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The Determinants of Mortgage Denial Using Public Data*

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Abstract

We analyze over 30 million home purchase mortgage applications from 2018–2024 using publicly available Home Mortgage Disclosure Act (HMDA) data to study the determinants of mortgage denial. We establish three primary findings. First, credit access is highly sensitive to monetary policy; the 2022–2023 tightening drove aggregate denial rates from 12.2% to 15.7% via the debt-to-income (DTI) channel. Second, we identify a critical nonlinearity in underwriting: While the 43% qualified mortgage (QM) threshold—below which lenders receive legal safe harbor from ability-to-repay claims—is non-binding in practice, denial rates jump by 15–17 percentage points at the 50% DTI mark, marking the functional market boundary. Third, substantial racial disparities persist; controlling for lender fixed effects and financials, Black applicants are 7.8 percentage points more likely to be denied than White applicants. Observable characteristics explain at most 41% of this gap. These results demonstrate how monetary tightening interacts with structural inequalities to disproportionately restrict credit access for vulnerable populations at the extensive margin.

JEL Classification: G21, R21, R31, D14, E52

Keywords: Mortgage lending, Credit access, Housing finance, Homeownership, Underwriting, Monetary policy

*The views expressed herein are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of St. Louis or the Federal Reserve System. All errors are our own.

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1 Introduction

For most households, their largest asset is housing and their largest liability is the mortgage. Access to mortgage credit determines homeownership, location choices, and wealth accumulation. In 2024, lenders denied more than 526,000 home purchase applications, about one in six. Understanding which applicants are denied and why is central to housing policy, financial regulation, and macroeconomic analysis.

We leverage the near-universe of U.S. mortgage applications to provide a comprehensive examination of mortgage denial. Our dataset comprises more than 30 million home purchase applications from 2018–2024 as reported under the Home Mortgage Disclosure Act (HMDA). While these publicly available records are aggregated at an annual frequency—unlike the restricted-access, date-specific confidential HMDA files—they feature significant enhancements mandated by the Dodd-Frank Act. Beginning in 2018, these expanded disclosures include debt-to-income (DTI) ratios, combined loan-to-value (LTV) ratios, specific denial reasons, and interest rates on originated loans. These variables offer a more granular view of underwriting decisions than was possible in prior research using earlier iterations of the public data.

We focus primarily on home purchase mortgages for owner-occupied principal residences. Denial rates vary dramatically across loan purposes: Home improvement loans face rates above 40 percent, while home purchases average between 12 percent and 16 percent. Crucially, home purchases represent the primary margin of entry into homeownership. Unlike refinances or home improvement loans, which are used to restructure debt or enhance the physical characteristics of an existing housing asset, a home purchase mortgage facilitates a transaction for the dwelling itself. Consequently, this segment determines whether a household acquires housing collateral to enter homeownership rather than to simply modify the financing or quality of an existing holding.

We document that mortgage denial rates are highly cyclical and move in close synchronization with interest rates. The aggregate denial rate fell from 13.6 percent in 2018 to 12.2 percent in 2021 as the Federal Reserve lowered rates toward the zero lower bound, subsequently rising to 15.7 percent by 2023 during a period of aggressive monetary tightening. This trend reflects a direct mechanical channel: Elevated interest rates increase projected monthly payments, thereby pushing a larger share of applicants above critical DTI thresholds.

Consistent with this interplay between macroeconomic policy and individual financial constraints, DTI is the most frequently cited reason for denial, accounting for 35 percent of all rejected applications. Furthermore, the prevalence of DTI-based denials increased significantly during the 2022–2023 rate-hiking cycle. We formalize this channel using a difference-in-differences design that compares applicants near the regulatory DTI thresholds (40–55 percent) with those with safer buffers (under 30 percent) across the pre- and post-tightening periods.

While the rise in DTI-driven denials is historically significant, the specific point at which these constraints bind challenges existing regulatory assumptions. The Dodd-Frank Act established a 43 percent DTI ratio as a key threshold for qualified mortgage (QM) status, providing lenders with a legal safe harbor. However, we find that this threshold does not strictly bind in practice. Denial rates remain relatively flat across the 20–50 percent DTI range, hovering between 8 percent and 10 percent. The true binding constraint operates at higher levels: Denial rates rise sharply only when DTI exceeds 50 percent, and the denial rate surpasses 80 percent for ratios above 60 percent. Neither bunching analysis nor regression discontinuity estimation detects meaningful effects at the 43 percent mark. These results suggest that policymakers concerned with credit access should focus on the 50–60 percent DTI range rather than the QM threshold.

We document substantial variation in denial rates across loan types, geography, and neighborhood characteristics. VA loans consistently have the lowest denial rates (8–10 percent), while FHA loans—despite being designed to expand credit access—have among the highest. Geographically, denial rates range from 7 percent to 28 percent across metropolitan areas and are systematically higher in census tracts characterized by lower incomes and higher minority population shares.

These geographic and product-level patterns set the stage for our analysis of racial and ethnic outcomes, which echo findings from earlier periods (Munnell et al. (1996); Ross and Yinger (2002)). In the raw data, Black applicants face a denial rate of 27.2 percent compared with 12.1 percent for White applicants. While these differences partly reflect observable constraints—such as lower average incomes, higher DTI ratios, and a higher propensity to use FHA loans—a significant portion remains unexplained. In our preferred specification with lender fixed effects, the Black-White gap remains at 7.8 percentage points. A Oaxaca-Blinder decomposition (Oaxaca (1973); Blinder (1973)) attributes at most 30 percent of this gap to observable characteristics in the public HMDA data. For Hispanic applicants, whose observable profiles are more similar to White applicants, these factors explain only 2.7 percent of the gap. We emphasize that these decompositions are descriptive: The unexplained component likely reflects unobserved creditworthiness factors not reported in public HMDA records—including credit scores, liquid wealth, and employment stability—as well as potential differential treatment.

This article makes three contributions. First, we provide comprehensive evidence on the determinants of mortgage denial using enhanced HMDA data, incorporating variables such as DTI and CLTV that were unavailable in prior large-scale studies. Second, we document the sensitivity of denial rates to monetary policy through the DTI channel, contributing to the literature on the transmission of credit shocks (Ross and Yinger (2002)). Third, we extend the literature on mortgage market disparities (Munnell et al. (1996); Bayer et al. (2018); Bartlett et al. (2022); Bhutta et al. (2022)) by providing within-lender estimates using the most recent data cycle and exploring how these gaps interact with specific loan products and underwriting thresholds.

Section 2 describes the data. Section 3 presents descriptive evidence. Section 4 presents our empirical framework and results. Section 5 concludes.

2 Institutional Setting and Data

To analyze the determinants of mortgage denial, we combine a high-frequency understanding of the U.S. mortgage market's regulatory framework with the most-comprehensive public record of home loan applications. Our analysis focuses on the post-2018 period, a regime shift in mortgage reporting that provides unprecedented visibility into the financial profiles of rejected applicants. Before describing the dataset, we first outline the institutional environment in which these credit decisions are made, focusing on the primary loan products and the regulatory standards that govern modern underwriting.

2.1 Institutional Setting

The mortgage application process is designed to mitigate informational asymmetries between borrowers and lenders. Applicants must disclose comprehensive data regarding income, employment, assets, and liabilities. Lenders evaluate these disclosures via automated underwriting systems (AUS) and manual review, primarily focusing on five risk dimensions: credit history (FICO scores), the debt-to-income ratio (DTI), the loan-to-value ratio (LTV), employment stability, and liquid reserves. Based on this multidimensional assessment, a lender may approve the application, issue a denial, or request further documentation.

The U.S. mortgage market is segmented by varying degrees of government involvement, each with distinct underwriting standards. *Conventional* loans lack a direct government guarantee and typically require higher credit scores; they are often sold to Fannie Mae or Freddie Mac if they meet conforming standards. Conversely, *FHA* loans, insured by the Federal Housing Administration, facilitate credit access with down payments as low as 3.5 percent and more-lenient credit score requirements. *VA* and *USDA* loans provide zero-down-payment options for eligible veterans and rural borrowers, respectively. Because these programs serve different demographic and risk profiles, they exhibit the significant heterogeneity in denial rates that we document in our empirical analysis.

A central feature of the modern regulatory landscape is the QM standard, established under the Dodd-Frank Act. Loans meeting QM criteria afford lenders a legal "safe harbor" from ability-to-repay litigation. Historically, the most-prominent regulatory benchmark for QM status was a DTI ratio not exceeding 43 percent. While this threshold is often cited as a potential bottleneck for credit access, its practical impact is complicated by various institutional exceptions and the evolving role of secondary market standards.

2.2 The Enhanced Public HMDA Data

Our empirical analysis utilizes data from the public HMDA. Enacted by Congress in 1975, the HMDA was a direct policy response to concerns over *redlining*—the systematic denial of credit to specific neighborhoods based on their racial or ethnic composition. By requiring banks, credit unions, and non-depository institutions to disclose their lending patterns, the Act intended to provide the transparency necessary to monitor and enforce fair lending laws. Today, with coverage encompassing approximately 95 percent of all U.S. mortgage activity, HMDA serves as a near-census of the market rather than a sample.

A primary advantage of HMDA is its visibility into the *extensive margin* of credit. Unlike many consumer finance datasets that observe only originated loans, HMDA records the full lifecycle of the application: whether it was originated, denied, withdrawn, or approved but not accepted. This allows for a direct examination of lender decisionmaking and the specific determinants of credit rejection, which is central to our investigation of socioeconomic and racial disparities.

We utilize the annual HMDA files for the 2018–2024 period. This window is specifically motivated by the substantial reporting expansions mandated by the Dodd-Frank Act, which became effective in January 2018. These enhancements introduced variables that are foundational to underwriting but were largely unavailable to researchers in previous decades: debt-to-income (DTI) ratios, combined loan-to-value (CLTV) ratios, property values, and the specific reasons for denial.

The data are publicly available through the Consumer Financial Protection Bureau's HMDA platform (`https://ffiec.cfpb.gov/data-browser/`). Researchers can download complete annual loan-level files in CSV format or use the data browser to construct filtered extracts by geography, loan type, or other characteristics. No registration or restricted-access agreement is required. Each annual file contains all reported applications (typically 15–20 million records across all loan purposes) and can be merged across years using the Legal Entity Identifier (LEI) for lender-level analysis.

2.3 Data Quality and Limitations

While the enhanced HMDA data provide unprecedented granularity, several features of the dataset merit discussion regarding their impact on our empirical strategy.

First, The public HMDA does not report credit scores—arguably the most-critical underwriting variable. This omission is a standard limitation of the public data and implies that our estimates of racial gaps likely capture some residual variation in creditworthiness. We discuss the implications for the interpretation of our Oaxaca-Blinder decompositions in Section 4.

Second, while DTI is reported for approximately 97 percent of applications, missingness is systematically concentrated among smaller lenders (see Section B). Consequently, specifications that condition on DTI primarily reflect the behavior of larger institutions. Additionally, HMDA reports DTI using a hybrid of numeric values and categorical buckets (e.g., "40 percent–<43 percent" and "43 percent–<45 percent"). We convert these buckets to midpoint values for our baseline regressions. However, for discontinuity tests surrounding the 43 percent QM threshold, this discretization necessitates a more cautious interpretation of local precision.

Third, HMDA provides *application*-level data rather than *applicant*-level data. Because we cannot track individuals across different institutions, a denial in our sample represents the rejection of a specific application rather than a household's ultimate exclusion from the mortgage market. An applicant denied by one lender may subsequently be approved by another; thus, our metrics capture the *probability of application denial* at the extensive margin.

Fourth, reported income is typically self-disclosed at the time of application. While lenders verify these figures during the underwriting process, the HMDA record reflects the information available at the initial decision stage, which may contain noise relative to final verified earnings.

Finally, while HMDA captures approximately 95 percent of market activity, it excludes very small lenders below the mandatory reporting thresholds. While these institutions account for a negligible share of total originations, they may serve specialized or niche markets that are outside the scope of this study.

2.4 Variable Definitions

The 2018 expansion of the HMDA reporting requirements dramatically increased the granularity of publicly available mortgage application data. Prior to the reform, HMDA primarily served as a tool for tracking aggregate lending volumes and detecting broad patterns of redlining or discrimination. After 2018, the dataset became high-dimensional, capturing many of the key risk parameters that modern lenders use in underwriting decisions—parameters that were previously unobserved in public data. This richer information allows us to control directly for the mechanical determinants of credit approval or denial, bringing the analysis closer to approximating the lender's objective function.

Our primary outcome is whether a mortgage application is denied. Following conventional mortgage literature, we define the denial rate for a group of applications (indexed by i) as

$$\text{Denial Rate}_i = \frac{\text{Number Denied}_i}{\text{Number Originated}_i + \text{Number Denied}_i}. \tag{1}$$

We exclude applications that were withdrawn by the applicant or approved but not accepted, though we report robustness results that incorporate these alternative outcomes.

The expanded HMDA data provide several financial characteristics that are central to underwriting. We observe the applicant's gross annual income (trimmed at \$1,000 and \$10 million to limit the influence of reporting errors), the DTI ratio, the requested loan amount, and the CLTV ratio. DTI is reported partly as continuous values and partly in categorical buckets; we convert the buckets to midpoints for regression analysis. For loans that are originated, we also observe the interest rate (rounded to the nearest eighth of a percentage point).

A particularly valuable addition since 2018 is information on AUS recommendations. Most large lenders submit applications to an AUS (such as Fannie Mae's Desktop Underwriter or Freddie Mac's Loan Product Advisor), which returns an initial "Approve," "Refer," or similar recommendation based on algorithmic scoring of credit, income, assets, and collateral. This field allows us to separate algorithmic assessments from subsequent human discretion in the final denial decision. For denied applications, lenders report up to four denial reasons; we code the first-listed reason as the primary driver (most commonly excessive DTI, adverse credit history, insufficient collateral, or unverifiable information) and examine how the distribution of these reasons varies over the interest-rate cycle and across demographic groups.

Race and ethnicity information is recorded in separate fields that permit multiple racial selections. To create consistent categories, we use the Consumer Financial Protection Bureau's derived race variable, which applies a standard hierarchy: Hispanic/Latino ethnicity takes precedence, and non-Hispanic applicants are assigned to a single racial category (White, Black, Asian, or Other). Although lenders are not always required to obtain self-reported race/ethnicity (they may rely on visual observation or surname for in-person applications), valid identifiers are available for roughly 85 percent of applications in our sample. Our main analysis focuses on the four largest groups: non-Hispanic White, Black, Hispanic, and Asian applicants.

Finally, each record includes geographic identifiers at the state, county, and census-tract level. We merge tract-level median household income and racial composition from the American Community Survey to capture neighborhood characteristics that may influence lending decisions. Crucially, every reporting institution is assigned a unique 20-character legal entity identifier (LEI). The presence of LEI allows us to include lender fixed effects, which absorb time-invariant institutional practices and enable within-lender comparisons of approval outcomes across applicants with similar observable risk characteristics.

2.5 Sample Construction

The raw public HMDA records encompass the full spectrum of mortgage activity, including *home purchases*, *rate-and-term refinances*, *cash-out refinances*, and *home improvement loans*. To isolate the determinants of primary housing acquisition, we impose four sequential restrictions on our sample. First, we retain only home purchase loans, excluding all forms of refinancing and home improvement lending. Second, we restrict the sample to owner-occupied principal residences, excluding second homes and investment properties. Third, we retain only first-lien mortgages to ensure a uniform collateral priority. Finally, we limit our analysis to completed applications that resulted in either origination or denial, excluding withdrawn applications and those approved but not accepted by the applicant. Our focus on home purchase mortgages for principal residences is motivated by the distinct economic drivers and risk profiles underlying different loan purposes.

