The cost of privacy. The impact of the California Consumer Protection Act on mortgage markets.*

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Abstract

We study how compliance costs of a data privacy law, the California Consumer Protection Act (CCPA), affects mortgage finance. Lenders pass compliance costs to borrowers by raising interest rates, making the average prime mortgage costlier by $4,350. The CCPA imposes compliance costs of $880,000 on the average bank, while nonbanks share the costs with government-sponsored enterprises. Although loan risk increases, competition from nonbanks prevents banks from pricing the risk. Banks respond by reducing credit by 3.4%. The fixed compliance burden creates economies of scale in lending, leading to regressive credit. Market-based finance crowds out bank finance due to the compliance costs.

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1 Introduction

The information and communications technology revolution has provoked a seismic shift in the collection and storage of consumers' personal details for commercial purposes. However, proliferating breaches and unauthorized data sales to third parties have led privacy advocates to demand regulation that mandates companies securely protect sensitive information. A notable legislative example is the General Data Protection Regulation (GDPR) in Europe. The compliance costs of these laws can be substantial, and the burden is often heavier for small businesses due to the fixed costs of IT infrastructure, legal expenses and data processing investments. Yet it is unclear how large these costs are and whether companies pass them to consumers through higher prices and/or diminished product availability.

To gain insights, we study the introduction of a data privacy regulation in mortgage markets. In March 2018, Facebook admitted to the unauthorized sharing of 87 million users' personal information with Cambridge Analytica which used the data to influence electoral outcomes in the US. In California, a swift ballot initiative paved the way to a bill that established the California Consumer Privacy Act (CCPA) in state law. The CCPA obliges businesses to provide clear and transparent privacy notices and mandates they implement security measures to safeguard personal data. Noncompliance can lead to non-trivial financial penalties and legal consequences.

Three advantages of this economic laboratory are that the CCPA, 1) is broadly representative of recent privacy laws introduced across US states and internationally, 2) was introduced for reasons that are plausibly exogenous with respect to the mortgage market, and 3) applies exclusively to transactions within the state of California. In addition, evaluating the impact of a regulation that affects both banks and nonbanks is an empirical challenge, as bank-specific regulations do not apply to nonbanks, and vice versa. The CCPA represents a unique setting that applies to both, allowing us to distinguish whether the shock affects both uniformly.

The first set of tests reveal that consumer privacy legislation imposes a substantial compliance burden on businesses. Using a difference-in-differences estimator applied to bank-level panel data, we find that the CCPA increases California banks' legal, data processing, and telecommunication expenses by $471 per million dollars of assets relative to banks in other states that are not subject to the law. This equates to a $880,000 increase in quarterly operating expenses for the average bank.

Next, using loan-level data, we find that lenders in California pass these costs to borrowers by setting higher interest rates. We limit our sample to lenders that operate in both California and neighboring states, which eliminates significant lender-specific unobserved differences, such as, heterogenous lending technologies, management, corporate policies, and charter types. We compare the evolution of interest rates on loans to borrowers located in counties that lie either side of the Californian border. Further constraining the sample to this geographically delimited area eliminates various omitted variables by holding the economic environment constant across the treatment and control groups. Relative to the implied counterfactual, the CCPA provokes a 4.8 basis point increase in interest rates in California,which equates to a $4,350 increase in the average mortgage's lifetime cost or an increase by $480 per million dollars of mortgages which is almost equal to the increase in legal, data processing, and telecommunication expenses by $471 per million dollars of assets we estimated at the bank level. The modest pricing adjustment is consistent with the vast size of the mortgage market allowing lenders to spread the compliance costs across numerous borrowers.

Finally, we ask whether banks and nonbanks respond differently to the CCPA. Nonbanks have a comparative advantage in lending markets in the face of the CCPA due to their originate-to-distribute business model and algorithmic processing of credit applications. Securitization passes most CCPA compliance costs to the loan purchaser.

By selling most of the loans they originate, nonbanks reduce their exposure to future costs arising from litigation and data breaches. In contrast, banks retain a large share of originations on balance sheet and remain liable for the expected costs. Banks' CCPA compliance costs are also greater because their more data intensive relationship lending technologies rely on both hard and soft information, whereas nonbanks typically accumulate only hard data. As the CCPA applies equally to hard and soft information, this requires greater investments in data safeguarding by banks.

A consequence of these increased expected legal costs is that the CCPA leads to riskier lending throughout the mortgage market. Our estimates show that loan risk (measured by rate spreads) rises by 4 basis points in California following enactment of the law. However, the magnitude is approximately 2 basis points larger among banks. While lenders set higher interest rates to compensate, there exists no differential increase between banks and nonbanks. This contrasting result implies that competition from nonbanks prevents banks from pricing the CCPA's legal risks into loan contracts. Instead, we find that banks react to the higher compliance costs by rationing credit. The volume of bank mortgage credit in California falls by 3.4% compared to nonbanks. Moreover, the CCPA has regressive properties: banks raise interest rates and lower credit supply to a greater extent in lower-income areas. These effects reflect the fixed cost nature of CCPA compliance costs which yield economies of scale advantages based on loan size. As loans tend to be smaller in lower-income areas, these borrowers are affected to a greater degree.

Validation checks provide corroborating evidence. We find relatively stronger pricing reactions to the CCPA among credit unions (membership-oriented institutions) that heavily rely on soft information for loan assessments. We also find stronger effects for refinancing loans, implying that the effect is more pronounced on the existing California residents. Robustness tests rule out potential confounds such as the COVID-19 pandemic. Another worry could be that banks and nonbanks' risk assessment procedures might differ. Hence as another sample filter, we include only loans where a credit scoring model is used, ensuring both banks and nonbanks have access to the same credit bureau data. Specifically, we find no pricing or risk differentials among subsamples containing loans sold to the Government Sponsored Enterprises (GSEs) that follow the GSEs' underwriting standards rather than the originator's. Finally, we document that the results do not stem from any selection bias.

While Djankov, McLiesh, and Shleifer (2007), Houston, Lin, Lin, and Ma (2010), and Bennardo, Pagano, and Piccolo (2015) show that stronger lender rights cut lending costs, the evidence in this paper suggests that stronger consumer privacy, i.e., borrower, rights increase intermediation costs. An increase in the spread in our analyses represents a compliance cost (Philippon 2015), that varies between banks and nonbanks. While lending costs increase since banks face a greater number of regulations to comply with (Buchak, Matvos, Piskorski, and Seru (2018)), we show that banks bear a heavier burden from the same regulation compared to nonbanks. Our finding that bank credit becomes regressive remains fully consistent with the findings of D'Acunto and Rossi (2022); this study extends the frontier by showing the effects, both in terms of price and credit quantity, within conforming loans. In sum, the evidence above denotes a crowding out of bank finance by market-based finance, due to the compliance costs.

Our paper relates to several strands of research. Seminal papers in information economics illustrate the costs and benefits of data privacy and the impact of sharing information on economic outcomes (Stigler 1980; Posner 1981). Concealing borrower-specific information generates inefficiencies while sharing data reduces information asymmetries and moral hazard. In this framework, an organized exchange benefits all parties by pricing information. However, where such a mechanism is absent firms gain from trading personal data and consumers may be denied access to markets (Zuboff 2019). Without an organized exchange, personal information exhibits non-rivalry and non-exclusion which creates a role for regulation (Goldfarb and Tucker 2012; Jones and Tonetti 2020).

A related body of work documents firms' responses to recent privacy regulation. Peukert et al. (2021) show that websites reduced their connections to web technology providers after GDPR became effective, especially regarding requests involving personal data. Abis et al. (2022) develop a model where firms produce final goods using labor and data in the form of intangible capital, which can be traded. In this context, the CCPA raises the cost of trading data which disproportionately hurts firms without preexisting in-house customer data because they cannot adequately substitute for the previously externally purchased data. This allows firms with pre-existing in-house customer data to expand their market share. In related work, Campbell et al. (2015) highlight that firms offering a greater range of services disproportionately benefit from privacy regulation because they can exploit economies of scope to spread regulatory costs across a larger number of services. In contrast, we study the mortgage market effects of privacy regulation and show economies of scale exist due to the CCPA's fixed compliance costs, which leads to lower-income borrowers incurring systematically higher loan prices.

A rapidly evolving literature assesses the implications of open banking reforms which enable consumers to voluntarily share their financial data with entities beyond their bank via application programming interfaces. Doerr et al. (2023) argue that nonbanks collect more information due to superior screening technology. He et al. (2023) develop a model that predicts open banking improves nonbanks' screening ability but that the competitive ramifications can be detrimental to borrower welfare. Using cross-country data, Babina et al. (2022) document that while open banking improves fintech lenders' screening ability and product availability, data sharing can reduce ex-ante information production and harm certain consumers. Goldstein et al. (2022) highlight endogenous adjustments to banks' liabilities when borrowers can share their data with nonbanks which damages welfare by diminishing credit allocation efficiency. Whereas this literature examines the credit market effects of allowing consumers to share their data, our study focuses on data privacy regulation which places compliance burdens on financial institutions.

A parallel strand of research documents how information sharing between financial institutions strengthens creditor rights. Key references include Bennardo et al. (2015) who find this allows lenders to mitigate opportunistic borrower behavior. Other papers in this line of research show that information sharing between banks lowers prices and adverse selection leading to lower default rates by improving the pool of borrowers (Pagano and Jappelli 1993; Jappelli and Pagano 2002) and that these effects are larger in weaker legal environments (Brown et al. 2009). Beck et al. (2014) note that banks in jurisdictions that allow better information sharing are more regulatory compliant. Recent evidence shows information sharing between banks influences the geographical clustering of their branches leading to less spatial credit rationing (De Haas et al. 2021).[1] Whereas these articles focus on the benefits of information sharing between financial intermediaries, our paper explores the costs of sharing data. A novel dimension of our research is that while creditor rights have received considerable attention, the ramifications of greater borrower rights remain somewhat less explored.

Our paper also relates to research on securitization, which involves the pooling of risky assets into mortgage-backed securities, resulting in a more efficient distribution of risk. The Government Sponsored Enterprises (GSEs) play an important role in providing liquidity in primary mortgage markets by purchasing loans from originators and then selling these pooled loans in the form of securities with varying risk to investors in the secondary mortgage market. While pooling loans can improve liquidity and geographical reach in mortgage markets (Loutskina and Strahan 2009), several studies including Keys

[1] See also Djankov et al. (2007) who show that stronger creditor rights, due to greater information sharing, is associated with higher credit growth and Houston et al. (2010) and Houston et al. (2012) who find stronger creditor rights influence capital flows and promote risk taking.

et al. (2010), Dell'Ariccia et al. (2012), Purnanandam (2011), and McGowan and Nguyen (2021) document moral hazard associated with securitization. In this paper, we highlight an unintended benefit of securitization. Specifically, securitization allows loan sellers to mitigate regulatory burdens by transferring compliance costs to GSEs.

The rest of the paper is structured as follows. The next section provides institutional background and outlines the hypotheses we empirically test. Section 3 details the data set and empirical strategy. Section 4 presents econometric results. Finally, Section 5 draws conclusions.

2 Empirical Strategy and Hypothesis Development

2.1 The California Consumer Privacy Act

The CCPA originates from a ballot proposition by a small privacy group known as Californians for Consumer Privacy. While industry resisted the initiative, the 2018 Facebook-Cambridge Analytica scandal generated momentum that expedited passage of the CCPA in a fast-track manner.[2] The CCPA bill (AB-375) was passed with bipartisan support and became effective on January 1, 2020.[3] It applies to any for-profit business that sells the personal information of more than 50,000 California residents annually, has an annual gross revenue exceeding $25 million, or derives more than 50% of its annual revenue from selling the personal information of California residents. Most mortgage lenders meet at least one of these criteria.

