column and a dummy variable that equals 1 if the tenant is of the race listed in the column header and equals zero otherwise. See the table notes for Exhibit 3 for detailed variable labels and descriptions of ZORI, toxic concentration, and PM 2.5. All variables listed in the first column are defined at the tract level other than ZORI, which is defined at the zip code level.*

Characterizing the Distribution of Unlisted Units

With each renter in the sample determined to be in a unit that is either listed or unlisted, we can observe which characteristics are more or less represented in neighborhoods with higher shares of unlisted units. **Exhibit 3.5** displays the pairwise Pearson correlation coefficient and its 95 percent confidence interval between the share of renters in each tract in the sample that live in unlisted units and each variable in a set of tract-level socio-demographic variables. **Exhibit 3.6** displays the histogram of each variable from **Exhibit 3.5** as well as the zip code-level Zillow Observed Rent Index (ZORI) (normalized by MSA-level ZORI) separately for renters in listed and unlisted units. The ZORI measures changes in asking rents over time, controlling for changes in the quality of the available rental stock.

Exhibit 3.5 | Tract-Level Pairwise Correlations between Different Covariates and Percent of In-Sample Renters Living in Unlisted Units

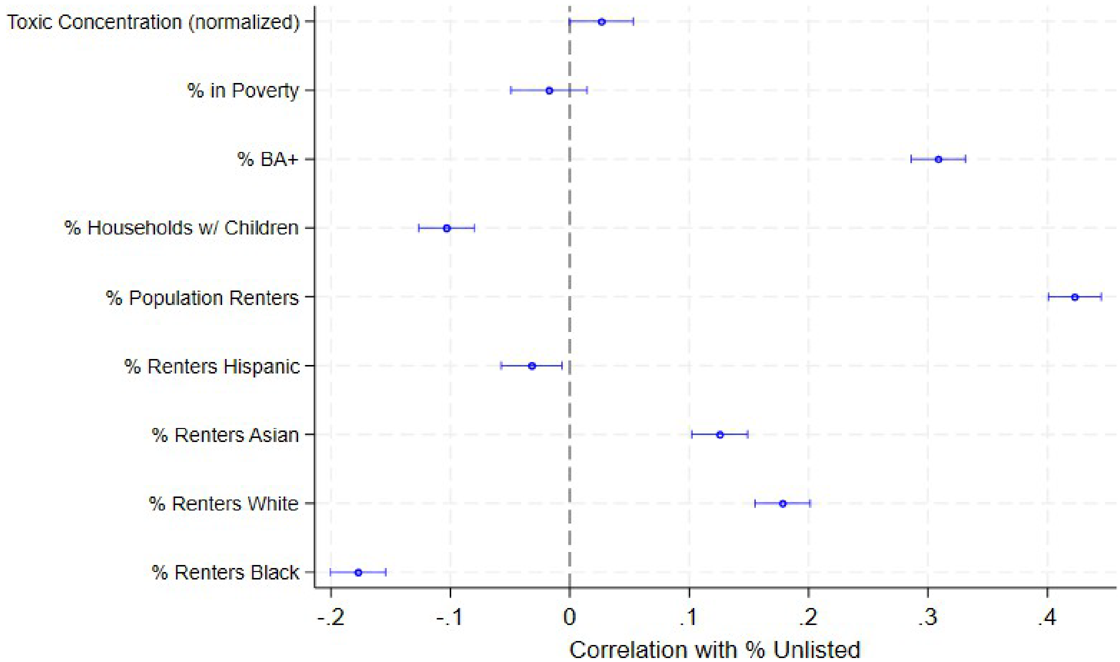
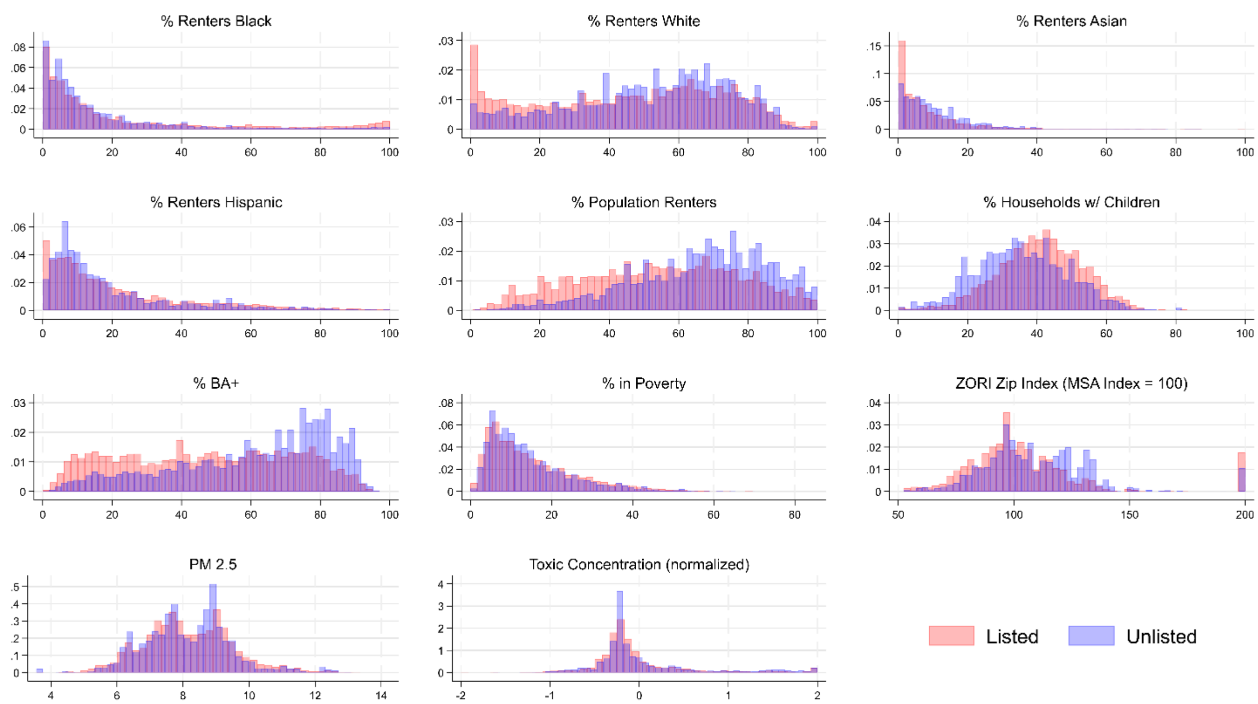


Exhibit 3.6 | Distribution of Different Covariates Based on the Listed Status of Renters in the Sample



Both figures suggest that unlisted units are more common in neighborhoods with larger shares of renters and people with at least a four-year college degree. Unlisted units are also more common in neighborhoods where a higher share of renters is White or Asian and less common in neighborhoods with higher shares of Black and Hispanic renters and households with children.

Simple correlations between tract attributes and share unlisted do not tell us about discrimination — learning about discrimination requires showing that a particular racial group is less likely to be in a particular unit because it was not listed, controlling for other tract characteristics that might increase or decrease that group's demand for that neighborhood in the first place.

Exhibit 3.7 provides an initial glimpse at the percentage of renters in listed apartment units across different race and ethnicity groups within principal cities. On average, 17.69 percent of tenants reside in listed apartment units, while the remainder live in unlisted apartments. The fact that approximately 18 percent of units are advertised in buildings where the fixed cost of advertising has already been incurred suggests that, unlike the owner-occupied market, most rental units are leased without being publicly advertised first. While this may seem surprising at first glance, it is important to consider that rental transactions are not officially recorded, whereas sales transactions are documented in the deeds office. This allows verification of whether an owner-occupied sale was publicly listed, but it is not feasible to do the same for rental records without tenant turnover data. As a result, landlords can choose not to list a rental property without considering the impact on equal information access for renters. Additionally, while the majority of sales transactions are listed by real estate agents who are almost always required to advertise properties on a centralized Multiple Listing Service (MLS), advertising requirements are much less stringent in the rental market.

One might be concerned that Dwellsy coverage does not capture the universe of online listings for a given property. We compared Dwellsy listings with rental listings we scraped from ten major online rental platforms between July and August 2023 in selected cities (Atlanta, Boston, DC, Minneapolis, Richmond, and Seattle). The results show that, among the professionally managed buildings covered by Dwellsy, very few listings would be listed in alternative listings appearing on other rental websites but not on Dwellsy. The comparison gives us high confidence that Dwellsy's coverage of listings in Dwellsy-covered buildings is nearly universal.

Another legitimate concern is that some buildings or managers may choose not to advertise units for valid reasons, even if they have access to the Dwellsy software. For instance, a building might be testing the effectiveness of different marketing methods, or some managers may rely on word-of-mouth to attract tenants with desirable characteristics unrelated to race, such as a strong record of paying rent. Regardless of these reasons, when the decision not to advertise rental properties becomes a social norm, it grants landlords significant discretion in deciding whether to list units, making it a potential tool for targeting preferred tenants.

To detect discriminatory patterns in unadvertised units, we employ an econometric model to estimate the extent to which unlisted properties are disproportionately occupied by White tenants. This model controls for racial composition and a comprehensive set of neighborhood characteristics, as well as building-, tract-, and manager-specific fixed effects to address other factors that might influence racial sorting. For example, if word-of-mouth recommendations primarily come from tenants who landlords "favor" and those tenants tend to recommend friends of the same race, we would expect the observed results only if landlords disproportionately favored White tenants. We present the details of this model in the Analysis section.

The average fraction of listed apartments may mask significant variability across cities. To explore this, **Exhibit A3.4** replicates **Exhibit 3.7** for each of the 27 cities in our sample. The percentage of renters in listed units ranges from 8 percent in Houston to 53 percent in Fort Worth, with a median of 25.16 percent. This fraction tends to be smaller in larger cities, likely due to the prevalence of moves arranged, for example, by corporations or through subleases within community networks—all of which reduce the likelihood of units being publicly advertised. However, if these were the only reasons units were not advertised before being occupied and if the tenants moving through subleases or in corporation-arranged transactions had similar racial composition as the neighborhood level population, we would expect White renters to be just as likely as Black renters to end up in listed apartments in our empirical setting.

Exhibit 3.7 | Share of Renters in Each Racial Group Occupying Units That Were Either Listed or Unlisted

Renter Race	% In Listed Units	% In Unlisted Units	# Obs
Asian	12.05	87.95	44,723
Black	27.99	72.01	39,416
Hispanic	20.08	79.92	59,888
Other	14.41	85.59	16,372
White	16.72	83.28	251,400
Total	**17.69**	**82.31**	**411,895**

Exhibits 3.7 and **A3.4** suggest otherwise. **Exhibit 3.7** shows that about 28 percent of Black tenants and 20 percent of Hispanic tenants rent listed units, compared to 17 percent of White tenants. **Exhibit A3.4** further reveals that, across cities, the proportion of renters in listed units is typically highest among Black and Hispanic renters. For example, in Kansas City, 55 percent of Black tenants and 48 percent of Hispanic tenants live in listed units, compared to 40 percent of White and 30 percent of Asian renters. Similarly, in Cleveland, 47 percent of Hispanic tenants and 40 percent of Black tenants occupy listed units, compared to 33 percent of White and 22 percent of Asian renters. These diverse patterns across cities suggest that non-advertisement strategies may selectively affect different racial groups depending on the city.

These patterns could, of course, result from sorting based on differences in preferences across racial groups or neighborhood characteristics. In the empirical analysis below, we aim to systematically address this with a clean identification strategy.

Analysis

In this section, we describe our baseline statistical specification — a multinomial logit model of the probability that an individual of each racial group (White, Black, Asian, Hispanic, other) ends up in a unit with attention paid to the role of the Listed attribute. We are particularly interested in how the role of Listed differs across racial groups. We show that listing matters more for a Black renter obtaining an apartment than for a White renter which suggests discrimination by selective advertising. The first subsection describes this model and the second subsection reports baseline parameter estimates. The third subsection describes how these estimates vary with neighborhood characteristics (i.e., rent level, White population share, and other metrics of discrimination) and other renter attributes (i.e., presence or absence of children). The fourth subsection reports results of a binary (e.g., Black versus all other races) linear probability model that allows for high-dimensional fixed effect controls.

Multinomial Logit

Our analysis undertakes a series of multinomial logit estimation procedures to explain the race of a resident of an apartment unit that turns over as a function of its listed/unlisted status. In particular, the probability of seeing a resident of race *j* in unit *i*

$$P(Y_{i,j}) = \frac{exp\{\alpha_j listed_i + X_i'\beta_j\}}{\sum_{j=1,\ldots,5} exp\{\alpha_k listed_i + X_i'\beta_k\}} \tag{1}$$

where:

- $Y_{i,j}$ = {White, Black, Asian, Hispanic, other}
- $listed_i$ = 1 if unit *i* is listed (= 0 if unlisted)
- X_i = Attributes of unit *i* and its neighborhood, including the ratio of quality-adjusted neighborhood rent to MSA-level rent, the fraction of renters, the racial composition of renters, the fraction of college graduates, the local poverty rate, and air quality indices.

The index underlying the multinomial logit is normalized to 0 for the White renter identity at each property *i*. One implicit assumption in the multinomial logit estimation model is the independence of irrelevant alternatives (IIA) assumption. It requires that the odds of the property manager selecting, for example, a White versus a Black occupant will not depend upon the presence or absence of a Hispanic or Asian renter alternative. The multivariate probit alternative relaxes this assumption but imposes a much greater computational burden on the model, requiring thousands of calculations of a high-dimensional integral. In considering whether our conclusions are robust to this assumption, we are encouraged by the results of our linear probability model (LPM) specifications (addressed later in this chapter), which are used to show robustness to the inclusion of high-dimensional fixed effects. The LPM makes a binary comparison (i.e., the likelihood of a Black renter versus a non-Black renter being in a listed unit) and does not use the IIA assumption. Our results in that analysis are equally strong or stronger than the results found in our multinomial logit analysis.

We focus attention only on units in buildings that have any units listed on Dwellsy, as we know that the property managers of these buildings will have incurred the fixed costs required to list on the platform and that the practical costs of listing any marginal units will be minimal. This approach may be conservative in detecting discrimination, depending on the racial composition of tenants in apartments outside Dwellsy's market coverage. Landlords might leave entire buildings unlisted to attract White tenants through referrals, which our method would miss. Conversely, if unlisted buildings were more frequently rented to Black tenants, our approach would overlook favorable treatment of minorities.

Baseline Multinomial Logit Estimates

Results are presented in **Exhibit 3.8**, where the dependent variables are Black, Hispanic, Asian, and other respectively, with non-Hispanic White as the reference category. **Exhibits A3.5–A3.8** report results of specifications showing how results vary with individual tract-level covariates. Our preferred specification uses both the percentage of renters in the census tract who are White along with the ZORI, measured by the zip code-level Zillow Observed Rent Index (ZORI) (normalized by MSA-level ZORI), for the corresponding zip code as controls. With those controls, we find significant evidence that Black renters are more likely to be found in listed units—that is, they are less likely than White renters (i.e., the excluded group) to appear in unlisted units. In particular, the listed odds ratio reveals that Black renters are about 12.5 percent more likely than their White counterparts to be in listed units. Similarly, Hispanics are 8.1 percent more likely than their White counterparts to be in listed units. Asian renters, by contrast, are significantly more likely than White renters to appear in unlisted units.

These estimates are robust to controls for a wide range of tract-level characteristics, including the percentage of White, Black, Asian, Hispanic renters, the overall renter population, the percentage of college-educated residents, the percentage of families with children, and apartment rent per square foot, as shown in **Exhibits A3.9–A3.10**.

Exhibit 3.8 | Multinomial Logit Model for Renters in Central Cities of MSAs

Outcome:	**Asian**	**Black**	**Hispanic**	**Other**
=1 if Unit is Listed	-0.434***	0.118***	0.078***	-0.197***
	(0.0317)	(0.0379)	(0.0253)	(0.0291)
ZORI Zip/Metro Index	0.005***	-0.016***	-0.009***	0.002**
	(0.0014)	(0.0017)	(0.0007)	(0.0008)
% Renters White	-0.017***	-0.056***	-0.019***	-0.012***
	(0.0007)	(0.0015)	(0.0006)	(0.0016)
Listed Odds Ratio	0.648	1.125	1.081	0.822
Log-likelihood: −339656				
Observations: 340, 080				
MSA and Year FE included				
Outcome:	**Asian**	**Black**	**Hispanic**	**Other**
1(Listed)	-0.434***	0.118***	0.078***	-0.197***
	(0.0317)	(0.0379)	(0.0253)	(0.0291)
ZORI Zip/Metro Index	0.005***	-0.016***	-0.009***	0.002**
	(0.0014)	(0.0017)	(0.0007)	(0.0008)
% Renters White	-0.017***	-0.056***	-0.019***	-0.012***
	(0.0007)	(0.0015)	(0.0006)	(0.0016)
Listed Odds Ratio	0.648	1.125	1.081	0.822
Log-likelihood: −339656				
Observations: 340, 080				
MSA and Year FE included				

Notes: *The stars ***, **, * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level. Standard errors are shown in parentheses.*

Heterogeneity in Selective Advertising

So far, we have observed that Black and Hispanic renters are more likely to occupy listed units when compared to White renters. Conversely, this implies that White renters are more likely to reside in unlisted units, suggesting that the practice of not listing may be a form of racial segregation. In this section, we investigate which neighborhoods exhibit a higher propensity for using unlisted units to target White households along with another form of household heterogeneity (the presence of children), and heterogeneity in more direct forms of discrimination.

Heterogeneity in Neighborhoods with Varying Amenities

To assess differentiation in amenity levels, we introduce an interaction between the "listed" dummy variable and a dummy variable indicating whether the zip code-level ZORI is above its corresponding MSA-level ZORI. In a competitive market, neighborhood amenities are capitalized into local rents, so the ZORI dummy indicates neighborhoods with better-than-average local amenities such as parks, schools, shopping and dining options, and transportation. The results are presented in **Exhibit 3.9**.