As shown in Figure 1, denial rates vary markedly across categories: Home improvement loans consistently exceed 35 percent, while refinances range from 17 percent to 30 percent depending on the prevailing interest rate environment.

In contrast, home purchases exhibit lower and more-stable denial rates, typically between 12 percent and 16 percent. Aggregating these disparate categories would obscure the specific credit transmission mechanisms and the "margin of entry" into homeownership that we aim to study.

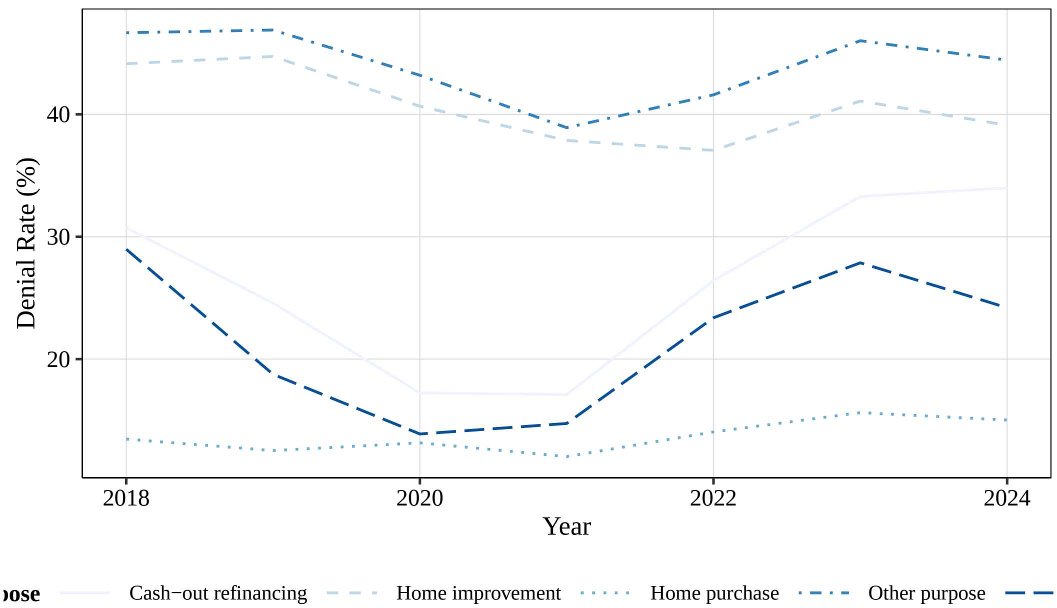

Figure 1: Denial Rates by Loan Purpose

Notes: This figure plots denial rates by loan purpose across the full HMDA sample for the 2018–2024 period.

Furthermore, Figure 2 illustrates that owner-occupied purchases paradoxically face higher denial rates (12–16 percent) than second homes and investment properties (10–13 percent).

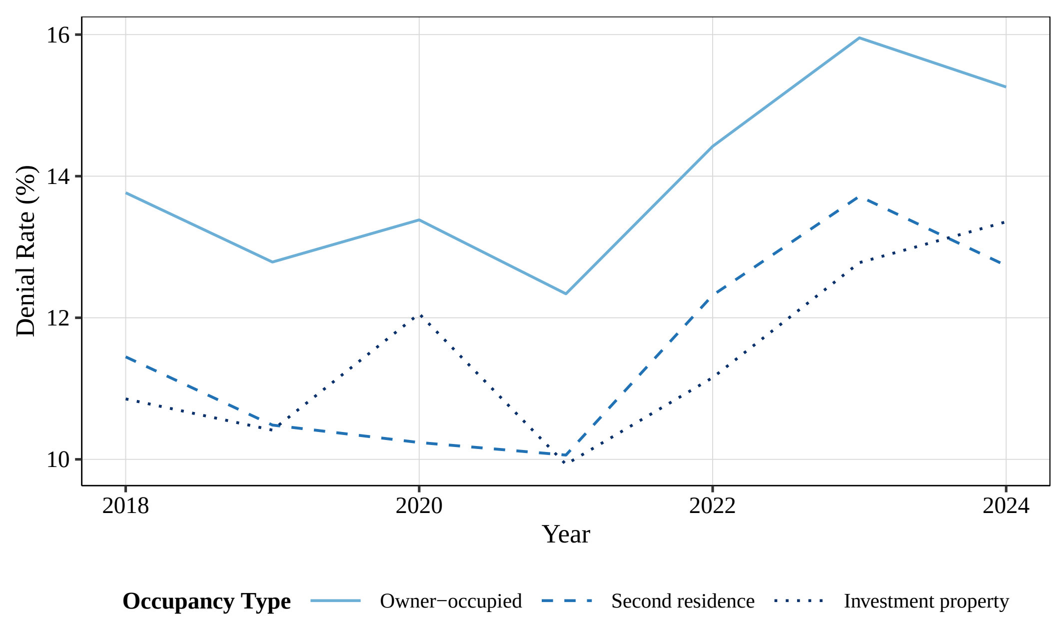

Figure 2: Denial Rates by Occupancy Type

Notes: Denial rates plotted by intended occupancy specifically for home purchase mortgages.

This pattern reflects a significant *selection effect*: purchasers of non-primary residences are typically wealthier borrowers with stronger financial profiles.

Table 1: Applicant Characteristics by Occupancy Type, 2024

	Owner-occupied	Second residence	Investment property
Panel A: All applicants			
Applications	3,653,534	102,733	382,664
Denial rate (%)	15.3	12.7	13.4
Mean income ($K)	143	387	264
Median income ($K)	104	235	173
Mean DTI (%)	40.4	34.7	35.0
Median DTI (%)	41.0	36.0	37.0
Mean CLTV (%)	85.1	71.4	73.0
Median CLTV (%)	90.9	75.0	75.0
Panel B: Denied applicants			
Denials	557,514	13,085	51,108
Mean income ($K)	102	278	202
Median income ($K)	71	152	120
Mean DTI (%)	47.0	44.2	42.7
Median DTI (%)	48.0	45.0	45.0
Mean CLTV (%)	87.7	74.2	75.1
Median CLTV (%)	95.0	78.1	75.0

Notes: Panel A includes all home purchase mortgage applications (originated and denied) in 2024. Panel B restricts to denied applications.
Income in thousands of dollars. DTI = debt-to-income ratio. CLTV = combined loan-to-value ratio.

Table 1 confirms this directly. Panel A shows that in 2024, second-home buyers had median income of $235,000—more than double the $104,000 median for owner-occupied applicants—and investment property buyers had median income of $173,000. DTI ratios are correspondingly lower: median DTI is 36% for second homes and 37% for investment properties, compared to 41% for owner-occupied purchases, placing non-primary-residence buyers well below the 50% underwriting cliff. CLTV ratios are also substantially lower (median 75% vs. 91%), reflecting larger down payments. Panel B shows that the same pattern holds among denied applicants: denied second-home and investment property buyers have median incomes of $152,000 and $120,000 respectively, compared to $71,000 for denied owner-occupied applicants, with lower DTI and CLTV ratios. These compositional differences explain why non-primary-residence applications face lower denial rates despite potentially stricter underwriting standards. By restricting our sample to primary residences, we focus on the critical margin of entry into homeownership, where credit constraints are most likely to bind.

2.6 Summary Statistics

Table 2: Sample Selection by Year (thousands)

Selection Step	2018	2019	2020	2021	2022	2023	2024
1. Total raw applications	15,139	17,574	25,699	26,270	16,099	11,564	12,229
2. Home purchase only	7,784	7,970	8,421	9,241	7,926	6,555	6,553
3. Owner-occupied only	7,784	7,970	8,421	9,241	7,926	6,555	6,553
4. First lien only (analysis sample)	5,170	5,328	5,959	6,293	5,368	4,350	4,300
– Of which: Originated	3,726	3,876	4,257	4,564	3,688	2,943	2,965
– Of which: Denied	585	560	653	634	607	549	526
– Of which: Withdrawn	716	744	888	934	907	721	674
– Of which: Approved not accepted	143	148	161	161	167	136	134

The final sample provides a comprehensive view of the shifting dynamics in the U.S. mortgage market. Table 2 details the outcome of this filtering process by year. From an initial pool of approximately 15-26 million raw applications per year, our restrictions yield a final analytical sample of roughly 4-6 million applications per year, totaling more than 35 million observations over 2018–2024. For the final year of our sample (2024), this process results in 2.965 million originated loans and 526,000 denied applications.

Table 3: Home Purchase Mortgage Applications and Denial Rates, 2018–2024

Year	Originated	Denied	Denial Rate (%)
2018	3,726,145	585,193	13.6
2019	3,875,533	560,439	12.6
2020	4,257,249	652,760	13.3
2021	4,564,102	634,457	12.2
2022	3,688,184	606,592	14.1
2023	2,942,809	549,344	15.7
2024	2,965,386	526,127	15.1

Table 3 presents the aggregate trends, while subsequent tables decompose these figures by applicant characteristics. Over 2018–2024, we observe 26 million originated loans and 4.1 million denials, yielding an aggregate denial rate of 13.7 percent. Application volume peaked in 2021 during the historic low-rate environment and declined sharply over 2022–2023 as monetary policy tightened. Mirroring this shift, denial rates moved in close synchronization with interest rates, falling to 12.2 percent in 2021 as the Federal Reserve cut rates toward the zero lower bound, and rising to 15.7 percent by 2023 during the subsequent hiking cycle.

Table 4: Summary Statistics by Race/Ethnicity, Home Purchase Applications, 2024

	White	Black	Hispanic	Asian
Observations	1,907,047	299,556	517,350	245,823
Denial rate (%)	12.1	27.2	21.0	10.1
Income ($000s, mean)	145	133	114	197
Income ($000s, median)	105	85	90	146
Loan amount ($000s)	349	303	323	547
DTI (%, mean)	42.9	43.5	43.7	43.3
FHA loan (%)	15.2	36.1	34.0	9.1

Notes: Sample restricted to home purchase applications resulting in origination or denial. Income in thousands of dollars. DTI = debt-to-income ratio.

Table 4 provides baseline summary statistics by race and ethnicity for the 2024 calendar year, offering an empirical foundation for the themes explored in our subsequent analysis. First, raw denial rates exhibit significant variation: Black applicants face a 27.2 percent denial rate compared with 12.1 percent for White applicants, while Hispanic and Asian applicants face rates of 21.0 percent and 10.1 percent, respectively. These unconditional differences mirror the persistent gaps documented in the literature and set the stage for our within-lender and decomposition analyses. Second, the data reveal notable differences in financial profiles and product selection that likely interact with the interest rate and DTI channels identified in the abstract. Median income for Black applicants ($85,000) is approximately 19 percent lower than that of White applicants ($105,000), while Asian applicants report the highest median income at $146,000. These income levels directly influence a household's sensitivity to the "mechanical" DTI shocks described in the introduction. Furthermore, Black and Hispanic applicants are over-represented in the FHA market—with usage rates of 36.1 percent and 34.0 percent, respectively, compared with 15.2 percent for White applicants—highlighting the importance of examining denial determinants across different loan programs.

Finally, while income and product choice vary, the mean DTI ratios are remarkably uniform across demographic groups, ranging narrowly from 42.9 percent to 43.7 percent. This aggregate similarity is particularly striking given the divergent denial outcomes. It suggests that the primary drivers of the observed gaps are not found in average debt burdens, but rather in how these distributions interact with specific underwriting thresholds (such as the 50 percent DTI mark) or in the residual factors that remain once these observable financial metrics are controlled for.

3 Descriptive Evidence

Before proceeding to our formal econometric analysis, we present descriptive evidence on the primary factors driving mortgage denial outcomes. In this section, we utilize the granular nature of the 2018–2024 public HMDA records to visualize how the interaction between macroeconomic shocks—specifically the interest-rate-hiking cycle—and individual financial characteristics shapes credit access. We first examine the aggregate comovement between interest rates and denial volumes, followed by an exploration of how specific underwriting thresholds and demographic variables correlate with the probability of rejection. These visual patterns provide the initial empirical support for the mechanical and residual channels of denial that we formalize in Section 4.

3.1 Interest Rates and Denial Rates

Figure 3 illustrates the close synchronization between mortgage denial rates and the prevailing interest rate environment. During 2020–2021, as median contract rates fell below 3.5 percent, the aggregate denial rate reached a sample low of 12.2 percent. Conversely, as rates climbed above 6.5 percent during the 2022–2023 monetary tightening cycle, denial rates rose to 15.7 percent.

This comovement suggests a primary mechanical channel operating through the DTI ratio. To illustrate, consider a borrower with a $6,000 monthly income and $500 in existing debt seeking a $400,000 mortgage. At a 3 percent interest rate, the monthly principal and interest payment is $1,686, resulting in a DTI of 36.4 percent. At a 7 percent rate, the same loan requires a $2,661 monthly payment, pushing the DTI to 52.7 percent. This nearly 16-percentage-point jump illustrates how monetary policy can unilaterally transition an applicant from a "safe" DTI range to the binding 50 percent cliff discussed in the following section. Because this arithmetic applies to all prospective borrowers, rising rates systematically shift the DTI distribution rightward, making credit harder to obtain even for applicants with stable financial profiles.

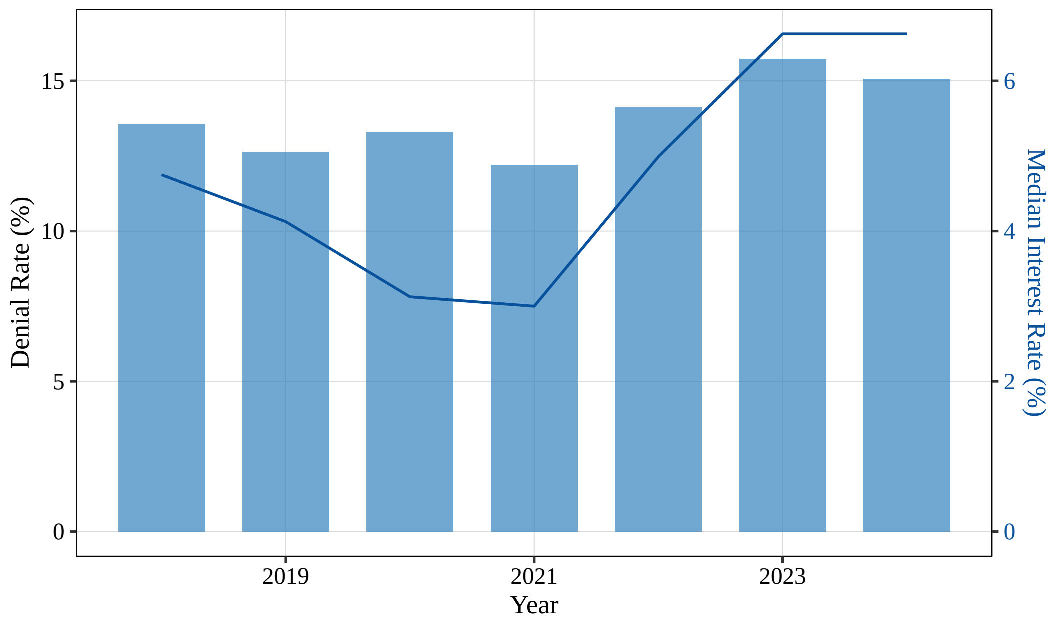

Figure 3: Denial Rates and Interest Rates Over Time, 2018–2024

Notes: Bars show denial rates (left axis). Line shows median contract interest rate on originated home purchase mortgages (right axis). Sample: owner-occupied, first-lien home purchase applications.

