Estimating Racial Disparities in Mortgage Underwriting and Pricing:

Evidence from National HMDA Data (2020)*

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Abstract

Mortgage credit is central to homeownership and wealth accumulation, so disparities in access or borrowing terms can contribute to persistent racial wealth gaps. Using the 2020 Home Mortgage Disclosure Act (HMDA) data, sampling conventional loan applications, this paper asks whether similarly situated borrowers experience different mortgage approval outcomes and interest rate pricing by race and ethnicity. I estimate linear probability models for approval and OLS regressions for interest rates with metropolitan-area fixed effects and then metropolitan-area and lender fixed effects, comparing borrowers within the same market and within the same lenging institution. Conditional on observables, non-Hispanic Black and Hispanic applicants are 7.4 and 3.2 p.p. less likely to be approved than non-Hispanic White applicants within MSAs; these gaps shrink to 5.7 and 2.8 p.p within lender. For pricing, non-Hispanic Black borrowers pay 7.9 b.p. more than non-Hispanic White borrowers within MSAs and 4.7 b.p. more within lender fixed effects, while the Hispanic pricing gap becomes statistically indistinguishable from zero once lender effects are included. These estimates capture conditional disparities rather than definitive evidence of discrimination, given unobserved underwriting factors and selection into origination, and contribute updated within-market and within-lender evidence on both access to and terms of mortgage credit.

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1 Introduction

Homeownership is a primary vehicle for wealth accumulation for many American households, and mortgage markets shape who can enter homeownership and on what terms. Approval decisions matter because a denial can delay a purchase, constrain residential choice, and prolong time in rental housing. The cost of credit matters as well. Even modest differences in mortgage interest rates can translate into meaningful gaps in monthly payments and total interest paid, with implications for disposable income, refinancing opportunities, and financial resilience. Given persistent racial gaps in wealth and homeownership, understanding whether similarly situated borrowers experience systematically different mortgage outcomes by race and ethnicity is central to debates about economic opportunity and the effectiveness of fair-lending protections.

This paper studies racial and ethnic differences in mortgage outcomes using data from the 2020 Home Mortgage Disclosure Act (HMDA). I focus on three questions. First, conditional on observed borrower, loan, and neighborhood characteristics, do approval probabilities differ by race and ethnicity among applications with final dispositions? Second, among originated loans, do contract interest rates differ by race and ethnicity after conditioning on the same observables? Third, how much of any gap reflects sorting across lenders with different underwriting and pricing practices, versus differences that persist within the same lender? HMDA is well suited to this analysis because it provides standardized, loan-level reporting across most lenders and metropolitan areas. At the same time, HMDA is not a full underwriting file. It does not include key determinants of credit decisions such as credit scores, liquid assets, or consistently measured points and fees across all products. For that reason, the estimates should be interpreted as conditional disparities based on HMDA-observed variables, not as conclusive evidence of discrimination.

To answer these questions, I construct a clean mortgage sample from the 2020 HMDA file. The analysis focuses on conventional, first-lien, owner-occupied applications for one- to four-unit properties, excluding home equity lines of credit, reverse mortgages, and business-purpose loans. I estimate linear probability models for approval and OLS models for contract rates with race and ethnicity indicators and a standard set of underwriting controls. The specifications include metropolitan-area fixed effects and then add lender fixed effects to tighten the comparison from within-market to within-lender differences. Standard errors are clustered at the lender level.

The results indicate sizable conditional gaps in approval and smaller, though still economically meaningful, differences in pricing. Within metropolitan areas, non-Hispanic Black and Hispanic applicants are 7.4 and 3.2 percentage points less likely to be approved than comparable non-Hispanic White applicants. Within the same lender, these gaps narrow to 5.7 and 2.8 percentage points. In pricing, non-Hispanic Black borrowers pay 7.9 basis points more than non-Hispanic White borrowers within MSAs and 4.7 basis points more within lenders. The Hispanic pricing difference becomes statistically indistinguishable from zero once lender fixed effects are included, while non-Hispanic Asian borrowers receive materially lower rates in both specifications. The attenuation of several estimates after adding lender fixed effects is consistent with borrower sorting across institutions, but gaps for non-Hispanic Black borrowers remain in both approval and pricing even within lenders after conditioning on observables.

This paper contributes in three ways. First, it examines disparities on both the access margin (approval) and the terms margin (pricing). Second, it combines within-market and within-lender comparisons in a large national dataset, helping separate local market factors from lender-specific practices and sorting. Third, it provides a transparent and replicable approach to constructing underwriting proxies from publicly available HMDA variables.

2 Literature Review

A large empirical literature documents racial and ethnic differences in mortgage credit outcomes, while emphasizing that the interpretation of "residual" gaps depends on which underwriting inputs and pricing components are observed. A canonical reference is the Boston Fed study, which augments HMDA-style records for the Boston market with richer applicant and loan information and still finds higher denial rates for Black and Hispanic applicants than for observably similar White applicants (Munnell et al., 1996). At the same time, subsequent debates over the Boston Fed evidence and related reviews in the fair-lending literature highlight a durable methodological lesson: conditional gaps in application or pricing regressions are not, by themselves, definitive evidence of disparate treatment because they may reflect unobserved risk, product choice, or other channels that are not captured in the data.

A second strand uses confidential or linked application data with stronger measures of borrower risk and lender decision inputs. A recent contribution is Bhutta, Hizmo, and Ringo (2022; revised 2024), which combines confidential mortgage applications with recommendations from race-blind government automated underwriting systems (AUS). They show that differences in observable risk explain a large share of approval disparities and use AUS outcomes to benchmark how much "excess" denial remains after conditioning on detailed underwriting information, underscoring both the value of richer risk controls and the limits of public HMDA for causal attribution (Bhutta, Hizmo, and Ringo, 2022; revised 2024).

Related work leverages the expanded post-2018 HMDA reporting collected by regulators to incorporate additional underwriting and pricing fields. For example, Popick (2022) highlights that newer HMDA reporting enables analysis of multiple dimensions of credit risk and mortgage pricing jointly, including richer risk factors and components such as interest rates and discount points. This line of work reinforces that even with expanded observables, key drivers of lender decisions can remain hard to observe in public files, so HMDA-based estimates should be interpreted as conditional on available proxies rather than on the full underwriting information set (Popick, 2022).

A parallel literature studies racial and ethnic differences in mortgage pricing and stresses that "price" is multidimensional. Bartlett et al. document interest-rate differences for Black and Hispanic borrowers in the conforming market and study how these patterns differ across traditional and FinTech originators (Bartlett et al., 2019; published 2022). Complementing rate-only analyses, Bhutta and Hizmo (2021) show that average rate differences can be offset by differences in discount points, and they provide evidence consistent with borrowers sorting to different points on a common rate–points schedule rather than receiving different schedules (Bhutta and Hizmo, 2021). Building on this menu perspective, Zhang and Willen (2021) formalize how standard regressions can mislead when borrowers choose among rate–points bundles and propose methods aimed at comparing menus more directly across groups (Zhang and Willen, 2021). Evidence on intermediaries further underscores the importance of channels: Ambrose, Conklin, and Lopez (2021) find that minority borrowers pay higher fees than similarly qualified White borrowers even when borrowing through the same broker, and that the premium varies with broker race (Ambrose, Conklin, and Lopez, 2021).

Beyond approvals and contract pricing, complementary studies document disparities at other stages of the lending process. Paired-testing audits at the pre-application stage find differential information provision and assistance to minority homebuyers in lender interactions (Turner et al., 2002; Ross et al., 2008). More recently, Wei and Zhao (2022) show that racial gaps can also appear in mortgage processing times, suggesting that disparities may arise in operational frictions even conditional on loan and borrower characteristics (Wei and Zhao, 2022).

Methodologically, these strands map into three common research designs: (i) observational regressions using HMDA-style coverage and controls; (ii) linked or confidential data that include credit scores, AUS recommendations, and other underwriting inputs; and (iii) audit-style designs that more directly test for differential treatment but at smaller scale (Turner et al., 2002; Bhutta, Hizmo, and Ringo, 2022). Within HMDA-based work, fixed effects are widely used as a diagnostic for mechanisms. Market fixed effects compare borrowers within the same local environment, while adding lender fixed effects probes whether gaps primarily reflect sorting across institutions with different underwriting and pricing policies or persist within the same lender (Bhutta and Hizmo, 2021; Bartlett et al., 2019).

This paper builds on that framework using the public 2020 HMDA data. It estimates conditional racial and ethnic disparities in approval and contract-rate outcomes in a conventional, first-lien, owner-occupied sample, and it compares specifications with metropolitan-area fixed effects to specifications that add lender fixed effects. Persistence under lender fixed effects is interpreted as evidence that across-lender sorting is not the sole driver of observed gaps, while recognizing that public HMDA omits major underwriting inputs and that pricing results are observed only for originated loans (Bhutta and Hizmo, 2021; Zhang and Willen, 2021; Popick, 2022).

3 Data and Methodology

Data

The Home Mortgage Disclosure Act (HMDA) was enacted in 1975 to increase transparency in U.S. mortgage markets and to support enforcement of fair-lending laws. Under HMDA, most depository institutions and nonbank mortgage companies are required to report standardized information on each mortgage application they receive, including the borrower's demographic characteristics, basic underwriting proxies, and key loan features. These data are collected by regulators and released annually as a loan-level public use file, with each cross-section corresponding to applications and originations in a given calendar year. The public HMDA files are designed to allow regulators, researchers, and the public to assess whether lenders are serving the housing needs of their communities, to identify potentially discriminatory patterns in access to credit, and to monitor broader trends in mortgage market activity.

This paper uses the 2020 public HMDA dataset, which contains standardized, loan-level records on mortgage applications reported by covered depository institutions and nonbank mortgage companies. HMDA reporting includes borrower demographics, loan purpose and product characteristics, several underwriting proxies, and, for many originated loans, the contract interest rate. The unit of observation is a mortgage application i, linked to lender $l(i)$ identified by its Legal Entity Identifier, LEI) and metropolitan area $m(i)$ (identified by the HMDA-derived MSA/MD code). Neighborhood covariates are measured at the census-tract level using the property location associated with each application.

To focus on a segment of the market in which underwriting and pricing decisions are more comparable across institutions, I construct a "clean mortgage" sample from the full 2020 HMDA file. I retain only conventional loans (`loan_type` = 1), first liens (`lien_status` $= 1$), and owner-occupied properties (`occupancy_type` $= 1$), and I restrict to 1–4 unit properties (`total_units` $\in \{1, 2, 3, 4\}$). I exclude products and purposes governed by distinct underwriting or pricing regimes: home equity lines of credit (`open_end_line_of_credit` $= 2$), reverse mortgages (`reverse_mortgage` $= 2$), and business-purpose loans (`business_or_commercial_purpose` $= 2$).