We find evidence that Black renters are potentially being steered away from neighborhoods with better amenities. Listed apartment units are 37.4 percent more likely to be occupied by Black tenants than their White counterparts in neighborhoods with above average rent compared to only 10.3 percent elsewhere. This suggests that access to these unlisted units is denied more often to Black renters in more desirable neighborhoods. The results below further show that such steering is more likely to occur in neighborhoods with lower poverty rates, improved air quality, and more college graduates. Thus, selective advertising not only limits Black renters' housing consumption but also restricts their access to better amenities.

On the other hand, the steering-away effect on Hispanic renters and the steering-in effect on Asian and other minority renters are similar in magnitude across neighborhoods, regardless of the level of local amenities as indicated by the ZORI. This suggests that the current practice of selective advertising may not result in uneven access to amenities for these racial groups.

Exhibit 3.9 | Interacting Listing Status with Indicator for Whether the Zip Code is Above the MSA Rent Price Average

Outcome:	**Asian**	**Black**	**Hispanic**	**Other**
=1 if Unit is Listed	-0.467***	0.098	0.085**	-0.229***
	(0.0478)	(0.0628)	(0.0376)	(0.0528)
(=1 if Unit is Listed)*(=1 if ZORI>100)	0.029	0.219**	-0.004	0.046
	(0.0545)	(0.0905)-	(0.0442)	(0.0599)
ZORI Zip/Metro Index	0.005***	-0.018***	-0.005***	0.002**
	(0.0012)	(0.0023)	(0.0012)	(0.0010)
% Renters White	-0.013***	-0.052***	-0.027***	-0.013***
	(0.0011)	(0.0021)	(0.0007)	(0.0012)
Below-mean Listed Odds Ratio	0.627	1.103	1.089	0.796
Above-mean Listed Odds Ratio	0.646	1.374	1.084	0.833
Log-likelihood: −366958				
Observations: 340, 080				
MSA and Year FE included				

Notes: *The stars ***, **, * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level. Standard errors are shown in parentheses.*

Disparities in access to better amenities between Black and White households are not new and may be attributed to factors such as the correlation between race and income or sorting based on preferences for local public goods. However, a more troubling source of racial disparity in the rental market is landlords' discrimination against Black renters. For example, Christensen, Sarmiento-Barbieri, and Timmins (2022) find significantly lower levels of air toxics in the proximity of rental units where landlords do not respond to inquiries from Black and Hispanic identities but do respond to White identities. Our findings reveal that another form of discrimination, which contributes to unequal housing outcomes, occurs at the entry stage of the rental search process when landlords decide whether to advertise vacant units.

Heterogeneity in White Population Share

We further explore the heterogeneity in the degree of selective advertising based on the percentage of White population in a neighborhood and show where discrimination occurs. Doing so also helps us learn about why such discrimination occurs.

We augment the test of selective advertising by categorizing the percentage of the White population into 10 equal bins and interacting these with the Listed dummy. Two patterns emerge from **Exhibit 3.10**. First, as the percentage of the White population increases, the probability of leasing a unit to a minority decreases almost monotonically, and this trend holds across all minority racial groups—Asian, Black, Hispanic, and other— consistent with homophily effects.[25]

Exhibit 3.10 | Interacting Listing Status with White Population Share

	Asian	Black	Hispanic	Other
=1 if Unit is Listed	-0.254*	0.406***	0.331***	0.027
	(0.1364)	(0.0811)	(0.0866)	(0.1084)
(=1 if Unit is Listed)×(=1 if 10 < % White < 20)	-0.108	-0.366***	-0.081	-0.136
	(0.1326)	(0.1175)	(0.0877)	(0.1437)
(=1 if Unit is Listed)×(=1 if 20 < % White < 30)	-0.163	-0.495***	-0.219**	-0.122
	(0.1510)	(0.1181)	(0.1060)	(0.1400)
(=1 if Unit is Listed)×(=1 if 30 < % White < 40)	-0.312**	-0.296**	-0.227**	-0.356***
	(0.1490)	(0.1168)	(0.0929)	(0.1371)
(=1 if Unit is Listed)×(=1 if 40 < % White < 50)	-0.138	-0.414***	-0.324***	-0.325**
	(0.1491)	(0.1280)	(0.0959)	(0.1351)
(=1 if Unit is Listed)×(=1 if 50 < % White < 60)	-0.220	-0.504***	-0.377***	-0.306**
	(0.1513)	(0.1181)	(0.0948)	(0.1453)
(=1 if Unit is Listed)×(=1 if 60 < % White < 70)	-0.140	-0.053	-0.360***	-0.162
	(0.1509)	(0.1205)	(0.0970)	(0.1385)
(=1 if Unit is Listed)×(=1 if 70 < % White < 80)	-0.119	0.061	-0.326***	-0.199
	(0.1487)	(0.1659)	(0.0974)	(0.1281)
(=1 if Unit is Listed)×(=1 if 80 < % White < 90)	-0.073	-0.314*	-0.407***	-0.188
	(0.1570)	(0.1819)	(0.1184)	(0.1626)
(=1 if Unit is Listed)×(=1 if % White > 90)	-0.141	-0.482	-0.003	0.096
	(0.4324)	(0.5297)	(0.3252)	(0.4348)
=1 if 10 < % White < 20	-0.329***	-1.017***	-0.401***	-0.202**
	(0.0980)	(0.1097)	(0.0535)	(0.0848)
=1 if 20 < % White < 30	-0.466***	-1.616***	-0.535***	-0.258***
	(0.0977)	(0.1131)	(0.0559)	(0.0858)
=1 if 30 < % White < 40	-0.321***	-2.225***	-0.767***	-0.302***
	(0.1166)	(0.1024)	(0.0533)	(0.0799)
=1 if 40 < % White < 50	-0.556***	-2.329***	-0.895***	-0.444***
	(0.1070)	(0.1274)	(0.0527)	(0.0827)
=1 if 50 < % White < 60	-0.525***	-2.510***	-0.990***	-0.421***
	(0.1165)	(0.1407)	(0.0524)	(0.0917)
=1 if 60 < % White < 70	-0.874***	-3.972***	-1.258***	-0.612***
	(0.1064)	(0.1402)	(0.0529)	(0.1180)

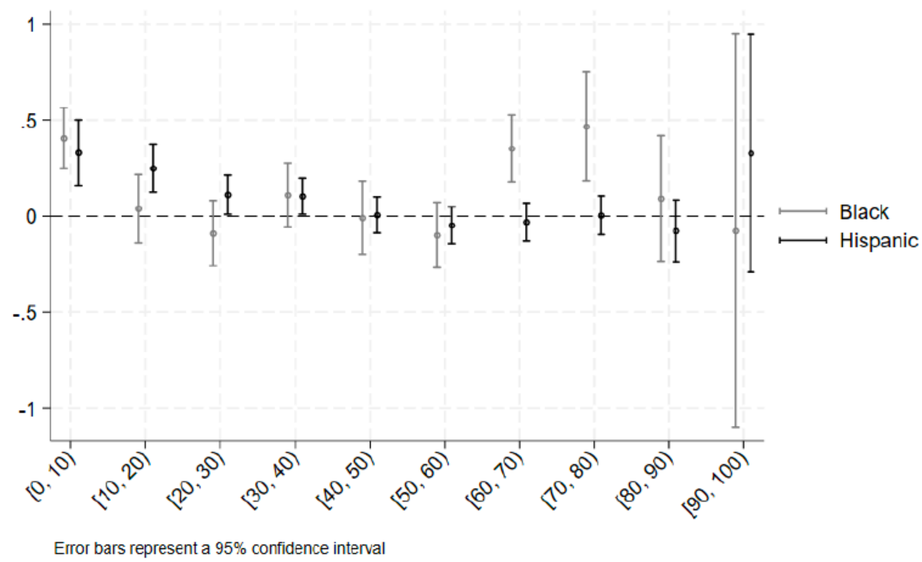
[25] Here, we refer specifically to the coefficients in Exhibit 3.10 where percent White bins are not interacted with Listed. For each non-White race group, these results suggest that group is less likely to end up in the apartment the greater the percent White in the neighborhood, aside from any effects of listing. This result could reflect homophily preferences. Homophily refers to a tendency for individuals to prefer to live amongst others with similar attitudes, beliefs, social status, or demographic characteristics. Here we refer specifically to race — in particular, White renters may be more likely to seek out rental units in predominantly White neighborhoods.

	Asian	Black	Hispanic	Other
=1 if 70 < % White < 80	-1.252***	-4.514***	-1.399***	-0.834***
	(0.1052)	(0.1547)	(0.0524)	(0.1430)
=1 if 80 < % White < 90	-1.677***	-4.855***	-1.687***	-1.031***
	(0.1165)	(0.1437)	(0.0656)	(0.1534)
=1 if % White > 90	-1.666***	-4.771***	-1.735***	-1.168***
	(0.2968)	(0.3048)	(0.1521)	(0.2135)
ZORI Zip/Metro Index	0.005***	-0.014***	-0.009***	0.002*
	(0.0011)	(0.0015)	(0.0006)	(0.0009)
Log-likelihood: -337838				
Observations: 340,551				
MSA and year FE included				

Notes: *The stars ***, **, * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level. Standard errors are shown in parentheses.*

Second, for Black renters, evidence of selective advertising—indicated by the absence of a significantly negative coefficient on the Listed dummy—becomes apparent when neighborhoods have approximately 60 to 80 percent White renters, or, 20 to 40 percent minority renters. This is apparent in **Exhibit 3.11**, where we plot the coefficients on Listed for Black and Hispanic renters, respectively, by the share of White population. Card, Mas, and Rothstein (2008) found that once minority share in a neighborhood exceeds a "tipping point," White residents tend to move out almost entirely. Using Census tract data from 1970 through 2000, the authors observed that White population flows exhibit tipping behavior in most cities, with tipping points for minority share ranging between 5 to 20 percent. Recognizing this, landlords may have incentives to prevent neighborhood tipping and could be more likely to discriminate in neighborhoods where the minority share is near this tipping point. Consistent with this, Page (1995) found increased discrimination in neighborhoods with exactly 20 percent African Americans; and Hanson and Hawley (2011) found that housing discrimination, measured by the landlords' response to email inquiries, was most severe in neighborhoods with a minority share between 5 to 20 percent. Our finding that selective advertising against Black renters is more severe in neighborhoods with 20 to 40 percent minority share suggests that this tipping behavior extends to discrimination at the entry stage of the rental search process.

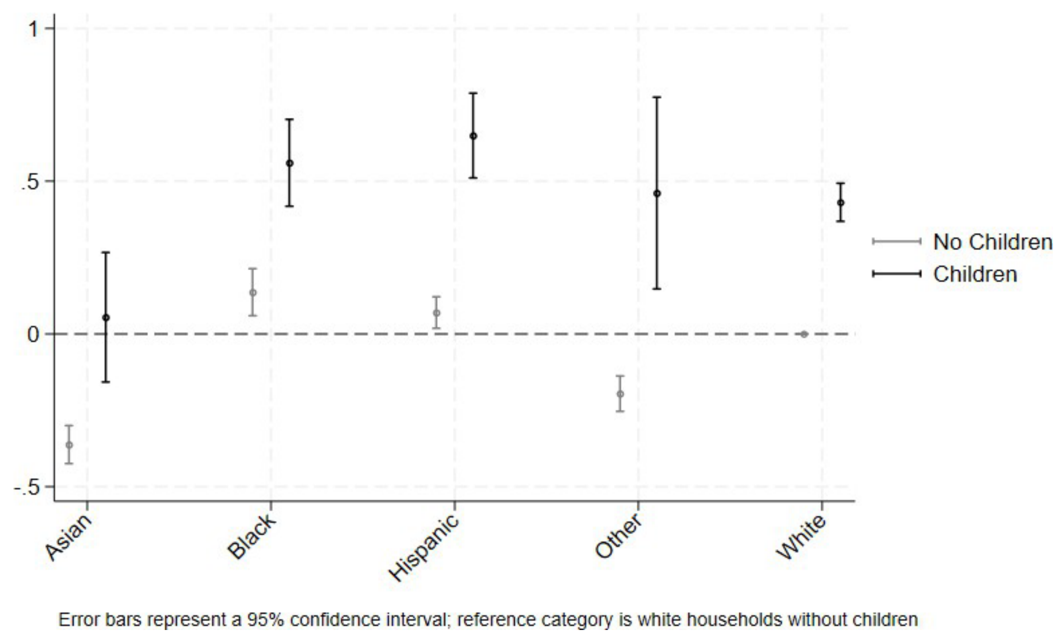
Exhibit 3.11 | Listed Coefficient by White Renter Share at the Tract Level



Heterogeneity Among Renters With and Without Children

We also find that families with children are more likely to be affected by selective advertising. **Exhibit 3.12** displays the coefficients on Listed for each racial group, both with and without children, using White families without children as the reference category. Across all racial groups, including White, families with children are more likely to rent listed units than those without children. In addition to being Black, Hispanic, or another minority race, having children is another factor that increases the likelihood of discrimination from selective advertising.

Exhibit 3.12 | Listed Coefficient for Each Group (Relative to White With no Children)



Heterogeneity with Other Forms of Discrimination

We further explore the heterogeneity in selective advertising, particularly in relation to other forms of discrimination. We examine whether selective advertising serves as a substitute for or complement to more detectable forms of discrimination by analyzing how the degree of heterogeneity in selective advertising varies with discrimination as measured by landlords' response to email inquiries.

To do so, we merge our data with the city-level average within-property relative response rate difference to email inquiries from a White identity compared to a Black or Hispanic identity for a given listing, as imputed by Christensen, Sarmiento-Barbieri, and Timmins (2021) in their correspondence study on a major online rental platform. In each city, Christensen, Sarmiento-Barbieri, and Timmins (2021) recover an average response rate differential between White and Hispanic or Black identities, and we apply this as a form of heterogeneity to all units in that city. A higher difference indicates greater discrimination, with landlords being less responsive to Black and Hispanic home seekers compared to White seekers.

We then augment our baseline estimation by interacting the Listed dummy with the White-Black response rate difference. Results are reported in **Exhibit 3.13**. As before, Black and Hispanic renters are more likely to occupy listed units, and this tendency increases as discrimination through response rates decreases. For example, in areas that are at the 75th percentile of the distribution of White-Black response rate differentials (i.e., where the difference in response rates is very high), the probability that a Black tenant lives in a listed unit is 32 percent higher than for a White tenant; this difference rises to 61 percent in areas where the difference is at the 25th percentile. Similarly, for Hispanic tenants, the probability of being in a listed unit is 13 percent higher than for White tenants in areas where the White-Hispanic response rate difference is at the 25th percentile, but this difference increases to 44 percent when the difference is at the 75th percentile.

Exhibit 3.13 | Interacting Listing Status with Differential Response Rate

Outcome:	Asian	Black	Hispanic	Other
(=1 if Unit is Listed)	-0.524***	0.511***	0.364***	-0.403***
	(0.0651)	(0.1094)	(0.0553)	(0.0650)
(=1 if Unit is Listed)*White-Black Correspondence Diff	-0.344	-2.584***	-2.744***	2.419***
	(0.6086)	(0.8926)	(0.3534)	(0.6114)
(=1 if Unit is Listed)*White-Hispanic Correspondence Diff	4.734***	-7.653***	-4.140***	0.203
	(0.7937)	(1.8122)	(1.4653)	(1.0188)
ZORI Zip/Metro Index	0.005***	-0.018***	-0.004***	0.002**
	(0.0012)	(0.0023)	(0.0012)	(0.0010)
% Renters White	-0.014***	-0.051***	-0.027***	-0.013***
	(0.0011)	(0.0022)	(0.0008)	(0.0012)
25% White-Black Diff Listed Odds Ratio	0.589	1.612	1.388	0.690
75% White-Black Diff Listed Odds Ratio	0.574	1.324	1.127	0.829
25% White-Hispanic Diff Listed Odds Ratio	0.592	1.667	1.439	0.668
75% White-Hispanic Diff Listed Odds Ratio	0.783	1.061	1.127	0.676
Log-likelihood: −350336				
Observations: 323, 927				
MSA and Year FE included				

Notes: *The correspondence differences represent the difference in the share of rental applications responded to according to the apparent race of the applicant from Christensen and Timmins. (2023). The stars ***, **, * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level. Standard errors are shown in parentheses.*

Overall, our findings suggest that when there is less callback discrimination by landlords, landlords may strategically shift to more subtle forms of discrimination. Unadvertised units are unlikely to be detected in audit or correspondence studies, thereby minimizing the risk of exposure. This gives landlords an incentive to avoid or minimize contact with unwanted populations by either not advertising at all or selectively advertising to reach only certain groups. For instance, the Fair Housing Justice Center recently completed an investigation involving a landlord who controls hundreds of rental units in a predominantly White Bronx neighborhood. The landlord avoided advertising available apartments, relying instead on referrals from existing White tenants to fill vacancies. [26]

The variation in selective advertising across areas with different response rates suggests that selective advertising, as a substitute for traditional forms of discrimination—like the number of units shown or landlords' response rates—may become increasingly popular in the housing search process if it goes undetected.

Linear Probability Model Estimation

One concern for our identification strategy is the potential presence of unobservable factors that simultaneously affect whether a property is listed on Dwellsy and the demographic composition of those searching in the neighborhood, particularly the percentage of Black searchers. In this case, a positive coefficient on the Listed dummy would not necessarily indicate evidence of discriminatory advertising. To address this concern, we employ the linear probability model (LPM) estimation, allowing us to control for granular fixed effects at the tract, building, or property manager level. The multinomial logit specification used above, while attractive in allowing for five different discrete outcomes, creates difficulties for the inclusion of large numbers of fixed effects. The linear probability model, while only permitting binary discrete outcomes, allows for any number of fixed effects. Our preferred identification strategy among the LPM specifications focuses on property manager fixed effects. These fixed effects control for any strategies aside from listing status used by the property manager across all their units that might appeal to one racial group more than another. By comparing the racial composition of tenants in listed versus unlisted units managed by the same property manager within the same year, we mitigate the confounding effects of any such strategies that might be correlated with discrimination across listed and unlisted units.

