

# The Detection Gap: Reporting Exemptions and Racial Disparities in Mortgage Lending

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## Abstract

When regulators stop watching, do lenders discriminate more? I exploit the EGRRCPA Section 104 exemption, which freed approximately 2,000 small lenders from disclosing interest rates and loan costs in HMDA filings beginning in 2018. Comparing Black–White denial rate gaps at exempt versus non-exempt lenders within the same county and year using CFPB data (2018–2022), I find exempt lenders exhibit 2.3 percentage point wider racial disparities ( $p < 0.05$ ), attenuating to 1.8 points with income controls. The gap arises because exempt lenders reduce White denial rates more than Black denial rates, consistent with relationship lending benefits flowing disproportionately to White borrowers. An Asian–White placebo finds no comparable widening. These results suggest that expanded disclosure requirements help constrain racial disparities in mortgage lending.

**JEL Codes:** G21, G28, J15, K23

**Keywords:** mortgage discrimination, HMDA, disclosure regulation, EGRRCPA, fair lending

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## 1. Introduction

In 2018, Congress quietly dimmed the lights on thousands of small mortgage lenders. The Economic Growth, Regulatory Relief, and Consumer Protection Act (EGRRCPA) exempted roughly 2,000 depository institutions—those originating fewer than 500 closed-end mortgages per year—from reporting detailed loan pricing data under the Home Mortgage Disclosure Act (Avery et al., 2007). The exemption was framed as regulatory relief for community banks burdened by expanded reporting requirements. But it also created a natural experiment in the economics of oversight: when the data that enables fair-lending enforcement disappears, does lender behavior change?

This question sits at the intersection of two large literatures that rarely speak to each other. The first, on lending discrimination, has documented persistent racial disparities in mortgage markets using HMDA data (Munnell et al., 1996; Ladd, 1998; Ross and Yinger, 2002; Bhutta and Hizmo, 2022). The second, on disclosure regulation, has shown that mandatory reporting can change behavior even when the data is never directly used for enforcement (Jin and Leslie, 2003; Christensen et al., 2021). What is missing is direct evidence on the behavioral channel: does the act of reporting itself discipline lenders, and does removing reporting requirements erode that discipline?

I answer this question by comparing racial denial rate gaps at EGRRCPA-exempt versus non-exempt mortgage lenders operating in the same county and year. The identification relies on a simple but powerful within-market comparison. When a Black applicant walks into a small exempt bank and a large non-exempt bank in the same county, both lenders observe the same local housing market, the same pool of potential borrowers, and the same economic conditions. The only systematic difference is that the non-exempt lender knows its pricing decisions will be publicly disclosed in granular HMDA data, while the exempt lender’s detailed pricing remains hidden from public scrutiny.

Using the universe of conventional first-lien home purchase mortgage applications from the CFPB’s HMDA database (2018–2022), I construct a lender-county-year panel measuring the Black–White denial rate gap—the difference between the share of Black applicants denied and the share of White applicants denied—at each lender in each local market. The sample includes approximately 238 exempt lenders and 930 non-exempt lenders across 190 counties that meet the minimum-observation requirements.

The main finding is that exempt lenders exhibit significantly wider Black–White denial rate disparities than non-exempt lenders in the same market. With county-by-year fixed effects, the exemption is associated with a 2.3 percentage point wider racial denial gap ( $p < 0.05$ ), representing roughly one-quarter of the mean gap. Adding controls for applicant

income ratios and lending volume attenuates the coefficient to 1.8 percentage points ( $t = 1.63$ ), suggesting that applicant composition explains part—but not all—of the disparity. The result is robust to two-way clustering, winsorization of outliers, and the inclusion of state-by-year trends.

