Racial Disparities in the U.S. Mortgage Market:

Evidence from Data Privacy Legislation*

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Abstract

We study the implications of state-level data privacy legislation on racial disparities in U.S. mortgage lending. Using a Difference-in-Difference-in-Differences model, we find that state privacy legislation reduces the denial gap between minority and non-minority borrowers by 4.2% and the interest rate gap by 0.09 percentage points. These effects stem from a shift toward data-driven mortgage decisions that rely more on hard rather than soft information and increased FinTech lending in minority-dense areas. With the increasing demand for FinTech lending, our results highlight the role of stronger data privacy laws in expanding credit access and promoting financial inclusion.

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

Keywords: Data Privacy Legislation; FinTech; Mortgage lending; Race; Financial Inclusion

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1. Introduction

Recent data privacy legislation (such as the EU's GDPR (General Data Protection Regulation) in 2016 and the CCPA (California Consumer Privacy Act) in 2018) had a significant impact on data-intensive industries such as the mortgage sector, where personal data determines mortgage approval rates and loan terms. While extant research has indicated that various legislations have profound impacts on racial and ethnic gaps in mortgage markets[1], disparities in mortgage approval and interest rates between different groups of borrowers persist even after accounting for borrowers' economic characteristics (Munnell et al., 1996).[2] While several U.S. states have introduced data privacy legislation in recent years (for example, Virginia, Indiana and Texas), evidence remains scant regarding the implications of data privacy legislation on the distributional effects of mortgage lending between different groups of borrowers and, more specifically, on racial and ethnic disparities in the mortgage market.

In this paper, we examine the impact of data privacy legislation in mortgage lending for minority and non-minority borrowers. Our findings suggest that state privacy laws can lead to a reduction in disparities between borrower groups, by reducing the denial gap and interest rate between minority and non-minority borrowers, affecting both the extensive margin (loan approvals) and the intensive margin (loan pricing). As data privacy legislation also enhances data availability and transparency, we argue that a reduction in disparities in mortgage lending is driven by a shift toward lending decisions that rely more on hard rather than soft information, with nonbanks, particularly FinTechs, further reducing disparities due to their geographic reach and greater attractiveness for minority applicants.

[1] The U.S. 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." The the dilution and reduction of the Voting Rights Act of 1965 may lead Black Americans to self-select out of the mortgage market (Park et al., 2024).

[2] 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. However, differences can be driven by factors other than race, such as borrower liquidity or preferences (Bhutta and Hizmo, 2021).

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.[3] 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 gain more control over their personal information 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.

We highlight two mechanisms for the implications of data privacy legislation on racial disparity and minorities' access to finance: First, the increasing data transparency requirements and increased customer data rights compel lenders to standardize and automate lending processes, focusing 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 standardization and transparency in lending decisions can lead to reduced discriminatory practices and racial bias. Second, increasing accessibility and control over 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 lenders* (see He et al., 2023; Parlour et al, 2022), as potential customers can provide more data more easily, thus facilitating the screening process. Particularly for minority 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

[3] See details in: https://www.oag.ca.gov/privacy/ccpa.

also offer more affordable mortgage options in minority-dense areas and areas with low bank branch density, ultimately enhancing access to finance in underbanked areas and among minority groups.

Using HMDA mortgage application data from 2018 to 2023, our main sample focusses on counties in U.S. states that have enacted privacy legislation as the treatment group, and neighboring uncovered counties (that do not belong to states that have enacted privacy legislation but border on counties that do) as the 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: after controlling for various credit characteristics, the denial gap between minority and non-minority applicants decreases by 4.2% and the gap in interest rate offered to minority borrowers and non-minority borrowers decreases by 0.09 percentage points. We find that the effects are more pronounced for mortgage decisions utilizing standardized credit model, banks with high IT investment and areas with a high level of explicit bias, implying a potential role of reduced racial bias. Particularly FinTech lenders experience an increase in mortgage applications after states sign data privacy legislation into law and widen their mortgage offerings (measured by the number of accepted mortgage applications and the loan amount) to both minority and non-minority lenders.

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 by Bertrand and Mullainathan (2003) to examine the dynamic and stacked effects of privacy legislation on racial disparities in mortgage lending. Additionally, we conduct subsample analyses based on individual states and different privacy laws. We assess the lagged

effects of privacy legislation and omit samples from states where mortgages were signed in the same year the privacy laws were enacted. Furthermore, we exclude samples from the COVID-19 period (2020-2021), and exclude samples from the top ten mortgage lending institutions. We implement propensity score matching (PSM) methodology and various fixed effects models. All models consistently confirm a reduction in denial and interest rate gaps between minority and non-minority groups after data privacy legislation.

Our contribution is threefold. First, we contribute to the emerging literature on data security and privacy protection legislation and its effects on the banking industry, particularly on mortgage lending by providing novel empirical insights into the impact of privacy legislation on racial disparities. Existing work has focused on the effects of the CCPA on mortgage lender and borrower costs (Gupta et al., 2023), on FinTech lending (Doerr et al. 2023) and of U.S. privacy laws on small banks' IT investment (Huang et al., 2024). In particular, Gupta et al. (2023) show an increase in data processing expenses (especially for soft information) after CCPA has come into effect, while Huang et al. (2024) demonstrate pre-emptive IT investments of small banks after privacy legislation proposals. Doerr et al. (2023) further show an increase in data sharing, due to decreased customer concerns on data security and data sharing. In our study, we focus on the impact of a wider range of data privacy laws on racial disparities in mortgage lending driven, driven by both hard information-driven mortgage decisions as well as wider FinTech offering.

Second, we contribute to the discourse on racial disparities in the mortgage market by offering new evidence on the impact of privacy regulation (that does not necessarily target discrimination and disparity) on racial disparity, enhancing understandings previously established by existing studies, such as by Munnell et al. (1996), Bayer et al. (2018), Ambrose et al. (2021) and Bartlett et al. (2022). Recent studies further highlight the role of automated lending decisions which have the potential to decrease racial discrimination and bias for both

small business lending (Howell et al., 2024) and mortgage markets (Gao et al., 2024; Bhutta et al. 2024). While Gao et al (2024) focus on the effects of automated underwriting on riskier (high Debt-to-Income) loans insured by the Federal Housing Administration (FHA), Bhutta et al. (2024) study the effects of automated underwriting on a wider set of mortgages. In contrast, we focus on conventional loans insured by government-sponsored enterprises (GSE), such as Freddie Mac and Fannie Mae, and study changes in denial and interest rate gaps due to data privacy legislation. While our results show a reduction in denial and interest rate gaps between minority and white non-Hispanic borrowers, we note that the differences could stem from both increases in automated mortgage decisions and shifts in data availability and transparency, with data privacy legislation having distributional effects for both credit demand and supply.

Finally, our study contributes to the wider exploration of automation and FinTech's role in mortgage lending and underwriting[4], as evidenced by Buchak et al. (2018), Fuster et al. (2019), Parlour et al. (2022), Das et al. (2023), among others. FinTech lenders are playing an increasingly important role in mortgage lending, as they use online applications and automated processes to offer faster loan evaluations (Fuster et al., 2019) and attract more minority applicants (Chernenko et al., 2022). We find that data privacy legislation has important effects on the role of FinTech and traditional lending for minority and nonminority borrowers.

Our study holds important policy implications, as data privacy legislation does not specifically target racial disparity but seems to have unintended consequences, such as beneficial effects for minority borrowers in the form of reduced denial and interest rate gaps, and heterogeneous effects on traditional and FinTech lending. Thus, the increased data portability and availability and nature of available data (namely hard information) can have wider consequences for the mortgage lending sector, with heterogeneous effects on different types of borrowers and lenders.

[4] See Berg et al. (2022) for an excellent overview of the FinTech lending literature.

2. Institutional Background and Related literature

2.1 Institutional Background

Since 2018, various U.S. states have introduced and enacted consumer privacy regulations that 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. 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 (1) the ability to access and delete personal information, (2) the option to opt out of selling personal information to third parties, and (3) 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.

[Insert Figure 1 about here]

As shown in Figure 1, 12 states had signed privacy legislation by the end of 2023, to address recent data breaches and privacy protection issues, requiring companies to develop and implement mandatory protective tools to safeguard private information (Huang et al., 2024). Figure 1a 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. For our analysis, we focus on the counties on the borders of states with privacy legislation (treatment) and without privacy legislation (control),

as depicted in Figure 1b. While specifics of each state's privacy legislation differ, all states include the basic rights, as outlined in the CCPA, to access/delete, opt-out, and non-discrimination. The event dates of each state's privacy legislation are provided in Internet Appendix Table IA1.

2.2 Economic Implications of Privacy Legislation

The recent wave of state-level data privacy legislation mandates substantial enhancements in the data protection capabilities of organizations, having substantial economic implications for both financial institutions and their customers. 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, highlighting the greater costs for banks that rely more on soft information and a shift in market share from banks to nonbanks. These increased compliance costs can be passed through to bank customers 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.

In terms of data availability, data privacy laws can reduce consumer concerns regarding data privacy, leading to *increased data sharing* and *availability*, which in turn can improve financial institutions' screening abilities when making mortgage decisions. 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. Parlour et al. (2022) highlight this effect as a form of unraveling that effectively forces everyone to share their data with financial institutions due to the data externality posed by other consumers who share their data. In terms of welfare effects, Jansen et al. (2024b) propose a theoretical framework and show that increased data availability can enable a form of third-degree price discrimination, leading to an increase in total welfare (through more efficient credit allocations) and transfer of surplus between different borrowers and lenders.

However, some theoretical studies caution against the unintended consequences of increased data portability and data sharing (through initiatives such as open banking) on borrowing rates (Parlour et al., 2022) and bank performance (Lin et al., 2024). Parlour et al. (2022) caution against disruption of information spillovers within traditional banks due to the shift of customer data to FinTechs and subsequent increases in information asymmetry and 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. Lin et al. (2024) find heterogeneous effects for banks that adopt open banking technology, as smaller banks experience improvements in value and growth prospects, while benefits to large banks are limited.

2.3 Information and Racial Disparities in the Mortgage Market

Significant racial disparities persist in mortgage lending, as minority applicants experience 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 risk-equivalent Latinx/African-American 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.[5] Ambrose et al. (2021) found mortgage brokers charged premiums to borrowers outside their ethnicity, with Hispanic brokers showing favoritism toward Hispanic borrowers. For Paycheck Protection Program (PPP) loans, Chernenko et al. (2024) and Howell et al. (2024) observed greater racial disparities in financing access in counties with higher racial animus, suggesting loan decisions may be influenced more by postal codes or lender biases than by individual default risk.