Exhibit 3.14 presents estimates from the LPM estimation where the dependent variable is an indicator for having a Black tenant. Unlike the baseline multinomial logit model, which uses White renters as the reference category, the reference category here includes all non-Black racial

[26] The enforcement literature (e.g., Freiberg and Squires 2015) notes that more complex testing procedures can be devised to uncover evidence of these alternative tools for intentional discrimination. This may involve the use of multiple testers interacting on multiple occasions with property managers. Given the resource requirements to implement such tests, having an indication of where selective advertising may be most prevalent, and which kind of renters it may be targeting most directly, will be useful. Our research provides this information.

groups. This changes the interpretation of the listed odds ratio compared to the baseline specification. However, the flexibility to include a rich set of fixed effects allows us to assess the robustness of the main findings.

Moving from left to right, columns add progressively richer sets of fixed effect controls. Adding tract covariates, MSA fixed effects, and year fixed effects reduces the coefficient on "listed" from 6.455 to 2.869 (columns 1-3). Inclusion of more stringent tract-level fixed effects and year fixed effects decreases the estimate further to 0.377 (column 4).

Exhibit 3.14 | Linear Probability Model for Black Renters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
=1 if Unit is Listed	6.455***	2.857***	2.869***	0.377***	0.270*	1.352***	1.217***	0.396***
	(0.1440)	(0.1315)	(0.5582)	(0.1248)	(0.1425)	(0.2488)	(0.2220)	(0.1223)
ZORI Zip/Metro Index		-0.098***	-0.065	-0.053**			-0.018	-0.052***
		(0.0021)	(0.0487)	(0.0204)			(0.0218)	(0.0170)
% Renters White		-0.384***	-0.416***				-0.288***	
		(0.0026)	(0.0695)				(0.0260)	
Mean Dep. Var.	9.40	9.40	9.40	9.38	8.54	9.29	9.29	9.27
Tract FE				✓				✓
Building FE					✓			
Manager MSA FE						✓	✓	✓
MSA FE			✓					
Year FE			✓	✓	✓	✓	✓	✓
Tract Covariates		✓	✓				✓	
Cluster level	None	None	MSA	Tract	Building	MSA	Manager	Tract
R^2	0.008	0.126	0.287	0.561	0.639	0.420	0.444	0.589
N	340,080	340,080	340,080	339,697	308,604	336,512	336,512	336,182

Notes: *The dependent variable is a binary variable that equals one hundred if the renter is Black and zero otherwise. Sample includes only renters in central cities. The stars ***, **, * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level. Standard errors are shown in parentheses.*

Another potential concern is that property managers may undertake other activities to recruit tenants aside from selective advertising that could contribute to a disproportionate racial composition with respect to listing status. To address this concern, we utilize manager-MSA fixed effects. Our identification assumption rests on the premise that once a manager adopts Dwellsy and lists a unit, there is no additional cost incurred to list additional units. Managers in our sample are typically professional commercial real estate managers who oversee multiple apartment buildings across various neighborhoods. Depending on the demographic makeup and property conditions within these neighborhoods, managers may have incentives to list vacant units in certain areas while opting not to list in others. In this case, observing a manager's decision to list some units but not others should reflect strategic incentives rather than the mere cost of using Dwellsy. Furthermore, if listed units systematically attract Black renters more than unlisted units, such selective advertising practices could suggest discrimination against Black renters.

Returning to **Exhibit 3.14,** column 6 introduces property manager fixed effects alongside MSA and year fixed effects. The coefficient for Listed now stands at 1.352, significant at the 1 percent level, confirming the importance of controlling for manager-MSA fixed effects. In column 7, a further inclusion of tract-level demographics reduces the Listed coefficient to 1.217, although it remains statistically significant. Column 8 replaces observed tract-level demographics with tract fixed effects and the resulting coefficient for Listed is further reduced to 0.396, aligning with what we found in previous results (Black renters are about 40 percent more likely to move into listed units than non-Black renters).

Exhibit 3.14 highlights the differences between Black and non-Black renters, with the latter category including Hispanic renters. The baseline estimates show that both Black and Hispanic renters face discrimination. In **Exhibit 3.15**, we present LPM estimates where the dependent variable indicates whether a tenant is Black or Hispanic. The reference category includes all non-Black and non-Hispanic racial groups. The patterns are consistent with those in **Exhibit 3.14**, confirming that our main findings are robust to the inclusion of unobservables at the neighborhood, manager, and building levels.

Exhibit 3.15 | Linear Probability Model for Black and Hispanic Renters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
=1 if Unit is Listed	9.576***	4.272***	3.951***	0.370*	-0.160	1.895***	1.680***	0.274
	(0.1922)	(0.1771)	(0.5140)	(0.2176)	(0.2644)	(0.3184)	(0.3385)	(0.220)
ZORI Zip/Metro Index		-0.126***	-0.133***	-0.106***			-0.056**	-0.063**
		(0.0032)	(0.0497)	(0.0352)			(0.0309)	(0.0266)
% Renters White		-0.589***	-0.525***				-0.416***	
		(0.0032)	(0.0461)				(0.0247)	
Mean Dep. Var.	23.08	23.08	23.08	23.05	21.92	22.95	22.95	22.92
Tract FE				✓				✓
Building FE					✓			
Manager MSA FE						✓	✓	✓
MSA FE			✓					
Year FE			✓	✓	✓	✓	✓	✓
Tract Covariates		✓	✓				✓	
Cluster level	None	None	MSA	Tract	Building	MSA	Manager	Tract
R^2	0.008	0.137	0.171	0.301	0.412	0.230	0.256	0.333
N	340,080	340,080	340,080	339,697	308,604	336,512	336,512	336,182

Notes: *The dependent variable is a binary variable that equals 100 if the renter is Black or Hispanic and zero otherwise. Standard errors are clustered by building manager-MSA. Sample includes only renters in central cities. The stars ***, **, * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level. Standard errors are shown In parentheses. The stars ***, **, * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level. Standard errors are shown in parentheses.*

External Validity

This section addresses a few concerns about the external validity of our results. The first concern about external validity is that within Dwellsy-covered buildings, landlords may use multiple channels to advertise available units. Therefore, a property not listed on Dwellsy might still be advertised elsewhere. To address this, we compared Dwellsy listings with rental listings scraped from major online platforms in selected cities. Appendix **Exhibit A3.1** shows that in Dwellsy-covered buildings, the number of units listed on Dwellsy closely matches the total number of units scraped from other sites. The difference is zero at the 25th, 50th, and 75th percentiles across all cities where data was scraped. On average, Dwellsy lists one fewer unit, likely due to its focus on professionally managed buildings and diligent efforts to verify listings, avoid duplicates, and remove off-market units. Overall, this comparison gives us high confidence that Dwellsy's online coverage of listed units in these buildings is nearly universal. In other words, very few units listed on other platforms are missing from Dwellsy. This aligns with the fact that Dwellsy does not charge per listing fees, allowing managers to advertise at no additional cost once the initial software installation fee is paid.

Another concern about external validity is how our findings from Dwellsy-covered buildings translate to the broader housing market. As discussed in Section 3.1, Dwellsy focuses on professionally managed rental buildings. In Seattle, Dwellsy-covered buildings represent at least one-third of the rental properties registered with the city, which reflects the universe of Seattle's rental market. When compared with the available rental stock, on average, Dwellsy listings cover 20 percent of the vacant rental units recorded in CoStar across cities like Atlanta, Chicago, DC, Minneapolis, Philadelphia, Pittsburgh, and Richmond. CoStar includes all vacant rental stock, listed or not, across multifamily properties, regardless of if they are professionally managed. In Chicago, Dwellsy's coverage of CoStar's vacant rental stock reaches 55.31 percent, reflecting the higher proportion of professionally managed properties and the increased turnover in larger cities, which leads to more units being listed on the market.

The extent to which our findings from the Dwellsy sample apply to the broader housing market depends on how similar the landlords, housing units, and neighborhoods in the Dwellsy sample are to the rest of the rental market. **Exhibit 3.3** shows that, on average, in neighborhoods covered by Dwellsy, 14.5 percent of the population live below the poverty line, 59 percent have college degrees or higher, and 64% are renters. These renters are 51.5 percent White, 16.4 percent Black, and 19.3 percent Hispanic. By contrast, the average Dwellsy-covered building has about 60 percent White renters, 9.5 percent Black renters, and 14.8 percent Hispanic renters. Thus, even within the Dwellsy sample, Dwellsy-covered buildings tend to have a lower fraction of Black and Hispanic renters relative to the rest of the neighborhood. While we can further compare the characteristics of neighborhoods and housing units between Dwellsy and the broader rental market, it is important to recognize the differences between professionally managed and non-professionally managed rental markets. We view our findings from Dwellsy as being most applicable to the professionally managed rental market, which constitutes a significant portion of the rental stock in large cities.

In non-professionally managed rental markets, there is not a central platform that covers nearly all rental listings. To extend our methodology to these markets, one approach could be to scrape listing data from all major rental websites available in each city and merge it with InfoUSA. This would allow the detection of selective advertising by linking the racial characteristics of tenants to landlords' advertising choices, using the methodology we developed.

Third, our findings are based on a sample of 27 cities previously used by HUD in Housing Discrimination Studies. As such, we do not know how our results might apply to other cities or suburban rental markets. However, since Dwellsy covers 47 major metropolitan areas in the United States, one way to scale up this analysis would be to include all 47 metropolitan areas. For those interested in additional metropolitan areas, we recommend scraping rental listing data from those locations and merging it with InfoUSA, allowing the application of the methodology developed here.

Finally, some minorities may not use online platforms to search for rental housing and thus may not be subject to the discrimination associated with selective advertising. However, adapting search behavior to avoid discriminatory behavior still imposes costs on the housing seeker. Moreover, if landlords strategically withhold certain units from online platforms, they are likely to do the same with offline advertising channels, such as word of mouth.

Conclusion

Audit and correspondence studies have played a key role in a growing body of research highlighting the ongoing issue of racial discrimination in rental housing markets. However, these methods may miss more subtle forms of discrimination. In our analysis, we uncover evidence that selective advertising can be a source of discrimination, where landlords choose not to advertise certain units, instead reserving them for prospective renters they have met in person after an initial screening or through other offline channels.

Detecting this practice is challenging, complicating fair housing enforcement efforts. We present a novel method for identifying selective advertising and examine its impact on minorities' access to neighborhoods with better amenities. Our approach leverages a large marketing dataset to track apartment turnovers across 27 major U.S. metropolitan areas. We match this data with a rental listings dataset to spot turnover units that were not publicly advertised. Our empirical design takes a conservative approach, using only units in buildings where an online listing platform with low marginal costs for additional listings was known to be present. Future research could extend this work to include other listing services, allowing the analysis to incorporate a broader set of buildings, particularly smaller, non-professionally managed buildings.

By comparing the racial composition of actual occupants in listed versus 'hidden' units, we evaluate the extent of discrimination through selective advertising. Our findings reveal discrimination against Black and Hispanic renters through selective advertising that is both significant in magnitude and especially pronounced in neighborhoods with superior amenities, where other forms of discrimination are less common, and in areas approaching racial "tipping points."

Appendix

Dwellsy Data Coverage

Exhibit A3.1 | Dwellsy Rental Market Coverage in the City of Seattle

	Coverage Statistic	
	% Rental Buildings	% Rental Units
Building in Dwellsy	19.3	31.4
Property manager in Dwellsy	34.7	43.3

Notes: *A building is determined to be in Dwellsy if a unit in it was listed on Dwellsy between January 2020 and July 2024. A property manager is determined to be in Dwellsy if they are listed as a contact of a building that had a unit listed on Dwellsy during the same period. The first column displays the share of buildings that are registered as rental properties in the city of Seattle in 2023 that are either in Dwellsy or have a property manager in Dwellsy. The second column displays the share of units in buildings that are registered as rental properties in 2023 that are either in Dwellsy or have a property manager in Dwellsy.*

Exhibit A3.2 | Dwellsy Coverage in the Costar Multifamily Sample

	Buildings with Vacancies		Units in Buildings with Vacancies	
City	**#**	**% Covered**	**#**	**% Covered**
Atlanta	1,136	13.47	191,560	9.58
Chicago	233	32.19	24,031	55.31
Washington, DC	1,116	11.47	134,414	16.54
Minneapolis	903	26.25	63,510	16.79
Philadelphia	1,158	20.98	98,305	14.73
Pittsburgh	556	26.26	49,165	14.37
Richmond	363	16.80	44,131	8.05

Notes: The geographic area for each city is determined by CoStar "markets," which are generally larger than a central city but smaller than a metropolitan area. A building in the CoStar sample is considered to have a vacancy if it had a nonzero count of housing units marked as available when the full multifamily sample for its city was downloaded between July and August of 2023. A building is considered covered by the Dwellsy sample if any of its units were listed on Dwellsy in 2023.

Exhibit A3.3 | Listing Coverage in Dwellsy-Covered Buildings

	Mean Listed Units		Dwellsy Listings – Scraped Listings		
	Dwellsy	**Scraped**	**25%ile**	**50%ile**	**75%ile**
Panel A: All scraped sources, by city					
Atlanta	2.2	2.4	0	0	0
Boston	1.7	1.9	0	0	0
Washington, DC	2.7	5.5	-1	0	0
Minneapolis	2.8	3.7	-1	0	0
Richmond	1.7	2.0	0	0	0
Seattle	2.4	3.0	0	0	0
Panel B: All cities, by scraped source					
Platform #1	2.1	3.2	-1	0	0
Platform #2	1.6	2.0	-1	0	0
Platform #3	1.6	1.9	0	0	0
Platform #4	12.4	16.8	-6	-4	-3
Platform #5	1.0	1.0	0	0	0
Platform #6	3.0	1.0	2	2	2
Platform #7	3.3	3.7	0	0	2
Platform #8	2.5	4.1	0	0	0
Platform #9	3.0	4.2	-2	-1	0
Platform #10	2.4	2.9	0	0	0
Total	**2.4**	**3.4**	**0**	**0**	**0**

Additional Exhibits

Exhibit A3.4 | Share of Renters in Listed Units by Racial Group and City

	% Renters in Group in Listed Units					
	Asian	**Black**	**Hispanic**	**Other**	**White**	**Total**
Albuquerque	27.01	37.50	32.85	30.70	32.03	**32.18**
Atlanta	11.19	22.55	12.83	11.82	12.34	**16.43**
Baltimore	16.52	38.46	22.26	20.85	28.46	**31.75**
Boston	7.28	23.96	11.94	7.89	11.00	**10.74**
Chicago	6.52	27.11	14.53	11.06	11.81	**12.78**
Cleveland	22.81	40.30	46.61	18.75	33.30	**36.17**
Columbia	28.57	37.84	35.94	35.00	28.82	**30.45**
Dallas	8.29	22.68	20.75	7.60	13.48	**14.83**
Washington, DC	10.15	20.36	12.44	10.73	13.15	**14.96**
Detroit	18.00	41.38	24.77	15.05	26.65	**37.85**
Fort Worth	53.80	45.17	56.14	58.97	52.04	**52.42**
Houston	9.38	14.79	12.39	6.90	6.46	**8.64**
Kansas City	29.91	54.63	47.97	33.70	40.55	**43.76**
Los Angeles	16.97	32.70	25.70	20.54	25.04	**23.92**
Miami	3.70	13.86	4.67	2.89	4.14	**4.47**
Minneapolis	14.86	26.57	20.20	21.74	22.14	**21.95**
New York	6.26	14.68	8.27	7.81	7.06	**7.50**
Newark	24.44	40.94	40.00	37.50	34.58	**39.08**
Philadelphia	17.00	38.60	29.87	27.52	22.13	**27.07**
Pittsburgh	21.48	37.94	25.37	26.32	38.05	**36.06**
Providence	8.16	17.86	32.26	17.50	19.08	**20.11**
Riverside	14.29	53.57	36.27	17.65	35.15	**33.97**
San Antonio	18.60	23.31	27.62	20.58	25.05	**25.66**
San Diego	23.51	20.38	27.14	22.86	25.10	**25.16**
San Jose	29.24	34.04	42.36	33.22	40.46	**37.12**
Seattle	13.45	22.70	22.57	16.61	24.16	**22.08**
Tampa	17.60	31.68	30.14	21.40	18.05	**21.17**
Mean	**12.05**	**27.99**	**20.08**	**14.41**	**16.72**	**17.69**
Median	**16.97**	**31.68**	**25.70**	**20.54**	**25.04**	**25.16**

Exhibit A3.5 | Multinomial Logit Results for Black Renters

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Outcome: Black					
=1 if Unit is Listed	0.674***	0.652***	0.321***	0.154***	0.118***
	(0.0662)	(0.0480)	(0.0356)	(0.0397)	(0.0379)
ZORI Zip/Metro Index			-0.054***		-0.016***
			(0.0016)		(0.0017)
% of Renters that are White				-0.063***	-0.056***
				(0.0013)	(0.0015)
MSA FE		✓	✓	✓	✓
Year FE		✓	✓	✓	✓
Listed Odds Ratio	1.963	1.920	1.379	1.166	1.125
Pseudo R^2	0.006	0.088	0.112	0.146	0.145
Log-likelihood	-410328	-376150	-353347	-351689	-339656
N	351,142	351,142	340,785	350,437	340,080

Notes: *The stars ***, **, * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level. Standard errors are shown in parentheses.*

Exhibit A3.6 | Multinomial Logit results for Hispanic Renters

	(1)	(2)	(3)	(4)	(5)
Outcome: Hispanic					
=1 if Unit is Listed	0.297***	0.183***	0.117***	0.097***	0.078***
	(0.0517)	(0.0306)	(0.0286)	(0.0247)	(0.0253)
ZORI Zip/Metro Index			-0.019***		-0.009***
			(0.0007)		(0.0007)
% of Renters that are White				-0.023***	-0.019***
				(0.0005)	(0.0006)
MSA FE		✓	✓	✓	✓
Year FE		✓	✓	✓	✓
Listed Odds Ratio	1.345	1.200	1.124	1.102	1.081
Pseudo R^2	0.006	0.088	0.112	0.146	0.145
Log-likelihood	-410328	-376150	-353347	-351689	-339656
N	351,142	351,142	340,785	350,437	340,080

Notes: *The stars ***, **, * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level. Standard errors are shown in parentheses.*

