FEDERAL RESERVE BANK *of* ATLANTA **WORKING PAPER SERIES**

Can Everyone Tap Into the Housing Piggy Bank? Racial Disparities in Access to Home Equity

James N. Conklin, Kristopher Gerardi, and Lauren Lambie-Hanson

Working Paper 2022-17a
November 2022 (Revised June 2024)

Abstract: We document large racial disparities in the ability of homeowners to access their accumulated housing wealth. Minority homeowners are significantly more likely to have their mortgage equity withdrawal (MEW) product applications rejected than White homeowners, and the unconditional disparities are significantly larger than those found in prior studies that focused on purchase and rate/term refinance loans. Had Black homeowners faced the same MEW denial rate as White homeowners in our sample period, we show they would have extracted an additional $11.2 billion in housing equity, or almost 25 percent of the total amount of actual equity extracted. Controlling for key underwriting variables significantly narrows the racial disparities, with the Black-White gap falling by more than 80 percent, and the Hispanic-White gap falling by more than 70 percent. Credit scores and debt-to-income ratios are the most important factors explaining the gaps, while differences in loan-to-value ratios contribute only modestly. "Residual" disparities after conditioning on observable underwriting factors are large and vary significantly across lenders. A battery of tests suggests that differences in unobserved underwriting factors are unlikely to fully explain the residual disparities, which tend to be larger in geographic areas characterized by more racial animus.

JEL classification: G21, G51, J15

Key words: housing wealth, mortgage, home equity, racial disparities

https://doi.org/10.29338/wp2022-17

The authors thank Stephanie Sezen for excellent research assistance and Bob Avery for sharing his Home Mortgage Disclosure Act lender file. They are also grateful to Neil Bhutta, Julie Cheney, Hajime Hadeishi, Bob Hunt, Jake Krimmel, Tesia Lemelle, Dan Ringo, Dubravka Ritter, Amanda Roberts, Anna Tranfaglia, Athena Tsouderou, and audience participants at the American Real Estate and Urban Economics Association National Conference, the FDIC Consumer Research Symposium, the Florida State University/University of Florida Critical Issues in Real Estate Symposium, and the Federal Reserve Bank of New York for providing helpful comments and suggestions. Barbara Brynko provided outstanding editorial assistance. An earlier version of this paper was posted as Atlanta Fed working paper 2022-17. The views expressed here are those of the authors and not necessarily those of the Federal Reserve Bank of Atlanta or the Federal Reserve System. No statements here should be treated as legal advice. Any remaining errors are the authors' responsibility.

James Conklin (jnc152@uga.edu) is at the Terry College of Business at the University of Georgia. Lauren Lambie-Hanson (lauren.lambie-hanson@phil.frb.org) is at the Federal Reserve Bank of Philadelphia. Please address questions regarding content to Kristopher Gerardi, Federal Reserve Bank of Atlanta, 1000 Peachtree Street NE, Atlanta, GA 30309, kristopher.gerardi@atl.frb.org.

1 Introduction

A large literature in economics has documented significant racial disparities in the ability to access mortgage credit to purchase a home.[1] This literature has garnered considerable attention due, in part, to the widespread belief that homeownership plays a key role in household wealth accumulation, especially for low-income and minority households.[2] The concern is that if minority households do not have the same opportunities to build wealth through homeownership, then it will be very difficult to close the large existing gaps in racial wealth inequality.

In this paper, we shift the focus toward a related question that has received much less attention: Can minority homeowners actually access their built-up housing wealth? The ability to access housing wealth is vital for many households, especially since housing is the largest asset in most financial portfolios. Housing equity is used for numerous purposes, such as smoothing consumption in the face of adverse income/employment shocks (Hurst and Stafford, 2004), and financing home improvement projects (Canner, Dynan, and Passmore, 2002; Greenspan and Kennedy, 2008), businesses (Adelino, Schoar, and Severino, 2015; Kerr, Kerr, and Nanda, 2022; Lastrapes, Schmutte, and Watson, 2022)), large durable goods purchases, and even educational costs (Canner, Dynan, and Passmore, 2002; Pence, 2015).[3] Thus, determining if there are large disparities along racial lines in the ease of accessing housing equity and addressing those disparities if they exist are critically important from a policy perspective.

Compared to many other assets, housing wealth is relatively illiquid. Although homeowners can access equity by selling, this entails changing residences and paying significant transaction

[1]See Black, Schweitzer, and Mandell (1978), Munnell et al. (1996), and Charles and Hurst (2002) for classic treatments. Ladd (1998) provides a survey of the literature.

[2]See Goodman and Mayer (2018), Charles and Hurst (2002), Shapiro (2006), Boehm and Schlottmann (2008). Wainer and Zabel (2020), and Killewald, Pfeffer, and Schachner (2017) for examples.

[3]Along with retirement savings, home equity associated with a primary residence is excluded from asset calculations in the federal student aid formula in Levine and Ritter (2022), so for this reason and others, it is an advantageous form of wealth to use for funding post-secondary education, if it can be extracted. Benetton, Kudlyak, and Mondragon (2022) document in credit bureau data that parents also use their home equity to assist their children with down payments when purchasing their first homes.

costs. Most households that desire to tap into their housing wealth would likely prefer to stay in their homes and extract home equity using a home equity loan (HELoan), a home equity line of credit (HELOC), or a cash-out refinance. In this paper, we analyze racial disparities in access to these three kinds of mortgage products, hereafter referred to collectively as mortgage equity withdrawal (MEW) products.[4]

Our paper is one of the first to measure racial disparities in access to MEW products, likely due to a dearth of quality data on these types of loans.[5] To conduct such an exercise, we use confidential Home Mortgage Disclosure Act (HMDA) data from 2018 through 2021, which contain extensive information on applications for MEW products not present in other commonly used mortgage datasets. In particular, the dataset has broad geographic coverage from many financial institutions and includes key underwriting factors used by lenders in making credit decisions, enabling us to systematically look at racial disparities in housing wealth extraction in a way that was not previously possible. Although the empirical evidence on race and housing wealth extraction is scant, there is anecdotal evidence suggesting that minority homeowners have a harder time accessing MEW products.[6]

We show that the data is, in fact, consistent with the anecdotal evidence. Minority households are much more likely to have their applications for MEW products denied compared to White households. Furthermore, we show that the differences in denial rates between minority and White households are significantly larger for MEW applications compared to the differences for non-MEW applications. Figure 1 shows that for non-MEW applications, Black homeowners are 9 percentage points more likely than White borrowers to be denied, while Hispanic and Asian borrowers are 4 percentage points and 1 percentage point more likely to be denied than White

[4]Reverse mortgages, a special kind of home equity mortgage product, are available only to borrowers who are 62 or older and have very different underwriting rules compared to "forward" equity withdrawal products (Mayer and Moulton, 2022). Because of their limited availability and different structure, we exclude them from our study.

[5]Two other studies deal with MEW and race (Carlin and Divringi, 2018; Do, 2012). We discuss both in some detail below.

[6]For example, see Chiwaya and Ross (2020).

borrowers, respectively. For MEW products, the Black-White, Hispanic-White, and Asian-White denial rate gaps widen to 21, 9, and 7 percentage points, respectively (Table 1). These differences are striking — the unconditional minority-White denial disparities are 2 to 7 times larger for MEW products than non-MEW mortgages. These large unconditional differences show that, on average, minority homeowners do not have the same ability as White homeowners to access their accumulated housing wealth to improve their overall economic and financial well-being. In other words, the results suggest that even if policymakers are able to close the large gap in the minority-White homeownership rate, there would still be an important source of racial inequality stemming from the differential ability to access the financial benefits of owning a home.

To determine the aggregate credit implications of these minority-White MEW application denial rate disparities we perform a simple back-of-the-envelope calculation. Between 2018 and 2021 Black homeowners applied for more than $46 billion in credit to extract their home equity, but were denied $23 billion. We show that if Black applicants experienced the unconditional denial rate of White applicants, they would have been denied only $11.8 billion and thus, would have extracted an additional $11.2 billion in housing equity. A similar calculation shows that Hispanic applicants would have extracted an additional $8.8 billion and Asian applicants an additional $8.5 billion.

In order to understand what drives these large disparities and determine the appropriate policy response, it is important to introduce controls for loan and borrower risk factors that are commonly used by lenders in the underwriting process. Using standard multivariate regression methods as well as Kitagawa-Blinder-Oaxaca decompositions, we show that nearly two-thirds of the Black-White and Hispanic-White disparities in MEW product denial rates can be explained by differences in homeowners' credit scores and debt-to-income (DTI) ratios alone. Including additional controls, such as the requested loan amount and the level of the applicant's income, further reduces MEW rejection rate disparities. Controlling for the applicant's combined loan-to-value (CLTV) ratio does not have a material effect on the estimated denial rate gaps, which suggests that minority borrowers are not being rejected for having insufficient levels of housing equity. We show that this is also supported by HMDA data on the (self-reported) reasons for why lenders rejected MEW product applications. While credit history and DTI ratios are the two most-cited reasons for why minority applications are denied in our sample, insufficient collateral is the least-cited reason.[7] Thus, the requirement that applicants have high credit scores and low DTI ratios to successfully navigate the underwriting process has a particularly large impact on minority households' ability to access their accumulated housing wealth.

For all three MEW products (cash-out refinances, HELoans, and HELOCs), accounting for standard borrower and loan characteristics used in mortgage underwriting significantly reduces–but does not fully eliminate–the gap in denial rates across borrowers. Black and Asian borrowers remain about 4 percentage points more likely to be denied for MEW products than White borrowers, and Hispanic borrowers are about 3 percentage points more likely to be denied (relative to White borrowers) after accounting for these observable factors. These residual racial disparities are non-trivial, and are consistent with, but certainly not proof of, racial discrimination. There are additional factors, such as liquid assets and information about an applicant's employment history, that lenders take into consideration in the underwriting process but are not included in the HMDA data.

In our remaining analysis, we focus on these residual denial rate disparities. We begin by examining patterns across types of financial institutions, which offer different mixes of loan products. For example, HELOCs generally are provided by banks and credit unions, while most cash-out refinances are originated by nonbank lenders. The underwriting criteria likely vary across different types of financial institutions, and thus, disparities in access to MEW may also. We find

[7]There are a few caveats that are worth noting about the small effect of CLTV on the size of the minority-White denial disparities. First, the CLTV measure for denied applications in HMDA data may reflect the applied-for CLTV rather than the "actual" CLTV, since a loan might reach a rejection decision before it receives an appraisal (which comes later in the underwriting process). Second, the sample period (2018–2021) was characterized by strong house price growth across the entire country, which somewhat mitigates cross-sectional variation in how much equity would be a binding constraint between racial groups. Thus, it isn't clear that this result is generalizable to periods with less robust house price growth.

that minority-White denial rate gaps exist for banks, nonbanks, and credit unions. Interestingly, although credit unions are the least likely to deny applications overall, the average residual Black-White gap is larger for credit unions than other types of lending institutions. We also test for differences in denial rates among different types of banks. We find that minority-White denial gaps are smaller at minority-owned banks than other types of banks, and in some cases, reversed (minorities are less likely to be denied). However, borrowers choose where to apply, so these effects may be driven by a combination of treatment and selection, and thus, this result should be interpreted with caution.

We then turn our attention to the underlying mechanisms and try to determine the extent to which the residual MEW denial rate disparities between White and minority applicants is due to racial discrimination versus other explanations such as omitted variables that lenders use in their approval process but that are unavailable in our data. While we do not have a direct test for discrimination or a precise way to discern between different mechanisms, we conduct four additional empirical exercises to dig deeper into the issue. In each case, the patterns we observe are consistent with – although not proof of – discrimination. First, we estimate Kitagawa-Blinder-Oaxaca decompositions separately by lender and show that the size of the unexplained denial disparities varies significantly across firms. Importantly, the size of lender-level unexplained denial disparities is not strongly correlated with the size of the explained disparities, which suggests that denial gaps are unlikely to be driven solely by unobserved underwriting factors. Second, for applications that are put through an automated underwriting system, significant residual racial disparities remain even after we account for the AUS decision. This helps indirectly control for borrower underwriting characteristics not included in HMDA data but that are used by an AUS. Third, we use a technique developed by Bhutta, Hizmo, and Ringo (2024) to test whether racial gaps are larger at "stricter" lenders (those who base denial decisions more heavily on factors not included in HMDA data). In contrast to their findings in a sample of purchase and refinance mortgage applications, we do not observe larger racial denial gaps for MEW applications at stricter lenders, casting further doubt on the argument that unobservable underwriting characteristics drive the racial gaps we measure. Fourth, we show that there is a positive correlation between the level of racial animus in a metropolitan statistical area and the size of the residual Black-White denial rate gaps, which suggests that discrimination may be partially driving conditional racial disparities in MEW rejection rates.

While the bulk of our analysis focuses on denial rate disparities, we also explore the relationship between MEW product pricing and borrower race. We use the interest rate spread on originated loans as our measure of price.[8] Large unconditional minority-White pricing gaps exist across all MEW products, but similar to our results on application denials, the gaps are significantly reduced, and in some cases, eliminated, once we include a host of control variables. In our conditional specifications, Asian homeowners pay less than comparable Whites across all MEW products. In contrast, Black borrowers face higher spreads than comparable White borrowers on HELOCs. To our knowledge, ours is the first paper to examine the relationship between race and mortgage pricing on MEW products.

The balance of the paper is organized as follows. We conduct a brief review of the relevant literature in Section 2. Section 3 describes the HMDA data that are used in the analysis and how we construct our sample. In Section 4, we present our main results on the extent of racial disparities in MEW product denial rates and the most important underwriting factors that drive those disparities. Section 5 discusses potential underlying causal mechanisms including discrimination and omitted underwriting factors and conducts a simple exercise to determine the quantitative importance of racial disparities in MEW rejection rates. Finally, Section 6 provides concluding remarks.

[8] The interest rate spread is defined as the difference between a loan's APR and the average prime offer rate (APOR). APR incorporates fees, points, and the contract interest rate. Thus, the interest rate spread captures multiple dimensions of mortgage pricing.

2 Literature Review

Our findings contribute to the broad literature on racial disparities in homeownership experiences. A number of studies examine the relationship between race and transition into homeownership (Boehm and Schlottmann, 2004; Dawkins, 2005; Hall and Crowder, 2011), while others focus on the forces that drive large unconditional minority-White gaps in homeownership rates, such as income, wealth, age, family structure, and location (Coulson and Dalton, 2010; Deng, Ross, and Wachter, 2003; Gabriel and Painter, 2003; Gabriel and Rosenthal, 2005; Gyourko, Linneman, and Wachter, 1999; Hilber and Liu, 2008). Another stream of research investigates racial differences in home equity and financial returns to homeownership (Flippen, 2004; Kahn, 2021; Kermani and Wong, 2021; Krivo and Kaufman, 2004). We study a related, but distinct question: After transitioning into homeownership, are there racial differences in the ability to access (and the cost of accessing) housing wealth via MEW products?

Our research is also closely related to the literature examining racial disparities in access to mortgage credit and mortgage pricing.[9] For example, Black, Schweitzer, and Mandell (1978) and Munnell et al. (1996) find that minority applicants are more likely to be denied a first-lien mortgage, even after conditioning on a large set of controls. More recently, Park (2021) finds racial disparities in denial rates in HMDA data even after conditioning on a model-based estimate of expected loss.[10] Frame et al. (2022) provide evidence that minority borrowers are less likely to have their mortgage applications denied when working with minority loan officers. Bhutta, Hizmo, and Ringo (2024) use the confidential HMDA data to show that conditioning on a "race-blind" automated underwriting decision, which accounts for underwriting factors that are unobservable in the HMDA data, reduces estimated disparities in mortgage denial rates.[11] This field is not

[9] See Ross and Yinger (2002) for a review of the early (pre-2000) literature and methodologies.

[10] Examining mortgage performance can provide insight into discrimination (see, for example, Becker (1993)). Intuitively, if minorities are more likely to be rejected, but have better subsequent loan performance, this points to discrimination. See Ross and Yinger (1999) and Park (2021) for a discussion of some of the limitations to this approach. Note that our data do not include post-origination mortgage performance information.

[11] Similarly, even after controlling for information not contained in HMDA data (e.g., assets, self-employment) and

populated for the HELOCs and HELoans we study.[12]

With respect to mortgage pricing, Bartlett et al. (2022) find that minorities pay slightly higher interest rates (conditional on underwriting variables), on average, than comparable White borrowers in a sample of GSE-securitized and FHA-insured mortgages, while Kau, Keenan, and Munneke (2012) find that borrowers in minority neighborhoods pay higher interest rates after controlling for differences in the likelihood of default. But, using FHA-insured purchase loans, Bhutta and Hizmo (2021) argue that higher interest rates paid by minorities are offset by lower fees (points) to obtain the loan.[13] In the subprime mortgage market, Ghent, Hernandez-Murillo, and Owyang (2014) find that Black and Hispanic borrowers pay higher rates than comparable White borrowers on their mortgages. Using a sample of loans from a large subprime lender, Ambrose, Conklin, and Lopez (2021) show that minority-White fee gaps depend on the race of the mortgage broker. In contrast with these previous studies that focus on first-lien mortgage products, we examine racial disparities in denial rates and mortgage pricing for MEW products (which often are not first liens), including two product types that are excluded from earlier studies: HELOCs and HELoans.

Finally, we contribute to the mortgage equity withdrawal literature. Canner, Durkin, and Luckett (1998) provide a detailed description of the institutional features of the HELOC and HELoan market as of the late-1990s, as well as borrower characteristics related to their use. In a theoretical contribution, Hurst and Stafford (2004) study home equity withdrawal as a mechanism to smooth consumption in the face of negative income shocks. Agarwal, Ambrose, and Liu (2006), Benito (2009), and Hurst and Stafford (2004) present empirical evidence consistent with home equity use as a financial buffer for consumption smoothing purposes. Several papers examine the correlates of the likelihood of withdrawing equity and the method (e.g., HELOC and HELoan) used to do

FHA's underwriting algorithm, Park (2022) still finds racial disparities in the likelihood of FHA loan endorsement.

[12]This is likely because standard AUS systems used for originating a large share of purchase and refinance loans (e.g., Desktop Originator, Loan Prospector) are not designed for underwriting HELOCs and HELoans.

[13]Willen and Zhang (2021) reconcile the contradictory findings of Bartlett et al. (2022) and Bhutta and Hizmo (2021), and they offer an econometric solution to what they call the "menu problem," which refers to the trade-off between the amount of upfront fees/points and the level of the interest rate that most borrowers face.

so (Benito, 2009; Canner, Durkin, and Luckett, 1998; Chen and Jensen, 1985; Duca and Kumar, 2014).[14] Whereas most of the empirical studies in this literature rely on survey data, Agarwal et al. (2011) use information on HELOC and HELoan applications to study dynamic contracting.

To our knowledge, there are only two studies that focus on the relationship between MEW and race. Do (2012) uses American Community Survey (ACS) data to show that Black homeowners are less likely than White homeowners to extract equity using MEW products. However, it isn't clear whether the difference in equity extraction is due to differences in underlying demand for MEW products or due to differences in the rate at which lenders accept or reject MEW applications. By focusing on MEW applications, we study racial disparities in MEW denials and pricing among individuals who actually wanted a MEW product. In other words, we focus more on the supply-side of MEW products.

The second study examining MEW and race, Carlin and Divringi (2018), focuses on mortgage equity withdrawals for a very specific purpose – home improvements. The authors use HMDA application data from 2015 through 2017 located in the Third Federal Reserve District, which covers Delaware, southern New Jersey, and eastern and central Pennsylvania. Among applications where the stated purpose of the loan is for home improvements, minority homeowners are approximately twice as likely to be denied credit after controlling for a number of factors. Whereas Carlin's analysis focuses on Pennsylvania, Delaware, and Southern New Jersey, our sample includes applications from all 50 states. We also cover a broader range of loan purposes, as only about 20% of our sample reported home improvement as the reason for attempting to extract housing equity. Finally, it is important to note that Carlin and Divringi (2018) are unable to control for the credit risk factors used in our study because those fields were unavailable in the HMDA data before 2018. As we show below, these underwriting factors have a large impact on the size of estimated racial disparities in MEW denials and pricing.

[14]For reasons already discussed, we exclude reverse mortgages from our analysis. For studies on the use and performance of HECMs see Case and Schnare (1994), Davidoff (2014), Davidoff, Gerhard, and Post (2017), Haurin et al. (2016), Moulton, Haurin, and Shi (2015), and Moulton, Loibl, and Haurin (2017).

3 Data Description and Sample Construction

3.1 Confidential HMDA Data

We use Home Mortgage Disclosure Act (HMDA) loan/application register data, which have been used extensively in previous studies. HMDA data are the most comprehensive publicly available source of mortgage lending application activity in the U.S. (Bhutta, Laufer, and Ringo, 2017), with over 90% coverage of the U.S. mortgage market (Consumer Financial Protection Bureau, 2019).[15]

For each application contained in the public version of HMDA data, the lender reports race and ethnicity, gender, and age of applicant and co-applicant (if applicable); combined income for the applicant and co-applicants; property location (census tract) and property type (single-family site-built and manufactured homes, as well as multi-family); occupancy type (primary residence, second home, investment property); and loan features (interest only, prepayment penalty, other non-amortizing features), as well as the amount of the loan. The data also record loan purpose (purchase, home improvement, rate/term refinance, cash-out refinance, other purpose) and lien priority (first or second lien). The lending institution that made the credit decision reports the record and is identified in the data.