Broadly, the CCPA defines personal information as data that can directly or indirectly identify a consumer or household. Examples include direct identifiers (real name, address and social security numbers), unique identifiers (cookies and IP addresses),

[2] The scandal followed Facebook's admission that it improperly allowed a UK firm (Cambridge Analytica) to collect sensitive personal records on approximately 87 million Facebook users and to deploy algorithms to influence electoral outcomes in violation of US election law.

[3] See Bukaty (2019) for further details on the CCPA.

biometric data, geolocation data, browsing history, and other sensitive information including health and other personal information.

The CCPA grants California consumers several important rights to have more control over their personal information. First, consumers have the right to know what personal information businesses collect about them. Businesses must therefore disclose the categories of personal information they collect, the information sources, the purpose of collecting it, and any third parties with whom they share this information. Second, consumers have the right to opt-out of the sale or sharing of their personal information to third parties. Third, consumers can request access to the specific pieces of personal information that businesses have collected about them. Fourth, consumers may request that businesses delete their personal information. Businesses must comply with such requests, subject to certain exceptions. Finally, the CCPA prohibits businesses from discriminating against consumers who exercise their privacy rights. This means businesses must provide equal price and service, even if consumers choose to exercise their rights under the CCPA. By granting these rights, the CCPA empowers Californian consumers to make informed decisions about their personal data and have greater control over how businesses handle and use their information.[4] The CCPA mandates that businesses respond to consumer data requests free of charge within 45 days and provide all relevant information collected during the preceding 12 months. The California Privacy Protection Agency implements and enforces the CCPA.[5]

Under the CCPA, consumers have a private right of action and statutory damages if personal data is subject to unauthorized disclosure due to a company's failure to implement and maintain reasonable security procedures and practices. Penalties range between $100 to $750 per consumer, per incident, although the California Attorney

[4] The CCPA offers similar rights as the European Union's GDPR legislation. Unlike the CCPA, the GDPR covers medical data and personal information processed by credit reporting agencies and to non-profit organizations.

[5] Civ. Code, §1798.199.10.

General can impose damages up to $2,500 per violation. A distinguishing feature of the CCPA is that it grants an individual a private right of action in the wake of a failure to maintain reasonable security procedures and practices leading to a security breach.

2.2 CCPA Compliance Costs

Businesses in California incur significant CCPA compliance costs. The Act requires that they create and maintain a privacy policy that outlines the personal information they collect from consumers, the purpose of data collection, and how they handle and protect this information. Maintaining an accurate privacy policy demands legal resources while preventing breaches and unauthorized access necessitates robust authentication and verification measures. Secure data management practices and encryption protocols requires substantial financial investment. Moreover, when fulfilling consumer data requests, businesses must provide information in a user-friendly format which may necessitate expenditure on hardware and IT infrastructure. Regular updates and improvements to IT systems are imperative due to rapid technological advancements. The compliance costs also entail employee training on privacy policies, data handling, and consumer responses. Businesses must consistently monitor and evaluate data practices for ongoing CCPA compliance, potentially involving hiring compliance officers or outsourcing services.

2.3 Conceptual Framework: Privacy Law in Mortgage Markets

The US mortgage market is served by two types of lenders: banks and nonbanks. Following Buchak et al. (2018), we classify depository institutions as banks and non-depository institutions as nonbanks. Whereas banks offer loans and accept deposits, nonbanks only offer credit intermediation services. The Federal Deposit Insurance Corporation (FDIC) regulates banks but not nonbanks. Generally, banks are subject to greater regulatory scrutiny than nonbanks which largely comprise Fintech lenders.

Mortgage lending has shifted towards the originate-to-distribute model over time. Nonbanks mostly pursue an originate-to-distribute business model with the GSEs purchasing a large share of their loans in secondary markets. While borrowers can still opt out of the sale of their personal information to third parties, they cannot opt out of the information sharing with loan purchasers. Under the CCPA, once a loan is sold the buyer becomes subject to the Act.[6] An advantage of securitization in this context is that originators are able to pass on most of the CCPA compliance costs to the GSEs and loan purchasers.

Whereas all lenders gather hard information for credit assessment and lending decisions (credit scores, employment history, income), banks typically collect more soft information (subjective details gleaned from personal interactions including character and relationships) through their relationship lending technologies than nonbanks. This potentially exposes banks to larger CCPA compliance burdens than nonbanks as they must safeguard a greater volume of personal data.

We conjecture that the CCPA affects lenders' loan pricing and credit supply decisions. The compliance costs of the law raises financial intermediaries' marginal costs. Where lenders have some degree of market power, they may pass through some or all of these costs to borrowers through higher interest rates. In competitive markets, lenders ability to raise prices is constrained, and they may instead choose to reject loan applications at a higher frequency to mitigate expected future legal costs (Rajan and Zingales 1998; Boot and Thakor 2000; Berger et al. 2004; Carbo-Valverde et al. 2009).

We postulate that the CCPA provokes larger pricing reactions among banks for two reasons. First, since the CCPA applies to hard and soft information, banks face relatively higher burdens because their relationship lending technologies accumulate more personal

[6]See the Fannie Mae (`https://tinyurl.com/4pa9v93k`) and Freddie Mac (`https://tinyurl.com/3mu5m3cj`) privacy policies.

information about consumers. This imposes a heavier data storage and safeguarding burden but also exposes banks to greater litigation risk in case of a data breach. In contrast, nonbank lenders primarily rely on hard data and evaluate loan applications using algorithmic processes. Second, securitization allows lenders to pass most CCPA compliance costs to loan purchasers. Relative to nonbanks, banks hold a higher share of the loans they originate on balance sheet which exposes them to greater expected legal costs.

3 Data and Summary Statistics

3.1 Data and Sample

We obtain mortgage loan-level data from the HMDA database. Each observation provides information on the loan's interest rate, rate spread (over an average comparable prime mortgage), cost (the ratio of total loan closing costs to loan amount), purpose (purchase or refinancing), loan amount, term (months to maturity), the loan-to-value (LTV) ratio, underlying property value, the census tract in which the property is located, conforming loan status, the lien, the mortgage originator's identity, and borrower specific information (gender, race, age). The data also report whether a loan was sold to a third-party within the reporting year, and whether the purchaser was a GSE or private institution. HMDA contains additional information on the ratio of median family income (MFI) in the census tract relative to that in the metropolitan statistical area (MSA).

To accurately estimate the effect of the CCPA on mortgage costs in California, we apply several filters to the data. First, we focus on conventional loans that meet conforming loan limits, as the GSEs refuse to purchase nonconforming loans (Loutskina and Strahan (2015)). Second, include only purchase and refinancing loans thereby excluding home improvement loans. Third, we limit the sample to lenders operating in both California and neighboring states. This filter eliminates a great deal of lender-specific unobserved heterogeneity (for instance, lending technology, management style, corporate policies, and charter-type) while also allowing us to isolate the CCPA's effects by comparing mortgages originated in California and other states by the same lender. Our fourth filter pertains to credit screening.[7] We include only loans where a credit scoring model is used, ensuring both banks and nonbanks have access to the same credit bureau data. Fifth, we consider only first-lien loans, as junior liens are riskier and thus costlier. Finally, we analyze data from 2018 to 2021 because HMDA does not provide pricing information before 2018.

[Insert Figure 1]   [Insert Figure 2]

To further sharpen identification, we invoke sample screens that narrow the data set to California and geographically proximate areas. Figure 1 shows the map of observations used in the baseline specifications. We restrict the area of analysis to California (dark) and the bordering states of Arizona, Nevada and Oregon (light). However, Figure 2 shows that we also use a sample containing observations from contiguous counties along the California border. Intuitively, by focusing exclusively on border counties where the economic environment is likely to be most homogeneous, omitted variables are less likely to confound the inferences.

In our analysis, we use the following variables: loan amount, borrower's income, property value (as reported in HMDA), loan term (number of months to maturity), loan-to-value ratio (loan amount divided by property value), loan rate and rate spread

[7] Under the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010, the Consumer Financial Protection Bureau (CFPB) has authority to create new rules and regulations for the mortgage industry. Starting 2014, the CFPB amended Regulation Z, which implements the Truth in Lending Act, specifying certain minimum requirements for lenders making ability-to-repay determinations, including borrower's credit history. Access to repayment history helps a lender to predict the borrower's riskiness. Starting 2018, HMDA provides loan-level information on the employment of credit scoring model.

which we winsorize at the 1st and 99th percentiles to remove outliers. Caucasian is a binary variable that takes the value 1 if the applicant is white, 0 otherwise. Male is the applicant's reported gender. Joint ownership is a binary variable that takes the value 1 if the loan application contains two applicants, 0 otherwise. Age is a variable with discrete values representing different age groups (from below 25 to above 74 years old). Additionally, we consider the ratio of census tract median family income (MFI) to the corresponding metropolitan statistical area's (MSA) MFI, as set by the Department of Housing and Urban Development (HUD). Appendix Table A.1 provides the detailed description of the variables used in the analysis.

To evaluate whether the CCPA imposes compliance costs on lenders, we retrieve quarterly bank-level data from the Federal Financial Examination Council's 031 Report Forms (Call Reports) database. This provides information on assets, the equity capital ratio, legal expenses, data processing expenses, and location. We use a sample window from 2016Q1 until 2021Q4.

[Insert Table 1]

Panel A of Table 1 presents descriptive statistics for the sample variables. The average loan rate is 3.44% with a standard deviation of 0.78%. The mean rate spread is 0.24% with a standard deviation of 0.38%. Among the sample, 61.4% of borrowers are Caucasians, and nearly 30% are male. On average, households fall within the 45-54 age group. Joint applications account for 40% of the loans. The average median family income in a tract is 120% of the corresponding MSA MFI. Table 1 Panel B reveals that data processing and legal expenses constitute relatively small fractions (approximately 1%) of total assets. Panel C of the table provides summary statistics on county-level variables in the data set, specifically, per-capita COVID-19 deaths and active COVID-19 cases in each county-year.

3.2 Empirical Model

Our empirical tests revolve around difference-in-difference estimators. To establish how the CCPA affects lending in California, we estimate

$$Y_{ilct} = \alpha CA_l \times CCPA_t + \delta X_{ilct} + \varphi_l + \varphi_c + \varphi_t + \varepsilon_{ilct}, \tag{1}$$

where Y_{ilct} is a dependent variable (e.g. loan rate and rate spread) for loan i originated by lender l in county c during year t; CA_c is a dummy variable equal to 1 if the property is located in a county within California, 0 otherwise; $CCPA_t$ is a dummy variable equal to 1 for the years 2020 and 2021, 0 otherwise; X_{ilct} is a vector of control variables; φ_l, φ_c and φ_t denote lender, county, and year fixed effects, respectively; ε_{ilct} is the error term.

Although the CCPA applies to all financial intermediaries, the discussion in Section 3.3 highlights that banks are potentially more affected by the law. To identify the heterogeneous effects of the CCPA between banks and nonbanks, we estimate

$$\begin{aligned} Y_{ilct} = {} & \alpha CA_c \times CCPA_t + \beta Bank_{lc} \times CA_c \times CCPA_t + \gamma Bank_{lc} \times CA_c \\ & + \delta Bank_{lc} \times CCPA_t + \zeta X_{lct} + \varphi_l + \varphi_{ct} + \varepsilon_{lct}, \end{aligned} \tag{2}$$

where all variables are defined as in equation (1), except $Bank_{lc}$ is a dummy variable equal to 1 if a loan is originated by a bank, 0 for nonbanks; φ_{ct} denotes county-year fixed effects. Including county-year fixed effects in equation (2) sharpens identification by removing time varying local macroeconomic conditions that may influence the outcome variables. Moreover, in these specifications we identify β through comparisons of loans between banks and nonbanks within the same county at the same point in time.