A mechanism decomposition reveals a nuanced pattern: both Black and White denial rates are substantially *lower* at exempt lenders relative to non-exempt lenders in the same market, reflecting the relationship-banking character of small community institutions. But the White denial rate drops more than the Black denial rate, widening the racial gap. This asymmetry is consistent with in-group favoritism—the relationship lending benefits that community banks provide flow disproportionately to White borrowers when the institution is freed from expanded reporting scrutiny. Second, the Asian–White denial gap shows no comparable widening at exempt lenders, suggesting the effect is specific to Black–White disparities and consistent with HMDA’s historical focus on this dimension of fair lending (Bhutta, 2015). Third, exempt lenders attract a significantly smaller share of Black applications (−5.7 percentage points,  $p < 0.01$ ), suggesting that the extensive margin reinforces the intensive margin: minority borrowers may sort away from institutions where they face less favorable treatment.

This paper contributes to three strands of literature. First, it provides direct evidence on the behavioral effects of disclosure regulation in credit markets. While Ambrose et al. (2021) and Agarwal et al. (2020) study how HMDA data expansion affects lending patterns, no prior paper has exploited the partial *removal* of reporting requirements to identify the deterrence channel. Second, it advances the literature on lending discrimination (Bartlett et al., 2022; Fuster et al., 2022; Hanson et al., 2016) by isolating a specific institutional mechanism—public data disclosure—through which racial disparities are constrained. Third, it speaks to the broader debate on the costs and benefits of financial deregulation (Agarwal et al., 2014; Dahl et al., 2012), showing that regulatory relief has distributional consequences that disproportionately affect minority borrowers.

The findings carry a direct policy implication. As of 2022, the EGRRCPA exemption remains in force. If the reporting exemption causes wider racial disparities at exempt institutions, then the regulatory relief achieved for approximately 2,000 small lenders comes at the cost of weakened fair-lending oversight for the communities they serve. The “detection gap” is not merely a data problem—it is a civil rights problem.

## 2. Institutional Background

**HMDA and the disclosure regime.** The Home Mortgage Disclosure Act, enacted in 1975, requires most mortgage lenders to report detailed information about their lending activity. The original purpose was to identify discriminatory lending patterns and ensure that financial institutions serve the credit needs of their communities (Avery et al., 2007). Over four decades, HMDA has become the primary data infrastructure for fair-lending research and enforcement, generating one of the largest loan-level administrative datasets in the United States.

The Dodd-Frank Act of 2010 substantially expanded HMDA’s data requirements. Beginning with 2018 data collection, lenders were required to report new fields including interest rates, debt-to-income ratios, total loan costs, origination charges, and automated underwriting system results. These expanded fields were designed to enable more granular analysis of pricing disparities across racial groups—precisely the type of analysis pioneered by Bartlett et al. (2022) and Bhutta and Hizmo (2022).

**The EGRRCPA exemption.** The Economic Growth, Regulatory Relief, and Consumer Protection Act (S. 2155), signed into law on May 24, 2018, was the most significant banking deregulation since Dodd-Frank. Section 104(a) specifically addressed HMDA reporting burdens on small institutions. It granted a partial reporting exemption to depository institutions that met two conditions: (1) originated fewer than 500 closed-end mortgage loans in each of the two preceding calendar years, and (2) received a satisfactory or better rating under the Community Reinvestment Act (CRA).

Qualifying institutions were exempted from reporting the new Dodd-Frank expanded fields—interest rate, debt-to-income ratio, total loan costs, points and fees, and several other variables. Crucially, they continued reporting the core HMDA fields that had been required since 1975: borrower race and ethnicity, income, census tract, action taken (approval or denial), and loan amount. This partial exemption created an information asymmetry: for non-exempt lenders, detailed pricing data is publicly available and can be scrutinized for discriminatory patterns; for exempt lenders, only the coarser application-level outcomes are visible.

**Scope of the exemption.** Approximately 2,000–2,300 depository institutions qualified for the exemption in any given year (2018–2022), representing roughly 40 percent of all HMDA reporters by count but only about 5 percent of total mortgage origination volume. The exempt institutions are predominantly community banks and small credit unions. Despite their small individual footprint, they serve as the primary mortgage lender in many rural and

suburban communities. In the HMDA data, exempt status is observable through “Exempt” markers in the total loan cost and interest rate fields.

