**Racial Disparities in the U.S. Mortgage Market: Evidence from Privacy Legislation** *

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**Abstract**

As digitizing personal financial data has facilitated easier data sharing, various U.S. states have identified the need for data privacy legislation and progressively enacted data privacy protection laws to ensure data security and usage transparency. Using a Difference-in-Difference-in-Differences model, we show that U.S. privacy legislation reduced racial disparities in mortgage lending as rejection rates for minority borrowers decreased 18% more compared to non-minority borrowers, and interest rates decreased by 2% more after privacy legislation has been passed. The effects are driven by increasingly data-driven mortgage decisions, reducing the reliance on soft information and the possibility of discriminatory practices, as well as by wider mortgage offers with lower interest rates in minority-dense and underserved banking areas, thereby reducing racial disparities and broadening credit access for minorities.

**JEL Classification: G21, G28, G18; J15; J71; O33**

**Keywords:** Privacy Legislation; Fintech; Mortgage lending; Diversity Equity and Inclusion; Minority

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# 1. Introduction

> "*Diversity, equity, and inclusion (DEI) in organizations and economies are increasingly important for sustainable growth, resilience, and fairer economic outcomes.*
> *Embracing DEI is not just a moral imperative, but also a strategic one that promotes sustainable growth.*"
>
> ——World Economic Forum 2024

As emphasized by the World Economic Forum and other organizations, diversity, equity, and inclusion are increasingly vital in contemporary society. However, discrimination remains prevalent in financial markets, including the mortgage sector where disparities in mortgage approval and interest rates between minority and non-minority borrowers persist (Black et al., 1978; Munnell et al., 1996). To mitigate racial disparities in the mortgage market, the United States enacted Title VIII of the Civil Rights Act of 1968 (Fair Housing Act), which "prohibits discrimination in the sale, rental, and financing of dwellings […] based on race, color, religion, sex, familial status, national origin, and disability." Extant research has indicated that various regulations have profound impacts on racial equality, such as the Voting Rights Act of 1965 (Bernini et al., 2023; Jones & Shi, 2022; Park et al., 2024) and disclosure of consumer complaints mandated by the Consumer Financial Protection Bureau (CFPB) (Li, 2024). Despite increased scholarly interest in the impact of the California Consumer Privacy Act (CCPA) on mortgage lenders and borrowers (Doerr et al. 2023; Gupta et al. 2022), evidence remains scant regarding the implications of data privacy legislation on racial disparities in the mortgage market.

In this paper, we examine the role of privacy legislation in reducing racial disparities in mortgage lending between minority and non-minority borrowers. Our findings suggest that privacy laws can mitigate these disparities by improving access to credit for minority borrowers through increased loan approvals and lower interest rates. Generally, we argue that privacy protection legislation enhances data availability and transparency, effectively reducing racial disparity and discrimination through a shift toward lending decisions that rely more on hard information rather than soft information. This shift reduces discriminatory practices in both banks and nonbanks, such as FinTechs, although FinTechs further benefit from their geographic reach in underbanked areas and greater attractiveness for minority applicants.

Several U.S. states have enacted data privacy legislation since 2018, one notable example being the CCPA which was signed into law in June 2018. Data privacy laws generally emphasize three key aspects: enhancing information transparency, granting consumers control over their data, and ensuring data security and integrity. First, data privacy laws enhance transparency regarding how businesses handle personal information. They inform consumers about the types of information collected, its purposes, and whether it will be sold or shared. Second, consumers have gained more control over their personal information, as emphasized in the CCPA through rights such as the right to know, the right to delete, the right to opt-out, and the right to non-discrimination when exercising these rights. Third, these privacy laws impose strict regulations on businesses to ensure the security and integrity of data post-collection, requiring businesses to protect customer data and prevent data breaches/security incidents.

The implications of data privacy legislation on racial disparity and minorities' access to finance are twofold: First, the increasing data transparency requirements and increased customer data rights compel lenders to standardize and automate lending processes, focussing more on data-driven assessments based on hard information, such as standardized credit models, rather than soft information (such as from personal interactions). Reduced human involvement and increased automation in lending decisions can lead to reduced discriminatory practices and racial bias. Second, increasing availability and accessibility of bank customer data makes it easier for bank customers to switch financial services providers and apply to different providers. This increased data portability benefits especially FinTech companies (see He et al., 2021; Parlour et al, 2021), as potential customers can provide more data more easily, thus facilitating the screening process. Particularly for minority borrowers and borrowers with thin credit files, this can lead to a rising uptake of FinTech offerings. Due to their independence from traditional bank branches, FinTechs can also offer more affordable mortgage options in minority-dense areas that are typically underserved by traditional banks (Howell et al., 2024), ultimately enhancing access to finance in these areas.

Using mortgage application data from 2018 to 2023, we construct our main sample from counties from U.S. states that enacted privacy legislation, neighboring covered counties as treatment group, and uncovered counties (not belonging to states that enacted privacy legislation) as control group, including information on mortgage market application, rejection rates, and racial origin data. We employ a

Difference-in-Difference-in-Differences (DDD) approach to examine disparities between minority and non-minority mortgage applicants across various states, before and after the enactment of privacy protection legislation. Our main findings suggest that privacy legislation reduces racial disparities in mortgage acceptance and mortgage interest rates: specifically, even after controlling for various credit characteristics (Bartlett et al., 2022; Bayer et al., 2018), denial rate for minority applicants decreases by 18% more than for non-minority applicants and interest rate offered to minority borrowers decreases by 2% more than for non-minority borrowers.

To address concerns about reverse causality and to validate the parallel trends assumption required for the Difference-in-Differences-in-Differences (DDD) approach, we apply the methodology developed by Bertrand and Mullainathan (2003) to examine the dynamic effects of privacy legislation on racial disparities in mortgage lending. Additionally, we implement various fixed effects models, exclude samples from the COVID-19 period, specifically between 2020 and 2021, and omit samples from states where mortgages were signed in the same year the privacy laws were enacted. We also assess the lagged effects of privacy legislation and exclude samples from the top ten mortgage lending institutions. Consistently, all models confirm that privacy legislation effectively leads to reduced interest rates and denial rates for minority groups, thereby promoting equality and financial inclusion.

Our contribution is threefold. First, we contribute to the emerging literature on data security and privacy protection laws on the banking industry, particularly on mortgage lending. We provide novel empirical insights into the impact of privacy legislation on racial disparities, extending the work of researchers such as Doerr et al. (2023), Gupta et al. (2023), and Huang et al. (2024). While existing work has focused on the effects of the CCPA on mortgage lender and borrower costs (Gupta et al., 2023) and on FinTech lending (Doerr et al. 2023), our focus is on the impact on racial disparities in mortgage lending based on a wider range of data privacy legislation enacted in U.S. states.

Second, it enriches the discourse on racial disparities in the mortgage market and diversity, equity, and inclusion (DEI) offering new perspectives that enhance understandings previously established by researchers including Ambrose et al. (2021), Black & Strahan (2001), Phelps (1972), Bartlett et al. (2022), Black et al. (1978), Munnell et al. (1996), Bayer et al. (2018), and Howell et al. (2024).

Finally, our study also contributes to the exploration of FinTech's role in the financial services industry, particularly in mortgage lending, as evidenced by works from Fuster et al. (2019), Berg et al. (2022), and Buchak et al. (2018).

The remainder of this paper is organized as follows: Section 2 provides background on privacy legislation and outlines our hypotheses. Section 3 describes the data and research methodology. Section 4 presents the main empirical results. In Section 5, we delve deeper into mechanism analysis by information transparency and bias. Section 6 studies the differing impacts of various types of lending institutions, especially FinTech lenders. Section 7 conducts additional analyses on lenders' characteristics such as gender and income levels the purposes of loans, the reasons for denials, and the demand side of the mortgage market. Finally, Section 8 summarizes the findings.

## 2. Related literature and hypothesis development

### 2.1 Institutional Background

Since 2018, various U.S. states have introduced and enacted consumer privacy regulations. California led the way with the California Consumer Privacy Act (CCPA), which was passed in early 2018 and signed into law on June 12 of the same year. The CCPA is specifically designed to protect the privacy rights and consumer rights of California residents, mandating data protection and privacy obligations for businesses that collect, process, or sell the personal information of California residents. The CCPA imposes strict regulations on these companies to ensure the security and integrity of collected data. It further introduces new rights for California residents, including the ability to access and delete personal information the option to opt out of selling personal information to third parties, and the right to non-discrimination when exercising these rights. These requirements come with significant penalties in case of non-compliant behavior. Depending on the nature of the violation, penalties under the CCPA can include civil fines of up to $7,500 per violation, along with additional fines ranging from $100 to $750 per consumer in the event of a data breach.

By the end of 2023, 12 states had signed privacy legislation, continuously addressing data breaches and privacy protection issues. These laws mandate companies to develop and implement mandatory protective tools to safeguard private information, significantly strengthening national data security

(Huang et al., 2024). Figure 1 shows the states that have enacted privacy legislation (treatment group): darker blue indicates earlier enactment, while lighter blue represents more recent enactments. Adjacent (control group) states are indicated in grey.

[Insert Figure 1 about here]

### 2.1.1 Economic implications of privacy legislation

The recent wave of state-level data privacy legislation mandates substantial enhancements in the data protection capabilities of organizations, including financial institutions. In particular, state-level privacy laws require entities to ensure the security and integrity of customer data as well as strengthen consumers' control over their data, increasing transparency and accountability in data handling. These novel requirements have substantial economic implications for both financial institutions and their customers.

On the one hand, financial institutions are faced with increasing compliance costs in the form of increased IT investment, as well as legal, data processing, and telecommunication expenses. Gupta et al. (2023) quantify the compliance costs associated with the introduction of the CCPA, higlighting the greater costs for banks that rely more on soft information. They further note the adverse effects of compliance costs for bank customers as these costs can be passed through to them through increased mortgage rates and reduced loan availability due to bank retrenchment. Huang et al. (2024) further highlight the disproportionate effects for small banks compared to larger banks as a result of privacy legislation proposals in the form of (relatively) higher IT investment spending.

On the other hand, data privacy laws can reduce consumer concerns regarding data privacy, leading to increased data sharing and data availability, which in turn can improve financial institutions' screening abilities when making mortgage decisions. In particular, Doerr et al. (2023) conjecture that CCPA alleviates consumer concerns around data sharing and show that increased data sharing primarily benefits FinTechs, as they show an improvement in FinTechs' screening processes and lower loan rates to under-served groups by using non-traditional data. While customers have the right to not share their data and are entitled to non-discrimination when deciding to do so, the possibility of data sharing and portability can compel customers to share more data to avoid a negative data externality. This is shown by Parlour et al. (2021) who highlight this effect as a form of unraveling which "effectively forces everyone to share data with the bank for free".

These effects have wider implications for the financial services industry. Theoretical studies caution against the unintended consequences of the increase in data portability and data sharing for bank customers (through initiatives such as open banking), for example in the form of higher borrowing rates. In particular, Parlour et al. (2022) caution against disruption of information spillovers within traditional banks due to the lack of available customer data and subsequent increases in interest rates. He et al. (2023) find that open banking can lead to over-empowerment of FinTechs, which can lead to a widening of the screening ability gap as some customer information might only be available to FinTechs.

### 2.1.2 Information and racial disparities in the mortgage market

Information plays a vital role in the financial lending sector, as the effective integration of hard and soft information in loan decisions can enhance default prediction accuracy (Berg et al., 2022; Iyer et al., 2016). In addition to more widely available hard information (such as credit scores and salaries), banks traditionally held an information monopoly on their clients, as they were able to infer soft information, for example from personal interactions, to further reduce information asymmetry. However, greater reliance on soft information can lead to biases, as credit officers may respond to perceived race or ethnicity based on an applicant's name or location (Howell et al., 2024) and could potentially disadvantage minority candidates in evaluations (Cornell & Welch, 1996; Fershtman & Pavan, 2021).

Discrimination and significant racial disparities persist in mortgage lending, as minority applicants experience higher incidence rates of higher annual interest rate spreads and are more frequently denied loans than their white counterparts (Black et al., 2003). Bartlett et al. (2022) show that Latinx/Black borrowers, given similar risks, pay substantially higher rates for GSE-securitized and FHA-insured loans, particularly in communities with high minority populations. Similarly, Bayer et al. (2018) found that after controlling for credit scores and other risk factors, African American and Hispanic borrowers were 103% and 78% more likely, respectively, to receive high-cost mortgage loans.

Distinguishing whether these racial disparities stem from statistical discrimination - where lenders observe attributes unknown to researchers (Arrow, 1971; Phelps, 1972) - or from direct taste-based discrimination, bias, and stereotypes (Becker, 1957) is challenging. If statistical discrimination were the primary cause of this discrepancy, loan costs would be unrelated to race (Antonovics & Knight, 2009; Howell et al., 2024). However, even after controlling for various credit characteristics, minority borrowers still incur significantly higher costs compared to white borrowers (Bayer et al., 2018; Black et al., 2003; Courchane & Nickerson, 1997).

In contrast, if stereotypes and bias drive these differences, loan costs would correlate directly with race. Institutions with pronounced racial biases exhibit stark disparities in approval rates between minority and non-minority applicants. For example, Ambrose et al. (2021) found mortgage brokers charged premiums to borrowers outside their ethnicity, with Hispanic brokers showing favoritism toward Hispanic borrowers. Further, Chernenko et al. (2022) and Howell et al. (2024) observed greater racial disparities in financing access in counties with higher racial bias, suggesting loan decisions may be influenced more by postal codes or lender biases than by individual default risk (Mann & Matzner, 2019). Mortgage institutions have been accused of "redlining" minority communities, denying loan applications, and contributing to their marginalization (Holmes & Horvitz, 1994; Tootell, 1996; Ross & Tootell, 2004).

### 2.2 Implications of data privacy legislation on minority borrowers

Based on our discussion of the economic implications of data privacy legislation on the mortgage market, how will it affect mortgages of minority borrowers and racial disparities? Given the prevalent discrimination of minority applicants, we conjecture that data privacy laws can help reduce racial disparities through increased data transparency and portability, thus having asymmetric effects on minority borrowers compared to non-minority borrowers.

In particular, denial rates of minority borrowers can be reduced as a result of privacy legislation. The increased data transparency requirements will force financial institutions to standardize and possibly automate their lending processes and rely more on hard data-driven assessments, thereby reducing the possibility of racial disparities due to discriminatory practices as a result. Furthermore, increasing data availability and portability allow lenders to provide more options to potential applicants and deny fewer mortgages due to reasons such as thin credit history.

Furthermore, greater reliance on hard information and wider availability of hard data can potentially decrease mortgage rates due to more accurate risk assessments. In addition, we conjecture that decreases in interest rates are further strengthened by the increasing market share of Fintechs that are able to offer more services to traditionally under-served areas and offer more competitive rates due to their automated processes and greater reliance on hard information. As suggested by Buchak et al (2018), nonbank lenders focus on more creditworthy borrowers , although they seem to use different information to set interest rates relative to other lenders.

Based on these consideration, we propose the following hypothesis:

***H1: Privacy legislation significantly reduces racial disparities in mortgage lending.***

### 2.2.1 Mechanism 1: Hard and Soft Information Reliance

Privacy legislation may lead to reduced racial disparities in the mortgage lending market through the increasing reliance on hard information and automated processes in lending decisions, as well as the reduction in discriminatory practices and bias through data-driven lending decisions. As lenders increasingly employ automated processes to assess loan applications, the use of algorithmic decision-making has the potential to reduce the impact of human credit officer biases, particularly benefiting minority borrowers by decreasing discrimination based on subjective biases and entrenched stereotypes (Fuster et al., 2019; Howell et al., 2024). [1]

Privacy laws further increase the availability of precise and detailed data, leading to lending decisions that rely more on data-driven assessments, such as standardized credit models, payment history of borrowers along with other verified information (Iyer et al., 2016). While considering soft information obtained from personal interactions with credit officers, such as background, informal qualifications, gender, or race, can mitigate banks' information asymmetry (Agarwal et al., 2011),

[1] For instance, standard credit scoring models such as the FICO Risk Score and Vantage Score are utilized, and developed by companies specializing in proprietary algorithms. Lenders and investors rely on these scores as indicators of credit risk. For example, FICO scores range from 400 to 900, with 650 being the widely relied-upon minimum score for mortgage eligibility, see https://www.fico.com/en/products/fico-score.

overreliance could potentially disadvantage minority candidates in professional evaluations (Cornell & Welch, 1996; Fershtman & Pavan, 2021).

Privacy laws enhance consumer control over personal data, increasing transparency and reducing dependence on assessments based on soft information and discriminatory practices in mortgage decisions. The transparency requirements of privacy statutes can compel financial institutions to disclose the standards and data points used in their credit decision-making processes, reducing the misuse of consumer data. This significantly lowers the occurrence of discrimination, biases, and stereotypes against minorities in the mortgage market. When discriminatory practices targeting specific races or groups emerge, borrowers can leverage their rights to delete and opt-out, as granted by privacy laws, compelling financial institutions to adopt more prudent lending strategies.

Furthermore, privacy legislation has strengthened the requirements for the management and disclosure of personal information collection, processing, and sharing, ensuring transparency and compliance in data handling. These regulations compel financial institutions to provide information in user-friendly formats, particularly requiring banks to invest in hardware and IT infrastructure to meet these standards (Huang et al., 2024).

### 2.2.2 Mechanism 2: FinTech lending

FinTech lending is playing an increasingly important role in mortgage lending. FinTech lenders use online applications and automated processes to offer faster loan evaluations (20% quicker than traditional lenders as Fuster et al., 2019), improving the accuracy and accessibility of hard information and reducing information frictions (Hagendorff et al., 2022). The use of standardized credit models and algorithms has made lending more objective and effective in predicting defaults, while also alleviating information asymmetries between borrowers and lenders (DeYoung et al., 2008; Fuster et al., 2019; Behr et al., 2013; Berger et al., 2005b; Stroebel, 2016). Compared to outdated methods that often showed higher default rates among minorities, newer algorithms more accurately identify creditworthy borrowers within minority groups (Berg et al., 2022), and automation has expanded lending opportunities for the Black community (Howell et al., 2024).