To quantify the magnitude of this effect, Table 5 presents a counterfactual decomposition of the 2021–2024 denial rate increase. The exercise proceeds as follows. First, we estimate the sensitivity of denial rates to interest rates using a pooled cross-sectional regression of individual denial outcomes on the median contract rate, controlling for applicant characteristics (log income, log loan amount, FHA status) and state fixed effects. The estimated coefficient on the median interest rate captures the marginal effect of a one percentage point rate increase on denial probability. Second, we multiply this coefficient by the observed 3.62 percentage point increase in median mortgage rates between 2021 and 2024 to obtain the predicted rate-driven increase in denials. Finally, we compare this predicted increase to the actual 2.9 percentage point rise in the aggregate denial rate over the same period.

We find that the increase in interest rates alone can account for the entirety of the rise in the aggregate denial rate, validating the dominance of the mechanical DTI channel during this cycle.

While the *level* of interest rates dictates the aggregate volume of denials, the *relative* pricing of credit also varies across demographic groups. Table 6 shows the median contract interest rate by race and ethnicity for originated mortgages. Between 2018 and 2022, Black and Hispanic borrowers typically faced median rates 12–13 basis points higher than White borrowers. However, this pattern underwent a notable reversal in 2023–2024, as Black and

Table 5: Impact of Interest Rate Increases, 2021–2024

Metric	Value
Denial rate 2021	12.2%
Denial rate 2024	15.1%
Change in denial rate	+2.9 pp
Median rate 2021	3.00%
Median rate 2024	6.62%
Rate change	+3.62 pp
DTI share 2021	30.7%
DTI share 2024	35.0%
Rate effect coefficient	0.0120
Share attributable to rates	100.0%

Hispanic borrowers began obtaining slightly lower median rates than White borrowers. Asian borrowers consistently maintained the lowest median rates throughout the sample.

Table 6: Median Interest Rate by Race/Ethnicity (%), Originated Loans, 2018–2024

Race/Ethnicity	2018	2019	2020	2021	2022	2023	2024
White	4.75	4.12	3.12	3.00	4.99	6.62	6.62
Black	4.88	4.25	3.25	3.12	5.12	6.58	6.50
Hispanic	4.88	4.25	3.25	3.12	5.12	6.62	6.50
Asian	4.50	3.88	3.00	2.88	4.62	6.38	6.50

Notes: Median interest rate for originated home purchase loans.

The modest magnitude of these pricing differences—and their recent convergence—suggests that the primary margin of disparity in the mortgage market is credit *access* (denial) rather than the *pricing* of approved loans. This observation reinforces our focus on the denial rate as the critical barrier to homeownership for minority households.

3.2 Applicant Characteristics and Demographic Disparities

Beyond the macroeconomic environment, credit access is fundamentally determined by an applicant's financial profile. Figure 4 illustrates the relationship between annual income and credit rejection during the sample period. The denial rate follows a strictly monotonic decrease: Applicants earning below $50,000 face rejection rates near 20 percent, while those earning above $200,000 experience rates below 8 percent. This income gradient reflects not only direct affordability but also the high correlation between income and unobserved creditworthiness factors, such as liquid assets and job stability.

The primary metric through which income translates into a credit decision is the DTI ratio. As shown in Figure 5, the relationship between DTI and denial is nonlinear and U-shaped. At very low DTI levels (below 20 percent), denial rates are elevated at approximately 22 percent, reflecting a selection effect: Applicants rejected at these levels are typically denied because of poor credit history or collateral issues rather than DTI constraints. Rejection rates reach their nadir in the 20–50 percent range before rising exponentially. Once DTI exceeds 50 percent, denial rates jump sharply, eventually exceeding 80 percent for applicants above the 60 percent threshold.

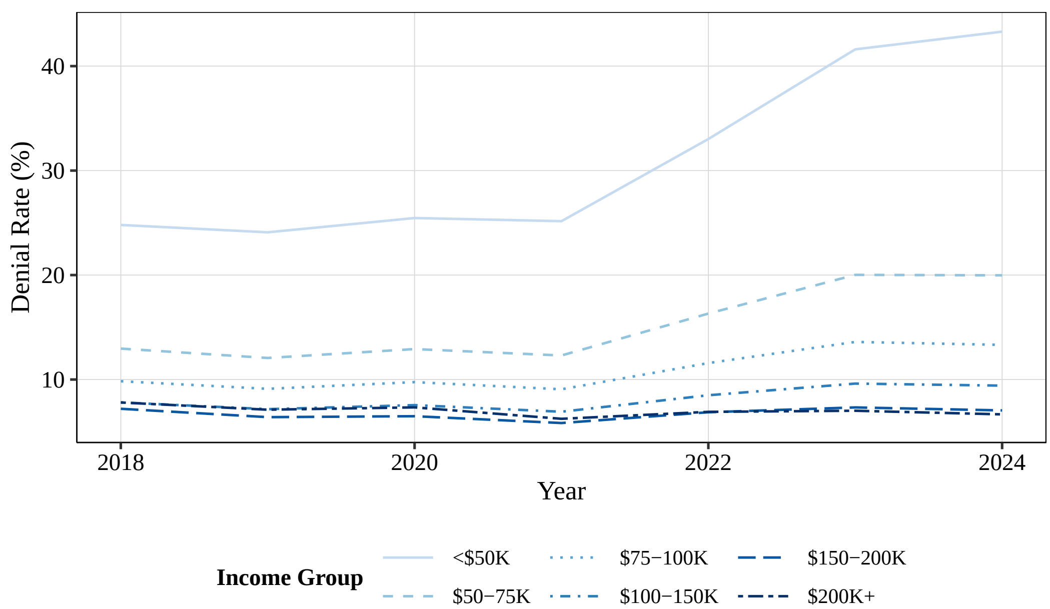

Figure 4: Denial Rates by Applicant Income Category

Notes: Denial rates by applicant annual income. Sample: owner-occupied, first-lien home purchase applications.

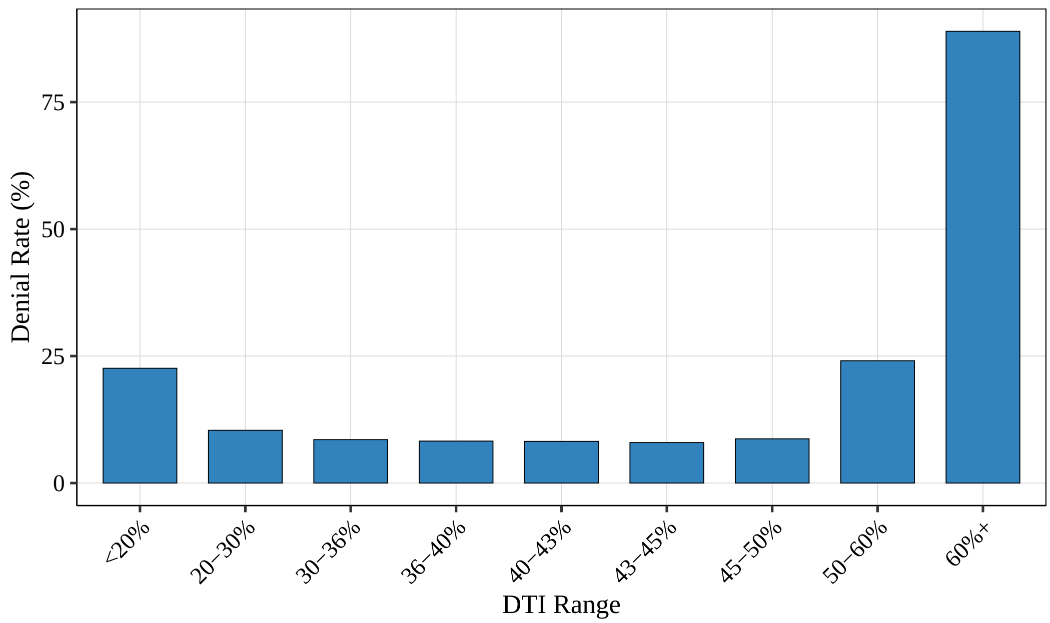

Figure 5: Denial Rates by Debt-to-Income Ratio

Notes: Denial rates by DTI category for 2024. Sample: first-lien home purchase applications for owner-occupied properties with non-missing DTI.

This sharp inflection point highlights the role of regulatory and institutional thresholds. We investigate two potential boundaries: the 43 percent QM threshold established by the Consumer Financial Protection Bureau, and the 50 percent effective limit often used under the "ability-to-repay" standard. Using two complementary approaches—bunching analysis and regression discontinuity (RD)—we test which of these thresholds binds in practice. Our bunching analysis shows no evidence of strategic manipulation or clustering at the 43 percent mark; applications are distributed smoothly across the threshold. Similarly, RD estimates at 43 percent yield a negligible discontinuity of 0.2 to 0.4 percentage points.

In contrast, we find a massive 15- to 17-percentage-point jump in denial rates at the 50 percent threshold. This "sharp cliff" suggests that while 43 percent may be a statutory guideline, the 50 percent mark serves as the functional underwriting boundary for most lenders. Detailed technical results and robustness checks for these RD specifications are provided in Appendix C. Moreover, Figure 6 demonstrates that while higher LTV ratios are associated with higher denial rates, the gradient for collateral is significantly less steep than the cliff observed for DTI, identifying DTI as the primary bottleneck in the current high-rate environment.

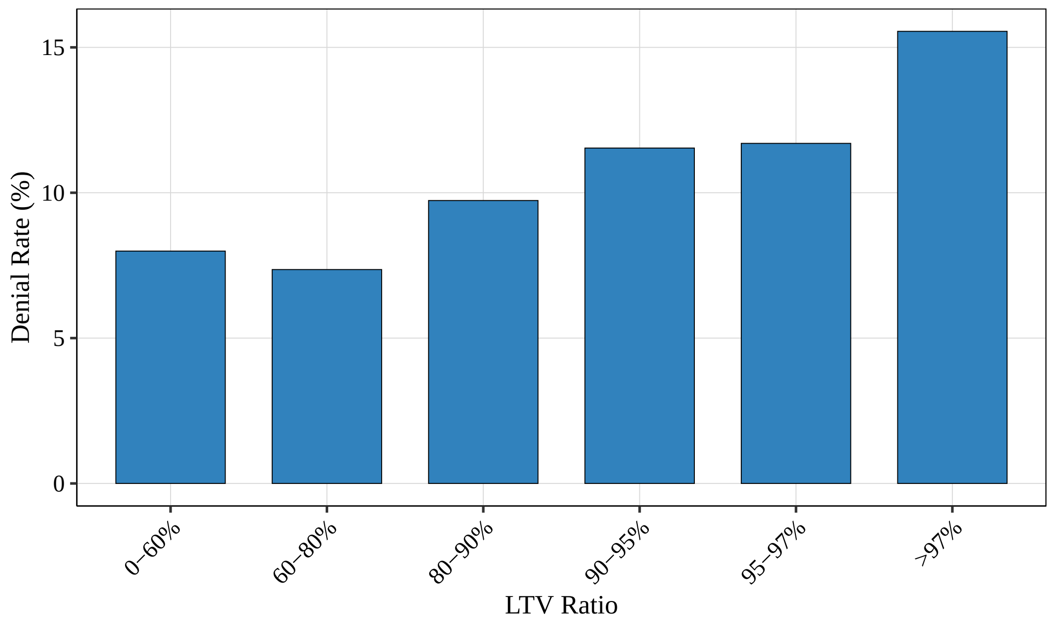

Figure 6: Denial Rates by Loan-to-Value Ratio

Notes: Denial rates by combined LTV ratio. Higher LTV indicates a smaller down payment.

The identification of the 50 percent DTI ratio as a functional underwriting boundary is particularly consequential given the systematic differences in financial profiles across demographic groups. As shown in Table 7, Black and Hispanic applicants face significantly higher denial rates than White and Asian applicants throughout 2018–2024.

Table 7: Denial Rates by Race/Ethnicity (%), 2018–2024

Race/Ethnicity	2018	2019	2020	2021	2022	2023	2024
White	11.3	10.5	10.5	10.0	11.3	12.8	12.1
Black	24.4	23.3	26.1	22.9	25.6	28.0	27.2
Hispanic	19.0	17.5	19.0	16.5	19.7	21.9	21.0
Asian	11.2	10.2	10.7	8.6	10.6	10.7	10.1
AIAN	27.4	25.4	25.5	24.4	28.6	31.7	30.2
NHPI	15.1	14.9	14.9	13.5	17.2	17.6	18.6

This gap between Black and White applicants has remained remarkably persistent, fluctuating between 13 and 15 percentage points despite varying economic conditions. Table 4 highlights the structural factors contributing to these outcomes. In 2024, Black applicants reported lower median incomes ($107,000 vs. $145,000 for White applicants) and higher average DTI ratios (44.9 percent vs. 39.4 percent). Crucially, the higher average DTI for Black and Hispanic households places a larger share of their application pool near the 50 percent "cliff" identified in Figure 5, making these borrowers disproportionately sensitive to interest rate shocks. Furthermore, Black and Hispanic applicants are over twice as likely to utilize FHA loans (36.1 percent and 34.0 percent, respectively) as White applicants (15.2 percent), reflecting the interplay between lower down-payment capacity (LTV) and stricter credit score requirements.

However, these disparities are not merely a function of aggregate income. Figure 7 demonstrates that differences in denial rates persist even when conditioning on income level. Among high-earners (above $200,000), Black applicants still face higher rejection rates than their White counterparts, though the delta narrows as income increases. At the lower end of the distribution, the disparity is stark: As visualized in the heatmap in Figure 8, Black denial rates approach 60 percent compared with 37 percent for White applicants in the same income bracket. These within-income differences suggest that residual factors—such as liquid wealth, credit history, or co-applicant status—play a decisive role.[1] Differences in denial rates persist even when conditioning on income.

The role of household structure provides further evidence that these disparities are not easily mitigated by increasing an application's financial strength. While the addition of a co-applicant generally reduces the probability of rejection by pooling income and diversifying credit risk, it does not close the racial divide.

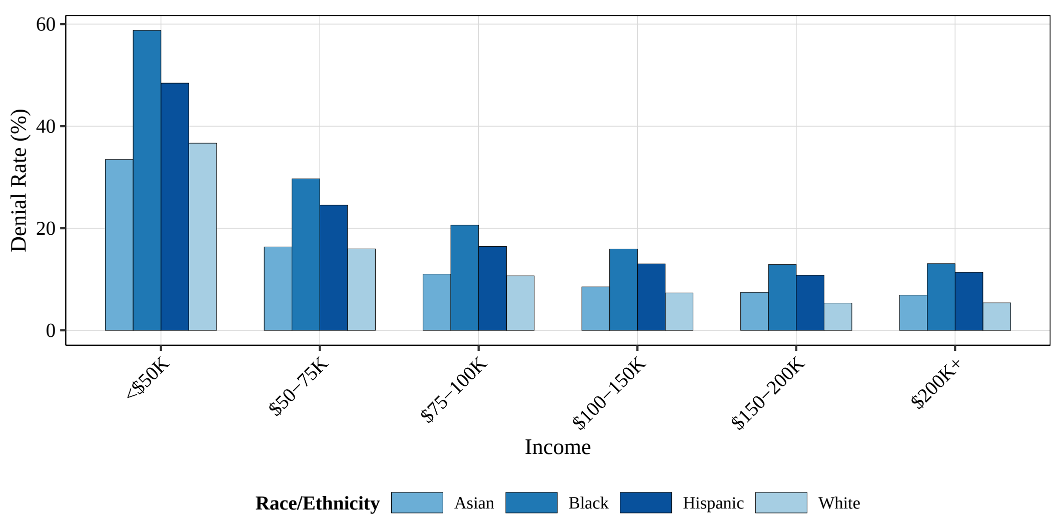

Figure 7: Denial Rates by Race and Income

Notes: Denial rates by race within income categories.