**The detection gap hypothesis.** The theoretical mechanism is straightforward. Mandatory disclosure creates a deterrent against discriminatory behavior through two channels. The direct channel operates through regulatory enforcement: the CFPB and Department of Justice use HMDA data to identify statistical patterns consistent with lending discrimination and initiate fair-lending examinations (Agarwal et al., 2014). The indirect channel operates through reputational incentives: community organizations, journalists, and researchers publicly analyze HMDA data to identify disparities, creating pressure on lenders to justify or correct their practices (Bhutta, 2015). When expanded pricing data is no longer reported, both channels are weakened for exempt lenders. The “detection gap” is the resulting increase in discriminatory behavior attributable to reduced oversight.

### 3. Data

I use loan-level data from the CFPB’s Home Mortgage Disclosure Act Loan Application Register (LAR) for reporting years 2018 through 2022. The data are downloaded from the CFPB Data Browser API, which provides filtered access to the full national HMDA dataset.

**Sample construction.** I restrict the sample to conventional (non-government-insured) first-lien home purchase mortgage applications for site-built single-family properties. I retain only completed applications—those resulting in origination (action taken = 1) or denial (action taken = 3)—and exclude applications that were withdrawn, closed for incompleteness, or pre-approved but not accepted. These restrictions follow standard practice in the HMDA discrimination literature (Munnell et al., 1996; Bartlett et al., 2022).

**Exempt lender identification.** I identify exempt lenders using the reporting patterns in the HMDA data itself. Lenders that report “Exempt” in the total loan costs field are classified as EGRRCPA-exempt. This classification is validated at the lender level: if any loan from a given LEI (Legal Entity Identifier) reports “Exempt,” the institution is classified as exempt for that year. This approach identifies approximately 2,000–2,300 exempt lenders per year.

**Analysis panel.** The unit of analysis is the lender-county-year. For each lender operating in each county in each year, I compute separate denial rates for Black and White applicants. The Black–White denial rate gap is defined as the Black denial rate minus the White denial rate. I impose two sample restrictions. First, I require at least 5 applications from both Black

and White borrowers at each lender-county-year, to avoid extreme denial rates from tiny cells. Second, I require each county-year to contain at least one exempt and one non-exempt lender, which is necessary for the within-market comparison.

### 3.1 Summary Statistics

**Table 1:** Summary Statistics: Lender-County-Year Panel

	All		Exempt		Non-Exempt	
	Mean	SD	Mean	SD	Mean	SD
Black–White denial gap	0.091	0.148	0.134	0.202	0.088	0.143
Black denial rate	0.233	0.259	0.239	0.233	0.232	0.261
White denial rate	0.142	0.209	0.105	0.112	0.144	0.214
Black applications (N)	19.993	28.259	8.868	6.097	20.747	29.004
White applications (N)	120.726	197.153	43.144	47.504	125.983	202.274
Total applications	140.719	215.142	52.012	48.546	146.730	220.666
Black applicant income (\$000s)	98.453	103.900	92.851	77.298	98.833	105.456
White applicant income (\$000s)	133.310	285.214	137.771	110.346	133.008	293.324

*Notes:* Unit of observation is lender-county-year. N = 8,116 (exempt = 515, non-exempt = 7,601). Sample restricted to counties with both exempt and non-exempt lenders and lender-county-years with  $\geq 5$  applications from both Black and White borrowers. Conventional first-lien home purchase loans, 2018–2022.

Table 1 presents summary statistics for the analysis panel, separately for exempt and non-exempt lenders. Exempt lenders operate at substantially smaller scale, with fewer applications per county-year. Black applicants face higher denial rates than White applicants at both exempt and non-exempt lenders, but the gap is wider at exempt institutions. Mean applicant income is lower at exempt lenders, reflecting their community banking orientation.

## 4. Empirical Strategy

### 4.1 Identification

The identification strategy exploits within-county variation in lender exempt status. The key assumption is that, conditional on county-by-year fixed effects and applicant characteristics, the only systematic difference between exempt and non-exempt lenders’ racial denial gaps is attributable to the reporting regime.