This increased data sharing enables FinTechs to more accurately assess applicants (DiMaggio et al., 2022), optimizing screening processes and reducing overall credit risk. Consequently, these groups gain access to lower interest rates (Doerr, 2023). Unlike traditional credit scoring, FinTechs rely heavily on hard data and algorithm-driven assessments (Howell et al., 2024), which significantly improves the screening and monitoring process (Berg et al., 2022; Buchak et al., 2018). This precision in data evaluation effectively assesses the credit risk of minority borrowers, offering them fairer access to credit opportunities.

Recent literature on privacy legislation and open banking has shown that data privacy legislation and increased data portability favor FinTechs rather than traditional banks (Parlour et al., 2021; He et al, 2022; Doerr et al, 2023; Gupta et al. 2024). As banks that have accumulated extensive amount of soft information through relationship lending techniques, they also face a higher burden with the implementation of privacy protection legislation, leading to increasing compliance costs for banks and retrenchment of mortgage origination (Gupta et al, 2024).

The implementation of privacy regulations has also allowed FinTech companies to play a greater role in serving underbanked areas. With high levels of automation, FinTechs can operate through online platforms, providing services without geographic constraints. In contrast, traditional banks rely on branch networks, which are often sparse in minority communities (Howell et al., 2024). FinTechs, through their entirely online and efficient loan processing, can adapt quickly to market and policy shifts (Buchak et al., 2018; Fuster et al., 2018), making it easier for automated lenders to serve minority-dominated areas underserved by traditional banks (Wang & Zhang, 2020).

From a demand perspective, privacy legislation has expanded credit options for minority borrowers who might otherwise face "redlining" in traditional lending. These laws grant consumers more rights, such as data portability, diverse loan choices, and opt-out options (Aridor et al., 2023). As a result, borrowers are no longer limited to traditional banks and can access loans from FinTech and non-FinTech shadow banks. While privacy laws have made borrowers more inclined to share data with FinTech lenders, attracting potentially higher-quality applicants, studies show no significant change in overall application quality for FinTechs and banks post-legislation (Doerr et al., 2023). Therefore, changes in rejection rates and interest rates are more influenced by the lender's screening and automation capabilities.

## 3. Data and Methodology

### 3.1 Privacy Legislation and Identification Strategy

Since 2018, various U.S. states have enacted privacy legislation, emphasizing the importance of protecting consumer personal data in the banking sector. We gathered information on consumer privacy legislation enacted in the U.S. between 2018 and 2023 by the International Association of Privacy Professionals (IAPP).

In our empirical analysis, we divide mortgage applications into two groups—treatment and control—to assess the impact of consumer privacy legislation on racial disparities in the mortgage market. Applications in states that enacted consumer privacy legislation constitutes our treatment group, whereas those in adjacent states without such legislation form our control group. Both the treatment and control groups are presented in Figure 1 (treatment states in blue and control states in grey).

To ensure a clearer identification and distinction between counties that are affected and counties that are unaffected by privacy legislation, we further restricted our sample to include only counties on the comparative borders of states with privacy legislation (treatment) and without privacy legislation (control). This approach helps eliminate potential confounding variables by maintaining relatively constant economic environments between the treatment and control groups. Figure 2 illustrates this distribution.

[Insert Figure 2 about here]

This specification compares the mortgage market outcomes of minority applicants in treatment counties with those in control counties from 2018-2023 in all border county pairs. This identification strategy (as shown in Figure 2) takes advantage of the similarity between applicants in neighboring counties over randomly selected households across counties. Moreover, this method accounts for changes over time between counties and races, such as local economic conditions or credit market situations.

### 3.2 Mortgage Lending Data

We collect comprehensive mortgage application data from 2018 to 2023 from the Home Mortgage Disclosure Act (HMDA) database, including detailed information on borrowers and the properties mortgaged (down to the census tract, county, and state levels). This dataset covers 90% of mortgage originations in the U.S. and provides detailed information on loan rates, spreads (relative to the average prime offer rate for comparable mortgages), costs (expressed as a ratio of total settlement costs to the loan amount), purpose (for purchase or refinancing), loan amount, term (in months until maturity), loan-to-value ratio (LTV), potential property value, property location by census tract, qualifying loan status, lien status, and originator identity. Additionally, specific borrower information such as gender, race, and age is included. We follow common data-cleaning procedures in mortgage lending studies (Buchak et al., 2018), including only loans that exceed GSE mortgage limits and retaining loans aimed at home purchases, improvements, refinancing, and cash-out refinancing, excluding reverse mortgages.

We construct our main sample from counties from U.S. states that enacted privacy legislation, neighboring covered counties as treatment group, and uncovered counties (not belonging to states that enacted privacy legislation) as control group, including information on mortgage market application, rejection rates, and racial origin data. Our neighboring county sample comprises 8,764,155 mortgage application observations, which leverages the homogeneity between applicants from adjacent counties and families randomly selected across county lines, enhancing the reliability of the comparative analysis. Additionally, for robustness tests, we include an extra sample from states which are adjacent to states where privacy legislation took effect, totaling 3,148,677 mortgage application observations.

***Minority Borrowers***

Following the research by Bartlett et al. (2022), we define borrowers of Latinx or Black descent as minorities, historically the most discriminated against groups in housing and financial sectors. Conversely, Asian Americans are excluded from this minority classification due to their generally higher wealth levels compared to other racial groups, with a median net worth significantly higher than that of White, Black, and Hispanic households.

***FinTech and Shadow Bank***

We further match the lender names and LEI IDs with RSSD IDs using HMDA data and followed the methodology of Buchak et al. (2018) to classify lending institutions into three mutually exclusive categories: (1) traditional banks, (2) non-fintech shadow banks, (3) FinTech shadow banks. We differentiate banks from non-bank institutions by checking whether the financial institution offers deposits and distinguished between FinTechs and shadow banks based on whether loan operations are entirely online with no human intervention. We also conduct cross-verification to overcome subjectivity in categorization.

### 3.3 Methodology

To examine the impact of the privacy legislation on racial disparities in the mortgage market, we combine data on mortgage market applications, rejection rates, and racial origins for our treatment group (neighboring covered counties belonging to states with enacted privacy protection laws) and control group (uncovered counties belonging to states without such laws). We primarily estimate the following triple difference (DDD) model as shown in Equation (1):

$$y_{i,l,t,c} = \alpha + \beta Treat_c \times Post_t \times Minority_i + \theta Treat_c \times Post_t + \mu Minority_i + \gamma Control_{i,t,c} + \varphi_l + \omega_t + \tau_c + \epsilon_{i,l,t,c} \quad (1)$$

where $i$, $l$, $t$, and $c$ represent the loan application, lender, year, and county, respectively. The coefficients of interest pertain to the sequence of estimates associated with the three-way interaction terms $\beta$. The independent dummy variable $Treat_c$ indicates whether the mortgage application was in a county (state) where the privacy legislation has been signed, while $Post_t$ indicates whether the mortgage application is submitted after the signing of privacy legislation. $Minority_i$ is a binary variable equal to one if the mortgage applicant belongs to a minority group and zero otherwise.

We focus on two dependent variables $y_{i,l,t,c}$: the loan interest rate in percent, the differential between the loan's Annual Percentage Rate (APR) and the Average Prime Offer Rate (APOR) for a comparable transaction at the time the interest rate is set, and the denial rate which reflects the rate mortgage applications are denied by lenders. For our control variables, we include borrower characteristics, in particular Credit Model (whether a credit model was used to make the credit decision), Debt-to-Income (DTI) Ratio, Loan-to-Value (LTV) Ratio, Loan-to-Income (LTI) Ratio, Ln Loan Amount, Observed Race, and Age, to control for possible determinants of default risk, which might influence the loan approval and loan pricing decision. Table A1 delineates all control variables used in our analysis. We include lender, year, and county fixed effects ($\varphi_l, \omega_t, \tau_c$). Standard errors are clustered at the state level.

### 3.4 Summary Statistics

Table 1 presents descriptive statistics for the variables used in our analysis. We winsorize all continuous variables at the 1st and 99th percentiles to mitigate the impact of potential outliers. Our sample includes 8,764,155 mortgage application observations from counties with enacted privacy legislation and their adjacent counties (as depicted in Figure 2) and 31,588,968 observations from states with enacted data privacy legislation and adjacent states (as depicted in Figure 1). The average value of the *Treat* × *Post* variable is 0.188, indicating that 18.8% of mortgage applications observed have been submitted in counties within states that have enacted significant privacy legislation. The average for minority applications is 0.182, suggesting that 18.2% of loan applications are made by minority individuals.

[Insert Table 1 about here]

In addition, we present visual evidence of the impact of the Privacy Legislation on mortgage lending across different ethnic/racial groups. As shown in Figure 3, we compare the average interest rate spread (the difference between the mortgage rate and the Annual Percentage Rate) and the loan application rejection rates for minority and non-minority groups over the five years before and after the enactment of the act. The x-axis marks the years relative to the enactment of the Privacy Legislation, with 'Year 0' denoting the year the act was officially passed. Blue lines represent minority groups, while red lines represent non-minority groups. Evidence indicates that before the enactment of the legislation, interest and rejection rates were significantly higher for minority groups relative to their non-minority counterparts, with both rates exhibiting parallel trajectories. However, after the enactment of state-level privacy protection legislation, there has been a noticeable reduction in these disparities.

[Insert Figure 3 about here]

## 4. Empirical Results

### 4.1 Baseline Results

We analyze the impact of U.S. privacy legislation on racial disparities in the mortgage market in terms of denial rates of loan applications and the offered loan interest rates. We compare samples from treatment counties within states that have enacted privacy legislation (covered counties) and control counties that have not (uncovered counties) in Table 2 Panel A, while Panel B is based on the samples from states with and without enacted privacy laws.

[Insert Table 2 about here]

In column (1)-(2), we assess whether privacy laws can reduce disparities in access to finance by a relative decrease in the rejection rates for minority loan applicants compared to non-minority applicatns, focusing particularly on samples from states with and without enacted data privacy laws. The $\beta$ coefficient illustrates the differential impact on minority versus non-minority mortgage denials rates and interest rates before and after enactment of data privacy legislation. Column (1) presents results from model (1) with treatment variables, but without control variables, while model (2) includes borrower-specific controls, commonly used in mortgage lending literature such as *Credit Model*, *Debt-to-Income*, *Loan-to-Value*, *Loan-to-Income*, *Ln_Loan_Amount*, *Race Observed*, and *Age*. Column (1) shows a 22.83 % decrease in the difference in denial rate between minority and non-minority borrowers. Column (2) shows qualitatively similar results that are economically and statistically significant, indicating that privacy legislation decreases minority rejection rates by 18.48%.[2]

The difference in interest rates offered to minority borrowers compared to non-minority borrowers, as shown by the *Treat × Post × Minority* interaction coefficient in Column (3)-(4), is also negative and statistically significant. Columns (4) and (6) include further control variables for borrower characteristics, yielding economically and statistically similar coefficients, indicating that privacy legislation decreases minority interest rates by 2% and reduces the differential from the standard interest rate by 14%. While minority borrowers generally face higher loan interest rates and denial rates compared to non-minorities, we show that privacy legislation can beneficially influences the loan costs and denial rates for minorities.

[2] These change represent 22.83% and 18.48% decrease relative to the average denial rate of 0.184 for all samples, i.e. 0.042/0.184 = 22.83 % and 0.034/0.184=18.48%.

### 4.2 Dynamic Effects

We further apply the methodology of Bertrand and Mullainathan (2003) to examine the dynamic effects of privacy legislation on racial disparities in mortgage lending and validate the parallel trends assumption for DDD models. If our results were influenced by reverse causality, or if there were pre-treatment trends (thus violating the parallel trends assumption), we would expect to observe significant changes in interest rates and rejection rates before the implementation of the privacy legislation. We estimate the following model:

$$y_{i,l,t,c} = \alpha + \sum_{k=-5}^{5} \delta_k \times D_{t,c}^{k} \times Minority_i + \gamma Control_{i,t,c} + \varphi_l + \omega_t + \tau_c + \epsilon_{i,l,t,c} \quad (2)$$

where dummy variables $D_{t,c}^{k}$ capture periods preceding and following the privacy legislation event, and $\delta_k$ the parameter of interest. More specifically, we decompose the periods before and after the event into eleven bins: (i) if the mortgage application is submitted in a state five, four, three, two or one year prior to the enactment of data privacy legislation , the indicators are equal to 1 (*Pre_5*, *Pre_4*, *Pre_3*, *Pre_2*, *Pre_1*); (ii) if the mortgage application is submitted in a state that enacts privacy legislation in the same year, the indicator is equal to 1 (*Post_0*); (iii) if the mortgage application is submitted in a state one, two, three, four, or five year after it has enacted data privacy legislation, the indicators are equal to 1 (*Post_1*, *Post_2*, *Post_3*, *Post_4*, *Post_5*). The replacing the traditional *Post* × *Treat* interaction term allows for a more precise examination of the effects before and after the enactment of privacy legislation. These indicators correspond to the five years before through to the five years after the legislation's implementation year.

[Insert Figure 4 and Table 3 about here]

The analysis indicates that the interaction terms on *Pre_4* × *Minority*, *Pre_3* × *Minority*, *Pre_2* × *Minority,* and *Pre_1* × *Minority* related to minority applicants are statistically insignificant in both the interest rate and loan rejection regressions, thus supporting the validity of the parallel trends assumption. Conversely, the coefficients for *Post_0* × *Minority*, *Post_1* × *Minority*, *Post_2* × *Minority*, *Post_3* × *Minority*, *Post_4* × *Minority*, and *Post_5* × *Minority* are negative and statistically significant, consistent with our baseline results. This demonstrates that the implementation of privacy legislation has a sustained effect on reducing interest rates and rejection rates for minority applicants, indicating that data privacy legislation can helps to decrease racial disparities in mortgage costs and approval rates.

**4.3 Effects of Effective Legislation**

To address concerns regarding the enactment and effective dates of privacy protection legislation, we refine our sampling and identification strategies (as shown in Figure A1) by incorporating mortgage applications from states where the privacy laws were already in effect, as compared to the signing dates utilized in Sections 4.2 and 4.3. Following the baseline methodology in Section 4.2, Table 11 illustrates the impact on columns (1) details the effects on loan rejection rates, while loan rates and interest rate spreads in columns (2) and (3). We include the same control variables, consistent with the baseline models.

[Insert Figure A1 and Table 11 here]

Consistent with baseline results, all models consistently demonstrate a significant negative coefficient for *Privacy_Effective* × *Minority*, indicating that privacy legislation positively affects the loan costs and approval rates for minorities, significantly reducing interest rates and rejection rates for minority applicants' post-legislation enactment.

**4.4 Robustness Checks**

Following our baseline specification, we conducted various additional tests to validate the robustness of our findings, including: (i) different combinations of fixed effects (Table A2); and (ii) excluding samples from the Covid period, specifically 2020 to 2021 (Table A3); (iii) excluding samples from states where the mortgage was signed within the same year of privacy legislation enactment (Table A4); (iv) examining the lagged effects of privacy legislation (Table A5); and (v) excluding samples from the ten largest mortgage lenders (Table A6).

These robustness checks mitigate concerns regarding biases, time series trends, and confounding effects. Consistently, all models show significant negative coefficients for *Treat* × *Post* × *Minority*, confirming our results that privacy legislation leads to a reduction in loan rates and rejection rates for minorities.

## 5. Mechanism 1: Hard Information Reliance

Mechanism 1 focusses on the data privacy legislation effects pertaining to lenders that rely on hard information when making mortgage decisions. The introduction of the data protection legislation introduced strict requirements for data processing and consumer data rights. While Gupta et al. (2023) find that banks with greater amount of soft information experience greater compliance costs, we argue that financial institutions with a greater focus on hard information will more likely apply automated processes and make more objective and data-driven mortgage decisions, leading to lower racial disparities in their decision making. In contrast, institutions that rely on soft information will have fewer options to leverage their compliance-related activities and retrench with respect to their mortgage originations (Gupta et al., 2023). Therefore, the impact of the privacy protection legislation on minority mortgage rates and rejection rates should depend on the use of soft and hard information.

Our assessment of hard information reliance involves two methods: (1) whether loan decisions relied on standardized credit models during the loan decision-making process (models are primarily based on applicants' financial data, such as standardized credit scores, which are quantifiable and standardized metrics); (2) Investment in technological infrastructure. Following Modi et al. (2022), we use the financial institutions' IT investment levels as an indicator of hard information reliance, as the processing of hard information requires the necessary technological infrastructure. Conversely, we measure reliance on soft information by assessing whether the applicant's race could be observed through facial or surname recognition. If lenders can identify the borrower's race from quite subjective information, it may suggest that this information is used for subjective assessments and judgments in the mortgage approval process.

To demonstrate the differential effects of privacy protection legislation on lenders that rely more or less on hard information, and the implications for racial disparities in mortgage rates and approval rates, we conduct a subsample test based on (i) the use of hard information (the use of standard credit models or not). (ii) the level of technological infrastructure at lending institutions (high or low IT investment), and (iii) the use of soft information (where the borrower's race has been observed or not). The results are displayed in Table 4.