Exhibit A3.7 | Multinomial Logit Results for Asian Renters

	(1)	(2)	(3)	(4)	(5)
Outcome: Asian					
=1 if Unit is Listed	-0.434***	-0.408***	-0.405***	-0.446***	-0.434***
	(0.0298)	(0.0323)	(0.0337)	(0.0314)	(0.0317)
ZORI Zip/Metro Index			0.000		0.005***
			(0.0011)		(0.0014)
% of Renters that are White				-0.014***	-0.017***
				(0.0008)	(0.0007)
MSA FE		✓	✓	✓	✓
Year FE		✓	✓	✓	✓
Listed Odds Ratio	0.648	0.665	0.667	0.640	0.648
Pseudo R^2	0.006	0.088	0.112	0.146	0.145
Log-likelihood	-410328	-376150	-353347	-351689	-339656
N	351,142	351,142	340,785	350,437	340,080

Notes: *The stars ***, **, * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level. Standard errors are shown in parentheses.*

Exhibit A3.8 | Multinomial Logit Results for Renters Who are Not White, Black, Asian, or Hispanic

	(1)	(2)	(3)	(4)	(5)
Outcome: Other					
=1 if Unit is Listed	-0.171***	-0.174***	-0.180***	-0.204***	-0.197***
	(0.0321)	(0.0296)	(0.0291)	(0.0288)	(0.0291)
ZORI Zip/Metro Index			-0.002		0.002**
			(0.0015)		(0.0008)
% of Renters that are White				-0.011***	-0.012***
				(0.0016)	(0.0016)
MSA FE		✓	✓	✓	✓
Year FE		✓	✓	✓	✓
Listed Odds Ratio	0.843	0.840	0.836	0.816	0.822
Pseudo R^2	0.006	0.088	0.112	0.146	0.145
Log-likelihood	-410328	-376150	-353347	-351689	-339656
N	351,142	351,142	340,785	350,437	340,080

Notes: *The stars ***, **, * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level. Standard errors are shown in parentheses.*

Exhibit A3.9 | MNL Results with Covariates

Outcome:	**Asian**	**Black**	**Hispanic**	**Other**
=1 if Unit is Listed	-0.329***	0.089**	-0.081***	-0.259***
	(0.0343)	(0.0435)	(0.0255)	(0.0526)
ZORI Zip/Metro Index	0.002***	-0.007***	-0.005***	0.001
	(0.0008)	(0.0028)	(0.0008)	(0.0008)
% of Renters that are White	-0.017***	-0.023	-0.007*	-0.007
	(0.0045)	(0.0183)	(0.0036)	(0.0060)
% of Renters that are Black	0.004	0.032*	0.005	0.009
	(0.0045)	(0.0179)	(0.0034)	(0.0056)
% of Renters that are Asian	0.024***	-0.018	0.005	0.007
	(0.0050)	(0.0180)	(0.0036)	(0.0062)
% of Renters that are Hispanic	-0.004	-0.019	0.010***	-0.011*
	(0.0046)	(0.0193)	(0.0035)	(0.0056)
% Population Renters	0.003***	0.012***	-0.002***	-0.002
	(0.0009)	(0.0023)	(0.0006)	(0.0013)
% Households w/ Children	-0.006***	-0.010***	-0.001	-0.001
	(0.0013)	(0.0033)	(0.0010)	(0.0014)
% BA+	0.008***	-0.003	-0.004***	-0.005**
	(0.0018)	(0.0031)	(0.0014)	(0.0022)
Rent per sq ft	0.016	-0.285***	-0.124***	0.006
	(0.0215)	(0.0465)	(0.0151)	(0.0229)
Listed Odds Ratio	0.720	1.093	0.922	0.772
Log-likelihood: −208648				
Observations: 211, 395				
MSA and Year FE included				

Notes: *The stars ***, **, * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level. Standard errors are shown in parentheses.*

Exhibit A3.10 | MNL Results with All Race Covariates

Outcome:	**Asian**	**Black**	**Hispanic**	**Other**
=1 if Unit is Listed	-0.335***	0.072**	0.053**	-0.177***
	(0.0307)	(0.0349)	(0.0242)	(0.0296)
ZORI Zip/Metro Index	0.002***	-0.015***	-0.007***	0.001
	(0.0009)	(0.0017)	(0.0007)	(0.0008)
% of Renters that are White	-0.015***	-0.024**	-0.003	-0.004
	(0.0032)	(0.0104)	(0.0026)	(0.0040)
% of Renters that are Black	-0.001	0.035***	0.014***	0.015***
	(0.0031)	(0.0101)	(0.0025)	(0.0038)
% of Renters that are Asian	0.025***	-0.014	0.009***	0.010**
	(0.0036)	(0.0102)	(0.0026)	(0.0046)
% of Renters that are Hispanic	-0.010***	-0.014	0.019***	-0.005
	(0.0031)	(0.0107)	(0.0025)	(0.0038)
Listed Odds Ratio	0.715	1.075	1.055	0.838
Log-likelihood: −332722				
Observations: 340, 080				
MSA and Year FE included				

Notes: *The stars ***, **, * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level. Standard errors are shown in parentheses.*

Chapter 4. Case Study: Discriminatory Lending Practices

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Abstract

This research examines discrimination in the mortgage underwriting process through both quantitative and qualitative lenses. Using data from the Home Mortgage Disclosure Act (HMDA), Multiple Listing Service (MLS), and the American Community Survey (ACS), we calculate time to close and closing cost indices. Additionally, the study draws on the insights of real estate and lending professionals with more than 20 years of experience. The analysis covers single-family, owner-occupied transactions in five high-growth and diverse counties of the Houston Metropolitan Statistical Area (MSA) between 2018 and 2022, a period that includes both pre- and post-Covid years as well as a tightening housing supply and historically low mortgage interest rates followed by sharp increases. The time to close index regression model reveals that Black borrowers take, on average, three days longer to close a loan compared to White borrowers. The closing costs index regression results show that Black borrowers pay, on average, 0.04 percent more in closing costs than their White counterparts.

Introduction

It is unfortunate that 56 years into the Fair Housing Act of 1968, we are still discussing and testing for discrimination in the housing market. The current lens or framing of discussion among community advocates is the role housing plays in creating generational wealth, and the disadvantages minorities face due to historical discriminatory practices coupled with practices that are new or yet to be identified. Identifying structural obstacles that impact generational wealth and the potential of economic parity for African Americans is one of the motivations for pursuing this study.

Discrimination in the housing market can occur at various stages of the home-buying process, from selecting a neighborhood to securing financing, and throughout the loan origination process up to closing. Addressing housing discrimination—whether intentional or a result of systemic inequities—requires ongoing evaluation of both the policies and the procedures followed by all parties involved. The objectives of fair lending are not achieved by simply closing a loan. Other discriminatory practices may still be present, such as disparities in closing costs, higher interest rates than credit history warrants, origination delays impacting time to close, and the overall treatment of applicants.

Since the passage of the Civil Rights Act, there have been successful efforts to address inequalities in homeownership (Apgar and Calder, 2005). Numerous studies, reports, and federal oversight have led to tighter regulations in the real estate and lending industries. The advent of the automated underwriting system touts the removal or reduction of discriminatory practices to the benefit or advantage of marginalized populations (Gates, Perry, and Zorn, 2022). These efforts address a factor or factors contributing to a broader pattern. Yet, concerns remain regarding undetected forms of bias that require more progressive methods of detection.

This research focuses on two critical aspects of the loan origination process that are rarely addressed in the literature. We investigate racial discrimination in closing costs and examine potential racial biases in the time between loan application and closing. The study hypothesizes that both time delays and fees in the home-buying process may serve as avenues for discrimination.

Time-to-Close

Time-to-close, or the loan origination process, are synonymous terms focusing on the time between application and the closing of a loan. There are numerous steps in the origination process. Dealing with complex time-sensitive documents and interactions with people, both internal and external to the lender and potential borrower. The average loan closing ranges between 30 to 60 days. Delays outside this range, however small, can impact the potential borrower in several ways.

Loans terms are locked-in for a specified time period—typically, 30 or 60 days. One day beyond that time frame results in a renegotiation of the loan with respect to interest rates. If interest rates are rising, the new interest rate will increase the borrower's debt-to-income ratio. For some borrowers, this will require a re-review of the loan. And, depending on the change in payments, conversations may be required regarding interest buy-downs (if the borrower is aware of and can afford that option) or additional money down to keep payments within an acceptable debt-to-income number. For others, the increased interest payments, without the extra funds to negotiate terms, make the loan unaffordable. To close on the loan, they may need to turn to alternative financing.

Compounding this situation is earnest money. Earnest money refers to those funds provided to the buyer and kept by a third party to take the property of interest off the market. The contract specifies the term allowing enough time for the buyer to secure financing. If the loan process is delayed and extends beyond the agreed upon term, the buyer can attempt to negotiate a contract extension, with additional earnest funds, or lose earnest funds and the house. Loss of earnest money impacts the ability to submit an offer for a subsequent home.

From the perspective of the borrower, delays are expensive and could exclude one from the housing market until funds, interest rates, or new loan products become available. Unfortunately, from the lender's perspective, the impacts of delayed loans do not appear to be as profound, at least in the short term. Realtors and brokers are aware of lending institutions within their service area that have a pattern of delayed decisions—especially if those delays commonly involve people of color. The agent or broker response: to avoid or recommend their clients avoid those lending institutions (Brahma et al., 2021). Over the long term, reduction in loan originations could compromise the lending institution's ability to meet its CRA requirements.

Capturing time to close, time elapsed between loan origination and closing, can be achieved by combining Home Mortgage Disclosure Act (HMDA) data with Multiple Listing Service Data (MLS). HMDA data provides loan origination dates while the MLS provides the closing date. Why measure time-to-close? Because discriminatory practices can lie in the process, as well as the outcome. Experience-based statements shared by focus group participants indicate that despite success in the home origination process, African American buyers encounter a more arduous loan qualification process. Requests for additional paperwork, for the same paperwork multiple times, or replacement of "lost" paperwork are factors that lead to a delayed loan process or incomplete applications. The existing research varies on if the delays are reflective of credit scores, race, and/or buyers' unpreparedness; are the result of specific lenders' biases; or are characteristics of discriminatory mortgage process.

Closing Costs

Closing costs consist of various service and government fees added to the sale price of a home. These costs vary based on jurisdiction, lender, home price, and the buyer's financial risk, with such differences generally considered acceptable. Some discretionary components of closing costs may still allow for racial bias, which has historically been embedded in housing discrimination practices.

Homebuyers unfamiliar with the process rely on real estate professionals for guidance. However, real estate agents are typically paid by commission, which may lead to a conflict of interest and an increase in overall housing costs (Jefferson and Thomas, 2020). Having available funds to pay for closing costs can be an obstacle in the home-buying process. Closing costs paid by minorities are substantially higher than the costs paid by White non-Hispanic[27] homebuyers (Woodward, 2008). Minorities often have limited understanding of how substantial the effects of amortizing inflated costs over the loan period can impact the final cost of a home. Educating buyers about the home-buying process can help mitigate this issue, but systemic discrimination remains a challenge. Real estate professionals, many of whom are White, often display bias against Black and Hispanic buyers, perpetuating racial inequalities in homeownership (Ondrich et al., 1998). Although minority

[27] Throughout this chapter, White non-Hispanics will be referenced as White.

homeownership rates have improved through advocacy and policy changes, excessive fees for brokerage and other conveyance services remain a significant burden (Inderst and Ottaviani, 2012). Inflated closing costs can be the difference in housing affordability for a minority buyer who is calculating financial viability based on the sales price. These inflated costs, often rooted in racial discrimination, can deny homeownership which contributes to widening the wealth gap between minorities and White homeowners, with long-term generational effects. Therefore, scrutinizing these costs is essential in the fight against discrimination.

Literature Review

There is an abundance of research addressing discrimination in the home lending process, a problem that continues to have profound implications for minority groups in the United States. This literature review, conducted within the context of this case study, follows a circular process. The initial review aimed to identify gaps in the existing underwriting literature. After conducting focus groups meetings and one-on-one interviews with professionals involved in the lending process, we performed a more targeted literature search using specific keywords to capture practices identified by participants.

Much of the existing literature review focuses on three key areas: credit risks, yield spread premiums (YSP), and loan service. While these areas of focus differ, the relationships between the variables identified in this research are crucial for understanding their role in the loan origination process.

Credit Scores and Risk

Credit scores have long been an indicator of the risk posed by the buyer and hence a significant factor in determining a borrower's ability to secure a loan. In many cases, credit scores are viewed as an objective measure to minimize or even eliminate potential discrimination in the loan origination process. However, this assumption becomes problematic and can inadvertently perpetuate racism considering that African Americans, on average, have lower credit scores compared to their White counterparts (Haberle and House, 2021; Bhutta, Hizmo, and Ringo, 2022).

The 2008 mortgage crisis illuminated these disparities. In a matched paired test conducted by Steve Tomkowiak (2009), 32 percent of African American prospective borrowers were asked about their credit compared to 13 percent of White prospective borrowers. In 2017, Steil et al. found that Black and Latino borrowers were more likely to be placed into higher-cost, higher-risk loans compared to White borrowers with similar characteristics, inclusive of credit scores. This study is referenced in our analysis under the credit score discussion, as it ties into the broader theory of durable inequality as referenced by Stein et al. and proposed by Charles Tilly. Tilly (1999) theorized broadly that groups in positions of power—particularly those controlling valuable resources—often exploit others to produce value while simultaneously excluding them from fully benefiting from it. In the context of mortgage lending, the resources in question are credit and capital, both of which minorities historically have had limited access to, due to long-standing systemic discrimination. Steil et al. refer to this phenomenon as opportunity hoarding, where privileged groups retain exclusive access to opportunities, thereby perpetuating inequality over time (Steil et al., 2017, p. 14). Courchane and Ross (2019) arrived at a similar conclusion. Their study, which combined HMDA and Dataquicks datasets, showed that most of the racial and ethnic differences can be explained by a measure of lender perceived foreclosure risk, which is predictive of the likelihood of receiving a high-cost loan. The substantial racial and ethnic differences in the incidence of high-cost lending arise because African American and Hispanic borrowers tend to be concentrated at these high-risk lenders, even when their credit scores are relatively unblemished. Haughwout et al. (2009) discussed how the post-financial crisis tightening of underwriting standards disproportionately impacted Black borrowers and those in minority neighborhoods, as these groups historically had lower credit scores. As a result, while credit scores may serve as a tool to reduce bias, they often reinforce systemic inequities in lending practices, particularly for marginalized communities.

In an earlier examination of this issue, Sengupta and Emmons (2007) expanded the credit conversation to include credit risk, or the likelihood that a borrower will default on a loan. Their research determined that risk is influenced by a variety of factors, including credit scores, loan-to-value ratios, and a borrower's financial history. They argue that both borrower characteristics (demand side) and lender characteristics (supply side) play a role in determining the likelihood of loan denial and the terms of the loan. These elements interact in the loan origination process and contribute to the prevalence of subprime lending, which has been disproportionately offered to minority communities. Over a decade later, Reynolds, Perry, and Choi (2021) considered the full scope of credit risk, emphasizing that credit characteristics go beyond the credit score and incorporate aspects such as credit history, collateral, and capacity—factors shaped by long histories of racial discrimination in both public and private institutions.

Yu (2022) extended this discussion by exploring structural discrimination and perceived bias of risk in the automated underwriting process. While automated underwriting systems are designed to reduce human bias, they may still perpetuate discrimination because they are based on historical data that can reinforce existing biases. Underwriters, although less involved in decision-making due to automation, still play a role in influencing final loan decisions, potentially reinforcing structural discrimination. This view is echoed by Horowitz, Ky, and Starling (2024), who posit that the real issue in lending is not solely the credit score, but the underlying credit history and the assumptions of risk associated with it. These assumptions, based on historical data, can perpetuate racial discrimination by disproportionately affecting minority borrowers.

Closing Costs and Yield Spread Premiums

There is a body of research examining racial disparities in yield spread premiums (YSP) for originated loans. Black, Boehm, and DeGennaro (2001) compared yield spread premiums across three racial groups over a two-year period in the late 1980s. They concluded that policies aimed at increasing minorities' bargaining power could be more effective at reducing racial differences in overages than further anti-discrimination legislation.

Susan Woodward (2008) focused on closing costs for Federal Housing Administration (FHA) mortgages, specifically examining yield spread premiums as loan fees. Her analysis of over 7,500 FHA 30-year fixed-rate loans revealed that yield spread premiums for brokered loans were higher than for direct lending, with African Americans and Latinos[28] paying more than other groups. This finding suggests that racial disparities in loan pricing are exacerbated by the type of lending institution and the terms of the mortgage. Her research also identified variables that affect closing costs: loan amount, property value, credit score, and title fees, as well as neighborhood characteristics such as education levels, racial composition, and neighborhood-level discount

[28] Authors use Hispanic throughout the chapter. Use of Latino here reflects the terminology used by the cited author.

points all contribute to the final number. This underscores the complexity of closing costs, which cannot be explained solely by the loan characteristics but also by factors related to systemic discrimination (Woodward, 2008).

Wheat and Henry-Nickie (2024) found that closing costs vary significantly by lender type, with banks generally offering lower closing costs compared to nonbanks and brokers. Still, they noted that minorities, particularly African Americans, tend to incur higher closing costs across lending institutions. Nonbanks and brokers, which disproportionately serve minorities and underserved communities, tend to charge higher fees, further exacerbating the economic barriers for these groups.

Level of Service and Discrimination

The level of service provided by lenders is another critical factor that may perpetuate discrimination in the home lending process. Hunter and Walker (1996) tested the "cultural affinity hypothesis" they had discussed in their paper “The Cultural Affinity Hypothesis and Mortgage Lending Decisions.” The hypothesis states:

> …white loan officers will rely more heavily on characteristics that can be observed at low cost when appraising the creditworthiness of minorities rather than invest marginal resources in gathering additional information about creditworthiness. Stated differently, if the majority of loan officers and applicants are white, white loan officers may feel they know more about white than about minorities, and thus they are more likely to acquire additional information about the creditworthiness of white applicants. On the other hand, we would expect these to rely more heavily on basic objective loan application information in appraising the creditworthiness of minorities. (2)

In 1996,Hunter and Walker analyzed 1,991 loan applications and found that White loan officers held Black applicants to higher quantitative standards than similarly situated White applicants. This suggests that implicit bias may influence loan approval decisions, even when applicants are in similar financial situations (Hunter and Walker, 1996).