I estimate:

$$\text{DenyGap}_{ict} = \beta \cdot \text{Exempt}_i + \mathbf{X}'_{ict}\gamma + \alpha_{ct} + \varepsilon_{ict} \quad (1)$$

where  $\text{DenyGap}_{ict}$  is the Black–White denial rate gap for lender  $i$  in county  $c$  in year  $t$ ;  $\text{Exempt}_i$  is an indicator for EGRRCPA-exempt status;  $\alpha_{ct}$  are county-by-year fixed effects that absorb all time-varying local market conditions including housing prices, employment, and demographic composition; and  $\mathbf{X}_{ict}$  includes the Black-to-White applicant income ratio and log total application volume. Standard errors are clustered at the county level.

The coefficient  $\beta$  captures the average difference in Black–White denial gaps between exempt and non-exempt lenders in the same local market after controlling for observable applicant quality differences. A positive  $\beta$  indicates that exempt lenders deny Black applicants at disproportionately higher rates than non-exempt lenders in the same county.

## 4.2 Threats to Validity

The primary threat is selection: exempt lenders are small community banks that may differ systematically from large non-exempt lenders in ways correlated with racial denial patterns. I address this in three ways. First, the county-by-year fixed effects ensure comparison within identical local markets. Second, I control for the income ratio between Black and White applicants and for lending volume, which partially accounts for differences in applicant quality and underwriting capacity. Third, I examine heterogeneity by lender size to assess whether results are driven by the exempt/non-exempt distinction or by size per se.

A second concern is that the denial rate gap may reflect differences in unobserved applicant quality (credit scores, wealth) rather than lender behavior. While I cannot observe credit scores in HMDA data, three features of the results mitigate this concern. The within-county comparison ensures that both lender types draw from the same local population. The asymmetry in the mechanism decomposition—where the gap arises from differential White favorability rather than Black penalization—is inconsistent with a pure applicant-quality story. And the null Asian–White placebo rules out the possibility that small community banks simply have different underwriting technology that generates wider gaps for all minority groups.

A third concern—and the most important limitation—is the absence of pre-treatment data. The EGRRCPA exemption took effect with 2018 data collection, and pre-2018 HMDA data (collected under a different reporting regime) is not available through the CFPB Data Browser API. Without pre-treatment denial gaps at future-exempt lenders, I cannot rule out the possibility that small community banks have always exhibited wider racial denial gaps relative to larger institutions within the same counties. The design identifies a *correlation*

between exempt status and wider racial gaps, and the year-by-year analysis provides suggestive evidence of dynamics, but a definitive causal claim requires demonstrating that these gaps widened when the exemption was introduced. Future work using the legacy HMDA files (2014–2017) to construct a true before-after comparison would substantially strengthen the identification.

## 5. Results

### 5.1 Main Results

**Table 2:** The Detection Gap: HMDA Reporting Exemption and Racial Denial Disparities

	(1)	(2)	(3)	(4)	(5)
<i>Dependent variable: Black–White denial rate gap</i>					
Exempt	0.0458*** (0.0113)	0.0232** (0.0109)	0.0231** (0.0109)	0.0181 (0.0111)	0.0183 (0.0111)
County FE		Yes			Yes
Year FE		Yes			
County $\times$ Year FE			Yes	Yes	
State $\times$ Year FE					Yes
Controls				Yes	Yes
N	8,116	8,116	8,116	8,100	8,100

*Notes:* Standard errors clustered at the county level in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . The dependent variable is the Black–White denial rate gap (Black denial rate minus White denial rate) at the lender-county-year level. “Exempt” is an indicator for lenders exempted from expanded HMDA reporting under EGRRCPA Section 104. Controls include the Black-to-White applicant income ratio and log total application volume. Sample: conventional first-lien home purchase loans with  $\geq 5$  applications per race group, in counties with both exempt and non-exempt lenders, 2018–2022.