[Insert Table 4 about here]

Comparing coefficients in columns (1) and (2) of Panel A, that show decisions made without standardized credit models, to columns (3) and (4) of Panel B, that show decisions made based on hard information (standardized credit models), display more pronounced coefficients for *Treat* × *Post* × *Minority*. Additionally, compared to columns (1) and (2) of Panel B (where lending institutions have poorer IT infrastructure), the coefficient of *Treat* × *Post* × *Minority* is greater in columns (3) and (4) of Panel C (where lending institutions have better IT infrastructure with higher IT investments). Meanwhile, we find a greater coefficient of *Treat* × *Post* × *Minority* in loan application decisions that rely less on soft information (column (3) and (4) of Panels A) compared to scenarios with a higher probability of relying on soft information (column (1) and (2) of Panels A). This suggests that the reduction in racial disparities in the mortgage decision-making process is stronger for lenders that rely more on hard information compared to lenders that incorporate soft information in their lending processes.

**5.1 The Role of Racial Bias**

To demonstrate that privacy protection legislation mitigates racial disparities in mortgage rates and approval rates between minority and non-minority applicants by reducing bias and discrimination, we conducted subsample tests. To more accurately measure discrimination, bias, and stereotypes, we assess the lending institution's situation using the region's bias and the representation of minorities. First, we follow Chernenko et al. (2022), Howell et al. (2024), and Xu et al. (2014) to construct county-level measures of "explicit bias" and "implicit bias" using average results from the Implicit Association Test (IAT).[3] Within this framework, explicit racial bias refers to conscious preferences or prejudiced emotional responses based on race (Daumeyer et al., 2019), and implicit bias refers to unconscious preferences or subtle discrimination in decision-making processes (Chernenko et al., 2022).

[Insert Figure A2 and Table 5 here]

[3] We utilize the structure of the Implicit Association Test (IAT) to construct county-level "explicit bias" outcomes, developing a measure of explicit bias at the county level based on average responses to this survey. We also focus on county-level implicit biases, reflecting the level of implicit bias among lenders. Similarly, implicit biases are subconscious attitudes or stereotypes that influence perception and behavior. Figure A2 displays the distribution of county-level explicit and implicit bias measurements, each standardized to zero mean and unit variance. IAT asks respondents to rate their preference for Black versus White individuals on a scale from 1 to 7: 1 being "I greatly prefer African Americans over European Americans," 4 being "I equally like European Americans and African Americans," and 7 being "I greatly prefer European Americans over African Americans." An absence of preference for one race over another would indicate a lack of explicit racial bias. Sources: https://osf.io/gwofk/

We defined explicit racial bias at the county level as strong preferences or aversions towards different races. A county is considered to have no explicit racial bias if it treats individuals of different races and skin colors equally, without regard to these characteristics (Chernenko et al., 2022; Schmidt et al., 2022). Each test measures biases against specific racial groups (e.g., Black, White), defining implicit and explicit biases as preferential or prejudicial emotional responses toward White and Black individuals. If treated equally irrespective of skin color and race, counties are considered devoid of both implicit and explicit biases. Figure A2 displays the county-level distribution of these bias measures, each standardized to have zero mean and unit variance. As illustrated in Table 5, Panel A, columns (3) and (4), compared to counties without explicit racial bias, those with explicit racial bias witnessed a significant reduction in the disparities in rates and rejection rates between minority and non-minority applicants under the privacy protection laws. This aligns with our expectations; the legislation enhances consumer data portability, prompting financial institutions to adopt more cautious credit strategies and reduce improper data usage due to concerns over legal repercussions, thereby decreasing overt racial discrimination and bias in compliance.

In addition, we categorized counties in our sample into those with implicit racial bias and those without. As shown in Table 5, Panel B, we found that the outcomes were not sensitive to the level of implicit racial bias at the county level. Implicit biases are typically more difficult to detect and hold accountable (Daumeyer et al., 2019), and they may play a lesser role compared to explicit biases, particularly in terms of reducing mortgage rates. As indicated in Panel B, columns (1) and (3), the privacy protection legislation had a uniformly significant effect on reducing rates for minorities, irrespective of the level of implicit racial bias in the county.

**6. Mechanism 2: Nonbank Lenders**

In this section, we aim to explore the varying responses of different loan providers following the introduction of privacy protection laws, particularly concerning the mortgages among minority groups. We follow the classification method of Buchak et al. (2018), distinguishing lenders into banks and non-bank financial institutions based on whether they also offer deposit services, and further categorize non-bank entities into fintech companies and shadow banks based on whether their lending process is entirely online. There are significant differences among lending institutions in terms of information processing capabilities and credit decision-making processes. Banks tend to use a mix of soft and hard information and rely on the judgments of loan officers in making lending decisions. However, fintech lenders rely more on automated processes and hard information to determine mortgage rates (Berg et al., 2022). Moreover, in areas with a higher minority population, existing bank branch networks often provide insufficient services (Wang & Zhang, 2020). We measure the potential lack of service faced by minority borrowers using the concentration of minority applicants in mortgage loan applications (Bartlett et al., 2022).

To test the nonbank lending mechanism, we constructed dummy variables for lending institutions that are shadow banks (with the dummy set to one if the lender neither accepts nor offers deposit services, and zero otherwise) and FinTech firms (set to one if the lender's loan process is entirely online, and zero otherwise). To analyze the role of lender type, we include a four-way interaction effects to our model in Equation (1), estimating the following model:

$$\begin{aligned} y_{i,l,t,c} = \alpha + +\theta Treat_c \times Post_t + \mu Minority_i + \beta Treat_c \times Post_t \times Minority_i \\ + \delta Treat_c \times Post_t \times Minority_i \times Nonbank_l + + \gamma Control_{i,t,c} + \varphi_l + \omega_t + \tau_c \\ + \epsilon_{i,l,t,c} \end{aligned} \quad (3)$$

where *i*, *l*, *t,* and *c* represent the loan application, lender, year, and county, respectively. The variables are the same as in Equation. The variable $Nonbank_l$ indicates if the lending institution is a FinTech (*FinTech*=1) or shadow bank (*ShadowBank*=1). The coefficients of interest pertain to the sequence of estimates associated with the four-way interaction terms *δ*. The results are shown in Table 6.

[Insert Table 6 about here]

We explored the role of FinTech in racial disparities in mortgage lending in columns (1)-(4). The significantly negative coefficient *Treat* × *Post* × *Minority* × *Fintech* indicates that FinTechs contributed more to the decrease in interest rates and rejection rates for minorities following the implementation of the privacy legislation, compared to other institutions. Columns (5)-(8) display the role of shadow banks, analyzed through *Treat* × *Post* × *Minority* × *Shadow bank*. Compared to traditional banks, both FinTechs and shadow banks showed a more pronounced effect in reduced racial disparities after enactment of data privacy legislation, confirming that the nonbank lending channel contributes to the reduction in racial disparities in mortgage lending.

### 6.1 Geographic Variation

We further assess whether effects could be driven by the widening of financial services in areas with a high minority population and low bank branch density. We conducted a subsample analysis based on the proportion of minority populations within census tracts and the density of bank branches within the county. First, based on the proportion of minority populations within a census tract,[4] we divide our samples into two groups: those above the median are designated as high minority concentration areas (Minority Intensity Areas), and those below the median as low minority concentration areas (Minority Non-Intensity Areas). Second, we divided the sample into two groups based on the branch density of banks within the county: regions with branch density above the median were classified as "bank branch-dense" and considered well-served by traditional lending, while those below the median were categorized as "bank branch-sparse" and underserved by traditional lending services. Results are presented in Table 7.

[Insert Table 7 about here]

The results show a wider offering of financial mortgages in underserved areas, reflected in the decrease in denial rates after data privacy enactment, particularly driven by FinTech lenders. Panel A in Table 7 indicates that privacy legislation does not seem to have significant effect in areas with low minority concentration, while effects are significant in areas with higher concentrations of minorities (columns (5)-(8)), confirming a reduction in discrimination in these areas particulary by FinTechs.

As high minority intensity could be correlated with the availability of bank services in these area, as areas with high minority population has been shown to be traditional underserved. The results are not fully explained by bank branch density. While we observe significant reduction in denial rates and interest rates in areas with low bank branch density, areas with higher density of bank branches still show a decrease in interest rates, with increasing FinTech offering one of the main drivers of reduction

[4] A census tract is a geographical area used by the United States Census Bureau for census and statistical analysis. Typically designed to be relatively permanent statistical subdivisions, each tract is intended to have a population size that is relatively balanced, usually around 4,000 people. Tracts are generally larger than a city block, but in densely populated urban areas, a tract can be as small as a single block. The design of census tracts aims to maintain demographic and socio-economic stability over time, facilitating effective data analysis and community comparisons by governments, researchers, and the public.

in racial disparities. We confirm that privacy protection laws significantly mitigate bias in mortgage lending particularly in minority-dense and underbanked areas, contributing to the broader goals of financial inclusion and wider access to finance.

### 6.2 Loan applications

We further analyze the confounding effects of loan applications by minority borrowers. In contrast to our previous individual loan-level analysis, we aggregate data on a county-level, by county, lender, and year, which will more effectively reveal the overall trends and patterns in loan demand. These aggregated datasets record the total number of loan applications received and the total loan amounts by financial institutions within specific timeframes, thus revealing the overall dynamics of borrower demand in the loan market. This approach allows us to understand from a macro perspective how privacy laws impact lending activities across different regions and borrower categories, rather than just based on individual applications and approvals. Meanwhile, fintech's impact on the mortgage market is increasingly significant, particularly in providing equitable services and responding to market demands (Buchak et al., 2018). While traditional banks are still undergoing loan officer training and process reforms to adapt to privacy legislation, FinTech's fully online and automated credit processing allows it to respond more flexibly to market demand and policy fluctuations. To assess the impact of privacy protection legislation on mortgage demand and the demand structure in fintech lending, we estimate the Difference-in-Differences model as shown in Equation (3) and (4):

$$y_{i,l,t,c} = \alpha + \beta Treat_c \times Post_t + \gamma Control_{i,t,c} + \varphi_l + \omega_t + \tau_c + \epsilon_{i,l,t,c} \tag{4}$$

$$y_{i,l,t,c} = \alpha + \beta Treat_c \times Post_t + \varepsilon Treat_c \times Post_t \times Fintech_l + \gamma Control_{i,t,c} + \varphi_l + \omega_t + \tau_c + \epsilon_{i,l,t,c} \tag{5}$$

where *i*, *l*, *t,* and *c* represent the loan application, lender, year, and county, respectively. In county *c* and year *t*, lender *l* presents three distinct observation points *i*, representing total loan applications for all applicants, minority applicants, and female applicants respectively. To explore how privacy protection laws influence loan demand across different types of borrowers, we have consolidated the data into two samples: one comprising all borrower applications within a specific county *c*, lender *l*, and year *t*; and another for minority borrower applications only.

To effectively capture the loan structure—the number of applications, the total loan amounts, and approval rates—we utilize three primary dependent variables: *Applications*, which aggregates the number of mortgage loan applications for all applicants and from only minorities at each lender, county, and annual levels; *Ln(Loan amounts)*, the natural logarithm of summed mortgage loan amounts from all applications and those from minorities under identical conditions; and *Approval rate* which aggregates the rates of loan approvals across all groups under the same conditions. The interaction variable $Treat_c \times Post_t$ represent whether the lender operates in a county where privacy legislation is enacted. Control variables aligned with the baseline model are similarly aggregated at each lender, county, and year level. Table 8 provides preliminary estimates of the impact of privacy legislation on mortgage lending. Specifically, columns (1) - (2) analyze the effects of these laws on the volume of mortgage applications from all applicants and from minority groups; columns (3) - (4) explore the impact on the total loan amounts requested by these groups; and columns (5) - (6) focus on the approval rates for these applications. Panel A comprehensively details the effects of privacy protection legislation on the volume of applications, requested amounts, and approval rates for all applicants and minority groups. Additionally, to analyze the nuanced changes in consumer loan demand, Panel B distinguishes whether lenders are Fintech. We also control for fixed effects for each lender annually and for each county per year to account for various unobservable impacts that differ over time and region, offering a robust framework to assess the impact of privacy legislation on lending practices among diverse borrower demographics and institutional types.

[Insert Table 8 about here]

The analysis reveals that in Panel A, the privacy protection legislation generally increased the volume of mortgage applications across all borrowers, though it did not significantly affect the volumes from minority applicants. This aligns with Gupta et al. (2023) findings that following the introduction of the CCPA law, non-bank financial institutions saw a significant rise in loan applications compared to banks. In Column (2) of Panel B, we found that after the enactment of privacy protection laws, fintech companies experienced a significant increase in loan applications from minority groups. Concurrently, the legislation significantly increased the total amounts of mortgage loans processed by FinTechs for all borrowers, including minorities and women, and also improved approval rates for these applications. By incorporating the coefficient of the interaction term *Treat* × *Post* × *Fintech*, we observe that the legislation not only increased the loan amounts handled by FinTechs but also enhanced the approval rates across all borrower groups. This demonstrates the specific effects of regulatory reforms within the fintech sector. These findings provide valuable insights into the specific impacts of privacy protection laws across different lending markets, revealing the potential positive role of regulatory changes in promoting inclusiveness in lending.

## 7. Alternative explanations and cross-sectional analysis

In this section, we explore possible alternative explanations for the observed reduction in racial disparities in mortgage lending, other than lenders that focus hard information for mortgage decisions and an increase in FinTech lending. In particular, we differentiate by various loan purposes and borrower characteristics, to explore whether reduced racial disparities might be driven by improvement in borrower quality, a shift in loan purposes, or alternative gender effects.

### 7.1 Loan Purpose Differentiations

We further assess the impact of privacy legislation on the differential mortgage results for minority populations based on varying loan purposes. As delineated by the HMDA, the principal purposes of loans include home purchasing, home improvement, refinancing, and cash-out refinancing. It is crucial to acknowledge that the refinancing market is distinct from the markets for home purchase and home improvement loans. Specifically, refinancing predominantly caters to existing mortgage holders who are either seeking to leverage their home equity or to secure more advantageous loan terms. Conversely, the home purchase loan market primarily serves first-time buyers and those transitioning between homes. This market typically necessitates an upfront down payment and bases the determination of loan amounts and rates on the applicant's credit history and lending capability, with the primary goal of facilitating the acquisition of new residential properties.

[Insert Table 9 about here]

In Table 9, columns (1) to (8) present the estimated results from the DDD model, examining loan applications segmented by the purposes of home purchase, home improvement, refinancing, and cash-out refinancing. Each column includes only the samples applicable to the respective loan purposes, and the analyses control for variables consistent with the baseline model. Our study investigates the effects of privacy legislation on the interest rates and rejection rates for minority borrowers. We find that following the enactment of this legislation, there is a significant reduction in both the mortgage interest rates and rejection rates for minorities, irrespective of the loan purpose. However, when comparing the coefficients of *Treat* × *Post* × *Minority* across different columns, it is evident that the interest rate benefits in the home purchase loan market are slightly more favorable for minorities than in the refinancing market. This discrepancy can be attributed to the fact that improvements in loan conditions in the refinancing market are more heavily dependent on the performance of existing loans and the value of the home rather than on initial credit assessments. Refinancing borrowers, being seasoned and experienced, may be less eager to renegotiate terms compared to typical home purchase mortgage borrowers (Bartlett et al., 2022). Therefore, even post-enactment of privacy protection laws, the rate adjustments in the refinancing market may not be as sensitive or significant as those in the home purchase market.

### 7.2 Borrower Characteristics Differentiations

As applicants are more willing to share their data after data privacy legislation, one concern could be that the beneficial effects on racial disparity are driven by the changing population of minority applicants. As more high-quality applicants choose to share data and apply for loans through FinTechs, low-quality applicants might suffer adverse effects from mortgage providers. To further explore whether privacy legislations impact minorities' mortgage lending differently based on borrower types, we divide our samples into different groups: the borrowers whose income above (below) the median is designated as High (Low)-income borrowers, and those whose loan amount above (below) the median as High (Low)-Loan amount borrowers. These subsample analyses are shown in Table 10.

[Insert Table 10 about here]

However, we found no significant differences based on borrowers' income types or loan amount categories, suggesting that privacy regulations do not inherently differ in their impact across different income levels of minority borrowers. This is related to the comprehensive and uniform protective measures of privacy regulation. The loan approval process increasingly relies on standardized credit scoring systems designed to minimize human bias and ensure fairness in processing. This standardized approach ensures that all borrowers, regardless of their income level or loan amount, are treated without bias or differential treatment, thus maintaining broad financial inclusion.

### 7.3 Effects on Gender Disparities

We test for differences in gender impact by replacing the Minority variable in our baseline model with Female, indicating whether the mortgage applicant was female.

[Insert Table 12 about here]

However, the impact of privacy legislation on gender disparities appears limited; it seems only to reduce rejection rates for mortgage applications by women, without effectively influencing interest rates. This might be due to the less pronounced correlation between gender and credit scores compared to race. Women's credit scores may not be subject to the same systemic biases as those related to race. Additionally, the challenges women face in the loan approval process may relate to factors independent of credit scores, such as income disparities or job stability, which are not directly addressed by privacy legislation.

### 7.4 Loan Denial Reason

We further explore whether privacy legislations lead to differential denial reasons for mortgage applications. Utilizing the reasons for loan denials among minority groups, we assess denial reasons for minority borrowers due to insufficient data. The HMDA provides detailed classifications of primary denial reasons offered by lending institutions. These include credit history issues such as insufficient credit references, unacceptable credit reference types, no credit file, limited credit experience, poor credit performance, delinquencies on current or past obligations, frequent inquiries by credit agencies, foreclosures, repossessions, write-offs, collection actions, judgments, and bankruptcy. Other reasons encompass insufficient cash for downpayments and closing costs, inadequate debt-to-income ratios where the applicant's income fails to cover the requested amount or excessive obligations related to income do not meet credit standards, employment history concerns like temporary or informal employment and insufficient length of employment, inadequate value or type of collateral, and denied mortgage insurance.