As detailed in Table 8, Black and Hispanic applicants with a co-applicant continue to

[1]While co-applicant status reduces denial rates for all groups, racial gaps persist regardless of whether an application is filed individually or jointly.

face higher denial rates than White single applicants, suggesting that the benefits of joint filing do not fully offset the underlying disparities in credit access.

Table 8: Denial Rates by Co-Applicant Status, 2024

Group	Single Applicant	With Co-Applicant	Gap
Overall	17.1	12.3	4.8
White	14.1	10.0	4.1
Black	27.8	25.4	2.4
Hispanic	22.3	18.9	3.4
Asian	10.3	9.7	0.6

Notes: Gap = Single applicant denial rate minus co-applicant denial rate.

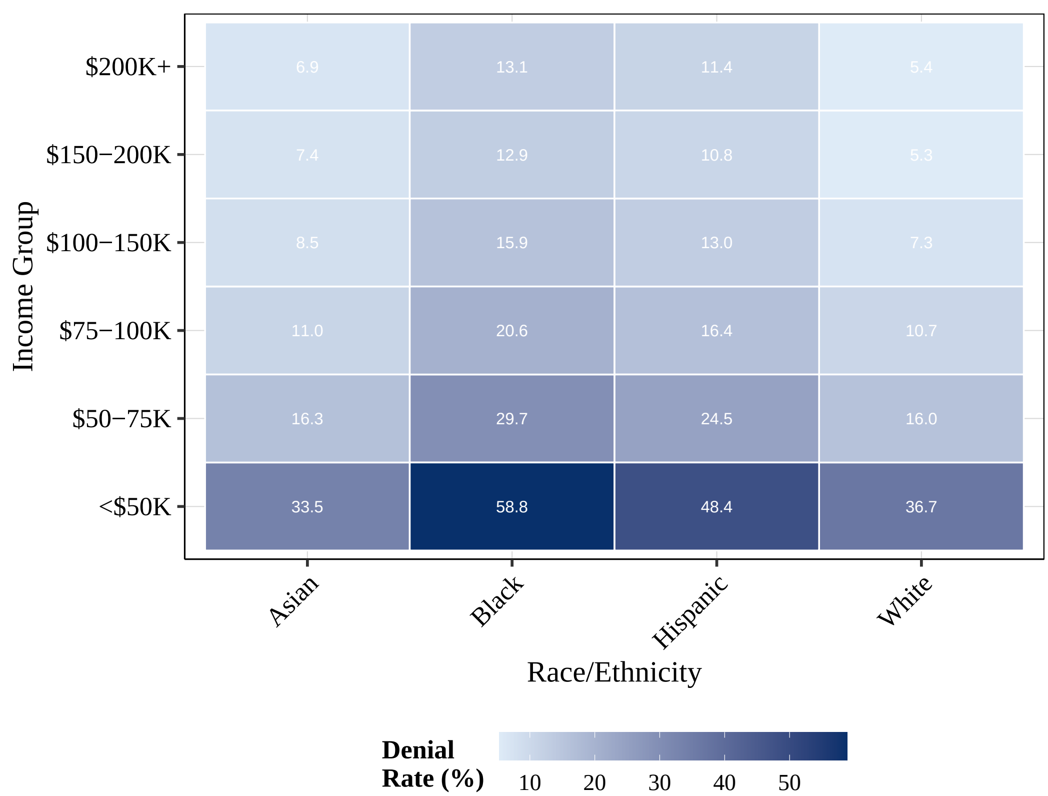

Figure 8: Denial Rates by Race and Income: Heatmap

Notes: Denial rates by race and income category for 2024. Darker colors indicate higher denial rates.

3.3 Loan Program and Market Structure

While DTI and income provide a baseline for creditworthiness, the specific underwriting standards applied to an application are governed by the chosen loan program. Figure 9 decomposes denial rates by loan type, revealing distinct institutional patterns. Historically, VA loans exhibit the lowest rejection rates, ranging between 8 percent and 10 percent. This relative stability likely reflects a combination of favorable government-backed terms and a positive selection effect among eligible veterans.

In contrast, denial rates for conventional, FHA, and USDA loans cluster between 12% and 16%, though their relative rankings have shifted notably over our sample period. While FHA loans—which typically cater to borrowers with lower down-payment capacity—had slightly higher denial rates in 2018–2019, conventional loans emerged as the most frequently denied category by 2023–2024. This reversal underscores the heightened sensitivity of conventional underwriting to the interest rate shocks and DTI constraints discussed previously. Because FHA and VA programs often allow for more flexible DTI offsets, the "mechanical" DTI channel appears most binding for borrowers in the conventional market who lack these programmatic protections.[2]

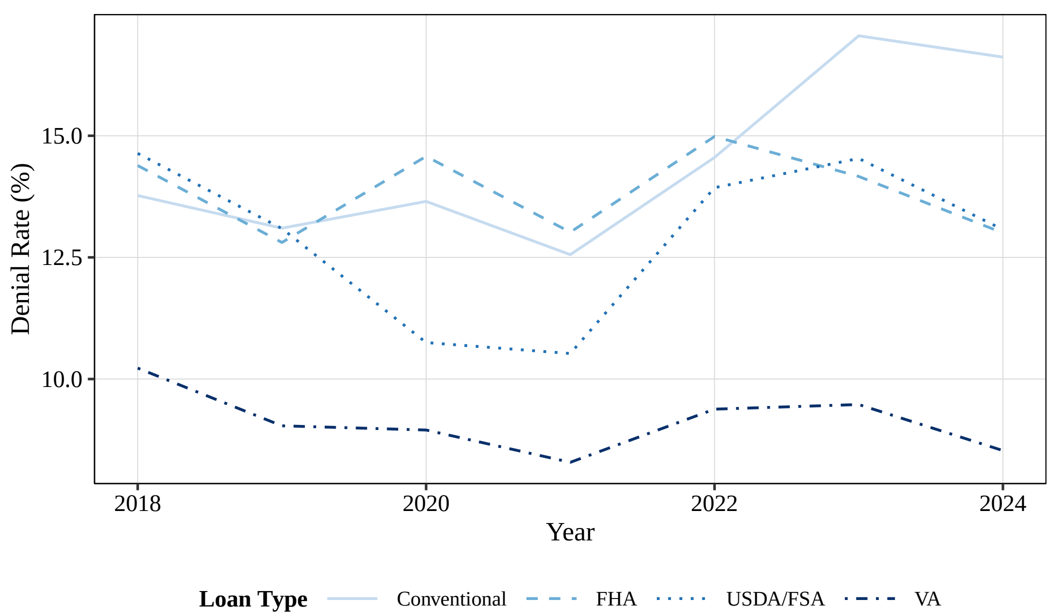

Figure 9: Denial Rates by Loan Type

Notes: Denial rates by loan type. FHA = Federal Housing Administration, VA = Veterans Affairs, USDA = Department of Agriculture. Sample: owner-occupied, first-lien home purchase applications.

[2]For a more granular view, Tables A.5, A.6, and A.7 in Appendix A provide comprehensive breakdowns by loan type, intended purpose, and property occupancy.

Table 9: Denial Rates by Lender Size (%), 2018–2024

Lender Size	2018	2019	2020	2021	2022	2023	2024
Large (10K+ apps)	16.5	15.4	16.3	14.6	17.1	19.5	19.0
Medium (1K-10K)	10.3	9.2	8.8	8.5	10.6	11.6	10.3
Small (100-1K)	10.4	9.6	10.4	9.7	9.9	9.6	9.5
Very small (<100)	15.5	15.2	15.9	14.7	13.0	13.3	12.6

Notes: Lender size based on annual application volume.

This programmatic variation is mirrored by shifts in the institutional landscape. As shown in Table 9, high-volume lenders, those processing more than 10,000 applications annually, have the highest denial rates, averaging 16 to 20 percent compared with 9 to 12 percent for medium and small lenders. This pattern likely reflects the composition of high-volume lenders, which include large non-bank mortgage companies that have captured a dominant share of originations relative to traditional depositories (Buchak et al., 2018). These institutions disproportionately serve lower-income and minority borrowers through FHA and other government-backed programs, populations more sensitive to binding DTI thresholds. Very small lenders (fewer than 100 applications) also exhibit elevated denial rates (13 to 16 percent), potentially reflecting less standardized underwriting processes. Medium and small lenders occupy an intermediate position, with denial rates that are both lower and more stable across the interest rate cycle, consistent with more standardized, automated underwriting processes that facilitate faster and more consistent decisioning (Fuster et al., 2022). Together, these patterns suggest that the current high-rate environment has not only raised the bar for individual borrowers but has also concentrated credit risk within specific loan programs and high-volume lending institutions.

3.4 Geographic Variation and Tract Composition

The national trends in credit access mask significant regional heterogeneity, as mortgage denial is often a function of local economic conditions and property-market characteristics. Figure 10 presents the geographic distribution of denial rates by state for 2024. Southern and rural states exhibit the highest rates of rejection, a pattern further detailed at the metropolitan level in Table 10.

Texas municipalities dominate the high-denial rankings, led by Houston (20.0 percent), San Antonio (18.0 percent), and McAllen (17.3 percent). These clusters often correlate with higher concentrations of FHA applications and a higher prevalence of non-bank lending, which, as previously noted, are associated with tighter credit constraints in a high-rate

Table 10: Top 10 MSAs by Denial Rate, 2024

MSA Code	Applications	Denied	Denial Rate (%)
Miami-Miami Beach-Kendall, FL	18,841	4,088	21.7
Fort Lauderdale-Pompano Beach-Deerfield Beach, FL	18,911	3,868	20.5
Houston-Sugar Land-Baytown, TX	94,936	19,027	20.0
Detroit-Livonia-Dearborn, MI	16,798	3,123	18.6
San Antonio-New Braunfels, TX	40,033	7,186	18.0
Orlando-Kissimmee-Sanford, FL	35,391	5,766	16.3
Fort Worth-Arlington-Grapevine, TX	32,989	4,984	15.1
Oklahoma City, OK	18,376	2,717	14.8
Tampa, FL	35,148	5,038	14.3
Jacksonville, FL	25,793	3,695	14.3

environment.

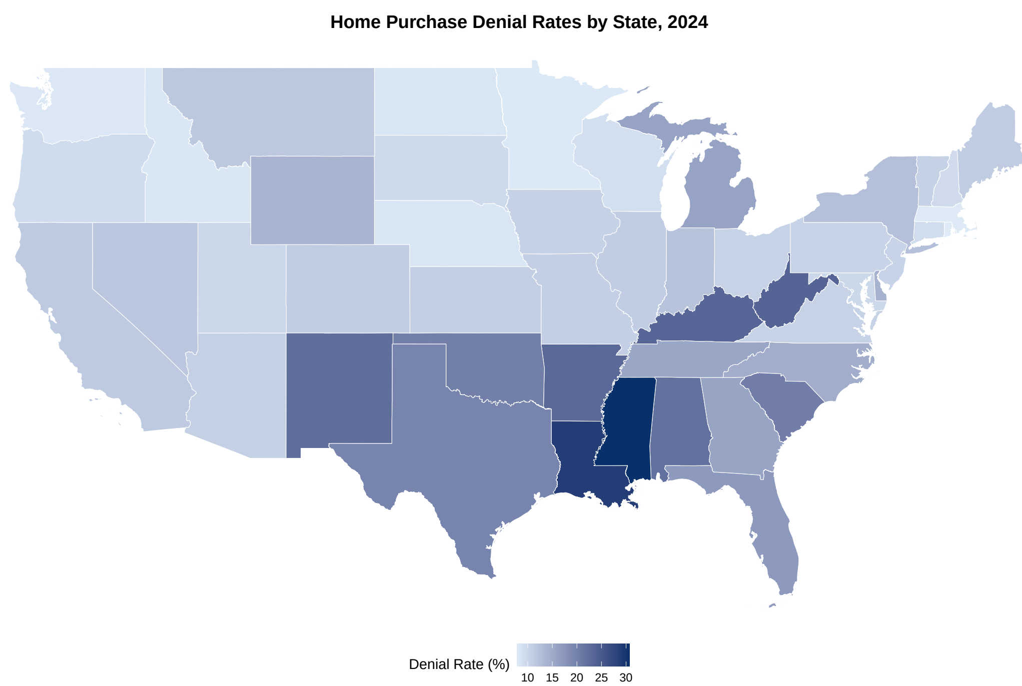

Figure 10: Denial Rates by State, 2024

Notes: Mortgage denial rates by state for the 2024 calendar year. Darker shades indicate higher aggregate denial rates.

To further explore the intersection of geography and demographics, we examine the relationship between a census tract's minority population share and its aggregate denial rate. This relationship follows a nonlinear, U-shaped pattern. As shown in Table 11, tracts with very-low-minority populations (below 10 percent) exhibit elevated denial rates exceeding 27 percent. This is largely driven by compositional factors: These tracts are disproportionately rural and characterized by a higher share of manufactured housing applications, which face significant collateral hurdles.

Table 11: Denial Rates by Census Tract Minority Share (%), 2018–2024

Tract Minority Share	2018	2019	2020	2021	2022	2023	2024
<10% minority	18.0	17.5	18.4	16.0	24.0	27.4	27.1
10-30% minority	10.4	9.4	9.9	9.4	10.8	12.0	11.4
30-50% minority	12.1	11.0	11.7	11.0	12.2	13.5	12.9
50-80% minority	14.5	13.3	14.4	13.5	15.0	16.3	15.4
80%+ minority	18.3	16.6	17.3	15.9	18.4	19.7	18.9

In contrast, denial rates reach their lowest point (approximately 11 percent) in moderate-minority tracts (10–30 percent), which are typically suburban areas with standardized housing stock. Rejection rates rise again as the minority share increases, reaching 19 percent in majority-minority tracts. While the low-minority peak reflects rural-market frictions, the high-minority peak is more closely linked to historical disinvestment and lower tract-level median incomes. Even after controlling for individual applicant income, we find that denial rates remain 3 to 5 percentage points higher in low- and moderate-income census tracts, underscoring the role of neighborhood-level effects in determining credit outcomes.

Collateral risk is a primary driver of these spatial patterns, particularly regarding non-traditional housing. As illustrated in Figure 11, manufactured housing applications face denial rates 5 to 8 percentage points higher than those for site-built homes. This disparity persists even after accounting for income, reflecting both the thinner secondary market for these loans and the heightened appraisal difficulties associated with personal property (chattel) lending.

3.5 Denial Reasons and Attribution

While the preceding sections establish the correlation between external shocks and credit rejection, the justifications cited by lenders provide a granular look at where the underwriting process breaks down. Figure 12 illustrates the shifting distribution of primary denial reasons over time. Across the full sample, the DTI ratio remains the most-frequent hurdle, accounting for approximately 35 percent of all denials, followed by credit history (29 percent), collateral (10 percent), and insufficient cash (5 percent).