After these product-level restrictions, I define two outcome-specific analytic samples. For approval, I restrict to applications with lender-facing final dispositions—originated, approved but not accepted, or denied (`action_taken` $\in \{1, 2, 3\}$)—and define an approval indicator

$$Approved_i = \mathbf{1}\{\texttt{action\_taken} \in \{1, 2\}\}, \tag{1}$$

excluding withdrawals and incomplete files to avoid mixing lender decisions with borrower demand or processing interruptions. For pricing, I restrict to originated loans (`action_taken` $= 1$) with a valid reported interest rate and drop implausible entries (e.g., `interest_rate` ≤ 0 or ≥ 25). Because pricing is observed only for originated loans, interest-rate estimates are conditional on origination and should be interpreted with that selection in mind. Unless otherwise noted, observations missing required covariates are dropped; for underwriting proxies where missingness is common and potentially informative (DTI and CLTV), I include explicit "Missing" categories rather than mechanically excluding those applications.

Key variables

The primary regressor is a mutually exclusive race/ethnicity indicator built from HMDA's derived race and ethnicity fields. Hispanic ethnicity is given precedence to produce transparent group comparisons: Hispanic (Hispanic or Latino, regardless of race), non-Hispanic (NH) White (reference category), NH Black, NH Asian, Other (remaining non-Hispanic categories), and Race Not Available (race/ethnicity missing, not provided, or not applicable).

All regressions condition on a common set of underwriting proxies and loan and neighborhood characteristics available in public HMDA. Borrower income enters as log(`income`). Debt-to-income (DTI) is included as a set of categorical indicators corresponding to HMDA's reported DTI bands, augmented with a "Missing" category. Combined loan-to-value (CLTV) enters as binned indicators designed to capture nonlinear underwriting cutoffs (including common leverage thresholds), again with a "Missing" category. I further control for log(`loan_amount`) and log(`property_value`) to proxy for transaction scale and collateral value. To account for neighborhood context correlated with appraisal conditions, local risk, and lending environments, I include tract minority population share (`tract_minority_population_percent`) and tract income relative to the MSA (`tract_to_msa_income_percentage`). Finally, I include loan-purpose indicators (purchase, refinance, home improvement, other), since underwriting and pricing standards differ systematically across products.

Empirical specifications

The empirical strategy estimates parallel specifications for approval and pricing. Let $RaceGroup_i$ denote the vector of race/ethnicity indicators (excluding NH White), X_i denote the set of controls, $\mu_{m(i)}$ an MSA fixed effect, and $\lambda_{l(i)}$ a lender fixed effect.

For approval, I estimate a linear probability model (LPM):

$$Approved_i = \alpha + \beta' RaceGroup_i + \gamma' X_i + \mu_{m(i)} + \varepsilon_i, \tag{2}$$

and then augment it with lender fixed effects:

$$Approved_i = \alpha + \beta' RaceGroup_i + \gamma' X_i + \mu_{m(i)} + \lambda_{l(i)} + \varepsilon_i. \tag{3}$$

In these specifications, the elements of β are interpreted as percentage-point differences in approval probability relative to NH White borrowers.

For pricing, I estimate OLS regressions with the contract interest rate (in percentage points) as the outcome:

$$Rate_i = \alpha + \beta' RaceGroup_i + \gamma' X_i + \mu_{m(i)} + \varepsilon_i, \tag{4}$$

and then add lender fixed effects:

$$Rate_i = \alpha + \beta' RaceGroup_i + \gamma' X_i + \mu_{m(i)} + \lambda_{l(i)} + \varepsilon_i. \tag{5}$$

In the pricing regressions, β is in percentage points and is discussed in basis points (1 bp = 0.01 percentage points).

Interpretation, inference, and limitations

MSA fixed effects absorb time-invariant differences across metropolitan areas—local economic conditions, housing-market fundamentals, and broad institutional and regulatory environments—so identification comes from comparisons among applicants within the same metro area. Adding lender fixed effects absorbs time-invariant differences in underwriting intensity, product mix, and pricing strategies across institutions, so identification comes from comparing applicants who apply to the same lender (within the same MSA) and look similar on observed HMDA covariates. Changes in β when moving from MSA-only to MSA-plus-lender specifications are therefore informative about whether disparities are driven in part by sorting across lenders versus differences that persist within institutions, while still allowing for the possibility that unobserved risk factors correlated with race account for some residual differences.

In MSA fixed-effect specifications, standard errors are clustered at the MSA level to allow correlated unobservables within local markets. In lender fixed-effect specifications, standard errors are clustered at the lender (LEI) level to allow correlation in outcomes within institutions. For each model, I report coefficient estimates, clustered standard errors, and sample sizes.

The results should be interpreted as conditional disparities rather than definitive evidence of discrimination. Public HMDA lacks key underwriting inputs such as credit scores, liquid assets, and fully harmonized measures of points and fees, all of which may vary systematically across borrowers and affect both approval and pricing. In addition, pricing is observed only for originated loans, so estimated rate differences apply to the selected set of borrowers who are approved and proceed to origination. Finally, some underwriting proxies are missing for a nontrivial share of applications, and missingness differs by race; including "Missing" categories makes this explicit and preserves sample size, but it does not eliminate the possibility of bias if missingness proxies for unobserved risk.

4 Data Overview and Descriptive Statistics

This section documents the construction of the HMDA 2020 analysis samples and summarizes the distribution of borrower, loan, neighborhood, and lender characteristics used in the empirical analysis. The objective is descriptive: to make the sample transparent, to show how key underwriting proxies are distributed across applications, and to highlight data-quality features (especially missingness and coverage) that are important for interpreting the regression estimates.

Sample construction and analysis samples. I begin with the full application universe and restrict to a relatively homogeneous "clean mortgage" segment: conventional, first-lien, owner-occupied applications on 1–4 unit properties, excluding open-end lines of credit (HELOCs), reverse mortgages, and business-purpose loans. From this clean universe, I define two outcome-specific samples. The approval sample retains applications with lender-facing final dispositions (originated, approved-but-not-accepted, or denied), and the pricing sample retains originated loans with valid reported interest rates. Figure 1 reports sample counts at each stage of filtration.

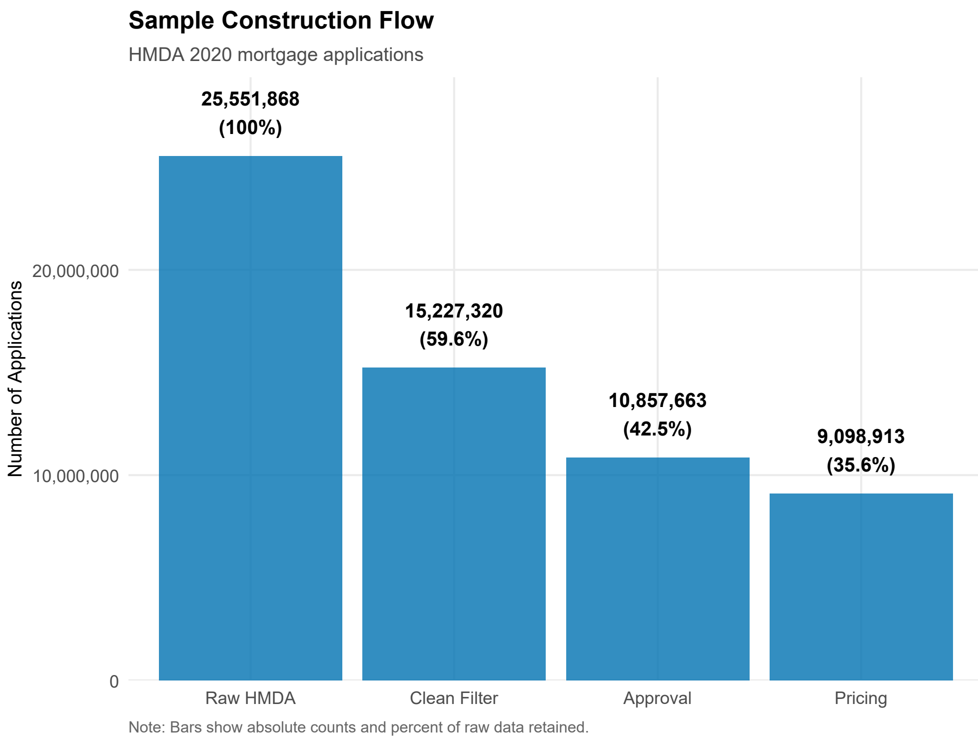

Figure 1: Sample construction flow (counts and retention across filters)

Composition of the analysis samples. Figure 2 provides a high-level view of the shares of race/ethnicity between samples. This exhibit is useful for two reasons: it clarifies which groups are most represented in the analysis, and it highlights that the pricing sample is mechanically a selected subset of originated loans with available interest-rate data.

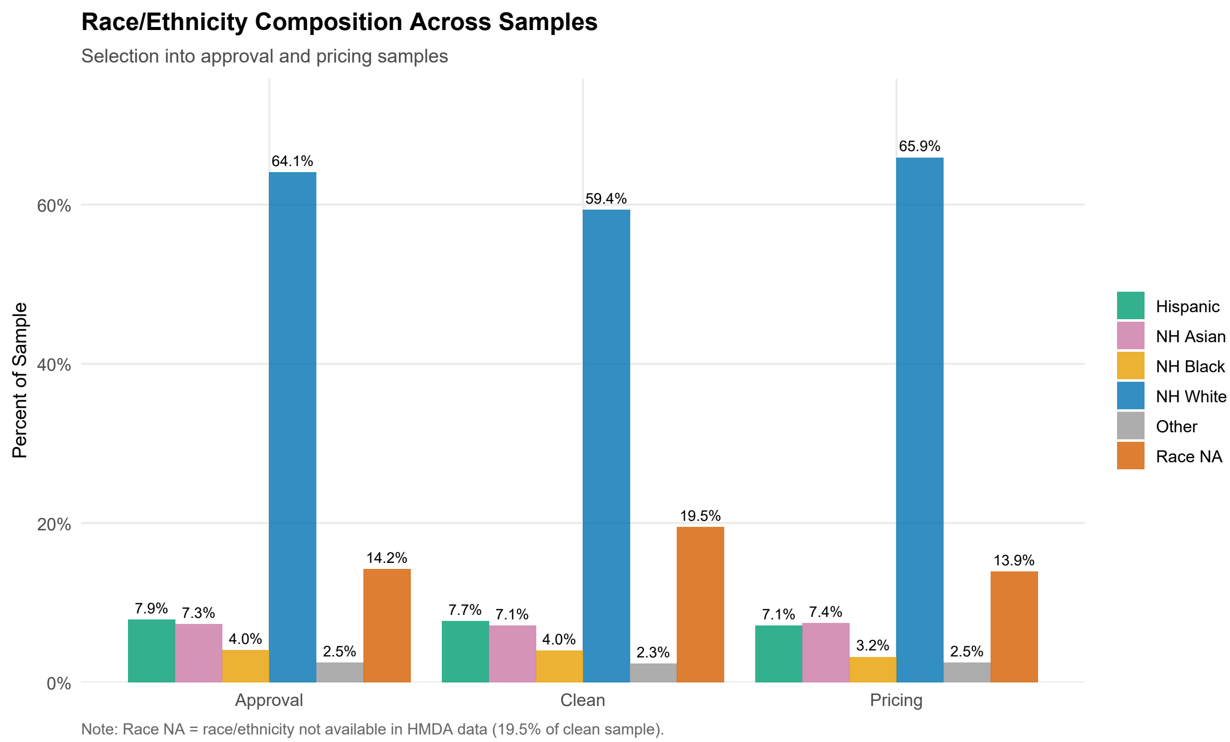

Figure 2: Race and ethnicity composition across clean, approval, and pricing samples