As shown in Table 13, the sample is exclusively on observations of mortgage loan applications that were denied and for which the lending institutions disclosed the reasons for denial. The dependent variables in columns (1) to (6) correspond to different reasons for loan denials: Credit history (equals 1 if the mortgage loan was denied due to insufficient credit history, otherwise 0), Insufficient cash (equals 1 if the mortgage loan was denied due to insufficient cash for downpayment and closing costs, otherwise 0), Debt-to-income ratio (equals to 1 if the mortgage loan was denied because the debt-to-income ratio did not meet credit requirements, otherwise 0), Employment history (equals to 1 if the mortgage loan was denied due to inadequate employment history or duration of employment not meeting credit requirements, otherwise 0), Collateral (equals to 1 if the mortgage loan was denied due to inadequate value or type of collateral, otherwise 0), and Mortgage insurance denied (equals to 1 if the mortgage loan was denied due to reasons related to mortgage insurance, otherwise 0).

[Insert Table 13 about here]

In Table 13, column (1), the coefficient for *Treat* × *Post* × *Minority* is -0.022, indicating that privacy legislation has reduced the likelihood of minorities being denied loans due to insufficient credit history. The introduction of privacy laws has enhanced transparency and accountability in lending, allowing financial institutions to facilitate more efficient and complete data sharing and to perform more accurate risk assessments for borrowers traditionally lacking sufficient credit history, thus reducing denials due to insufficient credit references or the absence of a credit file. Additionally, as shown in column (2) of Table 13, there is relatively weak evidence that privacy legislation may decrease the likelihood of minorities being denied loans due to insufficient funds (e.g., downpayments, closing costs). However, we did not find evidence suggesting a reduction in denials due to Debt-to-income ratio, Employment history, Collateral, or Mortgage insurance denied.

## 8. Conclusion

We employ a Triple-Difference (DDD) model to examine the effects of privacy legislation on racial disparities in the mortgage market. The findings demonstrate that even after controlling for various credit characteristics, privacy legislation indeed lead to a greater reduction in interest rates by 2% and reduction in rejection rates by 18% for minority borrowers compared to non-minority borrowers, thereby decreasing racial disparities faced by minority borrowers in the mortgage market. Our results are primarily driven by lenders that rely more on hard information rather than soft information. With the increasing transparency requirements, privacy legislation can further lead to a decrease in discriminatory practices and racial bias, as effects are more pronounced in areas with greater racial animus, higher minority intensity and lower bank branch density. We also find additional evidence suggesting that non-bank lending institutions, such as FinTech firms, further contribute to the reduction of racial disparities by providing mortgages to minority borrowers in areas with a high-minority population, and by attracting more applications from minority borrowers.

Our research significantly contributes to the literature on data security and privacy protection, extending previous research on the effects of privacy laws (Doerr et al., 2023; Gupta et al., 2023; Huang et al., 2024). Furthermore, our findings contribute new insights into the ongoing discussions on financial inclusion and racial disparities in the mortgage market (Bartlett et al., 2022; Bayer et al., 2018; Black et al.,1978; Munnell et al., 1996) and offer valuable perspectives for diversity, equity, and inclusion initiatives. Finally, our research also contributes to the understanding of the role of FinTech in financial activities, particularly in the mortgage lending sector, by building on the studies conducted by Fuster et al. (2019), Berg et al. (2022), Gupta et al. (2023), Buchak et al. (2018), and Howell et al. (2024).

Our study holds strong policy implications for both financial institutions and regulatory bodies, demonstrating that while the goal of data privacy protection laws is to alleviate consumer concerns about privacy and enhance data security controls, it can further have beneficial effects on financial inclusion and reduce racial disparities through enhanced data transparency and consumer rights.

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## Figures and Tables

**Figure 1. Coverage of enacted legislation in states and neighboring states**

This figure shows the privacy legislation signing dates across various states in the United States from 2018 to 2023. Different shades of blue represent the signing dates, with darker shades indicating earlier signing dates and lighter shades indicating later signing dates of privacy legislation. Neighboring states that did not sign the legislation are marked in gray, while non-neighboring states are marked in white.

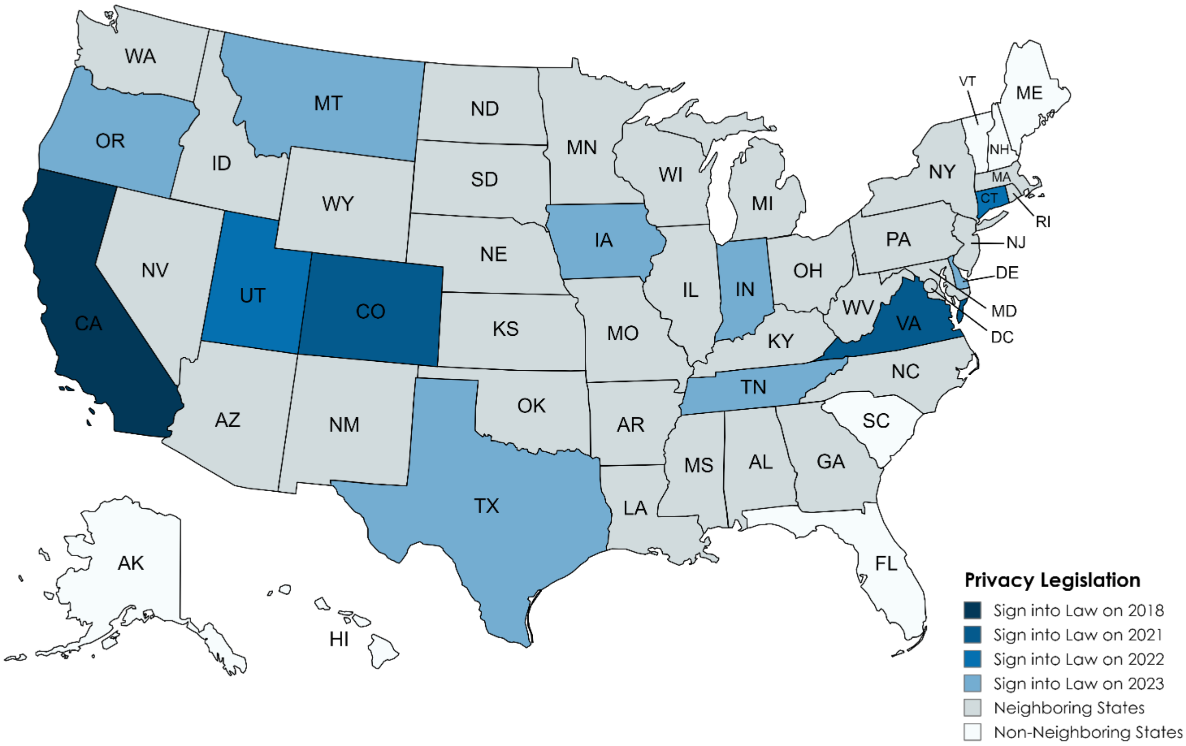


**Figure 2. Coverage of only counties adjacent to privacy legislation state borders**

This figure shows the signing dates of privacy legislation across various states in the United States from 2018 to 2023, focusing specifically on counties that are adjacent to other states. Different shades of blue represent the signing dates, with darker shades indicating earlier signing dates of the privacy legislation in the respective counties' states while lighter shades indicate later signing dates of privacy legislation. Counties in neighboring states are marked in gray, while non-neighboring counties are marked in white.

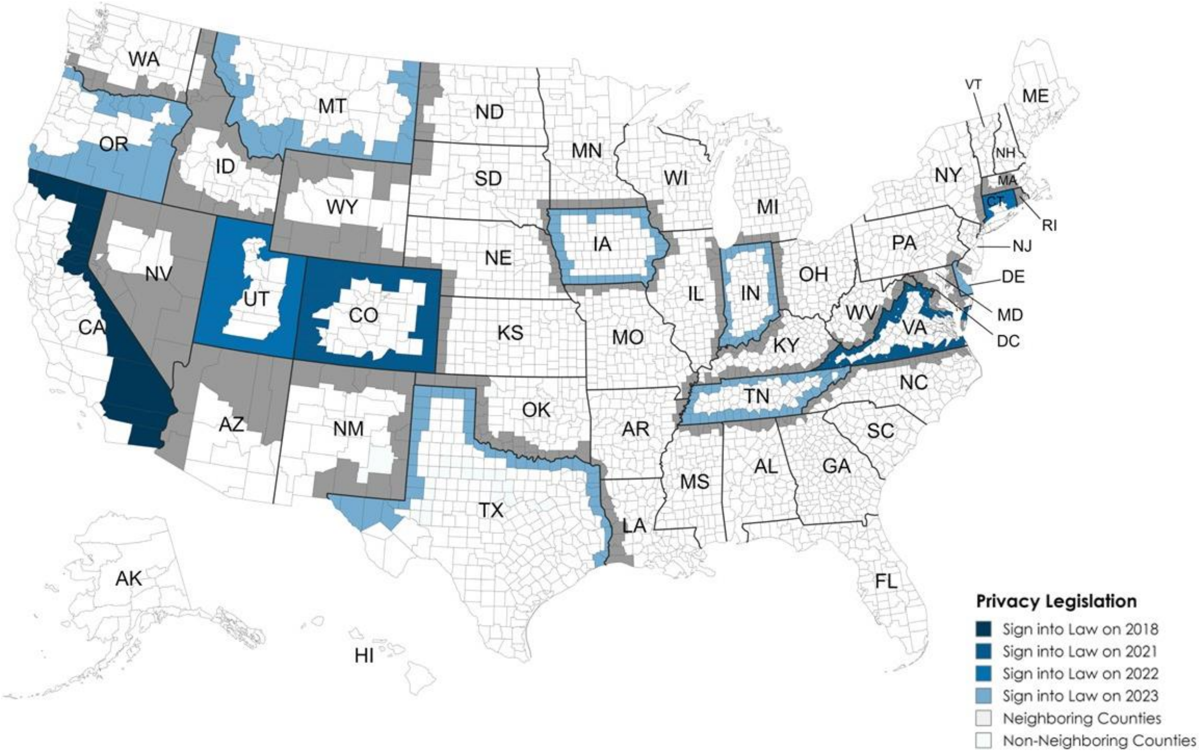
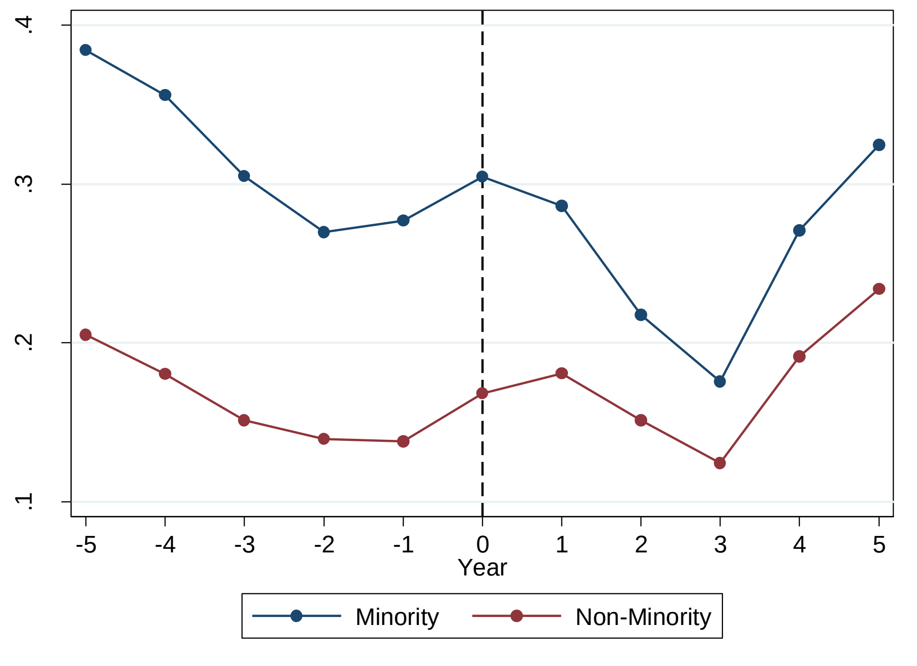


**Figure 3. Trends in Denial Rates and Interest Rates of Minorities and Non-Minorities**

These figures show the average interest rates and denial rates for minority and non-minority borrowers, in the years around privacy legislation enactment. The blue line represents the average outcomes for minority borrowers, while the red line depicts those for non-minority borrowers. We have synchronized the timelines across states based on the respective years when they adopted privacy legislation. Dashed lines mark the year of enactment, distinguishing the periods before and after the legislation's adoption. Our analysis is confined to counties that enacted privacy protection laws within the sample period.



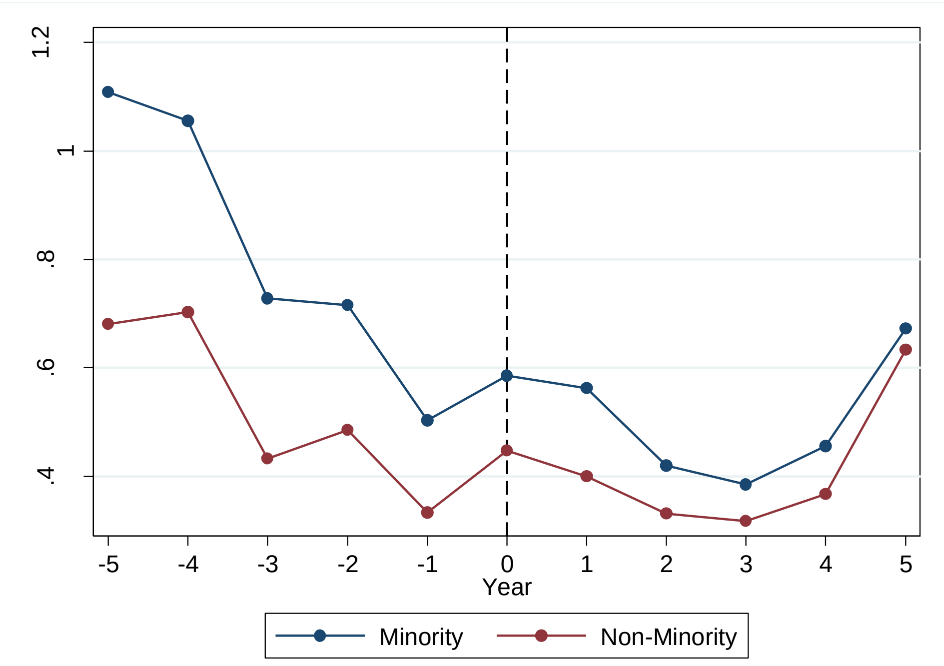



**Figure 4. Dynamic Effects of Privacy Legislation on Mortgage Racial Gap**

This figure shows the dynamic effects of privacy legislation on interest rates and denial rates, around the enactment date of the privacy legislation. The horizontal axis presents the year relative to the year of the enactment of data privacy legislation, split into 5 years prior to enactment *(Pre_5*, *Pre_4*, *Pre_3*, *Pre_2*, *Pre_1)*, 5 years after enactment (*Post_1*, *Post_2*, *Post_3*, *Post_4*, *Post_5*) and the same year *Post_0*,. The vertical axis presents the difference in denial rate and interest rates of minority and non-minority borrowers, estimated using Model (2). The bar chart represents a 95% confidence interval.

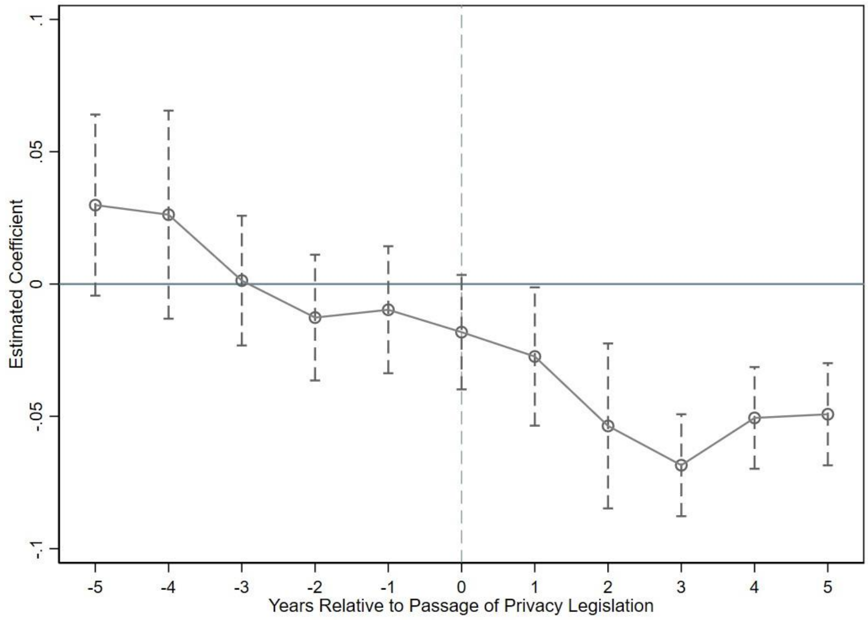



Figure 4a. Effect on Denial rates

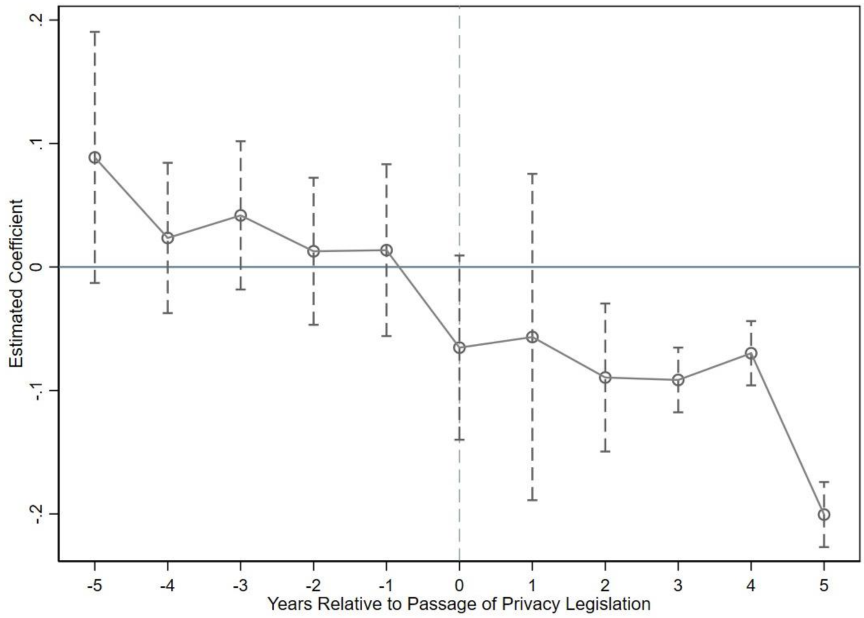



Figure 4b. Effect on interest rates

**Table 1. Summary Statistics**

The table reports descriptive statistics for all variables in our main empirical analysis. The sample consists of U.S. mortgage data from 2018 to 2023. The sample used for baseline results includes 8,764,155 application-level observations. For detailed information on the definition and construction of all variables, please refer to the online Appendix Table A1. Continuous variables, except macroeconomic variables, are weighted at the first and 99th percentiles.