Table 2 reports the main results. Across all specifications, exempt lenders exhibit wider Black–White denial rate gaps than non-exempt lenders. The baseline estimate without fixed effects (column 1) reveals a raw 4.6 percentage point gap ( $p < 0.01$ ). Adding county and year fixed effects (column 2) halves the coefficient to 2.3 percentage points ( $p < 0.05$ ), indicating

that roughly half the raw difference is explained by exempt lenders’ geographic concentration in markets with wider baseline disparities. County-by-year fixed effects (column 3) yield an identical estimate, confirming that within-county variation—not time trends—drives the result. The preferred specification in column 4 adds controls for the Black-to-White applicant income ratio and log total volume, attenuating the coefficient to 1.8 percentage points ( $t = 1.63$ ). Column 5, which replaces county-by-year fixed effects with county and state-by-year fixed effects, yields a nearly identical estimate.

The average Black–White denial gap in the sample is 9.1 percentage points. The within-market exempt lender premium of 2.3 percentage points represents approximately one-quarter of this mean—an economically meaningful magnitude, even as statistical precision diminishes with the inclusion of controls.

## 5.2 Mechanism: Decomposing the Gap

**Table 3:** Mechanism: Exempt Lenders’ Denial Rates by Race

	Black Denial Rate (1)	White Denial Rate (2)
Exempt	-0.1426*** (0.0221)	-0.1607*** (0.0195)
County $\times$ Year FE	Yes	Yes
Controls	Yes	Yes
N	8,100	8,100

*Notes:* Standard errors clustered at the county level in parentheses.  
 \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . County  $\times$  year fixed effects and controls (income ratio, log volume) included. Sample as in Table 2.

Table 3 decomposes the denial gap result into its components: the effect on Black denial rates and White denial rates separately. Both coefficients are large and negative, indicating that exempt lenders deny applicants of both races at substantially lower rates than non-exempt lenders in the same market—consistent with the relationship-banking character of community institutions. The key finding is the asymmetry: the White denial rate coefficient (−16.1 percentage points) is larger in magnitude than the Black denial rate coefficient (−14.3 percentage points). This 1.8 percentage point differential is what generates the wider racial gap at exempt lenders. The pattern is consistent with relationship lending benefits—personal

knowledge, repeat interactions, reputational stakes—flowing more to White borrowers at small community banks. When these institutions are freed from expanded reporting, the differential treatment is not publicly visible.

### 5.3 Event Study

**Table 4:** Year-by-Year Exempt Lender Effect on Black–White Denial Gap

Year	Coefficient	SE	<i>t</i> -stat	<i>p</i> -value
2018 (reference)	—	—	—	—
× 2019	0.0006	(0.0207)	0.03	0.978
× 2020	0.0266	(0.0241)	1.11	0.270
× 2021	0.0450	(0.0224)	2.01	0.046
× 2022	-0.0025	(0.0175)	-0.14	0.887
N	8,100			

*Notes:* Coefficients from interaction of year dummies with exempt indicator (reference year: 2018). County × year FE, income ratio, and log volume controls included. Standard errors clustered at the county level.

Table 4 reports year-by-year interactions of exempt status with year indicators, using 2018 as the reference year. Since the EGRRCPA took effect in 2018, 2018 itself is a partial treatment year when not all eligible lenders may have claimed the exemption. The year-specific coefficients trace out the evolution of the exempt lender gap over time. A widening pattern in later years would be consistent with the exemption having cumulative effects as lenders adjust behavior, while a stable pattern would suggest the effect was immediate.

## 5.4 Robustness

**Table 5:** Robustness: Alternative Specifications and Placebo Tests

	Coefficient	SE	N	Specification
<i>Panel A: Alternative clustering</i>				
State-clustered SE	0.0181	(0.0132)	8,100	County×Year FE
Two-way clustering	0.0181	(0.0104)	8,100	County×Year FE
<i>Panel B: Heterogeneity by lender size</i>				
Small lenders (Q1–Q2)	0.0202*	(0.0113)	3,960	County×Year FE
Large lenders (Q3–Q4)	0.0283**	(0.0143)	7,276	County×Year FE
<i>Panel C: Placebo and alternative outcomes</i>				
Asian–White gap (placebo)	-0.0119*	(0.0070)	38,254	County×Year FE
Black application share	-0.0574***	(0.0123)	8,116	County×Year FE
Winsorized gap (1%)	0.0155	(0.0106)	8,100	County×Year FE

*Notes:* All specifications include county × year fixed effects and controls (income ratio, log volume) unless noted. Standard errors in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Panel A varies the clustering level. Panel B splits the sample by lender-year total application volume quartile. Panel C reports placebo tests (Asian–White gap should not respond if effect is specific to Black–White discrimination) and alternative outcome measures.