An important feature of HMDA data is that firms report the outcome of each loan application (loan originated, application denied, application approved but not accepted, application withdrawn by applicant, or file closed for incompleteness), known as the "action" on the application. Thus, one can examine the correlates of loan outcomes, with application denials (rejections) being the primary outcome of interest. However, historically HMDA data do not include key underwriting variables that lenders use to make credit approval and pricing decisions. But, starting in 2018, the

[15]Coverage is not 100% because there are some reporting exemptions. Financial institutions that are exclusively rural or that originated fewer than 100 closed-end mortgages in either of the last two years are not required to report closed-end mortgage applications. See Federal Financial Institutions Examination Council (2019), Bhutta, Laufer, and Ringo (2017), and Frame et al. (2022) for a more detailed discussion on HMDA reporting requirements. Open-end line of credit (HELOC) reporting exemptions are discussed in further detail below. Note that both the publicly available data and the confidential data available to financial regulators are anonymized.

public HMDA data fields were expanded to include several new variables related to underwriting risk, including but not limited to, the CLTV and DTI buckets. A subset of the data also includes the contract interest rate and the interest rate spread, which captures the difference between the annual percentage rate on the loan and a benchmark rate at the time the rate is set. Lenders were also required to report borrower credit scores beginning in 2018, but this information is not available in the public HMDA data.

Traditionally, financial institutions did not report open-end lines of credit (HELOCs) in their HMDA data. However, beginning in 2018, HELOC reporting became mandatory, although there is an exemption for financial institutions that originated fewer than 500 HELOCs in either of the two previous years (Federal Financial Institutions Examination Council, 2019). Effectively, this means that HELOC coverage from small financial institutions is limited.

In this study, we use the confidential version of HMDA data available to regulatory agencies. There are two key features of the confidential version that distinguishes it from the public version. First, whereas the public version includes only the calendar year in which the loan action was taken, the confidential version includes the exact action and application dates. Second, the confidential version includes the applicant's credit score, which is one of the most important variables used in mortgage underwriting. The availability of credit score, CLTV, and DTI has sparked renewed interest in using HMDA data to analyze the relationship between race and mortgage application outcomes (Bhutta, Hizmo, and Ringo, 2024; Frame et al., 2022; Jiang, Lee, and Liu, 2021).

Not all inquiries consumers make to lenders become HMDA-reportable applications, so one important limitation of any study using HMDA data is that interested applicants who become discouraged from applying may be missing from the data. This can be problematic for studies of racial differences in lending patterns if minority applicants are more likely to be discouraged and thus excluded from the analysis. Although there is no way to directly count these missing applications, we test for differences between racial groups in the "missing mass" of applications along the dimension of credit scores. We describe this exercise (applied comparing Black and

White applicants) and the results in Section A.4 of the Online Appendix. We find no evidence of systematic differences in missing applications from Black as compared to White applicants, which suggests that discouragement based on credit scores is similar between minority and White borrowers. However, this should not be interpreted as proof that minority applicants experience the same amount of overall discouragement as White borrowers. Therefore, as with all studies that use HMDA data, our results should be interpreted as the outcomes consumers experience *conditional on applying*.

3.2 Sample Construction

We use the confidential version of HMDA data from 2018 to 2021. Our primary interest lies in products used for extracting mortgage equity, so our main sample excludes applications for rate/term refinances and applications for home purchase mortgages.[16] Thus, our main MEW sample includes cash-out refinances, HELoans, and HELOCs. Since we focus on credit approval and pricing outcomes, we omit observations where the financial institution purchased the loan from another lender or the application was a preapproval request. We also exclude reverse mortgages and applications with loan amounts less than $5,000 or greater than $1,000,000. We further restrict our sample to non-Hispanic White (hereafter "White"), Black, Hispanic White ("Hispanic"), and Asian applicants.[17] Our final MEW sample includes over 16 million observations across the 50 states and Washington, DC.

[16] At times we use rate/term refinances and purchase mortgage applications for comparison purposes. However, our main analysis excludes these loan types.

[17] For each applicant and co-applicant, we apply a waterfall to code the loans into mutually exclusive and exhaustive categories. Loans are classified as having an applicant who is Black if either the applicant or co-applicant is listed as Black in the first or second reported race field for that applicant. If not, then the observation moves on to the next phase of the waterfall, which identifies loans by Asian applicants. The third step of the waterfall looks for Hispanic White applicants. In the fourth step, remaining observations (for White applicants) are coded as non-Hispanic White if neither the applicant nor the co-applicant is coded as having a first or second race as Black or Asian and neither is coded as having ethnicity of Hispanic. All other observations (such as those with no race reported) are excluded from our analysis.

4 Results

We first look at mortgage denial rates by race and product type. We begin by exploring unconditional denial rate gaps and then explore how much of the gaps remain after taking into account typical underwriting criteria used in making these loans. Throughout the paper, unless otherwise noted, we focus on applications where a credit decision was made, which includes originated loans, applications approved but for which the borrower did not accept the lender's offer, and applications denied by the lender. We exclude applications where the file is closed for incompleteness or the application is withdrawn prior to a credit decision.[18]

4.1 Unconditional Denial Rates

Figure 1 reports unconditional denial rates (among those with a credit decision) by race for each MEW product. For the purposes of comparison, we also report denial rates for non-MEW mortgages in the bottom right panel of the figure. A number of interesting facts are documented in Figure 1. First, relative to non-MEW products (purchases and rate-term refinances), denial rates for MEW products are significantly higher for all races. For example, White applicants are denied credit on only 8% of non-MEW applications; however, this number doubles to 16% on cash-out refinances. White denial rates climb even further to 29% on HELoans and 32% on HELOCs. This pattern holds within each of the other races as well; denial rates are highest on HELOCs, followed by HELoans, cash-out refinances, and non-MEW products, respectively.

Second, minority-White denial rate gaps are larger for MEW products relative to non-MEW products. As an example, Black applicants are 9 percentage points (that is, 17% minus 8%) more likely than White applicants to be denied non-MEW products. On cash-out refinances, the Black-White gap increases dramatically to 16 percentage points. The gap is even larger for HELoans

[18] Appendix Table A.1 reports application outcome shares by race across all of these categories. The sample of applications where a credit decision is made includes almost 13 million observations.

(26 percentage points) and HELOCs (30 percentage points). This is notable as HELoans and HELOCs have relatively low transaction costs, and thus are generally regarded as low-cost methods of extracting home equity (Greenspan and Kennedy, 2008). The large racial disparities in denial rates in cash-out refinances, HELoans, and HELOCs highlights the importance of analyzing MEW products as we do in this study.

Third, although they are smaller than the Black-White gaps, the Hispanic- and Asian-White denial gaps are also large for HELoans and HELOCs. Hispanic applicants are 11 percentage points more likely to be denied than White applicants for HELoans and 22 percentage points more likely for HELOCs. The corresponding Asian-White gaps for HELoans and HELOCs are 8 and 14 percentage points, respectively.

Overall, these comparisons suggest very different levels of access to MEW products for different racial groups and that minority homeowners, in particular, may have an especially difficult time tapping into accumulated housing wealth. We can borrow a framework from the 1978 federal Uniform Guidelines for Employee Selection Procedures to assess the magnitude of these differences—the "four-fifths rule," used for measuring disparities in hiring rates between groups with the highest acceptance rates (usually White men) and a comparison group (usually a protected class). In this framework, one divides the acceptance rate for a minority group's job applications by the White male acceptance rate to generate an "adverse impact ratio" (AIR). If the ratio is less than 0.8, then there is evidence that the hiring practices have an adverse impact on the minority group (Newman and Lyon, 2009). Using this as a heuristic for acceptance rates in mortgage applications, non-MEW products meet the four-fifths rule (with ratios ranging from 0.83 to 0.91), whereas for HELOCs Black, Hispanic, and Asian applicants all have acceptance rates less than 80% of the White acceptance rate, indicating adverse impact.[19]

Although the unconditional denial rates exhibit large differences across race in Figure 1, sig-

[19] Among HELoan applications, the AIR is 0.63 for Black applicants but 0.85 and 0.89 for Hispanic and Asian applicants, respectively. For cash-out refinances, the AIR is just above the borderline, at 0.81 for Black applicants.

nificant differences in observable borrower and loan characteristics exist across racial groups as well. Table 1 reports average borrower and loan characteristics for MEW applications separately by race. Loan amounts and credit scores, in particular, vary considerably across racial groups. In the next section, we examine conditional correlations between race and MEW application denial rates.

4.2 Relationship Between Race and Application Denial Rates for MEW Applications, Conditional on Underwriting Factors

In the previous section, we documented large, unconditional differences in MEW product denial rates across races. But, as Table 1 shows, there are borrower and loan characteristics that likely covary with both race and the likelihood of an application being denied. To examine this possibility, we next estimate a series of loan application-level linear probability models (LPMs) of the following form:[20]

$$Y_i = \beta_1 Black_i + \beta_2 Hispanic_i + \beta_3 Asian_i + \boldsymbol{X_i}\gamma + \eta_t + \lambda_l + \omega_s + \epsilon_i, \tag{4.1}$$

where Y_i is an indicator for whether borrower i's mortgage application is denied. $Black_i$, $Hispanic_i$, and $Asian_i$ are indicator variables set to one if the applicant is Black, Hispanic, or Asian, respectively. White is the excluded category in the econometric model, so the β coefficients should be interpreted as relative to a White applicant. X_i is a vector of covariates that varies across models. η_t and λ_l are application year and lender fixed effects, respectively. State fixed effects are represented by ω_s. Finally, ϵ_i is an error term.

[20]We also consider logit models and find that the average marginal effects of race are similar to the LPM coefficient estimates. The logit results are reported in the Online Appendix.

4.2.1 Decomposition of Denial Rate Differences

Our empirical approach is to sequentially expand the covariates included in our regression models to determine whether the inclusion of additional controls reduces (in absolute magnitude) the β coefficients in equation (4.1). In other words, are the racial gaps smaller once we control for factors used by lenders in mortgage underwriting (such as credit score)?

Table 2 reports coefficient estimates from equation (4.1) using the sample of MEW applications where a credit decision was made. We pool all MEW products together in this table, but we estimate our models separately for each loan product type later in the analysis. Unless otherwise noted, standard errors are double-clustered at the lender and state levels. In the interest of concision, we only report the race coefficients;[21] however, the full set of coefficient estimates are available in Table A.3 in the Online Appendix. As a baseline, column (1) only controls for applicant race so the coefficients can be interpreted as unconditional differences in denial rates relative to White applicants. Black applicants are 21.2 percentage points more likely than White applicants to be denied credit, while Hispanic applicants and Asian applicants are 9.5 and 7.6 percentage points more likely to be denied, respectively.[22] These racial gaps are large relative to the mean denial rate of 26%, reported at the bottom of the table.

In column (2), we include application year fixed effects to account for temporal changes in economic conditions and denial rates at the national level. Because mortgage regulations vary across states, particularly with respect to foreclosure, we also include state fixed effects. Adding these controls has a marginal impact on the racial gaps. Likewise, estimating the models separately by year shows that the racial gaps persist throughout time in our sample, as discussed in Section A.2.7 of the Online Appendix.

[21] When an underwriting characteristic is not used to make a credit decision on a specific application, it is reported as "not applicable" in HMDA data. This applies to a small share of our sample (see Online Appendix Table A.2). We include "not applicable" indicators in our regression models.

[22] Notice that these unconditional differences are slightly larger than what can be inferred from Table 1 because denial rates are rounded to the nearest percentage in that table.

In column (3), we add controls for DTI and credit score, two key factors used by lenders in mortgage underwriting. More specifically, we flexibly control for these variables by creating DTI and credit score bin dummies.[23] Adding DTI and credit score bins reduces the racial gap for Black and Hispanic applicants to 6.8 and 3.4 percentage points, respectively, reductions on the order of 63%-65%. The Asian gap declines somewhat less to 7.3 percentage points, but this still represents a 16% reduction.

In column (4), we add dummies for the following CLTV bins: (0,60], (60,70], (70,75], (75,80], (80,85] (85,90], (90,95], (95,98], (98,100], and CLTV missing. Including these dummies has a minimal effect on the estimated racial gaps.[24] Thus, underwriting factors associated with the borrower's ability and willingness to pay (DTI, credit score) explain more of the racial gaps than the collateral-based factor of CLTV.

In column (5), we add a host of other application-level controls: loan amount bins, applicant income buckets, loan term bins, and product type dummies (HELoan, HELOC). We also include dummies indicating whether the proceeds are used for home improvements, the existence of a prepayment penalty, second-lien loan, FHA and VA loans, interest-only payments, other non-amortizing features, a second home purchase, an investment property purchase, the absence of a co-applicant, and number of units (1-4) dummies. The Black, Hispanic, and Asian gaps are reduced to 5.6, 2.7, and 5.8 percentage points, respectively.

Two recent studies document that minorities tend to sort into high-cost lenders and brokers (Ambrose, Conklin, and Lopez, 2021; Bayer, Ferreira, and Ross, 2018). A similar type of sorting could occur with respect to denials. For example, if minorities tend to apply to lenders with conservative underwriting guidelines, this could explain the observed racial gaps in denials. After adding lender fixed effects in column (6) to account for this possibility, we indeed see sizable

[23]The DTI bins are (0,25], (25,35], (35,45], (45,101], and DTI missing because it was reported as "not applicable." Credit score is binned as [300,620], [620,639), [640,660), [660,680), [680,700), [700,720), [720,740), [740,851), and credit score not applicable.

[24]This finding holds even using an alternative ordering of the model controls, in which CLTV is added before credit score and DTI. Results available upon request.

reductions in the Black-White and Asian-White denial gaps. Throughout the remainder of the paper, we refer to the specification in column (6) as the saturated model.[25]

Overall, Table 2 shows that the large, unconditional minority-White denial rate gaps are reduced considerably after including standard control variables. Yet, even after including these controls, the residual disparities are non-trivial (3–4 percentage points). We caution against interpreting the relationship between race and application denial as causal. There are underwriting factors that likely covary with both race and denial that are not included in HMDA data, such as an applicant's liquid assets and employment type (salaried or self-employed). One might also be tempted to interpret the reduction of racial disparities as we add controls to be evidence of only minor racial differences in access to MEW products. We are careful not to make this claim, as differences in control variables that affect access to MEW products may themselves be the result of systemic racial inequities. With these limitations in mind, the fact that controlling for basic underwriting variables reduces most of the minority-White gaps in denial rates suggests that taste-based discrimination is unlikely to explain most of those unconditional disparities.[26]

4.2.2 Product Type

In Table 3, we estimate our denial rate models separately for each MEW product type. The sample in Panels A, B, and C include cash-out refinances, HELoans, and HELOCs, respectively. Most of the MEW applications are for cash-out refinances (7 million), with the next largest group being

[25] Table A.4 in the Online Appendix presents marginal effects estimates from logit models. The models do not converge when we include lender fixed effects, but the marginal effects from the logits are similar to the LPM coefficients for the models we can estimate. Online Appendix Table A.5 explores the robustness of our results to alternative fixed effects specifications. The race coefficient estimates are similar when we include lender by location (census tract) fixed effects and location by time (county-year) fixed effects. Likewise, the results are similar when we restrict the sample to applications with collateral property located in census tracts with predominantly non-Hispanic white populations (90th percentile or higher), as well as when we exclude from the sample the 6.5% of applications in which the applicant's race and/or ethnicity is imputed by the lender based on visual observation or surname, as discussed in the Section A.1. See Table A.6.

[26] We are also mindful that interactions between risk factors, such as credit score and DTI or credit score and CLTV, can be important in underwriting decisions. However, including these interactions has almost no effect on the results in column (6) of Table 2.

HELOCs (4 million applications). Column (1) includes only applicant race controls, while column (2) reports estimates from the saturated specification (column (6) in Table 2).[27] Column (1) shows that unconditional minority-White denial rate disparities exist for all three product types, but the gaps are much larger in our sample of HELoans and HELOCs. For example, Black applicants are 16.8 percentage points more likely than White applicants to be denied on a cash-out refinance, but this Black-White gap increases to 25.9 percentage points for HELoans and 30.1 percentage points for HELOCs. Similar patterns hold for the Hispanic-White and Asian-White gaps. Note, though, that the mean denial rates for HELoans (33%) and HELOCs (37%) are also significantly higher than the mean for cash-out refinances (18%).

For cash-out refinances in Panel A, moving to the saturated model in column (2) reduces the Black coefficient from 16.8 to 4.0 percentage points, a reduction of 76%. The Hispanic coefficient declines by approximately 64% in the saturated model, relative to its value in column (1). In contrast, the Asian coefficient increases from 1.7 percentage points in column (1) to 2.6 percentage points in column (2). Panel B focuses on HELoans and shows that there are dramatic reductions in racial denial gaps once we include the full set of controls in column (2). The Black coefficient is reduced by 80%, the Hispanic coefficient by 71%, and the Asian coefficient by 47%. We see even larger coefficient reductions moving from column (1) to (2) for HELOCs, reported in Panel C.

Next we use an alternative methodology – Kitagawa-Blinder-Oaxaca decompositions – to study differences in rejection rates (Kitagawa (1955), Blinder (1973), and Oaxaca (1973)). This approach decomposes minority-White denial rate gaps into a part that is *explained* by group differences in characteristics, and a residual, or *unexplained*, component.[28] The unexplained component is often taken to be an estimate of the extent of discrimination, but we caution against such an

[27]Columns (1) and (2) in Table 3 are comparable to columns (1) and (6) in Table 2. Appendix Table A.7 shows the full build-out table by product type where we include additional controls sequentially, while Table A.8 shows that the results are consistent when we instead pool all the applications and interact race and product type.

[28]See Jones and Kelley (1984), Jann (2008), and Blau and Kahn (2017) for more detailed discussions of the methodology. Blascak and Tranfaglia (2021) use this approach to study gender differences in bankcard credit limits. We use the "twofold" decomposition, but results are similar using the "threefold" approach.

interpretation in this context due to omitted factors like liquid wealth and employment history that lenders may take into account.

The following equations illustrate the decomposition. We want to determine how much of the mean difference in rejection rates between two groups, A and B, can be attributed to explained and unexplained components. We begin with separate application-level OLS (LPM) denial models for each group:

$$Y_A = X_A'\beta_A + \epsilon_A, \tag{4.2}$$

and

$$Y_B = X_B'\beta_B + \epsilon_B, \tag{4.3}$$

where Y is an indicator for whether an individual's application is denied (we suppress i subscripts to simplify notation). X is a vector of of explanatory variables that affect denial.

Let $\hat{\beta}_A$ and $\hat{\beta}_B$ be the OLS estimates of β_A and β_B, respectively. Mean values are denoted with a bar over the variable. Assuming that there is no discrimination against group A (only against group B), we can decompose the group difference in denial rates as follows:

$$\overline{Y}_A - \overline{Y}_B = (\overline{X}_A - \overline{X}_B)'\hat{\beta}_A + \overline{X}_B'(\hat{\beta}_A - \hat{\beta}_B). \tag{4.4}$$

The first term on the right-hand side is the explained component; the amount of the mean difference in rejection rates that is due to the groups having different characteristics (Xs), on average. The second term, the unexplained component, captures that the two groups are treated differently in underwriting, as indicated by the difference in $\hat{\beta}s$.

In our context, we will focus on denial rate gaps between two groups: Black and White applicants. The decomposition approach has a few useful properties in our setting. First, it tells us what share of the rejection gaps are explained by differences in observed characteristics (e.g., credit score, DTI, LTV, location) between Black and White applicants. Second, the difference can further be decomposed to measure the detailed contributions of single predictors (or groups of predictors) on minority-White denial gaps. For example, it can tell us how much of the Black-White rejection gap is due to differences in credit scores across groups, and how much is due to DTI differences.[29]

In this analysis, we exclude Hispanic and Asian applicants and focus solely on the Black-White denial rate differences. We perform the decompositions separately by product type and display the results in Figure 2. The included controls are the same as in column (5) of Table 2, i.e., the main model but excluding lender fixed effects.[30] The total height of the bars in each product type is the mean difference in denial rates between Black and White applicants. The shading indicates how much of the overall denial rate difference is attributed to different factors. Across each of the three product types, approximately 5 percentage points of the Black-White denial gap remains unexplained.[31] However, large portions of the overall gap are explained by differences in characteristics between Black and White applicants. For example, the largest contributor to denial gaps across all three loan products is differences in credit scores between the two groups. DTI and other control differences also explain a sizable portion of the denial gaps in both HELoans and HELOCs. In contrast, there appears to be little difference in LTV ratios between Black and White applicants in all products.