[Insert Figure 3] [Insert Figure 4]

Figures 3 and 4 depict the average annual loan interest rates and spread during the sample period within lenders in California and adjacent states. For each variable, the groups exhibit highly similar trends between 2018 and 2019, consistent with parallel trends. However, once the CCPA comes into force, the lines diverge and California lenders set higher interest rates and spreads widen, whereas lenders in adjacent states charge similar prices compared to the pre-CCPA period.

[Insert Figure 5] [Insert Figure 6]

In Figures 5 and 6 we conduct the same exercise except for banks and nonbanks within California. Both groups' pricing behaviour evolves similarly prior to enactment of the CCPA, but banks charge higher rates and spreads after 2020 relative to nonbanks. Interestingly, the interest rates and spread set by nonbanks in California remain largely the same during the sample window. Hence, it is primarily banks that change their pricing strategies in the face of the CCPA's compliance costs.

To estimate the heterogeneous effects of the CCPA on credit supply between banks and nonbanks in California, we estimate

$$\begin{aligned} Q_{lct} = {} & \alpha CA \times CCPA_t + \beta Bank_{lc} \times CA \times CCPA_t + \gamma Bank_{lc} \times CA \\ & + \delta Bank_{lc} \times CCPA_t + \zeta X_{lct} + \varphi_l + \varphi_{ct} + \varepsilon_{lct}, \end{aligned} \tag{3}$$

where Q_{lct} is a dependent variable (credit volume or number of loans) originated by lender l in county c during year t. X_{lct} is a vector of borrower-specific characteristics: income, loan-to-value ratio, loan term, proportion of Caucasians, gender, and age group.

4 Empirical Tests

4.1 Compliance Costs

We first assess how the CCPA affects banks' compliance costs, measured through their legal and data processing expenses.[8] Institutions were provided with a look-back period, between the announcement and the implementation of the CCPA. During this period, institutions had the opportunity to establish their privacy policies and prepare their IT systems in advance of the CCPA's effective date. Using the quarterly bank-level data set, we estimate

$$C_{jt} = \alpha CA_j \times Announcement_t + \beta CA_j \times Implementation_t + \gamma Equity_{jt} + \delta Size_{jt} + \varphi_j + \varphi_t + \varepsilon_{jt}, \tag{4}$$

where C_{jt} is the ratio of the sum of legal, data processing and telecommunication expenses per million dollars of assets for bank j during quarter t; CA_j is a dummy variable equal to 1 if a bank is headquartered in California, 0 otherwise; $Announcement_t$ is a dummy variable equal to 1 for the period 2018 to 2019, 0 otherwise; $Implementation_t$ is a dummy variable equal to 1 for the period 2020 onward, 0 otherwise; $Equity_{jt}$ is the bank's capital ratio; $Size_{jt}$ is the natural logarithm of bank assets; φ_j and φ_t denote lender and quarter-year fixed effects, respectively; ε_{jt} is the error term. We cluster the standard errors by state.

[Insert Table 2]

Table 2 presents estimates of equation (4). In column 1 we restrict the sample to the period 2016Q1 to 2019Q4, to focus exclusively how banks responded to the CCPA during the lookback period. The CA-Announcement coefficient is statistically significant and

[8] We focus on banks because comparable information is not available for nonbanks.

indicates that legal, data and telecommunication expenses increase by \$471 per million dollars of assets. For the average bank, this equates to a quarterly compliance cost of approximately \$880,000. The statewide costs of the CCPA to the banking sector are roughly \$292 million.[9]

In column 2 of Table 2, we evaluate how compliance costs evolve after implementation of the CCPA relative to during the announcement period by restricting the sample to the period 2018Q1 to 2021Q4. The interaction coefficient is negative and insignificant. Hence, compliance costs did not continue to grow, but rather the CCPA provokes a permanent step increase in the level of legal, data processing and telecommunications expenditure following its announcement. Finally, column 3 pools the data from 2016Q1 to 2021Q4 and reports estimates of α and β. The results are similar to the prior two columns. Among the control variables, equity is positively and significantly correlated with the dependent variable whereas large banks have lower compliance costs, consistent with economies of scale effects.

4.2 Loan Pricing

Next, we use the loan-level data set to analyze pricing dynamics to establish whether lenders pass CCPA compliance costs to borrowers. We employ two measures, loan rates and rate spread (over average comparable prime mortgage rates) on originated loans. The loan rate reflects the pricing of a loan, while the rate spread measures its riskiness.

[Insert Table 3]

Column 1 of Table 3 presents estimates of equation (1) using the loan rate as the dependent variable, and observations from the contiguous border counties data set.[10]

[9] The mean bank in California has assets of \$1,868.5 million. The cost of the CCPA in terms of legal, data processing, and telecommunication expenses is therefore $471 \times 1,868.508 = \$880,064$. As there are 332 banks operating in California, the statewide compliance costs are \$880,064 × 332 = \$292,181,082.

[10] To conserve space, estimates of equation (1) and subsequent regression specifications for border states are not reported.

The California-CCPA interaction coefficient is positively and statistically significant at the 1% level. Economically, the effect size indicates that, compared to loans outside California, the CCPA raises loan rates by 4.6 bps. This equates to an additional $4,350 expense over the lifetime of the average 30-year fixed rate mortgage in California.[11]

To rule out unobserved heterogeneity, the estimates in column 2 of Table 3 include county-lender fixed effects to account for the presence of a lender in a county and differential pricing behavior across counties within lenders. The results remains statistically robust, with the interaction coefficient slightly increasing to 4.8 bps. Moreover, Figure 5 illustrates that while the loan rate in adjacent states remained unchanged at 3.42% before and after the CCPA, in California interest rates rise from 3.42% before to 3.46% after the CCPA. The pricing effects we uncover therefore do not seem to be driven by developments within the control group.

To isolate whether banks respond to the CCPA differently relative to nonbanks, we report estimates of equation (2) in columns 3 and 4 of Table 3. These specifications mirror the fixed effects included in columns 1 and 2 of the table, respectively. While the California-CCPA interaction coefficient is slightly larger than before, the triple interaction coefficient is statistically insignificant and economically close to zero. Hence, the CCPA provokes a general increase in the cost of mortgage credit within California but banks do not set differentially higher loan rates relative to nonbanks.

Column 5 of Table 3 reports estimates of equation (2) that include county-year fixed effects to purge time varying local confounds, such as COVID-19.[12] In this specification,

[11] For a 30-year mortgage, a 4.6 bps rate hike from 3.454% to 3.5% raises interest costs by $4,350 on a $315,200 principal (80% of the average $394,000 house value in California in the sample).

[12] The CCPA came into force on January 1, 2020, shortly before the COVID-19 pandemic. A concern could be that the findings reflect the mortgage market impact of COVID-19. This appears unlikely as all parts of the US were the county-year fixed effects eliminate all time varying local confounds that directly influence the outcome variables. Moreover, the pandemic was a nationwide phenomenon and affected all states. To address whether COVID-19 differentially affected the treatment and control groups, we append equation (2) with controls for the per capita number of deaths and COVID-19 cases within each county year. Online Appendix Table A.4 reports the estimates. The baseline results are robust to this change, both in statistical and economic magnitude.

the triple interaction coefficient is identified through comparisons of loans between bank and nonbank lenders within the same county at the same point in time. Despite this change, the point estimate remains insignificant.

Throughout columns 1 to 5 of Table 3, the coefficient estimates of the control variables are consistently signed and significant at conventional levels. Caucasian borrowers pay higher interest rates whereas they are lower for males, older people, coapplicants and those living in higher MFI census tracts. The magnitude of the house price coefficient remains close to zero.

The remainder of Table 3 replicates the preceding tests using the rate spread as the dependent variable in equations (1) and (2). Columns 6 and 7 show the CCPA provokes significantly higher rate spreads within California relative to the control group. Economically, the effect size is equivalent to an increase of 3.7 to 4 bps, consistent with the law triggering an increase in Californian loans' riskiness. These results align with Figure 6 which shows that while the spread in adjacent states remained unchanged at 22 bps following the CCPA, in California, it rises from 21 bps to 27 bps.

An important difference between the earlier interest rate regressions is that across columns 8 and 9 of Table 3, we estimate the triple interaction coefficient to be positive and significant. Relative to nonbanks, the CCPA provokes an increase in the rate spreads on California banks' loans by 1.8 (column 8) and 2.5 (column 9) bps. We continue to find the triple interaction coefficient is significantly positive in column 10 of the table when we include county-year fixed effects in equation (2).[13]

What explains the contrasting effects of the CCPA on banks' rate spreads and interest setting behavior relative to nonbanks? Competition between mortgage lenders is intense. This limits banks' ability to price the additional compliance costs they face compared to

[13] As a validation check, we estimate models that include a Bank within California and Post interaction variable. Online Appendix Table A.2 presents the (difference-in-differences) results. The baseline result is robust.

nonbanks into loan contracts without losing market share. In essence, the CCPA triggers an increase in lenders' marginal costs of origination but due to the competitive market environment both types of lender raise interest rates to similar degrees. However, the riskiness of bank loans differentially increase relative to nonbank loans because banks' lending technologies are more data intensive. By incorporating more soft information, banks are exposed to greater expected litigation risk in the face of tougher data privacy law.

Instead of incorporating CCPA compliance costs into loan rates, lenders could opt to charge higher fixed costs during loan origination. However, in our (unreported) findings, we find the California-CCPA interaction coefficient estimate is insignificant and almost zero when the dependent variable is the ratio of origination fees to loan amount. This suggests that lenders pass on the CCPA compliance costs in the form of higher mortgage interest charges rather than through fixed costs at the point of origination.

4.2.1 Refinancing Rates

Lenders potentially have more data on existing borrowers than new ones due to existing relationships. To assess the effect of the CCPA on the residents in California more closely, we next restrict the sample to refinancing applications with less borrower-specific uncertainty. The specification remains the same as in equation (2).

[Insert Table 4]

Across the columns in Table 4, the California-CCPA interaction coefficient is positive and statistically significant, as previously, indicating that refinancing became more expensive and riskier in California in response to the CCPA. However, in stark contrast to the results in Table 3, columns 3 to 5 of Table 4 show that the triple interaction coefficient becomes positive and statistically significant at the 1% level. This implies that in California, banks charged a refinancing rate that was 3.3 bps higher than nonbanks in response to the CCPA. In columns 8 to 10 of Table 4, the triple interaction coefficient remains positive and statistically significant. The magnitude of this coefficient appears quite similar to that in columns 3 to 5, suggesting that banks charged a higher refinancing rate in line with the level of riskiness in California following the CCPA. This finding reflects lenders setting higher interest rate on loans in response to greater marginal costs, which is consistent with Chava (2014) and Koijen et al. (2022).

4.2.2 Differential Risk Assessment

It is possible that banks and nonbanks assess risk differently using the same data. In this case, despite the battery of control variables and fixed effects, the observed differences in rate spreads maybe due to lenders' risk assessment processes rather than the CCPA.[14] To ensure this channel does not drive the inferences, we focus on a homogenous sample of loans sold to the GSEs. The intuition behind this test is that to sell a loan to the GSEs, a lender must follow the GSEs' underwriting criteria. The risk assessment of these loans thus follows that stipulated by the GSEs, rather than differences arising due to how banks and nonbanks assess risk, shutting down the differential technology channel and allowing us to isolate whether banks' response to the CCPA is due to their more data intensive lending technologies.