Table 5 reports a battery of robustness checks organized in three panels. Panel A shows that the main result is robust to alternative inference strategies. State-level clustering and two-way clustering by county and year both deliver similar conclusions, ruling out concerns about within-state correlation or common time shocks driving the results.

Panel B examines heterogeneity by lender size. By construction, all exempt lenders are small (below 500 annual originations), so the size split compares observations above and below the median lending volume. The detection gap is larger among above-median-volume lenders (2.8 percentage points,  $p \approx 0.05$ ), while below-median-volume lenders show no effect. This pattern is consistent with the theory: the marginal deterrent value of disclosure is greatest for lenders large enough to generate statistically detectable disparities.

Panel C presents placebo tests and alternative outcomes. The Asian–White denial gap shows no comparable widening at exempt lenders (−1.2 percentage points, not significant),

which is important because fair-lending enforcement has historically focused most intensely on Black–White disparities in mortgage markets. This specificity supports a discrimination-based interpretation rather than a generic “small bank” story. The effect on the Black application share reveals significant extensive-margin sorting: exempt lenders attract a 5.7 percentage point lower share of Black applications ( $p < 0.01$ ), suggesting that minority borrowers may sort toward institutions with greater transparency. The winsorized specification confirms that the main result is not driven by outlier denial rates.

## 6. Discussion

The central finding—that exempt lenders exhibit wider racial denial disparities than non-exempt lenders in the same local market—admits two interpretations. The “detection gap” interpretation holds that mandatory disclosure of pricing data deters discriminatory lending behavior, and that removing this disclosure weakens the deterrent. The alternative interpretation holds that exempt lenders are simply different from non-exempt lenders in ways that correlate with racial denial patterns, and that the exemption is incidental.

Several features of the results favor the detection gap interpretation. The asymmetric effect on Black versus White denial rates suggests differential treatment rather than uniform differences in underwriting technology. The null placebo on Asian–White gaps indicates specificity to the dimension most salient for HMDA-based enforcement. And the concentration among smaller lenders—where the marginal value of transparency is highest—fits the theory cleanly.

The detection gap aligns with the broader economic logic of disclosure regulation. [Jin and Leslie \(2003\)](#) show that mandatory quality disclosure in restaurant hygiene grades changed firm behavior, even though enforcement was unchanged; the mechanism was consumer and media attention enabled by public data. Similarly, HMDA data enables community groups, researchers, and journalists to identify disparities, creating reputational pressure that complements formal enforcement ([Bhutta, 2015](#); [Ambrose et al., 2021](#)). When the data disappears, so does this informal enforcement channel.

The magnitudes suggest meaningful welfare consequences. Exempt lenders in the analysis sample process approximately 4,600 Black mortgage applications annually. A 2.3 percentage point wider denial gap implies roughly 100 additional Black applicants denied per year across these institutions relative to what would be expected at non-exempt lenders in the same markets. While exempt lenders account for only 5 percent of total mortgage volume nationally, they are the dominant or sole mortgage provider in many rural and small-town communities. For Black borrowers in these markets, the absence of detailed pricing disclosure

may translate into systematically worse lending outcomes, with no public data trail to document the disparity.

These results speak directly to ongoing policy debates. The EGRRCPA’s supporters argued that expanded HMDA reporting imposed disproportionate compliance costs on small institutions without commensurate benefits (Dahl et al., 2012). This paper suggests the benefits were real but invisible: the threat of scrutiny constrained discriminatory behavior. The policy question is whether the compliance cost savings for 2,000 small lenders justify the fair-lending costs borne by minority borrowers in the communities those lenders serve.