Borrower, loan, and neighborhood characteristics. Appendix Tables 10 and 11 report summary statistics for the approval and pricing samples, overall and by mutually exclusive race/ethnicity category. They provide context for the regression covariates by summarizing the levels and dispersion of key HMDA underwriting proxies (income, DTI categories, and CLTV categories), loan size and collateral measures, neighborhood characteristics, and loan purpose. Because the pricing sample is restricted to originated loans with non-missing contract interest rates, Appendix Table 7 should be interpreted as describing the subset of originations with observed rates.

To complement these tables, Figures 6 and 7 plot the distributions of the DTI and CLTV categories used as core underwriting controls. Figure 8 compares borrower income and loan amounts across race/ethnicity groups, motivating logarithmic transformations for scale variables and reinforcing the role of underwriting controls in the conditional analysis. Finally, Figure 9 shows the distribution of contract interest rates in the pricing sample, highlighting the concentration of rates and a right tail.

Missingness and data quality. While HMDA provides several useful underwriting proxies, some covariates exhibit meaningful missingness, and the extent of missingness varies across race/ethnicity groups. Appendix Table 12 reports missingness rates for the key controls used in the main specifications, overall and by group, to provide a transparent accounting of data availability. Figure 3 complements the table by visualizing missingness in the primary underwriting proxies, particularly DTI and CLTV.

Together, these exhibits motivate the paper's approach to missing data in the main regressions, including the use of explicit "Missing" categories for binned measures where appropriate, and they help frame how conditional disparities should be interpreted given differential data availability.

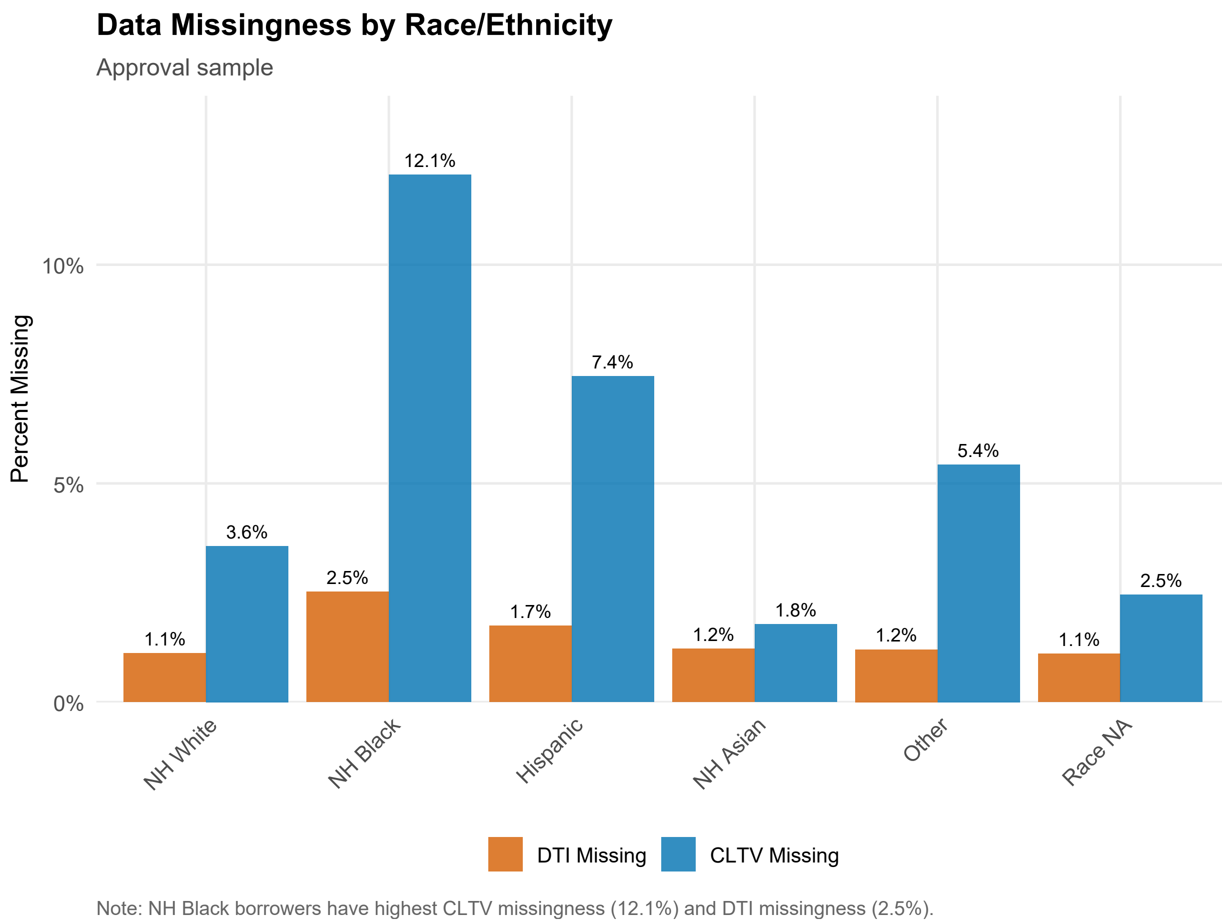

Figure 3

Geographic and institutional coverage. Because the empirical strategy relies on within-metropolitan-area comparisons and, in some specifications, within-lender comparisons, it is important to document the breadth of market and institutional coverage in the analysis samples. Appendix Table 13 summarizes MSA and lender coverage, as well as concentration, across the clean universe and the final analysis samples. Figure 10 complements the table by illustrating how much of the sample is accounted for by the largest MSAs, while Figure 11 summarizes concentration among lenders.

Taken together, these exhibits provide important context for the fixed-effects design and clarify whether the estimates primarily reflect comparisons across a broad set of markets and institutions or are driven by a relatively small number of dominant MSAs or lenders.

5 Results

This section reports (i) how the analysis samples are constructed, (ii) unadjusted patterns in approvals, pricing, and data completeness, and (iii) regression estimates of conditional disparities in approval and interest-rate outcomes. The main tables progressively tighten comparisons from within-market (MSA fixed effects) to within-lender (MSA plus lender fixed effects), which helps assess the extent to which disparities reflect differences in lender composition versus differences within the same institution.

5.1 Sample construction and analytic samples

Table 1: Sample construction and flow (2020 HMDA)

Step	Restriction	N remaining	% of raw
1. Raw HMDA 2020	Full 2020 HMDA loan application register (LAR)	25,551,868	100.0
2. Clean mortgage filter	Conventional, first-lien, owner-occupied, 1–4 unit properties	15,227,320	59.6
2a. Approval universe	`action_taken` $\in \{1, 2, 3\}$	10,857,663	42.5
2b. Approval regression sample	Approval universe + complete RHS covariates	10,525,077	41.2
3a. Pricing universe	`action_taken` $= 1$ and $0 <$ `rate` < 25	9,098,913	35.6
3b. Pricing regression sample	Pricing universe + complete RHS covariates	8,895,511	34.8

5.2 Descriptive patterns and data completeness

Table 2: Unadjusted outcomes and covariate completeness by race/ethnicity

	Sample Composition	Outcomes			Missingness		N	
Race/Ethnicity	Share (%)	Approval (%)	Mean Rate (%)	Median Rate (%)	DTI Miss (%)	CLTV Miss (%)	N (Approval)	N (Pricing)
NH White	59.4	89.2	3.184	3.125	1.1	3.6	6,957,308	5,998,032
NH Black	4.0	70.6	3.428	3.250	2.5	12.1	437,377	291,628
Hispanic	7.7	79.3	3.319	3.125	1.7	7.4	855,864	646,394
NH Asian	7.1	88.7	2.973	2.875	1.2	1.8	792,087	676,041
Other	2.3	86.2	3.175	3.000	1.2	5.4	268,388	222,973
Race NA	19.5	85.2	3.111	3.000	1.1	2.5	1,546,639	1,263,845