Stephen Holloway (1998) found that borrowers were treated differently when purchasing homes in predominantly White versus predominantly Black neighborhoods. This disparity in service levels underscores how geographical context and racial composition can affect loan origination outcomes. Using a qualitative approach to study the mortgage lending process, Massey et al. (2016) found that structural racism was evident in 76 percent of the cases studies. Statements taken from the documents reviewed indicated that African American borrowers had different experiences, including not being made aware their loan interest rate was not locked, paying higher interest rates, and being referred for a subprime loan despite their eligibility for a prime loan.

More recently, Meghan O’Neil (2018) found evidence of cultural affinity in mortgage lending, showing that White brokers and lenders were more likely to trust White borrowers and offer more leniency when they needed to provide additional documentation or compensating information. By contrast, Black borrowers were held to stricter guidelines, even when all other factors were equal. Evidence from research by Courchane and Ross (2019) suggests that loan officer and mortgage broker discretion, especially when combined with historical compensation systems, plays a substantial role in creating the racial differences that are observed in the market. Racial and ethnic differences in prime mortgage underwriting across lenders can be attributed to minority borrowers' applications not matching the criteria used by individual lenders, and loan officers, who should know the lenders' standards, may provide less assistance and information to minority borrowers.

Horowitz, Ky, and Starling (2024) further support the notion that the level of service provided by lenders varies based on race. They argue that minority applicants, particularly as it relates to supply-side characteristics, often receive less support during the application process, leading to higher rates of procedural denials. While this problem has been explored in previous literature, further research is needed because it has significant implications for understanding the dynamics of both loan denials and approvals.

Summary

Progress has been made in understanding the mechanisms of discrimination in home lending, still significant gaps remain. The interplay between credit scores, credit history, closing costs, yield spread premiums, and level of service provides a complex landscape of factors that contribute to unequal outcomes in the mortgage process. The demand-side characteristics (such as income level, credit history, and racial background of the borrower) interact with supply-side characteristics (like lender practices, policies, and institutional biases), and these interactions are influenced by systemic racism.

This research makes several contributions to the existing literature on discriminatory lending practices and underlines key areas and approaches that have not been considered in previous research. This research argues that both supply-side (lender decision-making) and demand-side (borrower characteristics) factors should be viewed as part of a single, interconnected process. Understanding how these factors interact in practice is crucial to fully comprehend the dynamics of discrimination in lending. Time-to-close plays a significant role in the borrowing experience and can be a point of discrimination. It is an unregulated aspect of the process that, when analyzed, could provide insights into delays or hurdles faced by minority borrowers that are not necessarily visible through traditional metrics like credit score or debt-to-income ratio.

Existing research presents a wide range of what constitutes "closing costs," but this variation complicates comparisons based on borrower characteristics like race, ethnicity, or gender. The closing cost index normalizes closing costs as a percentage of the loan amount. The proposed index allows for a more consistent comparison across different borrowers, regardless of the specific fees included in the closing process. This approach also helps mitigate the variability that makes it difficult to draw definitive conclusions from prior studies.

By focusing on loans within a specific region, the research acknowledges that regulatory differences across jurisdictions can significantly affect the structure and transparency of closing costs. By using the closing costs index and comparing data within the same jurisdiction, the study seeks to isolate the impact of these regulatory factors from other variables. This approach makes it possible to identify potential discriminatory practices that are a function of local regulations or institutional practices, rather than broader national policies.

Finally, this paper underscores that much of the discrimination in home lending remains unregulated or inadequately addressed. The focus group feedback discussed below suggests that the processes surrounding loan application, underwriting, and closing—particularly in terms of time-to-close and closing costs—are important factors. By bringing these aspects into focus, the research aims to contribute a more holistic view of discriminatory practices in the home lending process.

Focus Group

To obtain greater insight into the lending process, we invited real estate professionals associated with the National Association of Real Estate Brokers (NAREB) to participate in focus groups in November and December of 2023. Thirteen real estate professionals with experience ranging from 16 to 22 years in the field were willing to share their insights into the loan origination process. Participants often served several roles within the industry.

- Five of the participants were both realtors and brokers.
- Two participants were solely underwriters.
- Two participants were both brokers and instructors.
- One-third of the participants have served as a broker and are currently underwriters.
- Three of the participants were either a broker or a realtor.

The group provided insights into the many phases of the underwriting process that solidified the selection of variables for further study. Further, participants indicated there may be phases of the underwriting process that cannot easily be measured, as there are a variety of ways bias or discrimination may be manifested.

Key Insights from Conversations

Racial Discrimination: Participants unanimously recognized the existence of racial discrimination within the lending and underwriting process. Although Fair Housing laws prohibit asking borrowers to identify race, participants expressed that race is never unknown to lenders for two reasons:

- **Documentation**: Applicants are required to provide identification, such as a driver's license or state ID. While neither form of identification expressly states the race of the individual, participants contend that banks rely on visual cues from the photo, especially when the requests are for color copies.
- **In-person observation**: Race can be observed during the loan intake process unless the process is entirely online. Still, an ID must be uploaded and submitted with the application.

Appraisal Concerns: Participants mentioned specific issues related to racial discrimination in appraisals including:

- **Inaccuracies**: When a person of color is potentially purchasing property in a predominantly different racial neighborhood, appraisals may be inaccurate.
- **Additional Appraisals**: Requests for multiple appraisals, possibly due to accuracy concerns, can increase costs and extend the application process.
- **Undervaluation**: Properties in predominantly minority neighborhoods may be undervalued, influenced by the appraiser's own biases. Participants asserted "underwriters and brokers who are unfamiliar with the communities tend to under appraise." They referenced

unconscious biases and cited the Long Island Divide report (Choi, Herbert, and Winslow, 2019).

Income Documentation: Many participants within the focus group have clients of color with non-traditional jobs, are self-employed or have more than one source of income in which one or more of the sources are seasonal and/or primarily cash transactions.

- **Alternative Options:** These clients face challenges in providing documentation acceptable to support current or future income. Creative ways are needed to capture non-traditional forms of income that fall outside of tax returns (Form 1040), 1099 forms, bank statements, profit/loss statements or pay stubs.
- **Clarity in Request:** Requests for extensive and sometimes irrelevant documentation can lead to delays, loss of locked interest rates, or loss of earnest money. This often results in loans being neither approved nor documented as denied. One participant noted "in these cases, the loan is not documented as denied, just not approved. This happens more than the average person would expect and, the requests are not always related to income."

Underwriting Process: Underwriters have 30 days to review a loan. During this time, they are able to exercise "lender discretion" in a number of ways that can adversely impact minority applicants.

- **Discretion and Delays:** Underwriters have discretion during the review process, which can lead to delays. The process might involve multiple underwriters, each with a 30-day requirement, reviewing the loan from different perspectives, potentially leading to requests for information that is repetitive or believed to be unnecessary or excessive. While participants recognize that certain information is needed for the secondary market or regulations, they referred to those additional materials that make the underwriter 'feel' 1% better about making the loan as "fluff".
- **Documentation of Requests**: There is no standardized documentation of the frequency or relevance of additional documentation requests. However, loan folders and Mortgage Call Reports (MCR) contain records of requests and justifications. Despite this, some underwriters may use these records with "finesse" to justify their actions.
- **Re-underwriting and Tax Upfront:** Re-underwriting refers to a lending institution changing or modifying the product requirements if they perceive there is a credit risk or that a loan will fall into default. While there are many underlying reasons for a potential loan to be re-underwritten, the process results in more upfront costs at the time of closing.

The insights of a small group should not be negated due to its size. The respondents' unedited conversations suggested additional areas of literature to be considered. Those who had been in the industry for decades noted that the mortgage process had become more sophisticated over the years. Participants noted that while there are more laws and attempts at equity in the process and outcome, if one wants to discriminate, they still can and will.

Research Design

This feasibility study creates two indices to test its hypotheses.

H_1 = The time to close or loan origination process for a single-family mortgage loan is longer for African Americans

H_2 = Single-family mortgage loans closing costs are higher for African Americans

Study Area

This research focuses on the counties within the Houston Metropolitan Statistical Area (MSA). The feasibility test is piloted in these counties, and the effectiveness of the method will create the opportunity for a national study. These counties, shown in **Exhibit 4.1**, were selected for several key reasons:

- The Houston MSA is one of the largest in the United States
- The Houston MSA is one of the most racially diverse regions in the country.
- Researchers have access to comprehensive Multiple Listing Service (MLS) data for the entire area.
- Researchers are familiar with the Houston MSA housing market.

Houston and its surrounding network of smaller cities, towns, and suburbs have gradually merged through urbanization, forming first a metropolitan area and now a consolidated metropolitan statistical area (MSA), with a 2020 population exceeding 7.1 million. The Houston MSA consists entirely of "growth" counties, a term applied to counties experiencing double-digit population growth rates over the past three decades (Lang and Simmons, 2001). These counties serve as the core of the MSA, with Houston at its center, driving increased housing transactions for analysis.

Exhibit 4.1 | Counties in Houston MSA

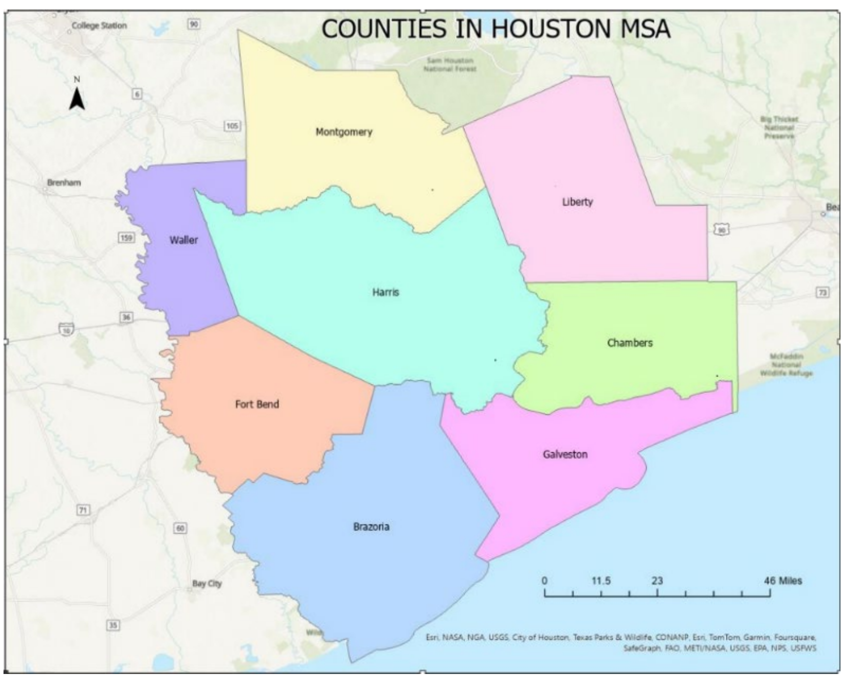


Exhibit 4.2 shows population growth trends between 1970 and 2020. Harris County is the largest within the MSA, followed by Fort Bend and Montgomery counties. Researchers also examined the diversity index of the counties, enhancing the likelihood of a robust and varied dataset. Three counties within the Houston MSA exceed both the national 2020 diversity index rate of 6.2 and the

Texas diversity index of 6.7. The fastest-growing counties—Harris, Montgomery, and Fort Bend—also have the highest diversity indices. In 2020, Montgomery County, Harris County, and Fort Bend County had diversity indices of 0.76, 0.70, and 0.57 respectively, with Fort Bend experiencing a significant increase from 0.45 to 0.70 over the previous decade (Understanding Houston, 2024). This high proportion of minorities may foster more integrated communities, potentially reducing housing discrimination.

Exhibit 4.2 | Houston MSA County Population Growth Rates 1970-2020

County	1970	1980	1990	2000	2010	2020
Brazoria	108,312	169,587	191,707	241,767	313,166	372,031
	-	0.57	0.13	0.26	0.19	0.19
Chambers*	12,187	18,538	20,088	26,031	35,096	46,571
	-	0.52	0.08	0.3	0.33	0.33
Fort Bend	52,314	130,846	225,421	354,452	585,375	822,779
	-	1.5	0.72	0.57	0.4	0.4
Galveston	169,812	195,940	217,399	250,158	291,309	350,682
	-	0.15	0.11	0.15	0.2	0.2
Harris	1,741,912	2,409,574	2,818,199	3,400,578	4,092,459	4,731,145
	-	0.38	0.17	0.21	0.16	0.16
Liberty*	47,088	33,014	31,595	70,154	75,643	91,628
	-	-0.3	-0.04	1.22	0.21	0.21
Montgomery	49,479	128,487	182,201	259,768	455,746	620,443
	-	1.6	0.42	0.43	0.36	0.36
Waller*	10,014	10,280	11,961	32,663	43,205	56,794
	-	0.03	0.16	1.73	0.31	0.31
Total	2,197,118	3,096,239	3,698,571	4,635,571	5,891,999	7,092,073
	-	0.41	0.19	0.25	0.27	0.2

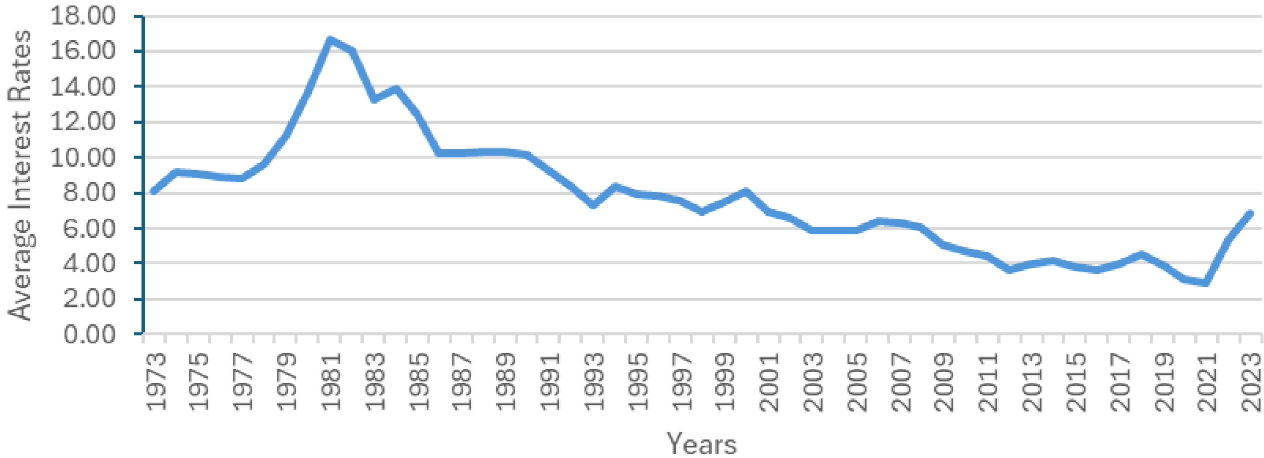
**As described in the text above, researchers removed these counties with no urban cities from the study sample.*

After deeper study of the number of records, percent change over time, and diversity rates among those records, researchers restricted the study sample to counties with urban cities. Rural home sales usually have high land to building ratios that can skew the analysis because the presence of farmland is usually the primary motivation for purchasing. Capturing growth counties with urban cities increases the probability of robust records within the urban area as well as the suburban communities that fall outside of, but that economically contribute to, the urban cores. This criterion reduced the number of counties for the study from eight to five: Brazoria County, with the city of Pearland; Fort Bend County, with the cities of Missouri City and Sugarland; Galveston County, with the city of Galveston; Harris County, with the cities of Houston and Pasadena; and Montgomery County, with the city of Conroe.

Research Time Frame

This research covers the five-year period from 2018 to 2022. This timeframe was chosen because it encompasses a variety of significant contexts, including both pre- and post-Covid years, the impact of the housing supply chain on the housing construction market, and a period of historically low mortgage interest rates followed by sharp increases, as demonstrated in **Exhibit 4.3**.

Exhibit 4.3 | 30-Year Fixed Mortgage Rates: 1973-2023



Data Source Freddie Mac, 2024

Additionally, the research time frame captures a U.S. election year and comes shortly after Hurricane Harvey, which led to every county in the MSA being declared a disaster area (Federal Department of Emergency Management, 2017).

Data Sources and Variables

Three data sources were the basis for this study: Multiple Listing Service (MLS), restricted-use HMDA, and American Community Survey (ACS).

Multiple Listing Services (MLS) is a private database that is created, maintained, and paid for by the real estate industry to help real estate professionals buy and sell properties. This database is selected because of the information it contains on the borrower, property, and its location. The MLS contains sales, buyer, realtor, property, and locational variables associated with individual transactions. Particularly, the MLS database contains variables such as *closing_date and days_on_market,* which are not available in other identified databases. The uniqueness of the MLS database contributes to analysis in calculating days to close and testing for neighborhood characteristics.

Home Mortgage Disclosure Data (HMDA), the primary source of information, has variables that the team considers integral to identifying discrimination in the underwriting process. The collection of HMDA data was originally enacted by Congress in 1975 and requires many financial institutions to publicly disclose loan-level mortgages (FDIC Consumer Compliance Examination Manual — July 2021). Information is compiled annually for each MSA aggregated by census districts. The restricted version of the HMDA provides all general information collected inclusive of *credit score* and *action date (decision on mortgage application)*.

American Community Survey (ASC-5 year) is a public product of the U.S. Census Bureau. The ACS provides socio-economic information aggregated at the census tract and block group level. The ACS provides information at either the three- or five-year time spread. The five-year estimates were selected because of their level of accuracy over the three-year estimate. The variables selected were used to track community demographics of census tracts in the study sample. These variables include population, race, education, and income.

The Appendix details the variables collected from our three sources and used within the analysis. Variables fall under five categories: identifiers, descriptives, independent, calculated, and dependent. Descriptives are those variables that were used as part of the narrative, whereas calculated variables were used to create dependent variables. All categorical variables were operationalized so that they could be analyzed.

Data Merging and Reduction

This feasibility study not only tests the viability of two variables in detecting the presence of discrimination, but it also tests the feasibility of the methods proposed. We have identified this step distinctly and separately due to the complexity of the process and the resulting number of transactions for final analysis.