However, Bhutta et al. (2024) show that observed and unobserved risk factors, rather than discrimination, can account for significant disparities in denial, but find that lenders provide lower-quality service to minority borrowers. Similarly, mortgage institutions have been accused of "redlining" minority communities, leading to differential treatment of loan applications from certain neighborhoods and offering fewer services and branches in these areas (Holmes and Horvitz, 1994; Tootell, 1996).

Furthermore, reliance on hard information might not necessarily lead to more objective loan-making processes, as loan offers made by human officers can be encumbered by agency problems, such as volume-based incentives (as shown by Berg et al., 2020), or the automation of mortgage decisions can extend human biases to algorithms. Our research thus touches on aspects of algorithmic bias and fairness, although a comprehensive exploration of these topics is beyond the scope of our paper. There are concerns that human bias might extend to algorithmic biases towards minorities, although empirical evidence is sparse and rather suggests a positive effect on minority borrowers. Das et al. (2023) provide a detailed overview of the literature on algorithmic fairness and provide evidence of the differential role of human

[5] Distinguishing whether these racial disparities stem from statistical discrimination - where lenders observe attributes unknown to researchers - or from direct taste-based discrimination, bias, and stereotypes is challenging. If statistical discrimination were the primary cause of this discrepancy, loan costs would be unrelated to race. However, even after controlling for various credit characteristics, minority borrowers still incur significantly higher costs compared to white borrowers (Bayer et al., 2018; Gerardi et al., 2023). In contrast, if stereotypes and bias drive these differences, loan costs would correlate directly with race.

and algorithmic underwriting on female/male and minority/nonminority borrowers. Morse and Pence (2021) highlight ambiguous effects of innovation and data privacy laws on discrimination in finance. Evidence by Howell et al. (2024) and Gao et al. (2024) suggests that automation and algorithmic underwriting leads to increases in PPP lending to Black borrowers and in mortgage lending to White and Hispanic borrowers, respectively. Furthermore, Jansen et al. (2024a) do not find a significant bias of algorithmic underwriting in funding rates for racial minorities, but rather a modest positive bias towards Hispanic workers.

2.4 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 mortgage applications of minority borrowers and racial disparities? We conjecture that data privacy laws have asymmetric effects on minority borrowers compared to non-minority borrowers, with the potential to reduce racial disparities through increased data transparency and portability.

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 information and 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 limited credit history, further increasing access to finance for minority borrowers with thin files (Dey and Brown, 2020; Blattner and Nelson, 2021).

Furthermore, increased data sharing due to reduced data privacy concerns (Doerr et al., 2023) 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 groups and offer more competitive rates due to their automated processes and greater reliance on hard information. Rather than widening borrowing to low-quality lenders, Buchak et al. (2018) find that nonbank lenders focus on more creditworthy borrowers, although they seem to use different information to set interest rates relative to other lenders. It might further point to better pre-screening abilities of nonbanks. Based on these considerations, we propose the following hypothesis:

H: Privacy legislation significantly reduces racial disparities in mortgage lending at both the extensive margin (access to loans) and intensive margin (loan costs).

2.4.1 Mechanism 1: Hard Information Reliance and Data Transparency

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 (Berger et al., 2005). 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 (Agarwal et al., 2011; Howell et al., 2024) and could potentially disadvantage minority candidates in evaluations and mortgage costs (Ambrose et al., 2021). [6]

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

[6] Gao et al. (2024) further show that a credit expansion using algorithmic underwriting by the Federal Housing Administration (FHA) in 2016 had heterogeneous effects on different types of borrowers and overall welfare improvements for disadvantaged borrowers. Furthermore, they show limited benefits of soft information for mortgage underwriting, as a shift to algorithmic underwriting had limited effects on default risk.

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 (Bartlett et al., 2022; Howell et al., 2024). [7]

Privacy laws enhance consumer control over personal data, increasing transparency and reducing dependence on assessments based on soft information 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 can potentially lower the occurrence of discrimination, biases, and stereotypes against minorities in the mortgage market. In case 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).

2.4.2 Mechanism 2: FinTech Lending

FinTech lenders can further impact racial disparities in mortgage lending decisions. Due to the increased automation and lack of bank branches, FinTechs rely more heavily on hard information and algorithm-driven assessments than traditional lenders (DiMaggio and Yao,

[7] 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.

2021; Howell et al., 2024). As more automated and data-driven evaluations reduce possible human officer biases, greater reliance on hard information can potentially provide minority borrowers with wider access to credit opportunities.

There is mixed evidence regarding the effects of automation and algorithmic decision-making on minorities' access to credit. Barlett et al. (2021) find that effects depend widely on the type of mortgage, particularly for FHA loans, minority borrowers experience a reduction in rate premia for FinTech loans, and thus a potential reduction in discrimination. There are further concerns about whether the widening of credit access to minority borrowers means including low-credit score borrowers and increasing credit risk, as shown for the consumer loan market by DiMaggio and Yao (2021). However, Fuster et al. (2019) show no increase in riskier mortgage loans issued by FinTechs. Several studies further show the potential of Machine Learning algorithms and Robo-advising to improve lending efficiency (Tantri, 2021) and reduce discrimination (D'Acunto et al., 2021).

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., 2022; He et al, 2023; Doerr et al, 2023; Gupta et al. 2023). As banks that have accumulated extensive amounts 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, 2023).

The implementation of privacy regulations has also allowed FinTech companies to play a greater role in serving underserved communities. 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). In addition, FinTechs, through their entirely online and

more efficient loan processing, can adapt quickly to market and policy shifts (Buchak et al., 2018; Fuster et al., 2019), making it easier for automated lenders to serve minority-dominated areas underserved by traditional banks.

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. As a result, borrowers are no longer limited to traditional banks and can access loans from FinTechs. 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. We gather information on consumer data privacy legislation enacted in the U.S. between 2018 and 2023 provided 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 the states that enacted consumer privacy legislation constitute our treatment group, whereas those submitted in adjacent states without such legislation form our control group. Both the treatment and control groups are presented in Figure 1a (treatment counties 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 restrict our sample to include only counties on the comparative borders of states with privacy legislation (treatment) and without privacy legislation (control). This identification strategy (as shown in Figure 1b) takes advantage of the similarity between applicants in neighboring counties over randomly selected households across counties, eliminating potential confounding variables by maintaining relatively constant economic environments between the treatment and control groups. 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 focus on conventional loans insured by GSEs by following common data filtering procedures (Buchak et al., 2018; Gupta et al., 2024), including only loans with conforming loan limits (in line with GSE mortgage purchasing limits (Loutskina and Strahan 2015)) and only first-lien loans (excluding junior liens), 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 7,677,579 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 that are adjacent to states where privacy legislation took effect, totaling 38,671,974 mortgage application observations.

Minority Borrowers

Following the research by Bartlett et al. (2022), we define borrowers of Latinx/Hispanic 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 Lenders

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 (1) traditional banks, and (2) FinTech lenders. We identify FinTech lenders by checking whether the financial institution offers deposits and whether mortgage applicants can obtain pre-approval online, as well as whether loan operations are entirely online with no human intervention. FinTech lenders operate differently from traditional banks, often relying on alternative data sources for credit assessment and excelling in big data analysis (Buchak et al., 2018). To ensure robustness and minimize subjectivity in our classification, we also conduct cross-verification to overcome subjectivity in categorization. Specifically, we compare our

FinTech lender classification with the list presented by Fuster et al. (2019) and confirm that our categorization remains consistent and reliable.

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 β. 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 dummy variable equal to one if the mortgage applicant belongs to a minority group (Black or Hispanic) and zero otherwise.

We focus on two dependent variables $y_{i,l,t,c}$: $Interest\ Rate_{i,l,t,c}$ - the loan interest rate in percent and $Denial_{i,l,t,c}$ - the denial situation which reflects whether the mortgage application is rejected by lenders or not. 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 7,677,579 mortgage application observations from counties with enacted privacy legislation and their adjacent counties without privacy legislation (as depicted in Figure 1b) and 38,671,974 observations from states with enacted data privacy legislation and their adjacent states without privacy legislation (as depicted in Figure 1a). 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 sumbitted 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 2, 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 three years before and after the enactment of the act in the treatment samples (which include applications submitted in states that enacted privacy legislation during the sample period). 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 2 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 Columns (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 applicants, focusing particularly on samples from states with and without enacted data privacy laws. The β coefficient illustrates the differential impact on minority versus non-minority mortgage denial 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 4.2% decrease in the difference in denial gap between minority and non-minority borrowers, down from a sample

average denial gap of 18.4% (11.1% when accounting for fixed effects). Column (2) shows qualitatively similar results that are economically and statistically significant.

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). Column (3) shows a 9.1% decrease, indicating that privacy legislation decreases minority interest rates by 0.09 percentage points. Column (4) includes further control variables for borrower characteristics; the coefficient remains negative and statistically significant, yielding economically and statistically similar results.

In addition, we also use an alternative lending cost metric—the interest rate spread, which captures 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 results are shown in Appendix Table A2, the coefficient of *Treat* × *Post* × *Minority* indicates that privacy legislation reduces the interest rate differential between minority and nonminority borrowers from the prime rate by 8.9 points. While minority borrowers generally face higher loan interest rates and denial rates compared to non-minorities, the reduction in loan costs and denial rates of minority borrowers is more pronounced than for non-minority borrowers.

4.2 Dynamic Effects

We further apply the methodology of Bertrand and Mullainathan (2003) to alleviate concerns about reverse causality and validate the parallel trends assumption. 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. Following Bertrand and

Mullainathan (2003), we capture dynamic effects by including dummy variables before and after privacy legislation is signed into law and estimating the following model[8]:

$$y_{i,l,t,c} = \alpha + \sum_{k=-3}^{3} \delta_k \times D_{t,c}^{k} \times Minority_i + \gamma Control_{i,t,c} + \varphi_l + \omega_t + \tau_c + \epsilon_{i,l,t,c} \quad (2)$$

where dummy variables $D_{t,c}^{k}$ capture periods preceding and following the privacy legislation event, and δ_k represents the parameter of interest. More specifically, we decompose the periods before and after the event into seven bins: (i) if the mortgage application is submitted in a state three, two, or one year before the enactment of data privacy legislation, the respective indicator is equal to 1 (*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 or three years after it has enacted data privacy legislation, the respective indicator is equal to 1 (*Post_1*, *Post_2*, *Post_3*). 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 three years before to the three years after the legislation's enactment year.