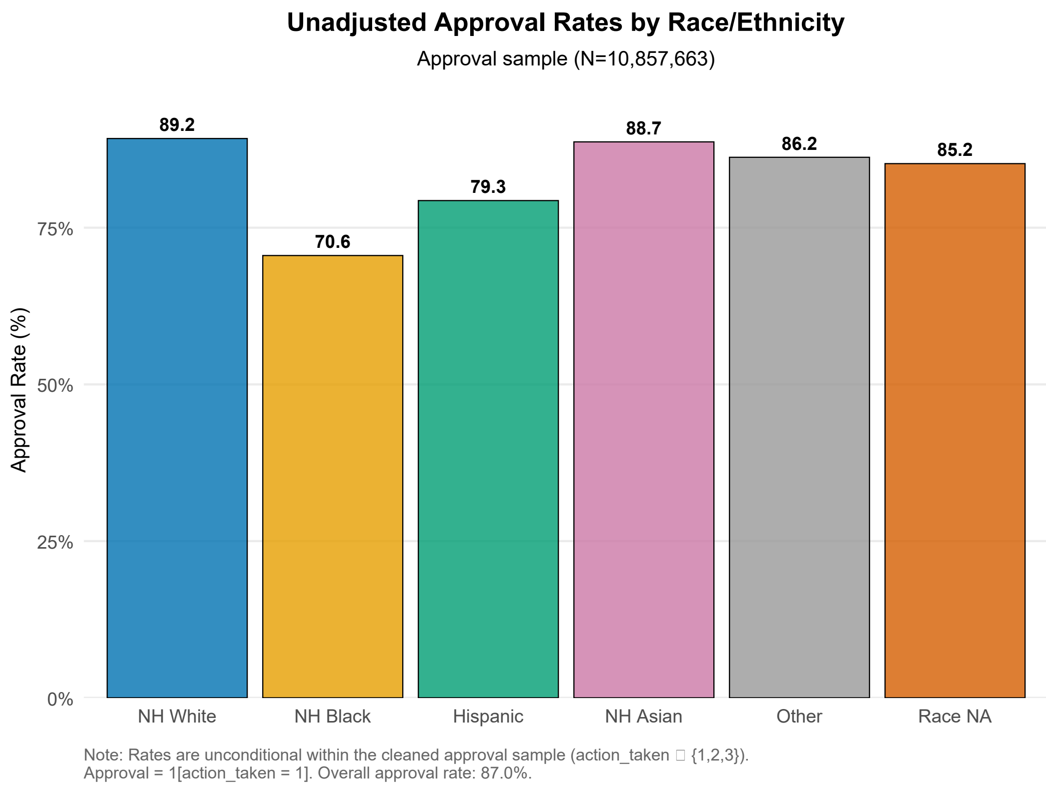

Figure 4

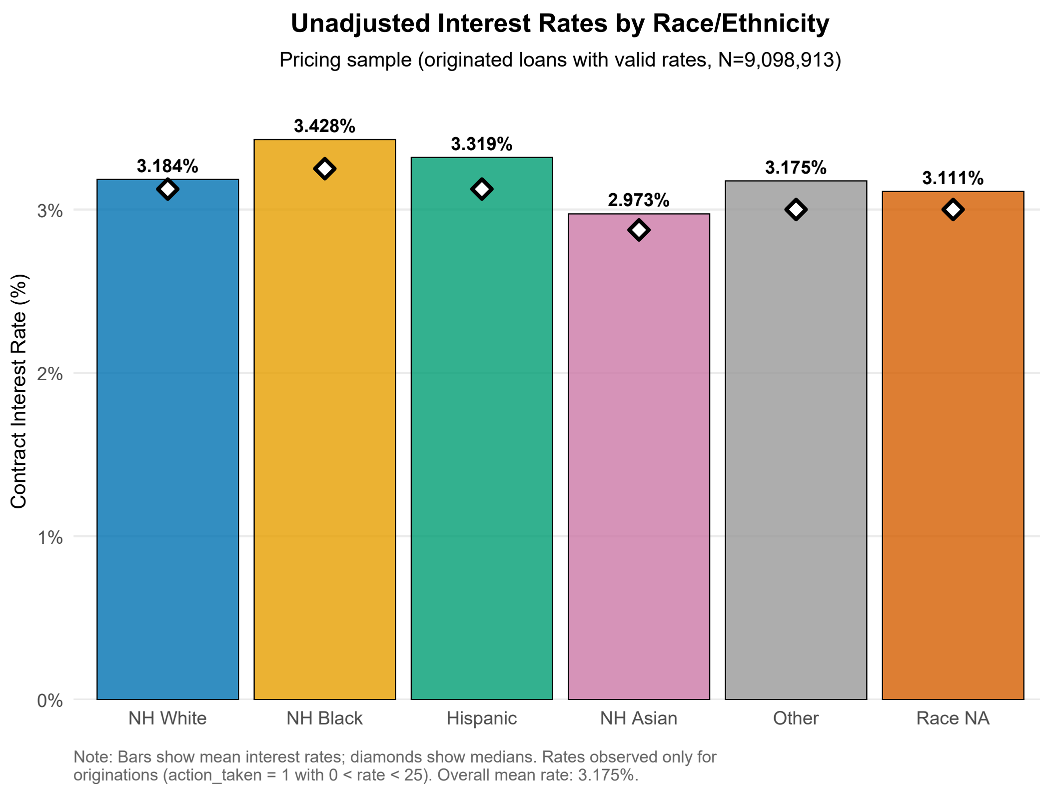

Figure 5

5.3 Main results: approval disparities (Table 3)

Table 3 shows conditional approval gaps by race/ethnicity from linear probability models. Across specifications, non-reference groups have lower approval probabilities than NH White applicants, conditional on the full set of borrower, loan, neighborhood, and product controls.

With MSA fixed effects (column 1), the largest gap is for NH Black applicants (−0.074, SE 0.003), followed by Hispanic (−0.032, SE 0.002), NH Asian (−0.021, SE 0.002), Other (−0.022, SE 0.003), and Race Not Available (−0.035, SE 0.001). All estimates are statistically significant at conventional levels.

Adding lender fixed effects (column 2) reduces each gap but leaves economically meaningful differences: NH Black falls to −0.057 (SE 0.006), Hispanic to −0.028, NH Asian to −0.017, Other to −0.015, and Race Not Available to −0.026. The attenuation indicates that lender selection contributes to observed approval differences, while the remaining within-lender gaps suggest persistent disparities conditional on observables (or unobserved risk correlated with race/ethnicity).

Estimated coefficients on underwriting proxies follow the expected risk gradient: higher DTI categories and very high CLTV bins are associated with substantially lower approval probabilities.

Table 3: Approval regressions (LPM): conditional disparities by race/ethnicity

	Approved	
	MSA FE	MSA + Lender FE
	(1)	(2)
NH Black	-0.074***	-0.057***
	(0.003)	(0.006)
	[23.64]	[−8.91]
Hispanic	-0.032***	-0.028***
	(0.002)	(0.004)
	[−15.97]	[−7.22]
NH Asian	-0.021***	-0.017***
	(0.002)	(0.003)
	[−10.11]	[−5.17]
Other	-0.022***	-0.015***
	(0.003)	(0.002)
	[−7.33]	[−7.43]
Race NA	-0.035***	-0.026***
	(0.001)	(0.004)
	[−24.75]	[−6.51]
# derived_msa_md	414	414
# lei	–	2,809
SE clustered by	derived_msa_md	lei
Observations	10,525,077	10,525,077
R^2	0.3	0.4
Within R^2	0.3	0.2

5.4 Main results: pricing disparities (Table 4)

Table 4 reports conditional differences in contract interest rates across race/ethnicity groups. With MSA fixed effects (column 1), NH Black borrowers pay higher rates than NH White borrowers (0.079, SE 0.023, i.e., +7.9 bps), and Hispanic borrowers face a small premium (0.024, SE 0.009, +2.4 bps). In contrast, NH Asian borrowers pay substantially lower rates (−0.130, SE 0.007, −13.0 bps). The estimate for the residual "Other" category is near zero, while Race Not Available is modestly negative (about −4.5 bps).

Adding lender fixed effects (column 2) changes the pattern for some groups. The NH Black premium attenuates but remains positive and statistically significant (0.047, SE 0.017, +4.7 bps). The Hispanic estimate flips sign and becomes statistically indistinguishable from zero (−0.006, SE 0.005), indicating that the small premium in column (1) is largely explained by lender mix. The NH Asian discount remains large and precisely estimated even within lender (−0.121, SE 0.007, −12.1 bps).

In terms of magnitudes, at a 3.175% interest rate on a $300,000, 30-year fixed-rate mortgage, a 4.7 bp increase corresponds to about $7.71 more per month (roughly $2,776 over 360 payments), while a 7.9 bp increase corresponds to about $12.98 per month (roughly $4,671). These comparisons are illustrative and abstract from refinancing and prepayment.

Table 4: Pricing regressions (OLS): contract interest rate (percentage points)

	Contract rate	
	MSA FE	MSA + Lender FE
	(1)	(2)
NH Black	0.079***	0.047***
	(0.023)	(0.016)
	[3.39]	[2.84]
Hispanic	0.024***	-0.006
	(0.009)	(0.005)
	[2.65]	[−1.14]
NH Asian	-0.130***	-0.121***
	(0.007)	(0.007)
	[−19.31]	[−16.73]
Other	-0.009	-0.016***
	(0.007)	(0.003)
	[−1.27]	[−5.44]
Race NA	-0.045***	-0.027***
	(0.002)	(0.007)
	[−21.15]	[−3.81]
# derived_msa_md	414	414
# lei	–	2,788
SE clustered by	derived_msa_md	lei
Observations	8,895,511	8,895,511
R^2	0.3	0.5
Within R^2	0.3	0.1

5.5 Cross-model synthesis (Table 5)

Table 5 summarizes how estimated disparities change when moving from within-market to within-lender comparisons. In both outcomes, adding lender fixed effects attenuates many coefficients, implying that lender mix and sorting across institutions account for a nontrivial share of the raw conditional gaps. At the same time, several differences remain economically meaningful within lender, most notably for NH Black applicants.

For NH Black applicants, the approval gap declines from -7.4 pp to -5.7 pp when lender fixed effects are added, and the pricing premium falls from +7.9 bps to +4.7 bps but remains positive. For Hispanic applicants, the approval gap is similar across specifications (-3.2 pp vs. -2.8 pp), while the pricing premium in the within-market model disappears once lender fixed effects are included (+2.4 bps to a statistically indistinguishable estimate).

Table 5: Synthesis of approval and pricing disparities

Race/Ethnicity	Approval Gaps (pp)		Rate Gaps (bps)	
	MSA FE	MSA + LEI	MSA FE	MSA + LEI
NH Black	-0.074	-0.057	7.9	4.7
Hispanic	-0.032	-0.028	2.4	-0.6
NH Asian	-0.021	-0.017	-13.0	-12.1
Other	-0.022	-0.015	-0.9	-1.6
Race NA	-0.035	-0.026	-4.5	-2.7

Note that full regression tables for both models are available in the Supplemntary Appendix.

6 Conclusion

This paper examines whether mortgage approval outcomes and interest-rate pricing differ systematically by race and ethnicity in the 2020 public HMDA data. Using a national, loan-level sample of conventional, first-lien, owner-occupied applications on 1–4 unit properties, I estimate models for two outcomes—approval probabilities for the application sample and contract interest rates for originated loans—conditioning on borrower, loan, and neighborhood covariates. The empirical design compares applicants within the same metropolitan area and, more tightly, within the same lender, using MSA and lender fixed effects to absorb local and institution-specific underwriting and pricing practices.

Across both outcomes, the results document persistent conditional racial and ethnic differences. In the approval regressions, minority applicants have lower approval probabilities than non-Hispanic White borrowers with similar observed characteristics, with the largest gaps for non-Hispanic Black applicants and meaningful gaps for Hispanic applicants. Adding lender fixed effects reduces, but does not eliminate, these disparities, indicating that differences in which lenders borrowers reach explain part of the gap while substantial differences remain even within the same institution. In the pricing regressions, non-Hispanic Black borrowers face higher interest rates than comparable non-Hispanic White borrowers in both specifications, with the premium attenuated but still present when comparing within lenders. Hispanic borrowers exhibit a small premium within markets that largely vanishes once lender fixed effects are included, suggesting an important role for cross-lender sorting in their pricing differences. By contrast, non-Hispanic Asian borrowers consistently receive lower rates than non-Hispanic White borrowers. Taken together, these patterns show that disparities arise on both the access and pricing margins, and that the relative contribution of within-lender differences versus lender composition varies across groups.