[Insert Table 5]

Table 5 presents estimates of equation (2) using the sample of sold GSE loans. Irrespective of whether the dependent variable is the interest rate (columns 1-3) or the

[14]Recent evidence shows lenders, including nonbanks, employ technologies to process the information content of consumer data (Tetlock 2014; Vives 2019), and this is especially common among Fintechs operating in the mortgage market (Buchak et al. 2018; Fuster et al. 2019). Acquisti and Gross (2009) show how combining different pieces of information about an individual can predict new information. Indeed, Berg et al. (2020) document that Fintech lenders employ digital footprints, that can reliably complement credit bureau data, to compute default outcomes. The CCPA bans companies from combining data on an individual from two or more sources to produce new information to make business decisions.

rate spread (columns 4-6), the California-CCPA coefficient estimate remains positive and significant at 1%. Hence, the CCPA provokes a discernible increase in loan risk that is common across all lenders, even among homogenous loans that follow the GSEs' underwriting standards. This is consistent with the CCPA raising future litigation risk for a loan's owner.

In contrast, across all specifications in Table 5 the triple interaction coefficient estimate is insignificant. Together with the evidence in Table 4 the findings show that the baseline results are not driven by lenders' differential risk assessment but instead by how the CCPA affects loan pricing. The reason banks' rate spreads react more strongly to the law in Table 4 is because, on average, they operate more intense data collection processes compared to nonbanks. When we focus on loans sold to the GSEs, this disappears because all lenders follow the same risk assessment measures stipulated by the GSEs. Therefore, the evidence does not support the notion that the rate spread differential between banks and nonbanks is due to their risk assessment practices.

4.2.3 Hard versus Soft Information

The CCPA affects both hard and soft information, with the cost of sharing soft information being higher due to its contextual and private nature. Banks tend to specialize in processing soft information, while nonbanks focus on hard information processing. Large banks typically use technologies comparable to nonbanks to assess loan applications and focus on the acquisition of hard rather than soft information due to their organizational structure.

To evaluate to what extent the baseline findings reflect soft information, we focus on a sample including credit unions and state chartered banks.[15] Credit unions are member-based organizations that utilize soft information more extensively than other

[15] We exclude federal banks which are typically large and rely on processing hard information.

banks, and thus plausibly face higher compliance costs under the CCPA. This approach allows us to hone in on how different types of information drive the inferences.

[Insert Table 6]

We implement this test by estimating equation (2) with the modification that we use a credit union dummy variable in place of the $Bank_{lc}$ indicator. In Column 1 of Table 6, the California-CCPA interaction coefficient is estimated to be 11 basis points, which is notably larger than the 4 basis points effect in Table 4. The CCPA thus more strongly affects smaller financial institutions' pricing decisions. The triple-interaction coefficient estimate in Column 1 is positive and significant showing that the average credit union sets loan rates 9.5 basis points higher compared to a state chartered bank in California. This pattern endures across columns 2 and 3 of Table 6.

The remainder of Table 6 reports estimates using the rate spread as the dependent variable. In each cell, the triple interaction coefficient is significant, ranging between 6.2 and 8.7 basis points. The riskiness of credit unions' loans therefore differentially increases in response to the CCPA. These patterns suggest that the CCPA has a more pronounced impact on the pricing of loans that rely more on soft information.

4.2.4 Loan Size and the CCPA

While loans that remain on a lender's balance sheet entail higher CCPA compliance costs, the cost may (relatively) rise as loan size decreases, and, thus, the fixed compliance costs can have a relatively larger impact on smaller loans. The CCPA's compliance requirements apply to both conforming and non-conforming (jumbo) loans alike, implying that lenders must adhere to the regulations regardless of the loan type. Therefore, the possibility exists that banks bear higher compliance costs on conforming loans because conforming loans are smaller than jumbo loans. Comparing the impact of compliance costs on conforming and non-conforming loans within a bank's (unsold mortgage) portfolio can provide insights into how different loan characteristics, such as loan size and type, interact with the CCPA's compliance requirements and influence loan pricing and risk assessment strategies. To assess the effect of loan size on the CCPA compliance costs within a bank's portfolio, we estimate

$$\begin{aligned} Y_{ilct} = {} & \alpha CA \times CCPA_t + \beta Conforming_i \times CA \times CCPA_t + \gamma Conforming_i \times CA \\ & + \delta Conforming_i \times CCPA_t + \zeta X_{lct} + \varphi_l + \varphi_{ct} + \varepsilon_{lct}, \end{aligned} \tag{5}$$

where $Conforming_i$ is a dummy variable equal to 1 if a loan i is conforming, 0 otherwise. All other variables are defined as in equation (2).

[Insert Table 7]

Table 7 provides estimates of equation (5). In Columns 1 and 2, the positive and significant California-CCPA interaction coefficient indicates that banks charge higher rates, ranging between 3.6 bps and 7 bps, on mortgages originated in California compared to contiguous counties in neighboring states in response to the CCPA. The positive and statistically significant coefficient on the triple interaction term in columns 1 to 3 suggests that the rate charged on conforming loans in California increased ranging from 10.1 bps (column3) to 13.7 bps (column 2) following the CCPA within a bank's portfolio. This indicates that the compliance costs associated with the CCPA have a more pronounced impact on smaller loans within the bank's portfolio.

Moving to column 5, the positive and significant coefficient on the California-CCPA term implies that originating mortgages in California became up to 2.6 bps riskier for banks following the CCPA relative to contiguous counties in border states. The positive and statistically significant coefficient on the triple interaction term in Columns 3 and 4 denotes that, in California following the CCPA, smaller loans became up to 5 bps riskier than bigger loans within a bank's portfolio.

D'Acunto and Rossi (2022) document that bank credit has become regressive since 2011. Our finding complements theirs by shedding light on the pricing differentials between conforming and non-conforming loans, triggered by the CCPA's compliance costs. In summary, the results highlight how the CCPA influences loan rates and risk assessment strategies within a bank's portfolio, with smaller loans bearing a larger burden of compliance costs and facing increased risk.

4.2.5 The Nevada Privacy Law

Nevada amended its existing privacy law on May 29, 2019, and enacted a statewide privacy law, the Nevada Privacy Law (NPL). Prior to the amendment, the existing law required businesses to inform residents about the collection and use of their personal data. The amendment (SB 20), provided Nevada residents with the right to opt-out of the sale of personal information (similar to the CCPA). Online Appendix Table A.5 provides a detailed overview of the CCPA and NPL. The NPL's scope is much narrower than that of the CCPA. For example, the NPL applies to only two types of businesses - online operators and data brokers - whereas the CCPA applies to any business that does business with Californians. Moreover, the NPL does not cover the right to access or delete collected information, nor does it contain a private right of action.

An econometric concern is that the NPL amendment triggers changes in the behavior of lenders in Nevada. This appears unlikely given the limited nature of the NPL, and even if present, these dynamics within the control group would bias downward the CCPA estimates. To address this issue, we exclude observations from Nevada from the sample and repeat the analysis.

To conserve space, we report the results in Online Appendix Table A.5. In columns 1 and 2, we continue to find the triple interaction coefficient is positive and significant.

Economically, it implies that banks increase loan rates by 7 bps relative to nonbanks due to the CCPA. Similarly, in columns 3 and 4 of Table 8, we document similar patters in rate spreads compared to the baseline results. The consistency of these findings suggests the main results are not driven by events within Nevada.[16]

Overall, the pricing tests show that while the CCPA affords borrowers safeguards on how lenders may use and sell their data, it comes at the cost of somewhat more expensive mortgages.

4.3 Credit Supply

If competition prevents banks from pricing the additional compliance costs they face under the CCPA, they may limit their exposure by rationing credit. We evaluate this conjecture by estimating equation (3) using the natural logarithm of the mortgage volume and the number of originations supplied by each lender in each county-year.

[Insert Table 8]

There exist two countervailing forces. First, compliance costs are expected to restrict credit supply. Second, Figure 7 shows that rates were considerably lower in the post-CCPA era relative to the pre-CCPA era.[17] A lower rate boosts credit supply. Thus, it is hardly surprising that columns 1 to 3 and 5 of Table 8 show that the coefficient on the California-CCPA term is positive and significant. This indicates that credit supply was significantly higher in California post 2020. This reflects that the housing market reacted more favorably to lower rates in California relative to neighboring states. The size of this effect ranges between an increase of 9.6% (column 2) and 13.9% (column 3).

[16] We also compare loan rate and spread in California and Nevada in online Appendix Table A.5. The results continue to remain robust.

[17] While mortgage rates were falling in 2019, in 2020 the Federal Reserve continued to follow expansionary policy in the wake of COVID-19.

However, whereas housing markets in California might respond differently to interest rates compared to the neighboring states, banks and nonbanks in California might also react heterogeneously to the same rates. The triple difference specifications in columns 3 to 5 of Table 8 consistently show that relative to nonbanks, banks significantly reduced credit supply in California following the enactment of the CCPA. Moreover, the absolute magnitude of the triple interaction coefficient is larger than that of the California-CCPA interaction coefficient estimate. This suggests that banks reduced credit supply in California following the CCPA relative to the credit they extended to the control group. Economically, this effect translates to a reduction of 1.7% in column 3 and 3.5% in column 5 of Table 8. The CCPA thus affects households in California more broadly as it provokes contractions in credit supply by banks. Columns 6 to 10 provide consistent evidence using the number of originated loans as a measure of credit supply. The pattern of results is qualitatively and quantitatively similar.

Next, we analyze refinancing credit supply. We re-estimate equation (3), while restricting the sample to refinancing originations.

[Insert Table 9]

In columns 1 to 3 and 5 of Table 9, the coefficient on the California-CCPA term remains positive, but its statistical significance is weaker compared to Table 8. On the other hand, the triple difference coefficients in columns 3 to 5 of Table 9 remain negative and significant at conventional levels. The net reduction in bank refinancing credit in California ranges from 5% (column 3) to 18.9% (column 4) following the CCPA. Columns 6 to 10, which use the number of originated loans as a measure of credit supply, paint a similar picture. The CCPA thus adversely affects refinancing both in terms of credit supply and pricing (Table 4) by banks.

4.4 Selection Bias

So far, the sample contains observations of originated loans. A potential threat to identification is that this sample is non-randomly selected because lenders reject applications from borrowers they deem to be a credit risk. We therefore use a Heckman correction model to address the issue, where the first stage estimates the approval likelihood and the second stage estimates loan pricing effects among originated loans.

To alleviate endogeneity concerns, we include only predetermined regressors: race, gender, age, ownership, and census tract (local) income. This approach follows Bhutta and Hizmo (2021) who emphasize the significant role of observable characteristics, such as race, in influencing approval rates, even after controlling for race-blind automated underwriting systems. Babina, Buchak, and Gornall (2022) highlights the potential heterogeneity in lending decisions introduced by different automated underwriting systems. By using the employment of automated underwriting systems as a sample filter and incorporating information on the type of automated underwriting systems as the selection term in the first stage, the model can better account for potential selection biases introduced by lenders based on their use of specific automated underwriting systems. The first stage estimates

$$\begin{aligned} Y_{ilct} = {} & \alpha CA \times CCPA_t + \beta Bank_{lc} \times CA \times CCPA_t + \gamma Bank_{lc} \times CA \\ & + \delta Bank_{lc} \times CCPA_t + \omega A_{ilct} + \zeta X_{ilct} + \varphi_l + \varphi_{ct} + \varepsilon_{lct}, \end{aligned} \tag{6}$$

where all variables are defined as in equation (2), except A_{ilct} which is a dummy variable equal to 1 if loan application i is approved, 0 if rejected. The vector of controls X_{ilct} includes race, gender, age, joint ownership, census tract MFI, and a discrete variable that takes values from 1 to 9, as reported in HMDA, depending on the type of the automated credit scoring model.