In summary, Figure 2 shows that a large portion of Black-White denial gaps is explained by differences in observable characteristics across the two groups of applicants, and that credit scores are the most important underwriting factor. However, a sizable portion of the denial gaps remain unexplained, even after determinants of credit decisions are taken into account. Finally,

[29]This is similar in spirit to our approach in Section 4.2.1, where we sequentially expanded the covariates in our regression model and observed changes in the race coefficients after adding controls, although the order in which controls are added can impact the magnitude of the subsequent changes in coefficient estimates. In contrast, the Kitagawa-Blinder-Oaxaca decompositions do not have this "ordering" issue.

[30]This is except the race coefficients, which are excluded, since we estimate models separately for Black and White applicants.

[31]This unexplained portion is similar to the Black coefficient in column (5) of Table 2.

while the unexplained gaps in the Kitagawa-Blinder-Oaxaca decompositions are consistent with discrimination, it is important to note that they may also be due to omitted factors in the underlying group-specific denial regressions used to create the decompositions.

4.2.3 Lender Type

The different MEW products we examine tend to be handled by different types of financial institutions. For example, HELOCs generally are offered by banks and credit unions, while a large share of cash-out refinances is originated by nonbank lenders. The underwriting criteria may vary across different types of financial institutions, and thus, disparities in access to MEW may also vary across lender types. Thus, in this section, we estimate our models separately for each of the product-by-institution type groupings. The first three columns of Table 4 include cash-out refinance applications from banks, nonbanks, and credit unions. Figure 3 plots model coefficients from this table. Nonbanks handle most of the cash-out refinances (61%), followed by banks (31%), with the remaining market share belonging to credit unions. The coefficient estimates in the first three columns show that minority applicants are more likely than White applicants to be denied a cash-out refinance, regardless of the type of financial institution. Interestingly, for all three minority groups, racial denial gaps are smallest at nonbanks.

Turning to the observation counts in columns (4)-(6), we see that credit unions have a much larger market share in HELoans compared to cash-out refinances (35% versus 9%). Similar to the cash-out refinance patterns, all of the minority coefficient estimates for HELoans are positive across the different types of financial institutions. The Black-White denial gap is largest at credit unions.

Columns (7)-(9) focus on HELOCs. Banks handle most HELOC applications (77%), followed by credit unions (22%). Nonbanks receive a trivial share of the HELOC applications (1%). Similar to cash-out refinances and HELoans, the minority coefficients for HELOCs are all positive across lender types. However, the Hispanic gap is small and indistinguishable from zero for nonbanks.

Again, we see that the residual Black-White denial rate gap is largest at credit unions.

To summarize, there are two key findings in Table 4 and Figure 3. First, across all product types and lender types, minorities are more likely to be denied credit relative to comparable White applicants. Second, the residual Black-White denial rate gap is largest at credit unions, especially for HELOCs and HELoans. This is particularly interesting because the inclusiveness of lending by credit unions, especially with respect to low-to-moderate income borrowers, has been questioned in previous empirical studies.[32]

Table 5 tests whether minority-White applicant denial rate gaps vary between majority- and minority-owned banks. We merge the HMDA data with the "Avery HMDA Lender File," that distinguishes banks' ownership based on National Information Center data.[33] Because minority ownership does not vary within lender, we exclude lender fixed effects from our models in Table 5. Minority-owned banks tend to be small lenders, so we control for bank size in all regressions in Table 5.[34] We exclude HELOCs from our analysis here because very few minority lenders offer them. Specifically, there are only 2-3 minority-owned banks that receive HELOC applications in any year in our sample. In contrast, on average, there are 16 minority-owned banks with cash-out applications each year and 14 with HELoan applications.

Column (1) of Table 5 provides a baseline regression for the sample of cash-out refinancing and HELoan applications by majority- and minority-owned banks, with coefficient estimates similar to our full MEW sample in Table 2 (with no lender fixed effects). In column (2), we include a minority-owned bank dummy and its interaction with applicant race. Minority banks

[32] See Marshall and Pellerin (2017) and citations therein.

[33] The Avery file is provided by Bob Avery of the Federal Housing Finance Agency for 2018–2021 and is available at https://sites.google.com/site/neilbhutta/data.

[34] Banks are classified into one of three groups: small, intermediate small, and large using Community Reinvestment Act (CRA) asset size thresholds available at https://www.ffiec.gov/cra/pdf/2021_Asset_Size_Threshold.pdf. Asset size for HMDA-reporting banks is available in the Avery file and is sourced from the Call Report. If asset information is missing, but the bank is affiliated with another banking institution, we use the affiliate's asset information to classify bank size. Visual inspection of bank names and (low) mortgage origination volumes for independent banks that have missing asset information suggests that these are small banks, and we classify them as such. Appendix Table A.10 shows denial regressions separated out by bank size categories.

are 6.9 percentage points less likely to deny a White applicant, on average, compared to non-minority owned banks. Hispanic and Asian applicants are 3.9 percentage points (0.036 + -0.075 = -0.039) and 6.7 percentage points (0.061 + -0.128 = -0.067), respectively, less likely to be denied than comparable White applicants at minority-owned banks. In column (3), we separate out the minority-owned banks by the race of minority ownership. We group others, including Black-, Native American-, and multiracial minority-owned banks, into one category (Other Minority Bank) because the number of institutions in each of these groups is small. Hispanic-White applicant denial gaps are reduced at all minority-owned bank types (Hispanic, Asian, and other minority-owned banks). In contrast, the Asian-White gap is only statistically significantly reduced at Asian-owned banks. No clear pattern emerges for Black applicants at minority-owned banks. Although there is some evidence consistent with minority applicants receiving more favorable treatment at minority-owned banks, we caution against interpreting the majority- versus minority-owned bank results too strongly because applications to minority-owned banks represent a small share (0.65%) of the sample in Table 5, and a borrower's choice of which type of lender to apply to may be endogenous.

4.3 Denial Reasons

For denied mortgage applications, lenders report the reason(s) for denial: credit history, collateral, incomplete application, employment history, insufficient cash for down payment/closing, unverifiable info, and insurance denied. The last four categories constitute a small share of the denials, so we group these together in a category called "Other." Lenders can report multiple reasons for denial, however, the overwhelming majority (79%) of denied applications in our sample include only one denial reason. Our analysis in this section is based on the first denial reason listed, but results are similar when we allow for multiple denial reasons (see Online Appendix Figure A.1).

Figure 4 shows the rate of each denial reason (conditional on denial) for each race category split out by MEW product type. Notice that within any race-product type combination, the shares sum to 100%. The top panel includes application denials for cash-out refinances. For White applicants, the share is fairly similar across all denial reasons. However, for Black applicants credit history stands out as the most likely reason for denial. Hispanic and Asian applicants, on the other hand, tend to be denied due to high DTI ratios.

Credit history appears to be a larger driver of denials in HELoans. Relative to cash-out refinances, the share of HELoan denials due to credit history is higher for all racial groups. The increase is particularly high for Black and Hispanic homeowners. For example, whereas 23% of Hispanic cash-out refinance denials are due to credit history, this number climbs to 35% for HELoans (the middle panel of Figure 4). Turning to HELOCs, the share of denials due to credit history climbs even further for White, Black, and Asian applicants. As with HELoans, the share is particularly high for Black and Hispanic applicants, at 57% and 46%, respectively.

A key takeaway from Figure 4 is that credit history is a major reason for MEW denial, particularly for Black homeowners on HELoans and HELOC applications. Collateral (e.g., lack of equity) plays a fairly limited role in denials for all races in HELoans and HELOCs. Thus, it appears that denied applicants tend to have adequate equity in their homes, but their credit history precludes them from accessing this equity.

4.4 Relationship Between Race and Price on MEW Products

In this section, we examine whether mortgage pricing for MEW products varies by race. In a recent study, Bartlett et al. (2022) show that Black and Hispanic borrowers pay higher interest rates on first-lien GSE-securitized mortgages and FHA-insured loans. In related work, Bhutta and Hizmo (2021) recognize that in addition to interest rates, fees and points are important dimensions of mortgage pricing. In a sample of FHA-insured first-lien mortgages, Bhutta and Hizmo (2021) show that minorities pay higher interest rates, but this is offset by lower fees. In contrast with these previous studies, we focus on MEW products, many of which are not first-lien mortgages.

In addition, whereas the studies mentioned previously focus on FHA-insured and GSE-securitized loans, a large share of the MEW products in our study, in particular HELoans and HELOCs, are not backed by the U.S. government. There is limited research on MEW product pricing, and to our knowledge, this paper is the first to examine racial pricing disparities in this market.

Our measure of mortgage pricing is the interest rate spread, defined as the difference between the loan's APR and the average prime offer rate (APOR). Rate spread is meant to capture the premium (or discount) that a borrower pays, relative to a benchmark rate on a prime mortgage with similar terms (e.g., fixed-rate or adjustable-rate, lien status, and loan maturity). Note that the APR is calculated based on the interest rate, points, and fees associated with a loan, and thus, it accounts for the different dimensions of mortgage pricing discussed in Bhutta and Hizmo (2021).[35] In earlier waves of HMDA data, lenders were only required to report whether the rate spread on a loan was greater than 150 bps (1.5 percentage points). However, during the period covered in our sample, the rate spread is reported for nearly all applications that result in originated loans.

We estimate pricing regressions using equation (4.1) where the dependent variable Y_i now becomes rate spread. Our sample includes only originated mortgages, since we do not have pricing information for applications that are denied. Columns (1) and (2) of Table 6 report results for cash-out refinances. For these loans, the average rate spread is 43 bps. Controlling just for origination month and state, Black and Hispanic borrowers pay an additional 13.6 and 11.1 bps, respectively, relative to White borrowers for cash-out refinances. Asian homeowners, on the other hand, pay 6.3 bps less than White homeowners. Once we account for underwriting factors and other controls in column (2), pricing differences for Black and Hispanic borrowers disappear. The Asian pricing discount also declines after including controls.

Columns (3) and (4) focus on HELoan pricing differences. Note that the mean rate spread for HELoans (139 bps or 1.39 percentage points) is much higher than for cash-out refinances (43 bps or 0.43 percentage points). Conditioning on just origination month and state, Black borrowers

[35]Bhutta and Hizmo (2021) also discuss limitations of the APR measure.

pay an additional 47.6 bps on average, while the corresponding figure for Hispanic borrowers is 20.2 bps. Similar to column (1), Asian borrowers pay lower prices for HELoans in column (3). In the saturated regression model reported in column (4), there is no statistically significant difference between what Black and Hispanic borrowers pay for HELoans relative to comparable White borrowers, while Asian borrowers pay 7.3 bps less.

In columns (5) and (6), the mean rate spread for HELOCs (85 bps or 0.85 percentage points) falls between cash-out refinances and HELoans. Consistent with columns (1) and (3), Black and Hispanic borrowers pay higher prices on average for HELOCs, while Asian borrowers pay less. Once we add controls, the gaps significantly narrow; Black borrowers pay 10.0 bps more for HELOCs than comparable White borrowers, while Asian borrowers pay 5.6 bps less. Like with cash-out refinances and HELOans, the HELOC pricing gap for Hispanic and White borrowers is not statistically different from zero.[36]

Similar to our results on mortgage denials, we find that unconditional minority pricing gaps on all MEW products are large. However, once we account for a number of control variables, these gaps are significantly reduced. Black borrowers pay more than comparable White borrowers for HELOCs (about 10 bps), while Asian borrowers face slightly lower mortgage prices than comparable White borrowers. Hispanic and White borrowers' pricing look statistically indistinguishable, conditional on controls.

5 Discussion

We have documented large, unconditional differences in average denial rates for mortgage equity withdrawal products across racial groups. Similarly, we also find large unconditional differences

[36]We caution that HELOCs often come with introductory pricing that is different from what the borrower will pay later in the life of the loan. We are not able to distinguish introductory from subsequent pricing and assume the rate spreads we observe correspond to what the borrower is charged at the beginning of the life of the loan. This could affect the interpretation of racial differences in pricing over the life of the loan, if some racial groups are more likely than others to take out HELOCs with low introductory rate periods.

in MEW pricing across racial groups in a sample of originated loans. In both cases, the racial disparities significantly decline when we control for differences in observable loan and borrower characteristics as well as lender fixed effects. In this section, we begin by discussing a few ways one might interpret these patterns. We implement four additional pieces of analysis to shed light on the extent to which discrimination could explain our results. We then conduct a back-of-the-envelope calculation to try to determine how much racial differences in denial rates translate into differences in the amount of housing wealth accessed by minority vs. White homeowners.

5.1 Interpretation and Mechanisms

One may be tempted to interpret the small, conditional denial rate disparities as evidence that racial discrimination in the MEW product market is quantitatively unimportant. However, we believe that this would be a naïve interpretation, as it is unclear exactly what factors some of our controls are picking up. For example, while controlling for credit scores, DTI ratios, and CLTV ratios significantly lowers denial rate disparities between Black and White applicants by approximately two-thirds (columns (1) vs. (3) in Table 2), the differences in the levels of these controls across racial groups may themselves be reflective of structural discrimination against minority applicants. For example, the large differences in average credit scores and DTI ratios between White and minority individuals documented in Table 1 may be due to historical lending practices that were discriminatory. Alternatively, discrimination in other markets (e.g., labor markets) may cause racial disparities in factors used in underwriting. Although incorporating these factors into credit decisions may be justified in terms of credit risk, by doing so, credit markets may "import" structural discrimination from other markets. Regardless of the source of minority-White disparities in underwriting factors, credit markets have the potential to serve as a mechanism for perpetuating disparities through differential access to MEW products.

Similarly, it may be tempting to interpret the remaining, small, but statistically significant conditional disparities in MEW product denial rates and prices as arising from racially discriminatory practices on the part of lenders. However, while the existence of such disparities is consistent with the presence of racial discrimination, it is also consistent with more benign explanations. One such explanation is the absence of information in the HMDA data about variables that may play a significant role in the underwriting process for certain lenders. For example, the HMDA data do not include any information on an applicant's liquid assets. Many mortgage lenders require that a potential borrower have sufficient liquid assets (i.e., funds in a checking/savings account) to be able to cover a certain number of mortgage payments in the event of an adverse financial shock. Additionally, the HMDA data do not include any information about an applicant's employment history. Many lenders require proof that a potential borrower has held a stable job for a certain amount of time prior to approval. If minority applicants have lower amounts of liquid assets and higher employment volatility compared to White applicants, then we would expect to see disparities in denial rates that would reflect those differences.

Although we cannot definitively say whether unobserved underwriting factors or racial discrimination explain the residual denial rate gaps, we perform four types of additional analysis that provide suggestive evidence on this front. First, we exploit lender-level heterogeneity in our Kitagawa-Blinder-Oaxaca decomposition. Second, we examine the relationship between race, AUS decisions, and lender denials. Third, we implement an exercise that correlates residual denial rate gaps with a lender-specific measure of "strictness" on unobservable underwriting factors. All three of these exercises speak to the unobservable underwriting factors hypothesis.[37] Finally, we examine whether racial disparities are more pronounced in geographic areas that are characterized by high levels of racial animus, which would be consistent with discrimination.

[37] The AUS and lender strictness analsyis were first developed in Bhutta, Hizmo, and Ringo (2024).

5.1.1 Lender-Level Decompositions

We begin by separately estimating the Kitagawa-Blinder-Oaxaca decompositions of Black-White denial rate gaps for each of the 50 largest lenders (in terms of volume) in each product type. The results are displayed in Figure 5. In a given panel (product type), each vertical bar represents a different lender.[38] The height of the bar, marked with a black dot, is the total (unconditional) Black-White denial rate gap for that lender, with the gray and red portions indicating the explained and unexplained components, respectively. For each product type, lenders are ordered by the size of the explained component. This means that Black and White applicants are observably similar at a lender that falls on the left-hand side of the figure. On the other hand, Black and White applicants are very different on observable dimensions at lenders that lie on the right side of the panels.

The first notable observation from Figure 5 is that all of the black dots have positive values, meaning that Black applicants have higher unconditional rejection rates at every single lender in all product types. Within each product type, however, significant heterogeneity exists across lenders in the overall Black-White denial gap, the explained component, and the unexplained portion of the gap. For example, there is almost no difference in denial rates for the leftmost lender in the bottom panel, but other HELOC lenders have Black-White gaps of nearly 40 percentage points. For several of those high-gap HELOC lenders, though, virtually all of the gap is due to differences in observable characteristics between Black and White applicants. In a few cases, the unexplained component is actually negative, suggesting that Black applicants may actually get more favorable treatment at those lenders.

Although the heterogeneity across lenders and product types in Figure 5 is interesting in its own right, the results may also speak to whether unobservable underwriting factors drive residual racial disparities in rejection rates. For example, it may be reasonable to assume that if a specific lender receives applications from Black and White applicants that are very different on observable

[38]The same lender can appear in more than one of the product types.

underwriting variables, those same borrowers likely also differ significantly along underwriting factors that are observable to the lender, but not included in the HMDA data. For example, if a lender's Black and White applicants have very different credit scores, DTIs, and CLTVs, we might expect the applicants to also have very different levels of liquid assets and employment histories. Conversely, if a lender's Black and White applicants are similar in terms of HMDA variables, they may also be similar in terms of underwriting factors that are unobservable to the econometrician. If this assumption is reasonable, then we would expect to see a strong correlation between the size of explained (gray) and unexplained (red) components of the denial gap across lenders. However, this is not borne out in Figure 5, which shows that the size of the unexplained denial disparities between Black and White applicants is not highly correlated with the size of the explained disparities.[39] This provides suggestive evidence that residual Black-White denial rate gaps are not purely driven by underwriting factors that are not observed in HMDA.

5.1.2 AUS Decisions and Lender Denials

As an additional test of whether unobserved credit risk factors drive minority-White denial gaps, we follow the approach of Bhutta and Hizmo (2021) by focusing on a subset of mortgage applications that received an Automated Underwriting System (AUS) recommendation. Applicant information for most of the cash-out refinances in our sample was entered into an AUS, which scores the loans for credit risk using statistical models and ultimately provides a recommendation for whether the application may be approved. Importantly, the AUS recommendation is based not only on the credit risk factors observed in HMDA, but also on an extensive set of other credit-relevant information. For example, Fannie Mae's Desktop Underwriter (DU), one of the most commonly used AUSs, considers the risk factors observed in HMDA as well as characteristics including, but not limited to, the borrower's liquid reserves, public record information, length of

[39]The correlation coefficient for the explained and unexplained components is actually negative for HELoans (r = -0.10, p = .492) and HELOCs (r = -0.38, p = .007). The correlation is positive but weak and marginally significant for cash-out refinances (r = 0.26, p = .073).

credit history, and income variability. Note that AUSs are explicitly forbidden from considering race, other prohibited factors, and neighborhood location, and regulators review these systems to ensure that they are race-blind (Bhutta, Hizmo, and Ringo, 2024).

If inherently race-blind AUS denial recommendations are conditionally correlated with applicant race, this would suggest that unobserved risk factors vary across racial groups. To test this, we estimate our fully saturated model (column 2, Panel A of Table 3) using the AUS denial recommendation indicator as the dependent variable. This indicator takes a value of one for applications that did not receive an "accept/eligible" or equivalent AUS decision. Our sample here includes cash-out refinance applications where an AUS decision is observed.[40] Column (1) of Table 7 shows that minority applicants are more likely to receive an AUS denial recommendation. Because AUSs are race-blind, this implies that race is correlated with unobserved credit risk factors.

Note, though, that an AUS decision is only a recommendation. A lender can still deny an application that receives an AUS approval recommendation, and it can originate a loan that had a negative AUS recommendation. This enables estimation of our application denial regression after conditioning on the AUS decision, which will largely account for quantifiable credit risk factors that are correlated with race, but unobserved in HMDA. Column (3) of Table 7 shows that compared to column (2) (which does not include the AUS denial indicator), racial denial rate gaps decline after controlling for the AUS recommendation. However, significant residual racial denial rate gaps persist in column (3). Black, Hispanic, and Asian applicants are still 2.7, 1.0, and 2.0 percentage points more likely to be denied after conditioning on AUS recommendation. Our cash-out results echo the first-lien mortgage application findings of Bhutta, Hizmo, and Ringo (2024). We cannot rule out the possibility that unobserved credit risk factors fully explain racial denial rate gaps, but since AUS recommendations capture many of these factors, the results in Table 7 cast doubt on this interpretation.

[40] AUS recommendations are not applicable in HMDA data for the vast majority of HELOC and HELoan applications, because standard AUS are not designed for use with these product types.

5.1.3 Lender "Strictness"

In this section we implement an additional exercise, developed in Bhutta, Hizmo, and Ringo (2024), to test whether unobservable underwriting factors explain variation in the residual denial rate gaps. The exercise involves two steps. First, we estimate our fully saturated denial rate model by product type (column 2, Table 3) on our sample of the top 50 lenders (within each product type). The models are estimated using only applications from White borrowers. We extract the estimated lender fixed effects from the regression output and interpret them as a measure of lender "strictness" in underwriting with respect to variables that are omitted from the HMDA dataset. The measure is constructed using only White applicants in order to isolate differences across lenders in strictness that are not contaminated by differential treatment of minority applicants. Positive values indicate lenders that impose tougher underwriting standards than average on White applicants, while a value of zero means a lender's rejection rate of White borrowers is average, conditional on observable factors.