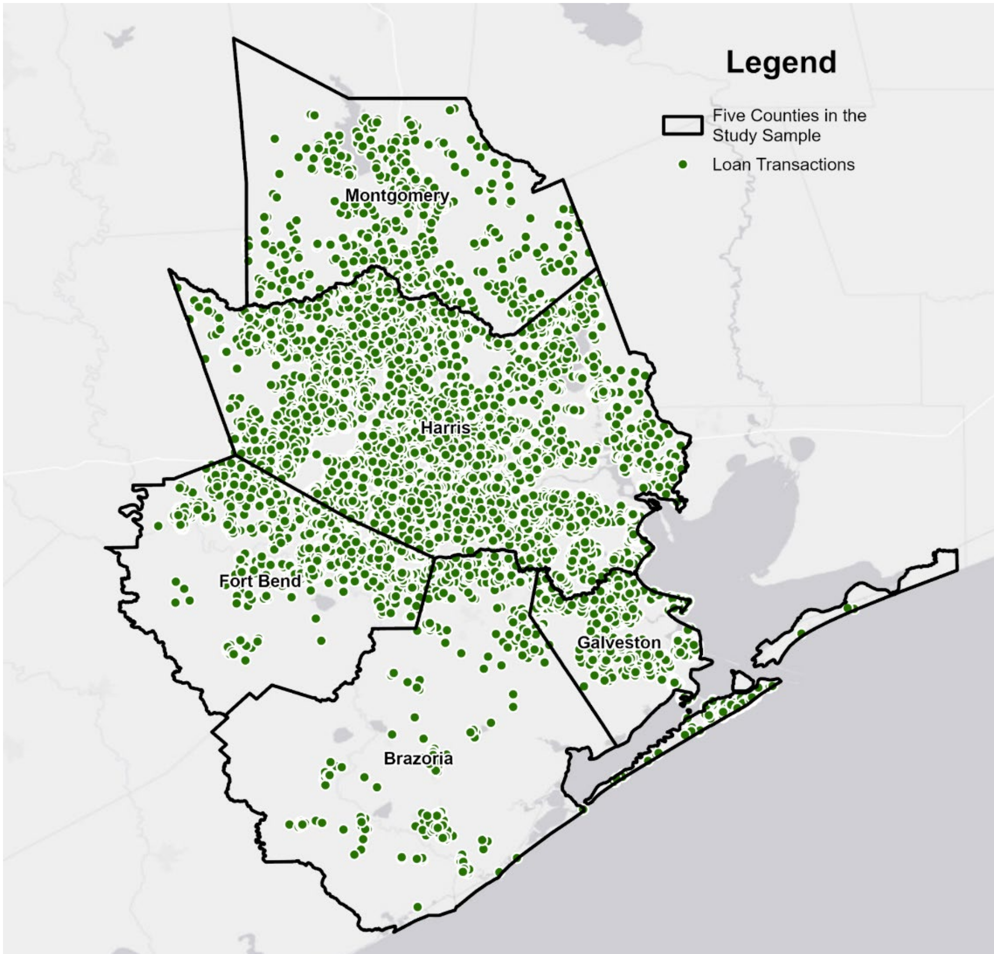
For each data source, variables were shared among the databases that could be used as the base for a merge. The availability of variables differs among data sets. For example, ACS and MLS databases each had census tracts and years, whereas MLS and HMDA data have the year and addresses. When the datasets were merged in the correct order, all databases could be merged into a single data set for each year. Our approach included the following steps:

> **Step 1:** MLS data and ACS data contained the same census tract 11-digit federal information processing standards code (FIPS).[29] Census Tracts in the two datasets were joined by year, then FIPS code, creating the MLS_ACS database.
>
> **Step 2:** HMDA data was geocoded by addresses to create latitude and longitude variables.
>
> **Step 3:** MLS_ACS was joined with HMDA data by year, then the calculated latitude and longitudinal variables. The resulting dataset was then reduced to reflect single-family one unit, owner occupied, FHA, and Conventional forward transactions with a resulting sample of 55,335 records.

[29]Census tract FIPS Codes include a 2-digit state code, a 3-digit county code, and a 6-digit census tract code.

Exhibit 4.4 shows the distribution of the sample records across the study area.

Exhibit 4.4. Distribution of Sample within Houston MSA



Over 1.8 million transactions occurred in the Houston MSA. The selection criteria reduced that number to 688,619 records. The merge of the HMDA database with MLS records reduced the sample size to 55,335. These transactions, as shown in **Exhibit 4.4**, are distributed across the five-county area with concentrations within the major cities. Appendix **Exhibit A4.2** shows the distribution of records by year, by county, by race.

The sample represents a significant decrease in number. The area of limitation and potential avenues of research is how to improve the merging process to increase the number of observations. This will be discussed further in the conclusion.

Coding

Coding of the specific variables necessary to set up analysis is highlighted below:

Geographic Indicators. The Houston MSA comprises eight counties, however the data spans five of them: Waller, Chambers, and Liberty were excluded because they are more rural and the presence of farmland as part of the homestead would skew the analysis. To capture the effects of location in the model, Brazoria, Fort Bend, Montgomery, Harris and Galveston counties were coded as dummy variables. The presence of a house in a county is denoted by 1 and the absence is 0.

Using the ACS Census data, each census tract was grouped based on its racial composition. Census tracts that have a racial or ethnic composition that is greater or equal to 50 percent were identified as that race or ethnic neighborhood. These designations are consistent with Gibbon's (2021) delineation of Philadelphia. Using this method, dummy variables were created for White, Black, Asian, and Hispanic neighborhoods. Census tracts not having a dominant race or ethnic majority were coded as diverse.

Time Fixed Effects. To create the quarterly time series variables for the time to close model, each study year was broken down into four quarters. This unit is used because federal interest rate changes are done by quarters, and this impacts the mortgage interest rates. During the study period, mortgage interest rates fluctuate more than any era in history, declining from an average of 4.70 percent in 2018 to a historic low of 2.65 percent in 2021, then escalating to a high of 7.08 percent in 2022 (Bankrate, 2024). Covering the five-year period of 2018 to 2022, the 20 quarterly time series variables were converted to dummy variables. To examine the effect of pre-Covid, Covid, and post-Covid periods on the closing cost index, the transaction years were grouped to represent them. The pre-Covid era is represented by 2018 and 2019, the Covid era is represented by 2020 and 2021, while 2022 represents the Covid era. All three eras were coded as dummy variables.

Home Value. We expected that home value would impact time to close. Income and house price are directly correlated: home buyers with higher income generally have higher credit scores. This lower level of risk reduces the time to close. Buyers with lower income affordability are limited to lower price homes but the level of scrutiny is higher. Since house prices were clustered by neighborhood and income, home values were recorded into ranges to capture the effect at different price levels. Seven ranges were created for home values: value below $150,000 denotes the lowest price houses, lower price homes range from $150,000 to less than $250,000, while $250,000 to less than $350,000 covers the median house prices; $350,000 to 499,999 covers the median new construction value, and upper houses prices are categorized as $500,000 to $749,999, $750,000 to $999,999, and over $1,000,000.

Housing Age, Square Footage, and Bathroom Count. Housing age is a continuous variable calculated as year of sale minus the year built. Housing age is a function of depreciation. House square foot is the living area of the house. The bathroom count is the number of bathrooms in the house.

Credit Scores. Credit scores were coded into ranges to match the Optimal Blue methods of stratification. Optimal Blue is the leading marketplace for secondary mortgage data that supplies banks, brokers, and other vendors with current and critical mortgage indices. Optimal Blue reports mortgage interest rates based on categories of credit scores. Credit scores less than 680 are at high risk and experience difficulties obtaining a mortgage. Credit scores of 680 to 699 command a higher interest rate while credit scores of 700 to 719 and 720 to 739 have negotiation powers. Credit scores over 740 command the lowest interest rates.

Loan-to-Value and Debt-to-Income. A dummy variable was created for loan to value. Loan to value is the loan value divided by the appraised value of the house. The variable was delineated into loans that are less than 80 percent and those 80 percent or greater. Transactions with loan to value greater than 80 percent are required to pay mortgage insurance, which increases the cost of the loan. The variable debt-to-income is the ratio of a buyer's debt to their income. The HMDA data set has established categories for debt-to income ratios, which were adopted for this study.

Discount Points, Interest Rate, Median Income, and Loan Type. The purchasing of discount points is a buy down of interest rate: buyers pay an upfront cost to lower their monthly payment. Interest rate is a continuous variable that measures the level of risk and helps to determine the cost of the loan. The log of the median income in the neighborhood or census tract was used to normalize the distribution. The study used Conventional and FHA as loan types. Conventional loans are offered by traditional banks and have less restrictions.

Buyer Race. The buyer's race was derived from the HMDA data set. Five major races were coded into dummy variables: White, Black, Asian, Hawaiian and/ Pacific Islander, and Native American. Buyers who were not classified in the race categories were coded as Other.

Analysis

Creation of Indices. Two indices are integral to the analysis testing the study hypotheses: time to close and closing cost. The time-to-close index measures the origination process. It is used to identify the process time for all originations occurring within the five counties over the five years. Results were then analyzed to determine differences, if any, by race accounting for credit score. Time to close calculated:

Closing Date – Application Date

Closing cost consists of all fees and cost of services rendered that facilitate the conveyance of the property. The list of costs covers those directly associated with the property including taxes and insurance; those associated with the loan including origination fee; and those associated with real estate professions, including sales commission and other government fees such as deed recording. The HMDA dataset does not have a breakdown of these fees but records a total closing cost. This study assumes that the closing cost composition is consistent and because the study area is limited to one MSA, no adjustment is warranted. Dummy variables created for the counties will capture location adjustments. The focus on closing cost is based on the degree of change to the final cost of the house. The closing cost index was calculated by dividing the total closing cost by the sale price of the house. The index was converted to a percentage by multiplying it by 100. In simple terms, the closing cost index is the percentage change in the sales prices when the closing costs are added. The closing cost index measures the financial contribution of the buyer at the time of closing. The total closing cost is provided by the HMDA data and is calculated for each house in the five counties over a five-year period. Closing costs is calculated as a percentage of the property value:

Closing Cost/Closing price

Regression Model. Two separate models were built around each index with the index serving as the dependent variable.

We use regression analysis to explore the relationship between the two indices and race, while controlling for factors that could potentially influence the index. In the analysis, the outcomes are continuous variables, and we recoded some of the explanatory variables into binary variables. We used an Ordinary Least Squares (OLS) estimation to calculate the average partial effect of the variables of interest. We ran the regression analysis for subsamples such as property value, credit score, and discount points to better understand distinct effects of race on the index based on earlier literature. Since the time to close and closing cost indexes may have significant variation between counties and years, we use county-year fixed effects.

The regression model for both indices were constructed as follows:

$$Y_{ijt} = \beta_0 + \beta_1 X_{ijt} + Z_j + \nu_t + \epsilon_{ijt}$$

where β_0 is the intercept, X_{itj} is a vector of independent variables or covariates for property *i* in county *j* at time *t*, Z_j are county fixed effects that may be correlated with relevant explanatory variables of interest and ν_t are time fixed effects.

Time to Close. We developed regression models to examine the relationship between race and the time to close index while controlling for credit score, loan-to-value, interest rate, loan type, property characteristics, and borrower characteristics.

We started the analysis by examining the relationship of the index with each of the explanatory variables using simple cross tabulations, followed by correlation tests. We also established relationships between the explanatory variables of interest—race, credit score, property value, loan-to-value, interest rate, loan type, borrower's income, borrower's debt to income ratio, education, house age, and median income of the area.

Following these tests, we built model specifications by regressing time to close on race, while controlling for borrower's credit score range, county, and year fixed effects. We next used multiple model specifications by varying combinations of the explanatory variables listed above to identify the model best suited to explain variations in time to close while observing the association of race with time to close.

Closing Cost. We developed regression models to examine the relationship between race and the closing cost index while controlling for credit score, loan-to-value, interest rate, loan type, property characteristics, and borrower characteristics.

We started the analysis by examining the relationship of the index with each of the explanatory variables using simple cross tabulations, followed by correlation tests. We also established relationships between the explanatory variables of interest—race, credit score, property value, loan-to-value, interest rate, loan type, borrower's income, borrower's debt to income ratio, education, house age, and median income of the area.

Following these tests, we built model specifications by regressing the closing cost index on race, while controlling for borrower's credit score range, county, and year fixed effects. We next used multiple model specifications by varying combinations of the explanatory variables listed above to identify the model best suited to explain variations in closing cost index while observing the association of race with closing costs.

Sensitivity Analysis. To validate the findings from the OLS regression model, we examined the model specification by varying the reference groups for categorical variables, changing the time fixed effects from year to quarter fixed effects. The results were validated across model specifications.

Findings

Time to close or origination process was the first index created. A total of 55,339 records were used to calculate the TTC index. The mean time to close is 39 days. The minimum days to close is 3 days and the maximum is 578 days, or approximately 19 months. Typically, these outliers would be trimmed from a data set but the focus of this study is to examine their impact and explore if racial bias exists in the upper bound. Interestingly, the mean and range in time differ across the years. In 2018, the mean time to close was 35.8 days with the maximum being 307 days. In 2019, the mean was virtually unchanged at 35.7 days with a maximum of 413 days. In 2020, there was a noticeable increase in the mean: the mean time to close was 40 days with a maximum time of 578 days. This can be attributed to the Covid-19 global economic shutdown that disrupted all industries. By 2021, when the number of loan originations was at its highest within the five-year period, the mean had reached 42 days, and the maximum had dropped to 456 days. This can be attributed to the contraction of the labor market and the increase in housing demand in 2021.

It is worth noting that between 2018 and 2021, the number of loan originations increased, as did the standard deviation, which began at 21 days in 2018 and increased to 29 days in 2021. By the final year (2022) of the study, the number of originations had dramatically decreased as had the mean of 36.7 days, with a maximum time to close of 407 days.

An Ordinary Least Squares (OLS) regression model was used to analyze the data. The OLS model assumes and captures linear relationships between the dependent and the independent variables. The independent variable coefficient measures the degree of correlation, and the t-statistic is a measure of significance.

Exhibit 4.5 | Overall Model; Dependent Variable: time_to_close

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	49	1267100.43	25859.19	36.41	<.0001
Error	54222	38505193.65	710.14		
Corrected Total	54271	39772294.08			

R-Square	Coeff Var	Root MSE	Time_to_ close Index Mean
0.029102	68.79375	29.68219	38.78576

Parameter		Estimate	Standard Error	t Value	Pr > |t|
Intercept		58.02228318	3.92021637	14.80	<.0001
yrqtr	**2018Q1**	-6.99785255	1.10112236	-6.36	<.0001
yrqtr	**2018Q2**	-2.15437675	0.93056318	-2.32	0.0206
yrqtr	**2018Q3**	-0.48411876	0.91999633	-0.53	0.5987
yrqtr	**2018Q4**	-0.93103747	0.94110455	-0.99	0.3225
yrqtr	**2019Q1**	-1.74327935	0.97973520	-1.78	0.0752
yrqtr	**2019Q2**	-0.59342358	0.92895828	-0.64	0.5230
yrqtr	**2019Q3**	-0.41012618	0.96213814	-0.43	0.6699
yrqtr	**2019Q4**	-0.65623378	0.98898054	-0.66	0.5070
yrqtr	**2020Q1**	-0.69984477	1.01765685	-0.69	0.4916
yrqtr	**2020Q2**	0.44977518	1.01755484	0.44	0.6585
yrqtr	**2020Q3**	1.73402062	1.02422321	1.69	0.0905
yrqtr	**2020Q4**	3.44305684	1.07198516	3.21	0.0013
yrqtr	**2021Q1**	1.45414964	1.60601094	0.91	0.3652

Parameter		Estimate	Standard Error	t Value	Pr > |t|
yrqtr	2021Q2	-1.61352709	1.57259839	-1.03	0.3049
yrqtr	2021Q3	-1.20602266	1.57515861	-0.77	0.4439
yrqtr	2021Q4	-1.71400090	1.57055371	-1.09	0.2751
yrqtr	2022Q1	-2.80186886	1.02713159	-2.73	0.0064
yrqtr	2022Q2	0.24135521	0.91659689	0.26	0.7923
yrqtr	2022Q3	-0.07434415	0.91684863	-0.08	0.9354
yrqtr	2022Q4 (reference)	.	.	.	.
county	Brazoria	1.14426719	1.24683783	0.92	0.3588
county	Galveston	2.15719707	0.58933456	3.66	0.0003
county	Harris	2.63401159	0.41119135	6.41	<.0001
county	Montgomery	5.29868181	0.74091749	7.15	<.0001
county	Fort Bend (reference)	.	.	.	.
Race	African American	2.13564048	0.43780621	4.88	<.0001
Race	American Indian	0.96178600	1.17402485	0.82	0.4127
Race	Asian	-0.74985168	0.45029952	-1.67	0.0959
Race	Native Hawaiian	0.72345433	2.78297032	0.26	0.7949
Race	Other	0.11348417	0.33476897	0.34	0.7346
Race	White (reference)	.	.	.	.
Property value range $150,000-$249,999		-3.35628685	0.54282442	-6.18	<.0001
Property value range $250,000-$349,999		-2.77144498	0.58557082	-4.73	<.0001
Property value range $350,000-$499,999		-2.42588387	0.62719898	-3.87	0.0001
Property value range $500,000-$749,999		-1.25288956	0.70301430	-1.78	0.0747
Property value range $750,000-$1M		0.84081285	0.87154993	0.96	0.3347
Property value range Greater than $1M		1.12026588	0.74391467	1.51	0.1321
Property value range Less than $150,000 (reference)		.	.	.	.
FICO score range 680 to 699		-0.25107633	0.52082491	-0.48	0.6298
FICO score range 700 to 719		-0.51527373	0.52262309	-0.99	0.3242
FICO score range 720 to 739		-0.02088201	0.51715723	-0.04	0.9678
FICO score range Above 740		-0.36140714	0.39099328	-0.92	0.3553
FICO score range Less than 680 (reference)		.	.	.	.
Loan-to-value	Greater than 80 percent	-0.24298313	0.29052879	-0.84	0.4030
Loan-to-value	Less than 80 percent (reference)	.	.	.	.
Interest rate		-0.97647213	0.18049866	-5.41	<.0001
Debt-to-income	20 to 30	-0.89895945	0.60668205	-1.48	0.1384
Debt-to-income 30 to 36		-0.90994108	0.60841371	-1.50	0.1348
Debt-to-income Greater than 36		-0.90110707	0.57077693	-1.58	0.1144
Debt-to-income Missing		-2.93982342	1.12104646	-2.62	0.0087
Debt-to-income Less than 20 (reference)		.	.	.	.
Housing age (years)		-0.13503566	0.00510825	-26.43	<.0001
Predominantly black neighborhood Yes		3.51690324	0.50165767	7.01	<.0001
Predominantly black neighborhood No (reference)		.	.	.	.
Discount points Yes		-0.68845736	0.23996000	-2.87	0.0041
Discount points No (reference)		.	.	.	.
Natural log of neighborhood median income		-0.91917805	0.30237886	-3.04	0.0024
Loan type	Conventional	-0.34147364	0.34898007	-0.98	0.3278
Loan type	FHA (reference)	.	.	.	.