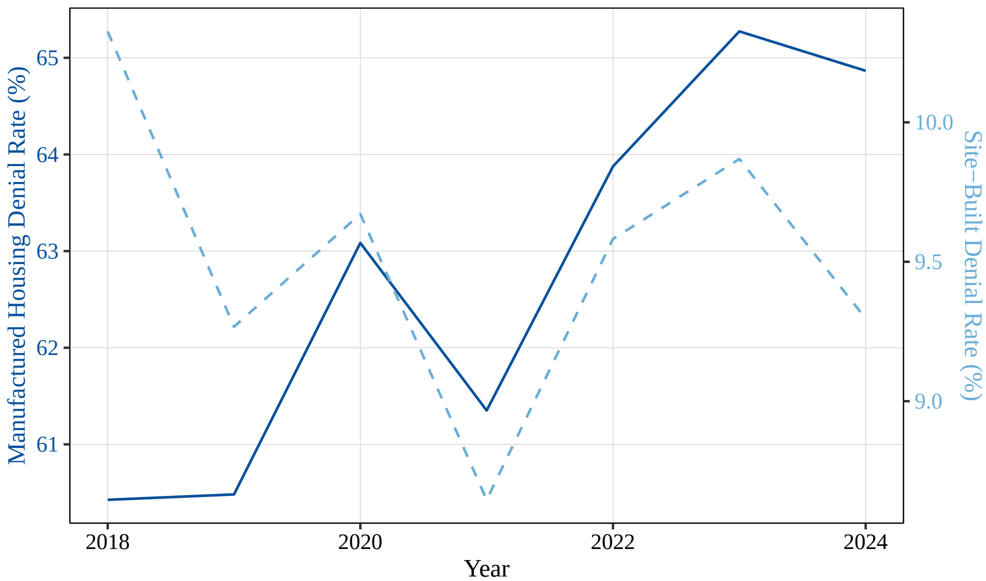

Figure 11: Denial Rates by Property Type

Notes: Comparative denial rates for site-built versus manufactured housing. Sample: owner-occupied, first-lien home purchase applications.

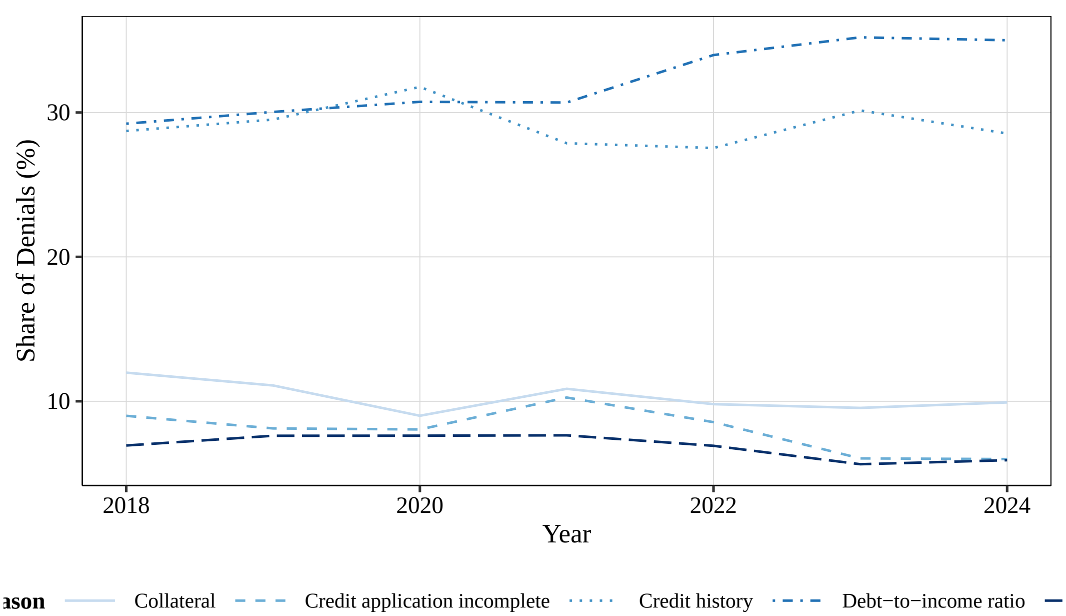

Figure 12: Primary Denial Reasons Over Time

Notes: Distribution of primary denial reasons by year. "DTI" indicates the debt-to-income ratio.

The temporal shift in these reasons provides direct evidence for the "mechanical" channel of interest rate transmission. As rates rose in 2022–2023, DTI-related denials became significantly more prominent. This validates our earlier numerical example: As

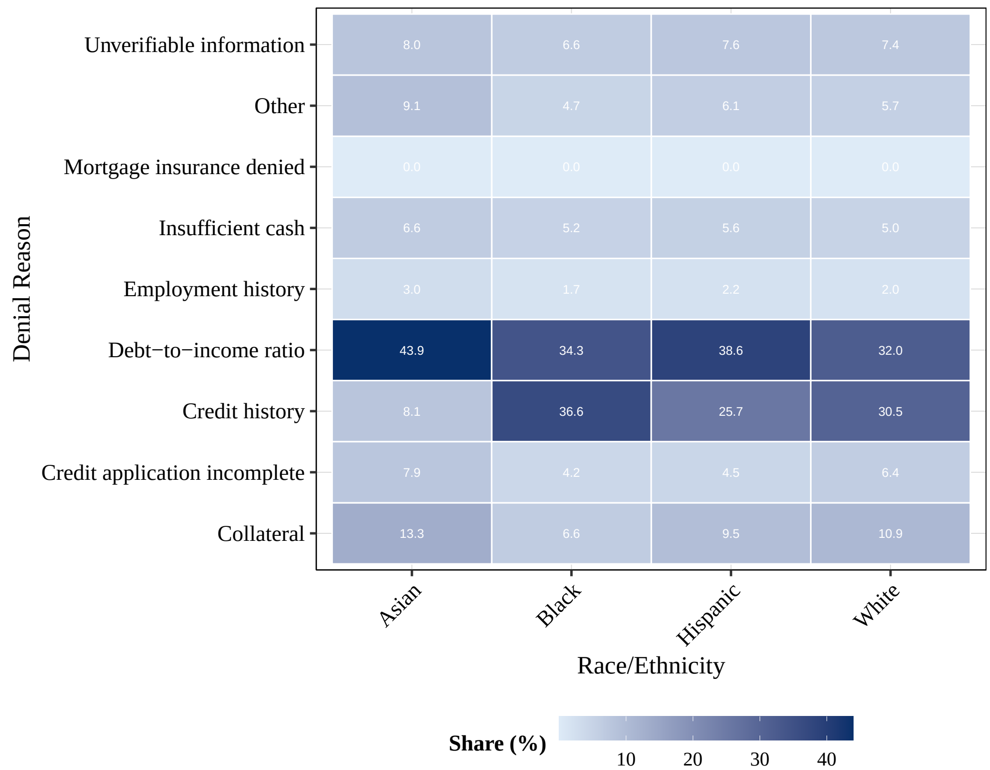

Figure 13: Denial Reasons by Race

Notes: Distribution of primary denial reasons by race for 2024. Darker colors indicate a higher proportion of denials attributed to that reason.

the Federal Reserve tightened policy, the resulting spike in mortgage payments pushed a growing share of applicants over the binding 50 percent DTI threshold, shifting the primary cause of rejection from creditworthiness to simple affordability.

However, the attribution of denial varies significantly across demographic groups. Figure 13 presents a heatmap of denial reasons by race and ethnicity. While DTI is cited at relatively similar rates across groups, there is a notable divergence in credit-related rejections. Credit history is cited as the primary reason for 37 percent of Black-applicant denials, compared with 31 percent for White applicants.

This disparity is particularly revealing when placed alongside our finding that mean DTI ratios are similar across groups. It supports the hypothesis that residual racial gaps are driven by variables not fully captured in HMDA data—specifically credit scores and historical credit depth. Consequently, while interest rate shocks act primarily through the DTI channel for all borrowers, the structural gap in credit history remains a persistent secondary barrier that disproportionately impacts Black and Hispanic applicants.

The composition of the applicant pool has not remained static. Figure 14 demonstrates

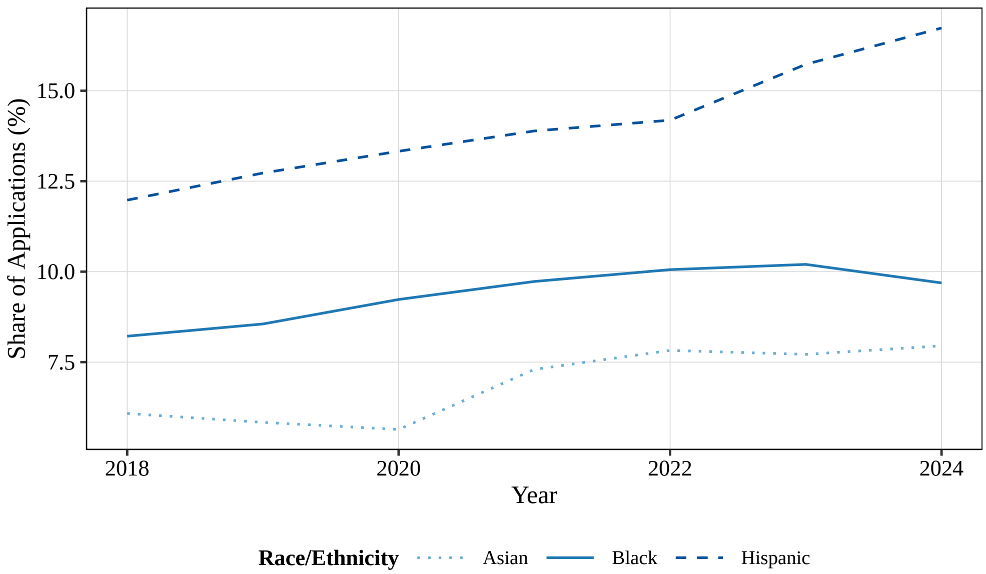

Figure 14: Applicant Composition Trends, 2018–2024

Notes: Distributional trends in applicant financial and demographic characteristics over the sample period.

that while the minority share of applicants has increased modestly, income levels and DTI ratios have fluctuated in response to the interest rate cycle. These shifting tailwinds make it difficult to ascertain from raw data alone whether the widening denial gaps are driven by changing applicant quality or changing lender sensitivity. This ambiguity motivates the formal decomposition analysis in the following section.

3.6 Alternative Application Outcomes: Withdrawals and Non-Acceptance

To ensure that our focus on formal denial rates provides a comprehensive view of credit access, we also examine alternative application outcomes. Withdrawn applications account for 15 to 20 percent of total volume, with withdrawal rates typically rising during periods of high interest rate volatility. Additionally, "approved-but-not-accepted" applications—where a lender offers credit but the borrower declines—represent 5 to 8 percent of the sample. As shown in Table 12, Black and Hispanic applicants exhibit slightly higher withdrawal rates than White and Asian applicants.

This divergence may reflect differences in pre-approval status, shifts in financial circumstances during the underwriting process, or a higher sensitivity to the interest rate fluctuations discussed in Section 3.1. While these alternative outcomes are distinct from formal rejections, their elevated levels among minority households suggest that the barriers to homeownership may be even broader than the denial data alone suggest.

Table 12: Application Withdrawal Rates by Race/Ethnicity (%), 2018–2024

Race/Ethnicity	2018	2019	2020	2021	2022	2023	2024
White	12.8	13.0	13.7	13.5	15.3	15.3	14.6
Black	15.3	15.1	16.2	16.3	17.9	17.5	16.6
Hispanic	13.6	13.6	15.5	14.8	16.4	15.8	14.7
Asian	15.7	16.3	18.1	18.4	22.2	20.8	19.1

Notes: Share of applications withdrawn before decision.

4 Empirical Framework

The descriptive evidence in the preceding section establishes three key facts: (1) Denial rates are highly sensitive to the interest rate environment via the DTI channel; (2) substantial racial gaps in credit access persist over time; and (3) the composition of the applicant pool is shifting. However, these raw correlations leave open the question of whether racial disparities are driven by differences in observable creditworthiness or by institutional factors such as lender sorting. To disentangle these channels, we move to a formal econometric framework.

4.1 Specification and Baseline Results

Our baseline analysis utilizes a linear probability model (LPM) to estimate the determinants of denial while controlling for the high-dimensional fixed effects necessary to account for lender-specific heterogeneity. The primary specification is:

$$\text{Denied}_{ijst} = \alpha + \mathbf{X}_i'\beta + \gamma_s + \delta_t + \lambda_j + \varepsilon_{ijst} \tag{2}$$

where Denied_{ijst} is a binary indicator for the rejection of application i at lender j in state s and year t. The vector $\mathbf{X}_i$ contains the fundamental underwriting variables discussed in Section 3: log income, log loan amount, loan type indicators (FHA, VA, USDA), and the DTI ratio. We include state (γ_s) and year (δ_t) fixed effects to absorb geographic and temporal shocks, while our preferred specification adds lender fixed effects (λ_j) to compare applicants within the same institution.

We favor the LPM for its direct interpretability and computational efficiency when handling thousands of lender fixed effects. However, as a robustness check, we also estimate a logit model:

$$\Pr(\text{Denied}_{ist} = 1) = \Lambda(\alpha + \mathbf{X}_i'\beta + \gamma_s + \delta_t) \tag{3}$$

where $\Lambda(\cdot)$ is the logistic function. To maintain comparability, we report average marginal effects. Note that lender fixed effects are excluded from the logit specification to avoid the incidental parameters problem.

Recall that we restrict the sample to applications with non-missing values for income, loan amount, loan type, DTI, and race in the four main categories. We exclude income below $1,000 or above $10 million. HMDA reports DTI as either an exact numeric value or a categorical bucket (e.g., "30 percent–<36 percent"); we convert buckets to midpoint values for regression analysis. Using a consistent sample ensures comparability across specifications.

The baseline results confirm the "mechanical" nature of underwriting. A 10 percent increase in income is associated with a 0.7- to 0.8-percentage-point (pp) reduction in denial probability, while larger loan amounts—holding income constant—predictably increase the likelihood of rejection. Consistent with our descriptive findings, FHA loans carry a 4-pp "denial penalty" relative to conventional loans, while VA loans enjoy a 3-pp advantage. Notably, the inclusion of lender fixed effects causes the R^2 to jump from 0.10 to over 0.30, suggesting that *where* one applies is nearly as important as *what* one earns.

Table 13 presents the progressive addition of controls to isolate the racial gap. The raw Black-White gap of 14.6 pp (Column 1) is only partially explained by financial fundamentals. Controlling for income and loan amount reduces the gap to 12.3 pp (Column 2). Interestingly, adding loan type *increases* the gap to 13.9 pp (Column 3). This occurs because Black applicants' heavy reliance on FHA loans—which have higher baseline denial rates—was actually masking the true magnitude of the disparity in the conventional market.

Our preferred "within-lender" specification (Column 6) reveals a residual Black-White gap of 7.8 pp. This means that even among applicants at the same institution with identical incomes, loan amounts, and DTI ratios, Black applicants are nearly 8 percentage points more likely to be denied. This persistent "residual" gap motivates our deeper decomposition analysis.