The second step of the exercise involves estimating the correlation across lenders between the strictness measure and residual Black-White denial gap disparities. If those disparities are due to differences in how lenders account for unobservable factors that differ between Black and White applicants in their underwriting processes, then we should expect a positive correlation between the strictness measures and the residual disparities. Bhutta, Hizmo, and Ringo (2024) find a strong, positive correlation for both purchase mortgages and refinance loans and concludes that residual denial gaps for those mortgage products are "at least partly a result of tight lender standards on unobservable factors." (p. 16)

Figure 6 displays scatter plots of residual Black-White denial gaps (y-axis) against the lender strictness measures (x-axis) for each of the three MEW product types in our sample. We show two plots for cash-out refinances in the upper panel of the figure. The upper left plot includes in the lender fixed effect regressions a control for the AUS decision, while the upper right plot does not.

Comparing the two plots suggests that the AUS control, which is not available for HELOCs and HELoans, does not have a significant impact on this analysis.

In contrast to the results in Bhutta, Hizmo, and Ringo (2024) corresponding to purchase and refinance mortgages, the correlations between the lender strictness measures and the residual Black-White denial gaps for MEW products are weak. The correlation is essentially zero for cash-out refinances and HELoans and is slightly negative for HELOCs. These patterns are consistent with the results from the lender-level Kitagawa-Blinder-Oaxaca decompositions in the previous section and suggest that underwriting factors that are not observed in HMDA are unlikely to explain all of the residual denial rate gaps.

5.1.4 Media Market Racial Animus

To shed light on whether the racial disparities in denial rates might be the result of discrimination, we exploit geographic variation in racial animus and test whether the size of racial disparities in rejection rates positively covaries with the level of racial animus across metropolitan statistical areas (MSAs). Intuitively, are the minority-White denial gaps more pronounced in areas with more prejudiced populations? To proxy for racial animus, we employ the Racial Animus Index developed by Stephens-Davidowitz (2014), which relies on the percentage of Google search queries containing racially charged language.[41] Higher levels of the index represent greater racial bias against people who are Black. Stephens-Davidowitz's racial animus measure has been used to study income mobility (Chetty et al., 2019) and discrimination in labor markets (Kline, Rose, and Walters, 2022) and higher education bond markets ((Dougal et al., 2019). For the markets covered in our data, the mean (median) of the index is 63 (60), while the standard deviation is 19.

[41] Stephens-Davidowitz's animus measure is available for 196 media markets in the United States. The measure was calculated using data from the 2004–2007 period and may not accurately reflect geographic differences in the extent of racial animus during our sample period. Since HMDA data do not include a media market identifier, we manually match loans' counties to their MSAs and then to media markets. There are 184 separate media markets represented in our mortgage data. Also, the measure is based on racially charged terms related to the Black population. This may not be a good indicator of the level of racial animus toward other minority groups.

We estimate our main regression model separately for each of the 184 media markets and collect the Asian, Black, and Hispanic coefficients from each regression.[42] Figure A.4 displays binned scatter plots of the race coefficients by the media market's level of racial animus. All three panels show that minority-White gaps are elevated in areas characterized by greater racial animus.[43] The correlation between racial animus and the Black, Hispanic, and Asian coefficients is 0.30, 0.20, and 0.30, respectively, all statistically significantly at the 1% confidence level.

Further, by incorporating it into our main model as a control, we find that a one-standard-deviation increase in media market racial animus leads to a statistically and economically significant 0.7-1.0 percentage point increase in the Black-White denial gap and a 0.9 percentage point increase in the Asian-White gap (see Table A.11). The increase in the Hispanic-White gap (0.5 percentage point) is smaller and not statistically significant when state fixed effects are included. Taken together, these results are consistent with discrimination partially driving the conditional racial disparities in MEW denial rates. A stronger measure of animosity, especially one more targeted to picking up bias against Hispanic and Asian people, might have greater explanatory power.

5.2 Aggregate Differences in MEW Amounts by Race

The high denial rates for MEW products apparent in Figure 1 suggest considerable unmet demand for these products. Moreover, the significantly higher minority denial rates that we have documented in this paper imply that the unmet demand is much higher for minority homeowners. In this section, we perform a simple back-of-the-envelope calculation to estimate the differences in the amount of housing equity accessed by minority and White homeowners. We perform the exercise using both conditional and unconditional denial rate differences, since as we discussed previously, both measures are relevant from a policy perspective. Although this exercise is infor-

[42] Independent variables exclude state fixed effects, but otherwise are the same as in Table 2, column (5). The results are very similar if state fixed effects are included.

[43] These results use the animus index where the property is located. An alternative approach is to use the animus measure where the mortgage loan originator is located. Results are similar when using this alternative approach.

mative and relevant to policy discussions, it should not be interpreted as a welfare analysis because we are unable to measure the full benefits and costs (e.g., higher default rates) of increased access to mortgage equity withdrawals.

Table 8 presents the results of these calculations for all four racial groups we study. We estimate that, in total between 2018 and 2021, Black homeowners in our sample applied to extract \$46.4 billion in home equity, but were denied \$23 billion.[44] Had they experienced the denial rate of White applicants (ignoring underwriting factors), they would have only been denied \$11.8 billion, or about half as much demand would have gone unmet.[45]

"Excess" denials conditional on borrower and mortgage characteristics are much smaller but still reflect a large amount of locked-up home equity that borrowers were unable to access. A back-of-the-envelope calculation using our regression model results in Table 3 suggests that the "excess" denials for Black borrowers, controlling for observable loan and borrower characteristics, was \$2.0 billion over this 4-year period.[46] Hispanic and Asian applicants were denied the ability to cash out about \$2.2 billion and \$3.9 billion in equity more than White borrowers, respectively, after controlling for these factors. Although excess denials are smaller after accounting for underwriting factors, they are still large, at 18%, 25%, and 46% of the unconditional excess denials for Black, Hispanic, and Asian applicants, respectively. Or in other words, observable underwriting factors

[44] We estimate the amount of loan proceeds that each product application, if successful, would yield using a simple formula: Loan proceeds for HELOCs and HELoans are equal to 97.5% of the applied-for loan amount. (We assume 2.5% closing costs, which represent equity withdrawn but not received as cash by the borrower.) Because cash-out refinances include paying off the existing mortgage lien(s), a smaller portion of the loan amount becomes cash to the borrower. Gross loan proceeds for cash-out refinances are estimated as 16% of the loan amount for conventional loans and 11% for FHA/VA loans in the data used by Gerardi, Lambie-Hanson, and Willen (2022), with net proceeds subtracting \$2,000 and 1% of the total loan amount.

[45] For example, Black HELOC applicants had an unconditional denial rate of 62.4%, vs. 32.3% for White applicants. They were denied \$11.5 billion in equity withdrawal via these HELOCs, an estimated \$5.5 billion "excess" relative to the rate at which White applicants were denied (\$18.4 billion * (0.624-0.323)).

[46] We can calculate this by multiplying the estimated total loan proceeds applied for by Black homeowners (\$18.4 billion in the case of HELOCs) by the corresponding Black coefficient (0.044) in Table 3's Model 2. Calculations are very similar if we instead use loan proceeds-weighted denial rates and weighted regression coefficients. Some applicants apply more than once. In Section A.5, we make an adjustment to the calculation so as to not overestimate the total amount of equity that could realistically be extracted if more than one of a borrower's applications was approved. When these adjustments are applied, the total estimated equity extraction foregone for Black borrowers falls from \$2.0 billion to \$1.7 billion.

can explain only about four-fifths of the Black-White gap, three-quarters of the Hispanic-White gap, and a bit over half of the Asian-White gap.

6 Conclusion

Scrutiny of the racial homeownership gap has led to initiatives to help address purchase lending disparities, such as Fannie Mae and Freddie Mac's Equitable Housing Finance Plans announced in June 2022. Likewise, recent studies have documented lower rates of rate/term refinancing among Black and Hispanic consumers in periods of falling interest rates, calling for the consideration of ratchet mortgages and other interventions that would better ensure that lower mortgage interest rates get passed on to borrowers equitably (Gerardi, Lambie-Hanson, and Willen, 2022; Gerardi, Willen, and Zhang, 2023). But far less attention has been paid to date about the barriers to accessing mortgage financing to help a homeowner withdraw the housing wealth he or she has accumulated.

Lenders offering home equity products often advertise to homeowners using messages such as "Don't borrow from a bank! Borrow from yourself." Indeed, home equity products generally offer lower interest rates than credit cards or other products, and they can be a useful tool for borrowers who need cash to complete home repairs or improvements, pay medical debt, or send a child to college. But as we show in this paper, MEW products have very high denial rates, especially for minority homeowners. Much of the minority-White gap in denial rates can be explained by borrower characteristics such as credit score, signaling that the underwriting system for these loans has a particularly large impact on these consumers. Americans hold record levels of home equity, following the historic house price increases of 2020–2021. Policymakers and researchers should not assume this newfound housing wealth will be equally liquid among all homeowners.

References

Adelino, M., A. Schoar, and F. Severino. 2015. House prices, collateral, and self-employment. *Journal of Financial Economics* 117:288–306. ISSN 0304-405X. doi:https://doi.org/10.1016/j.jfineco.2015.03.005.

Agarwal, S., B. W. Ambrose, S. Chomsisengphet, and C. Liu. 2011. The role of soft information in a dynamic contract setting: Evidence from the home equity credit market. *Journal of Money, Credit and Banking* 43:633–55.

Agarwal, S., B. W. Ambrose, and C. Liu. 2006. Credit lines and credit utilization. *Journal of Money, Credit and Banking* 1–22.

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

Bartlett, R., A. Morse, R. Stanton, and N. Wallace. 2022. Consumer-lending discrimination in the fintech era. *Journal of Financial Economics* 143:30–56.

Bayer, P., F. Ferreira, and S. L. Ross. 2018. What drives racial and ethnic differences in high-cost mortgages? The role of high-risk lenders. *The Review of Financial Studies* 31:175–205.

Becker, G. S. 1993. Nobel lecture: The economic way of looking at behavior. *Journal of Political Economy* 101:385–409.

Benetton, M., M. Kudlyak, and J. Mondragon. 2022. Dynastic home equity. Working Paper, Federal Reserve Bank of San Francisco.

Benito, A. 2009. Who withdraws housing equity and why? *Economica* 76:51–70.

Bhutta, N., and A. Hizmo. 2021. Do minorities pay more for mortgages? *The Review of Financial Studies* 34:763–89.

Bhutta, N., A. Hizmo, and D. Ringo. 2024. How much does racial bias affect mortgage lending decisions? Evidence from data on human and algorithmic decisions. *The Journal of Finance (forthcoming)* .

Bhutta, N., S. Laufer, and D. R. Ringo. 2017. Residential mortgage lending in 2016: Evidence from the Home Mortgage Disclosure Act data. *Federal Reserve Bulletin* 103:1–27.

Black, H., R. L. Schweitzer, and L. Mandell. 1978. Discrimination in mortgage lending. *The American Economic Review* 68:186–91.

Blascak, N., and A. Tranfaglia. 2021. Decomposing gender differences in bankcard credit limits. Working Paper, Federal Reserve Bank of Philadelphia.

Blau, F. D., and L. M. Kahn. 2017. The gender wage gap: Extent, trends, and explanations. *Journal of Economic Literature* 55:789–865.

Blinder, A. S. 1973. Wage discrimination: reduced form and structural estimates. *Journal of Human Resources* 436–55.

Boehm, T., and A. Schlottmann. 2004. The dynamics of race, income, and homeownership. *Journal of Urban Economics* 55:113–130.

Boehm, T. P., and A. Schlottmann. 2008. Wealth accumulation and homeownership: Evidence for low-income households. *Cityscape* 10:225–56.

Canner, G., K. Dynan, and W. Passmore. 2002. Mortgage refinancing in 2001 and early 2002. *Fed. Res. Bull.* 88:469–81.

Canner, G. B., T. A. Durkin, and C. A. Luckett. 1998. Recent developments in home equity lending. *Federal Reserve Bulletin* 84:241–51.

Carlin, A., and E. Divringi. 2018. Home improvement lending in the Third Federal Reserve District: Patterns by income, race, and gender. *Cascade Focus* 1–19.

Case, B., and A. B. Schnare. 1994. Preliminary evaluation of the HECM reverse mortgage program. *Real Estate Economics* 22:301–46.

Charles, K. K., and E. Hurst. 2002. The transition to home ownership and the black-white wealth gap. *Review of Economics and Statistics* 84:281–97.

Chen, A., and H. H. Jensen. 1985. Home equity use and the life cycle hypothesis. *Journal of Consumer Affairs* 19:37–56.

Chetty, R., N. Hendren, M. R. Jones, and S. R. Porter. 2019. Race and Economic Opportunity in the United States: An Intergenerational Perspective. *The Quarterly Journal of Economics* 135:711–83. ISSN 0033-5533. doi:10.1093/qje/qjz042.

Chiwaya, N., and J. Ross. 2020. The american dream while black: 'locked in a vicious cycle'. *NBC News* .

Consumer Financial Protection Bureau. 2019. Data point: 2018 mortage market activity and trends. Working Paper.

Coulson, N. E., and M. Dalton. 2010. Temporal and ethnic decompositions of homeownership rates: Synthetic cohorts across five censuses. *Journal of Housing Economics* 19:155–66.

Davidoff, T. 2014. Reverse mortgage demographics and collateral performance. Working Paper, SSRN No. 2399942.

Davidoff, T., P. Gerhard, and T. Post. 2017. Reverse mortgages: What homeowners (don't) know and how it matters. *Journal of Economic Behavior & Organization* 133:151–71.

Dawkins, C. 2005. Racial gaps in the transition to first-time homeownership: The role of residential location. *Journal of Urban Economics* 58:537–554.

Deng, Y., S. L. Ross, and S. M. Wachter. 2003. Racial differences in homeownership: The effect of residential location. *Regional Science and Urban Economics* 33:517–56. ISSN 0166-0462. doi:https://doi.org/10.1016/S0166-0462(02)00058-3.

Do, C. 2012. Withdrawing home equity: Differences across race and ethnicity. *Housing Studies* 27:299–323.

Dougal, C., P. Gao, W. J. Mayew, and C. A. Parsons. 2019. What's in a (school) name? Racial discrimination in higher education bond markets. *Journal of Financial Economics* 134:570–90. ISSN 0304-405X. doi:https://doi.org/10.1016/j.jfineco.2019.05.010.

Duca, J. V., and A. Kumar. 2014. Financial literacy and mortgage equity withdrawals. *Journal of Urban Economics* 80:62–75.

Federal Financial Institutions Examination Council. 2019. A guide to HMDA reporting: Getting it right! Working Paper.

Flippen, C. 2004. Unequal returns to housing investments? A study of real housing appreciation among Black, White, and Hispanic households. *Social Forces* 82:1523–1551.

Frame, W. S., R. Huang, E. J. Mayer, and A. Sunderam. 2022. The impact of minority representation at mortgage lenders. Working Paper, National Bureau of Economic Research.

Gabriel, S., and G. Painter. 2003. Pathways to homeownership: An analysis of the residential location and homeownership choices of black households in Los Angeles. *The Journal of Real Estate Finance and Economics* 27:87–109.

Gabriel, S. A., and S. S. Rosenthal. 2005. Homeownership in the 1980s and 1990s: Aggregate trends and racial gaps. *Journal of Urban Economics* 57:101–27.

Gerardi, K., L. Lambie-Hanson, and P. Willen. 2022. Housing policy: Part I. Mortgage-Borrowers. In W. Edelberg, L. Sheiner, and D. Wessel, eds., *Recession Remedies: Lessons Learned from the U.S. Economic Policy Repsonse to COVID-19*, chap. 5, 166–91. Brookings Institution Press.

Gerardi, K., P. S. Willen, and D. H. Zhang. 2023. Mortgage prepayment, race, and monetary policy. *Journal of Financial Economics* 147:498–524. ISSN 0304-405X. doi:https://doi.org/10.1016/j.jfineco.2022.12.001.

Ghent, A. C., R. Hernandez-Murillo, and M. T. Owyang. 2014. Differences in subprime loan pricing across races and neighborhoods. *Regional Science and Urban Economics* 48:199–215.

Goodman, L. S., and C. Mayer. 2018. Homeownership and the American dream. *Journal of Economic Perspectives* 32:31–58.

Greenspan, A., and J. Kennedy. 2008. Sources and uses of equity extracted from homes. *Oxford Review of Economic Policy* 24:120–44.

Gyourko, J., P. Linneman, and S. Wachter. 1999. Analyzing the relationships among race, wealth, and home ownership in America. *Journal of Housing Economics* 8:63–89.

Hall, M., and K. Crowder. 2011. Extended-family resources and racial inequality in the transition to homeownership. *Social Science Research* 40:1534–46.

Haurin, D., C. Ma, S. Moulton, M. Schmeiser, J. Seligman, and W. Shi. 2016. Spatial variation in reverse mortgages usage: House price dynamics and consumer selection. *The Journal of Real Estate Finance and Economics* 53:392–417.

Hilber, C. A., and Y. Liu. 2008. Explaining the Black-White homeownership gap: The role of own wealth, parental externalities and locational preferences. *Journal of Housing Economics* 17:152–74.

Hurst, E., and F. Stafford. 2004. Home is where the equity is: Mortgage refinancing and household consumption. *Journal of Money, Credit and Banking* 985–1014.

Jann, B. 2008. The Blinder-Oaxaca decomposition for linear regression models. *The Stata Journal* 8:453–79.

Jiang, E. X., Y. Lee, and W. S. Liu. 2021. Disparities in consumer credit: The role of loan officers in the fintech era. Working Paper, SSRN No. 4035764.

Jones, F. L., and J. Kelley. 1984. Decomposing differences between groups: A cautionary note on measuring discrimination. *Sociological Methods & Research* 12:323–43.

Kahn, M. E. 2021. Racial and ethnic differences in the financial returns to home purchases from 2007 to 2020. Working Paper, National Bureau of Economic Research.

Kau, J. B., D. C. Keenan, and H. J. Munneke. 2012. Racial discrimination and mortgage lending. *The Journal of Real Estate Finance and Economics* 45:289–304.

Kermani, A., and F. Wong. 2021. Racial disparities in housing returns. Working Paper, National Bureau of Economic Research.

Kerr, S. P., W. R. Kerr, and R. Nanda. 2022. House prices, home equity and entrepreneurship: Evidence from US census micro data. *Journal of Monetary Economics* 130:103–19.

Killewald, A., F. T. Pfeffer, and J. N. Schachner. 2017. Wealth inequality and accumulation. *Annual Review of Sociology* 43:379–404.

Kitagawa, E. M. 1955. Components of a difference between two rates. *Journal of the American Statistical Association* 50:1168–94.

Kline, P., E. K. Rose, and C. R. Walters. 2022. Systemic Discrimination Among Large U.S. Employers. *The Quarterly Journal of Economics* 137:1963–2036. ISSN 0033-5533. doi:10.1093/qje/qjac024.

Krivo, L., and R. Kaufman. 2004. Housing and wealth inequality: Racial-ethnic differences in home equity in the United States. *Demography* 41:585–605.

Ladd, H. F. 1998. Evidence on discrimination in mortgage lending. *Journal of Economic Perspectives* 12:41–62.

Lastrapes, W. D., I. Schmutte, and T. Watson. 2022. Home equity lending, credit constraints and small business in the US. *Economic Inquiry* 60:43–63.

Levine, P., and D. Ritter. 2022. The racial wealth gap, financial aid, and college access. Working Paper 22-32, Federal Reserve Bank of Philadelphia.

Marshall, L., and S. Pellerin. 2017. Credit unions: A taxing question. *Econ Focus* 20–3.

Mayer, C., and S. Moulton. 2022. The market for reverse mortgages among older Americans. In O. S. Mitchell, ed., *New Models for Managing Longevity Risk*. Oxford University Press.

Moulton, S., D. R. Haurin, and W. Shi. 2015. An analysis of default risk in the Home Equity Conversion Mortgage (HECM) program. *Journal of Urban Economics* 90:17–34.

Moulton, S., C. Loibl, and D. Haurin. 2017. Reverse mortgage motivations and outcomes: Insights from survey data. *Cityscape* 19:73–98.

Munnell, A. H., G. M. Tootell, L. E. Browne, and J. McEneaney. 1996. Mortgage lending in Boston: Interpreting HMDA data. *The American Economic Review* 25–53.

Newman, D. A., and J. S. Lyon. 2009. Recruitment efforts to reduce adverse impact: Targeted recruiting for personality, cognitive ability, and diversity. *Journal of Applied Psychology* 94:298–317.

Oaxaca, R. 1973. Male-female wage differentials in urban labor markets. *International Economic Review* 693–709.

Park, K. A. 2021. Measuring risk and access to mortgage credit with new disclosure data. *The Journal of Structured Finance* 26:53–72.

———. 2022. A comparison of mortgage denial and default rates by race, ethnicity, and gender. *Ethnicity, and Gender (February 7, 2022)* .

Pence, K. 2015. Discussion of Brown, Stein, and Zafar. *Journal of Money, Credit and Banking* 47:215–20.

Ross, S. L., and J. Yinger. 1999. The default approach to studying mortgage discrimination: A rebuttal. *Mortgage lending discrimination: A review of existing evidence* 107–27.