[Insert Figure 3 and Table 3 about here]

The analysis indicates that the interaction terms on *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* and *Post_3* × *Minority* are negative and statistically significant, consistent with our baseline results. This demonstrates that the implementation of privacy legislation has a

[8] We acknowledge the prevalence of staggered Diff-in-Diff estimates, as proposed by Callaway and Sant'Anna (2021) and discussed by Baker et al. (2022). However, methodologies to account for similar biases in a DDD framework are more limited and we thus follow more traditional diff-in-diff framework applied by Bertrand and Mullainathan (2003).

sustained effect on reducing interest rates and rejection rates for minority applicants, indicating that data privacy legislation decreases 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 IA1) by incorporating mortgage applications from states where the privacy laws were already in effect, as compared to the signing dates utilized in Sections 4.1 and 4.2. Following the baseline methodology in Section 4.1, Table 4 illustrates the impact on loan rejection rates in Column (1) and interest rates in Column (2). We include the same control variables, consistent with the baseline models.

[Insert Figure IA1 and Table 4 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 conduct various additional tests to validate the robustness of our findings, including: (i) differentiating by state-specific effects and privacy legislation (Table IA2); (ii) examining the lagged effects of privacy legislation (Table IA3); (iii) excluding samples from states where the mortgage was signed within the same year of privacy legislation enactment (Table IA4); (iv) excluding samples from the Covid period, specifically 2020 to 2021 (Table IA5); (v) excluding samples from the ten largest mortgage

lenders (Table IA6); (vi) using propensity score matching (PSM) methodology (Table IA7); and (vii) different combinations of fixed effects (Table IA8).

To address any concerns regarding state-specific effects or differences in privacy legislation across states, we report the effects for each state individually (we run the regression model in Equation (1) for each state separately). The classification of U.S. states and the results can be found in Table IA2. We indicate political affiliation of each state based on the outcome of the last three elections in 2016, 2020, and 2024, and classify states based on whether their privacy legislation emphasizes Customer Protection (CP) or Transparency (TP). Our by-state results highlight some hetereogeneity of the effects for different states. We observe some increases in denial rate disparities for Utah and Delaware, which represent a relatively small fraction in terms of observations and population. We further note that states that explicitly mention data transparency in their privacy legislation exhibit stronger reductions in interest rate gap, whilst some states that do not mention transparency exhibit increased denial gaps, confirming our notion that the decrease in racial gaps stem from increased data transparency requirements of state legislators.

We also examined lagged effects by analyzing the impact of privacy legislation on mortgage outcomes one year after implementation in Table IA3, which allows us to capture any delayed effects of the law. Furthermore, as the number of pre- and post-event observations are unbalanced across different states, lagged effects allow for a more balanced panel of observations. Despite some heterogeneity across states shown in Table IA2, effects are not be driven by early adopting states and results are consistent for lagged effects.[9]

In addition, considering that the signing date of privacy legislation can fall at the beginning, middle, or end of a year, we exclude observations from the year of the law's enactment to avoid ambiguity regarding whether that year should be classified as pre- or post-

[9] We re-estimate the remaining tables with the lagged treatment variable. The results are qualitatively similar and are available upon request.

legislation. The results in Tables IA4 alleviate concerns, showing that states affected by privacy legislation experienced a significant reduction in racial disparities in mortgage denial rates and interest rates, while unaffected states did not exhibit such patterns.

The outbreak of COVID-19 and the accompanying social distancing measures have accelerated the shift towards digital financial solutions, with individuals increasingly relying on online platforms for financial transactions and loan services, reducing visits to physical bank branches. To address potential concerns that effects are focusing on COVID-19 period, we exclude the COVID-19 period from the data. As shown in Table IA5, the results continue to be robust and significant after excluding the COVID-19 period.

To further ensure that our findings are not driven by large banks or financial institutions, and to address concerns about cross-state operations of large national banks, we conduct additional tests. Although privacy legislation imposes regulatory requirements on businesses[10], nearly all U.S. lenders meet at least one of the legislative criteria. We rank lenders based on total mortgage application volume and loan amounts and exclude observations from the ten largest U.S. lenders, accounting for approximately 30% of the mortgage market. The results, as shown in Table IA6, remain consistent with the baseline findings.

To address the potential concern about borrower heterogeneity between states with privacy protection legislation and those without, we follow Di Maggio and Yao (2021) and employ propensity score matching (PSM) methodology. For each loan in a state with privacy protection legislation, we identify the closest match among loans in states without such legislation. The results are shown in the Internet Appendix, Table IA7, and again show effects that are consistent with the baseline model.

[10] The regulations under the California Consumer Privacy Act (CCPA) apply to businesses that meet at least one of the following criteria: (A) annual gross revenue exceeding $25 million; (B) possession of personal information from 50,000 or more consumers, households, or devices; or (C) earning more than half of their annual revenue from the sale of consumers' personal information. See: https://www.oag.ca.gov/privacy/ccpa.

Finally, our robustness checks incorporate a variety of fixed effects configurations, combining different sets of lender, county, and year fixed effects to evaluate the consistency of our results when not controlling for lender effects, time variations, or county-specific factors. As demonstrated in Table IA8, the results remain robust and statistically significant, reinforcing the conclusion that privacy legislation plays a crucial role in mitigating racial disparities in the mortgage market.

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 racial disparities in loan rates and denial rates.

5. Mechanism 1: Hard Information Reliance

Mechanism 1 focuses 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 a 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 institution's reliance on soft and hard information.

Our assessment of hard information reliance involves two methods: (1) whether loan decisions rely 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 5.

[Insert Table 5 about here]

Comparing coefficients in Columns (1) and (2) of Panel A which show decisions made without standardized credit models, to Columns (3) and (4) of Panel B which 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 B (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 Panel C) compared to scenarios with a higher probability of relying on

soft information (Column (1) and (2) of Panel C). 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 implicit bias. We follow Chernenko et al. (2024), 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).[11] Within this framework, explicit racial bias refers to conscious preferences or prejudiced emotional responses based on race, and implicit bias refers to unconscious preferences or subtle discrimination in decision-making processes (Daumeyer et al., 2019).

[Insert Figure A1 and Table 6 here]

We define 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., 2024; Schmidt et al., 2022). Each test measures biases against specific racial

[11] We utilize the structure of the Implicit Association Test (IAT) to construct county-level "explicit bias" and "implicit bias" measures based on average responses to this survey, inferring the potential level of explicit and implicit bias of lenders in that county. Implicit biases are subconscious attitudes or stereotypes that influence perception and behavior. Figure A1 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/.

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 A1 displays the county-level distribution of these bias measures, each standardized to have zero mean and unit variance. As illustrated in Table 6, 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 categorize counties in our sample into those with implicit racial bias and those without. As shown in Table 6, Panel B, we find 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 (2) and (4), the privacy protection legislation had a uniformly significant effect on reducing interest rates for minorities, irrespective of the level of implicit racial bias in the county.

6. Mechanism 2: FinTech Lending

In this section, we aim to explore the varying responses of different loan providers following the introduction of privacy protection laws, particularly concerning 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 classify non-bank entities into FinTech companies 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 (Fuster et al., 2019). Moreover, in areas with a higher minority population, existing bank branch networks often provide insufficient services (Wang and 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 FinTech lending mechanism, we constructed dummy variables for FinTech firms (set to one if the lender neither accepts nor offers deposit service and the lender's loan process is entirely online, and zero otherwise). To analyze the role of lender type, we include a four-way interaction effect to our model in Equation (1), estimating the following model (3):

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

where *i*, *l*, *t,* and *c* represent the loan application, lender, year, and county, respectively. The variables are the same as in Equation (1). The variable $FinTech_l$ indicates if the lending institution is a FinTech (*FinTech*=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 7.

[Insert Table 7 about here]

We explore the role of FinTech in racial disparities in mortgage lending in Table 7. 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. Compared to

traditional banks, FinTechs show a more pronounced effect in reduced racial disparities after enactment of data privacy legislation, confirming that the FinTech lending channel contributes to the reduction in racial disparities in mortgage lending.

6.1 Geographic Variation

We further assess whether effects are 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[12], 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 8.

[Insert Table 8 about here]

The results show a wider offering of financial mortgages in high-minority intensity areas, reflected in the decrease in denial rates after data privacy enactment, particularly driven by FinTech lenders. Panel A in Table 8 indicates that privacy legislation does not seem to have significant effects 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 particularly for loan applications to FinTechs.

[12] 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. 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.

High minority intensity could be correlated with the availability of bank services in these areas, as areas with a high minority population have been shown to be traditionally underserved (Wang and Zhang, 2020). The results are not fully explained by bank branch density. While we observe a 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 in racial disparities. We confirm that privacy protection laws significantly mitigate bias in mortgage lending, particularly in minority-dense areas, contributing to the broader goals of financial inclusion and wider access for underserved communities.

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 (4) and (5):

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

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

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 $Treat_c \times Post_t$ represents 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 9 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 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 9 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 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. To alleviate any concerns that these effects are driven by new lenders rather than existing lenders, we classify lenders into existing and new lenders in a separate analysis in the Internet Appendix, Table IA9, demonstrating that effects are driven by existing rather than any new lenders.

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. In particular, we differentiate by various loan purposes and borrower characteristics, to explore whether reduced racial disparities might be driven by a shift in loan purposes, changes in borrower quality, or race, ethnicity, or gender effects.

7.1 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 10, 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 10 about here]

In Table 10, 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 10, there is relatively weak evidence that privacy legislation may decrease the likelihood of minorities being denied loans due to insufficient funds (e.g., down-payments, 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.

7.2 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 11 about here]

In Table 11, 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 reduction in interest rate gap is more pronounced for home purchase loans than for refinancing loans. 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.

7.3 Borrower Income and Credit Quality Differentiations

The changing population of minority applicants, rather than the shift towards hard information-driven decisions, could be alternative drivers for the reduction in racial disparity. We thus account for differing levels of borrower income, loan amount, and credit risk. 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 Panel A and B of Table 12.

[Insert Table 12 about here]

As shown in Panel A and B in Table 12, we find no significant differences in effects based on borrowers' income or loan amount, suggesting that privacy regulations do not inherently differ in their impact across different income levels of minority borrowers.