*Panel A: Full Sample*

| Variables | Obs. | Mean | Std. Dev. | 1st Perc. | Median | 99th Perc. |
|---|---|---|---|---|---|---|
| ***Independent Variables*** | | | | | | |
| Treat × Post | 8,764,155 | 0.188 | 0.391 | 0 | 0 | 1 |
| Privacy_Effective | 3,148,677 | 0.250 | 0.433 | 0 | 0 | 1 |
| Minority | 7,679,759 | 0.182 | 0.386 | 0 | 0 | 1 |
| Female | 8,764,155 | 0.259 | 0.438 | 0 | 0 | 1 |
| ***Dependent Variables*** | | | | | | |
| Denial | 8,764,155 | 0.184 | 0.388 | 0 | 0 | 1 |
| Interest Rate | 7,103,757 | 4.167 | 1.619 | 1.990 | 3.695 | 9.500 |
| Interest Rate Spread | 6,724,514 | 0.444 | 0.983 | -2.190 | 0.298 | 4.220 |
| ***Control Variables*** | | | | | | |
| Credit Model | 8,764,155 | 0.887 | 0.316 | 0 | 1 | 1 |
| Debt_to_Income | 8,764,155 | 0.624 | 0.484 | 0 | 1 | 1 |
| LTV | 8,764,155 | 0.608 | 0.279 | 0.050 | 0.686 | 1 |
| Loan_to_Income | 8,764,155 | 2.609 | 5.246 | 0.165 | 2.204 | 8.598 |
| Ln_Loan_Amount | 8,764,155 | 12.094 | 0.903 | 9.616 | 12.231 | 13.860 |
| Age category | 8,764,155 | 3.826 | 1.425 | 1 | 4 | 7 |
| Gender Observed | 8,758,322 | 0.045 | 0.208 | 0 | 0 | 1w |
| Race Observed | 8,764,155 | 0.044 | 0.206 | 0 | 0 | 1 |

*Panel B: Counties with and without Privacy Legislation*

| | Non-Privacy counties | | Privacy counties | |
|---|---|---|---|---|
| **Variables** | **Obs.** | **Mean** | **Obs.** | **Mean** |
| Minority | 4,373,286 | 0.181 | 3,304,501 | 0.182 |
| Female | 4,373,286 | 0.266 | 3,304,501 | 0.249 |
| Interest Rate | 3,535,362 | 4.148 | 2,700,117 | 4.191 |
| Interest Rate Spread | 3,355,095 | 0.425 | 2,545,554 | 0.468 |
| Denial | 4,373,286 | 0.188 | 3,304,501 | 0.179 |
| Credit Model | 4,373,286 | 0.885 | 3,304,501 | 0.891 |
| Debt_to_Income | 4,373,286 | 0.622 | 3,304,501 | 0.628 |
| LTV | 4,373,286 | 0.612 | 3,304,501 | 0.604 |
| Loan_to_Income | 4,373,286 | 2.534 | 3,304,501 | 2.709 |
| Ln_Loan_Amount | 4,373,286 | 12.086 | 3,304,501 | 12.105 |
| Race Observed | 4,373,286 | 0.045 | 3,304,501 | 0.044 |
| Gender Observed | 4,371,767 | 0.046 | 3,302,970 | 0.045 |
| Age | 4,373,286 | 3.804 | 3,304,501 | 3.854 |

(continued next page)

**Table 1. Summary Statistics (cont'd)**

| *Panel C: Mean value for Sub-Sample* | | | | |
|---|---|---|---|---|
| | **Obs.** | Minority | Denial | Interest Rate |
| ***Lender Classifications*** | | | | |
| Bank | 4,064,128 | 0.167 | 0.232 | 4.364 |
| Fintech | 702,896 | 0.192 | 0.100 | 3.950 |
| Shadow bank | 2,685,362 | 0.200 | 0.142 | 3.983 |
| ***Loan Purposes*** | | | | |
| Home Purchase | 2,867,778 | 0.188 | 0.112 | 4.406 |
| Home Improvement | 725,079 | 0.206 | 0.390 | 5.360 |
| Refinancing | 2,132,410 | 0.160 | 0.149 | 3.396 |
| Cash-out refinancing | 1,312,665 | 0.187 | 0.171 | 3.980 |

**Table 2. Effect of Privacy Legislation on Mortgage Racial Denial and Interest Gap**

This table presents the regression results and t-statistics (in parentheses) for the impact of privacy legislation on reject rate, interest rate and interest rate spread among minorities in the U.S. from 2018 to 2023. *Treat* indicates whether the mortgage application was in a state where the privacy legislation was signed, *Post* indicates whether the mortgage application was submitted after the enactment of the privacy legislation in the state, and *Minority* indicates whether the applicant belongs to an ethnic minority. For the dependent variable, we primarily use the dummy variable *Denial* to represent whether this application has been rejected or not. In addition, we use *Interest Rate* to represent the cost of mortgage loans and *Interest Rate Spread* refers to the difference between the loan's Annual Percentage Rate and the Average Prime Offer Rate. For detailed information on the definition and construction of all control variables, please refer to Appendix Table A1. Continuous variables, except macroeconomic variables, are winsorized at the first and 99th percentiles. Panel A includes only mortgage application samples from *counties* adjacent to states where privacy legislation has been enacted versus counties adjacent to states where it has not been enacted. Panel B includes mortgage application samples from *states* both with and without enacted privacy legislation. Standard errors are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

*Panel A. Neighboring County*

| | Denial | | Interest Rate | | Interest Rate Spread | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Treat × Post | 0.007** | 0.007*** | 0.010 | 0.016 | 0.008 | 0.014 |
| | (2.17) | (2.74) | (0.34) | (0.51) | (0.28) | (0.50) |
| Minority | 0.111*** | 0.081*** | 0.113*** | 0.046*** | 0.146*** | 0.065*** |
| | (14.79) | (14.25) | (10.51) | (3.66) | (15.36) | (7.04) |
| Treat × Post× Minority | -0.042*** | -0.034*** | -0.091*** | -0.073*** | -0.089*** | -0.062*** |
| | (-3.19) | (-3.25) | (-3.78) | (-2.79) | (-4.54) | (-3.54) |
| Credit Model | | -0.167*** | | -0.567*** | | -0.333*** |
| | | (-13.48) | | (-8.48) | | (-5.43) |
| Debt_to_Income | | 0.087*** | | 0.077*** | | 0.046*** |
| | | (30.12) | | (21.05) | | (13.94) |
| LTV | | 0.017 | | 0.182*** | | 0.408*** |
| | | (1.53) | | (4.66) | | (8.62) |
| Loan_to_Income | | 0.005*** | | -0.005*** | | -0.006*** |
| | | (13.60) | | (-6.16) | | (-7.48) |
| Ln_Loan_Amount | | -0.059*** | | -0.252*** | | -0.302*** |
| | | (-22.69) | | (-10.91) | | (-13.85) |
| Race Observed | | 0.007 | | 0.074*** | | -0.017 |
| | | (1.36) | | (4.16) | | (-1.01) |
| Age | | 0.002* | | -0.013*** | | -0.007 |
| | | (1.97) | | (-3.08) | | (-1.63) |
| Constant | 0.169*** | 0.942*** | 4.163*** | 7.659*** | 0.433*** | 4.183*** |
| | (114.45) | (35.32) | (702.74) | (23.64) | (69.72) | (15.10) |
| Lender FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y |
| Observations | 7,679,546 | 7,679,546 | 6,236,958 | 6,236,958 | 6,982,601 | 5,902,077 |
| R-squared | 0.174 | 0.226 | 0.651 | 0.659 | 0.294 | 0.317 |

(continued next page)

**Table 2. Effect of Privacy Legislation on Mortgage Racial Interest Gap (cont'd)**

| Panel B. Neighboring State | | | | | | |
|---|---|---|---|---|---|---|
| | Denial | | Interest Rate | | Interest Rate Spread | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Treat × Post | 0.006* | 0.007*** | -0.055 | -0.047 | -0.034 | -0.025 |
| | (1.9) | (2.1) | (-0.95) | (-0.88) | (-0.81) | (-0.66) |
| Minority | 0.1123*** | 0.083*** | 0.134*** | 0.062*** | 0.169*** | 0.084*** |
| | (23.4) | (20.66) | (15.58) | (7.69) | (21.15) | (11.76) |
| Treat × Post× Minority | -0.036*** | -0.032*** | -0.086*** | -0.088*** | -0.079*** | -0.078*** |
| | (-3.55) | (-3.52) | (-3.73) | (-4.23) | (-5.05) | (-5.54) |
| Credit Model | | -0.156*** | | -0.463*** | | -0.282*** |
| | | (-12.37) | | (-5.68) | | (-3.47) |
| Debt_to_Income | | 0.088*** | | 0.079*** | | 0.047*** |
| | | (45.77) | | (27.26) | | (20.09) |
| Loan_to_Value | | 0.023*** | | 0.204*** | | 0.416*** |
| | | (3.01) | | (4.84) | | (9.56) |
| Loan_to_Income | | 0.004*** | | -0.003*** | | -0.004*** |
| | | (10.91) | | (-4.79) | | (-5.69) |
| Ln_Loan_Amount | | -0.059*** | | -0.278*** | | -0.320*** |
| | | (-21.27) | | (-18.19) | | (-18.64) |
| Race Observed | | 0.006** | | 0.078*** | | -0.030* |
| | | (2.21) | | (5.98) | | (-1.80) |
| Age | | 0.002*** | | -0.013*** | | -0.008 |
| | | (3.34) | | (-3.02) | | (-1.67) |
| Constant | 0.167*** | 0.931*** | 4.152*** | 7.860*** | 0.411*** | 4.337*** |
| | (219.37) | (31.93) | (374.33) | (34.44) | (52.54) | (18.81) |
| Lender FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y |
| Observations | 38,671,974 | 38,671,974 | 31,588,968 | 31,588,968 | 29,870,062 | 29,870,062 |
| R-squared | 0.1729 | 0.225 | 0.643 | 0.661 | 0.298 | 0.337 |

**Table 3. Dynamic Effect of Privacy Legislation**

The table presents the results of the dynamic regression model that analyzes the effects of privacy legislation signed in t=0 on the interest rate and denial rates for minority mortgage borrowers, based on dummy variables *Pre_5*, *Pre_4*, *Pre_3*, *Pre_2*, *Pre_1*, *Post_0*, *Post_1*, *Post_2*, *Post_3*, *Post_4*, and *Post_5*. T-statistics are presented in parentheses. The coefficients on all the Pre_5 to Post_5 is omitted for brevity. Standard errors are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| | Denial | Interest Rate |
|---|---|---|
| VARIABLES | (2) | (1) |
| Pre_5 × Minority | 0.032 | 0.089* |
| | (1.45) | (1.76) |
| Pre_4 × Minority | 0.027 | 0.023 |
| | (1.45) | (0.78) |
| Pre_3 × Minority | 0.002 | 0.042 |
| | (0.18) | (1.40) |
| Pre_2 × Minority | -0.012 | 0.013 |
| | (-1.00) | (0.43) |
| Pre_1 × Minority | -0.005 | 0.014 |
| | (-0.37) | (0.40) |
| Post_0 × Minority | -0.021* | -0.065* |
| | (-1.69) | (-1.77) |
| Post_1 × Minority | -0.032* | -0.057 |
| | (-1.94) | (-0.87) |
| Post_2 × Minority | -0.054*** | -0.090*** |
| | (-3.16) | (-3.01) |
| Post_3 × Minority | -0.068*** | -0.091*** |
| | (-7.10) | (-7.04) |
| Post_4 × Minority | -0.044*** | -0.070*** |
| | (-4.67) | (-5.42) |
| Post_5 × Minority | -0.050*** | -0.201*** |
| | (-5.25) | (-15.36) |
| Minority | 0.110*** | 0.108*** |
| | (11.67) | (8.37) |
| Pre and Post | Y | Y |
| Lender FE | Y | Y |
| Year FE | Y | Y |
| County FE | Y | Y |
| Observations | 7,677,579 | 7,677,579 |
| R-squared | 0.174 | 0.651 |

**Table 4. Mechanism – Hard and Soft Information Reliance in Mortgage Decisions**

These tables examine the subsample analysis of data privacy legislation effects on mortgage interest rates and denial rates, based on institutions that rely more on either hard or soft information. *Treat* indicates whether the mortgage application was in a state where the privacy legislation was signed, *Post* indicates whether the mortgage application was submitted after the enactment of the privacy legislation in the state, and *Minority* indicates whether the applicant belongs to an ethnic minority. For the dependent variable, we primarily use *Denial* to represent whether this application has been rejected or not and *Interest Rate* to represent the cost of mortgage loans. Panel A-Panel C shows subsample results based on the benchmark model in Equation (1) categorized by subsamples of mortgage applications. These categories include whether the applicant's race was observable, whether the lending decision process used traditional credit models, and whether the lenders' IT investments/expenses were high or low. Panel A shows that results based on a subsample where a credit model has not been applied (Columns (1) and (2)) and where a credit model has been applied (Columns (3) and (4)), reflecting the reliance on hard information produced by standard credit models. Panel B shows the results based on a subsample where lenders' IT investments/expenses are below the sample medium (Columns (1) and (2)) and where lenders' IT investments/expenses are higher than the sample medium (Columns (3) and (4)), reflecting the lender's IT capabilities and their ability to process hard information. Panel C shows the results where race has been observed (Columns (1) and (2)) and unobserved (Columns (3) and (4)), reflecting the reliance on soft information when race is observed. The control variables include *Credit Model*, *Debt_to_Income*, *Loan_to_Value*, *Loan_to_Income*, *Ln_Loan_Amount*, *Race Observed,* and *Age*. The coefficients on all the control variables are omitted for brevity. For the definitions of all the control variables and the details of their construction, see Online Appendix A1. T-statistics are shown in parentheses. Standard errors are clustered at the state level. We employ fixed effects at the lender, year, and county levels. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

*Panel A Credit Model Usage*

| | No Credit model | | Using Credit model | |
|---|---|---|---|---|
| | Denial | Interest Rate | Denial | Interest Rate |
| | (1) | (2) | (3) | (4) |
| Treat × Post | 0.012* | -0.003 | 0.006** | 0.014 |
| | (2.01) | (-0.04) | (2.21) | (0.42) |
| Minority | 0.129*** | 0.116*** | 0.071*** | 0.038*** |
| | (16.49) | (10.94) | (14.33) | (3.36) |
| Treat × Post × Minority | -0.041*** | -0.038 | -0.029*** | -0.067** |
| | (-3.15) | (-1.21) | (-3.26) | (-2.63) |
| Control Variables | Y | Y | Y | Y |
| Lender FE | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y |
| Observations | 865,375 | 462,782 | 6,814,030 | 5,774,032 |
| R-squared | 0.263 | 0.679 | 0.169 | 0.663 |

(continued next page)

**Table 5. Mechanism-Transparency and Information Frictions (cont'd)**

*Panel B. IT investment*

| | Low IT investment | | High IT investment | |
|---|---|---|---|---|
| | Denial | Interest Rate | Denial | Interest Rate |
| | (1) | (2) | (3) | (4) |
| Treat × Post | -0.004 | 0.024 | 0.023*** | 0.077 |
| | (-1.12) | (0.63) | (3.18) | (1.25) |
| Minority | 0.103*** | 0.005 | 0.118*** | 0.070*** |
| | (16.47) | (0.29) | (19.77) | (4.30) |
| Treat × Post × Minority | -0.017* | -0.054 | -0.040*** | -0.061** |
| | (-2.01) | (-0.87) | (-6.96) | (-2.09) |
| Control Variables | Y | Y | Y | Y |
| Lender FE | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y |
| Observations | 1,609,267 | 1,204,179 | 1,327,322 | 1,003,220 |
| R-squared | 0.288 | 0.645 | 0.171 | 0.639 |

*Panel C. Race can be observed or not*

| | Race observed | | Race unobserved | |
|---|---|---|---|---|
| | Denial | Interest Rate | Denial | Interest Rate |
| | (1) | (2) | (3) | (4) |
| Treat × Post | 0.001 | 0.035 | 0.007*** | 0.012 |
| | (0.08) | (0.19) | (2.74) | (0.45) |
| Minority | 0.119*** | 0.109*** | 0.079*** | 0.043*** |
| | (18.17) | (5.30) | (14.00) | (3.54) |
| Treat × Post × Minority | -0.035** | -0.108 | -0.033*** | -0.070*** |
| | (-2.04) | (-1.57) | (-3.27) | (-2.77) |
| Control Variables | Y | Y | Y | Y |
| Lender FE | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y |
| Observations | 340,947 | 257,933 | 7,338,252 | 5,978,667 |
| R-squared | 0.217 | 0.622 | 0.228 | 0.661 |