———. 2002. *The color of credit: Mortgage discrimination, research methodology, and fair-lending enforcement*. MIT press.

Shapiro, T. M. 2006. Race, homeownership and wealth. *Washington University Journal of Law & Policy* 20:53–74.

Stephens-Davidowitz, S. 2014. The cost of racial animus on a Black candidate: Evidence using Google search data. *Journal of Public Economics* 118:26–40.

Wainer, A., and J. Zabel. 2020. Homeownership and wealth accumulation for low-income households. *Journal of Housing Economics* 47:101624–44.

Willen, P. S., and D. H. Zhang. 2021. Do lenders still discriminate? A robust approach for assessing differences in menus. Working Paper, National Bureau of Economic Research.

7 Figures

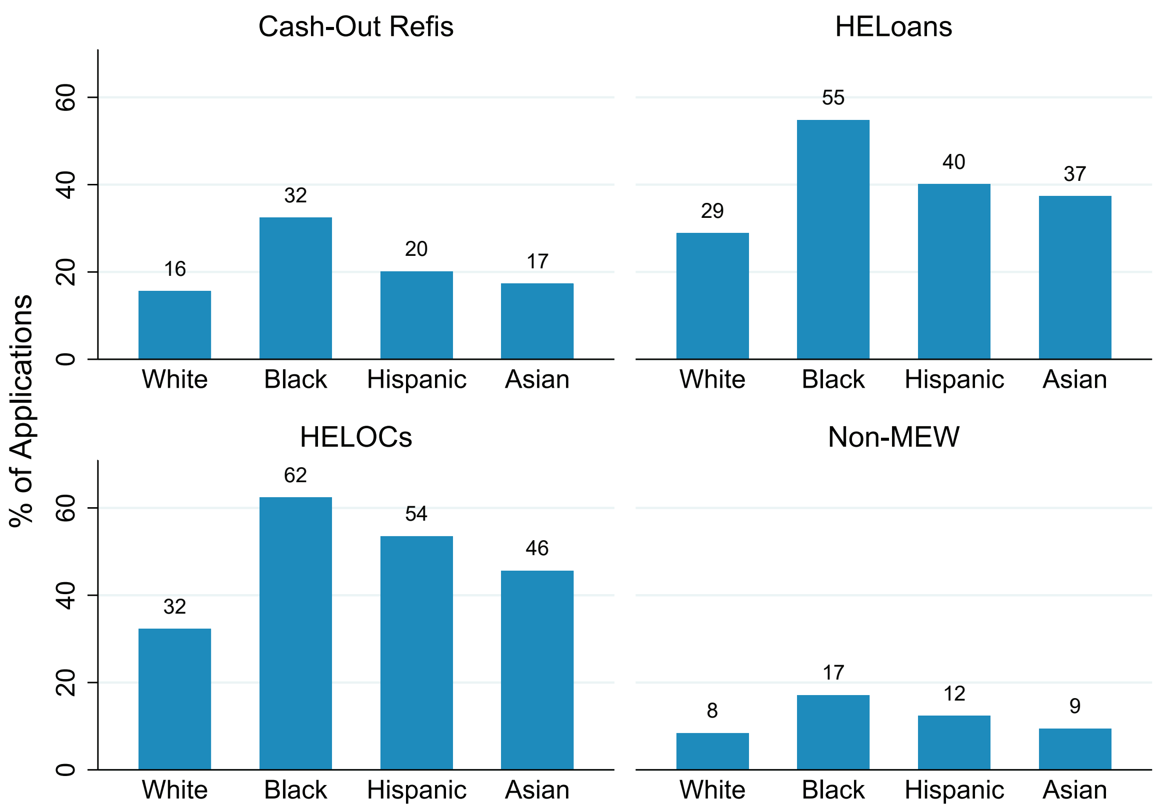


Figure 1. Application Denial Rates

Note: Denial rates conditional on credit decision, 2018–2021. Non-MEW includes first-lien purchase loans and rate/term refinances. Source: Home Mortgage Disclosure Act data.

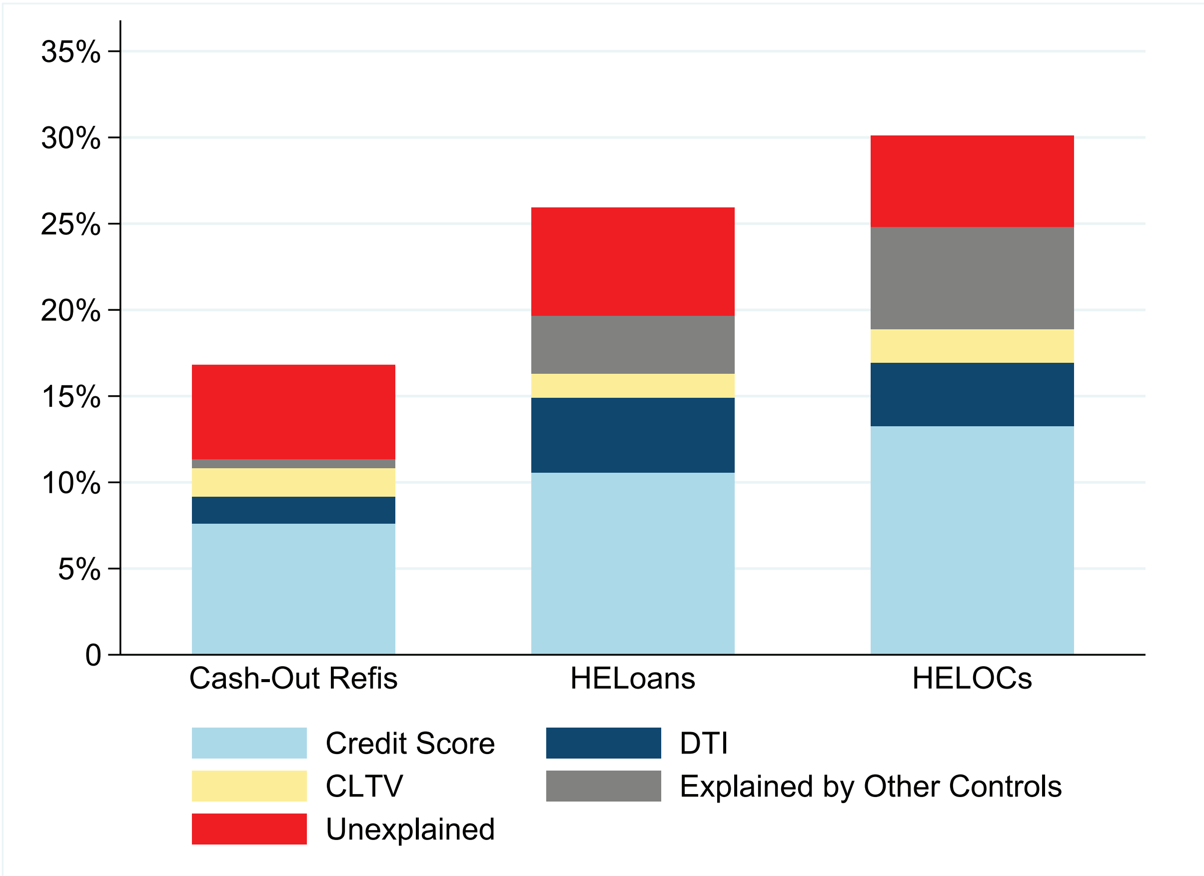


Figure 2. Decomposition of Denial Rate Differences by Product Type

Note: Kitagawa-Blinder-Oaxaca decomposition of Black-White denial rate differences by product type, 2018–2021. Independent variables are the same as in Table 2 column (5). Source: Home Mortgage Disclosure Act data.

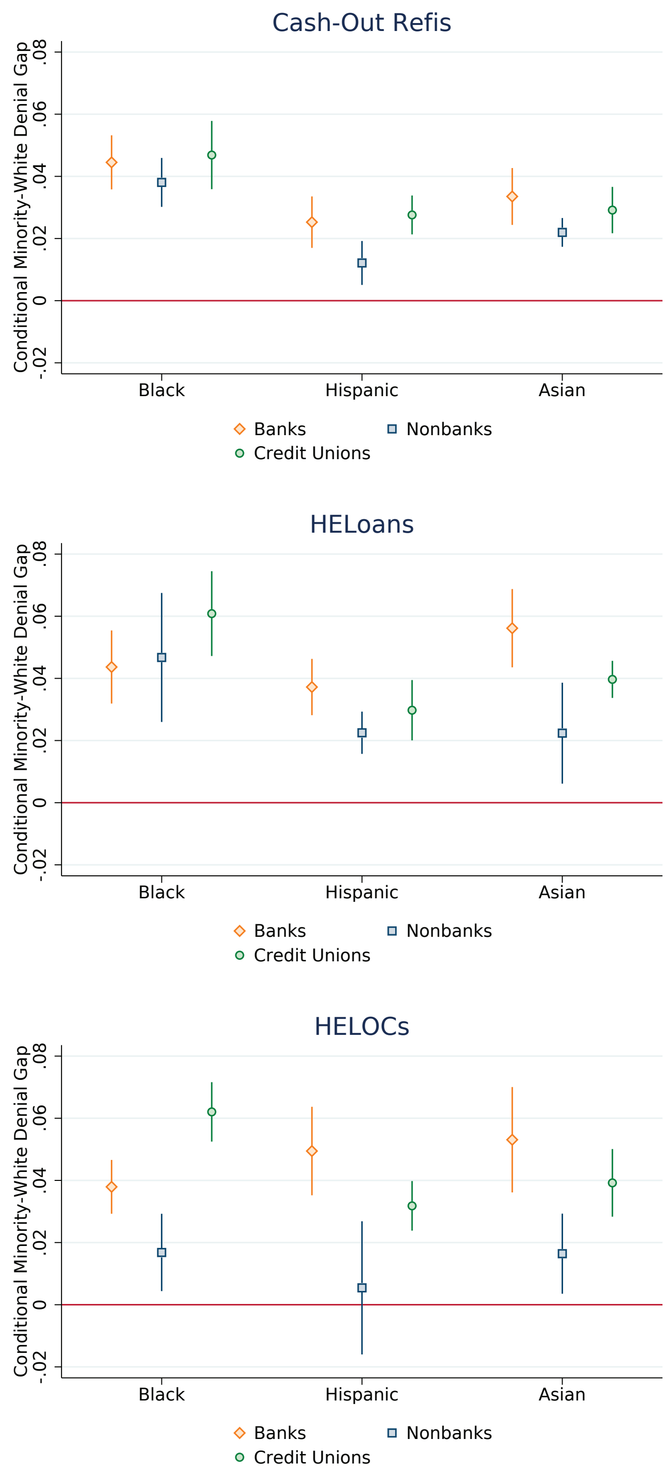


Figure 3. Conditional Minority-White Differences in Denial Rates by Institution Type and Product Type

Note: Coefficients and 95% confidence intervals from denial rate models with full set of borrower and loan controls. Model specifications are the same as in Table 4. Source: Home Mortgage Disclosure Act data.

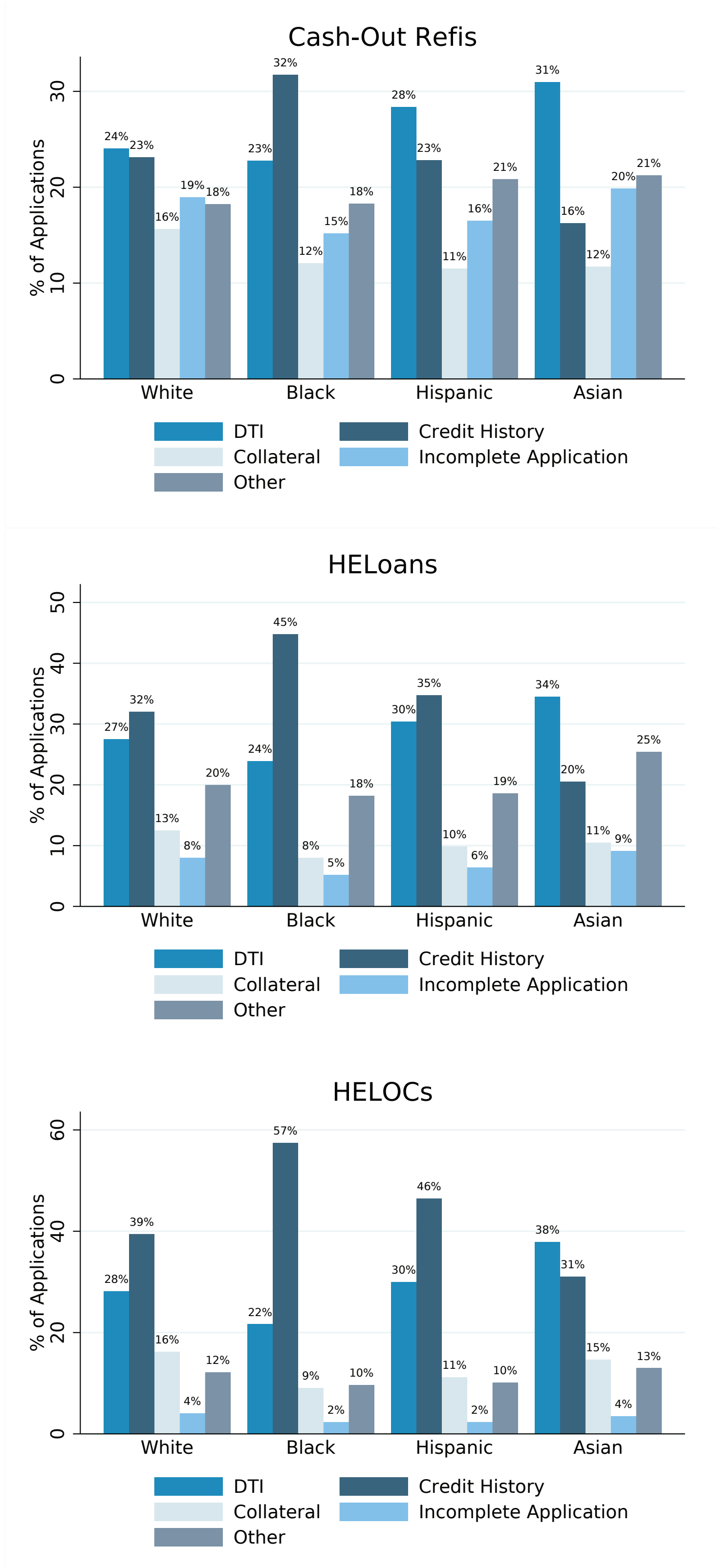


Figure 4. Application Denial Reason

Note: First reported denial reason for denied applications, 2018–2021. Source: Home Mortgage Disclosure Act data.

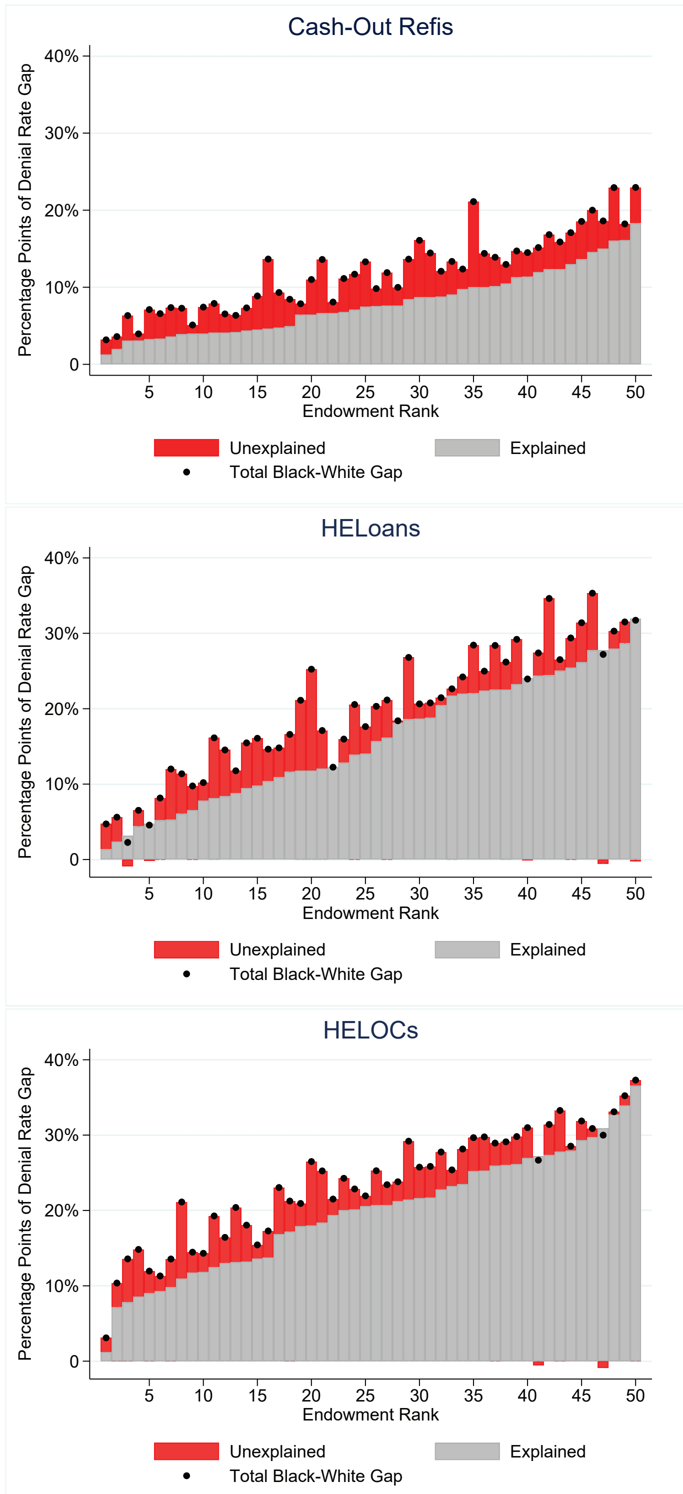


Figure 5. Decomposition of Denial Rate Differences by Lender

Note: Kitagawa-Blinder-Oaxaca decomposition of Black-White denial rate differences by product type, 2018–2021. Each panel includes separate decompositions for the top 50 largest lenders in that product type. Independent variables are the same as in Table 2 column (5). Source: Home Mortgage Disclosure Act data.

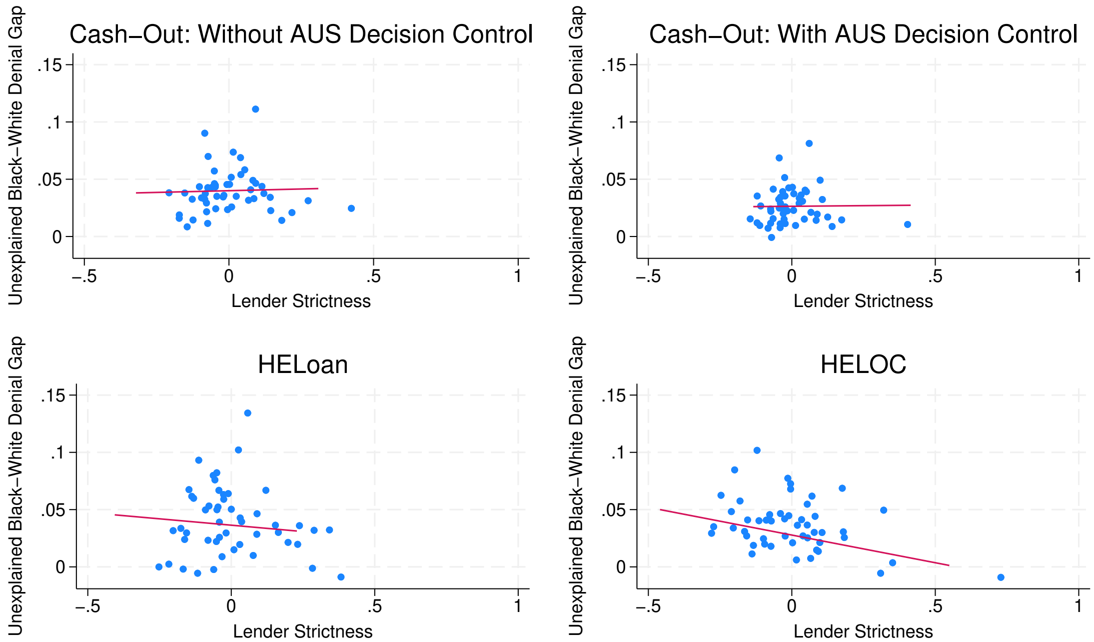


Figure 6. Lender Strictness and Unexplained Racial Gaps

Note: Includes cash-out refinance, home equity loan, and home equity line of credit applications from Black and White consumers reported by financial institutions in 2018–2021. Sample is restricted to the top 50 lenders by application within each product type. "Strictness" (x-axis) reflects lender fixed effects from the fully saturated denial rate model, estimated on White applicants only. "Unexplained racial gap" (y-axis) is the unexplained Black-White denial rate gap from the decompositions reported in Figure 5. Source: Home Mortgage Disclosure Act data.