In Panel C of Table 12, we show the analysis of whether borrowers' credit quality changes among the introduction of privacy legislation. We focused on four key factors highly correlated with applicant credit scores and default likelihood: income, loan-to-income ratio, loan-to-value (LTV) ratio, and debt-to-income (DTI) ratio (Albanesi et al., 2022; Fuster et al., 2021; Doerr et al., 2023). Using principal component analysis (PCA), we generated two principal components, *PCA1* and *PCA2*, with *PCA1* explaining 42.51% of the total variance and *PCA1* and *PCA2* combined explaining a cumulative 68.78% of the variance. We created a new variable, *PCA1_2*, as a weighted linear combination of *PCA1* and *PCA2*, using their explained variance proportions as weights, which captures 68.78% of the variance. Following the baseline

model, we included lender, county, and time-fixed effects and clustered at the state level, but excluded any control variables to avoid multicollinearity issues. Our results in Panel C of Table 12 show no significant changes in minority borrower characteristics after privacy legislation, further alleviating concerns about changes in borrower characteristics after enactment of privacy legislation.

Our results confirm the comprehensive and uniform protective measures of privacy regulation. As the loan approval process increasingly relies on hard information and reduces human bias, this process ensures that all borrowers, regardless of their income level, loan amount, or race, are treated without bias or differential treatment, and are judged primarily on their characteristics pertaining to their credit risk.

7.4 Race and Ethnicity Differentiations

To account for possible heterogeneity of effects depending on borrowers' race or ethnicity, we further differentiate between Black/non-Black and Hispanic/non-Hispanic borrowers, as presented in Table A3. We confirm substantial gaps in denial and interest gaps for Black borrowers, as shown previously in related studies (such as Bartlett et al, 2022; Das et al., 2023) compared to non-Black and Hispanic borrowers. We further show that after privacy legislation, the reduction in denial gaps is more pronounced for Black borrowers, compared to non-Black borrowers, while the reduction in interest rate gap is more pronounced for Hispanic borrowers. As noted by Gerardi et al. (2024), racial gaps could be due to difficulties in obtaining refinancing mortgages by minority borrowers and the ability of non-Hispanic white borrowers to exploit periods of falling interest rates.

7.5 Effects on Gender Disparities

We further test for differences in gender impact by replacing the Minority variable in our baseline model with Female, indicating whether the mortgage applicant was female. The results are presented in Table A4. However, the impact of privacy legislation on gender disparities appears limited, as shown in Panel A of Table A4; it seems only to reduce rejection rates for mortgage applications by women, without effectively influencing interest rates.

Furthermore, we also tested whether the privacy protection legislation alleviated disparities in mortgage outcomes between minority female borrowers and other applicants, and we found robust results. In Columns (1) and (2) of Panel B, we introduced the dummy variable *Female_Minority*, which equals 1 if the loan applicant is a minority female and 0 otherwise. In Columns (3) and (4) of Panel B, we further restricted the sample to female applicants to examine whether the privacy legislation mitigated disparities between minority and non-minority within this group (female applications).

The significant negative coefficients of interaction terms *Treat* × *Post* × *Female_Minority* indicate that after the privacy legislation, the differences between female minorities and other applicants (male minorities, male non-minorities, and female non-minorities) have significantly narrowed. Additionally, the significant negative coefficient of *Treat* × *Post* × *Minority* shows that privacy legislation helped alleviate racial and gender disparities for female minorities and female non-minorities. This suggests that privacy protection legislation helps alleviate racial and gender disparities among female minority borrowers compared to other groups.

We further include additional control variables in our baseline model, in particular, an indicator variable for the borrower's gender (*Female*) and the principal component *PCA1_2* derived from the PCA for credit risk variables (as described above). The results in Table IA10 are consistent with our baseline findings.

8. Conclusion

Using a Triple-Difference (DDD) model, we demonstrate that U.S. privacy legislation leads to a reduction in racial disparity between minority and non-minority borrowers in the mortgage market, even after accounting for various credit characteristics. Specifically, mortgage interest rate differences decrease by 0.09 percentage points, and differences in application rejection rates drop by 4.2%. Our results are primarily driven by lenders that rely more on hard information rather than soft information. The increased transparency requirements of privacy legislation help reduce discriminatory practices and racial bias, with more pronounced effects in areas with greater racial animus and higher minority populations. FinTech lenders 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 contributes to the literature on data security and privacy protection and on the role of FinTech lending in the mortgage lending sector.

Our study holds practical implications for both financial institutions and regulatory bodies. While the goal of data privacy protection legislation 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. Our results provide new insights into the ongoing discussions on financial inclusion and racial disparities in the mortgage market, offering valuable perspectives on initiatives to widen financial inclusion and credit access for underrepresented groups.

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Figures and Tables

Figure 1. Coverage of privacy legislation in U.S. states and neighboring states and counties

These figures show 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. In Figure 1a, neighboring states that did not sign the legislation are marked in gray, while non-neighboring states are marked in white. Figure 1b focusses on counties in states with enacted privacy legislation and that are adjacent to states with legislation enactment, with counties in neighboring states marked in gray, while non-neighboring counties are marked in white.

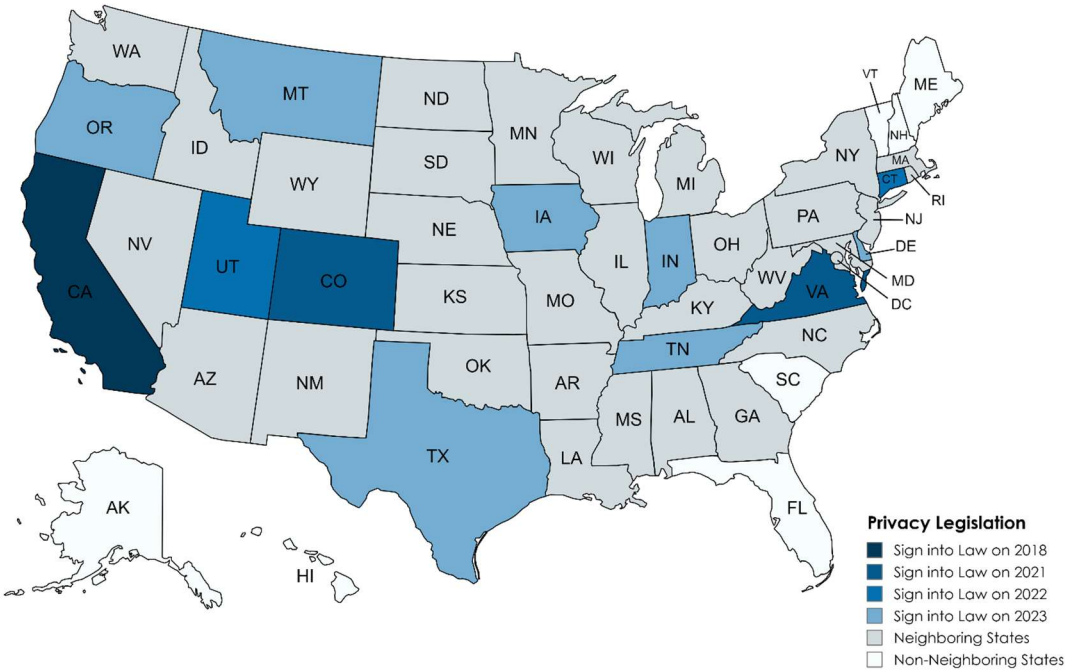


Figure 1a. State-level coverage and neighboring states

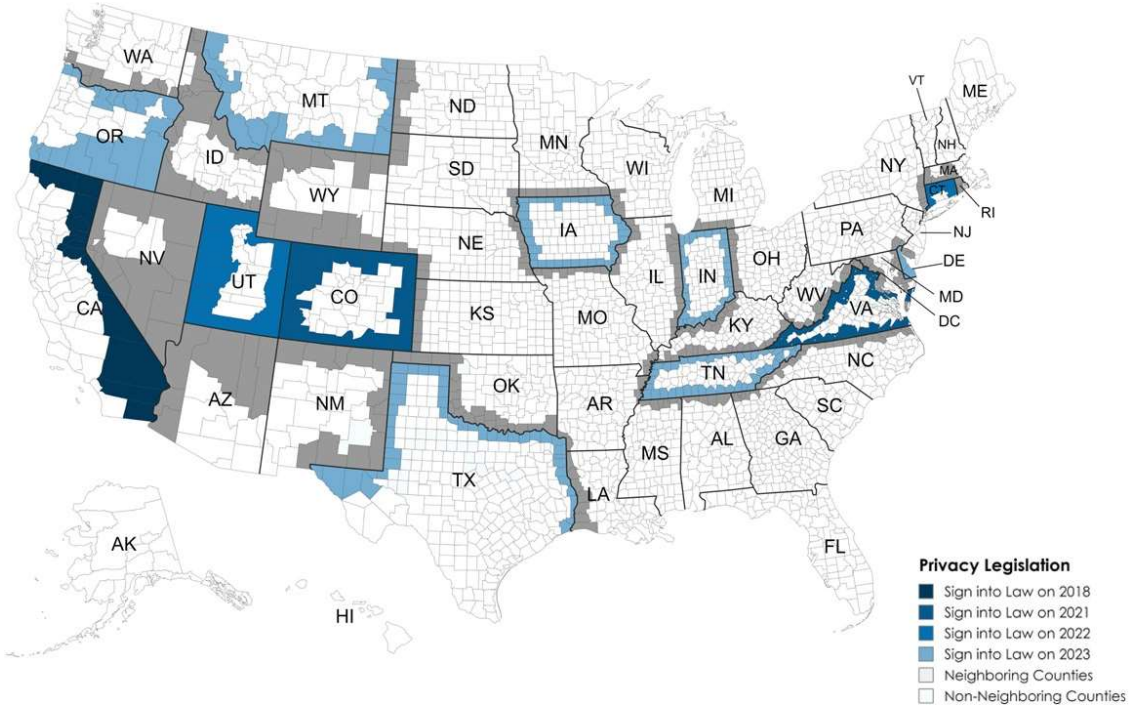


Figure 1b. County-level coverage and neighboring counties

Alt text: Figure depicting map of U.S. states and counties, with different shading depending on when state signed privacy legislation into law.

Figure 2. Trends in Denial Rates and Interest Rate Spreads of Minorities and Non-Minorities
These figures show the average interest rate spreads 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. The timelines across states are synchronized based on the respective years when the state 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.