These findings should be interpreted in light of important data limitations. Public HMDA does not include several core inputs to underwriting and pricing—most notably credit scores, detailed measures of credit history, liquid asset reserves, and harmonized information on points and fees—and interest rates are observed only for originated loans. The estimates therefore capture conditional differences in outcomes given HMDA-observed covariates and fixed effects, rather than cleanly separating unobserved risk from differential treatment. Attenuation of some coefficients when lender fixed effects are added is consistent with a role for lender sorting, while the persistence of others within lender is consistent with within-lender differences correlated with race and ethnicity, but neither pattern by itself is sufficient to identify discrimination in a legal or structural sense.

Even with these caveats, the results have clear implications for policy and future research. For regulators and policymakers, the coexistence of sizeable approval gaps and nontrivial pricing differences for some groups underscores the value of continued fair-lending monitoring, as well as market- and lender-level diagnostics that can flag where conditional disparities are most pronounced. For researchers, a natural next step is to pair HMDA with richer underwriting and pricing information—through linkages to credit bureau files, GSE datasets, or loan-level servicing records—or to complement HMDA-based analyses with audit and paired-testing designs that can more directly isolate differential treatment at a given risk level. Extending the analysis along dimensions such as loan purpose, neighborhood context, and lender type can further clarify where gaps are concentrated and which institutional or market features are associated with larger disparities.

Ultimately, differences in mortgage approvals and pricing matter because they shape both entry into homeownership and the cost of sustaining it, a central wealth-building mechanism for many U.S. households. Conditional gaps of the magnitude documented here, even when modest on a single loan, can compound through delayed home purchase, higher cumulative borrowing costs, and reduced resilience to adverse shocks. The evidence from 2020 HMDA highlights both the importance of transparent, high-quality data and the need for ongoing empirical and regulatory attention to ensure more equitable access to mortgage credit.

A Cross-year robustness: evolution of conditional gaps (2020–2022)

Tables 6 and 7 extend the within-market, within-lender design to the 2021 and 2022 HMDA samples. The cross-year patterns reinforce three takeaways.

First, conditional approval gaps persist within lender throughout 2020–2022. The NH Black approval gap remains the largest in each year and is more negative in 2022 than in 2020–2021. Hispanic approval gaps are consistently meaningful, while the NH Asian approval gap is modest in 2020–2021 and noticeably more negative in 2022.

Second, pricing disparities within lender are also stable in sign for the main groups. NH Black borrowers face a positive rate premium in every year, and the magnitude increases from 2020 to 2022. NH Asian borrowers receive a large discount in each year that is remarkably stable in size.

Third, the evolution of Hispanic pricing is the primary change over time: the within-lender differential is near zero in 2020 but becomes positive and statistically significant in 2021 and larger in 2022, suggesting a shift in conditional pricing patterns for this group in the later samples.

Table 6: Evolution of Conditional Approval Gaps (MSA + Lender Fixed Effects)

	approved		
	2020	2021	2022
	(1)	(2)	(3)
NH Black	-0.057***	-0.055***	-0.066***
	(0.006)	(0.005)	(0.007)
Hispanic	-0.028***	-0.024***	-0.031***
	(0.004)	(0.004)	(0.004)
NH Asian	-0.017***	-0.016***	-0.031***
	(0.003)	(0.003)	(0.004)
Other	-0.015***	-0.016***	-0.023***
	(0.002)	(0.002)	(0.003)
Race NA	-0.026***	-0.027***	-0.032***
	(0.004)	(0.004)	(0.003)
# derived_msa_md	414	414	413
# lei	2,809	2,986	3,039
Observations	10,525,077	11,064,850	5,172,062
R^2	0.4	0.4	0.4
Within R^2	0.2	0.2	0.2

Table 7: Evolution of Conditional Pricing Gaps (MSA + Lender Fixed Effects)

	rate_num		
	2020	2021	2022
	(1)	(2)	(3)
NH Black	0.047***	0.063***	0.078***
	(0.016)	(0.010)	(0.009)
Hispanic	-0.006	0.014***	0.058***
	(0.005)	(0.005)	(0.008)
NH Asian	-0.121***	-0.132***	-0.120***
	(0.007)	(0.009)	(0.007)
Other	-0.016***	-5.54×10^{-5}	0.009**
	(0.003)	(0.002)	(0.004)
Race NA	-0.027***	-0.020***	-0.033***
	(0.007)	(0.004)	(0.008)
# derived_msa_md	414	414	413
# lei	2,788	2,967	3,026
Observations	8,895,511	9,347,608	4,123,553
R^2	0.5	0.5	0.3
Within R^2	0.1	0.2	0.2

B Appendix Supplementary Tables and Figures

Table 8: Mortgage Approval Rate with Full Set of Controls

	Approved	
	MSA FE	MSA + Lender FE
	(1)	(2)
Race/Ethnicity (ref: NH White)		
NH Black	-0.074***	-0.057***
	(0.003)	(0.006)
	[−23.64]	[−8.91]
Hispanic	-0.032***	-0.028***
	(0.002)	(0.004)
	[−15.97]	[−7.22]
NH Asian	-0.021***	-0.017***
	(0.002)	(0.003)
	[−10.11]	[−5.17]
Other	-0.022***	-0.015***

	Approved (cont.)	
	MSA FE	MSA + Lender FE
	(1)	(2)
	(0.003)	(0.002)
	[−7.33]	[−7.43]
Race NA	-0.035***	-0.026***
	(0.001)	(0.004)
	[−24.75]	[−6.51]
Borrower / Underwriting proxies		
Log(income)	0.017***	0.029***
	(0.001)	(0.008)
	[11.68]	[3.78]
DTI 20–30	0.047***	0.046***
	(0.002)	(0.005)
	[19.81]	[9.28]
DTI 30–36	0.050***	0.051***
	(0.003)	(0.006)
	[18.36]	[8.75]
DTI 36	0.051***	0.052***
	(0.003)	(0.006)
	[17.43]	[8.44]
DTI 36–40	0.050***	0.052***
	(0.003)	(0.006)
	[17.63]	[8.12]
DTI 40–45	0.043***	0.045***
	(0.003)	(0.007)
	[15.54]	[6.96]
DTI 45–50	0.005	0.009
	(0.003)	(0.007)
	[1.60]	[1.32]
DTI 50–60	-0.548***	-0.507***
	(0.012)	(0.030)
	[−46.49]	[−17.09]
DTI >60	-0.728***	-0.664***
	(0.018)	(0.033)
	[−41.19]	[−19.92]
DTI Missing	-0.441***	-0.508***
	(0.020)	(0.053)
	[−22.36]	[−9.62]
CLTV (120,200]	-0.341***	-0.310***
	(0.012)	(0.045)
	[−29.36]	[−6.86]
CLTV (60,80]	0.239***	0.234***
	(0.012)	(0.047)
	[19.83]	[4.97]

	Approved (cont.)	
	MSA FE	MSA + Lender FE
	(1)	(2)
CLTV (80,90]	0.210***	0.202***
	(0.012)	(0.046)
	[17.76]	[4.35]
CLTV (90,95]	0.209***	0.193***
	(0.012)	(0.045)
	[17.62]	[4.29]
CLTV (95,100]	0.168***	0.156***
	(0.012)	(0.044)
	[14.41]	[3.53]
CLTV [0,60]	0.248***	0.248***
	(0.012)	(0.047)
	[21.11]	[5.25]
CLTV Missing	-0.063***	-0.017
	(0.014)	(0.078)
	[−4.46]	[−0.22]
Log(loan amount)	0.008$^{\cdot}$	0.001
	(0.005)	(0.009)
	[1.72]	[0.15]
Log(property value)	0.015$^{\cdot}$	-0.001
	(0.009)	(0.005)
	[1.76]	[−0.24]
Tract minority share	-0.00002	0.00001
	(0.00005)	(0.00013)
	[−0.46]	[0.08]
Tract-to-MSA income	0.00004*	0.00008
	(0.00002)	(0.00006)
	[2.16]	[1.47]
Loan purpose indicators (ref: purpose = 1)		
Purpose = 2	-0.137***	-0.098***
	(0.007)	(0.014)
	[−20.86]	[−6.80]
Purpose = 4	-0.188***	-0.149***
	(0.007)	(0.017)
	[−27.49]	[−8.66]
Purpose = 5	-0.094*	-0.170**
	(0.040)	(0.055)
	[−2.37]	[−3.09]
Purpose = 31	-0.053***	-0.046***
	(0.002)	(0.007)
	[−30.98]	[−6.98]
Purpose = 32	-0.073***	-0.065***
	(0.002)	(0.008)

	Approved (cont.)	
	MSA FE	MSA + Lender FE
	(1)	(2)
	[−38.33]	[−8.63]
# derived_msa_md	414	414
# lei	–	2,809
SE clustered by	derived_msa_md	lei
Observations	10,525,077	10,525,077
R^2 (Adj.)	0.304	0.365
Within R^2	0.285	0.232

Table 9: Mortgage Interest Rate with Full Set of Controls

	Interest rate	
	MSA FE	MSA + Lender FE
	(1)	(2)
Race/Ethnicity (ref: NH White)		
NH Black	0.079***	0.047**
	(0.023)	(0.017)
	[3.39]	[2.84]
Hispanic	0.024**	-0.006
	(0.009)	(0.005)
	[2.65]	[−1.14]
NH Asian	-0.130***	-0.121***
	(0.007)	(0.007)
	[−19.31]	[−16.73]
Other	-0.009	-0.016***
	(0.007)	(0.003)
	[−1.27]	[−5.44]
Race NA	-0.045***	-0.027***
	(0.002)	(0.007)
	[−21.15]	[−3.81]
Borrower / Underwriting proxies		
Log(income)	0.076***	0.034**
	(0.008)	(0.013)
	[9.74]	[2.68]
DTI 20–30	0.061***	0.047***
	(0.004)	(0.004)
	[13.80]	[10.55]
DTI 30–36	0.116***	0.091***
	(0.007)	(0.007)