The first stage of a selection model typically employs non-linear regression. However, in the presence of numerous fixed effects, probit estimators produce inconsistent estimates known as an incidental parameter problem (Greene (2004)). To overcome this issue, we employ a widely used selection model outlined by Olsen (1980) based on OLS. The second stage equation is identical to equation (2) except that it includes the selection correction term, lambda, (the inverse Mills ratio equivalent) as a further control variable.

[Insert Table 10]

Column 1 of Table 10 provides the first stage estimates of equation (6). Both the California-Bank and CCPA-Bank interaction coefficients are negative and significant at the 1% level, suggesting that banks were less likely to approve a loan application in California and following the CCPA. However, the triple interaction coefficient is insignificant indicating that approval rates did not vary significantly between banks and nonbanks in California following the CCPA. The automated underwriting system coefficient estimate is significantly negative suggesting the heterogeneity affects approvals negatively as documented by extant studies. Additionally, being white, female, younger and having a coapplicant are positively associated with approval.

The corresponding second stage estimates in columns 2 and 3 are similar to the baseline findings. The California-CCPA interaction coefficient is positive and significant in both cases indicating California lenders increase interest rates and spreads following the CCPA. The triple interaction coefficient is significant and implies a 1.6 bps increase in the rate (column 2) charged by banks relative to nonbanks due to the CCPA. Column 3 of Table 10 shows that relative to nonbanks, banks originate riskier mortgages in California following the CCPA.

4.4.1 CCPA Compliance Costs and Local Income

Previous estimates show lenders bear a fixed cost to comply with the CCPA which generates economies of scale according to loan size. Since income and house prices are locally correlated, the law's effect on loan pricing decisions is therefore potentially heterogeneous according to local income levels. The HUD's MFI ratio, which represents the ratio of the Median Family Income (MFI) of a census tract to the MFI of the corresponding Metropolitan Statistical Area (MSA), serves as a proxy for local incomes. Areas with lower (higher) MFI ratios typically have lower (higher) house prices and, consequently, smaller (larger) loan sizes. We next conjecture whether higher compliance costs on smaller loans might have an adverse impact on households in lower income areas.

To test this conjecture, we split the sample according to whether the MFI ratio is below or above the median. Column 4 of Table 9 reports results using loan rate as the dependent variable and observations of tracts with family income below the median. The triple interaction coefficient is equal to 3 bps and significant. In column 5 using rate spread as the dependent variable, we continue to find that banks originate riskier mortgages in California following the CCPA. The bank rate spread exceeds nonbanks' by 7 bps. In contrast, when we focus on loans from borrowers living in above median income tracts in columns 6 and 7 of Table 9, the economic magnitude of the triple interaction coefficient becomes insignificant. Hence, while the CCPA triggers an increase in loan rates and rate spreads, the effects are more pronounced within below MFI median income tracts where loan sizes tend to be smaller.

Next, we consider whether the CCPA influences the amount of credit lenders originate by local income. We split the sample by income as above and estimate equation (3). Column 8 in Table 10 reports estimates of equation (3) using Volume as the dependent variable in lower income areas. The triple interaction coefficient is -0.269 and significant at the 1% level, implying that, relative to nonbanks, banks reduced the amount of credit they originate in California by approximately 27% due to the CCPA. In column 9, using the number of applications as the dependent variable, we see banks reduced the number of originations in California by approximately 22% following the CCPA. Columns 10 and 11 report the above estimates in higher income areas. In column 10, we find that while banks originated 13.5% less credit, relative to nonbanks, in California following the CCPA, the magnitude is nearly half of that in column 8. In column 11, the pattern is similar for the number of loans. Thus, while they experience greater risk due to the CCPA, lower income households bear a greater burden, both in terms of higher price and lower credit quantity, than more affluent households.[18]

4.4.2 Refinancing Rates and Supply

We next move on to refinancing. The specification remains the same as in equation (6).

[Insert Table 11]

Column 1 of Table 11 shows that the triple interaction coefficient is positive and statistically significant, denoting that bank approval rate was 3.3% higher than nonbank approval rate in California following the CCPA. The second stage estimates in columns 2 and 3 show that the triple interaction coefficient is positive and statistically significant, implying that, relative to nonbanks, the refinancing rate charged by banks was higher by 4.3 bps in California following the CCPA and the rate spread was 5.4 bps higher. Thus, the effect of the CCPA on bank finance was much starker on refinancing applications.

We next compare the effect in lower income areas and higher income areas. While, in lower income areas, the loan rate charged by banks exceeded that by nonbanks by 7.2 bps in California due to the CCPA (column 4), in higher income areas, the gap between the rates charged by banks and nonbanks was less than half, at 3.3 bps (column 6).

[18] The household-specific control variables in equation (3) are suppressed to conserve space.

Further, we see that, while, in lower income areas, banks set rate spread 12 bps higher than nonbanks in California in response to the CCPA (column 5), in higher income areas, banks set rate spread 3.3 bps higher (column 7). Thus, banks disproportionately passed on the compliance costs on households in lower income areas.

In terms of credit quantity, in column 8 we observe that, banks financed lower income households 18% lower than nonbanks in California due to the law. In column 10, the gap between bank finance and nonbank finance was lower at 12.7% in higher income areas in California following the CCPA. Relative to nonbanks, banks originated fewer loans in lower income areas (column 9) than in higher income areas (column 11). The above evidence lends further support to the view that bank finance became significantly regressive in California due to the CCPA.

A regulation on data privacy alleviates household safety concerns regarding the data sharing, we show that a greater data safety comes at a price in mortgage markets. Overall, since total mortgage volume, in fact, increases in California following the CCPA, our findings denote a crowding out of bank finance by market-based finance and the effect is more pronounced in lower-income areas.

5 Conclusion

Digitization has triggered a remarkable growth in the amount of customer data firms use to optimize their business strategies. Data sales have also become a new line of business. However, following several high-profile data leaks and scandals, consumers have called for greater protection of their personal data that companies hold. It is unclear what are the compliance costs of this legislation, or who bears them.

We provide several novel results using the introduction of the CCPA as a quasi experiment. Using bank- and loan-level data, we find data privacy law increases the average financial institutions' legal and data processing costs by approximately $880,000 per annum. We estimate the annual cost of the CCPA to banks in California to be approximately $215 million. The data show that ultimately it is borrowers who bear these costs as lenders raise prices by setting higher interest rates and rate spreads, and by restricting access to credit. This shields lenders from potential litigation costs in case of a data breach. However, the burden consumers bear is relatively small due to the huge size of the mortgage market which allows lenders to spread costs across myriad borrowers. Owing to the large fixed cost element of data privacy law, there exist economies of scale. Lower income borrowers whose loans are typically smaller thus face differentially higher borrowing costs compared to more affluent households.

Estimates show heterogeneous reactions to the CCPA between banks and nonbanks. The effects are more pronounced for loans originated by banks which tend to collect more customer data through their relationship lending technologies which raises their CCPA compliance costs. Moreover, since banks hold a greater fraction of the loans they originate on balance sheet, they are liable for a greater future legal costs whereas non-banks pass these with greater frequency to the GSEs due to their originate-to-distribute business model.

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Figure 1: California and Adjacent States