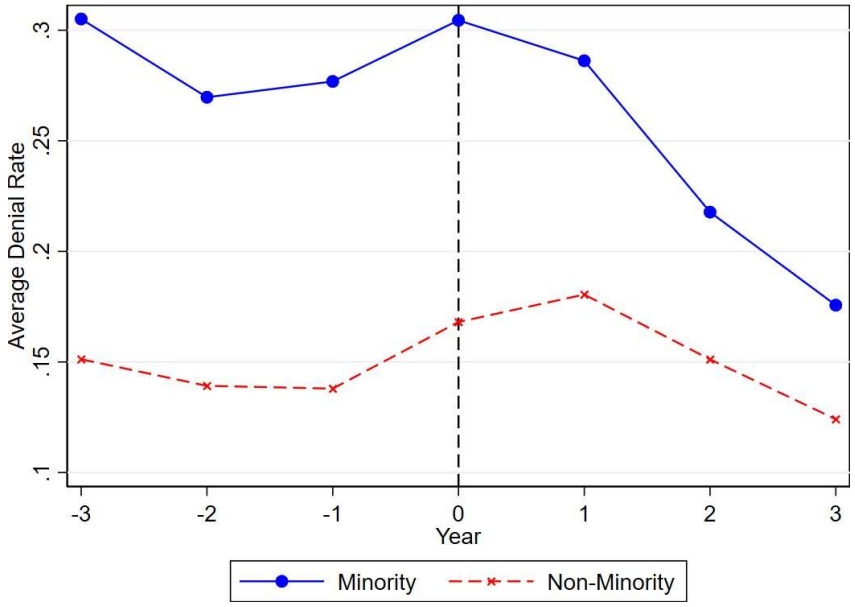


Figure 2a. Denial rates of minorities and non-minorities

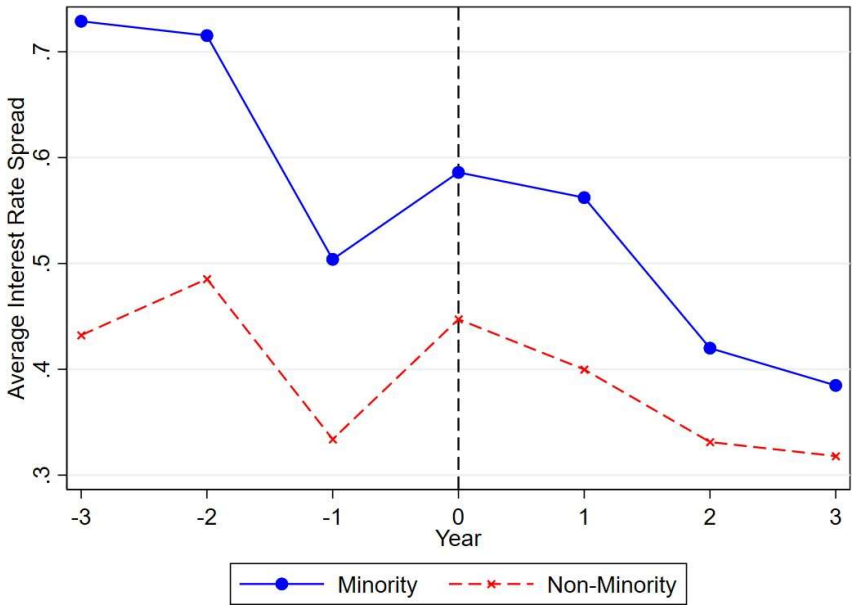


Figure 2b. Interest rate spreads of minorities and non-minorities

Alt text: Linegraphs depicting the trend in average denial rate and interest rate spread for minority and non-minority borrowers over time in years relative to signature date of respective privacy law.

Figure 3. Dynamic Effects of Privacy Legislation on Mortgage Racial Gap

These figures show 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 3 years prior to enactment *(Pre_3*, *Pre_2*, *Pre_1)*, 3 years after enactment (*Post_1*, *Post_2*, *Post_3*) and the same year *Post_0*. The vertical axis presents the difference in denial rate (Figure 3a) and interest rates (Figure 3b) of minority and non-minority borrowers, estimated using Model (2). The bar chart represents a 95% confidence interval.

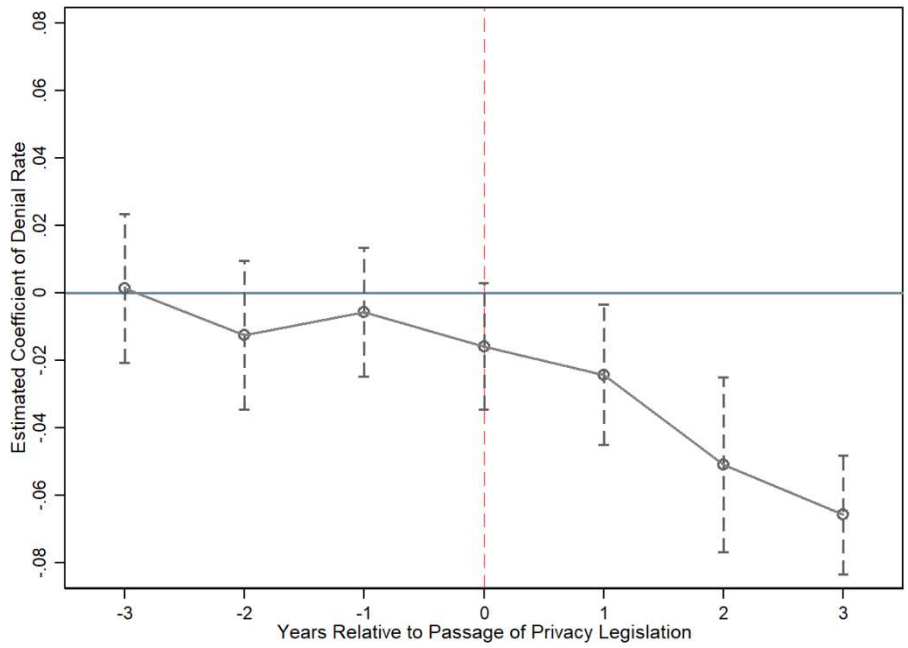


Figure 3a. Effect on denial rates

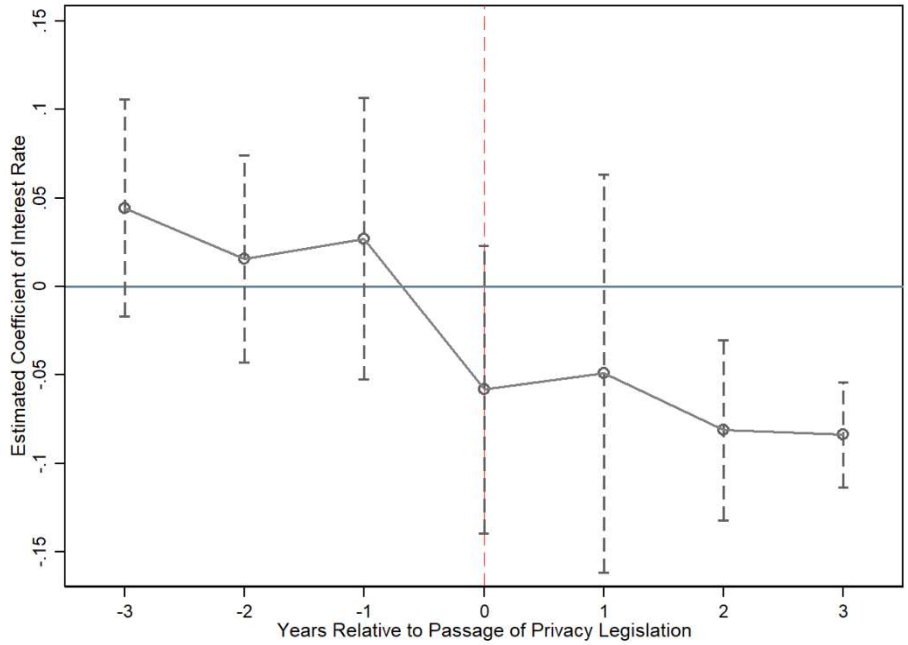


Figure 3b. Effect on interest rates

Alt text: Linegraphs depicting the difference in denial rate and interest rates between minority and non-minority borrowers over time in years relative to signature date of respective privacy law.

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 7,677,579 application-level observations. For detailed information on the definition and construction of all variables, please refer to the 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	7,677,579	0.188	0.391	0	0	1
Privacy_Effective	38,671,974	0.250	0.433	0	0	1
Minority	7,677,579	0.182	0.386	0	0	1
Female	7,677,579	0.259	0.438	0	0	1
Dependent Variables						
Denial	7,677,579	0.184	0.388	0	0	1
Interest Rate [%]	6,236,958	4.167	1.619	1.990	3.695	9.500
Interest Rate Spread	5,902,077	0.444	0.983	-2.190	0.298	4.220
Control Variables						
Credit Model	7,677,579	0.887	0.316	0	1	1
Debt_to_Income	7,677,579	0.624	0.484	0	1	1
LTV	7,677,579	0.608	0.279	0.050	0.686	1
Loan_to_Income	7,677,579	2.609	5.246	0.165	2.204	8.598
Ln_Loan_Amount	7,677,579	12.094	0.903	9.616	12.231	13.860
Age category	7,677,579	3.826	1.425	1	4	7
Gender Observed	7,674,530	0.045	0.208	0	0	1
Race Observed	7,677,579	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
Panel D: Mean value for Minority and non-minority				
	Minority borrower		Non- Minority borrower	
Lender Classifications	Denial	Interest Rate	Denial	Interest Rate
Bank	0.389	4.660	0.199	4.319
Fintech	0.150	4.093	0.088	3.918
Shadow bank	0.195	4.131	0.118	3.941