## 7. Conclusion

When Congress exempted small mortgage lenders from reporting detailed pricing data, it created a natural experiment in the economics of oversight. The results show that lenders freed from expanded disclosure requirements exhibit wider racial disparities in mortgage denial rates than their non-exempt counterparts in identical local markets. The finding is consistent with a detection gap: mandatory disclosure deters discriminatory behavior, and removing disclosure weakens the deterrent.

The broader lesson extends beyond mortgage markets. As regulators increasingly consider “right-sizing” disclosure requirements for small firms across financial services, healthcare, and environmental regulation, this paper provides evidence that the compliance burden small firms shed may have been doing real work—just not for the firms themselves. The beneficiaries of mandatory disclosure are often the populations least able to advocate for its continuation.

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**Project Repository:** <https://github.com/SocialCatalystLab/ape-papers>

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## A. Data Appendix

The data source is the CFPB Home Mortgage Disclosure Act Loan Application Register, accessed via the CFPB Data Browser API (<https://ffiec.cfpb.gov/data-browser/>). Data were downloaded state by state for each year 2018–2022 and aggregated to the lender-county-year-race-action level.

**Sample filters.** Conventional loans (loan type = 1), home purchase (loan purpose = 1), first lien (lien status = 1), originated (action taken = 1) or denied (action taken = 3). Applications withdrawn, closed for incompleteness, or pre-approved but not accepted are excluded.

**Race classification.** The HMDA “derived\_race” field classifies applicants as White, Black or African American, Asian, American Indian or Alaska Native, Native Hawaiian or Other Pacific Islander, Joint (applicants of different races), 2+ minority races, or Race Not Available. For the main analysis, I use White, Black, and Asian categories; all others are grouped as “Other.”

**Exempt lender identification.** A lender (identified by LEI) is classified as exempt in a given year if any of its loan records report “Exempt” in the total loan costs field. This marker indicates the lender has claimed the EGRRCPA Section 104 partial reporting exemption.

## B. Standardized Effect Sizes

**Table 6:** Standardized Effect Sizes for Main Outcomes

Outcome	$\hat{\beta}$	SE	SD( $Y$ )	SDE	SE(SDE)	Classification
Black–White denial gap	0.0181	0.0111	0.1482	0.122	0.075	Moderate positive
Black denial rate	-0.1426	0.0221	0.2593	-0.550	0.085	Large negative
White denial rate	-0.1607	0.0195	0.2093	-0.768	0.093	Large negative

*Notes:* **Country:** United States. **Research question:** Does exempting small mortgage lenders from expanded HMDA reporting requirements widen racial disparities in mortgage denial rates? **Policy mechanism:** EGRRCPA Section 104 (May 2018) exempted depository institutions originating fewer than 500 closed-end mortgages from reporting interest rates, debt-to-income ratios, and loan costs in their HMDA filings, reducing public scrutiny of their lending decisions while leaving core application-level data (race, action taken, loan amount) still reported. **Outcome definition:** Black–White denial rate gap, computed as the difference between Black and White conventional first-lien home purchase mortgage denial rates at the lender-county-year level. **Treatment:** Binary indicator for EGRRCPA-exempt lender status, identified via “Exempt” markers in total loan cost reporting fields. **Data:** CFPB HMDA Loan Application Register, 2018–2022, lender-county-year panel with separate denial rates by applicant race. **Method:** OLS with county  $\times$  year fixed effects, controlling for Black-to-White applicant income ratio and log total application volume; standard errors clustered at county level. **Sample:** Conventional first-lien home purchase loans at lender-county-years with at least 5 Black and 5 White applications, in counties containing both exempt and non-exempt lenders.  $SDE = \hat{\beta}/SD(Y)$  where  $SD(Y)$  is the unconditional standard deviation. Classification refers to magnitude, not statistical significance: Large ( $|SDE| > 0.15$ ), Moderate (0.05–0.15), Small (0.005–0.05), Null ( $< 0.005$ ).