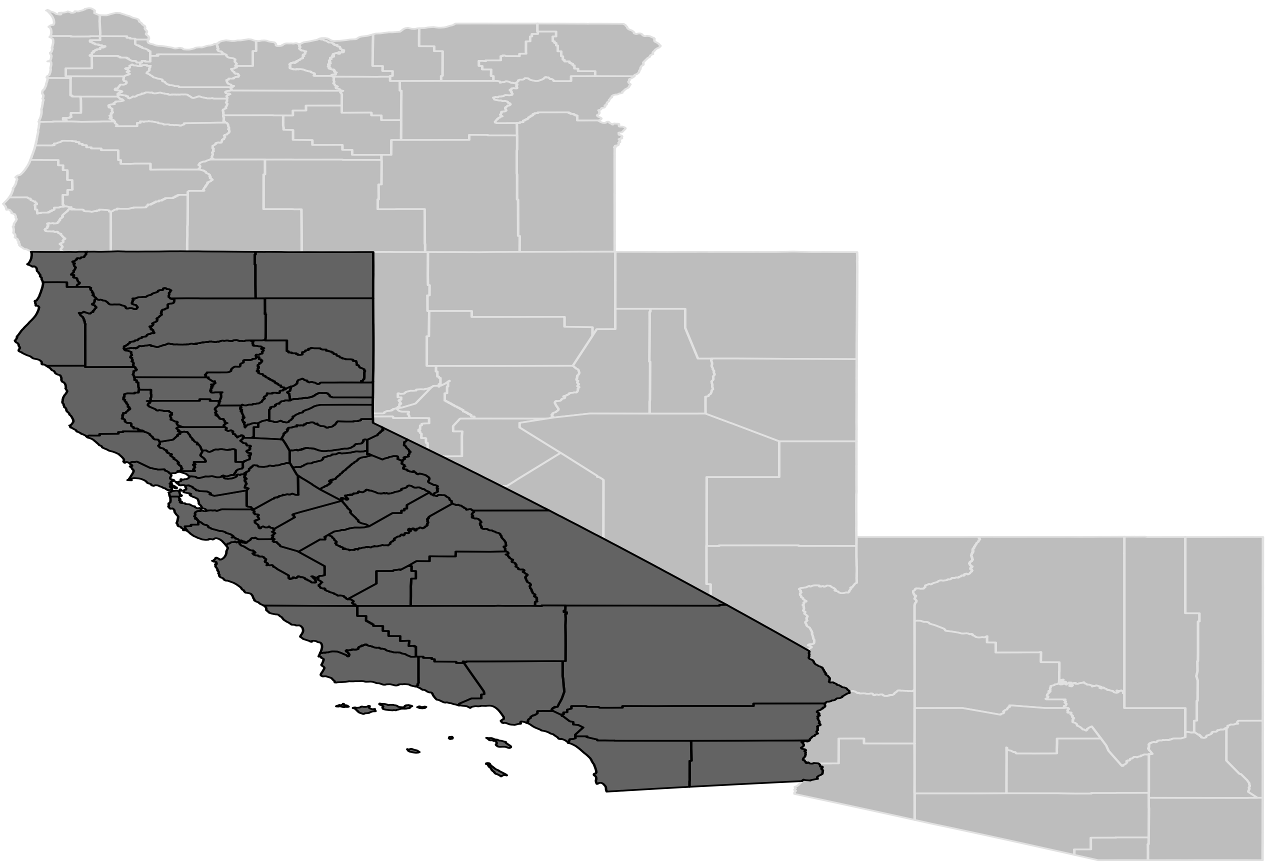

Figure 2: California and Adjacent States - Contiguous Counties

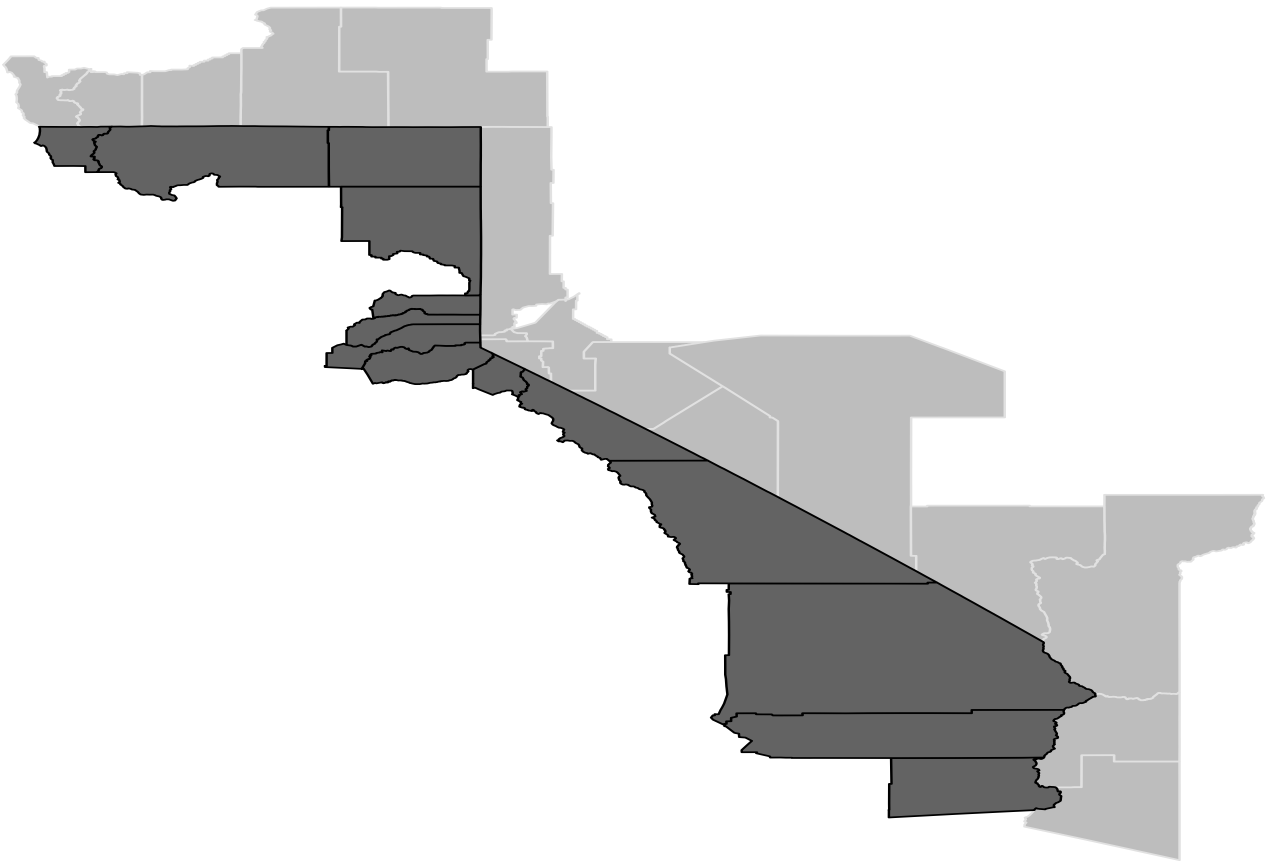

Figure 3: Rate - California vs. Adjacent States

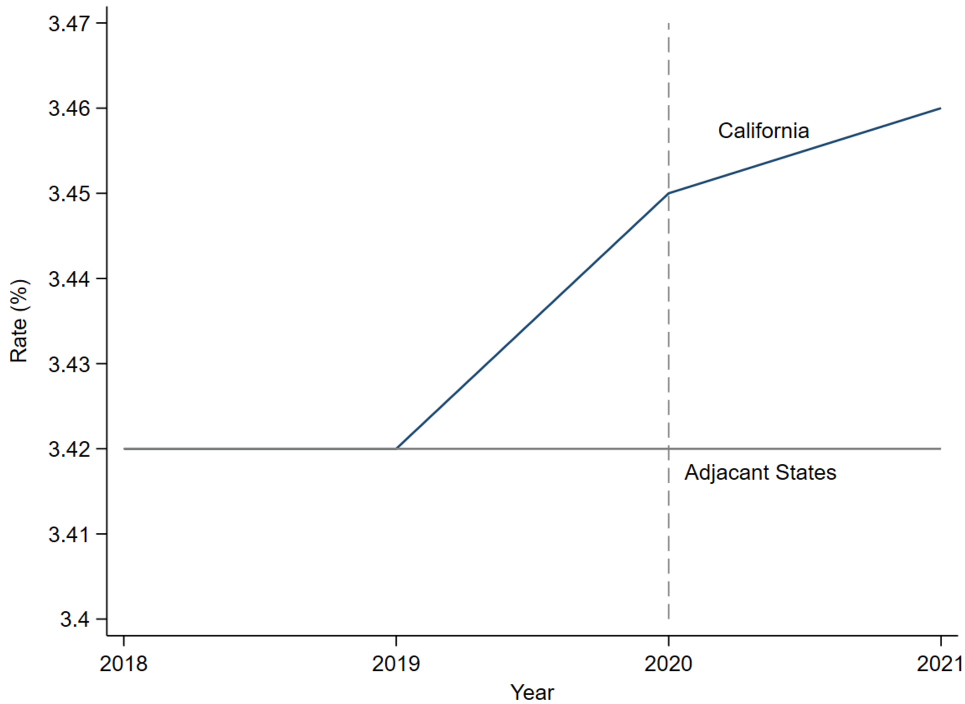

Figure 4: Spread - California vs. Adjacent States

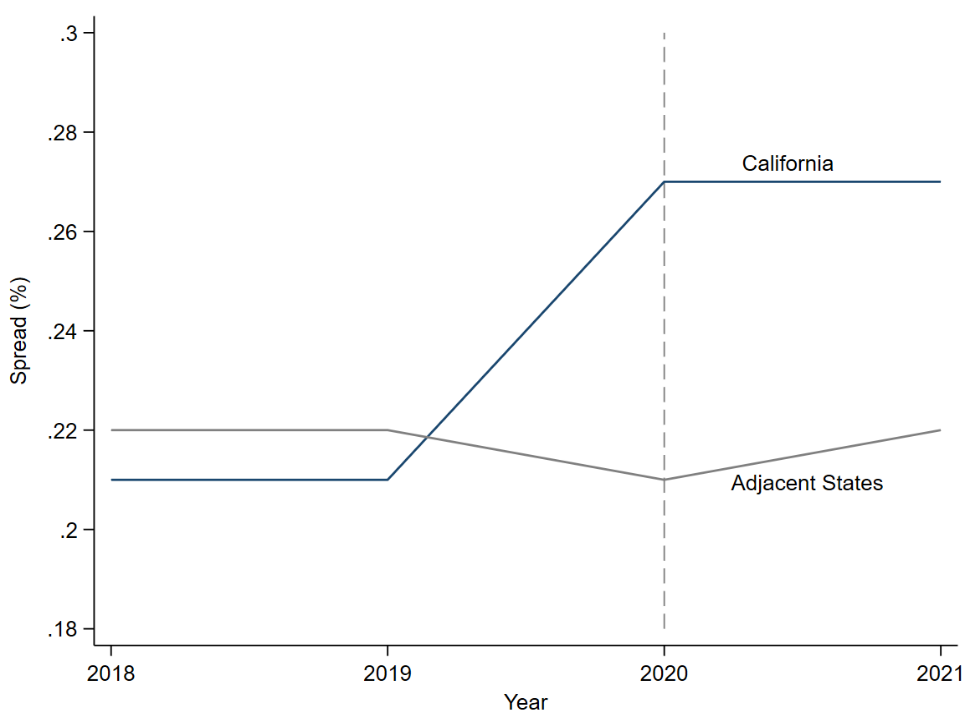

Figure 5: Rate in California - Bank vs. Nonbank

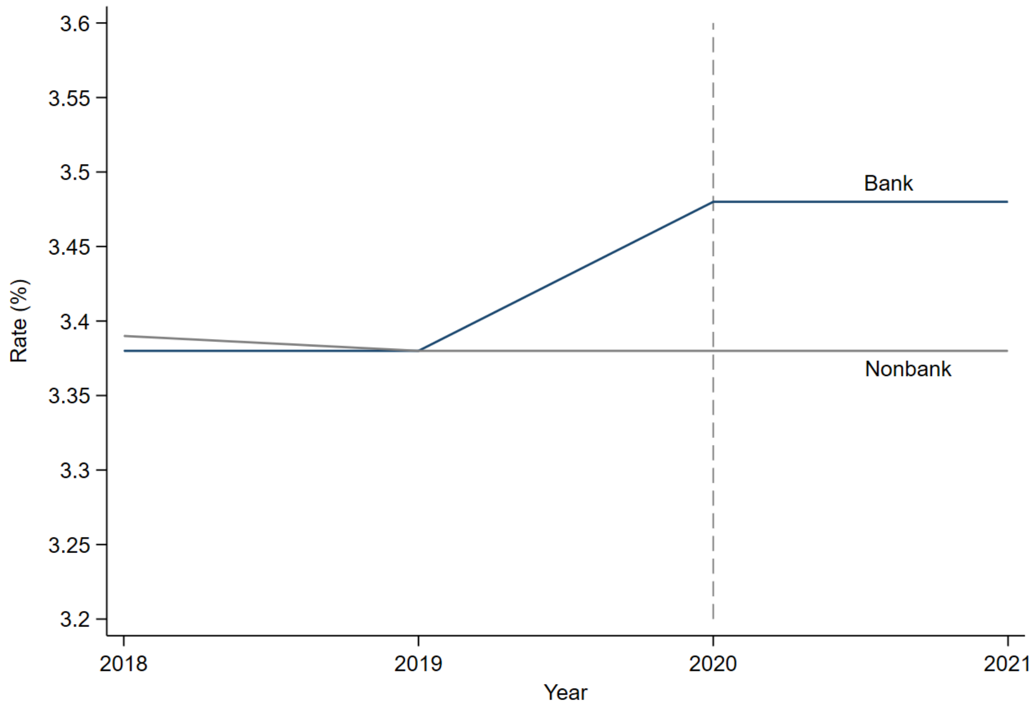

Figure 6: Spread in California - Bank vs. Nonbank

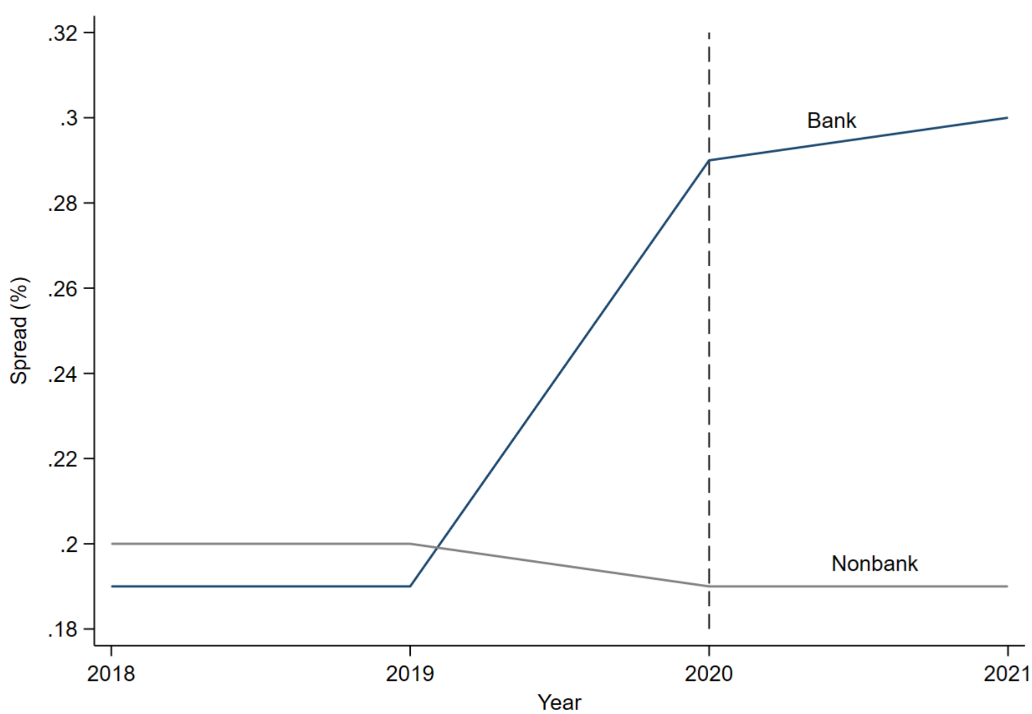

Figure 7: 30-year Mortgage Rate

Table 1. Summary statistics

Variable Name	Units	Observations	Mean	SD	Min	Max
Panel A: Loan-level Statistics						
Loan rate	%	5,331,398	3.436	0.778	2.375	5.750
Spread	%	5,161,432	0.241	0.379	-0.314	1.440
Caucasian	1/0	5,338,487	0.614	0.487	0	1
Male	1/0	5,338,487	0.292	0.455	0	1
Age	1/0	5,336,769	3.959	1.408	1	7
Joint	1-7	5,338,487	0.403	0.490	0	1
Median Family Income Ratio	%	5,338,487	119.558	43.066	0	399
Panel B: Bank Statistics						
Legal, Telecommunication, and Data Processing Expenses/Assets	-	103,479	0.002	0.005	0	0.213
Equity (logs)	-	135,103	0.128	0.098	0	1
Assets (logs)	-	139,728	12.436	1.451	0	21.221
Panel C: County-level Statistics						
Per-capita COVID-19 Deaths	-	3,793,674	0.001	0.001	0	0.005
Per-capita COVID-19 Cases	-	3,793,674	0.070	0.026	0.009	0.148