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 denial rate and interest rate 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 and *Interest Rate* to represent the cost of mortgages. For detailed information on the definition and construction of all control variables, please refer to Appendix Table A1. Panel A includes only mortgage application samples from *counties* in states where privacy legislation has been enacted and counties adjacent to these states with privacy legislation (see Figure 1b). Panel B includes mortgage application samples from *states* with enacted privacy legislation and neighboring states to these states (see Figure 1a). 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	
	(1)	(2)	(3)	(4)
Treat × Post	0.007**	0.007***	0.010	0.016
	(2.17)	(2.74)	(0.34)	(0.51)
Minority	0.111***	0.081***	0.113***	0.046***
	(14.79)	(14.25)	(10.51)	(3.66)
Treat × Post× Minority	-0.042***	-0.034***	-0.091***	-0.073***
	(-3.19)	(-3.25)	(-3.78)	(-2.79)
Credit Model		-0.167***		-0.567***
		(-13.48)		(-8.48)
Debt_to_Income		0.087***		0.077***
		(30.12)		(21.05)
LTV		0.017		0.182***
		(1.53)		(4.66)
Loan_to_Income		0.005***		-0.005***
		(13.60)		(-6.16)
Ln_Loan_Amount		-0.059***		-0.252***
		(-22.69)		(-10.91)
Race Observed		0.007		0.074***
		(1.36)		(4.16)
Age		0.002*		-0.013***
		(1.97)		(-3.08)
Constant	0.169***	0.942***	4.163***	7.659***
	(114.45)	(35.32)	(702.74)	(23.64)
Lender FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
Observations	7,677,579	7,677,579	6,236,958	6,236,958
R-squared	0.174	0.226	0.651	0.659

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

Panel B. Neighboring State				
	Denial		Interest Rate	
	(1)	(2)	(3)	(4)
Treat × Post	0.006*	0.007***	-0.055	-0.047
	(1.9)	(2.1)	(-0.95)	(-0.88)
Minority	0.1123***	0.083***	0.134***	0.062***
	(23.4)	(20.66)	(15.58)	(7.69)
Treat × Post× Minority	-0.036***	-0.032***	-0.086***	-0.088***
	(-3.55)	(-3.52)	(-3.73)	(-4.23)
Credit Model		-0.156***		-0.463***
		(-12.37)		(-5.68)
Debt_to_Income		0.088***		0.079***
		(45.77)		(27.26)
LTV		0.023***		0.204***
		(3.01)		(4.84)
Loan_to_Income		0.004***		-0.003***
		(10.91)		(-4.79)
Ln_Loan_Amount		-0.059***		-0.278***
		(-21.27)		(-18.19)
Race Observed		0.006**		0.078***
		(2.21)		(5.98)
Age		0.002***		-0.013***
		(3.34)		(-3.02)
Constant	0.167***	0.931***	4.152***	7.860***
	(219.37)	(31.93)	(374.33)	(34.44)
Lender FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
Observations	38,671,974	38,671,974	31,588,968	31,588,968
R-squared	0.1729	0.225	0.643	0.661

Table 3. Dynamic Effect of Privacy Legislation

The table presents the results of the dynamic regression model examining the effects of privacy legislation on the interest rate and denial rates for minority mortgage borrowers. The analysis replaces the test variable *Treat* × *Post* with a set of dummy variables *Pre_3*, *Pre_2*, *Pre_1*, *Post_0*, *Post_1*, *Post_2* and *Post_3* —which capture the periods before and after the data privacy legislation. T-statistics are presented in parentheses. The coefficients on all the *Pre_3* to *Post_3* are 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_3 × Minority	0.001	0.044
	(0.13)	(1.46)
Pre_2 × Minority	-0.012	0.016
	(-1.14)	(0.54)
Pre_1 × Minority	-0.006	0.027
	(-0.60)	(0.69)
Post_0 × Minority	-0.016	-0.058
	(-1.68)	(-1.44)
Post_1 × Minority	-0.024**	-0.049
	(-2.36)	(-0.88)
Post_2 × Minority	-0.051***	-0.081***
	(-3.96)	(-3.23)
Post_3 × Minority	-0.066***	-0.084***
	(-7.53)	(-5.69)
Minority	-0.012	0.016
	(-1.14)	(0.54)
Pre and Post	Y	Y
Lender FE	Y	Y
Year FE	Y	Y
County FE	Y	Y
Observations	7,677,579	6,235,270
R-squared	0.187	0.641

Table 4. Effects of Effective Privacy Legislation

This table presents the effects of privacy legislation on denial rates and interest rates, based on a subsample of states where privacy legislation is already in effect and their adjacent states. Specifically, the treatment group consists of states where the privacy legislation has been enacted, while the control group includes neighboring states without such legislation (see Figure IA1). 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 and 3). 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 Appendix A1. Standard errors are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Denial	Interest Rate
	(1)	(2)
Privacy_Effective	0.001	0.047**
	(0.55)	(2.14)
Minority	0.077***	0.051***
	(16.36)	(5.90)
Privacy_Effective × Minority	-0.040***	-0.077***
	(-7.75)	(-4.10)
Control Variables	Y	Y
Lender FE	Y	Y
Year FE	Y	Y
County FE	Y	Y
Observations	19,372,134	15,867,976
R-squared	0.214	0.663

Table 5. 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. Panel A shows that results based on a subsample of applications where a standardized credit model has not been applied (Columns (1) and (2)) and where a standardized 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 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

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Table 5. Mechanism –– Hard and Soft Information Reliance in Mortgage Decisions (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 observed or unobserved			
	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 6. Mechanism – Role of Racial 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 racial biases (Columns (1) and (2)) and those with overt racial biases (Columns (3) and (4)), illustrating the effects of explicit racial bias. Panel B reports result for applications in counties without covert racial biases (Columns (1) and (2)) and those with covert 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 7. Mechanism – Role of Fintech Lenders

This table presents the results for the role of Fintech. We include a *FinTech* dummy variable indicating whether the lender is a FinTech, which captures whether the lending process is conducted exclusively online. *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 (2) display the interaction effects on denial rates, while Columns (3) to (4) 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 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)
Treat × Post		0.007**		0.012
		(2.62)		(0.36)
Minority		0.082***		0.044***
		(14.59)		(3.48)
Treat × Post × Minority		-0.027***		-0.054**
		(-2.70)		(-2.17)
Treat × Post × Minority × Fintech	-0.007*	-0.046***	-0.099***	-0.090***
	(-1.72)	(-15.53)	(-3.28)	(-6.70)
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	7,452,183	7,452,183	6,032,456	6,032,456
R-squared	0.224	0.228	0.658	0.658

Table 8. Mechanism – 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 results of the benchmark model in Equation (1) categorized based on subsamples of mortgage applications. Panel A reports result for applications in areas (tracts) with low intensity of minorities (Columns (1) - (4)) and those with high intensity of minorities (Columns (5) and (8)). Panel B reports result for 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

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Table 8. Mechanism – 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 9. Mechanism – Credit Demand: Loan applications divided by lender type

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, or minorities in the U.S. from 2018 to 2023, based on aggregated observational data by county, year, and lender. 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 details of the effects of privacy protection legislation on the number of applications, requested loan amount, and approval rates for all applicants and minority groups. Conversely, Panel B specifically examines these variables within FinTech lending institutions. The coefficients for control variables are omitted for brevity and are consistent with baseline models. 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 10. 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 Appendix A1. 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

Table 11. Loan Purpose Differentiations

This table presents the regression results and t-statistics (in parentheses) for the impact of privacy legislation on the denial 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 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 12. Borrower characteristics

This table presents the effects of privacy legislation 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). In addition, to more accurately assess borrowers' credit scores and default risk, Panel C examines whether privacy legislation has led to changes in credit risk of different applicants. We focused on four key factors highly correlated with applicants' credit scores and default likelihood: income, loan-to-income ratio, loan-to-value ratio, and debt-to-income ratio. Using principal component analysis (PCA), we generated two principal components, PCA_1 and PCA_2, and created a new variable, *PCA1_2*, as a weighted linear combination of them to serve as the dependent variable. The coefficients for control variables are omitted for brevity and are consistent with baseline models. For the definitions of all the control variables and the details of their construction, see 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. Borrower 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. Borrower 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

(continued next page)

Table 12. Borrower characteristics (cont'd)

Panel C. Borrower credit risk			
	(1)	(2)	(3)
	Loan_to_Income	PCA1	PCA1_2
Treat × Post	-0.099*	-0.013	-0.009
	(-1.89)	(-0.87)	(-0.87)
Minority	0.116***	-0.146***	-0.101***
	(3.33)	(-4.81)	(-4.81)
Treat × Post× Minority	0.018	0.018	0.013
	(0.43)	(0.62)	(0.62)
Lender FE	Y	Y	Y
Year FE	Y	Y	Y
County FE	Y	Y	Y
Observations	7,677,579	7,677,579	7,677,579
R-squared	0.055	0.262	0.262

Appendix

Figure A1. 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. 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.