**Table 5. Implications for Discrimination Decrease and Bias**

These tables examine the potential mechanisms by which privacy legislation affects mortgage interest rates and denial rates, specifically through racial biases and stereotypes. *Treat* indicates whether the mortgage application was in a state where the privacy legislation was signed, and *Post* indicates whether the mortgage application was submitted after the enactment of the privacy legislation in the state. Panel A and Panel B show subsample results based on the benchmark model in Equation (1) categorized by subsamples of mortgage applications. Panel A shows results for applications in counties without overt certain types of racial biases (Columns (1) and (2)) and those with overt certain types of racial biases (Columns (3) and (4)), illustrating the effects of explicit racial bias. Panel B reports results for applications in counties without covert certain types of racial biases (Columns (1) and (2)) and those with covert certain types of racial biases (Columns (3) and (4)), reflecting the impact of implicit racial bias. The coefficients for control variables are omitted for brevity and are consistent with baseline models. T-statistics are shown in parentheses. Standard errors are clustered at the state level. We employ fixed effects at the lender, year, and county levels. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

*Panel A. Explicit Bias classification*

| | No Bias | | Biased | |
|---|---|---|---|---|
| | Denial | Interest Rate | Denial | Interest Rate |
| | (1) | (2) | (3) | (4) |
| Treat × Post | 0.004 | 0.020 | 0.005* | -0.006 |
| | (1.26) | (0.64) | (1.74) | (-0.13) |
| Minority | 0.081*** | 0.041*** | 0.080*** | 0.075*** |
| | (13.45) | (3.15) | (10.00) | (2.82) |
| Treat × Post × Minority | -0.009 | -0.027 | -0.042*** | -0.094*** |
| | (-1.37) | (-0.42) | (-5.20) | (-3.12) |
| Control Variables | Y | Y | Y | Y |
| Lender FE | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y |
| Observations | 6,148,179 | 4,996,861 | 1,528,557 | 1,237,837 |
| R-squared | 0.226 | 0.657 | 0.235 | 0.671 |

*Panel B. Implicit Bias classification*

| | No Bias | | Biased | |
|---|---|---|---|---|
| | Denial | Interest Rate | Denial | Interest Rate |
| | (1) | (2) | (3) | (4) |
| Treat × Post | 0.008*** | 0.019 | -0.009* | -0.011 |
| | (3.26) | (0.60) | (-2.00) | (-0.15) |
| Minority | 0.082*** | 0.046*** | 0.074*** | 0.049 |
| | (13.34) | (3.45) | (8.91) | (1.65) |
| Treat × Post × Minority | -0.035*** | -0.070** | -0.005 | -0.130*** |
| | (-3.38) | (-2.60) | (-0.36) | (-4.29) |
| Control Variables | Y | Y | Y | Y |
| Lender FE | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y |
| Observations | 7,044,250 | 5,723,566 | 632,482 | 511,119 |
| R-squared | 0.225 | 0.657 | 0.244 | 0.669 |

**Table 6. Mechanism 2 - The Role of Fintech and Shadow Banks**

This table presents the results for the role of Fintech and Shadow Bank. We include a *FinTech* dummy variable indicating whether the lender is a FinTech, which captures whether the lending process is conducted exclusively online. Additionally, we incorporate a *Shadow Bank* dummy variable, defined as non-traditional depository institutions that integrate both online and offline lending processes. *Treat* indicates whether the mortgage application was in a state where the privacy legislation was signed, and *Post* indicates whether the mortgage application was submitted after the enactment of the privacy legislation in the state. Interaction terms are included in our regressions to examine the combined effects. Columns (1) to (4) display the interaction effects on denial rates, while Columns (5) to (7) present the effects on interest rates. The control variables include *Credit Model*, *Debt_to_Income*, *Loan_to_Value*, *Loan_to_Income*, *Ln_Loan_Amount*, *Race Observed,* and *Age*. The coefficients on all the control variables are omitted for brevity. For the definitions of all the control variables and the details of their construction, see Online Appendix A1. T-statistics are shown in parentheses. Standard errors are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| | Denial | | | | Interest Rate | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Treat × Post | | 0.007** | | 0.005** | | 0.012 | | 0.009 |
| | | (2.62) | | (2.23) | | (0.36) | | (0.27) |
| Minority | | 0.082*** | | 0.082*** | | 0.044*** | | 0.044*** |
| | | (14.59) | | (14.60) | | (3.48) | | (3.49) |
| Treat × Post × Minority | | -0.027*** | | 0.014** | | -0.054** | | 0.046* |
| | | (-2.70) | | (2.60) | | (-2.17) | | (1.91) |
| Treat × Post × Minority × Fintech | -0.007* | -0.046*** | | | -0.099*** | -0.090*** | | |
| | (-1.72) | (-15.53) | | | (-3.28) | (-6.70) | | |
| Treat × Post × Minority × Shadow bank | | | 0.004 | -0.077*** | | | -0.086*** | -0.169*** |
| | | | (0.67) | (-12.82) | | | (-3.03) | (-7.06) |
| Control Variables | Y | Y | Y | Y | Y | Y | Y | Y |
| Lender FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Observations | 7,452,183 | 7,452,183 | 7,452,183 | 7,452,183 | 6,032,456 | 6,032,456 | 6,032,456 | 6,032,456 |
| R-squared | 0.224 | 0.228 | 0.224 | 0.228 | 0.658 | 0.658 | 0.658 | 0.658 |

**Table 7. Geographic Variation for Areas with High Minority Population and Bank Branch Density**

These tables examine the potential mechanisms by which privacy legislation affects mortgage interest rates and denial rates, specifically through the credit supply side. *Treat* indicates whether the mortgage application was in a state where the privacy legislation was signed, and *Post* indicates whether the mortgage application was submitted after the enactment of the privacy legislation in the state. Panel A and Panel B show subsample results based on the benchmark model in Equation (1) categorized by subsamples of mortgage applications. Panel A report results in applications in areas (tracts) with low intensity of minorities (Columns (1) - (4)) and those with high intensity of minorities (Columns (5) and (8)), which panel B report results applications in areas (states) with high intensity of bank branches (Columns (1) and (4)) and those with low intensity of bank branches (Columns (5) and (8)). The coefficients for control variables are omitted for brevity and are consistent with baseline models. T-statistics are shown in parentheses. Standard errors are clustered at the state level. We employ fixed effects at the lender, year, and county levels. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| Panel A. Minority intensity subsample analysis | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Minority non-intensity area (tract) | | | | Minority intensity area (tract) | | | |
| | Denial | | Interest Rate | | Denial | | Interest Rate | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Treat × Post | 0.003 | 0.003 | -0.008 | -0.008 | 0.009** | 0.017*** | 0.031 | 0.042** |
| | (1.17) | (1.04) | (-0.53) | (-0.50) | (2.47) | (6.48) | (0.75) | (2.35) |
| Minority | 0.065*** | 0.066*** | 0.055*** | 0.055*** | 0.080*** | 0.077*** | 0.051*** | 0.060*** |
| | (21.64) | (21.00) | (8.02) | (7.82) | (11.98) | (11.22) | (3.62) | (5.85) |
| Treat × Post × Minority | -0.009 | -0.002 | -0.023 | -0.020 | -0.032*** | -0.033*** | -0.070*** | -0.064*** |
| | (-1.49) | (-0.35) | (-1.11) | (-1.06) | (-2.94) | (-3.64) | (-2.89) | (-3.63) |
| Treat × Post × Minority × Fintech | | -0.053*** | | -0.008 | | -0.032*** | | -0.068*** |
| | | (-5.32) | | (-0.26) | | (-9.25) | | (-2.94) |
| Control Variables | Y | Y | Y | Y | Y | Y | Y | Y |
| Lender FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Observations | 3,468,545 | 3,352,589 | 2,915,070 | 2,655,471 | 4,210,767 | 3,381,790 | 3,321,641 | 2,835,071 |
| R-squared | 0.212 | 0.242 | 0.552 | 0.538 | 0.239 | 0.213 | 0.692 | 0.551 |

(continued next page)

**Table 8. Geographic Variation for Areas with High Minority Population and Bank Branch Density (cont'd)**

| Panel B. Bank branches intensity subsample analysis | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Bank branches intensity area (state) | | | | Bank branches non-intensity area (state) | | | |
| | Denial | | Interest Rate | | Denial | | Interest Rate | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Treat × Post | 0.000 | 0.002 | 0.108** | 0.114** | 0.007** | 0.007** | -0.004 | -0.012 |
| | (0.05) | (0.34) | (2.12) | (2.21) | (2.52) | (2.27) | (-0.11) | (-0.29) |
| Minority | 0.088*** | 0.089*** | 0.027* | 0.026* | 0.075*** | 0.076*** | 0.062*** | 0.060*** |
| | (28.83) | (28.08) | (2.02) | (1.90) | (9.07) | (9.23) | (3.96) | (3.91) |
| Treat × Post × Minority | -0.009 | -0.007 | -0.203*** | -0.177*** | -0.029** | -0.022* | -0.087*** | -0.070** |
| | (-1.19) | (-0.73) | (-6.29) | (-6.23) | (-2.51) | (-2.00) | (-3.19) | (-2.65) |
| Treat × Post × Minority × Fintech | | -0.057*** | | -0.512*** | | -0.046*** | | -0.086*** |
| | | (-3.82) | | (-9.98) | | (-13.22) | | (-7.33) |
| Control Variables | Y | Y | Y | Y | Y | Y | Y | Y |
| Lender FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Observations | 2,607,938 | 2,548,449 | 2,134,464 | 2,080,708 | 5,069,370 | 4,903,470 | 4,100,546 | 3,951,497 |
| R-squared | 0.239 | 0.241 | 0.653 | 0.651 | 0.222 | 0.223 | 0.662 | 0.664 |

**Table 8. Credit Demand: Loan applications divided by lender type**

To effectively capture the structure of loans—including the number of applications, total loan amounts, and approval rates—we aggregated observational data by county, year, and lender. This table presents the regression results and t-statistics (in parentheses) for the impact of privacy legislation on the number of applications, total amount of loans, and approval rate among all borrowers, and minorities in the United States from 2018 to 2023. We employed three primary dependent variables: *Applications*, which aggregates the number of mortgage applications by county, lender, and year for all applicants, and Minority % (i.e., the ratio of minority borrowers to the total number of applicants. *Ln (Loan Amount)*, the natural logarithm of the total mortgage amount requested by all applicants, Minority % (i.e. the ratio of the total loan amount of minority borrowers to the total loan amount of all applicants) under identical conditions; and *Approval Rate*, the aggregate loan approval rates for all groups under the same conditions. *Treat* indicates whether the mortgage application was in a state where the privacy legislation was signed, *Post* indicates whether the mortgage application was submitted after the enactment of the privacy legislation in the state, and *Minority* indicates whether the applicant belongs to an ethnic minority. Columns (1) - (2) analyze the impact of these laws on the volume of mortgage applications for all applicants and minority groups; columns (3) - (4) explore the effect on the total loan amount requested by these groups; columns (5) - (6) focus on the approval rates of these applications. Panel A provides a comprehensive detail of the effects of privacy protection legislation on the number of applications, request volume, and approval rates for all applicants and minority groups. Conversely, Panel B specifically examines the performance of these groups within fintech lending institutions. The coefficients for control variables are omitted for brevity and are consistent with baseline models. Continuous variables, except macroeconomic variables, are winsorized at the first and 99th percentiles. Standard errors are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| | | | | | | |
|---|---|---|---|---|---|---|
| *Panel A. Demand side analysis of all lenders* | | | | | | |
| | Applications | | Ln (Loan amounts) | | Approval rate | |
| | All | Minority % | All | Minority % | All | Minority |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Treat × Post | 3.108* | 0.488 | 0.010 | 0.028 | -0.002 | -0.001 |
| | (1.70) | (1.29) | (0.40) | (0.51) | (-1.20) | (-0.24) |
| Controls | Y | Y | Y | Y | Y | Y |
| Lender FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y |
| Observations | 304,622 | 304,622 | 304,622 | 304,622 | 304,622 | 304,622 |
| R-squared | 0.103 | 0.112 | 0.502 | 0.349 | 0.355 | 0.269 |
| *Panel B. Demand side analysis Fintech lenders* | | | | | | |
| | Applications | | Ln (Loan amounts) | | Approval rate | |
| | All | Minority % | All | Minority % | All | Minority |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Treat × Post | 3.918 | -0.004 | -0.003 | -0.002 | -0.002 | -0.002 |
| | (1.65) | (-1.27) | (-0.12) | (-0.46) | (-0.81) | (-0.96) |
| Treat × Post × Fintech | 3.038 | 0.007** | 0.150** | 0.020** | 0.008** | 0.007** |
| | (1.31) | (2.32) | (2.57) | (2.43) | (2.28) | (2.41) |
| Controls | Y | Y | Y | Y | Y | Y |
| Lender FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y |
| Observations | 307,310 | 307,310 | 307,310 | 307,310 | 307,310 | 307,310 |
| R-squared | 0.099 | 0.297 | 0.501 | 0.305 | 0.350 | 0.242 |

**Table 9. Loan Purpose Differentiations**

This table presents the regression results and t-statistics (in parentheses) for the impact of privacy legislation on the denial (reject) rate and interest rate among minorities in the United States from 2018 to 2023, categorized by different loan purposes, i.e., Home purchase, Home improvement, Refinancing, and Cash-out refinancing. *Treat* indicates whether the mortgage application was in a state where the privacy legislation was signed, *Post* indicates whether the mortgage application was submitted after the enactment of the privacy legislation in the state, and *Minority* indicates whether the applicant belongs to an ethnic minority. For the dependent variable, we primarily use *Denial* to represent whether this application has been rejected or not and *Interest Rate* to represent the cost of mortgage loans. The control variables include *Credit Model*, *Debt_to_Income*, *Loan_to_Value*, *Loan_to_Income*, *Ln_Loan_Amount*, *Race Observed,* and *Age*. The coefficients on all the control variables are omitted for brevity. For the definitions of all the control variables and the details of their construction, see Online Appendix A1. Continuous variables, except macroeconomic variables, are winsorized at the first and 99th percentiles. Standard errors are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| | Home Purchase | | Home Improvement | | Refinancing | | Cash-out refinancing | |
|---|---|---|---|---|---|---|---|---|
| | Denial | Interest Rate | Denial | Interest Rate | Denial | Interest Rate | Denial | Interest Rate |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Treat × Post | 0.003 | 0.030 | 0.020*** | 0.000 | -0.001 | 0.046* | 0.003 | -0.111 |
| | (1.25) | (1.40) | (3.08) | (0.00) | (-0.22) | (1.98) | (0.61) | (-1.37) |
| Minority | 0.045*** | 0.045*** | 0.151*** | 0.209*** | 0.076*** | 0.024*** | 0.074*** | 0.056*** |
| | (13.79) | (3.18) | (20.48) | (8.69) | (14.03) | (3.81) | (11.27) | (4.23) |
| Treat × Post × Minority | -0.021** | -0.089*** | -0.053*** | -0.149** | -0.040*** | -0.036*** | -0.039*** | -0.067** |
| | (-2.53) | (-3.01) | (-4.26) | (-2.24) | (-4.27) | (-3.47) | (-3.84) | (-2.52) |
| Control Variables | Y | Y | Y | Y | Y | Y | Y | Y |
| Lender FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Observations | 2,867,511 | 2,529,947 | 724,807 | 437,983 | 2,132,166 | 1,812,002 | 1,312,426 | 1,086,611 |
| R-squared | 0.272 | 0.691 | 0.251 | 0.640 | 0.166 | 0.646 | 0.138 | 0.669 |

**Table 10. Cross-sectional borrower's characteristics**

This table further presents the effects of privacy legislation signing based on subsamples for borrowers with high and low income (Panel A) and borrowers with high and low loan amounts (Panel B), based on the regression model in Equation (1). The control variables include *Credit Model*, *Debt_to_Income*, *Loan_to_Value*, *Loan_to_Income*, *Ln_Loan_Amount*, *Race Observed,* and *Age*. The coefficients on all the control variables are omitted for brevity. For the definitions of all the control variables and the details of their construction, see Online Appendix A1. T-statistics are shown in parentheses. Standard errors are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

*Panel A. Borrowers' income subsample analysis*

| | High-income borrowers | | Low-income borrowers | |
|---|---|---|---|---|
| | Denial | Interest Rate | Denial | Interest Rate |
| | (1) | (2) | (3) | (4) |
| Treat × Post | 0.007*** | 0.015 | 0.004 | 0.033 |
| | (3.39) | (0.73) | (0.94) | (0.89) |
| Minority | 0.080*** | 0.112*** | 0.073*** | 0.026*** |
| | (19.35) | (10.38) | (12.02) | (2.90) |
| Treat × Post × Minority | -0.039*** | -0.075** | -0.028** | -0.071*** |
| | (-4.37) | (-2.52) | (-2.44) | (-3.50) |
| Control Variables | Y | Y | Y | Y |
| Lender FE | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y |
| Observations | 3,841,099 | 3,325,740 | 3,838,189 | 2,910,965 |
| R-squared | 0.169 | 0.687 | 0.256 | 0.637 |