The overall time to close model, shown in **Exhibit 4.5**, is significant ($F = 36.41$ $p < 0.05$). All variables were tested to check for their strength. The strongest model provided an R-square of three percent. While the model is significant, its impact is minimized based on the goodness of fit. A reasonable explanation is that the model was built on variables that represent the demand side of lending. Lender profiles included loan broker's race, sex, age, and location; number of individuals involved in the loan application review process, and the type of lending institution are variables that were absent from the model because they are not available in the HMDA or MLS. Findings from the focus group reinforce that broker race and age are factors that impact racial bias in the loan application process.

Another factor is that while we examine time to close, time elapsed before a loan is forfeited or denied are also variables worth examining. Racial discrimination might be higher in unsuccessful loan applications. However, while the variable selection warrants improvement, those that are statistically significant have valid correlations that should not be undermined. Their interpretation offers valuable insight about the factors that contribute to housing discrimination and their degree of impact.

Interestingly, the variable loan type shows that there is no difference in time to close between conventional and FHA loans. The quarterly time series variables have significance for four of the quarters. As shown in **Exhibit 4.5**, houses closed seven days faster in the first quarter of 2018 than in the last quarter of 2024. Those sold in the second quarter of 2018 closed two days faster than houses that closed in the last quarter of 2024. Similarly, for the first quarter of 2022, houses closed three days faster than houses that closed in the fourth quarter of 2022. The motivation for a buyer to lock in an interest rate early depends on its anticipated directional movement: rising interest rates prompt a faster decision while falling interest rates harbor delays in the process.

Examining the location variables reveals that houses in Galveston County took two days longer to close than those in Fort Bend County. Houses in Harris County took almost three days more to close while houses in Montgomery County took five days more than those in Fort Bend County. Fort Bend County is one of the most diverse counties and has one of the highest levels of education as well as income.

As depicted in **Exhibit 4.5,** the value of the house had some association with time to close. Compared to houses valued at less than $150,000, houses valued between $150,000 to a maximum of $750,000 took less time to close (between 3 and 1 days, depending on the category). Homes valued greater than $750,000 did not have a statistically different time to close than those valued at less than $150,000. The lowest valued homes may have more defects that could delay closing. Additionally, higher price homes have bigger loans, so banks are exposed to greater risk and therefore might require more time for verification.

The age of the house also had an association with time to close. For every 10-year increase in the housing age, time to close decreases by approximately one day. This finding is counterintuitive as, typically, older houses have higher depreciation, and the wear and tear create defects that if left uncured are detected in home inspection reports. The need to remedy such defects sometimes delays closing. However, this could be offset by delayed new home sales. The Houston MSA has experienced tremendous growth through the building of new houses over the last three decades. Both Fort Bend and Montgomery counties have been ranked among the fastest growing in the nation. In 2020, Houston MSA ranked number one for the construction of new homes by the National Association of Home Builders. With a limitation of housing inventory, buyers are involved through the new construction phase with site selection and the choice of upgrades. The new construction of houses and the loan application process are concurrent. The industry is famous for delays in new construction, which impacts delivery dates and causes delays in the time to close.

Surprisingly, none of the ranges in FICO scores, shown in **Exhibit 4.5**, were significant, nor were the variables loan-to-value and debt to income. Low credit scores and high debt to income both indicate a higher risk, and therefore the expectation was for them to negatively impact time to close. Buyers who purchase discount points took a day less to close than those who did not. Purchasing discount points lowers the interest rate and reduces the spread of risk with upfront lump sum charges. Lenders are comfortable with this risk mitigation, which lowers the time to close.

The race variables, shown in **Exhibit 4.5**, are statistically significant. Blacks took two days longer to close than Whites. This is consistent with the findings from our focus group discussion, where participants argued that Blacks take a longer time to close because the level of scrutiny is higher and some of the steps in the workflow for document verification are designed to frustrate minority applicants. Houses sold in predominantly Black neighborhoods took three more days to close than houses in other neighborhoods.

The results of the regression, although significant, provide no insight into the concerns expressed by the focus group and literature. Analyzing the data from a different perspective, a simple histogram running the index over time by race, hinted at a different story.

Exhibit 4.6 | Relationship Between Time to Close

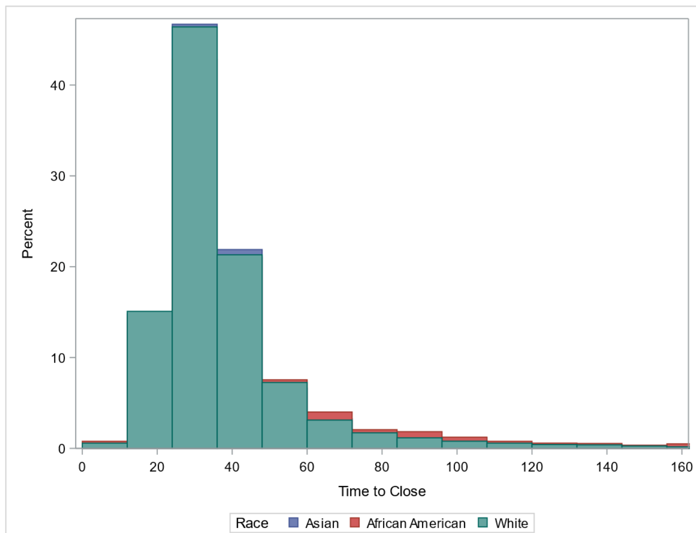
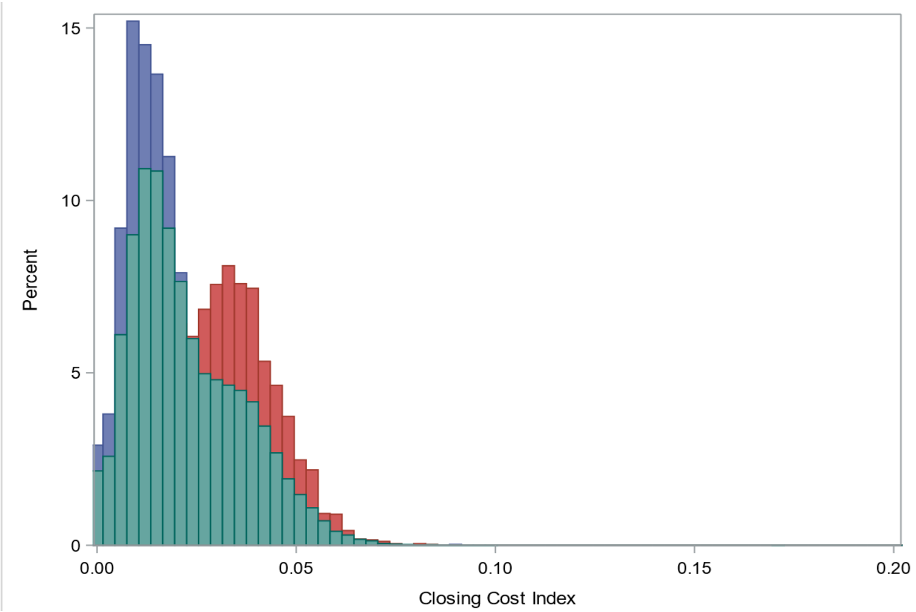


Exhibit 4.6 shows that the preponderance of loans closing in 60 days or less are for Whites. There is a slight appearance of African Americans between 50 to 60 days. Beyond 60 days, the percentage of African Americans increases between 60 to 70 days as well as 90 to 100 days out.

Closing Cost

The loan cost of housing is higher for African Americans than any other race. Without controlling for other factors, African Americans pay $1,380 more in closing cost when compared to Asian buyers. When compared to White home buyers, African Americans' closing cost is $959 higher. This difference is staggering considering that African Americans median house price of $284,210 is more than $100,000 less than Whites median house price of $394,547. The median house price for Asians is approximately $200,000 more than African American at $470,684. The differences in interest rates compound the disparity. The mean interest rate for African Americans is 4.12 percent while for Whites it is 4 percent and 3.75 percent for Asians.

Exhibit 4.7 | Relationship Between Closing Cost and Sales Price by Race



The OLS model is used to investigate if these differences are due to racial bias. The multicollinearity test eliminated some of the variables that are highly correlated and had unacceptable variance inflation factor scores. The overall model is significant (F= 4048.16, $p < 0.05$). The adjusted R Square of 0.62 indicates that 62 percent of closing cost is explained by the independent variables in the model.

The closing cost index is the percentage premium or fee that is paid on the sale price. In the Houston MSA, closing costs accounted for 2.27 percent of the sale price of a house. Houses sold in Harris County have a 0.04 percent lower closing cost premium than those in Fort Bend County. The counties of Brazoria, Galveston, and Montgomery have no significant impact on closing costs. House size had an inverse relationship with closing cost: for every 1,000 square feet increase in house size, closing cost decreased by 0.13 percent. Examining housing age shows that the older the house, the higher the closing cost. Understandably, higher depreciation increases the risk and the insurance cost. Houses sold during Covid, represented by the time series variable years 2020 and 2021, had no significant impact. Compared to the pre-Covid era, closing cost premiums decreased in the post-Covid era by 0.66 percent.

Exhibit 4.8 | Overall Model; Dependent Variable: close_cost_pct

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	21	64341.8401	3063.8971	4048.16	<.0001
Error	53237	40293.0897	0.7569		
Corrected Total	53258	104634.9297			

R-Square	Coeff Var	Root MSE	close_cost_ pct Index Mean
0.614917	38.25284	0.869978	2.274284

Parameter		Estimate	Standard Error	t Value	Pr > |t|
Intercept		3.380155218	0.04484532	75.37	<.0001
Race	**African American**	0.043044280	0.01431152	3.01	0.0026
Race	**American Indian**	0.012008321	0.03956050	0.30	0.7615
Race	**Asian**	-0.088336124	0.01473586	-5.99	<.0001
Race	**Native Hawaiian**	0.089917549	0.09234793	0.97	0.3302
Race	**Other**	-0.002037805	0.01100437	-0.19	0.8531

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Race White (reference)	.	.	.	.
FICO score range 680 to 699	-0.037444673	0.01729190	-2.17	0.0304
FICO score range 700 to 719	-0.055851791	0.01730092	-3.23	0.0012
FICO score range 720 to 739	-0.084448440	0.01715590	-4.92	<.0001
FICO score range Above 740	-0.154429734	0.01281665	-12.05	<.0001
FICO score range Less than 680 (reference)	.	.	.	.
loan-to-value Greater than 80 percent	0.277135550	0.00921421	30.08	<.0001
loan-to-value Less than 80 percent (reference)	.	.	.	.
interest rate	0.080077855	0.00486870	16.45	<.0001
loan type Conventional	1.798727947	0.01127973	159.47	<.0001
loan type FHA (reference)	.	.	.	.
natural log of neighborhood median income	-0.369186730	0.00765331	-48.24	<.0001
housing age (years)	0.002050297	0.00016805	12.20	<.0001
square footage total	-0.000127864	0.00000510	-25.09	<.0001
Year 2020 or 2021	-0.004762565	0.01025419	-0.46	0.6423
Year 2022	-0.668870421	0.02063510	-32.41	<.0001
Year 2018 or 2019 (reference)	.	.	.	.
county Brazoria	0.041286201	0.04079765	1.01	0.3116
county Galveston	0.024354814	0.01935967	1.26	0.2084
county Harris	-0.035471096	0.01338369	-2.65	0.0080
county Montgomery	-0.043915543	0.02426267	-1.81	0.0703
county Fort Bend (reference)	.	.	.	.

For every percent increase in the buyer's income, the closing cost premium decreased by 0.4 percent, which reflects discussion from the focus groups that people with higher income are more informed about the process, may have better negotiation skills, and may have better assistance from agents and brokers. Conventional loans had a 1.79 percent premium when compared to FHA loans. FHA loans are regulated while traditional banks aim to maximize their profit.

A higher interest rate reflects elevated buyer's risk. For every percent increase in interest rate, the closing cost premium increases by 0.08 percent. Additionally, buyers that had a loan to value greater than 80 percent paid a 0.28 percent premium when compared to those that had a loan to value of less than 80 percent. Private mortgage insurance is a requirement for mortgages with loan to value of more than 80 percent.

An increase in credit score reduces the closing cost and this relationship is constant for all the different ranges. Buyers with FICO scores between 680 and 699 had a 0.4 percent lower closing cost compared to buyers with FICO scores of less than 680. Buyers with FICO scores of 700 to 719 had a 0.55 percent decrease in cost premium while the ascending range of 720 to 739 showed an additional 0.08 percent reduction, and rangers over 740 had a 0.15 percent reduction.

The mean closing cost index for African Americans is 2.5 percent while the mean index for Whites is 1.61 percent**.** Racial bias accounts for a part of this difference. Consistent with other studies, African Americans paid 0.04 percent more in closing costs when compared to Whites (Woodard, 2008). Analyzing the race variable shows that Asians paid 0.09 percent less in cost premium when compared to Whites. The Asian population had the highest level of education, which denotes awareness and an increase in income; so, despite the bias in race toward Whites, education supersedes the effect of racial bias. Applying the racial bias portion of the index to the mean sale price shows that African Americans pay $159 more than Whites and $358 more than Asians in closing cost.

Conclusions

The housing cost for African Americans is higher than other races due to higher interest rates and closing costs. African Americans pay $959 more in closing cost than White buyers and $1,380 more than Asian buyers despite purchasing houses at substantial lower values. Part of the difference is associated with racial bias. Using an Ordinary Least Squares (OLS) regression model, this study identified statistically significant differences in the closing costs paid by Black, White, and Asian borrowers in the Houston Metropolitan Statistical Area (MSA). Closing costs in the Houston MSA, on average, add 2.27 percent to the sale price of a home, but for African American buyers, this increase is slightly higher at 2.9 percent. After controlling for variables such as credit score, loan-to-value ratio, sales price, interest rate, income, and loan type, our analysis revealed that African American borrowers paid, on average, $159 more in closing costs than their White counterparts and $358 more than Asian borrowers. Additionally, the average time to close for African Americans was 42 days, while White borrowers average time to close was 38 days. The data set focuses on sold properties, but future research should be done on loans denied after 60 days. This difference was statistically significant after adjusting for other variables. Homes in predominantly Black neighborhoods also took three days longer to close compared to homes in other neighborhoods.

These findings underscore disparities in both closing costs and time to close, which indicate the persistence of discriminatory practices in mortgage lending. Though the differences are small, they are still statistically significant and racial bias cannot be ignored based on the scale of impact. Housing discrimination is a cumulative and compound effect of bias on a wide range of practices. To correct and foster a just mortgage lending process with equitable outcomes, it is essential to fully understand the loan origination process and the role of the individuals involved. The introduction of loan intermediaries, varying loan products, and artificial intelligence in underwriting processes further complicate these issues. Additionally, the potential impact of legal actions on transparency in the real estate market, particularly regarding broker fees, underscores the need for more informed buyers.

Contribution to the Research

This research utilized the creation of an index that allows for the interaction of key variables as a percentage of the overall mortgage activity within a given space and time. Such indices can provide a valuable approach for understanding disparities in the mortgage process. Several theories were introduced in the literature review that are best validated by a qualitative approach. Setting up a study with both qualitative and quantitative perspectives enhances not only the breadth of the study, but also understanding of the impacts of discriminatory actions.

While there are several databases for consideration for this type of research, including those discussed in the literature review, the use of MLS data proved invaluable, as it includes variables that are not available in the HMDAfiles.

Limitations

This study faced limitations that impact this test's results and the potential feasibility of implementing this study at the national level.

File Merger: Several limitations emerged in the data merging process. One key challenge was the loss of 86 percent of the database during the merging of the HMDA, MLS, and ACS data. Although this reduction minimized outliers and improved the weighting of variables during analysis, it resulted in a smaller sample size than preferred. The merger between ACS and MLS required geocoding because the HMDA did not provide latitude longitudinal records. After the geocoding, the initial merger required multiple merges to reach 55K. The number of records lost do not convey a full picture of the loan transactions. Additionally, some redundancies and duplication of records were encountered, which could impact the reliability of the results. While a slower, stepwise approach to geocoding was considered, it was not part of the final process, limiting the ability to offer more timely solutions or alternatives to the HMDA-MLS-ACS merging process. Given that both data sets have borrower address, name of applicant, and loan amount, matching along these identifiers was initially attempted; however, there was no consistency between data sets regarding entries such as St. versus Street or 1234 Main as one entry versus street number in one cell and street name in a second cell.

Analysis: While the MLS, HMDA, and ACS data sets are rich, many of the study's limitations stemmed from lack of control over data merging or analysis. Several limitations emerged in the data merging process. Additionally, the researchers were not in control of the final analysis due to restrictions in access to the HMDA data, which added challenges to data interpretations and time delays in the various analysis steps.

Although the MLS database is robust and includes data not available in HMDA, inconsistency within the records across the study area posed challenges in maintaining uniformity, which resulted in the loss of records. Furthermore, data quality control issues in both databases were noted and require attention for future research efforts.