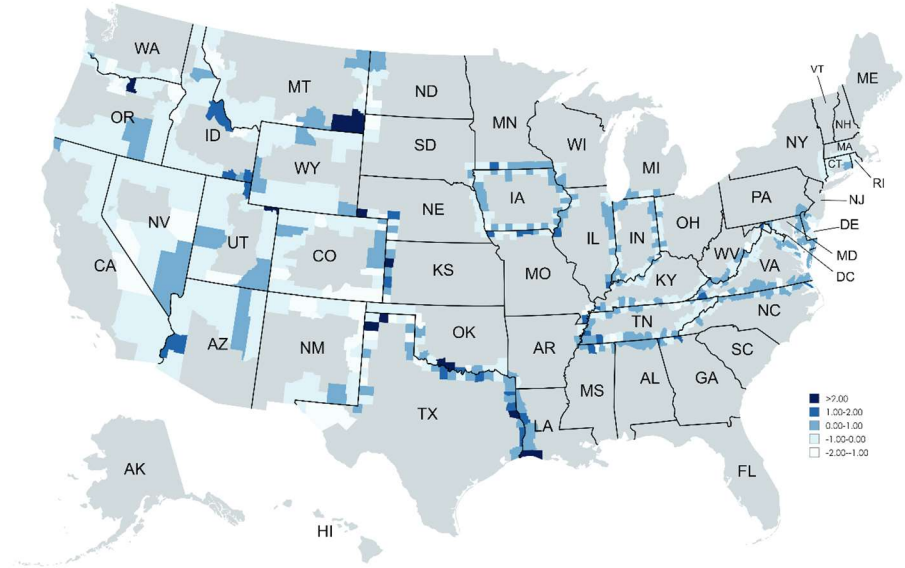


Figure A1a. County-level distribution of explicit bias

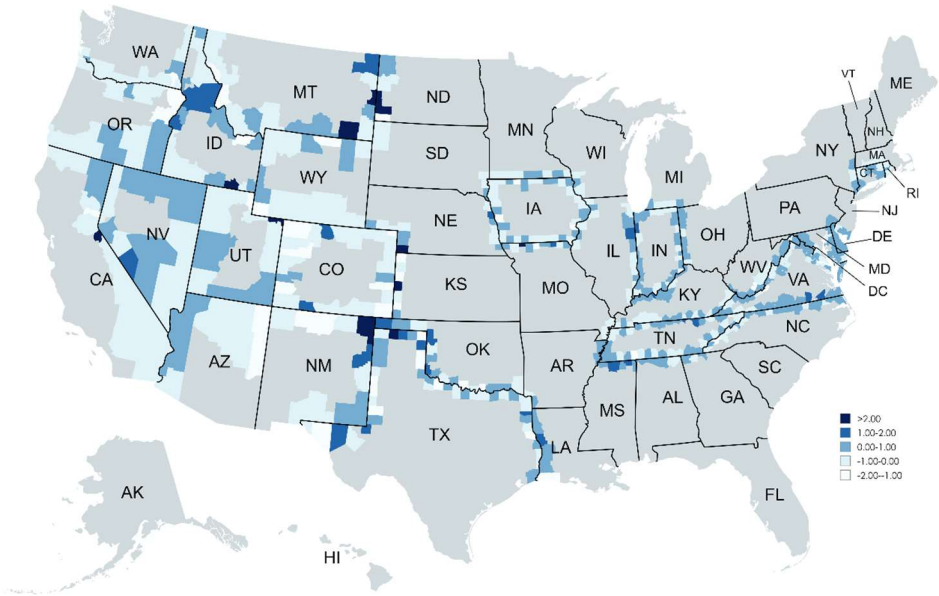


Figure A1b. County-level distribution of implicit bias

Alt text: Figure depicting map of U.S. states and counties, with different shading depending on when state signed privacy legislation into law.

Table A1. Variable definitions

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)
Bank	Whether the lender is a bank or not

Table A2. Alternative measure of lending cost

This table presents the regression results and t-statistics (in parentheses) for the impact of privacy legislation on 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 use *Interest Rate Spread* to alternatively represent the cost of mortgage loans, which refers to the difference between the loan's Annual Percentage Rate (APR) and the Average Prime Offer Rate (APOR). 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. Columns (1)- (2) are the 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, while Columns (3) - (4) include 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.

	Interest Rate Spread			
	(1)	(2)	(3)	(4)
Treat × Post	0.008	0.014	-0.034	-0.025
	(0.28)	(0.50)	(-0.81)	(-0.66)
Minority	0.146***	0.065***	0.169***	0.084***
	(15.36)	(7.04)	(21.15)	(11.76)
Treat × Post× Minority	-0.089***	-0.062***	-0.079***	-0.078***
	(-4.54)	(-3.54)	(-5.05)	(-5.54)
Credit Model		-0.333***		-0.282***
		(-5.43)		(-3.47)
Debt_to_Income		0.046***		0.047***
		(13.94)		(20.09)
LTV		0.408***		0.416***
		(8.62)		(9.56)
Loan_to_Income		-0.006***		-0.004***
		(-7.48)		(-5.69)
Ln_Loan_Amount		-0.302***		-0.320***
		(-13.85)		(-18.64)
Race Observed		-0.017		-0.030*
		(-1.01)		(-1.80)
Age		-0.007		-0.008
		(-1.63)		(-1.67)
Constant	0.433***	4.183***	0.411***	4.337***
	(69.72)	(15.10)	(52.54)	(18.81)
Lender FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
Observations	5,902,077	5,902,077	29,870,062	29,870,062
R-squared	0.294	0.317	0.298	0.337

Table A3. Differentiation by Race and Ethnicity

This table presents the regression results and t-statistics (in parentheses) for the impact of privacy legislation on interest rate and denial among minorities, differentiating between Black and Hispanic borrowers by including dummy variables *Black* and *Hispanic*. *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. 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. 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 Appendix A1. Standard errors are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Black and Non-Black				
	(1)	(2)	(3)	(4)
	Denial	Interest Rate	Denial	Interest Rate
Treat × Post	0.003	0.005	0.003**	0.009
	(1.40)	(0.17)	(2.13)	(0.28)
Black	0.097***	0.076***	0.097***	0.077***
	(14.35)	(4.43)	(14.37)	(4.42)
Treat × Post × Black	-0.030***	-0.017	-0.030***	-0.018
	(-3.22)	(-0.51)	(-3.28)	(-0.54)
Borrower Controls	Y	Y	Y	Y
State Controls	N	N	Y	Y
Lender FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
Observations	7,402,576	6,041,544	7,402,576	6,041,544
R-squared	0.220	0.657	0.221	0.657
Panel B. Hispanic and Non-Hispanic				
	(1)	(2)	(3)	(4)
VARIABLES	Denial	Interest Rate	Denial	Interest Rate
Treat × Post	0.002	0.009	0.002	0.012
	(1.11)	(0.29)	(1.55)	(0.40)
Hispanic	0.046***	0.020*	0.045***	0.020*
	(8.37)	(1.91)	(8.38)	(1.93)
Treat × Post × Hispanic	-0.021***	-0.077***	-0.021**	-0.077***
	(-2.71)	(-4.39)	(-2.69)	(-4.40)
Borrower Controls	Y	Y	Y	Y
State Controls	N	N	Y	Y
Lender FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
Observations	7,402,576	6,041,544	7,402,576	6,041,544
R-squared	0.218	0.657	0.218	0.657

Table A4. Gender Disparities

This table presents the effect of privacy legislation on gender disparities (Panel A) and racial and gender combined disparities (Panel B) on denial rates and interest rates on mortgage applications filed. For independent variables: *Female*, which equals 1 if the loan applicant is female and 0 otherwise, and *Female_Minority*, which equals 1 if the applicant is a minority female and 0 otherwise. In Panel B, Columns (1)-(2) use the full sample, while Columns (3)-(4) restrict the sample to female applicants only. 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 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 Privacy Legislation on Racial and Gender Combined Disparities

	Denial	Interest Rate	Denial	Interest Rate
	(1)	(2)	(3)	(4)
Treat × Post	0.003	0.008	0.006*	0.032
	(1.41)	(0.26)	(1.90)	(0.84)
Female_Minority	0.063***	-0.005		
	(10.14)	(-0.39)		
Treat × Post × Female_Minority	-0.024**	-0.050*		
	(-2.30)	(-1.95)		
Minority			0.073***	0.029**
			(13.14)	(2.10)
Treat × Post × Minority			-0.025**	-0.065**
			(-2.28)	(-2.35)
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	7,677,579	6,235,270	1,987,743	1,547,759
R-squared	0.223	0.658	0.263	0.674

Internet Appendix

Figure IA1. 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.

Alt text: Figure depicting map of U.S. states and counties, with different shading depending on when state privacy legislation has become effective.

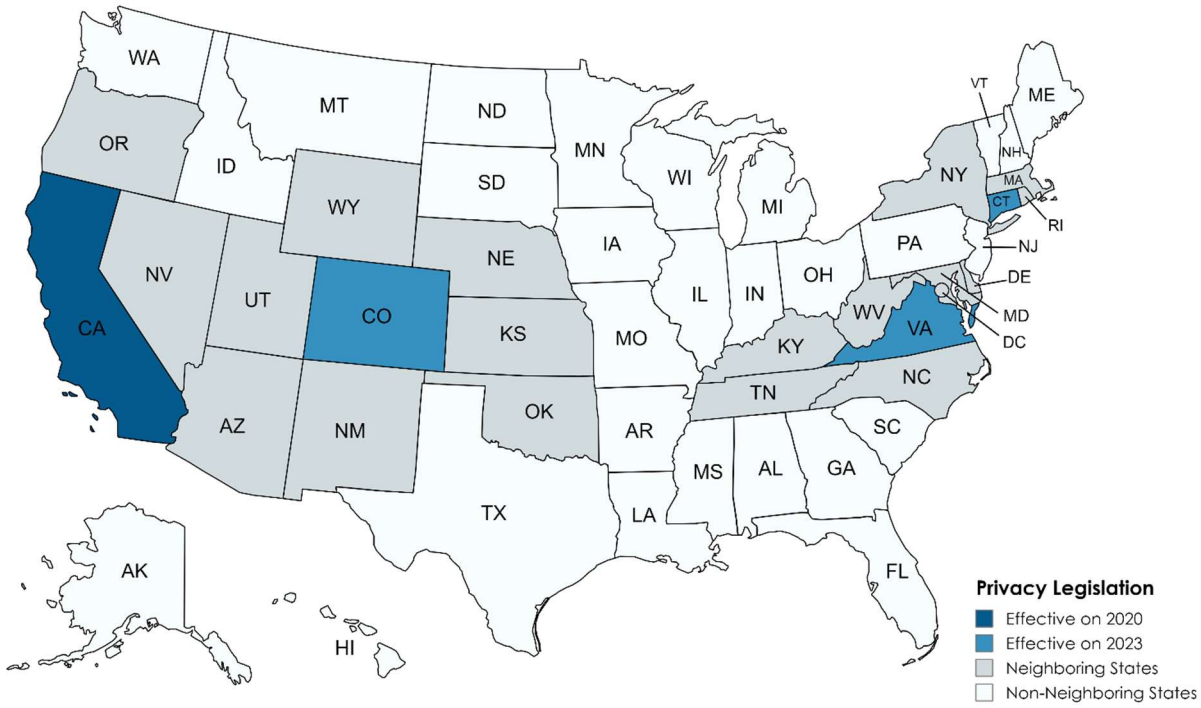


Figure IA2. CFPB complaints

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 2018-2023. 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 y-axes represent the density of complaints. Figure A2a illustrates the complaints received by lenders in the sample regarding the improper use of consumer reports before and after the implementation of privacy protection laws. Figure A2b compares 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).

Alt text: Figure depicting kernel and normal density of CFPB complaints over time in months relative to signature date of respective privacy law for the overall sample (Figure A2a) and subsamples by states with and without privacy legislation.