4.2 Within-Lender Analysis and Sorting

A critical question is whether these gaps arise because minority applicants are treated differently within a bank, or because they "sort" into lenders with higher baseline rejection rates. By comparing applicants within the same institution, we can determine the extent to which lender composition drives aggregate disparities. Table 14 isolates this effect.

The inclusion of lender fixed effects reduces the Black-White gap from 13.9 pp to 7.8

Table 13: Determinants of Mortgage Denial, Home Purchase Applications, 2024

	(1)	(2)	(3)	(4)	(5)	(6)
Black	0.1460***	0.1226***	0.1388***	0.1105***	0.1207***	0.0780***
	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0007)	(0.0006)
Hispanic	0.0848***	0.0730***	0.0831***	0.0579***	0.0598***	0.0418***
	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0005)
Asian	-0.0201***	0.0455***	0.0339***	0.0289***	0.0238***	0.0208***
	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Log(Income)		✓	✓	✓	✓	✓
Log(Loan Amount)		✓	✓	✓	✓	✓
Loan Type			✓	✓	✓	✓
DTI				✓		
State FE					✓	
Lender FE						✓
Observations	2,844,927	2,844,927	2,844,927	2,844,927	2,821,396	2,829,925
R^2	0.022	0.094	0.102	0.189	0.107	0.333
White mean denial			0.117			

Notes: OLS estimates. Dependent variable is denial (=1 if denied, 0 if originated). White is the omitted reference category. Standard errors in parentheses. *** p<0.01. Sample restricted to home purchase applications.

Table 14: Within-Lender Racial Gaps, 2024

	No FE	Lender FE
Black	0.1385***	0.0779***
	(0.0007)	(0.0006)
Hispanic	0.0833***	0.0418***
	(0.0005)	(0.0005)
Asian	0.0340***	0.0207***
	(0.0008)	(0.0007)
Controls	✓	✓
Lender FE		✓
Observations	2,808,267	2,808,267
Lenders	–	1,445

Notes: Within-lender comparison. Sample restricted to lenders with 100+ applications.

pp and the Hispanic-White gap from 8.4 pp to 4.2 pp. This implies that approximately 50 percent of the observed racial disparity in the mortgage market is due to sorting—minority applicants are simply more likely to apply to "high-rejection" lenders (often non-banks). However, the remaining 50 percent exists *within* the same institution, pointing toward unobserved credit factors such as the FICO score or discretionary differences in underwriting.

4.3 Oaxaca-Blinder Decomposition

To precisely quantify how much of the denial gap is from "explained" by the variables in our data versus from "unexplained" residual factors, we employ the Oaxaca-Blinder decomposition:

$$\bar{Y}_A - \bar{Y}_B = \underbrace{(\bar{X}_A - \bar{X}_B)'\hat{\beta}_B}_{\text{Explained}} + \underbrace{\bar{X}_A'(\hat{\beta}_A - \hat{\beta}_B)}_{\text{Unexplained}}. \tag{4}$$

The "explained" component represents the portion of the gap attributable to differences in characteristics (e.g., lower average income or higher DTI). The "unexplained" component captures differences in the "returns" to those characteristics, often serving as a proxy for unobserved variables such as credit scores or, potentially, differential treatment. Table 15 presents a progressive Oaxaca-Blinder decomposition of the 2024 denial gaps, moving from basic financial fundamentals to a full underwriting specification.

In Panel A, income and loan amount differences (Column 1) explain approximately 30.7 percent of the 14.6-percentage-point denial gap for Black applicants. Notably, the addition of loan type controls in Column 2 actually reduces the explained share to 17.8 percent. This "suppression effect" confirms that Black applicants' heavy utilization of FHA products—which have higher baseline denial rates—was partially masking the underlying disparity in the conventional market. When DTI is included in our most-saturated specification (Column 3), the explained share rises to 41.1 percent, yet a staggering 58.9 percent of the gap (10.9 pp) remains unexplained by observable HMDA characteristics.

In Panel B, the results for Hispanic applicants are even more striking. Despite Hispanic applicants possessing financial profiles—specifically income and DTI ratios—that more closely resemble the White applicant pool, observable fundamentals explain almost none of the 8.5-percentage-point disparity. In our most-comprehensive specification, over 94 percent of the gap remains in the "unexplained" category. These results suggest that while the interest rate shock exerts a uniform pressure via the DTI channel, the residual barriers to mortgage access for Hispanic and Black households are largely driven by unobserved

Table 15: Oaxaca-Blinder Decomposition of Racial and Ethnic Denial Gaps, 2024

	(1) Basic	(2) +Loan Type	(3) +DTI
Panel A: Black-White Denial Gap			
Raw Gap	-0.1460	-0.1460	-0.1460
Endowments (Explained)	-0.0447	-0.0259	-0.0601
Coefficients (Unexplained)	-0.1255	-0.1344	-0.1092
% Explained	30.7%	17.8%	41.1%
Observations		2,106,210	
Panel B: Hispanic-White Denial Gap			
Raw Gap	-0.0848	-0.0848	-0.0848
Endowments (Explained)	-0.0023	-0.0019	-0.0051
Coefficients (Unexplained)	-0.0825	-0.0829	-0.0797
% Explained	2.7%	2.2%	6.0%
Observations		2,317,212	

Notes: This table presents the Oaxaca-Blinder threefold decomposition of mortgage denial gaps for the 2024 calendar year. *Basic* controls include log income and log loan amount. *+Loan Type* adds indicators for FHA, VA, and USDA loans. *+DTI* adds the applicant's debt-to-income ratio. "Endowments" represents the portion of the gap attributable to differences in observable characteristics, while "Coefficients" captures the unexplained residual.

factors—likely a combination of lower liquid wealth and thinner credit histories—that HMDA records are currently unable to capture.

Sensitivity to Unobservables. Because credit scores are the "missing link" in HMDA data, we use the Oster (2019) framework to test the robustness of our results. In Table 16 we calculate δ, the ratio of selection on unobservables to observables required to nullify the racial gap. Our estimates yield a δ of 0.37 with lender fixed effects.

Table 16: Oster (2019) Bounds: Sensitivity to Unobserved Selection, 2024

	Coefficient		δ	
	Uncontrolled	Controlled	Basic	Lender FE
Black–White	0.1460	0.1105	1.06	0.37
Hispanic–White	0.0848	0.0579	0.73	0.31
Asian–White	-0.0201	0.0289	-0.20	-0.16
R^2 (Uncontrolled)		0.0217		
R^2 (Controlled)		0.1893		
R^2_{max}		0.2461		

Notes: δ measures how much more important selection on unobservables (e.g., credit scores) would need to be relative to selection on observables to fully explain the racial gap. Values >1 indicate that unobservables would need to be more important than all observed controls combined. $R^2_{max} = 1.3 \times \tilde{R}^2$ following Oster (2019). "Uncontrolled" = race dummies only. "Controlled" = with income, loan amount, loan type, and DTI. "Lender FE" adds lender fixed effects.

This suggests that if unobserved factors (such as credit scores) are only one-third as influential as our observed controls (income, DTI, etc.), they could explain the gap. Given the predictive power of credit scores, this is a plausible threshold, suggesting that unobserved creditworthiness is a primary—though perhaps not exclusive—driver of the residual gap.

4.4 Interest Rate Channel: A Difference-in-Differences Approach

Having established the baseline gaps, we return to the "mechanical" DTI channel discussed in Section 3.1. To isolate the effect of rising rates from monetary policy and general economic shifts, we utilize a difference-in-differences (DiD) design centered on the 2022–2023 rate hikes. We compare "Near Threshold" applicants (DTI 40–55 percent) to "Safe" applicants (DTI < 30 percent).

The results in Table 17 show that the rate hike disproportionately harmed those near the DTI "cliff." However, when lender fixed effects are added (Column 4), the interaction

Table 17: Difference-in-Differences: Effect of Rate Hikes on Near-Threshold Applicants

	(1)	(2)	(3)	(4)
Near threshold (40–55% DTI)	0.0265***	0.0611***	0.0556***	0.0268***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Post-hike (2022–23)	0.0195***	0.0183***	0.0180***	0.0038***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Near threshold × Post-hike	-0.0121***	-0.0009**	0.0021***	0.0006*
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Controls		✓	✓	✓
State FE			✓	
Lender FE				✓
Observations	11,465,898	11,465,898	11,414,616	11,452,479
R^2	0.001	0.056	0.065	0.230
Pre-hike control mean	0.090			

Notes: Difference-in-differences estimates. "Near threshold" = applicants with DTI between 40% and 55%. Control group = applicants with DTI below 30%. "Post-hike" = 2022–2023 (federal funds rate above 4%). "Pre-hike" = 2020–2021 (near-zero rates). The interaction term captures the differential increase in denial rates for near-threshold applicants after rate increases. Standard errors in parentheses (heteroskedasticity-robust). *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

effect becomes marginally significant. Taken together, the results suggest that the rate-hike episode is associated with a large aggregate rise in denials, but it provides limited evidence of a large incremental tightening specifically at the DTI threshold once compositional differences are absorbed.

4.5 Algorithmic Underwriting and Lender Discretion

The information in HMDA allows investigating the "black box" of the underwriting decision. Mortgage approvals typically involve a two-stage process: An AUS—such as Fannie Mae's Desktop Underwriter or Freddie Mac's Loan Prospector—issues a baseline recommendation, followed by a human underwriter's final sign-off. By conditioning on the AUS recommendation, we can isolate the role of lender discretion from algorithmic risk assessment.

Table 18: AUS Recommendations and Denial Outcomes by Race, 2024

Panel A: Denial Rates by AUS Recommendation and Race

AUS Recommendation	White	Black	Hispanic	Asian
Approve	5.3	14.0	11.0	8.1
Refer/Caution	9.1	17.3	13.0	13.6

Panel B: Racial Gaps Among AUS-Approved Applicants

	(1) Raw gap	(2) Controls	(3) Lender FE
Black	0.0858***	0.0719***	0.0658***
	(0.0007)	(0.0007)	(0.0007)
Hispanic	0.0562***	0.0416***	0.0347***
	(0.0005)	(0.0005)	(0.0005)
Observations	2,000,454	2,000,454	1,988,273

Notes: Panel A shows denial rates conditional on AUS recommendation. Panel B restricts to applicants receiving an AUS "Approve" recommendation and estimates racial gaps in denial. These gaps capture lender discretion beyond the algorithmic recommendation. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

The findings in Table 18 reveal a persistent divergence between algorithmic recommendations and final outcomes. As shown in Panel A, even among applicants who received an "Approve" recommendation, the final denial rate for Black applicants (14.0 percent) is nearly triple that of White applicants (5.3 percent). Hispanic and Asian applicants also face elevated conditional denial rates of 11.0 percent and 8.1 percent, respectively. This disparity persists among "Refer/Caution" applications, where the algorithm flags risk but does not mandate a rejection. In this category, Black applicants face a 17.3 percent rejection rate compared with 9.1 percent for White applicants, suggesting that human underwriters are less likely to grant the benefit of the doubt to minority borrowers when the algorithm is uncertain.

Panel B quantifies this "discretionary gap" in a regression framework restricted exclusively to AUS-approved applicants. The raw Black-White gap of 8.6 percentage points (Column 1) is only marginally attenuated by the inclusion of financial controls and lender fixed effects. In our preferred within-lender specification (Column 3), Black and Hispanic applicants remain 6.6 pp and 3.5 pp more likely to be denied than White applicants, respectively, despite receiving the same algorithmic approval at the same institution.

These findings contribute to a growing literature on the role of technology in credit access. Our results align with Bartlett et al. (2022), who find that while algorithmic decision-making can reduce racial gaps in interest rate pricing, it does not eliminate them. We document a similar pattern at the extensive margin: Substantial differences in denial rates persist even conditional on identical algorithmic recommendations.

This suggests that the "human element" of underwriting—operating through the evaluation of documentation quality, the stringency of income verification, or the assessment of unobserved credit depth—introduces a secondary layer of disparity that algorithms do not fully mitigate. These results are consistent with the evidence in Bhutta et al. (2022) that human-in-the-loop systems can maintain or even amplify disparities even when automated systems suggest a baseline level of creditworthiness. Whether these patterns reflect legitimate underwriting factors omitted from the AUS, differential applicant behavior during the underwriting process, or unobserved credit history remains an open question that merits further research with more granular data.

5 Conclusion

The transition from a low-rate environment to a period of aggressive monetary tightening has fundamentally recalibrated the barriers to entry in the American mortgage market. By analyzing over 30 million applications from 2018 to 2024, we document how the "mechanical" channel of rising interest rates interacts with pre-existing structural disparities to reshape the American homeownership landscape. Our findings suggest that the mortgage market does not merely "cool" in response to higher rates; it hits a nonlinear threshold—the 50% DTI cliff—that disproportionately excludes vulnerable populations.

The core of our analysis reveals that the 2022–2023 interest rate shock acted as a massive aggregate barrier, pushing a significant share of the applicant pool over binding DTI thresholds. Our counterfactual analysis confirms that the rise in the cost of capital, rather than a degradation in applicant quality, was the primary driver of the spike in aggregate denial rates. Within this cycle, racial disparities remained remarkably persistent. Even after controlling for income, loan type, and lender-specific effects, Black and Hispanic applicants face denial rates 4 to 8 percentage points higher than their White counterparts.

This bifurcated result suggests that the credit gap is driven by two distinct mechanisms: approximately half is attributable to lender sorting, as minority applicants are more likely to apply to high-rejection non-bank institutions, while the remainder persists as a "discretionary gap" within the same institutions. Our investigation into algorithmic underwriting confirms this, revealing that disparities persist even when automated systems issue an "Approve" recommendation. This suggests that human discretion and the evaluation of "soft information" continue to play a decisive role in the final credit decision, effectively acting as a secondary filter that algorithms do not fully mitigate.

We must candidly acknowledge a central limitation inherent in public HMDA data: the absence of applicant credit scores (FICO). Our sensitivity analysis suggests that if unobservable factors like credit history and liquid wealth are even moderately correlated with race, they could account for much of the "unexplained" residual gap we document. However, we argue that this unexplained portion should not be dismissed as a mere statistical artifact. Instead, it represents the structural residue of historical inequality. While the DTI channel acts as a visible, flow-based constraint on affordability, the unobserved credit score serves as a latent, stock-based barrier. In a market where credit history is a primary gatekeeper, the generational gap in wealth ensures that minority households remain more sensitive to macro-shocks; when interest rates tighten the flow constraint, they effectively amplify the impact of these latent stock-based disparities.

These findings carry significant implications for the future of housing policy. First, central banks should account for the nonlinear "cliff effects" of rate hikes; the transmission of monetary policy is not demographic-neutral, as it hits lower-wealth households first and hardest. Second, the prevalence of credit history as a primary denial reason suggests a need to expand underwriting criteria to include "cash-flow" metrics, such as rental and utility payment history, to better evaluate "thin-file" applicants. Third, to facilitate more precise fair-lending research, regulatory bodies should consider including anonymized credit score ranges in public HMDA releases to distinguish between risk-based pricing and systemic barriers.

Our finding that the 43% QM threshold is non-binding while the 50% DTI mark serves as the effective underwriting boundary has implications for both existing research and policy. **?** study the effects of the QM rule's 43% DTI cap on nonconforming loans and find significant reductions in credit supply in that market segment. Our results are consistent with theirs: the 43% threshold can bind in the nonconforming market, where the GSE patch did not apply. However, in the conforming market—which constitutes the vast majority of mortgage originations—our data show that 43% has limited practical relevance. This distinction matters for interpreting the broader literature: studies finding modest aggregate effects of the QM rule may be detecting a real phenomenon rather than a null result, but one confined to a specific market segment.