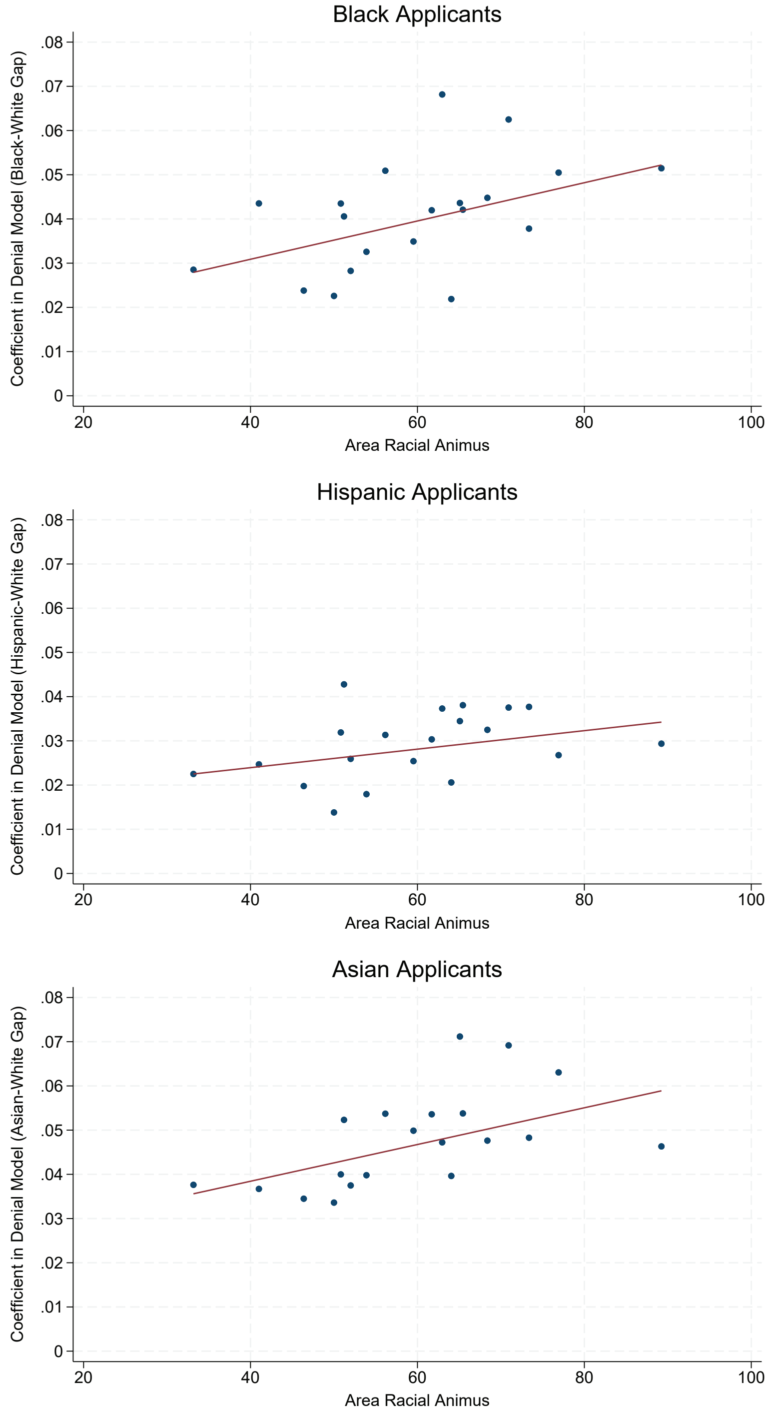


Figure 7. Denial Rate Differences and Racial Animus

Note: Minority-White difference, 2018–2021. Each panel represents a binned scatterplot of minority coefficients obtained from separate regressions for each of the 184 media markets in our sample. Media market level racial animus is from Stephens-Davidowitz (2014). Independent variables exclude state fixed effects, but otherwise are the same as in Table 2 column (5). Source: Home Mortgage Disclosure Act data.

8 Tables

Table 1. Descriptive Statistics for MEW Products

	White	Black	Hispanic	Asian
Income (thousands $)	118.1	93.1	102.3	147.8
DTI (%)	36.5	41.2	40.7	40.3
Credit Score	735	688	715	745
CLTV (%)	65.2	68.4	64.9	63.4
Loan Amount	185,529	166,378	195,211	264,885
Units	1.0	1.1	1.1	1.0
Loan Term (months)	301	311	310	315
Second Home (d)	0.02	0.01	0.01	0.02
Investment Property (d)	0.04	0.06	0.06	0.10
No Co-applicant (d)	0.53	0.72	0.54	0.53
Home Improvement (d)	0.22	0.23	0.21	0.23
Second Lien (d)	0.30	0.27	0.28	0.35
Prepayment Penalty (d)	0.08	0.08	0.08	0.13
Interest Only (d)	0.16	0.09	0.11	0.15
Other Nonamortizing Features (d)	0.02	0.02	0.03	0.03
Application to Minority-Owned Bank (d)	0.001	0.001	0.002	0.009
Application Denied (d)	0.23	0.44	0.32	0.30
Cash-Out Refinance (d)	0.55	0.59	0.59	0.51
Home Equity Loan (HEloan) (d)	0.12	0.12	0.12	0.10
Home Equity Line of Credit (HELOC) (d)	0.33	0.29	0.29	0.39
# Observations	9,572,670	1,011,791	1,184,479	870,398

Note: This table reports mean values for observations populated on the variable in question. The sample includes MEW products (cash-out refinances, HELoans, and HELOCs) for which a credit decision was made. See the Table A.2 of the Online Appendix for data on the rate at which these fields are missing by loan type and racial/ethnic group. Dichotomous variables are signified by (d). Source: Home Mortgage Disclosure Act data.

Table 2. Applicant Race and Likelihood of Denial on MEW Products

Dependent Var: Loan Denied (d)	(1)	(2)	(3)	(4)	(5)	(6)
Black (d)	0.212***	0.192***	0.068***	0.065***	0.056***	0.042***
	(0.022)	(0.019)	(0.008)	(0.008)	(0.005)	(0.004)
Hispanic (d)	0.095***	0.092***	0.034**	0.034**	0.027**	0.028***
	(0.025)	(0.015)	(0.011)	(0.011)	(0.008)	(0.005)
Asian (d)	0.076***	0.087***	0.073***	0.075***	0.058***	0.043***
	(0.018)	(0.013)	(0.012)	(0.012)	(0.008)	(0.005)
Year FE	N	Y	Y	Y	Y	Y
State FE	N	Y	Y	Y	Y	Y
DTI Buckets	N	N	Y	Y	Y	Y
Credit Score Buckets	N	N	Y	Y	Y	Y
CLTV Buckets	N	N	N	Y	Y	Y
Other Controls	N	N	N	N	Y	Y
Lender FE	N	N	N	N	N	Y
# Observations	12,638,969	12,638,969	12,638,969	12,638,969	12,638,969	12,638,969
Adjusted R^2	0.020	0.047	0.240	0.259	0.316	0.380
Mean Denial Rate	0.26	0.26	0.26	0.26	0.26	0.26

Note: This table reports coefficient estimates from linear probability models where the dependent variable is an indicator for whether the application was denied. The sample includes MEW products (cash-out refinances, HELoans, HELOCs) for which a credit decision was made. Dichotomous variables are signified by (d). Standard errors, clustered at the state and lender levels, are in parentheses. *** p<0.001, ** p<0.01, * p<0.05. Source: Home Mortgage Disclosure Act data.

Table 3. Applicant Race and Likelihood of Denial by Product Type

Panel A: Cash-Out Refinances

	(1)	(2)
Black	0.168***	0.040***
	(0.023)	(0.004)
Hispanic	0.045**	0.016***
	(0.014)	(0.004)
Asian	0.017*	0.026***
	(0.007)	(0.003)
# Observations	7,030,943	7,030,943
Adjusted R^2	0.015	0.289
Mean Denial Rate	0.18	0.18

Panel B: Home Equity Loans (HELoans)

Black	0.259***	0.050***
	(0.026)	(0.005)
Hispanic	0.112***	0.032***
	(0.017)	(0.004)
Asian	0.085***	0.045***
	(0.024)	(0.006)
# Observations	1,479,900	1,479,900
Adjusted R^2	0.027	0.445
Mean Denial Rate	0.33	0.33

Panel C: Home Equity Lines of Credit (HELOCs)

Black	0.301***	0.044***
	(0.012)	(0.004)
Hispanic	0.213***	0.046***
	(0.021)	(0.006)
Asian	0.133***	0.051***
	(0.018)	(0.008)
# Observations	4,128,076	4,128,076
Adjusted R^2	0.039	0.469
Mean Denial Rate	0.37	0.37
Year FE	N	Y
State FE	N	Y
DTI Buckets	N	Y
Credit Score Buckets	N	Y
CLTV Buckets	N	Y
Other Controls	N	Y
Lender FE	N	Y

Note: This table reports coefficient estimates from linear probability models where the dependent variable is an indicator for whether the application was denied. The sample in Panels A, B, and C are cash-out refinances, HELoans, and HELOCs, respectively, for which a credit decision was made. Standard errors, clustered at the state and lender levels, are in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$. Source: Home Mortgage Disclosure Act data.

Table 4. Likelihood of Denial by Type of Financial Institution

	Cash-Out Refinances			HELoans			HELOCs		
	Banks (1)	Nonbanks (2)	Credit Unions (3)	Banks (4)	Nonbanks (5)	Credit Unions (6)	Banks (7)	Nonbanks (8)	Credit Unions (9)
Black	0.045***	0.038***	0.047***	0.044***	0.047***	0.061***	0.038***	0.017**	0.062***
	(0.004)	(0.004)	(0.005)	(0.006)	(0.010)	(0.007)	(0.004)	(0.006)	(0.005)
Hispanic	0.025***	0.012**	0.028***	0.037***	0.023***	0.030***	0.049***	0.005	0.032***
	(0.004)	(0.004)	(0.003)	(0.005)	(0.003)	(0.005)	(0.007)	(0.011)	(0.004)
Asian	0.034***	0.022***	0.029***	0.056***	0.022**	0.040***	0.053***	0.016*	0.039***
	(0.005)	(0.002)	(0.004)	(0.006)	(0.008)	(0.003)	(0.008)	(0.006)	(0.005)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
DTI Buckets	Y	Y	Y	Y	Y	Y	Y	Y	Y
Credit Score Buckets	Y	Y	Y	Y	Y	Y	Y	Y	Y
CLTV Buckets	Y	Y	Y	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
# Observations	2,152,332	4,258,328	620,279	723,378	237,960	518,558	3,169,720	56,414	901,942
Adjusted R-^{2}	0.329	0.281	0.346	0.469	0.388	0.403	0.487	0.147	0.363
Mean Denial Rate	0.17	0.18	0.13	0.41	0.27	0.23	0.42	0.30	0.21

Note: This table reports coefficient estimates from linear probability models where the dependent variable is an indicator for whether the application was denied. The saturated model is estimated separately for each lender type / MEW product combination. Standard errors, clustered at the state and lender levels, are in parentheses. *** p<0.001, ** p<0.01, * p<0.05. Source: Home Mortgage Disclosure Act data.

Table 5. Likelihood of Denial by Lender Minority Ownership Status

	(1)	(2)	(3)
Black Applicant	0.060***	0.060***	0.060***
	(0.006)	(0.006)	(0.006)
x Minority Bank		-0.021	
		(0.029)	
x Hispanic Bank			0.023
			(0.083)
x Asian Bank			-0.013
			(0.036)
x Other Minority Bank			-0.042
			(0.036)
Hispanic Applicant	0.035***	0.036***	0.036***
	(0.008)	(0.008)	(0.008)
x Minority Bank		-0.075***	
		(0.019)	
x Hispanic Bank			-0.079**
			(0.025)
x Asian Bank			-0.088**
			(0.028)
x Other Minority Bank			-0.054*
			(0.026)
Asian Applicant	0.056***	0.061***	0.061***
	(0.010)	(0.010)	(0.010)
x Minority Bank		-0.128**	
		(0.046)	
x Hispanic Bank			0.089
			(0.053)
x Asian Bank			-0.140**
			(0.041)
x Other Minority Bank			-0.023
			(0.024)
Minority Bank		-0.069***	
		(0.015)	
Hispanic Bank			-0.072*
			(0.031)
Asian Bank			-0.065***
			(0.012)
Other Minority Bank			-0.072**
			(0.024)
Year FE	Y	Y	Y
State FE	Y	Y	Y
DTI Buckets	Y	Y	Y
Credit Score Buckets	Y	Y	Y
CLTV Buckets	Y	Y	Y
Other Controls	Y	Y	Y
Lender FE	N	N	N
Lender Size	Y	Y	Y
# Observations	2,875,830	2,875,830	2,875,830
Adjusted R^2	0.35	0.35	0.35
Mean Denial Rate	0.23	0.23	0.23

Note: This table reports coefficient estimates from linear probability models where the dependent variable is an indicator for whether the application was denied. The estimation sample is restricted to applications for cash-out refinances and HELoans reported by bank lenders. Minority ownership status is provided in Bob Avery's HMDA Lender File, using National Information Center data. Standard errors, clustered at the state and lender levels, are in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$. Source: Home Mortgage Disclosure Act data.

Table 6. Applicant Race and Mortgage Pricing by Product Type

	Cash-Out Refis		HELoans		HELOCs	
	(1)	(2)	(3)	(4)	(5)	(6)
Black	0.136***	0.009**	0.476***	0.005	0.529***	0.100***
	(0.017)	(0.003)	(0.098)	(0.018)	(0.078)	(0.028)
Hispanic	0.111***	0.004	0.202***	-0.004	0.200***	0.012
	(0.014)	(0.004)	(0.030)	(0.007)	(0.029)	(0.008)
Asian	-0.063***	-0.048***	-0.097	-0.073***	-0.087*	-0.056**
	(0.013)	(0.009)	(0.060)	(0.017)	(0.033)	(0.016)
Year–Month FE	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y
DTI Buckets	N	Y	N	Y	N	Y
Credit Score Buckets	N	Y	N	Y	N	Y
CLTV Buckets	N	Y	N	Y	N	Y
Other Controls	N	Y	N	Y	N	Y
Lender FE	N	Y	N	Y	N	Y
# Observations	5,324,103	5,324,103	862,169	862,169	2,333,437	2,333,437
Adjusted R^2	0.086	0.505	0.047	0.685	0.069	0.610
Mean Rate Spread	0.43	0.43	1.39	1.39	0.85	0.85

Note: This table reports coefficient estimates from regressions where the dependent variable is interest rate spread. The sample includes originated loans. Standard errors, clustered at the state and lender levels, are in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$. Source: Home Mortgage Disclosure Act data.

Table 7. AUS Decisions in Cash-Out Refinances

	(1) "AUS Denial"	(2) Application Denial without AUS Outcome Control	(3) Application Denial with AUS Outcome Control
Black	0.020***	0.037***	0.027***
	(0.003)	(0.004)	(0.003)
Hispanic	0.006***	0.013***	0.010***
	(0.002)	(0.003)	(0.003)
Asian	0.007***	0.023***	0.020***
	(0.001)	(0.002)	(0.002)
AUS "Denial"			0.464***
			(0.025)
Year FE	Y	Y	Y
State FE	Y	Y	Y
DTI Buckets	Y	Y	Y
Credit Score Buckets	Y	Y	Y
CLTV Buckets	Y	Y	Y
Other Controls	Y	Y	Y
Lender FE	Y	Y	Y
AUS "Denial"	N	N	Y
# Observations	6,138,590	6,138,590	6,138,590
Adjusted R^2	0.203	0.208	0.311
Mean Outcome	0.08	0.13	0.13

Note: Includes cash-out refinance applications. Standard errors, clustered at the state and lender levels, are in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$. Source: Home Mortgage Disclosure Act data.

Table 8. Estimated Aggregate Dollars of Loan Proceeds to Borrowers Denied

		White	Black	Hispanic	Asian
	Cash-out				
[1]	Average estimated cash to borrower per application	$34,197	$28,807	$35,649	$50,755
	Estimated aggregate loan proceeds (in billions)				
[2]	All applications with credit decision	$180.9	$17.1	$24.9	$22.7
[3]	Denial Rate	15.6%	32.4%	20.1%	17.3%
[4]	Denied $, [2] * [3]	$28.2	$5.5	$5.0	$3.9
[5]	Denied $, given White denial rate [2] * [3, White]	$28.2	$2.7	$3.9	$3.5
[6]	Unconditional "excess" denied $, [4] - [5]		$2.9	$1.1	$0.4
[7]	Table 3, model 2 coefficient		0.040	0.016	0.026
[8]	Conditional "excess" denied $, [2] * [7]		$0.7	$0.4	$0.6
	HELoan				
[9]	Average estimated cash to borrower per application	$111,257	$86,718	$106,033	$181,452
	Estimated aggregate loan proceeds (in billions)				
[10]	All applications with credit decision	$124.9	$10.9	$15.3	$15.9
[11]	Denial Rate	28.9%	54.8%	40.1%	37.4%
[12]	Denied $, [10] * [11]	$36.1	$6.0	$6.1	$5.9
[13]	Denied $, given White denial rate [10] * [11, White]	$36.1	$3.2	$4.4	$4.6
[14]	Unconditional “excess” denied $, [12] - [13]		$2.8	$1.7	$1.3
[15]	Table 3, model 2 coefficient		0.050	0.032	0.045
[16]	Conditional “excess” denied $, [10] * [15]		$0.5	$0.5	$0.7
	HELOC				
[17]	Average estimated cash to borrower per application	$92,870	$62,865	$82,600	$150,726
	Estimated aggregate loan proceeds (in billions)				
[18]	All applications with credit decision	$293.3	$18.4	$28.2	$50.6
[19]	Denial Rate	32.3%	62.4%	53.5%	45.6%
[20]	Denied $, [18] * [19]	94.7	$11.5	$15.1	$23.1
[21]	Denied $, given White denial rate [18] * [19, White]	$94.7	$5.9	$9.1	$16.4
[22]	Unconditional “excess” denied $, [20] - [21]		$5.5	$6.0	$6.7
[23]	Table 3, model 2 coefficient		0.044	0.046	0.051
[24]	Conditional “excess” denied $, [18] * [23]		$0.8	$1.3	$2.6
	Total MEW				
	Estimated aggregate loan proceeds (in billions)				
[25]	All applications with credit decision	$599.1	$46.4	$68.4	$89.2
[26]	Denied $, [4] + [12] + [20]	$159.0	$23.0	$26.2	$32.9
[27]	Unconditional “excess” denied $, [6] + [14] + [22]		$11.2	$8.8	$8.5
[28]	Conditional “excess” denied $, [8] + [16] + [24]		$2.0	$2.2	$3.9

Source: Home Mortgage Disclosure Act data.

Can Everyone Tap into the Housing Piggy Bank?
Racial Disparities in Access to Home Equity

Online Appendix

This Appendix supplements the empirical analysis in Conklin, Gerardi, and Lambie-Hanson (2023).

Table of Contents

A.1 In-Person Lending Proxy

We can use a feature of HMDA data reporting instructions to calculate a proxy for in-person lending: Lenders that meet with applicants during the application process (prior to closing) must impute each applicant's race, ethnicity, and gender "based on visual observation or surname" of the applicant if the applicant declines to supply that information in the application process. Although most applicants (81%) supply the information themselves, the rate of imputation among the remainder is an imperfect but useful indicator of the frequency with which applications are taken in person. Among applications without race supplied by the applicant, lenders imputed race on 46% of HELOC and 31% of HELoans applications, vs. 7% for cash-out and rate/term refinances and 13% of purchases, suggesting that lenders are much more likely to work with HELOC and HELoan applicants in person, as compared to applicants seeking other types of mortgages.

It is important to note that, overall in our data, only about 6.5% of loan applications that have race and ethnicity information populated are flagged as having one or both of those pieces of information imputed by the lender. Although this is a small share of applications, we do estimate our main models separately and confirm that excluding applications with this imputation does not meaningfully change our estimates. See Table A.6.

A.2 Additional Summary Statistics, Full Model Results, and Robustness Checks

A.2.1 Application Outcomes

Table A.1. Application Outcomes by Race

	(1) White	(2) Black	(3) Hispanic	(4) Asian
Purchase				
Loan originated	77.6	66.5	72.6	72.1
Application approved but not accepted	2.0	2.3	2.2	2.3
Application denied	5.0	10.8	8.0	6.3
Application withdrawn by applicant	13.7	17.7	15.1	16.6
File closed for incompleteness	1.6	2.6	2.1	2.7
Denied (among loans with decisions)	5.9	13.6	9.6	7.8
Rate/Term				
Loan originated	66.9	52.1	58.8	65.4
Application approved but not accepted	2.7	4.0	3.5	2.6
Application denied	8.7	15.7	12.2	8.5
Application withdrawn by applicant	15.2	18.1	17.2	16.1
File closed for incompleteness	6.5	10.2	8.3	7.4
Denied (among loans with decisions)	11.2	21.9	16.4	11.1
Cash-out Refi (MEW)				
Loan originated	63.8	46.5	58.0	59.5
Application approved but not accepted	2.1	2.3	2.6	2.6
Application denied	12.2	23.4	15.3	13.0
Application withdrawn by applicant	16.0	19.1	17.2	17.5
File closed for incompleteness	5.9	8.7	6.9	7.5
Denied (among loans with decisions)	15.6	32.4	20.1	17.3
HELoan (MEW)				
Loan originated	54.5	33.7	44.4	43.0
Application approved but not accepted	3.0	2.5	3.4	3.2
Application denied	23.3	44.0	32.0	27.6
Application withdrawn by applicant	13.6	13.8	13.7	17.1
File closed for incompleteness	5.7	6.0	6.5	9.1
Denied (among loans with decisions)	28.9	54.8	40.1	37.4
HELOC (MEW)				
Loan originated	57.5	31.2	38.9	44.3
Application approved but not accepted	3.2	2.8	2.7	3.0
Application denied	29.0	56.5	48.0	39.7
Application withdrawn by applicant	6.7	6.0	6.2	7.5
File closed for incompleteness	3.6	3.4	4.2	5.5
Denied (among loans with decisions)	32.3	62.4	53.5	45.6
Observations	35,618,574	4,531,154	5,364,350	4,653,681

Note: This table reports mortgage application outcomes by applicant race. The first two panels include product types (purchase and rate/term refinances) that are not mortgage equity withdrawals. The third, fourth, and fifth panels include mortgage equity withdraw (MEW) products. Source: Home Mortgage Disclosure Act data.