	Interest rate (cont.)	
	MSA FE	MSA + Lender FE
	(1)	(2)
	[16.20]	[13.18]
DTI 36	0.140***	0.111***
	(0.008)	(0.008)
	[16.99]	[13.37]
DTI 36–40	0.160***	0.128***
	(0.008)	(0.009)
	[19.27]	[14.84]
DTI 40–45	0.181***	0.152***
	(0.009)	(0.010)
	[21.10]	[15.47]
DTI 45–50	0.165***	0.134***
	(0.009)	(0.011)
	[19.37]	[11.95]
DTI 50–60	0.490***	0.221***
	(0.028)	(0.042)
	[17.22]	[5.29]
DTI >60	0.660***	0.395***
	(0.046)	(0.052)
	[14.25]	[7.57]
DTI Missing	-0.198	0.212*
	(0.158)	(0.102)
	[−1.25]	[2.09]
CLTV (120,200]	0.033	-0.162
	(0.081)	(0.130)
	[0.41]	[−1.25]
CLTV (60,80]	-0.678***	-0.629***
	(0.033)	(0.127)
	[−20.64]	[−4.93]
CLTV (80,90]	-0.614***	-0.551***
	(0.034)	(0.126)
	[−18.20]	[−4.36]
CLTV (90,95]	-0.705***	-0.587***
	(0.041)	(0.124)
	[−17.35]	[−4.72]
CLTV (95,100]	-0.618***	-0.510***
	(0.035)	(0.118)
	[−17.65]	[−4.31]
CLTV [0,60]	-0.782***	-0.760***
	(0.029)	(0.128)
	[−26.60]	[−5.96]
CLTV Missing	1.904***	1.178
	(0.256)	(0.934)
	[7.43]	[1.26]

	Interest rate (cont.)	
	MSA FE	MSA + Lender FE
	(1)	(2)
Log(loan amount)	-0.021**	-0.009
	(0.008)	(0.020)
	[−2.72]	[−0.45]
Log(property value)	-0.282***	-0.184***
	(0.023)	(0.020)
	[−12.33]	[−9.09]
Tract minority share	0.00001	-0.00011*
	(0.00040)	(0.00005)
	[0.03]	[−2.21]
Tract-to-MSA income	0.00026	0.00003
	(0.00016)	(0.00005)
	[1.60]	[0.59]
Loan purpose indicators (ref: purpose = 1)		
Purpose = 2	0.271***	0.294***
	(0.018)	(0.027)
	[15.14]	[11.10]
Purpose = 4	0.308***	0.295***
	(0.022)	(0.026)
	[14.10]	[11.17]
Purpose = 5	0.632***	0.389**
	(0.181)	(0.146)
	[3.49]	[2.65]
Purpose = 31	-0.146***	-0.069***
	(0.013)	(0.013)
	[−10.92]	[−5.42]
Purpose = 32	0.064**	0.156***
	(0.020)	(0.019)
	[3.20]	[8.09]
# derived_msa_md	414	414
# lei	–	2,788
SE clustered by	derived_msa_md	lei
Observations	8,895,511	8,895,511
R^2 (Adj.)	0.285	0.477
Within R^2	0.267	0.129

Table 10: Summary Statistics - Approval Sample

Race	Variable	Mean	SD	Median	P25	P75	N
All	approved	0.87	0.34	1.00	1.00	1.00	10,857,663
All	inc_num	130.00	1347.82	99.00	64.00	150.00	10,702,146
All	loan_amount	304962.89	477728.64	255000.00	165000.00	375000.00	10,857,663
All	pv_num	472362.93	1092655.47	375000.00	245000.00	565000.00	10,658,532
All	tract_minority_population_percent	29.52	23.85	22.31	11.07	41.71	10,857,663
All	tract_to_msa_income_percentage	121.96	44.96	116.00	94.00	145.00	10,857,663
NH White	approved	0.89	0.31	1.00	1.00	1.00	6,957,308
NH White	inc_num	128.86	1497.63	99.00	65.00	149.00	6,853,634
NH White	loan_amount	292234.58	361104.93	245000.00	165000.00	365000.00	6,957,308
NH White	pv_num	451584.29	965646.13	355000.00	245000.00	535000.00	6,836,106
NH White	tract_minority_population_percent	22.65	18.40	17.40	8.88	31.22	6,957,308
NH White	tract_to_msa_income_percentage	123.30	43.21	117.00	96.00	144.00	6,957,308
Race NA	approved	0.85	0.35	1.00	1.00	1.00	1,546,639
Race NA	inc_num	142.65	773.72	106.00	70.00	160.00	1,527,039
Race NA	loan_amount	337979.86	707547.25	275000.00	185000.00	405000.00	1,546,639
Race NA	pv_num	537852.20	1469811.84	415000.00	275000.00	625000.00	1,524,059
Race NA	tract_minority_population_percent	32.29	24.19	25.86	13.19	46.07	1,546,639
Race NA	tract_to_msa_income_percentage	124.78	46.66	119.00	95.00	148.00	1,546,639
Hispanic	approved	0.79	0.40	1.00	1.00	1.00	855,864
Hispanic	inc_num	107.31	1470.06	77.00	52.00	113.00	844,628
Hispanic	loan_amount	264932.71	751001.72	235000.00	155000.00	335000.00	855,864
Hispanic	pv_num	386045.19	1104493.48	325000.00	215000.00	485000.00	832,467
Hispanic	tract_minority_population_percent	52.56	28.41	51.98	28.60	78.04	855,864
Hispanic	tract_to_msa_income_percentage	106.85	45.72	102.00	77.00	131.00	855,864
Other	approved	0.86	0.34	1.00	1.00	1.00	268,388
Other	inc_num	157.01	2103.69	120.00	79.00	180.00	264,151
Other	loan_amount	358338.26	280163.41	305000.00	195000.00	445000.00	268,388
Other	pv_num	554815.78	2018691.46	435000.00	285000.00	675000.00	262,995
Other	tract_minority_population_percent	33.98	23.80	28.26	15.25	48.13	268,388
Other	tract_to_msa_income_percentage	123.11	46.42	118.00	94.00	147.00	268,388
NH Asian	approved	0.89	0.32	1.00	1.00	1.00	792,087
NH Asian	inc_num	149.40	423.00	124.00	84.00	177.00	782,112
NH Asian	loan_amount	416033.40	575743.63	365000.00	255000.00	505000.00	792,087
NH Asian	pv_num	670153.16	678278.43	555000.00	385000.00	815000.00	779,669
NH Asian	tract_minority_population_percent	46.54	24.73	43.43	26.40	66.52	792,087
NH Asian	tract_to_msa_income_percentage	132.07	48.82	128.00	99.00	161.00	792,087
NH Black	approved	0.71	0.46	1.00	0.00	1.00	437,377
NH Black	inc_num	95.87	214.19	76.00	50.00	115.00	430,582
NH Black	loan_amount	235107.78	174385.09	205000.00	125000.00	305000.00	437,377
NH Black	pv_num	326336.94	1145382.87	265000.00	165000.00	415000.00	423,236
NH Black	tract_minority_population_percent	50.48	29.00	48.21	26.38	75.46	437,377
NH Black	tract_to_msa_income_percentage	101.30	44.01	99.00	74.00	126.00	437,377

Table 11: Summary Statistics - Pricing Sample

Race	Variable	Mean	SD	Median	P25	P75	N
All	rate_num	3.18	0.68	3.00	2.88	3.38	9,098,913
All	inc_num	133.23	1292.00	103.00	69.00	153.00	8,977,391
All	loan_amount	311387.98	248677.70	265000.00	175000.00	385000.00	9,098,913
All	pv_num	479760.76	489711.47	385000.00	255000.00	575000.00	9,011,246
All	tract_minority_population_percent	29.07	23.26	21.99	11.17	40.77	9,098,913
All	tract_to_msa_income_percentage	124.04	43.75	118.00	96.00	146.00	9,098,913
NH White	rate_num	3.18	0.66	3.12	2.88	3.38	5,998,032
NH White	inc_num	131.36	1531.51	102.00	68.00	151.00	5,912,602
NH White	loan_amount	296703.76	231904.35	255000.00	175000.00	365000.00	5,998,032
NH White	pv_num	456043.33	448172.54	365000.00	255000.00	535000.00	5,941,120
NH White	tract_minority_population_percent	22.70	18.21	17.52	9.10	31.19	5,998,032
NH White	tract_to_msa_income_percentage	124.72	42.31	118.00	97.00	145.00	5,998,032
Race NA	rate_num	3.11	0.57	3.00	2.75	3.38	1,263,845
Race NA	inc_num	146.95	766.98	111.00	74.00	163.00	1,248,866
Race NA	loan_amount	342631.62	327625.20	285000.00	195000.00	415000.00	1,263,845
Race NA	pv_num	542525.70	612349.11	425000.00	285000.00	635000.00	1,254,486
Race NA	tract_minority_population_percent	31.80	23.63	25.47	13.21	45.02	1,263,845
Race NA	tract_to_msa_income_percentage	126.38	45.73	120.00	96.00	150.00	1,263,845
Hispanic	rate_num	3.32	0.91	3.12	2.88	3.50	646,394
Hispanic	inc_num	109.60	496.65	82.00	57.00	118.00	639,659
Hispanic	loan_amount	277427.14	169429.78	245000.00	165000.00	355000.00	646,394
Hispanic	pv_num	399723.96	313618.75	345000.00	235000.00	505000.00	638,051
Hispanic	tract_minority_population_percent	52.91	27.67	51.89	29.34	77.77	646,394
Hispanic	tract_to_msa_income_percentage	110.41	43.99	104.00	80.00	134.00	646,394
Other	rate_num	3.18	0.75	3.00	2.77	3.38	222,973
Other	inc_num	158.09	739.00	127.00	86.00	187.00	219,672
Other	loan_amount	373488.38	275440.80	315000.00	215000.00	455000.00	222,973
Other	pv_num	571107.15	495953.69	455000.00	305000.00	695000.00	220,779
Other	tract_minority_population_percent	33.97	23.27	28.27	15.60	47.70	222,973
Other	tract_to_msa_income_percentage	126.14	44.89	120.00	97.00	149.00	222,973
NH Black	rate_num	3.43	1.09	3.25	2.88	3.62	291,628
NH Black	inc_num	104.38	237.25	84.00	58.00	124.00	288,670
NH Black	loan_amount	259778.04	168612.12	225000.00	155000.00	335000.00	291,628
NH Black	pv_num	353470.88	290172.46	295000.00	205000.00	435000.00	288,454
NH Black	tract_minority_population_percent	51.36	27.96	48.68	27.58	75.47	291,628
NH Black	tract_to_msa_income_percentage	107.69	41.15	103.00	79.00	131.00	291,628
NH Asian	rate_num	2.97	0.49	2.88	2.62	3.25	676,041
NH Asian	inc_num	151.13	362.28	127.00	87.00	180.00	667,922
NH Asian	loan_amount	417514.09	266919.58	365000.00	255000.00	505000.00	676,041
NH Asian	pv_num	673518.81	683324.93	565000.00	385000.00	825000.00	668,356
NH Asian	tract_minority_population_percent	46.52	24.59	43.28	26.51	66.31	676,041
NH Asian	tract_to_msa_income_percentage	133.01	48.31	129.00	100.00	161.00	676,041