The policy implications are concrete. In 2021, the CFPB replaced the 43% DTI-based QM definition with a price-based standard, motivated explicitly by concerns that the DTI cap constrained credit access. Our evidence suggests that this reform addressed a threshold that was largely non-binding in practice, while the de facto 50% cutoff—where denial rates jump by 15–17 percentage points—has received no comparable regulatory attention. This misalignment has distributional consequences: Black applicants in our sample have a mean DTI of 44.9%, placing them past the 43% threshold but below the 50% cliff. Policy interventions aimed at expanding credit access may be more effective if directed at the margin where underwriting constraints actually bind.

Ultimately, addressing the persistent disparities in the American mortgage market may require a transition toward more granular underwriting models that supplement traditional DTI-centric thresholds with a broader array of creditworthiness indicators. While the 2018–2024 period demonstrated the structural resilience of the U.S. housing finance system, it also highlighted the sensitivity of credit access to macroeconomic shifts. Ensuring that the path to homeownership is determined by a precise assessment of an applicant's future repayment capacity, while mitigating the compounding effects of historical wealth disparities, remains a central objective for the next generation of housing policy.

References

Bartlett, Robert, Adair Morse, Richard Stanton, and Nancy Wallace, "Consumer-Lending Discrimination in the FinTech Era," *Journal of Financial Economics*, 2022, *143* (1), 30–56.

Bayer, Patrick, Fernando Ferreira, and Stephen L. Ross, "What Drives Racial and Ethnic Differences in High-Cost Mortgages? The Role of High-Risk Lenders," *Review of Financial Studies*, 2018, *31* (1), 175–205.

Bhutta, Neil, Aurel Hizmo, and Daniel Ringo, "How Much Does Racial Bias Affect Mortgage Lending? Evidence from Human and Algorithmic Credit Decisions," Working Paper, Federal Reserve Board 2022.

Blinder, Alan S., "Wage Discrimination: Reduced Form and Structural Estimates," *Journal of Human Resources*, 1973, *8* (4), 436–455.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru, "Fintech, Bigtech, and the Evolution of U.S. Consumer Lending," *Journal of Financial Economics*, 2018, *130* (3), 471–502.

Fuster, Andreas, Matthew Plosser, Philipp Schnabl, and James Vickery, "The Role of Technology in Mortgage Lending," *Review of Financial Studies*, 2022, *32* (5), 1854–1899.

Kuhn, Moritz, Moritz Schularick, and Ulrike I. Steins, "Income and Wealth Inequality in America, 1949–2016," *Journal of Political Economy*, 2020, *128* (9), 3469–3519.

Munnell, Alicia H., Geoffrey M. B. Tootell, Lynn E. Browne, and James McEneaney, "Mortgage Lending in Boston: Interpreting HMDA Data," *American Economic Review*, 1996, *86* (1), 25–53.

Oaxaca, Ronald, "Male-Female Wage Differentials in Urban Labor Markets," *International Economic Review*, 1973, *14* (3), 693–709.

Oster, Emily, "Unobservable Selection and Coefficient Stability: Theory and Evidence," *Journal of Business & Economic Statistics*, 2019, *37* (2), 187–204.

Ross, Stephen L. and John Yinger, *The Color of Credit: Mortgage Discrimination, Research Methodology, and Fair-Lending Enforcement*, Cambridge, MA: MIT Press, 2002.

A Robustness and Supplemental Results

A.1 Robustness Checks

Our main finding—large racial gaps persisting after extensive controls—faces several identification threats. We organize robustness checks around these concerns.

Geographic sorting. If minority applicants concentrate in regions with tighter credit markets, geographic confounds could inflate estimated gaps. Adding state fixed effects (Table A.1) reduces the Black-White gap from 13.9 to 12.1 percentage points. Geographic sorting thus explains roughly 13 percent of the baseline gap. The remaining 12.1-percentage-point within-state gap reflects disparities operating within specific geographic markets rather than cross-state variation.

Loan product composition. FHA loans serve a disproportionately minority population and have higher denial rates. Excluding FHA loans *increases* the Black-White gap from 13.9 to 15.2 percentage points. This pattern confirms that FHA, despite its higher denial rates, partially equalizes access by serving applicants who would face even larger gaps in conventional markets. This implies our baseline estimates are conservative: Absent the FHA program, racial disparities in the private market would be substantially larger.

Functional form. The linear probability model assumes constant marginal effects. Table A.2 reports logit estimates; average marginal effects are nearly identical to LPM coefficients (13.6 vs. 13.9 percentage points). This confirms our findings are not artifacts of functional form selection.

Covariate overlap. Table A.3 examines covariate distributions by race. While Black applicants have lower mean incomes and higher FHA usage, substantial overlap remains across all covariates, ensuring our regressions compare applicants within the common support.

Table A.1: Robustness Checks: Black-White Denial Gap

Specification	Black Coef.	Std. Error	N
Baseline	0.1388***	(0.0007)	2,844,927
Excl. FHA	0.1517***	(0.0008)	2,258,976
Income>$100K	0.0888***	(0.0009)	1,485,085
Income<$75K	0.1843***	(0.0014)	829,180
State FE	0.1207***	(0.0007)	2,821,396

Table A.2: Logit Model: Determinants of Mortgage Denial, 2024

	Coefficient	Marginal Effect
Black	0.9914***	0.1228
	(0.0053)	
Hispanic	0.6755***	0.0836
	(0.0045)	
Asian	0.2984***	0.0369
	(0.0078)	
Controls	Log income, Log loan, FHA, VA	
Observations	2,844,927	

Notes: Logit model. Marginal effects evaluated at mean predicted probability.

Table A.3: Characteristics of Originated vs. Denied Applications, 2024

	Originated	Denied	Difference
N	2,965,386	526,127	
Income (mean, $000s)	151	100	51
Income (median, $000s)	111	70	41
Loan amount ($000s)	382761	263071	119690
DTI (%)	39.5	48.7	-9.1
FHA share (%)	20.4	17.2	3.2
Minority share (%)	21.1	36.1	-15.0

Notes: Minority includes Black and Hispanic applicants.

A.2 Heterogeneity and Interpretation

Income heterogeneity. Gaps vary across the income distribution. For applicants below \$75,000, the Black-White gap is 18.4 percentage points; above \$100,000, it falls to 8.9 percentage points. We consider three potential mechanisms: (i) Discrimination may be more prevalent against lower-income minorities; (ii) racial gaps in unobserved credit history may be more dispersed at lower income levels; or (iii) higher-income minority applicants may be positively selected on unobservables compared with observationally similar White applicants.

Macroeconomic regimes. Table A.4 shows the Black-White gap widened from 11.4 percentage points pre-COVID to 13.7 post-rate-hike. The further widening post-2022 gap is consistent with our DTI channel analysis: As rates rose, minority applicants—more likely to be near underwriting margins—were disproportionately affected by the DTI "cliff."

Table A.4: Racial Gaps by Time Period

	Pre-COVID (2018-19)	COVID (2020-21)	Post-Rate-Hike (2022+)
Black	0.1139	0.1272	0.1365
	(0.0004)	(0.0004)	(0.0004)
Hispanic	0.0648	0.0686	0.0826
	(0.0004)	(0.0003)	(0.0003)
Controls	Log income, Log loan, FHA		
N	7,504,830	8,513,032	9,380,262

Notes: OLS regression coefficients by period. White is reference category.

Omitted creditworthiness and Wealth. The absence of FICO scores and liquid asset data remains a central limitation. Oster (2019) bounds suggest unobserved factors would need to be of similar importance to observed factors to account for the gap. Given the predictive power of credit scores and the documented racial wealth gap Kuhn et al. (2020), these factors likely explain a significant share of the residual gap. However, the persistence of the gap among high-income applicants suggests unobservables alone cannot fully account for the disparity.

Table A.5: Denial Rates by Loan Type (%), 2018–2024

Loan Type	2018	2019	2020	2021	2022	2023	2024
Conventional	13.8	13.1	13.7	12.6	14.6	17.1	16.6
FHA	14.4	12.8	14.6	13.0	15.0	14.2	13.0
USDA/FSA	14.6	13.1	10.7	10.5	13.9	14.5	13.1
VA	10.2	9.0	9.0	8.3	9.4	9.5	8.5

Table A.6: Denial Rates by Loan Purpose (%), 2018–2024

Loan Purpose	2018	2019	2020	2021	2022	2023	2024
Cash-out refinancing	30.7	24.6	17.2	17.1	26.4	33.3	34.0
Home improvement	44.1	44.7	40.7	37.9	37.1	41.1	39.1
Home purchase	13.5	12.5	13.2	12.0	14.0	15.6	15.0
Other purpose	46.7	46.9	43.2	38.9	41.6	46.0	44.4
Refinancing	29.0	18.8	13.9	14.7	23.4	27.9	24.2

Table A.7: Denial Rates by Occupancy Type (%), Home Purchase Loans, 2018–2024

Occupancy Type	2018	2019	2020	2021	2022	2023	2024
Owner-occupied	13.8	12.8	13.4	12.3	14.4	16.0	15.3
Second residence	11.4	10.5	10.2	10.1	12.3	13.7	12.7
Investment property	10.9	10.4	12.1	9.9	11.2	12.8	13.4

Notes: Denial rates for home purchase mortgage applications by property occupancy type.
Main analysis sample is restricted to owner-occupied (principal residence) loans.

Table A.8: Denial Rates by Loan-to-Value Ratio (%), 2018–2024

LTV Ratio	2018	2019	2020	2021	2022	2023	2024
0-60%	8.8	8.0	8.0	7.2	7.6	7.7	8.0
60-80%	7.5	6.9	6.9	6.2	7.4	7.7	7.4
80-90%	9.7	9.2	9.0	8.5	10.1	10.4	9.7
90-95%	9.3	8.5	8.8	8.3	10.3	12.4	11.5
95-97%	12.3	10.8	12.8	11.0	12.6	12.5	11.7
>97%	14.1	13.0	13.3	13.5	16.0	16.5	15.6

Table A.9: Primary Denial Reasons (%), 2018–2024

Reason	2018	2019	2020	2021	2022	2023	2024
Collateral	12.0	11.1	9.0	10.9	9.8	9.5	9.9
Credit application incomplete	9.0	8.1	8.0	10.3	8.6	6.0	6.0
Credit history	28.7	29.5	31.8	27.9	27.5	30.1	28.5
Debt-to-income ratio	29.2	30.0	30.7	30.7	34.0	35.2	35.0
Employment history	2.8	2.9	3.2	2.9	2.8	2.5	2.0
Insufficient cash	4.3	4.3	3.4	3.4	4.2	4.5	5.3
Mortgage insurance denied	0.1	0.1	0.1	0.1	0.1	0.0	0.0
Other	6.9	7.6	7.6	7.6	6.9	5.6	5.9
Unverifiable information	7.0	6.3	6.1	6.3	6.2	6.5	7.2

Table A.10: Primary Denial Reasons by Race/Ethnicity (%), 2024

Denial Reason	White	Black	Hispanic	Asian
Collateral	10.9	6.6	9.5	13.3
Credit application incomplete	6.4	4.2	4.5	7.9
Credit history	30.5	36.6	25.7	8.1
Debt-to-income ratio	32.0	34.3	38.6	43.9
Employment history	2.0	1.7	2.2	3.0
Insufficient cash	5.0	5.2	5.6	6.6
Mortgage insurance denied	0.0	0.0	0.0	0.0
Other	5.7	4.7	6.1	9.1
Unverifiable information	7.4	6.6	7.6	8.0

Notes: Share of denied applications citing each reason as primary denial reason.

Table A.11: Applicant Pool Composition Over Time

Year	N	Income	Loan Amt	FHA%	Black%	Hispanic%	Asian%
2018	4,311,338	77	260837	20.0	8.2	12.0	6.1
2019	4,435,972	78	274037	20.2	8.6	12.7	5.8
2020	4,910,009	79	292243	19.7	9.2	13.3	5.6
2021	5,198,559	83	334435	17.6	9.7	13.9	7.3
2022	4,294,776	94	359321	16.6	10.1	14.2	7.8
2023	3,492,153	100	349457	19.4	10.2	15.7	7.7
2024	3,491,513	105	364725	19.9	9.7	16.7	8.0

Table A.12: Denial Rates by Race and COVID Period (%)

Race/Ethnicity	Pre-COVID (2018–2019)	COVID (2020–2021)	Post-COVID (2022+)
White	10.9	10.3	12.0
Black	23.8	24.4	26.8
Hispanic	18.2	17.7	20.8
Asian	10.7	9.5	10.5

A.3 Supplemental Tables and Figures

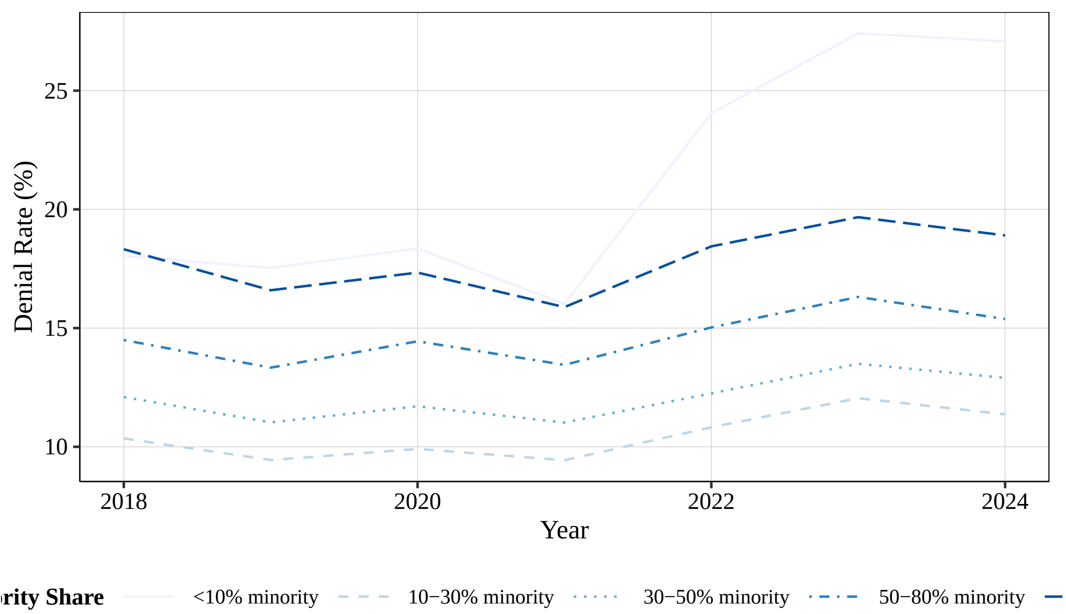

Figure A.1: Denial Rates by Census Tract Minority Share

Notes: Denial rates by tract minority population share (percentage non-White).