*Panel B. Borrowers' loan amount subsample analysis*

| | High-Loan amount borrowers | | Low-Loan amount borrowers | |
|---|---|---|---|---|
| | Denial | Interest Rate | Denial | Interest Rate |
| | (1) | (2) | (3) | (4) |
| Treat × Post | 0.002 | 0.011 | 0.004 | -0.030 |
| | (1.60) | (0.78) | (0.89) | (-0.43) |
| Minority | 0.055*** | 0.090*** | 0.109*** | 0.074*** |
| | (14.66) | (9.77) | (14.65) | (3.94) |
| Treat × Post × Minority | -0.021*** | -0.065*** | -0.033** | -0.139*** |
| | (-3.50) | (-5.02) | (-2.35) | (-2.75) |
| Control Variables | Y | Y | Y | Y |
| Lender FE | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y |
| Observations | 3,770,901 | 3,357,698 | 3,908,359 | 2,878,977 |
| R-squared | 0.127 | 0.729 | 0.243 | 0.621 |

**Table 11. Effects of Effective Privacy Legislation**

This table presents the effects of privacy legislation on denial rates, interest rates and interest rate spread, based on a subsample of counties in states where privacy protection laws are already in effect. Specifically, the treatment group consists of states where the privacy legislation has been enacted, while the control group includes neighboring states without such legislation. The $Privacy\_Effective_t$ variable represents the year *t* when the privacy legislation became effective, as opposed to the signing dates used in Tables 2 – Table 4. The control variables include *Credit Model*, *Debt_to_Income*, *Loan_to_Value*, *Loan_to_Income*, *Ln_Loan_Amount*, *Race Observed,* and *Age*. The coefficients on all the control variables are omitted for brevity. For the definitions of all the control variables and the details of their construction, see Online Appendix A1. Standard errors are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| | Denial | Interest Rate | Interest Rate Spread |
|---|---|---|---|
| | (1) | (2) | (3) |
| Privacy_Effective | 0.001 | 0.047** | 0.065*** |
| | (0.55) | (2.14) | (2.89) |
| Minority | 0.077*** | 0.051*** | 0.073*** |
| | (16.36) | (5.90) | (12.68) |
| Privacy_Effective × Minority | -0.040*** | -0.077*** | -0.065*** |
| | (-7.75) | (-4.10) | (-4.88) |
| Control Variables | Y | Y | Y |
| Lender FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| County FE | Y | Y | Y |
| Observations | 19,372,134 | 15,867,976 | 14,965,273 |
| R-squared | 0.214 | 0.663 | 0.327 |

**Table 12. Gender Disparities**

This table presents the effect of privacy legislation signing (Panel A) and effective dates (Panel B) on denial rates, interest rates, and interest rate spread on mortgage applications filed by female applicants (*Female*). The control variables include *Credit Model*, *Debt_to_Income*, *Loan_to_Value*, *Loan_to_Income*, *Ln_Loan_Amount*, *Race Observed,* and *Age*. The coefficients on all the control variables are omitted for brevity. For the definitions of all the control variables and the details of their construction, see Online Appendix A1. T-statistics are shown in parentheses. Standard errors are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

*Panel A. Effect of privacy legislation on gender disparities*

| | Denial | | Interest Rate | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Treat × Post | 0.002 | 0.002 | -0.004 | 0.008 |
| | (0.81) | (1.32) | (-0.15) | (0.25) |
| Female | 0.048*** | 0.008*** | 0.038*** | -0.016*** |
| | (29.93) | (5.01) | (8.33) | (-3.75) |
| Treat × Post × Female | -0.008*** | -0.006*** | 0.007 | -0.009 |
| | (-3.78) | (-4.05) | (0.58) | (-0.96) |
| Control Variables | N | Y | N | Y |
| Lender FE | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y |
| Observations | 7,101,984 | 7,101,984 | 9,907,903 | 9,907,903 |
| R-squared | 0.660 | 0.155 | 0.652 | 0.652 |

*Panel B. Effects of Effective Privacy Legislation on Mortgage Racial and Gender Gap*

| | Denial | | Interest Rate | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Privacy_Effective | -0.006** | -0.006** | 0.038* | 0.031 |
| | (-2.41) | (-2.37) | (1.74) | (1.41) |
| Female | 0.031*** | 0.011*** | 0.031*** | -0.022*** |
| | (19.58) | (7.45) | (12.01) | (-4.67) |
| Privacy_Effective× Female | -0.012*** | -0.010*** | -0.009 | -0.000 |
| | (-7.87) | (-5.89) | (-1.00) | (-0.02) |
| Control Variables | N | Y | N | Y |
| Lender FE | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y |
| Observations | 19,362,883 | 19,362,883 | 15,859,373 | 15,859,373 |
| R-squared | 0.167 | 0.210 | 0.646 | 0.663 |

**Table 13. Denial Reason Differentiations**

This table presents the regression results and t-statistics (in parentheses) for the impact of privacy legislation on the denial (reject) reason among minorities in the United States from 2018 to 2023, categorized by different denial reasons, i.e., Credit history, Insufficient cash (downpayment, closing costs), Debt-to-income ratio, Employment history, Collateral, Mortgage insurance denied. We only include samples that have been denied by lending institutions and provide specific reasons for denial. *Treat* indicates whether the mortgage application was in a state where the privacy legislation was signed, *Post* indicates whether the mortgage application was submitted after the enactment of the privacy legislation in the state, and *Minority* indicates whether the applicant belongs to an ethnic minority. The control variables include *Credit Model*, *Debt_to_Income*, *Loan_to_Value*, *Loan_to_Income*, *Ln_Loan_Amount*, *Race Observed,* and *Age*. The coefficients on all the control variables are omitted for brevity. For the definitions of all the control variables and the details of their construction, see Online Appendix A1. Continuous variables, except macroeconomic variables, are winsorized at the first and 99th percentiles. Standard errors are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| | Credit history | Insufficient cash (downpayment, closing costs) | Debt-to-income ratio | Employment history | Collateral | Mortgage insurance denied |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Treat × Post | 0.017*** | 0.002 | -0.000 | -0.001 | -0.003 | -0.000 |
| | (3.95) | (0.67) | (-0.01) | (-1.54) | (-0.80) | (-0.53) |
| Minority | 0.063*** | 0.003** | 0.011*** | -0.002*** | -0.035*** | 0.000*** |
| | (10.31) | (2.49) | (3.15) | (-3.35) | (-10.69) | (3.84) |
| Treat × Post × Minority | -0.022*** | -0.003* | 0.003 | 0.001 | 0.002 | -0.000 |
| | (-3.87) | (-1.99) | (0.66) | (0.57) | (0.49) | (-1.47) |
| Control Variables | Y | Y | Y | Y | Y | Y |
| Lender FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y |
| Observations | 1,414,753 | 1,414,753 | 1,414,753 | 1,414,753 | 1,414,753 | 1,414,753 |
| R-squared | 0.183 | 0.093 | 0.229 | 0.036 | 0.106 | 0.032 |

**Online Appendix**

**Figure A1. Coverage of Effective legislation in states and neighboring states**

This figure shows the privacy legislation effective dates across various states in the United States from 2018 to 2023. Different shades of blue represent the effective dates, with darker shades indicating earlier effective dates. Neighboring states that do not have the legislation in effect are marked in gray, while non-neighboring states are marked in white.

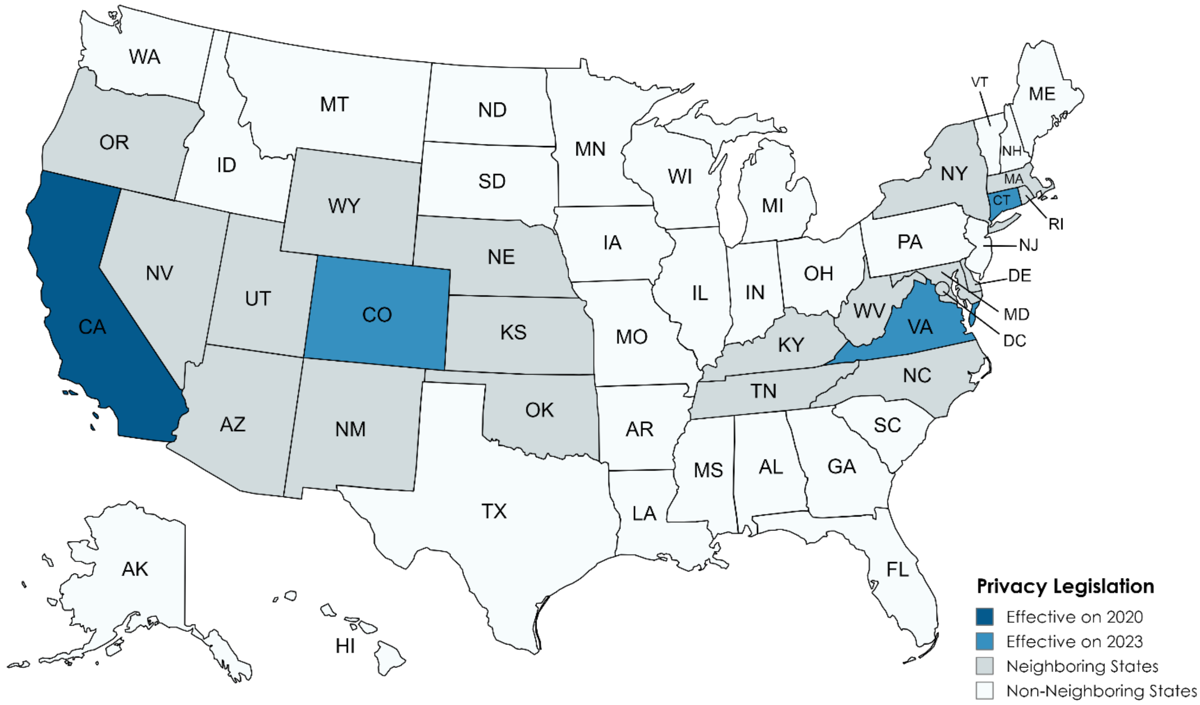


**Figure A2. IAT data distribution**

These figures display the county-level distribution of these bias measures, each standardized to have zero mean and unit variance. These data are derived from the Implicit Association Test (IAT) and utilize measures of both implicit and explicit biases, data derived from the Implicit Association Test (IAT) database (https://osf.io/gwofk/). Each test measures biases against specific racial groups (e.g., Black, White), defining implicit and explicit biases as preferential or prejudicial emotional responses toward White and Black individuals. The darker the color and the larger the labeled number, the stronger the preference for White individuals and the bias against Black people and other minorities. Conversely, lighter colors and smaller labeled numbers indicate a stronger preference for Black individuals and other minorities. Colors that are intermediate and numbers that are closer to zero suggest a near absence of bias, indicating no significant preference for either Black or White individuals. Following Chernenko et al. (2022) the biases are standardized to have a mean of zero.

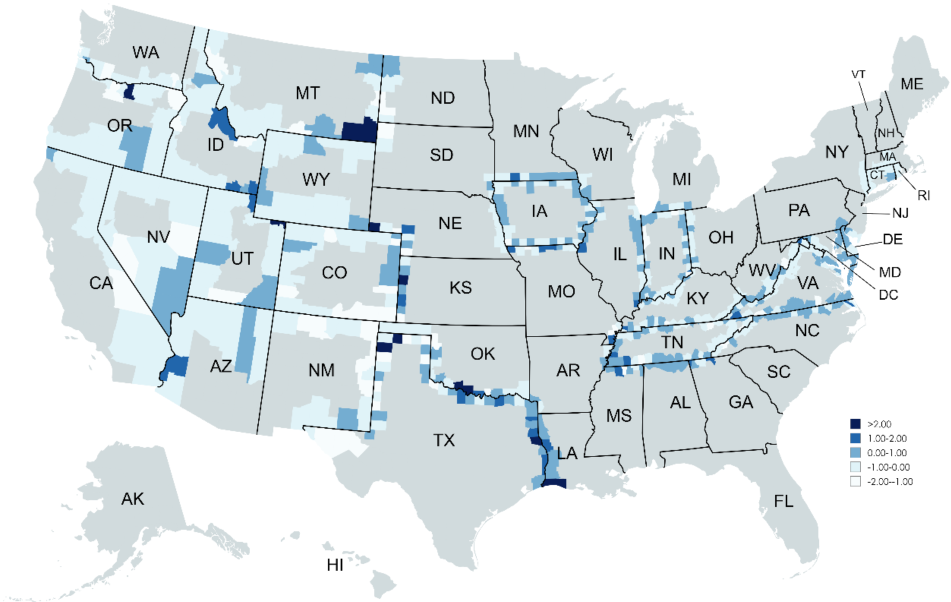



Figure A2a. County-level distribution of explicit bias

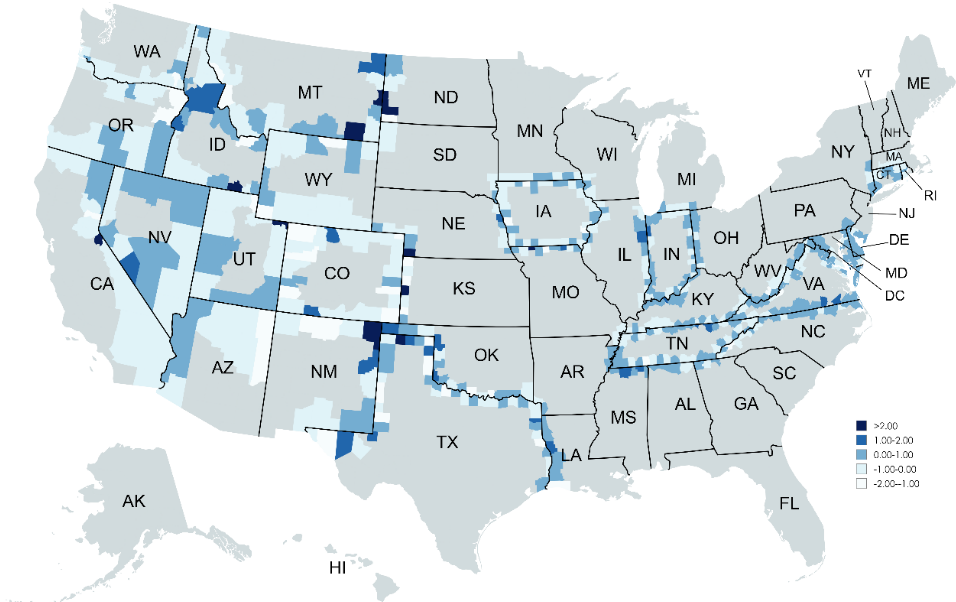



Figure A2b. County-level distribution of implicit bias

**Figure A3. CFPB complaints**

These figures display the density of complaints related to the improper use of consumer reports, both before and after the implementation of privacy legislation. The data is from the Consumer Financial Protection Bureau (CFPB) and covers the years 2018-2022. The x-axis represents time, such as the number of months relative to the implementation of the privacy law, with a red dashed line marking the point of the law's enactment. The vertical axes represent the density of complaints, while the vertical axes of the last two figures represent the number of complaints. The figure A3b compare complaints about the improper use of consumer reports between states that were about to implement privacy protection laws (marked as 0) and neighboring states that did not implement such laws (marked as 1).

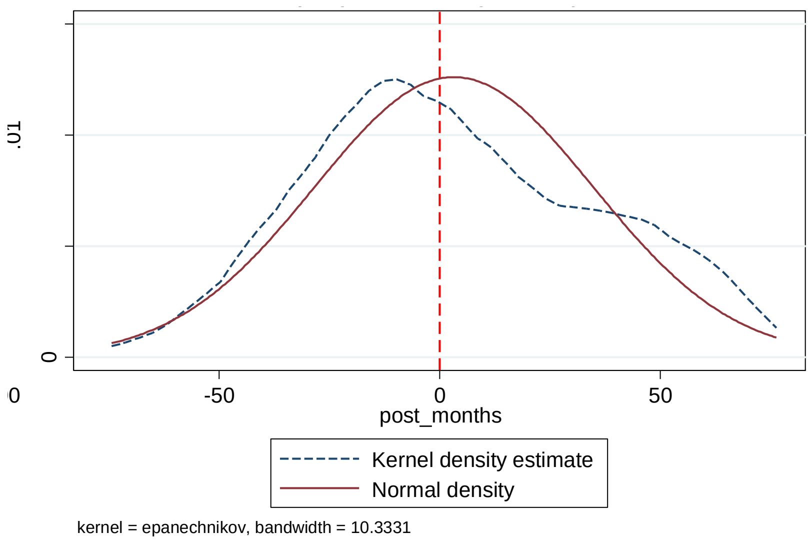



Figure A3a. Distribution of “improper use of your report” complaints

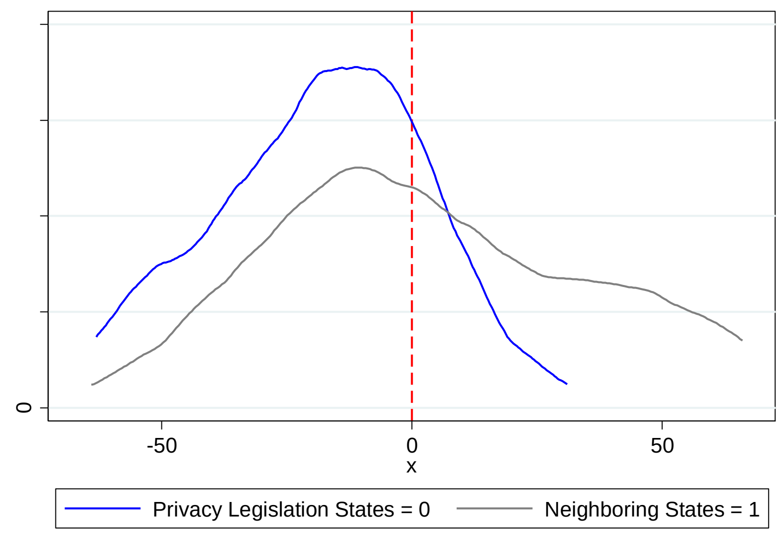



Figure A3b. Distribution of “improper use of your report” complaints between different states