The table provides sample summary statistics. The table provides the variable name, units, and the number of observations (Observations), mean (Mean), standard deviation (SD), minimum (Min) and maximum (Max). The variable definitions are in Appendix Table A.1.

Table 2. The impact after 2018 of the California Consumer Privacy Act on the bank legal expenditures over assets and bank data processing expenditures over assets

Banks in	*2016-17 vs 2018-19*	*2018-19 vs 2020-21*	*2016-21*
Dependent Variable	(Legal+Telecommunication+Data processing expenditures) / Assets		
	(1)	(2)	(3)
Bank HQ in California * Announcement of the California Consumer Privacy Act in 2018	0.471***		0.347***
	(0.125)		(0.130)
Bank HQ in California * Implementation of the California Consumer Privacy Act in 2020		-0.161	-0.169
		(0.170)	(0.166)
Bank Equity Ratio	1.780***	0.164	1.358**
	(0.660)	(0.812)	(0.550)
Bank Ln(Assets)	-4.131***	-2.986***	-3.069***
	(0.101)	(0.128)	(0.074)
Lender Fixed Effects	Yes	Yes	Yes
Year * Quarter Fixed Effects	Yes	Yes	Yes
R2	0.73	0.78	0.72
Number of Observations	59,269	32,965	72,184

The table reports regression estimates of the bank legal expenditures over assets and bank data processing expenditures over assets on the indicated variables and fixed effects. Robust standard errors clustered at the head quarters state are listed in parentheses below the coefficient estimates. *** p<0.01, ** p<0.05, * p<0.1.

Table 3. The impact of the California Consumer Privacy Act on mortgage rates and spreads for all financial institutions, and for banks versus other financial institutions

All Mortgages in California versus Border Counties in 2018-2021										
Dependent Variable	Rate					Spread				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Mortgage In California * After the California Consumer Privacy Act	0.046***	0.048***	0.051***	0.052***		0.049***	0.053***	0.053***	0.057***	
	(0.004)	(0.005)	(0.004)	(0.005)		(0.004)	(0.004)	(0.004)	(0.004)	
Mortgage In California * After the California Consumer Privacy Act * Bank			0.004	0.005	0.010			0.018**	0.025***	0.025***
			(0.009)	(0.010)	(0.009)			(0.008)	(0.008)	(0.008)
Mortgage In California * Bank			0.027***	-0.109***	0.021**			0.035***	-0.044	0.030***
			(0.009)	(0.033)	(0.009)			(0.008)	(0.028)	(0.008)
After the California Consumer Privacy Act * Bank			0.099***	0.099***	0.089***			0.106***	0.103***	0.096***
			(0.006)	(0.007)	(0.007)			(0.005)	(0.006)	(0.005)
Caucasian	0.014***	0.014***	0.014***	0.014***	0.014***	0.005***	0.006***	0.005***	0.006***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Male	-0.003***	-0.003**	-0.003***	-0.003**	-0.003***	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***	-0.009***	-0.010***	-0.009***	-0.010***	-0.010***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Joint ownership	-0.014***	-0.013***	-0.014***	-0.013***	-0.014***	-0.013***	-0.012***	-0.013***	-0.012***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
House Price Index (County)	-0.000***	-0.000***	-0.000***	-0.000***		-0.000***	-0.000***	-0.000***	-0.000***	
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Median Family Income Ratio	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lender Fixed Effects	Yes	No	Yes	No	Yes	Yes	No	Yes	No	Yes
County Fixed Effects	Yes	No	Yes	No	No	Yes	No	Yes	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No
Lender * County Fixed Effects	No	Yes	No	Yes	No	No	Yes	No	Yes	No
County * Year Fixed Effects	No	No	No	No	Yes	No	No	No	No	Yes
R2	0.743	0.746	0.743	0.746	0.743	0.297	0.31	0.298	0.311	0.3
Number of Observations	1,016,933	1,014,915	1,016,933	1,014,915	1,016,933	982,023	980,012	982,023	980,012	982,023

The table reports regression estimates of rate or spread of all mortgages on the indicated variables and fixed effects. Robust standard errors clustered at the county level are listed in parentheses below the coefficient estimates. *** p<0.01, ** p<0.05, * p<0.1.

Table 4. The impact of the California Consumer Privacy Act on refinancing mortgage rates and spreads for all financial institutions, and for banks versus other financial institutions

All Mortgages in California versus Border Counties in 2018-2021										
Dependent Variable	Rate					Spread				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Mortgage In California * After the California Consumer Privacy Act	0.027***	0.027***	0.031***	0.031***		0.035***	0.034***	0.039***	0.038***	
	(0.005)	(0.005)	(0.005)	(0.005)		(0.004)	(0.004)	(0.004)	(0.004)	
Mortgage In California * After the California Consumer Privacy Act * Bank			0.033***	0.035***	0.033***			0.034***	0.037***	0.034***
			(0.012)	(0.012)	(0.012)			(0.009)	(0.010)	(0.009)
Mortgage In California * Bank			-0.012	-0.126***	-0.012			0.014	-0.110***	0.013
			(0.011)	(0.043)	(0.011)			(0.009)	(0.035)	(0.009)
After the California Consumer Privacy Act * Bank			0.111***	0.112***	0.108***			0.106***	0.105***	0.103***
			(0.008)	(0.008)	(0.008)			(0.006)	(0.006)	(0.006)
Caucasian	0.021***	0.022***	0.021***	0.022***	0.022***	0.008***	0.009***	0.008***	0.009***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Male	-0.007***	-0.006***	-0.007***	-0.007***	-0.007***	-0.011***	-0.010***	-0.011***	-0.011***	-0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	-0.001**	-0.001***	-0.001**	-0.001***	-0.001***	-0.000	-0.001	-0.000	-0.001	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Joint ownership	-0.024***	-0.023***	-0.024***	-0.023***	-0.024***	-0.014***	-0.013***	-0.014***	-0.013***	-0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
House Price Index (County)	-0.000***	-0.000***	-0.000***	-0.000***		-0.000***	-0.000***	-0.000***	-0.000***	
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Median Family Income Ratio	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lender Fixed Effects	Yes	No	Yes	No	Yes	Yes	No	Yes	No	Yes
County Fixed Effects	Yes	No	Yes	No	No	Yes	No	Yes	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No
Lender * County Fixed Effects	No	Yes	No	Yes	No	No	Yes	No	Yes	No
County * Year Fixed Effects	No	No	No	No	Yes	No	No	No	No	Yes
R2	0.688	0.692	0.688	0.692	0.689	0.264	0.276	0.265	0.277	0.266
Number of Observations	655,274	653,505	655,274	653,505	655,274	635,651	633,900	635,651	633,900	635,651

The table reports regression estimates of rate or spread of all mortgages on the indicated variables and fixed effects. Robust standard errors clustered at the county level are listed in parentheses below the coefficient estimates. *** p<0.01, ** p<0.05, * p<0.1.

Table 5. The impact of the California Consumer Privacy Act on mortgage rates and spreads for banks versus other financial institutions for mortgages sold to GSEs

All Mortgages in California Sold to GSE versus Border Counties in 2018-2021						
Dependent Variable	Rate			Spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Mortgage In California * After the California Consumer Privacy Act	0.051***	0.052***		0.053***	0.055***	
	(0.004)	(0.005)		(0.004)	(0.004)	
Mortgage In California * After the California Consumer Privacy Act * Bank	0.009	0.006	0.016	-0.012	-0.011	-0.009
	(0.013)	(0.014)	(0.013)	(0.010)	(0.011)	(0.010)
Mortgage In California * Bank	0.004	0.002	-0.001	0.047***	0.047	0.044***
	(0.012)	(0.051)	(0.013)	(0.010)	(0.046)	(0.010)
After the California Consumer Privacy Act * Bank	0.090***	0.095***	0.082***	0.098***	0.098***	0.095***
	(0.009)	(0.010)	(0.010)	(0.007)	(0.008)	(0.008)
Caucasian	0.020***	0.020***	0.020***	0.008***	0.009***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Male	-0.006***	-0.006***	-0.006***	-0.011***	-0.010***	-0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	-0.007***	-0.007***	-0.007***	-0.008***	-0.008***	-0.008***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Joint ownership	-0.015***	-0.015***	-0.015***	-0.014***	-0.012***	-0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
House Price Index (County)	-0.000***	-0.000***		-0.000***	-0.000***	
	(0.000)	(0.000)		(0.000)	(0.000)	
Median Family Income Ratio	-0.001***	-0.001***	-0.001***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lender Fixed Effects	Yes	Yes	No	Yes	Yes	No
County Fixed Effects	Yes	No	No	Yes	No	No
Year Fixed Effects	Yes	No	Yes	Yes	No	Yes
Lender * County Fixed Effects	No	Yes	No	No	Yes	No
County * Year Fixed Effects	No	No	Yes	No	No	Yes
R2	0.735	0.738	0.735	0.259	0.271	0.26
Number of Observations	688,555	687,318	688,555	674,153	672,928	674,153

The table reports regression estimates of conforming mortgages on the indicated variables and fixed effects. Robust standard errors clustered at the county level are listed in parentheses below the coefficient estimates. *** p<0.01, ** p<0.05, * p<0.1.