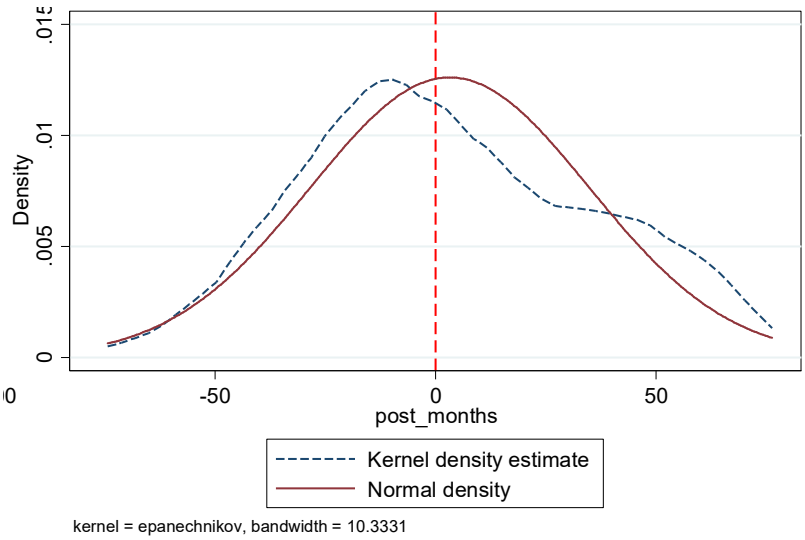


Figure A2a. Distribution of "improper use of your report" complaints

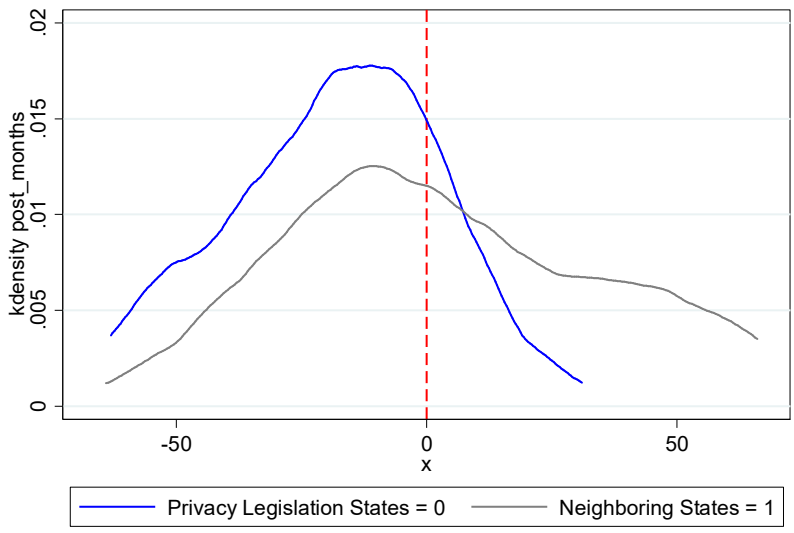


Figure A2b. Distribution of "improper use of your report" complaints between different states

Table IA1. 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.

Table IA2. Robustness_ State-specific Effects of Privacy Laws

This table presents the regression results and t-statistics (in parentheses) for the impact of privacy legislation on interest rate and denial among minorities, differentiating between individual states (Panel A) and states that include customer protection and/or data transparency. Panel A classifies states based on whether their privacy legislation emphasizes Customer Protection (CP) or Transparency (TP) and provides the political leaning based on the previous three election results in 2024, 2020, and 2016 (D-Democratic, R-Republican). If a state's privacy law highlights "Customer Protection", the indicator variable equals 1; otherwise, it is 0. If a state's privacy law highlights "Transparency", the indicator variable equals 1; otherwise, it is 0. Panel B and Panel C show the subsample results of State-specific privacy legislations. To be more specific, Panel B examines the effects of privacy laws emphasizing "Customer Protection" on interest rates and denial rates for minority and non-minority borrowers before and after implementation, comparing affected states with their neighboring states. Panel C analyses the effects of privacy laws focusing on "Transparency" on interest rates and denial rates for minority and non-minority borrowers before and after implementation, again comparing affected states with their neighboring states. 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. 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 Appendix A1. Standard errors are clustered at the state level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Effects of privacy laws by state

No.	Privacy Date	State	Obs.	Denial	Interest Rate	Polti	CP	TP
(1)	Jun 28, 2018	California	1,364,337	-0.006***	-0.033***	D	1	1
				(-4.47)	(-16.20)			
(2)	Jul 7, 2021	Colorado	287,798	-0.002	-0.082**	D	1	1
				(-0.14)	(-3.22)			
(3)	May 10, 2022	Connecticut	893,691	0.011	-0.138**	D	1	1
				(1.49)	(-3.55)			
(4)	Mar 24, 2022	Utah	260,398	0.031***	0.029	R	1	0
				(9.72)	(1.07)			
(5)	Mar 2, 2021	Virginia	1,217,958	-0.014**	-0.015	D	1	1
				(-2.87)	(-1.76)			
(6)	Sep 11, 2023	Delaware	475,341	0.009**	-0.082***	D	1	0
				(2.46)	(-4.07)			
(7)	May 1, 2023	Indiana	1,548,845	0.006	-0.156***	R	0	1
				(1.41)	(-30.94)			
(8)	Mar 28, 2023	Iowa	309,855	-0.024***	-0.034	R	1	0
				(-6.63)	(-1.43)			
(9)	May 19, 2023	Montana	96,798	-0.030***	-0.117***	R	0	1
				(-6.24)	(-6.18)			
(10)	Jun 22, 2023	Oregon	550,616	0.003	-0.024	D	1	1
				(0.60)	(-1.65)			
(11)	May 11, 2023	Tennessee	621,593	-0.006	-0.008	R	1	0
				(-0.96)	(-0.79)			
(12)	Jun 18, 2023	Texas	249,865	-0.013	-0.273***	R	0	1
				(-1.86)	(-10.03)			

(continued next page)

Table IA2. Robustness_ State-specific Effects of Privacy Laws (Cont'd)

Panel B. Effects of privacy laws emphasizing "Customer Protection"				
	Denial		Interest Rate	
	(1)	(2)	(3)	(4)
Treat × Post (CP)	0.006**	0.006***	0.039	0.044*
	(2.43)	(3.52)	(1.47)	(1.77)
Minority	0.081***	0.080***	0.044***	0.044***
	(12.31)	(12.34)	(3.27)	(3.28)
Treat × Post (CP) × Minority	-0.035***	-0.035***	-0.061**	-0.061**
	(-3.37)	(-3.37)	(-2.19)	(-2.25)
Borrower Controls	Y	Y	Y	Y
State Controls	N	Y	N	Y
Lender FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
Observations	6,699,960	6,699,960	5,436,730	5,436,730
R-squared	0.226	0.226	0.659	0.659
Panel C. Effects of privacy laws emphasizing "Transparent"				
	Denial		Interest Rate	
	(1)	(2)	(3)	(4)
Treat × Post (TP)	0.009***	0.008***	0.017	0.020
	(3.46)	(3.93)	(0.44)	(0.54)
Minority	0.080***	0.080***	0.042***	0.042***
	(12.40)	(12.41)	(3.31)	(3.32)
Treat × Post (TP) × Minority	-0.035***	-0.035***	-0.064**	-0.063**
	(-3.46)	(-3.44)	(-2.43)	(-2.47)
Borrower Controls	Y	Y	Y	Y
State Controls	N	Y	N	Y
Lender FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
Observations	6,718,886	6,718,886	5,443,577	5,443,577
R-squared	0.228	0.228	0.659	0.659

Table IA3. 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 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 IA4. 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 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 IA5. 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 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 IA6. 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 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 IA7. Robustness_ PSM matching borrowers' credit quality and property

This table presents the regression results and t-statistics (in parentheses) for the impact of privacy legislation on mortgage market racial disparities in the United States from 2018 to 2023, based on a propensity score matched sample. We applied propensity score matching (PSM) to identify the closest matches between loans in states with privacy protection legislation and those in states without such legislation. The matching criteria included information on collateral, types of mortgages and lien status, demographics, and all credit attributes listed in Table 2, i.e. loan-to-income ratio, loan-to-value ratio, debt-to-income ratio, applicant age, and mortgage value. *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 mortgages. 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 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.

	(1)	(2)
	Denial	Interest Rate
Treat × Post	0.007*	0.085*
	(1.93)	(1.76)
Minority	0.069***	0.037**
	(7.49)	(2.67)
Treat × Post× Minority	-0.025**	-0.111***
	(-2.11)	(-5.61)
Controls	Y	Y
Lender FE	Y	Y
Year FE	Y	Y
County FE	Y	Y
Observations	3,454,719	2,784,876
R-squared	0.233	0.656

Table IA8. Robustness_ Different combinations of 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 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 IA9. Classification into new and existing lenders

This table presents the regression results and t-statistics (in parentheses) for the impact of privacy legislation on mortgage market racial disparities in the United States from 2018 to 2023, along with a subsample analysis distinguishing between existing lenders and new entrants. The Columns (1)-(2) display results for existing lenders (those that provided loans in each state before the implementation of privacy protection laws), while the Columns (3)- (4) present data for new entrants (those that began offering loans after these laws were enacted in each state). *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. 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 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.

VARIABLES	Existing Lenders		New Lender	
	Denial	Interest Rate	Denial	Interest Rate
	(1)	(2)	(3)	(4)
Treat × Post	0.007***	0.016		
	(2.75)	(0.53)		
Minority	0.081***	0.046***	0.071	0.180
	(14.24)	(3.66)	(1.65)	(1.19)
Treat × Post× Minority	-0.034***	-0.073***	-0.048	-0.126
	(-3.24)	(-2.79)	(-1.10)	(-0.86)
Controls	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
Observations	7,672,211	6,230,619	5,308	4,589
R-squared	0.226	0.657	0.169	0.820

Table IA10. Robustness_ Include gender and credit risk variables

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 include gender and credit risk variables as additional control variables. *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. We include gender as a control (Column (1)) as well as the principal component of credit risk variables (Column (2)). Other 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 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	Denial	Interest Rate
	(1)	(2)	(3)
Treat × Post	0.007***	0.007***	0.015
	(2.76)	(2.76)	(0.50)
Minority	0.082***	0.082***	0.047***
	(14.22)	(14.22)	(3.82)
Treat × Post × Minority	-0.034***	-0.034***	-0.076***
	(-3.26)	(-3.26)	(-2.88)
Female	0.013***	0.013***	0.035***
	(8.16)	(8.16)	(13.08)
PCA1_2 (Credit Risk)		-0.116***	
		(-23.19)	
Control Variables	Y	Y	Y
Lender FE	Y	Y	Y
Year FE	Y	Y	Y
County FE	Y	Y	Y
Observations	7,628,404	7,628,404	6,198,615
R-squared	0.226	0.226	0.658