Table 12: Missingness Diagnostics by Race/Ethnicity

Variable	Overall	NH White	NH Black	Hispanic	NH Asian	Other	Race NA
Income	1.4%	1.5%	1.6%	1.3%	1.3%	1.6%	1.3%
DTI	1.2%	1.1%	2.5%	1.7%	1.2%	1.2%	1.1%
CLTV	4.0%	3.6%	12.1%	7.4%	1.8%	5.4%	2.5%
Property Value	1.8%	1.7%	3.2%	2.7%	1.6%	2.0%	1.5%
Interest Rate	13.2%	11.0%	29.6%	20.8%	11.4%	13.9%	15.0%

Table 13: Market and Lender Coverage

Panel	Metric	Value
MSAs	Number of MSAs	414
MSAs	Median apps per MSA	10,100.5
MSAs	P90 apps per MSA	100,702.4
MSAs	Top 10 MSAs share	27.6%
Lenders	Number of lenders	2,863
Lenders	Median apps per lender	820
Lenders	P90 apps per lender	7,681.4
Lenders	Top 10 lenders share	28.9%

Table 14: Race/Ethnicity Composition Across Samples

Race	Clean	Clean (%)	Approval	Approval (%)	Pricing	Pricing (%)
NH White	9,040,332	59.4%	6,957,308	64.1%	5,998,032	65.9%
NH Black	603,531	4.0%	437,377	4.0%	291,628	3.2%
Hispanic	1,173,721	7.7%	855,864	7.9%	646,394	7.1%
NH Asian	1,085,068	7.1%	792,087	7.3%	676,041	7.4%
Other	357,603	2.3%	268,388	2.5%	222,973	2.5%
Race NA	2,967,065	19.5%	1,546,639	14.2%	1,263,845	13.9%

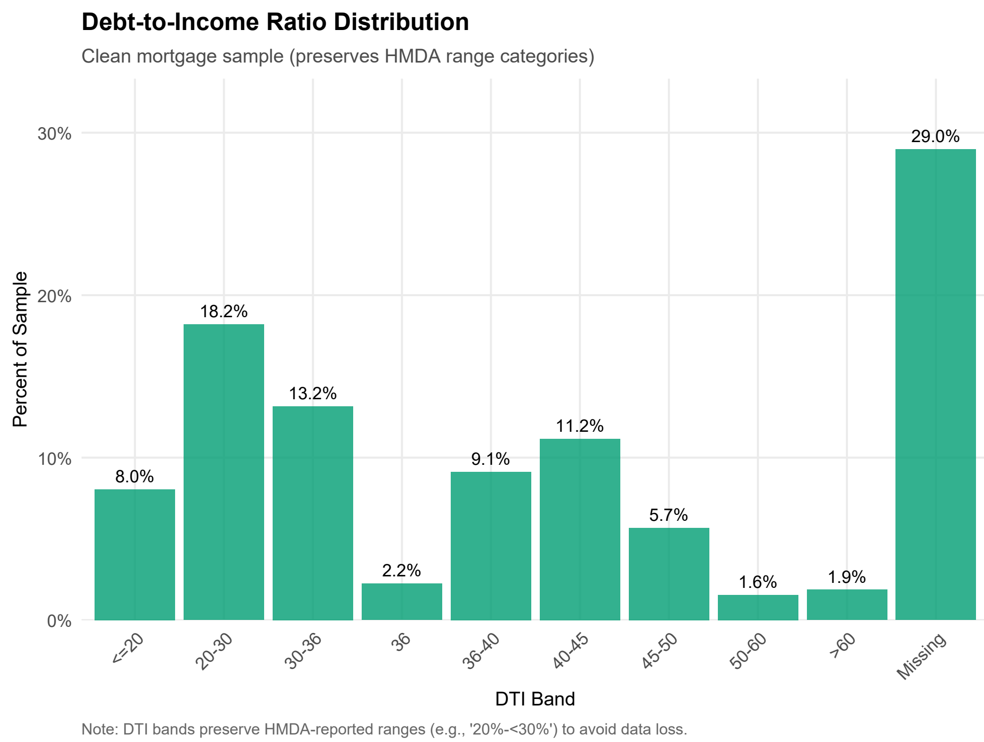
Debt-to-Income Ratio Distribution
Clean mortgage sample (preserves HMDA range categories)
Percent of Sample
30%
20%
10%
0%
8.0%
18.2%
13.2%
2.2%
9.1%
11.2%
5.7%
1.6%
1.9%
29.0%
<=20
20-30
30-36
36
36-40
40-45
45-50
50-60
>60
Missing
DTI Band
Note: DTI bands preserve HMDA-reported ranges (e.g., '20%-<30%') to avoid data loss.