A.2.2 Observations Without Underwriting Characteristics

Table A.2. Proportion of Observations Without Underwriting Characteristics

	(1) White	(2) Black	(3) Hispanic	(4) Asian
Cash-out Refi (MEW)				
Income	0.01	0.01	0.01	0.02
DTI	0.02	0.03	0.03	0.03
Credit Score	0.02	0.02	0.03	0.03
CLTV	0.02	0.03	0.03	0.02
HELoan (MEW)				
Income	0.02	0.03	0.02	0.03
DTI	0.03	0.06	0.04	0.03
Credit Score	0.04	0.06	0.04	0.04
CLTV	0.05	0.09	0.06	0.04
HELOC (MEW)				
Income	0.02	0.03	0.03	0.03
DTI	0.02	0.05	0.03	0.03
Credit Score	0.02	0.03	0.02	0.02
CLTV	0.03	0.07	0.04	0.03

Note: This table reports the proportion of observations in the estimation sample that are reported as “not applicable” on control variables. Source: Home Mortgage Disclosure Act data.

A.2.3 Primary Regressions with All Coefficients Reported

Table A.3. Likelihood of Denial for MEW Products

	(1)	(2)	(3)	(4)	(5)	(6)
Race and Ethnicity (d) (omitted: Non-Hispanic White)						
Black	0.212***	0.192***	0.068***	0.065***	0.056***	0.042***
	(0.022)	(0.019)	(0.008)	(0.008)	(0.005)	(0.004)
Hispanic	0.095***	0.092***	0.034**	0.034**	0.027**	0.028***
	(0.025)	(0.015)	(0.011)	(0.011)	(0.008)	(0.005)
Asian	0.076***	0.087***	0.073***	0.075***	0.058***	0.043***
	(0.018)	(0.013)	(0.012)	(0.012)	(0.008)	(0.005)
Year (d) (omitted: 2018)						
2019		-0.036***	-0.015*	-0.014*	0.002	0.007
		(0.007)	(0.006)	(0.006)	(0.007)	(0.005)
2020		-0.111***	-0.039***	-0.030**	0.014	0.036***
		(0.011)	(0.010)	(0.010)	(0.008)	(0.008)
2021		-0.141***	-0.071***	-0.060***	-0.007	0.013
		(0.015)	(0.014)	(0.014)	(0.008)	(0.009)
DTI (d) (omitted: < 25)						
[25, 35)			-0.045***	-0.045***	-0.044***	-0.047***
			(0.007)	(0.007)	(0.005)	(0.005)
[35, 45)			-0.055***	-0.054***	-0.062***	-0.069***
			(0.011)	(0.011)	(0.008)	(0.008)
[45, 101)			0.224***	0.215***	0.184***	0.164***
			(0.015)	(0.015)	(0.016)	(0.014)
NA			0.208***	0.063	0.055	0.100*
			(0.059)	(0.053)	(0.046)	(0.038)
Credit Score (d) (omitted: ≥ 740)						
[300, 620)			0.563***	0.538***	0.560***	0.532***
			(0.021)	(0.020)	(0.019)	(0.016)
[620, 640)			0.286***	0.272***	0.313***	0.306***
			(0.027)	(0.025)	(0.024)	(0.023)
[640, 660)			0.242***	0.228***	0.262***	0.256***
			(0.024)	(0.022)	(0.022)	(0.021)
[660, 680)			0.178***	0.168***	0.192***	0.187***
			(0.017)	(0.016)	(0.016)	(0.016)
[680, 700)			0.118***	0.110***	0.128***	0.126***
			(0.011)	(0.010)	(0.011)	(0.011)
[700, 720)			0.077***	0.071***	0.084***	0.083***
			(0.008)	(0.008)	(0.009)	(0.009)
[720, 740)			0.044***	0.040***	0.050***	0.050***
			(0.005)	(0.005)	(0.006)	(0.006)
NA			0.299***	0.255***	0.259***	0.342***
			(0.053)	(0.051)	(0.052)	(0.045)

Table A.3. (cont.) Likelihood of Denial for MEW Products

	(1)	(2)	(3)	(4)	(5)	(6)
CLTV (d) (omitted: ≤ 60)						
(60, 70]				-0.033***	-0.011**	-0.006*
				(0.005)	(0.003)	(0.002)
(70, 75]				-0.028***	-0.004	0.006
				(0.007)	(0.005)	(0.003)
(75, 80]				-0.025**	0.006	0.018**
				(0.008)	(0.008)	(0.006)
(80, 85]				0.048**	0.082***	0.085***
				(0.014)	(0.013)	(0.012)
(85, 90]				0.053**	0.072***	0.094***
				(0.016)	(0.018)	(0.017)
(90, 95]				0.260***	0.269***	0.287***
				(0.029)	(0.027)	(0.027)
(95, 98]				0.240***	0.272***	0.300***
				(0.030)	(0.028)	(0.026)
(98, 100]				0.031	0.128***	0.141***
				(0.025)	(0.023)	(0.020)
NA				0.246***	0.252***	0.301***
				(0.054)	(0.040)	(0.047)
Income (d) (omitted: $\geq \$500,000$)						
[0, $30k)					0.113***	0.148***
					(0.020)	(0.014)
[$30k, $60k)					0.023	0.054***
					(0.013)	(0.010)
[$60k, $90k)					-0.013	0.017
					(0.011)	(0.009)
[$90k, $150k)					-0.027**	-0.002
					(0.010)	(0.008)
[$150k, $500k)					-0.026***	-0.012
					(0.007)	(0.006)
NA					-0.069**	-0.075***
					(0.021)	(0.020)
Loan Amount (d) (omitted: $\geq \$750,000$)						
[$5,000, $50,000)					-0.035*	-0.040**
					(0.015)	(0.012)
[$50,000, $100,000)					-0.043**	-0.061***
					(0.014)	(0.010)
[$100,000, $250,000)					-0.053***	-0.069***
					(0.013)	(0.010)
[$250,000, $500,000)					-0.057***	-0.055***
					(0.010)	(0.009)
[$500,000, $750,000)					-0.034***	-0.027***
					(0.007)	(0.006)

Table A.3. (cont.) Likelihood of Denial for MEW Products

	(1)	(2)	(3)	(4)	(5)	(6)
Loan Term (d) (omitted: (20-30] years)						
$\leq$ 5 years					-0.060	-0.020
					(0.041)	(0.015)
(5, 15] years					-0.046***	-0.013*
					(0.010)	(0.005)
(15, 20] years					-0.017	-0.004
					(0.012)	(0.007)
(30, 40] years (HELOCs only)					-0.033	-0.123
					(0.117)	(0.152)
FHA (d) (cash-out only)					-0.131***	-0.108***
					(0.024)	(0.017)
VA (d) (cash-out only)					-0.098**	-0.137***
					(0.028)	(0.015)
HELoan (d)					0.075**	0.045***
					(0.024)	(0.012)
HELOC (d)					0.147***	0.140***
					(0.027)	(0.032)
Second Lien (d)					0.013	0.008
					(0.009)	(0.006)
Home Improvement (d)					0.005	0.007
					(0.006)	(0.005)
Prepayment Penalty (d)					0.097**	0.033
					(0.030)	(0.028)
Interest Only (d)					-0.097**	-0.110***
					(0.030)	(0.028)
Other Nonamortizing Features (d)					0.159**	0.218**
					(0.057)	(0.070)
Second Residence (d)					0.105***	0.107***
					(0.010)	(0.008)
Investment Property (d)					0.049***	0.081***
					(0.012)	(0.010)
No Co-applicant (d)					0.043***	0.034***
					(0.003)	(0.002)
Total Units (d) (omitted: 1)						
2					0.043***	0.045***
					(0.006)	(0.006)
3					0.047***	0.056***
					(0.011)	(0.009)
4					0.048***	0.051***
					(0.012)	(0.011)
# Observations	12,638,969	12,638,969	12,638,969	12,638,969	12,638,969	12,638,969
Adjusted R^2	0.020	0.047	0.240	0.259	0.316	0.380
Mean Denial Rate	0.26	0.26	0.26	0.26	0.26	0.26
Year FE	N	Y	Y	Y	Y	Y
State FE	N	Y	Y	Y	Y	Y
DTI Buckets	N	N	Y	Y	Y	Y
Credit Score Buckets	N	N	Y	Y	Y	Y
CLTV Buckets	N	N	N	Y	Y	Y
Other Controls	N	N	N	N	Y	Y
Lender FE	N	N	N	N	N	Y

Note: This table reports expanded coefficient estimates from linear probability models where the dependent variable is an indicator for whether the application was denied. The sample includes MEW products (cash-out refinances, HELoans, HELOCs) for which a credit decision was made. Standard errors, clustered at the state and lender levels, are in parentheses. *** p<0.001, ** p<0.01, * p<0.05. Source: Home Mortgage Disclosure Act data.

A.2.4 Logit Models

Table A.4. Logit Models of Denial for MEW Products

	(1)	(2)	(3)	(4)	(5)
Black	0.212***	0.186***	0.059***	0.056***	0.046***
	(0.007)	(0.010)	(0.005)	(0.005)	(0.003)
Hispanic	0.095***	0.091***	0.031***	0.032***	0.024***
	(0.010)	(0.010)	(0.009)	(0.008)	(0.006)
Asian	0.076***	0.088***	0.073***	0.075***	0.054***
	(0.006)	(0.004)	(0.005)	(0.005)	(0.006)
# Observations	12,639,272	12,639,272	12,639,272	12,639,272	12,639,272
Mean Denial Rate	0.26	0.26	0.26	0.26	0.26
Year FE	N	Y	Y	Y	Y
State FE	N	Y	Y	Y	Y
DTI Buckets	N	N	Y	Y	Y
Credit Score Buckets	N	N	Y	Y	Y
CLTV Buckets	N	N	N	Y	Y
Other Controls	N	N	N	N	Y
Lender FE	N	N	N	N	N

Note: This table reports average marginal effect estimates from logit models where the dependent variable is an indicator for whether the application was denied. The sample includes MEW products (cash-out refinances, HELoans, HELOCs) for which a credit decision was made. Standard errors, clustered at the state level, are in parentheses. *** p<0.001, ** p<0.01, * p<0.05. Source: Home Mortgage Disclosure Act data.

A.2.5 Denial Rate Regressions with Alternative Fixed Effects and Sub-samples

Table A.5. Likelihood of Denial–Robustness to Alternative Geographic Controls

	(1)	(2)	(3)	(4)
Black	0.042***	0.035***	0.035***	0.041***
	(0.004)	(0.003)	(0.003)	(0.003)
Hispanic	0.028***	0.025***	0.027***	0.026***
	(0.005)	(0.004)	(0.004)	(0.004)
Asian	0.043***	0.045***	0.047***	0.045***
	(0.005)	(0.005)	(0.005)	(0.005)
Year FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
DTI Buckets	Y	Y	Y	Y
Credit Score Buckets	Y	Y	Y	Y
CLTV Buckets	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y
Lender FE	Y	Y	N	Y
Census Tract FE	N	Y	N	N
Lender x Tract FE	N	N	Y	N
County x Year FE	N	N	N	Y
# Observations	12,638,969	12,638,969	10,864,102	12,505,642
Adjusted R^2	0.380	0.383	0.399	0.387
Mean Denial Rate	0.26	0.26	0.26	0.26

Note: This table reports coefficient estimates from linear probability models where the dependent variable is an indicator for whether the application was denied. Model 1 is the main model (Model 6 from Table 2). Model 2 adds tract fixed effects. Model 3 substitutes lender-by-tract fixed effects for the separate lender and tract fixed effects in Model 2. Model 4 substitutes county-by-year fixed effects for the tract fixed effects in Model 2. Standard errors, clustered at the state and lender levels, are in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$. Source: Home Mortgage Disclosure Act data.

Table A.6. Likelihood of Denial–Robustness to Sample Selection

	Full Sample		Low-Minority Tracts		Excl. Imputed Race/Ethnicity	
	(1)	(2)	(3)	(4)	(5)	(6)
Black (d)	0.212***	0.042***	0.157***	0.034***	0.208***	0.041***
	(0.022)	(0.004)	(0.016)	(0.005)	(0.022)	(0.003)
Hispanic (d)	0.095***	0.028***	0.078***	0.023***	0.088***	0.025***
	(0.025)	(0.005)	(0.013)	(0.004)	(0.025)	(0.005)
Asian (d)	0.076***	0.043***	0.074***	0.040***	0.073***	0.042***
	(0.018)	(0.005)	(0.012)	(0.004)	(0.018)	(0.005)
Year FE	N	Y	N	Y	N	Y
State FE	N	Y	N	Y	N	Y
DTI Buckets	N	Y	N	Y	N	Y
Credit Score Buckets	N	Y	N	Y	N	Y
CLTV Buckets	N	Y	N	Y	N	Y
Other Controls	N	Y	N	Y	N	Y
Lender FE	N	Y	N	Y	N	Y
# Observations	12,638,969	12,638,969	1,189,698	1,189,698	11,798,168	11,798,168
Adjusted R^2	0.020	0.380	0.002	0.368	0.019	0.380
Mean Denial Rate	0.26	0.26	0.23	0.23	0.25	0.25

Note: This table reports coefficient estimates from linear probability models where the dependent variable is an indicator for whether the application was denied. Model 1 is the unconditional model and model 3 is the main model (Models 1 and 6, respectively, from Table 2). Models 3 and 4 restrict the sample to applications made in census tracts at or below the 10th percentile for percent of the population that is non-White or Hispanic (5%). Models 5 and 6 instead restrict the sample to applications in which the lender imputed neither the race nor ethnicity of the applicant. (In other words, all of the applications included in the model had race and ethnicity reported directly by the applicant.) Standard errors, clustered at the state and lender levels, are in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$. Source: Home Mortgage Disclosure Act data.

A.2.6 Decomposing Denial Rate Gaps by Product Type

Table A.7. Applicant Race and Likelihood of Denial on MEW Products

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Cash-Out Refinances						
Black	0.168***	0.153***	0.064***	0.060***	0.054***	0.040***
	(0.023)	(0.019)	(0.007)	(0.007)	(0.006)	(0.004)
Hispanic	0.045**	0.049***	0.011	0.012	0.010	0.016***
	(0.014)	(0.009)	(0.007)	(0.007)	(0.006)	(0.004)
Asian	0.017*	0.033***	0.030***	0.031***	0.030***	0.026***
	(0.007)	(0.005)	(0.006)	(0.006)	(0.006)	(0.003)
Observations	7,030,943	7,030,943	7,030,943	7,030,943	7,030,943	7,030,943
Adjusted R-squared	0.015	0.037	0.198	0.203	0.220	0.289
Mean Denial Rate	0.18	0.18	0.18	0.18	0.18	0.18
Panel B: Home Equity Loans (HELoans)						
Black	0.259***	0.237***	0.079***	0.076***	0.063***	0.050***
	(0.026)	(0.022)	(0.009)	(0.010)	(0.009)	(0.005)
Hispanic	0.112***	0.111***	0.034***	0.034***	0.031**	0.032***
	(0.017)	(0.012)	(0.009)	(0.009)	(0.009)	(0.004)
Asian	0.085***	0.094***	0.075***	0.079***	0.084***	0.045***
	(0.024)	(0.021)	(0.016)	(0.016)	(0.016)	(0.006)
Observations	1,479,900	1,479,900	1,479,900	1,479,900	1,479,900	1,479,900
Adjusted R-squared	0.027	0.041	0.289	0.309	0.330	0.445
Mean Denial Rate	0.33	0.33	0.33	0.33	0.33	0.33
Panel C: Home Equity Lines of Credit (HELOCs)						
Black	0.301***	0.272***	0.088***	0.085***	0.055***	0.044***
	(0.012)	(0.010)	(0.008)	(0.008)	(0.008)	(0.004)
Hispanic	0.213***	0.170***	0.072***	0.070***	0.057***	0.046***
	(0.021)	(0.012)	(0.008)	(0.009)	(0.007)	(0.006)
Asian	0.133***	0.115***	0.082***	0.084***	0.066***	0.051***
	(0.018)	(0.013)	(0.014)	(0.013)	(0.009)	(0.008)
# Observations	4,128,076	4,128,076	4,128,076	4,128,076	4,128,076	4,128,076
Adjusted R^2	0.039	0.066	0.329	0.358	0.402	0.469
Mean Denial Rate	0.37	0.37	0.37	0.37	0.37	0.37
Year FE	N	Y	Y	Y	Y	Y
State FE	N	Y	Y	Y	Y	Y
DTI Buckets	N	Y	Y	Y	Y	Y
Credit Score Buckets	N	Y	Y	Y	Y	Y
CLTV Buckets	N	N	Y	Y	Y	Y
Other Controls	N	N	N	Y	Y	Y
Lender FE	N	N	N	N	Y	Y

Note: This table reports coefficient estimates from linear probability models where the dependent variable is an indicator for whether the application was denied. The sample in Panel A, B, and C are cash-out refinances, HELoans, and HELOCs, respectively, for which a credit decision was made. Standard errors, clustered at the state and lender levels, are in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$. Source: Home Mortgage Disclosure Act data.

Table A.8. Applicant Race and Likelihood of Denial on MEW Products, Pooling Product Types

	(1)	(2)
Black	0.168***	0.017***
	(0.023)	(0.005)
Hispanic	0.045**	-0.002
	(0.014)	(0.004)
Asian	0.017*	0.017***
	(0.007)	(0.003)
HELoan	0.133***	0.037**
	(0.028)	(0.011)
HELOC	0.167***	0.123***
	(0.031)	(0.031)
Black x HELoan	0.091**	0.041***
	(0.028)	(0.010)
Black x HELOC	0.133***	0.068***
	(0.023)	(0.008)
Hispanic x HELoan	0.067***	0.037***
	(0.007)	(0.005)
Hispanic x HELOC	0.167***	0.084***
	(0.018)	(0.007)
Asian x HELoan	0.068**	0.035***
	(0.022)	(0.007)
Asian x HELOC	0.116***	0.061***
	(0.016)	(0.007)
Year FE	N	Y
State FE	N	Y
DTI Buckets	N	Y
Credit Score Buckets	N	Y
CLTV Buckets	N	Y
Other Controls	N	Y
Lender FE	N	Y
# Observations	12,638,969	12,638,969
Adjusted R^2	0.071	0.381
Mean Denial Rate	0.26	0.26

Note: This table reports coefficient estimates from linear probability models where the dependent variable is an indicator for whether the application was denied. The sample includes MEW products (cash-out refinances, HELoans, HELOCs) for which a credit decision was made. Standard errors, clustered at the state and lender levels, are in parentheses. *** p<0.001, ** p<0.01, * p<0.05. Source: Home Mortgage Disclosure Act data.

A.2.7 Application Year

Since MEW products can be used to smooth consumption, and many households experienced negative income and wealth shocks during the COVID-19 pandemic, MEW demand may have shifted as a result. At the same time, mortgage lenders may have updated underwriting policies in response to evolving market conditions. These mortgage supply and demand shifts may have impacted racial disparities in access to mortgage equity starting in 2020. We estimate our saturated denial model separately by application year on the pooled sample of MEW products and report the results in Table A.9. Notice first that the number of applications increases monotonically over time. In contrast, the mean denial rate declines every year in our sample and is almost halved moving from 2018 to 2021. The explanatory power of the fully saturated model, as indicated by the adjusted R-squared, is relatively stable across all years, which might suggest that the implementation of underwriting guidelines was also stable. Both the Hispanic and Asian coefficients decline over time, but relative to the mean denial rate for the corresponding year (reported at the bottom of the table), the magnitude of the gap is similar across years. In contrast, the Black coefficient decreases modestly through 2020 but then reverts to 2018 levels in 2021. Relative to the mean denial rate, this increase represents a near doubling in the Black-White gap from 2018 to 2021.