Implications for Future Research

While this study provides evidence of discrimination in mortgage lending, it primarily focuses on the demand side of housing—the borrowers themselves. Future research should explore the supply side, examining variables that represent the lending institutions and real estate professionals involved in the process. Key factors such as the race, gender, age, and location of loan officers and brokers, as well as the number of individuals involved in the review process and the type of lending institution, were not included in this model but should be incorporated in future research. This data, which is currently absent from public datasets, should be made available for academic study. Although HUD redacts certain key variables to maintain confidentiality, regional HUD offices could serve as oversight bodies to ensure these data are accessible for research purposes.

Public education about the home-buying process is also vital, particularly for minority buyers, who are often at a disadvantage due to a lack of knowledge about the loan application process, leading to higher closing costs. Asians are notable exceptions among minorities that validates the need for proper education about the loan application process. Asians have the highest level of education and purchase the most expensive homes, yet their days to close are the shortest and their closing costs are the lowest. Providing more accessible and transparent information can help reduce these disparities.

Findings from focus groups in this study revealed that time—specifically delays in the loan approval process—acts as a deterrent and discrimination tool in the home-buying process. Future research should consider expanding this analysis to examine the time spent on loans that ultimately do not close, as these instances may also reveal additional discriminatory practices or barriers faced by minority borrowers.

In conclusion, our research highlights significant racial disparities in both the time to close loans and the closing costs faced by minority borrowers in the Houston MSA. The findings suggest the persistence of discriminatory practices in the mortgage process, which are exacerbated by factors such as loan origination processes, broker incentives, and a lack of transparency. Addressing these disparities will require a multifaceted approach, including greater transparency in loan products and fees, improved access to information for buyers, and a closer examination of supply-side factors in lending practices. Future research should aim to deepen our understanding of these issues and contribute to the development of more equitable policies and practices in the housing finance system.

Appendix

Exhibit A4.1 | List of Variables by Source

Variable	Description and Reason for Selection	Data Source(s)/Role
activity_year	This is the calendar year of the application. Data will be used in one of the ways to categorize the application.	HMDA/identifier
Application Date	Date application made at financial institution.	HMDA/Restricted Needed to calculate dependent variable
Credit Score	Applicant's credit score.	HMDA/Restricted independent variable
State_code	Two-digit code.	HMDA and ACS/Identifier
county_code	3-digit State-County FIPS code. Within each MSA, we expect to have more than one county to be identified for analysis.	HMDA and ACS/Identifier
Census_tract	The 11-digit census tract number of the intended property.	HMDA and ACS/Identifier
Derived loan product type	Derived loan product type from Loan Type and Lien Status fields for easier querying of specific records. This study focuses on transactions where loan is the first lien (as opposed to refinance).	HMDA/independent variable
Derived_dwelling_category	Derived dwelling type from Construction Method and Total Units fields for easier querying of specific records.	HMDA/identifier
Derived_race	Single aggregated race categorization derived from applicant/borrower and co-applicant/co-borrower race fields.	HMDA/independent variable
Action_taken	The action taken on the covered loan or application.	HMDA/identifier
Loan_type	The type of covered loan or application.	HMDA/independent variable
Loan_purpose	The purpose of covered loan or application. For this study, we will subset transactions to Home purchases (1).	HMDA/independent
Loan_amount	The amount of the covered loan, or the amount applied for.	HMDA/independent
Interest_rate	The interest rate for the covered loan or application.	HMDA/independent

Variable	Description and Reason for Selection	Data Source(s)/Role
Combined_loan_to_value_ratio	The ratio of the total amount of debt secured by the property to the value of the property relied on in making the credit decision.	HMDA/independent (Also identifier if restricted-use HMDA data is unavailable)
Hoepa_status	Whether the covered loan is a high-cost mortgage.	HMDA/identifier
Total_loan_costs	The amount, in dollars, of total loan costs.	HMDA/independent
Total_points_and fees	The total points and fees, in dollars, charged in connection with the covered loan.	HMDA/independent
Origination_charges	The total of itemized amounts, in dollars, that are designated borrower-paid at or before closing.	HMDA/independent
Discount points	The points paid, in dollars, to the creditor to reduce the interest rates.	HMDA/independent
Lender_credits	The amount, in dollars, of lender credits.	HMDA/independent
Loan_term	The number of months after which the legal obligation will mature or terminate, or would have matured or terminated.	HMDA/independent
Property_value	The value of the property securing the covered loan or, in the case of an application, proposed to secure the covered loan, relied on in making the credit decision.	HMDA/independent
Occupancy Type	This research will focus on principal residences.	HMDA/identifier
Income	The gross annual income, in thousands of dollars, relied on in making the credit decision, or if a credit decision was not made, the gross annual income relied on in processing the application.	HMDA/independent
Debt_to_income_ratio	The ratio, as a percentage, of the applicant's or borrower's total monthly debt to the total monthly income relied on in making the credit decision.	HMDA/independent
Applicant_race	Race of the applicant or borrower. In cases of more than one application, applicant race created for new variable.	HMDA/independent
Tract_minority_population_percent	Percentage of minority population to total population for tract, rounded to two decimal places.	ACS/independent
FIPS	11-digit FPS code identifying state, county, city, census tract.	ACS/identifier
Race	Distribution of race across the census tract.	ACS/independent
Median income	Median Household Income for census tract.	ACS/independent
Population	Total population of census tract.	ACS/descriptive
Median house price	Median house price of census tract.	ACS/independent
Education – college degree	Percentage of census tract with college degree.	ACS/independent
County	County within Texas.	MLS/descriptives
Zip Code	Zip code assignment.	MLS/descriptives
City	City	MLS/descriptives
Days to Closing	Number of days between application to closing.	MLS/dependent
Closing Date	Loan closing date.	MLS/calculated
Listing price	For sale price on HAR.	MLS/identifier
Year Built	Year of permit for development.	MLS/independent
Bldg square footage	Size of building.	MLS/independent

Exhibit A4.2 | Final Transactions by Year/County/Race

	Native American	Asian	Black	Hawaiian	White	Other	Total
Brazoria							
2018	0	2	1	0	14	1	18
2019	10	180	170	2	608	152	1122
2020	0	1	3	0	20	5	29
2021	1	1	1	0	19	3	25
2022	7	29	50	0	355	80	521
Total	18	213	225	2	1016	241	1715
% of total	.01	.12	.13	<.01	.59	.16	
Fort Bend							
2018	4	149	186	2	549	120	1010
2019	10	180	170	2	608	152	1122
2020	11	196	184	2	727	212	1332
2021	10	216	189	4	563	176	1158
2022	10	137	138	1	406	133	825
Total	45	878	867	11	2853	793	5447
% of total	<.01	.16	.16	<.01	.52	.13	
Galveston							
2018	3	8	31	1	341	93	477
2109	10	21	48	2	712	174	967
2020	5	35	78	3	897	117	1135
2021	12	40	83	3	834	157	1129
2022	10	24	38	0	471	82	625
Total	40	128	278	9	3255	623	4333
% of total	<.01	.03	.06	<.01	.75	.14	
Harris							
2018	73	592	605	13	6318	1065	8666
2019	91	627	744	19	7307	1449	10237
2020	116	659	911	15	7465	1548	10714
2021	126	853	1080	20	7838	1710	11627
2022	81	463	694	13	3764	1006	6021
Total	487	3194	4034	80	32692	6778	47265
% of total	.01	.07	.09	<.01	.69	.14	
Montgomery							
2018	1	10	8	0	193	36	248
2019	0	9	14	0	226	46	295
2020	136	903	1193	22	9383	1940	13577
2021	6	23	19	1	293	56	398
2022	10	22	47	2	564	131	778
Total	153	967	1281	25	10659	2209	15296
% of total	.01	.06	.08	<.01	.70	.14	

Notes: *Race information from the American Community Survey race data produced by the Census Bureau. The authors did not use ethnicity (Hispanic vs. non-Hispanic) information.*

Chapter 5. Conclusion

The feasibility tests confirm that the innovative methodologies selected by the U.S. Department of Housing and Urban Development (HUD) Office of Policy Development and Research (PD&R) offer potentially viable approaches to research aspects of housing discrimination previously understudied by PD&R-supported Housing Discrimination Studies (HDS). This chapter details some of the limitations PD&R should consider when scaling up these methodologies for future research, documents the lessons learned from the three feasibility tests, and recommends some avenues for future housing discrimination research.

Considerations for Scaling Up the Methodologies in Future Research

Discrimination in Refinance Appraisals used Federal Housing Administration (FHA) data that lacked information on how appraisers value homes, including information on comparable homes that appraisers use to determine the value of the home they are assessing. A potential source of data to address this limitation is the Uniform Appraisal Dataset, which is a component of the Uniform Mortgage Data Program under the Federal Housing Finance Agency. These data include information on the appraised home as well as the surrounding neighborhood and comparable homes. There is a public version of the dataset that provides aggregate statistics[30]; however, PD&R may also be able to access a restricted version that would include property-level information.

Selective Advertising in the Rental Housing Market relied on Dwellsy, which does not capture all landlords and property managers in the market, to supply information on rental units that were publicly advertised within its sample. Dwellsy primarily includes professional property management companies that manage multiple properties and rental units and excludes smaller property managers and landlords. More data is needed for the method to approach the universe of publicly advertised units in a given geography. One potential avenue for future work is web scraping of public listing web sites that renters commonly use to identify available units (for example, Apartments.com, Truilia). The National Rental Project at the University of Washington[31] has begun to collect data using this approach. Web scraping, however, comes with its own challenges. During the feasibility test design, the research team planned to collect public listing data via web scraping and developed and tested Python code to facilitate the process; however, the team was unable to complete the work due to legality concerns from their university. In addition, some websites prohibit and/or actively discourage web scraping with blockers, captchas, and other methods designed to deter web scraping. Identifying specific apartment units using web scraping can also be challenging, as not all listings provide the unit number.

Although web scraping has the potential to produce a robust database of publicly listed rental units, the challenges may prove too difficult to overcome. Another alternative PD&R may consider is the exploration of additional datasets that can supplement Dwellsy. One potential dataset is the rental property listing data collected by Altos, which includes listing date, address, asking rent, and some property characteristics for a large number of rental listings in the U.S. market since 2010.[32]

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[30] For more information, see: https://www.fhfa.gov/data/uniform-appraisal-dataset-aggregate-statistics.
[31] For more information, see: https://national-rent.github.io/.
[32] For more information, see: https://altosresearch.com/data_products.

Finally, PD&R could reach out directly to listing companies (such as Trulia or Apartments.com) to discuss ways to access their data for research purposes, without the need for web scraping.

Discriminatory Lending Practices relies on the use of information from separate data sources that were challenging to merge, the Multiple Listing Service (MLS) and Home Mortgage Disclosure Act (HMDA), to calculate the time-to-close and closing cost indices. In the feasibility test, the research team experienced significant challenges with merging the two data sources on address information. The research team tried both exact matching of latitude and longitude and fuzzy matching of address information, with only limited success. The lack of access to the restricted HMDA data exacerbated this challenge, as the research team had to implement a blind coding process for the merge in which they put together a shell and asked an HUD analyst who had access to update the code to fit the specifics of the HMDA data. If HUD were to implement this methodology in future research, they may mitigate this issue by dedicating resources to determine the best approach to merge the data sources together.

HMDA data also has limitations. The data lacks detailed information on the loan approval process such as the number of income verification requests, dates for key points in the process (such as when the loan went in to underwriting), and information on why applications were withdrawn, all of which could be potential indicators of discriminatory behavior. The HMDA also lacks information on real estate agents and the different lending actors involved in the process. This information is extremely hard to track; the two indices approximate the information but are not precise.

Lessons Learned

The feasibility tests provide suggestive empirical evidence that discrimination exists in different stages of the housing process that prior HDS have not focused on. In addition, unlike with previous HDS, the methodologies are not designed to calculate the total amount of discrimination, but rather show its effects in terms of money and time lost (*Discrimination in Refinance Appraisals* and *Discriminatory Lending Practices*) and the quality of the neighborhood in which people live (*Selective Advertising in the Rental Housing Market*). The discrimination audit studies that PD&R has completed in the past remain an important way to measure the prevalence of discrimination, predominantly in the initial stages of the housing search process.

The feasibility tests found that the likelihood of discrimination varies across neighborhoods. In *Discrimination in Refinance Appraisals*, the authors found that minority homes were more likely to be undervalued by appraisers in areas with less population density. The authors hypothesize this is because these locations are more likely to have fewer housing transactions and, as a result, less information on comparable homes. Appraisers may thus use more subjective information when valuing homes in these locations. Given this finding, a next step could be for key stakeholders, such as the Property Appraisal and Valuation Equity (PAVE) Taskforce[33], to hold good faith discussions on standards that can substitute for comparable homes when there is insufficient information on these homes. Examples of standards may include information from the rental market and additional sources that go beyond previous sales transactions.

The feasibility tests show that the application of these methods to enforcement of fair housing laws is somewhat limited. Unlike audit studies, none of the methodologies can identify individual acts of discrimination that could be prosecuted. That said, each of the three methodologies could

[33] For more information, see: https://pave.hud.gov/.

be extended to identify specific geographies with particularly strong evidence of discriminatory actions (such as appraisal bias or selective advertising). This could support more targeted enforcement by fair housing agencies by focusing their efforts on specific neighborhoods or regions.

The feasibility tests demonstrate the importance of facilitating access to the large amount of information that the Federal Government has that can support housing discrimination research. Two of the feasibility tests, *Discrimination in Refinance Appraisals* and *Discriminatory Lending Practices*, utilized restricted data to conduct their analyses. Obtaining access to these data posed significant challenges for these feasibility studies. Replications and other future housing discrimination research may be aided if HUD and partner agencies can allow for easier access to these data while maintaining the necessary security. One possible strategy may be to store data in the Federal Statistical Research Data Centers managed by the U.S. Census.

In the case of the HMDA, which was used for *Discriminatory Lending Practices,* even if providing secure access to the data is not possible, HUD, working with the Consumer Financial Protection Bureau (which owns the data), could consider adding additional variables that would not identify individual borrowers to facilitate research. For *Discriminatory Lending Practices*, this would specifically include the number of days between the application date and closing date of the loan (the time to close index) and ranges for borrower credit score. Alternatively, the government could provide an indicator variable of whether the time to close exceeded a benchmark such as 60 days, which is often when the interest rate lock expires. All other necessary information is available in the public HMDA. The addition of this information would eliminate the need for information from the MLS and avoid the challenge of merging the two datasets together.

Recommended Further Research Avenues

The lessons learned from the feasibility tests, as well as some of the ideas submitted that were ultimately not selected for feasibility tests, suggest further avenues for research.

Additional research is needed to understand the discriminatory effects of how homes and available units are advertised as well as the prevalence of discrimination as a result of advertising practices. Extensions of the *Selective Advertising in the Rental Housing Market* methodology are a logical next step in this area. One straightforward extension is to expand the scope of the feasibility test beyond the 27 cities that the research team focused on. In addition, as noted above, future research using this methodology could also attempt to collect additional public advertising information from web scraping of public listing websites. Other research in this area could focus on the content of the housing advertisements. One of the submitted methodologies outlined a method to determine if there is algorithmic bias in the content of Facebook advertisements targeted to different users of platform. Future research could implement this approach as well as investigate the impact of more intentional bias in advertising in different types of neighborhoods (for example, landlords using phrases such as “ideal for young professionals” to attempt to exclude families with children).

There is still a need for audit and correspondence studies that investigate the prevalence of discrimination during interactions with sellers, lenders, landlords, and property managers. Extending these studies to different groups/protected classes that have not been studied extensively is one avenue, as is incorporating additional follow-ups from testers to measure discrimination that may occur after the initial interaction. In addition, while less conclusive than the paired testing approach, large scale surveys of renters and homebuyers could provide additional information on the likely prevalence of discrimination across various stages of the housing search process, and such surveys avoid legal hurdles that audit studies face as testers cannot pretend to apply for loans or housing.

Additional research is needed on discrimination that occurs during stages of the home process that audit studies cannot track. This includes the work of the *Discriminatory Lending Practices* methodology, which studies the mortgage loan process. Additional research could expand the approach to include more regions, especially if more resources are available to support merging or HMDA can provide more information on the time to close, as noted above in the lessons learned section. Research could also identify ways to adapt this method to the rental housing market (for instance, time to approval, deposits, application fees, etc.). Research could also focus on identifying biases in algorithms that are used to determine approval for loan financing or rental contracts.

Additional research is needed on discrimination in the valuation of homes through both automated means and appraisals. *Discrimination in Refinance Appraisals* provides empirical evidence of a race differential in the appraised value of homes. Research could expand this to other characteristics and could investigate how this bias has changed over time, especially with the advent of increased attention to the issue after the development of the PAVE task force. Second, automated valuation models (AVMs) are used almost universally, but there is limited research on the potential for these algorithms to introduce bias. Most AVMs supposedly undergo significant testing to avoid the potential for bias, but research can confirm whether this works. One of the methods submitted for consideration focused on estimating bias in AVMs.

The above is not an exhaustive list of future research directions, but points to some key areas informed by the work completed for this contract. There is a wide range of avenues that future innovative housing discrimination research can pursue; this report highlights three methodologies that show significant promise in building evidence of discrimination in areas that prior HDS work has not emphasized.

Appendix – Review Criteria for Submitted Methodologies

Exhibit A1.1 | Criteria Applied During 2M's Review of the Submitted Methodologies

Criteria	Max Points
Description of the Methodology	
Authors describe the specific forms of discrimination the methodology is designed to test	5
Authors describe how the methodology measures or tests for discrimination	10
Authors describe how the method can avoid detection by housing providers or why the issue of detection is not applicable to the methodology	5
Authors describe the strengths of the methodology, including how it augments other forms of testing	15
Authors describe the limitations of the methodology, including forms of discrimination it may miss and instances in which the methodology may not identify discrimination even though it is occurring	10
Authors describe how the methodology differs from conventional paired testing	15
Approach to Perform a Feasibility Test of the Methodology	
Authors detail a clear work plan describing how a feasibility test would be implemented	15
Authors include a detailed timeline that does not exceed 6 months	10
Authors describe how the feasibility test will provide evidence that the methodology accurately measures housing discrimination	10
Authors provide general labor categories and level of effort for a feasibility test	5
Total	**100**

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U.S. Department of Housing and Urban Development
Office of Policy Development and Research
Washington, DC 20410-6000

January 2025