Figure 6

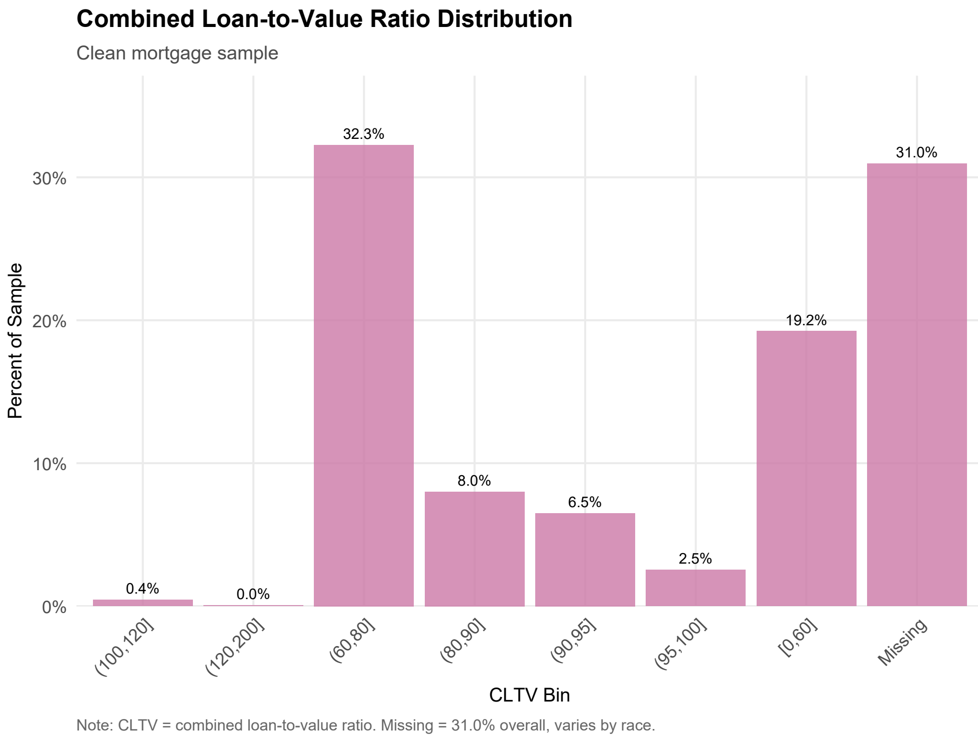

Figure 7

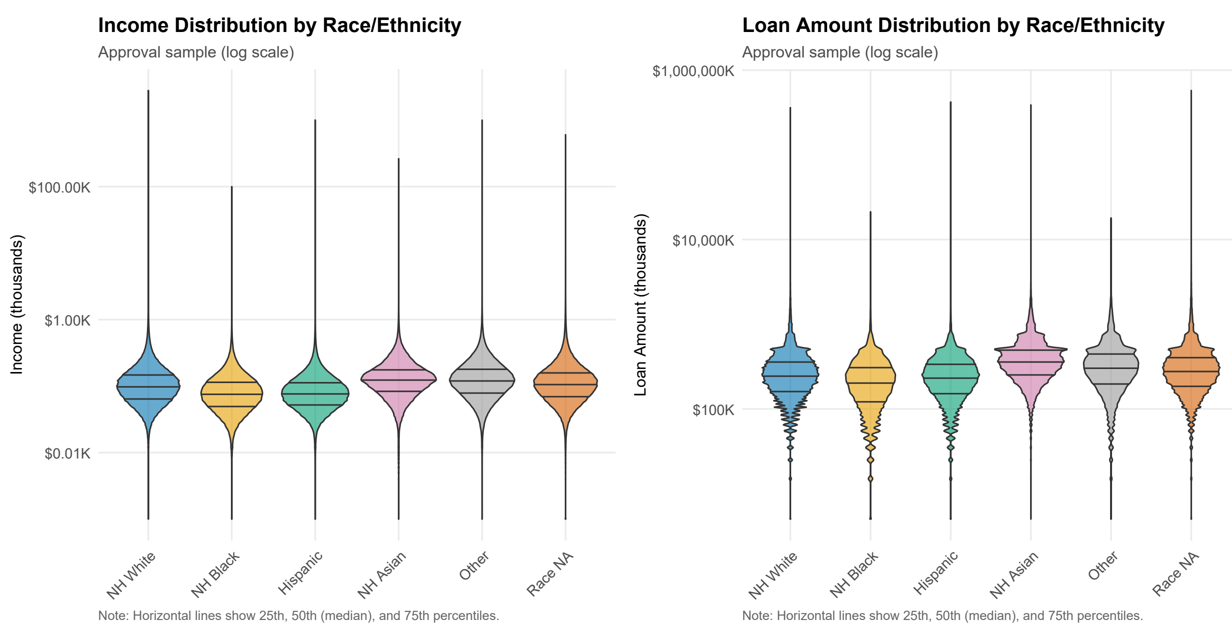

Figure 8

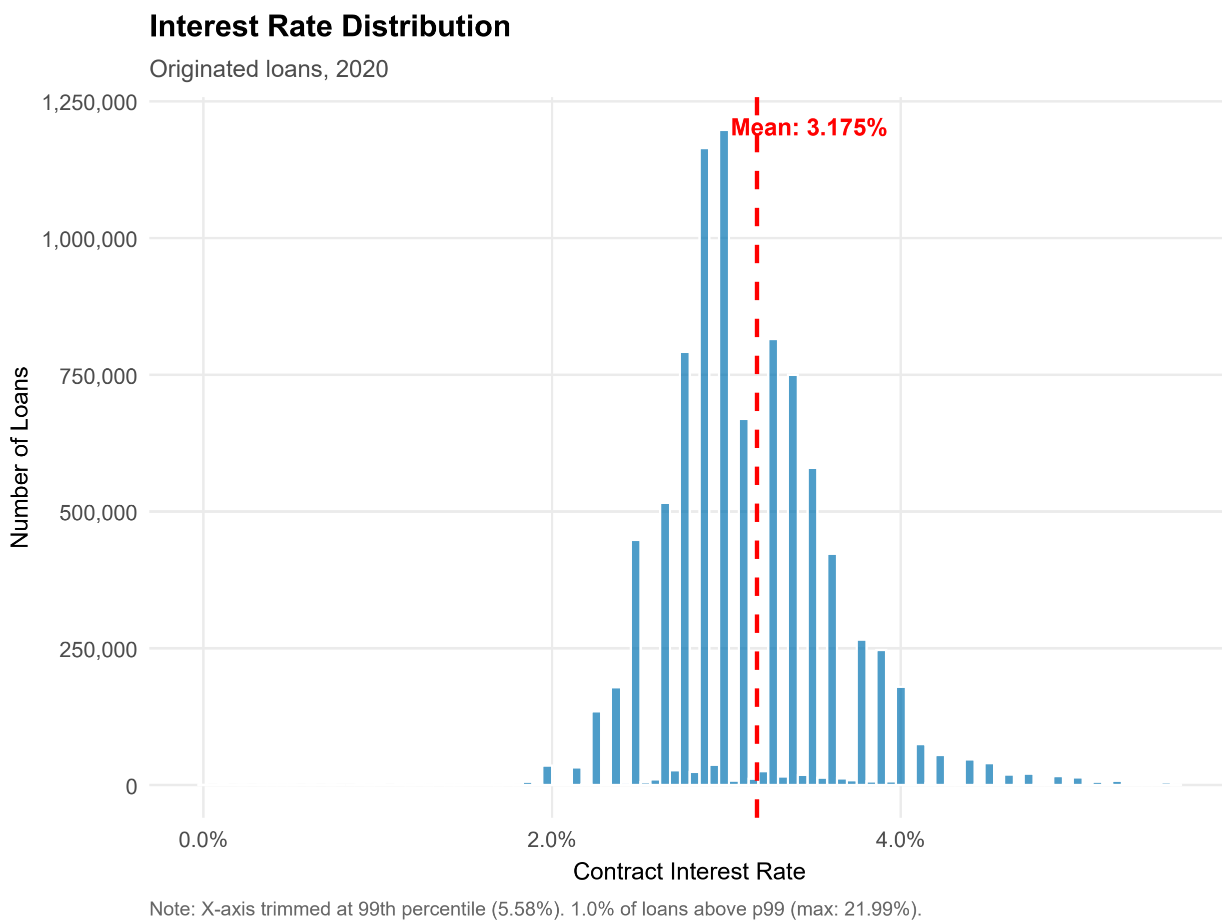

Figure 9: Distribution of contract interest rates (pricing sample)

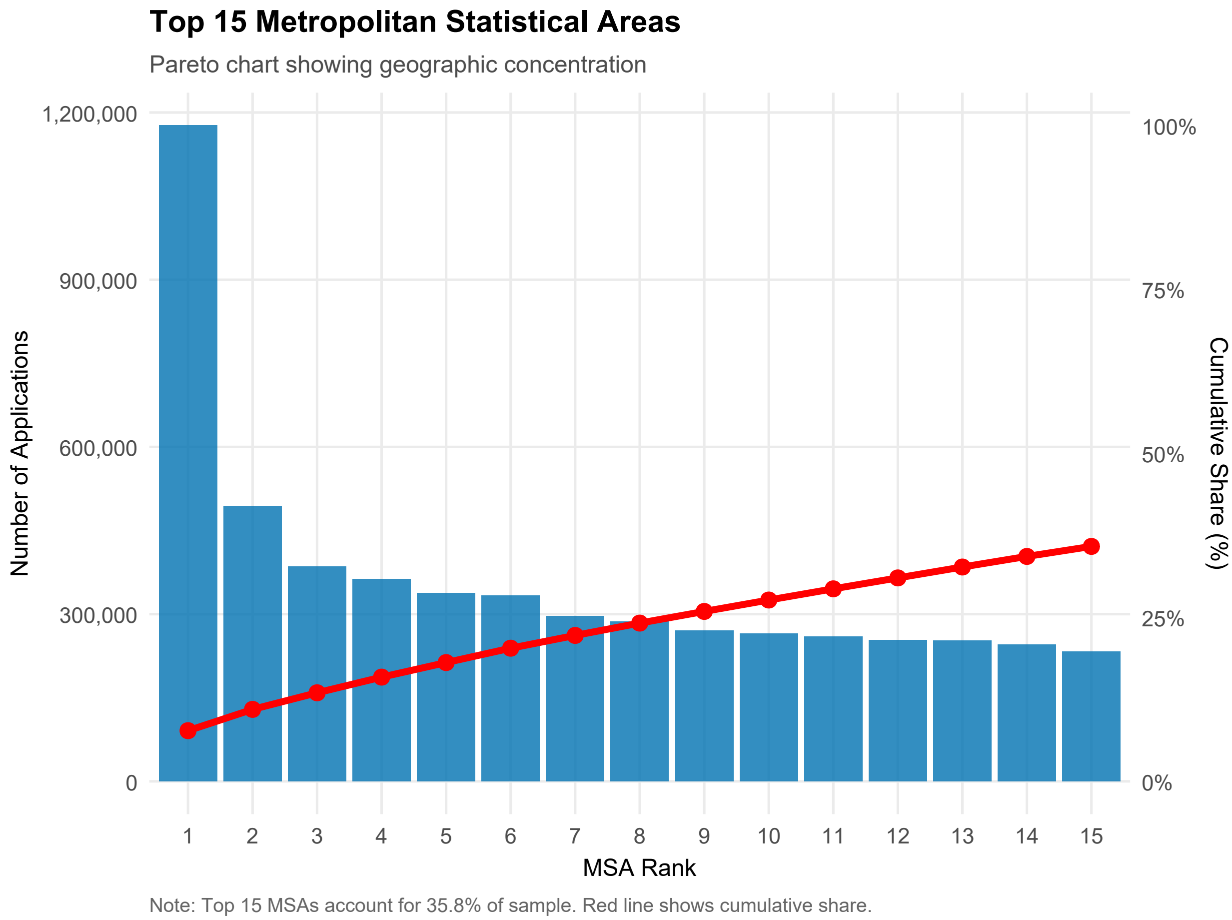
Top 15 Metropolitan Statistical Areas
Pareto chart showing geographic concentration
1,200,000
900,000
600,000
300,000
0
Number of Applications
100%
75%
50%
25%
0%
Cumulative Share (%)
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
MSA Rank
Note: Top 15 MSAs account for 35.8% of sample. Red line shows cumulative share.

Figure 10

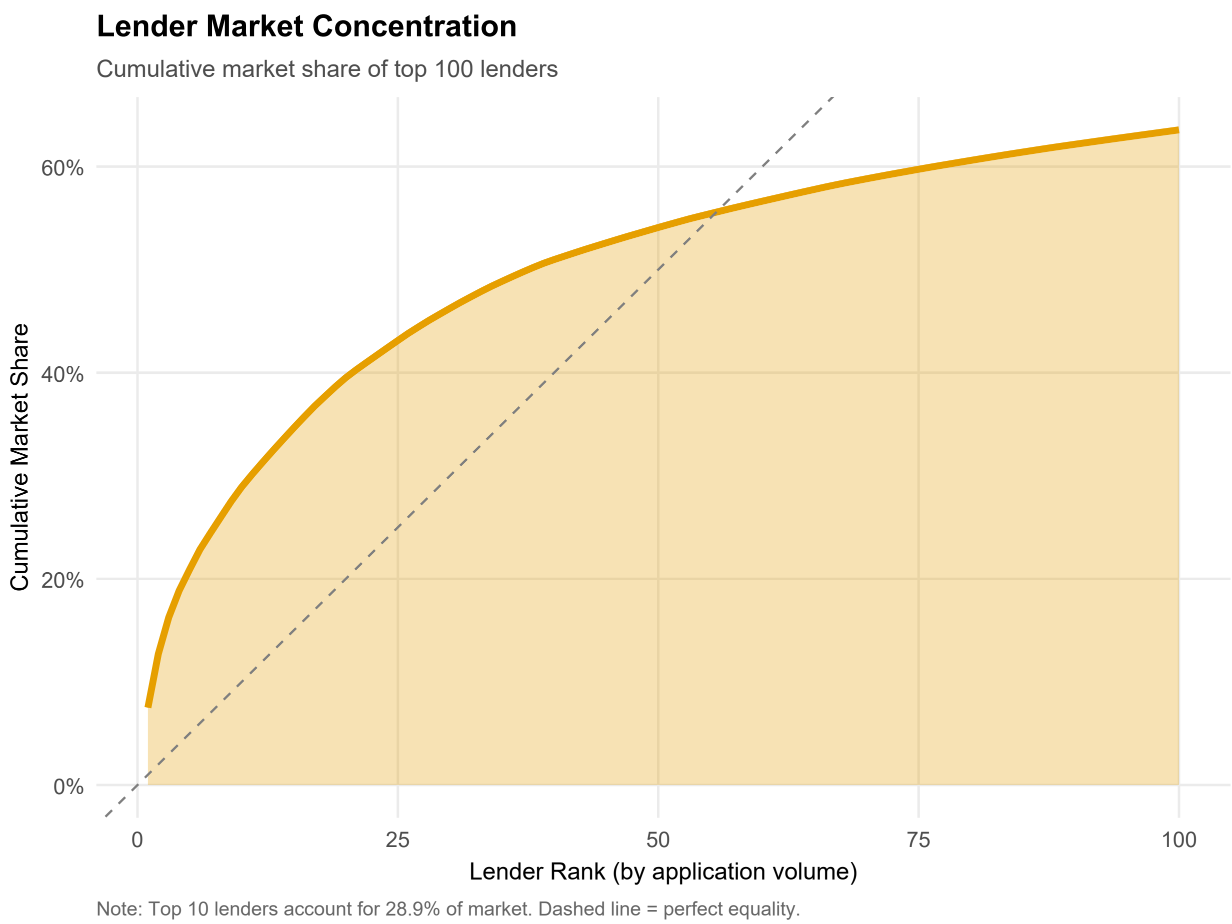
Lender Market Concentration
Cumulative market share of top 100 lenders
Cumulative Market Share
60%
40%
20%
0%
0
25
50
75
100
Lender Rank (by application volume)
Note: Top 10 lenders account for 28.9% of market. Dashed line = perfect equality.

Figure 11

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