**Table A1. Variable definition**

| Variable | Definition |
|---|---|
| Treat × Post | *Treat* indicates whether the mortgage application was in a state where the privacy legislation was signed, and *Post* indicates whether the mortgage application was submitted after the privacy legislation has been signed into law in the state. |
| Privacy_Effective | Equals 1 if the application *i* in year *t* at state *s*'s privacy legislation is effective, 0 otherwise |
| Minority | Equals 1 if the applicant's ethnicity is Latino, or their race is Black, 0 otherwise. |
| Female | Equals 1 if the applicant is female, 0 otherwise. |
| Denial | Whether lenders deny this mortgage application |
| Interest Rate | The cost of mortgage loans in percent |
| Interest Rate Spread | The difference between the loan's Annual Percentage Rate (APR) and the Average Prime Offer Rate (APOR) for a comparable transaction at the time the interest rate is set. |
| Credit Model | Whether a credit scoring model is used to generate the credit score, or scores, relied on in making the credit decision |
| Debt_to_Income | The ratio, as a percentage, of the applicant's or borrower's total monthly debt to the total monthly income relied on in making the credit decision. |
| Loan_to_Value | The ratio of the total amount of debt secured by the property to the value of the property relied on in making the credit decision. |
| Loan_to_Income | The ratio, as a percentage, of the applicant's or borrower's current amount of lending to the total monthly income relied on in making the credit decision. |
| Ln_Loan_Amount | The amount of the covered loan, or the amount applied for |
| Age | The age of the applicant is categorized into seven groups using numeric values from 1 to 7: age<25, 25-34, 35-44, 45-54, 55-64, 65-74, >74 |
| Gender Observed | Whether the gender of the applicant or borrower was collected based on visual observation or surname |
| Race Observed | Whether the race of the applicant or borrower was collected based on visual observation or surname |
| IAT bias | These data are derived from the Implicit Association Test (IAT) and utilize measures of both implicit and explicit biases, data derived from the Implicit Association Test (IAT) database (https://osf.io/gwofk/). |
| Fintech | Whether the lender is a Fintech or not, indicates whether lending progress is online only or not (Buchak et al., 2018) |
| Shadow bank | Whether the lender is a shadow bank or not, it is defined as a non-traditional depository institution that combines online and offline lending processes (Buchak et al., 2018) |
| Bank | Whether the lender is a bank or not |

**Table A2. Robustness_ Fixed effects**

This table presents the regression results and t-statistics (in parentheses) for the impact of privacy legislation on denial rate, interest rate and interest rate spread among minorities in the United States from 2018 to 2023. *Treat* indicates whether the mortgage application was in a state where the privacy legislation was signed, *Post* indicates whether the mortgage application was submitted after the enactment of the privacy legislation in the state, and *Minority* indicates whether the applicant belongs to an ethnic minority. For the dependent variable, we primarily use dummy *variable Denial* to represent whether this application has been rejected or not, while we use *Interest Rate* to represent the cost of mortgage loans and *Interest Rate Spread* refers to the difference between the loan's Annual Percentage Rate (APR) and the Average Prime Offer Rate (APOR). The control variables include *Credit Model*, *Debt_to_Income*, *Loan_to_Value*, *Loan_to_Income*, *Ln_Loan_Amount*, *Race Observed,* and *Age*. The coefficients on all the control variables are omitted for brevity. For the definitions of all the control variables and the details of their construction, see Online Appendix A1. Continuous variables, except macroeconomic variables, are winsorized at the first and 99th percentiles. Standard errors are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| | Denial | | | Interest Rate | | | Interest Rate Spread | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Treat × Post | 0.011 | 0.018* | 0.010 | 0.555** | 0.106*** | 0.033** | 0.012 | 0.092*** | 0.008 |
| | (1.63) | (1.77) | (1.64) | (2.03) | (6.33) | (2.13) | (0.94) | (5.34) | (0.65) |
| Minority | 0.087*** | 0.106*** | 0.087*** | 0.152*** | 0.085*** | 0.050*** | 0.063*** | 0.116*** | 0.067*** |
| | (16.39) | (15.41) | (16.36) | (6.71) | (3.38) | (3.60) | (5.08) | (5.00) | (6.04) |
| Treat × Post × Minority | -0.035*** | -0.042*** | -0.035*** | -0.317** | -0.108*** | -0.076*** | -0.061*** | -0.095*** | -0.063*** |
| | (-3.49) | (-2.98) | (-3.58) | (-2.68) | (-3.00) | (-3.09) | (-3.54) | (-2.99) | (-3.91) |
| Control Variables | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Lender FE | Y | N | Y | Y | N | Y | Y | N | Y |
| Year FE | N | Y | Y | N | Y | Y | N | Y | Y |
| County FE | N | N | N | N | N | N | N | N | N |
| Observations | 7,679,546 | 7,679,759 | 7,679,546 | 6,236,958 | 6,237,172 | 6,236,958 | 5,902,077 | 5,902,290 | 5,902,077 |
| R-squared | 0.224 | 0.125 | 0.225 | 0.230 | 0.572 | 0.658 | 0.310 | 0.106 | 0.315 |

**Table A3. Robustness_ Exclude Covid period 2020-2021**

This table presents the regression results and t-statistics (in parentheses) for the impact of privacy legislation on denial rate, interest rate and interest rate spread among minorities in the United States from 2018 to 2023 but excludes the Covid period (2020 and 2021). *Treat* indicates whether the mortgage application was in a state where the privacy legislation was signed, *Post* indicates whether the mortgage application was submitted after the enactment of the privacy legislation in the state, and *Minority* indicates whether the applicant belongs to an ethnic minority. For the dependent variable, we primarily use dummy *variable Denial* to represent whether this application has been rejected or not, while we use *Interest Rate* to represent the cost of mortgage loans and *Interest Rate Spread* refers to the difference between the loan's Annual Percentage Rate (APR) and the Average Prime Offer Rate (APOR). The control variables include *Credit Model*, *Debt_to_Income*, *Loan_to_Value*, *Loan_to_Income*, *Ln_Loan_Amount*, *Race Observed,* and *Age*. The coefficients on all the control variables are omitted for brevity. For the definitions of all the control variables and the details of their construction, see Online Appendix A1. Continuous variables, except macroeconomic variables, are winsorized at the first and 99th percentiles. Standard errors are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

*Panel A. Effect of privacy legislation signing on racial disparities*

| | Denial | Interest Rate | Interest Rate Spread |
|---|---|---|---|
| | (1) | (2) | (3) |
| Treat × Post | 0.009*** | 0.003 | 0.003 |
| | (3.15) | (0.06) | (0.06) |
| Minority | 0.091*** | 0.050** | 0.062*** |
| | (13.94) | (2.55) | (3.80) |
| Treat × Post × Minority | -0.033*** | -0.094** | -0.072** |
| | (-3.19) | (-2.61) | (-2.66) |
| Control Variables | Y | Y | Y |
| Lender FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| County FE | Y | Y | Y |
| Observations | 4,019,358 | 3,116,054 | 2,926,161 |
| R-squared | 0.237 | 0.504 | 0.301 |

*Panel B. Effect of Privacy Legislation signing on gender disparities*

| | Denial | Interest Rate | Interest Rate Spread |
|---|---|---|---|
| | (1) | (2) | (3) |
| Treat × Post | 0.005** | -0.007 | -0.008 |
| | (2.52) | (-0.13) | (-0.18) |
| Female | 0.015*** | -0.022*** | -0.026*** |
| | (7.53) | (-3.65) | (-4.73) |
| Treat × Post × Female | -0.007*** | -0.011 | 0.001 |
| | (-3.72) | (-0.93) | (0.08) |
| Control Variables | Y | Y | Y |
| Lender FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| County FE | Y | Y | Y |
| Observations | 4,017,122 | 3,113,977 | 2,924,239 |
| R-squared | 0.232 | 0.504 | 0.301 |

**Table A4. Robustness_ Exclude Privacy legislation current year.**

This table presents the regression results and t-statistics (in parentheses) for the impact of privacy legislation on interest rate, interest rate spread, and denial among minorities in the United States from 2018 to 2023 but excludes the current year of the privacy legislation signed into law. *Treat* indicates whether the mortgage application was in a state where the privacy legislation was signed, *Post* indicates whether the mortgage application was submitted after the enactment of the privacy legislation in the state, and *Minority* indicates whether the applicant belongs to an ethnic minority. For the dependent variable, we primarily use dummy *variable Denial* to represent whether this application has been rejected or not, while we use *Interest Rate* to represent the cost of mortgage loans and *Interest Rate Spread* refers to the difference between the loan's Annual Percentage Rate (APR) and the Average Prime Offer Rate (APOR). The control variables include *Credit Model*, *Debt_to_Income*, *Loan_to_Value*, *Loan_to_Income*, *Ln_Loan_Amount*, *Race Observed,* and *Age*. The coefficients on all the control variables are omitted for brevity. For the definitions of all the control variables and the details of their construction, see Online Appendix A1. Continuous variables, except macroeconomic variables, are winsorized at the first and 99th percentiles. Standard errors are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| *Panel A. Effect of Privacy Legislation signing on racial disparities* | | | |
|---|---|---|---|
| | Denial | Interest Rate | Interest Rate Spread |
| | (1) | (2) | (3) |
| Treat × Post | 0.009*** | 0.058 | 0.059 |
| | (3.82) | (1.18) | (1.23) |
| Minority | 0.081*** | 0.041*** | 0.061*** |
| | (14.27) | (3.43) | (7.09) |
| Treat × Post × Minority | -0.042*** | -0.068** | -0.055*** |
| | (-4.38) | (-2.60) | (-2.80) |
| Control Variables | Y | Y | Y |
| Lender FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| County FE | Y | Y | Y |
| Observations | 7,169,108 | 5,827,713 | 5,517,165 |
| R-squared | 0.226 | 0.642 | 0.320 |

| *Panel B. Effect of Privacy Legislation signing on gender disparities* | | | |
|---|---|---|---|
| | Denial | Interest Rate | Interest Rate Spread |
| | (1) | (2) | (3) |
| Treat × Post | 0.003 | 0.046 | 0.048 |
| | (1.35) | (0.93) | (0.99) |
| Female | 0.011*** | -0.021*** | -0.023*** |
| | (6.36) | (-4.81) | (-6.34) |
| Treat × Post × Female | -0.007*** | 0.005 | 0.007* |
| | (-4.25) | (0.98) | (2.01) |
| Control Variables | Y | Y | Y |
| Lender FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| County FE | Y | Y | Y |
| Observations | 7,166,137 | 5,824,963 | 5,514,681 |
| R-squared | 0.221 | 0.642 | 0.320 |

**Table A5. Robustness_ Lag effect of privacy legislation**

This table presents the regression results and t-statistics (in parentheses) for the impact of privacy legislation on interest rate, interest rate spread, and denial among minorities in the United States from 2018 to 2023. *Treat* indicates whether the mortgage application was in a state where the privacy legislation was signed, and *Post* indicates whether the mortgage application was submitted after the enactment of the privacy legislation in the state, we lagged the Post in these regressions. *Minority* indicates whether the applicant belongs to an ethnic minority. For the dependent variable, we primarily use dummy *variable Denial* to represent whether this application has been rejected or not, while we use *Interest Rate* to represent the cost of mortgage loans and *Interest Rate Spread* refers to the difference between the loan's Annual Percentage Rate (APR) and the Average Prime Offer Rate (APOR). The control variables include *Credit Model*, *Debt_to_Income*, *Loan_to_Value*, *Loan_to_Income*, *Ln_Loan_Amount*, *Race Observed,* and *Age*. The coefficients on all the control variables are omitted for brevity. For the definitions of all the control variables and the details of their construction, see Online Appendix A1. Continuous variables, except macroeconomic variables, are winsorized at the first and 99th percentiles. Standard errors are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| | Denial | Interest Rate | Interest Spread |
|---|---|---|---|
| VARIABLES | (1) | (2) | (3) |
| Treat × Post-1 | 0.003 | 0.018 | 0.037 |
| | (1.13) | (0.41) | (1.03) |
| Minority | 0.080*** | 0.041*** | 0.059*** |
| | (15.18) | (3.71) | (7.61) |
| Treat × Post-1 × Minority | -0.042*** | -0.072*** | -0.050*** |
| | (-4.59) | (-3.02) | (-2.98) |
| Control Variables | Y | Y | Y |
| Lender FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| County FE | Y | Y | Y |
| Observations | 7,679,546 | 6,236,958 | 5,902,077 |
| R-squared | 0.226 | 0.659 | 0.317 |

**Table A6. Robustness_ Exclude the 10 largest lenders**

This table presents the regression results and t-statistics (in parentheses) for the impact of privacy legislation on interest rate, interest rate spread, and denial among minorities in the United States from 2018 to 2023. We exclude the top ten lenders (which have received the most applications). *Treat* indicates whether the mortgage application was in a state where the privacy legislation was signed, *Post* indicates whether the mortgage application was submitted after the enactment of the privacy legislation in the state, and *Minority* indicates whether the applicant belongs to an ethnic minority. For the dependent variable, we primarily use dummy *variable Denial* to represent whether this application has been rejected or not, while we use *Interest Rate* to represent the cost of mortgage loans and *Interest Rate Spread* refers to the difference between the loan's Annual Percentage Rate (APR) and the Average Prime Offer Rate (APOR). The control variables include *Credit Model*, *Debt_to_Income*, *Loan_to_Value*, *Loan_to_Income*, *Ln_Loan_Amount*, *Race Observed,* and *Age*. The coefficients on all the control variables are omitted for brevity. For the definitions of all the control variables and the details of their construction, see Online Appendix A1. Continuous variables, except macroeconomic variables, are winsorized at the first and 99th percentiles. Standard errors are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| *Panel A. Effect of Privacy Legislation signing on racial disparities* | | | |
|---|---|---|---|
| | Denial | Interest Rate | Interest Rate Spread |
| | (1) | (2) | (3) |
| Treat × Post | 0.002 | 0.029 | 0.030 |
| | (0.72) | (0.90) | (1.16) |
| Minority | 0.072*** | 0.053*** | 0.072*** |
| | (12.84) | (4.89) | (7.76) |
| Treat × Post × Minority | -0.031** | -0.097*** | -0.089*** |
| | (-2.58) | (-3.34) | (-4.15) |
| Control Variables | Y | Y | Y |
| Lender FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| County FE | Y | Y | Y |
| Observations | 5,447,896 | 4,516,186 | 4,234,844 |
| R-squared | 0.244 | 0.656 | 0.340 |
| *Panel B. Effect of Privacy Legislation signing on gender disparities* | | | |
| | Denial | Interest Rate | Interest Rate Spread |
| | (1) | (2) | (3) |
| Treat × Post | -0.002 | 0.017 | 0.018 |
| | (-1.11) | (0.51) | (0.69) |
| Female | 0.012*** | -0.015*** | -0.016*** |
| | (6.22) | (-2.88) | (-2.97) |
| Treat × Post × Female | -0.006** | -0.003 | -0.001 |
| | (-2.23) | (-0.29) | (-0.32) |
| Control Variables | Y | Y | Y |
| Lender FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| County FE | Y | Y | Y |
| Observations | 5,444,845 | 4,513,368 | 4,232,297 |
| R-squared | 0.241 | 0.656 | 0.340 |

**Table A7. Details of state-level privacy legislation**

| | Event date | State | Description |
|---|---|---|---|
| (1) | Jun 28, 2018 | California | The California Consumer Privacy Act (CCPA) was signed into law on June 28, 2018, and went into effect on January 1, 2020. The CCPA applies to any business, including any for-profit entity that collects consumers' data, which does business in California |
| (2) | Jul 7, 2021 | Colorado | Colorado Senate Bill 190 (SB 190), also known as the Colorado Privacy Act (CPA), was introduced and signed into law on July 7, 2021, and its effective Date is July 1, 2023 |
| (3) | May 10, 2022 | Connecticut | Connecticut Data Privacy Act (CTDPA), it has been signed into Law by Governor Ned Lamont on May 10, 2022, and its effective Date is July 1, 2023. |
| (4) | Mar 24, 2022 | Utah | Utah Senate Bill 227 (SB 227), also known as the Utah Consumer Privacy Act (UCPA), was signed into law by Governor Spencer Cox on March 24, 2022. The law is set to take effect on December 31, 2023. |
| (5) | Mar 2, 2021 | Virginia | Virginia Senate Bill 1392 (SB 1392), known as the Virginia Consumer Data Protection Act (VCDPA), was signed into law by Governor Ralph Northam on March 2, 2021. The law is set to take effect on January 1, 2023. |
| (6) | Sep 11, 2023 | Delaware | Delaware Personal Data Privacy Act (DPDPA) was signed into law on September 11, 2023, and it will take effect on January 1, 2025. |
| (7) | May 1, 2023 | Indiana | Indiana Consumer Data Protection Act (ICDPA) was signed into law on May 1, 2023, and it will take effect on January 1, 2026. |
| (8) | Mar 28, 2023 | Iowa | Iowa Consumer Data Protection Act (ICDPA) was signed into law on March 28, 2023, and it will take effect on January 1, 2025. |
| (9) | May 19, 2023 | Montana | Montana Consumer Data Privacy Act (MCDPA) was signed into law on May 19, 2023, and it will take effect on October 1, 2024. |
| (10) | Jun 22, 2023 | Oregon | Oregon Consumer Privacy Act (OCPA) was signed into law on June 22, 2023, and it will take effect on July 1, 2024. |
| (11) | May 11, 2023 | Tennessee | Tennessee Information Protection Act (TIPA) was signed into law on May 11, 2023, and it will take effect on July 1, 2025. |
| (12) | Jun 18, 2023 | Texas | Texas Data Privacy and Security Act (TDPSA) was signed into law on June 18, 2023, it will take effect on July 1, 2024. |