Table A.9. Likelihood of Denial by Year

	2018	2019	2020	2021
	(1)	(2)	(3)	(4)
Black	0.044***	0.042***	0.039***	0.043***
	(0.005)	(0.004)	(0.004)	(0.004)
Hispanic	0.035***	0.032***	0.023***	0.021***
	(0.006)	(0.005)	(0.005)	(0.005)
Asian	0.055***	0.047***	0.040***	0.032***
	(0.007)	(0.005)	(0.005)	(0.005)
Year FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
DTI Buckets	Y	Y	Y	Y
Credit Score Buckets	Y	Y	Y	Y
CLTV Buckets	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
# Observations	2,764,965	2,915,279	3,065,300	3,893,569
Adjusted R^2	0.379	0.403	0.381	0.361
Mean Denial Rate	0.34	0.30	0.22	0.20

Note: This table reports coefficient estimates from linear probability models where the dependent variable is an indicator for whether the application was denied. The saturated model is estimated separately for each application year. Standard errors, clustered at the state and lender levels, are in parentheses. *** p<0.001, ** p<0.01, * p<0.05. Source: Home Mortgage Disclosure Act data.

A.2.8 Bank Size Regressions

Table A.10. Likelihood of Denial by Bank Size

	(1) All Banks	(2) Large Banks	(3) Intermediate Banks	(4) Small Banks
Black	0.040***	0.039***	0.031***	0.045***
	(0.005)	(0.005)	(0.004)	(0.004)
Hispanic	0.040***	0.040***	0.015***	0.026***
	(0.006)	(0.006)	(0.003)	(0.006)
Asian	0.053***	0.054***	0.027***	0.022**
	(0.006)	(0.006)	(0.004)	(0.007)
Year FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
DTI Buckets	Y	Y	Y	Y
Credit Score Buckets	Y	Y	Y	Y
CLTV Buckets	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
Lender Size	N	N	N	N
# Observations	6,045,550	5,551,570	296,170	197,810
Adjusted R^2	0.446	0.448	0.335	0.390
Mean Denial Rate	0.33	0.35	0.12	0.22

Note: This table reports coefficient estimates from linear probability models where the dependent variable is an indicator for whether the application was denied. Models are restricted to applications made to bank lenders. Lenders are classified by asset size as of the end of the year prior to the HMDA reporting year, according to the Call Report, with data accessed through Bob Avery's HMDA Lender File. Standard errors, clustered at the state and lender levels, are in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$. Source: Home Mortgage Disclosure Act data.

A.2.9 Investigating Additional Denial Reasons

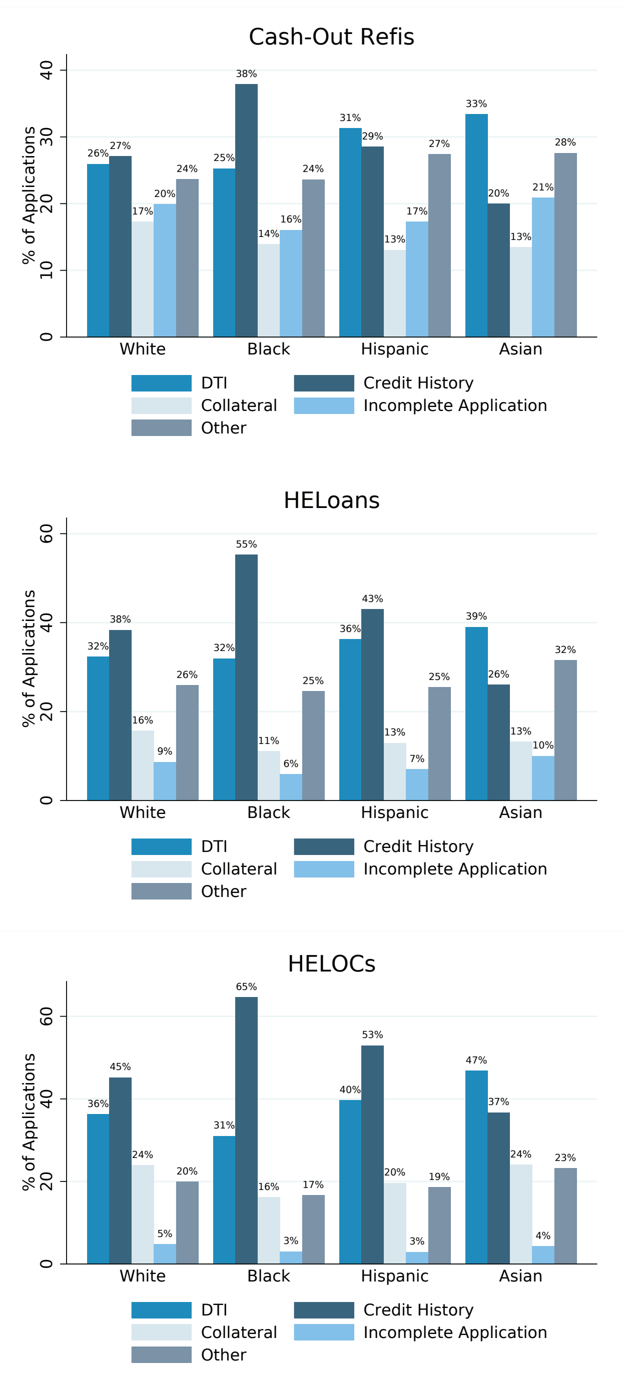


Figure A.1. All Application Denial Reasons Reported

Note: Reported denial reasons, 2018–2021. Lenders report up to 4 principal denial reasons for each denied application. Source: Home Mortgage Disclosure Act data.

A.3 Media Market Racial Animus

Table A.11. Likelihood of Denial by Media Market Racial Animus

Dependent Var: Loan Denied (d)	(1)	(2)	(3)	(4)	(5)
Black	0.043***	0.045***	0.047***	0.046***	0.043***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Hispanic	0.027***	0.030***	0.030***	0.032***	0.028***
	(0.005)	(0.007)	(0.007)	(0.007)	(0.005)
Asian	0.043***	0.043***	0.044***	0.046***	0.046***
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
Racial Animus, Standardized				0.002	-0.001
				(0.002)	(0.002)
x Black				0.007*	0.010***
				(0.003)	(0.003)
x Hispanic				0.005	0.005*
				(0.005)	(0.002)
x Asian				0.009***	0.009***
				(0.002)	(0.002)
Year FE	Y	Y	Y	Y	Y
State FE	Y	N	N	N	Y
DTI Buckets	Y	Y	Y	Y	Y
Credit Score Buckets	Y	Y	Y	Y	Y
CLTV Buckets	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y	Y
# Observations	12,379,914	12,379,914	9,711,394	9,711,394	9,711,394
Adjusted R^2	0.363	0.362	0.363	0.363	0.364
Mean Denial Rate	0.25	0.25	0.25	0.25	0.25

Note: This table reports coefficient estimates from linear probability models where the dependent variable is an indicator for whether the application was denied. Media market level racial animus is from Stephens-Davidowitz (2014), standardized to mean = 0 and standard deviation = 1. Model 1 is the main model (Model 6 from Table 2) but restricted to applications with NMLS ID populated for the loan officer taking the loan application (to facilitate robustness checks available upon request). Model 2 removes state fixed effects. Model 3 restricts to loans for collateral properties located with core-based statistical areas. Model 4 adds standardized racial animus and its interaction with applicant race and ethnicity dummy variables. Model 5 adds state fixed effects to demonstrate robustness. Standard errors, clustered at the state and lender levels, are in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$. Source: Home Mortgage Disclosure Act data.

A.4 Discouragement of Potential Applicants

A caveat that applies universally to research using HMDA data to study denials is that applicants' outcomes are only observed if they formally apply for a loan (or in the case of a purchase mortgage, apply for a loan or for preapproval). Loan officers often have conversations with prospective applicants before formal applications are submitted in order to discuss potential loan products and terms, as well as provide guidance on what a borrower might qualify for, given a soft credit check or circumstances a borrower shares with the lender (e.g., self-reported income and approximate home value). If at this stage loan officers are more likely to discourage minority homeowners from moving forward with an application relative to White homeowners, then the applications observed in HMDA data will provide an incomplete picture of all interested applicants, and results of differential denial rates conditional on applying could be biased.

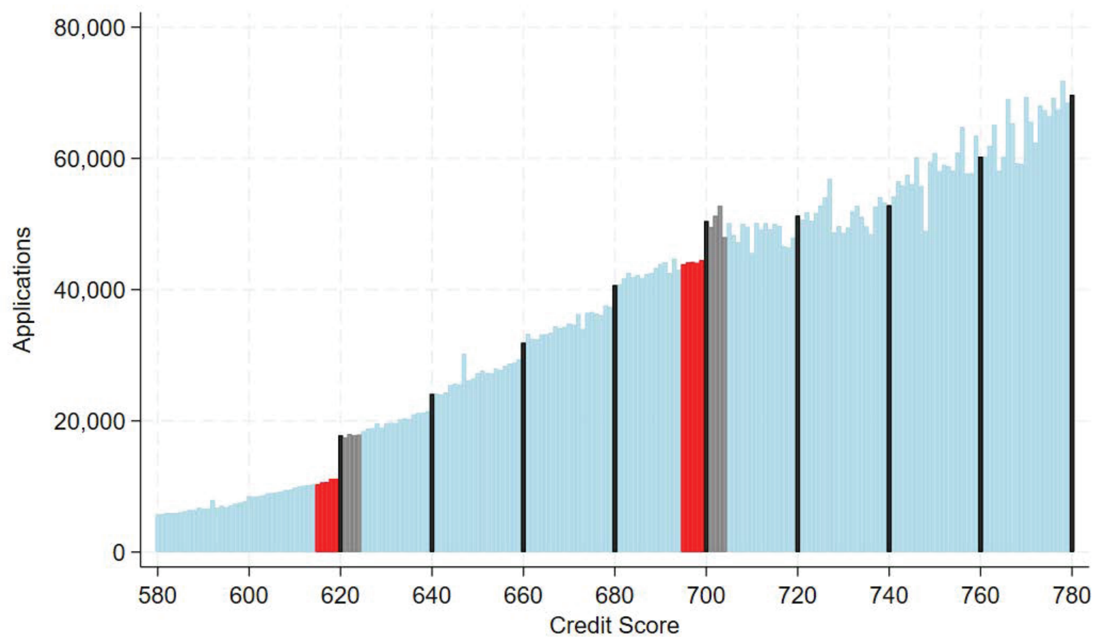
One way in which this scenario may play out is if an applicant's credit score is slightly below the threshold required to qualify for a certain loan product or particular pricing for that product. The loan officer may discourage an applicant from proceeding with the application, and if no application is made, the applicant will not appear in HMDA data. As shown in Figure A.2, there does appear to be a "missing mass" of applications just below salient credit score thresholds (indicated in black) for Black and White borrowers.[1] In particular, there are notably fewer loans just below 620 and 700 than at or just above those scores.

If loan officers are biased against working with Black applicants, one might expect the missing mass just below these credit score thresholds to be greater for Black than White borrowers, which would bias the results presented in papers such as this one. For the mortgage equity withdrawal applications we study, there is no evidence of a differential in missing mass. As shown in Figure A.3, the ratio of applications by homeowners with scores of 615–619 to those with scores of 620–624 (and for 695–699 compared to 700–704) is actually *higher* for Black than white borrowers.

[1]Our analysis in this section focuses exclusively on Black and White borrowers, but in unreported results the patterns are very similar for Asian and Hispanic borrowers.

Thus, we find no evidence of racial differences in discouragement with respect to credit score. Note, though, that differential rates of discouragement may apply along other dimensions, such as income, wealth, employment status, or credit history characteristics not captured within the credit score itself.

Figure A.2. Credit Score Distribution of Mortgage Equity Withdrawal Applications Submitted by Black and White Borrowers



Note: Includes cash-out refinance, home equity loan, and home equity line of credit applications from Black and White consumers reported by financial institutions in 2018–2021, with action type codes 1–5. Source: Home Mortgage Disclosure Act data.

Figure A.3. Ratio of Applications Just below to Just above 620 and 700 Credit Score Thresholds

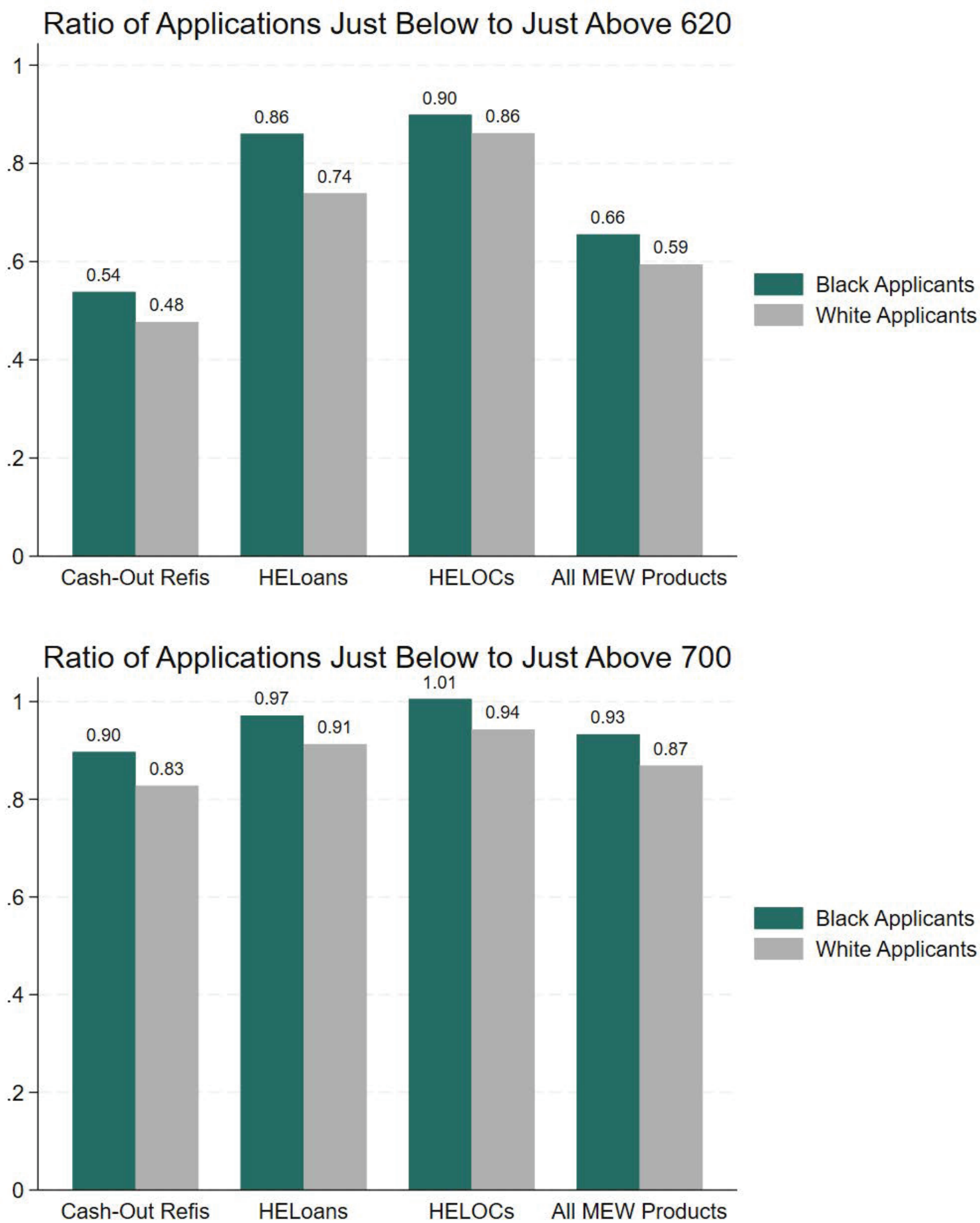


Figure A.4. Distribution of Credit Scores and Ratio of Scores Just below to Just above Common Thresholds

Note: In the top panel, the ratio is the number of applications from borrowers with scores 615–619 to those with scores 620–624. In the lower panel, the ratio is for those with scores 695–699 to 700–704. Source: Home Mortgage Disclosure Act data.

A.5 Adjusting Potential Equity Withdrawal Calculations for Multiple Applications from Same Borrowers

To estimate the aggregate amount of equity that minority borrowers could have withdrawn if their denial rates were equal to white borrowers (conditional on risk factors), we should account for the fact that multiple applications can come from the same applicant(s). To simply sum the requested loan proceeds from those loans would over-count the amount of equity that could actually be drawn, since not all of those loans could be originated. Because the confidential HMDA data do not include applicant or household identifiers, the only available option is to try to proxy for applications that appear to come from the same applicants, based on reported borrower and loan characteristics.

Specifically, we group applications into "clusters" that occur in the same year and same census tract and have the same product type (cash-out refinance, HELOC, or HELoan), lien status (1st or 2nd lien), income bucket, FICO bucket, borrower race, units in property, and occupancy status (primary home, second home, or investment property).[2] Within each cluster *that does not contain an originated loan application*, we select one denied application to serve as the placeholder "unique" application for the cluster.

We then calculate a multiplier that is equal to (sum of $ loan proceeds from "unique applications" denied) / (sum of $ loan proceeds from all denied applications). We then apply this multiplier to the total loan proceeds of denied applications to form an adjusted denied loan proceeds in lines [6], [11], and [14] of Table A.12, to account for the dollars of equity that could have been drawn in total but for the denials.

This method is clearly not flawless. We acknowledge that we may underestimate dollars denied if we "over-group" applications that are from different borrowers with the same sets of characteristics in the same calendar year. Conversely, we may "under-group" applications (and overestimate

[2]Bucketed continuous variables match those used in Table A.3.

dollars denied) if applicants shop for MEW products over multiple calendar years or if their FICO scores or incomes change such that they appear in different buckets on these variables at different points in time. In general, we have tried to avoid "over-grouping" applications, to form a more conservative estimate. Although this is not an exact science, we believe this adjustment does help produce a rough but reasonably credible lower bound on the amount of equity that could have been extracted but for the unexplained higher denial rate gap that minority applicants face.

Table A.12. Estimated Aggregate Dollars of Loan Proceeds to Borrowers Denied, Adjusted for Multiple Applications

		White	Black	Hispanic	Asian
	Cash-out				
[1]	Average estimated cash to borrower per application	$34,197	$28,807	$35,649	$50,755
[2]	Estimated aggregate loan proceeds (in billions)				
	All applications with credit decision	$180.9	$17.1	$24.9	$22.7
[3]	Denial Rate	15.6%	32.4%	20.1%	17.3%
[4]	Denied $, [2] * [3]	$28.2	$5.5	$5.0	$3.9
[5]	Adjustment factor to remove duplicate applications	0.51	0.73	0.72	0.67
[6]	Adj. Denied $, [4] * [5]	$14.3	$4.0	$3.6	$2.6
[7]	Adj. Denied $, given White denial rate [2] * [3, White] * [5]	$14.3	$1.9	$2.8 $	2.4
[8]	Unconditional "excess" denied $, [6] - [7]		$2.1	$0.8	$0.3
[9]	Table 3, model 2 coefficient		0.040	0.016	0.026
[10]	Conditional "excess" denied $, [2] * [9] * [5]		$0.5	$0.3	$0.4
	HELoan				
	Average estimated cash to borrower per application	$111,257	$86,718	$106,033	$181,452
	Estimated aggregate loan proceeds (in billions)				
	All applications with credit decision	$124.9	$10.9	$15.3	$15.9
	Denial Rate	28.9%	54.8%	40.1%	37.4%
	Denied $	$36.1	$6.0	$6.1	$5.9
	Adjustment factor to remove duplicate applications	0.85	0.95	0.94	0.91
[11]	Adj. Denied $	$30.7	$5.7	$5.8	$5.4
	Adj. Denied $, given White denial rate	$30.7	$3.0	$4.1	$4.2
[12]	Unconditional “excess” denied		$2.7	$1.6	$1.2
	Table 3, model 2 coefficient		0.050	0.032	0.045
[13]	Conditional “excess” denied		$0.5	$0.5	$0.6
	HELOC				
	Average estimated cash to borrower per application	$92,870	$62,865	$82,600	$150,726
	Estimated aggregate loan proceeds (in billions)				
	All applications with credit decision	$293.3	$18.4	$28.2	$50.6
	Denial Rate	32.3%	62.4%	53.5%	45.6%
	Denied $	$94.7	$11.5	$15.1	$23.1
	Adjustment factor to remove duplicate applications	0.64	0.90	0.88	0.72
[14]	Adj. Denied $	$60.3	$10.4	$13.2	$16.5
	Adj. Denied $, given White denial rate	$60.3	$5.4	$8.0	$11.7
[15]	Unconditional “excess” denied		$5.0	$5.2	$4.8
	Table 3, model 2 coefficient		0.044	0.046	0.051
[16]	Conditional “excess” denied		$0.7	$1.1	$1.9
	Total MEW				
	Estimated aggregate loan proceeds (in billions)				
	All applications with credit decision	$599.1	$46.4	$68.4	$89.2
	Adj. Denied $, [6] + [11] + [14]	$159.0	$23.0	$26.2	$32.9
[27]	Unconditional “excess” denied $, [8] + [12] + [15]		$9.8	$7.6	$6.3
[28]	Conditional “excess” denied $, [10] + [13] + [16]		$1.7	$1.9	$2.9

Source: Home Mortgage Disclosure Act data.