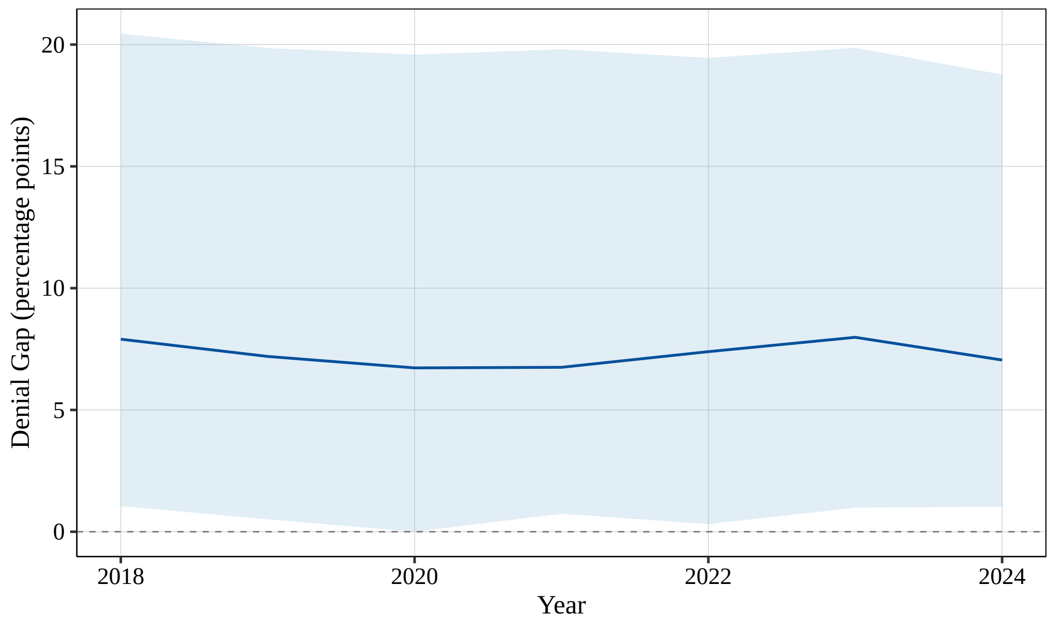

Figure A.2: Distribution of Within-Lender Racial Gaps

Notes: Within-lender Black-White denial gaps across lenders with ≥100 applications.

B DTI Missingness and Sample Sensitivity

Conditioning on non-missing DTI raises sample selection concerns. Missingness is concentrated among small lenders: Large lenders report DTI for more than 99 percent of applications, while small lenders report it for roughly half. Missingness varies only modestly across racial groups (Figure B.1). Regression estimates (Table B.2) are similar across the full and DTI-available samples, suggesting selection bias is limited.

Table B.1: Characteristics by DTI Reporting Status

Panel A: Sample Characteristics		
	DTI Available	DTI Missing
Observations	24,690,694	775,573
Denial rate (%)	12.9	23.8
Mean income ($000s)	115	132
Mean loan amount ($000s)	309441	245401
FHA share (%)	19.6	8.3
Black share (%)	9.8	6.6
Hispanic share (%)	14.6	9.0
Panel B: DTI Reporting Rate by Race (%)		
	All Years	Latest Year
White	96.2	96.3
Black	97.4	98.0
Hispanic	97.7	98.0
Asian	97.1	97.3
Panel C: DTI Reporting Rate by Lender Size (%)		
Large (10K+)	99.1	
Medium (1K-10K)	94.4	
Small (100-1K)	50.0	
Very small (<100)	38.2	

Notes: Comparison of sample characteristics for applications with and without reported debt-to-income ratios. DTI missingness is non-random: It correlates with lender size, race, and loan type. Panel B shows the share of applications with reported DTI by race. Panel C shows reporting rates by lender size.

Table B.2: Sensitivity of Racial Gaps to DTI Sample Restriction, 2024

	(1) Full No DTI	(2) DTI Avail. No DTI	(3) DTI Missing No DTI	(4) DTI Avail. + DTI	(5) Full Lender FE
Black	0.1418***	0.1388***	0.3252***	0.1105***	0.0791***
	(0.0007)	(0.0007)	(0.0059)	(0.0006)	(0.0006)
Hispanic	0.0851***	0.0831***	0.2024***	0.0579***	0.0424***
	(0.0005)	(0.0005)	(0.0044)	(0.0005)	(0.0005)
Asian	0.0349***	0.0339***	0.0863***	0.0289***	0.0215***
	(0.0007)	(0.0007)	(0.0062)	(0.0007)	(0.0007)
Controls	✓	✓	✓	✓	✓
DTI				✓	
Lender FE					✓
Observations	2,926,496	2,844,927	81,569	2,844,927	2,885,776
R^2	0.104	0.102	0.142	0.189	0.335

Notes: OLS estimates of racial denial gaps under alternative sample restrictions. Columns (1)–(3) use the same specification without DTI control, varying only the sample: full sample (column 1), DTI-available subsample (column 2), and DTI-missing subsample (column 3). Column (4) adds DTI as a control on the DTI-available subsample. Column (5) adds lender fixed effects on the full sample. Comparing columns (1) and (2) tests whether restricting to DTI-available observations changes racial gap estimates; comparing (2) and (4) shows the effect of controlling for DTI. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

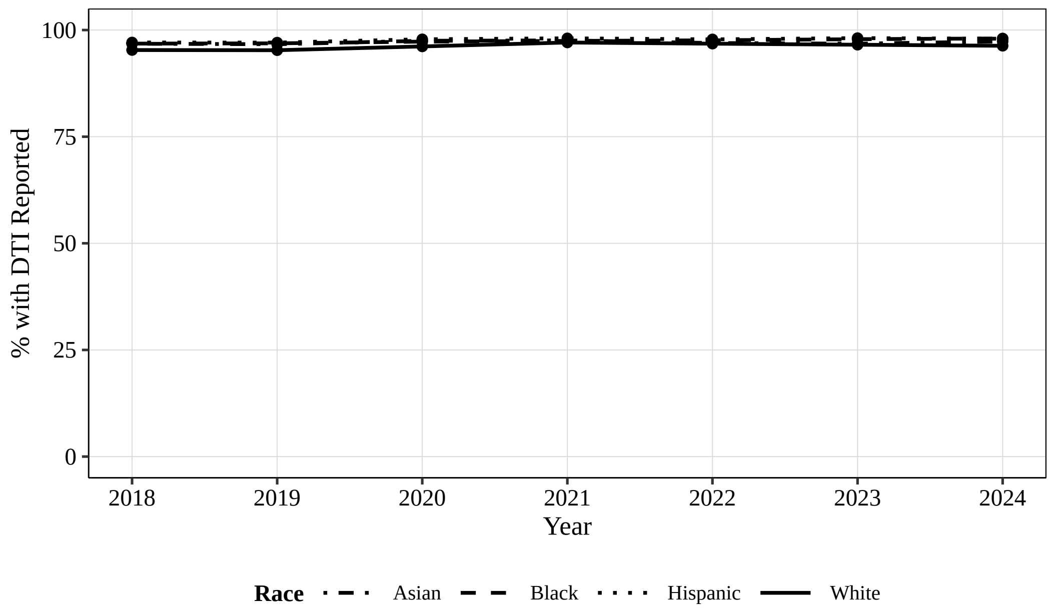

Figure B.1: DTI Reporting Rates by Race, 2018–2024

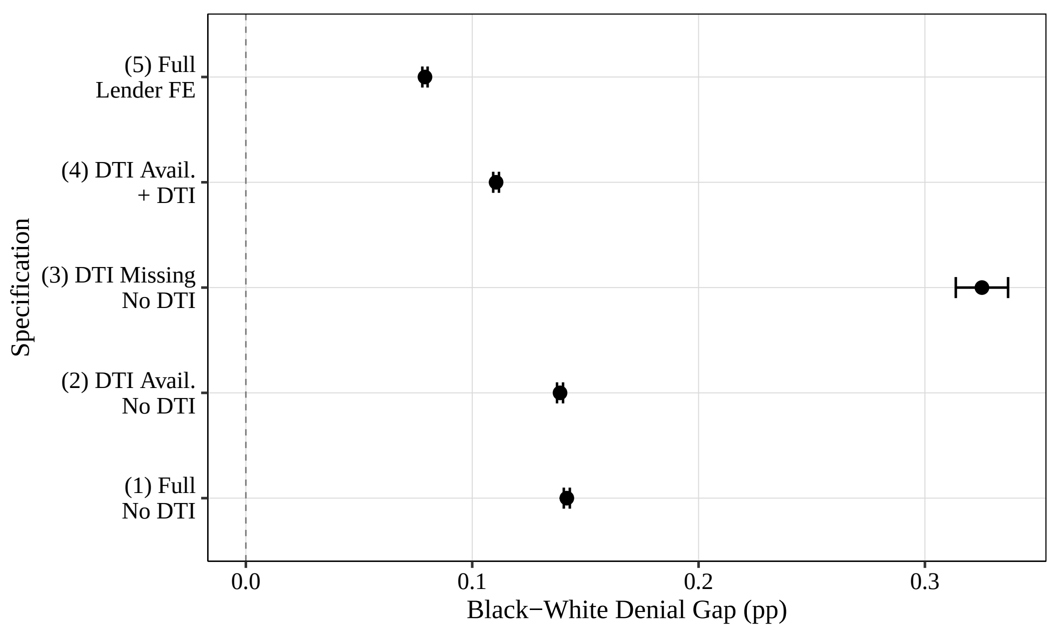

Figure B.2: Sensitivity of Black-White Gap to Sample and Specification

C DTI Threshold Analysis

Bunching analysis. Table C.1 tests for strategic adjustment around thresholds. At the 43 percent QM threshold, we find no evidence of bunching below the cutoff. At the 50 percent threshold, categorical data limit the precision of density tests.

Regression discontinuity analysis. Table C.2 estimates local polynomial regressions. At the 43 percent threshold, the estimated discontinuity is economically negligible (0.2–0.4 pp). At the 50 percent threshold, denial rates jump significantly by 15 to 17 percentage points (Figure C.2). These results suggest 50 percent is the effective underwriting cutoff in practice.

Table C.1: Application Density Around DTI Thresholds, 2024

Threshold	Window	N Below	N Above	Below/Above	Excess Mass (%)
43%	±3pp	380,063	400,152	0.95	-2.6^{***}
50%	±3pp	482,642	0	Inf	100.0^{***}
43%	±5pp	603,902	658,689	0.92	-4.3^{***}
50%	±5pp	734,261	0	Inf	100.0^{***}

Notes: Counts of applications in symmetric windows around each DTI threshold. "Excess mass" measures the percentage deviation of the below-threshold share from 50%, the expected share under a locally uniform distribution. Significance from two-sided binomial test. Bunching below a threshold indicates lenders or applicants adjusting to stay below. *** p<0.01, ** p<0.05, * p<0.10.

Table C.2: Discontinuity Tests at DTI Thresholds, 2024

	43% (QM) Threshold		50% Threshold	
	Linear	Quadratic	Linear	Quadratic
Jump at threshold	0.0021^{***}	0.0044^{***}	0.1508^{***}	0.1682^{***}
	(0.0007)	(0.0009)	(0.0011)	(0.0037)
Slope (below)	-0.0004	-0.0018	0.0006	-0.0013
Bandwidth	±10pp		±10pp	
N (below)	1,280,957		1,389,557	
N (above)	1,009,494		380,930	

Notes: Local linear and quadratic regression discontinuity estimates of the jump in denial probability at each DTI threshold. "Jump at threshold" is the coefficient on an indicator for being above the threshold, with running variable (DTI − threshold) allowed to have different slopes on each side. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

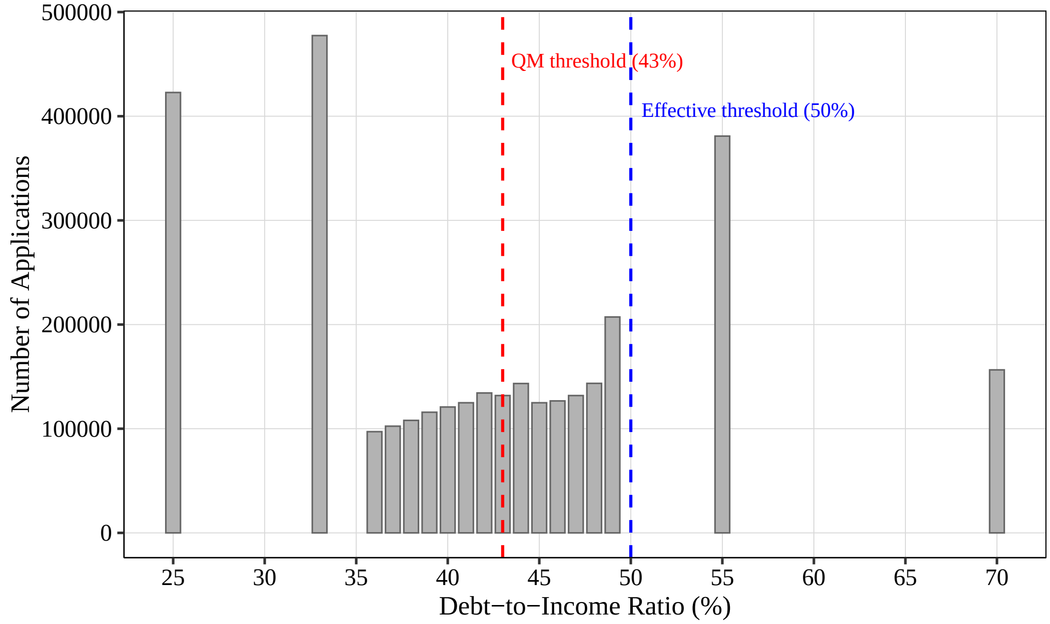

Figure C.1: Application Density Around DTI Thresholds

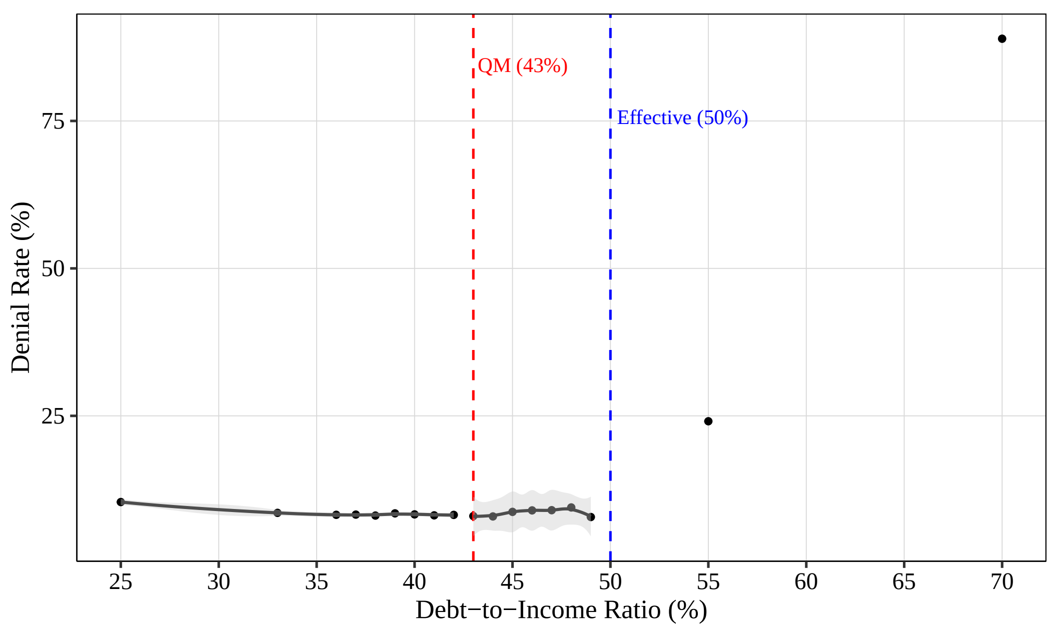

Figure C.2: Denial Rates Around DTI Thresholds