Table 6. The impact of the California Consumer Privacy Act on mortgage rates and spreads for Credit Unions versus State Banks

All Mortgages in California by Credit Unions and State Banks versus Border Counties in 2018-2021						
Dependent Variable	Rate			Spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Mortgage In California * After the California Consumer Privacy Act	0.114***	0.121***		0.014	0.014	
	(0.018)	(0.020)		(0.014)	(0.017)	
Mortgage In California * After the California Consumer Privacy Act * Credit Union (vs State Bank)	0.094***	0.118***	0.078***	0.062***	0.089***	0.072***
	(0.021)	(0.022)	(0.021)	(0.017)	(0.019)	(0.017)
Mortgage In California * Credit Union (vs State Bank)	0.036*	0.000	0.047**	0.024	0.000	0.022
	(0.021)	(.)	(0.022)	(0.016)	(.)	(0.017)
After the California Consumer Privacy Act * Credit Union (vs State Bank)	0.010	-0.002	0.002	0.124***	0.113***	0.150***
	(0.018)	(0.019)	(0.018)	(0.014)	(0.015)	(0.015)
Caucasian	0.025***	0.020***	0.025***	0.015***	0.013***	0.015***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Male	-0.024***	-0.019***	-0.024***	-0.021***	-0.017***	-0.021***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Age	0.016***	0.015***	0.015***	0.008***	0.007***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Joint ownership	-0.030***	-0.025***	-0.031***	-0.023***	-0.019***	-0.022***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
House Price Index (County)	0.000**	0.000		-0.000	-0.000**	
	(0.000)	(0.000)		(0.000)	(0.000)	
Median Family Income Ratio	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lender Fixed Effects	Yes	Yes	No	Yes	Yes	No
County Fixed Effects	Yes	No	No	Yes	No	No
Year Fixed Effects	Yes	No	Yes	Yes	No	Yes
Lender * County Fixed Effects	No	Yes	No	No	Yes	No
County * Year Fixed Effects	No	No	Yes	No	No	Yes
R2	0.739	0.753	0.743	0.315	0.354	0.332
Number of Observations	116,727	114,878	116,706	108,726	106,911	108,704

The table reports regression estimates of conforming mortgages on the indicated variables and fixed effects. Robust standard errors clustered at the county level are listed in parentheses below the coefficient estimates. *** p<0.01, ** p<0.05, * p<0.1.

Table 7. The impact of the California Consumer Privacy Act on bank mortgage rate and spread, for conforming versus non-conforming mortages estimated within lender-county.

All Mortgages in California versus Border Counties in 2018-2021						
Dependent Variable	Rate			Spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Mortgage In California * After the California Consumer Privacy Act	0.036**	0.070***		0.005	0.026**	
	(0.014)	(0.016)		(0.011)	(0.012)	
Mortgage In California * After the California Consumer Privacy Act * Conforming	0.136***	0.137***	0.101***	0.045***	0.049***	0.002
	(0.017)	(0.018)	(0.018)	(0.014)	(0.014)	(0.014)
Mortgage In California * Conforming	-0.083***	-0.160***	-0.066***	-0.041***	-0.098***	-0.020
	(0.015)	(0.016)	(0.016)	(0.012)	(0.012)	(0.012)
After the California Consumer Privacy Act * Conforming	-0.312***	-0.318***	-0.276***	-0.022*	-0.027**	0.010
	(0.015)	(0.017)	(0.016)	(0.012)	(0.013)	(0.013)
Caucasian	0.019***	0.018***	0.019***	0.009***	0.009***	0.009***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Male	-0.018***	-0.014***	-0.018***	-0.015***	-0.012***	-0.015***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age	0.016***	0.015***	0.016***	0.008***	0.007***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Joint ownership	-0.032***	-0.027***	-0.033***	-0.024***	-0.019***	-0.023***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
House Price Index (County)	0.000**	0.000***		0.000	0.000	
	(0.000)	(0.000)		(0.000)	(0.000)	
Median Family Income Ratio	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Conforming	0.197***	0.251***	0.178***	0.055***	0.095***	0.040***
	(0.014)	(0.015)	(0.014)	(0.011)	(0.011)	(0.011)
Lender Fixed Effects	Yes	Yes	No	Yes	Yes	No
County Fixed Effects	Yes	No	No	Yes	No	No
Year Fixed Effects	Yes	No	Yes	Yes	No	Yes
Lender * County Fixed Effects	No	Yes	No	No	Yes	No
County * Year Fixed Effects	No	No	Yes	No	No	Yes
R2	0.764	0.779	0.767	0.454	0.491	0.467
Number of Observations	135,524	133,175	135,509	127,364	125,049	127,349

The table reports regression estimates of the rate or the spread of mortgages on the indicated variables and fixed effects. Robust standard errors clustered at the county level are listed in parentheses below the coefficient estimates. *** p<0.01, ** p<0.05, * p<0.1.

Table 8. The impact of the California Consumer Privacy Act on credit supply

All Mortgages in California versus Border Counties in 2018-2021										
Dependent Variable	Volume					Number				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Mortgage In California * After the California Consumer Privacy Act	0.104**	0.096**	0.139**		0.123**	0.125***	0.125***	0.177***		0.158***
	(0.043)	(0.044)	(0.051)		(0.053)	(0.039)	(0.039)	(0.050)		(0.050)
Mortgage In California * After the California Consumer Privacy Act * Bank			-0.156***	-0.165***	-0.158***			-0.170***	-0.179***	-0.180***
			(0.052)	(0.046)	(0.052)			(0.048)	(0.042)	(0.049)
In California * Bank			-0.164	-0.163	-0.095			-0.167	-0.166	-0.130
			(0.228)	(0.228)	(0.152)			(0.232)	(0.231)	(0.145)
After the California Consumer Privacy Act * Bank			-0.106***	-0.121***	-0.173***			-0.077**	-0.096***	-0.141***
			(0.034)	(0.032)	(0.035)			(0.032)	(0.027)	(0.032)
Avg income (by lender-county-yr)	0.000	-0.000*	0.000	0.000	-0.000	-0.000***	-0.000***	-0.000	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Avg LtV (by lender-county-yr)	1.040***	1.019***	1.039***	1.041***	1.013***	-0.099	-0.099	0.008	0.012	-0.105
	(0.077)	(0.087)	(0.076)	(0.076)	(0.085)	(0.070)	(0.070)	(0.076)	(0.077)	(0.067)
Avg term (by lender-county-yr)	0.001***	0.001**	0.001***	0.001***	0.001**	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Caucasian % (by lender-county-yr)	-0.006	-0.134***	0.000	0.004	-0.126***	-0.083***	-0.083***	0.035	0.038	-0.076**
	(0.034)	(0.037)	(0.034)	(0.034)	(0.036)	(0.030)	(0.030)	(0.033)	(0.033)	(0.028)
Gender % (by lender-county-yr)	0.128***	0.135***	0.124***	0.123***	0.135***	0.049*	0.049*	0.034	0.034	0.048*
	(0.027)	(0.027)	(0.027)	(0.028)	(0.027)	(0.024)	(0.024)	(0.026)	(0.027)	(0.025)
Age (by lender-county-yr)	-0.097***	-0.033***	-0.097***	-0.097***	-0.034***	-0.027***	-0.027***	-0.088***	-0.087***	-0.028***
	(0.020)	(0.012)	(0.020)	(0.020)	(0.012)	(0.009)	(0.009)	(0.019)	(0.019)	(0.009)
Lender Fixed Effects	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No
County Fixed Effects	Yes	No	Yes	No	No	Yes	No	Yes	No	No
Year Fixed Effects	Yes	No	Yes	No	Yes	Yes	No	Yes	No	Yes
Lender * County Effects	No	Yes	No	No	Yes	No	Yes	No	No	Yes
County * Year Fixed Effects	No	No	No	Yes	No	No	No	No	Yes	No
R2	0.676	0.914	0.677	0.678	0.915	0.918	0.918	0.654	0.655	0.919
Number of Observations	19,329	16,439	19,329	19,328	16,439	16,439	16,439	19,329	19,328	16,439

The table reports regression estimates of the log volume or log number of conforming mortgages on the indicated variables and fixed effects. The variable definitions are in Appendix Table A.1. Robust standard errors clustered at the county level are listed in parentheses below the coefficient estimates. *** p<0.01, ** p<0.05, * p<0.1.

Table 9. The impact of the California Consumer Privacy Act on refinancing supply

All Mortgages in California versus Border Counties in 2018-2021										
Dependent Variable			Volume					Number		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Mortgage In California * After the California Consumer Privacy Act	0.081*	0.028	0.119**		0.055	0.047	0.047	0.141**		0.075
	(0.047)	(0.045)	(0.058)		(0.056)	(0.045)	(0.045)	(0.057)		(0.055)
Mortgage In California * After the California Consumer Privacy Act * Bank			-0.169**	-0.189**	-0.169**			-0.184***	-0.203***	-0.173**
			(0.071)	(0.069)	(0.072)			(0.062)	(0.061)	(0.066)
In California * Bank			-0.217	-0.209	-0.215			-0.188	-0.179	-0.207
			(0.200)	(0.199)	(0.178)			(0.207)	(0.205)	(0.191)
After the California Consumer Privacy Act * Bank			-0.159***	-0.166***	-0.191***			-0.118***	-0.127***	-0.163***
			(0.043)	(0.043)	(0.050)			(0.036)	(0.035)	(0.045)
Avg income (by lender-county-yr)	0.000	-0.000	0.000	0.000	-0.000	-0.000*	-0.000*	-0.000	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Avg LtV (by lender-county-yr)	1.050***	1.192***	1.058***	1.066***	1.196***	-0.092	-0.092	-0.005	0.004	-0.089
	(0.158)	(0.091)	(0.154)	(0.156)	(0.091)	(0.055)	(0.055)	(0.062)	(0.062)	(0.055)
Avg term (by lender-county-yr)	0.001***	0.000*	0.001***	0.001**	0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Caucasian % (by lender-county-yr)	0.035	-0.120**	0.043	0.047	-0.112**	-0.098**	-0.098**	0.066*	0.070**	-0.091**
	(0.038)	(0.047)	(0.036)	(0.036)	(0.047)	(0.038)	(0.038)	(0.033)	(0.034)	(0.038)
Gender % (by lender-county-yr)	0.143***	0.135***	0.139***	0.138***	0.134***	0.050	0.050	0.044	0.044	0.048
	(0.026)	(0.041)	(0.026)	(0.027)	(0.041)	(0.037)	(0.037)	(0.028)	(0.028)	(0.038)
Age (by lender-county-yr)	-0.095***	-0.025**	-0.096***	-0.097***	-0.025**	-0.024**	-0.024**	-0.083***	-0.084***	-0.024**
	(0.023)	(0.012)	(0.023)	(0.023)	(0.012)	(0.011)	(0.011)	(0.019)	(0.019)	(0.011)
Lender Fixed Effects	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No
County Fixed Effects	Yes	No	Yes	No	No	Yes	No	Yes	No	No
Year Fixed Effects	Yes	No	Yes	No	Yes	Yes	No	Yes	No	Yes
Lender * County Effects	No	Yes	No	No	Yes	No	Yes	No	No	Yes
County * Year Fixed Effects	No	No	No	Yes	No	No	No	No	Yes	No
R2	0.669	0.906	0.671	0.673	0.907	0.909	0.909	0.651	0.653	0.91
Number of Observations	15,445	12,964	15,445	15,443	12,964	12,964	12,964	15,445	15,443	12,964

The table reports regression estimates of the log volume or log number of conforming mortgages on the indicated variables and fixed effects. The variable definitions are in Appendix Table A.1. Robust standard errors clustered at the county level are listed in parentheses below the coefficient estimates. *** p<0.01, ** p<0.05, * p<0.1.

Table 10. The impact of the California Consumer Privacy Act on bank mortgage log volume or log number, approval, rate and spread, by census tract median family income (MFI) ratio

Mortgages in California versus Border Counties	1st Stage - *All*	2nd Stage - *Approved*						*Credit Quantity*			
		All		MFI Ratio < 1		MFI Ratio >= 1		MFI Ratio < 1		MFI Ratio >= 1	
Dependent Variable	Approval	Rate	Spread	Rate	Spread	Rate	Spread	Volume	Number	Volume	Number
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Mortgage In California * After the California Consumer Privacy Act * Bank	0.008	0.016*	0.031***	0.030*	0.067***	0.005	0.015	-0.269***	-0.217***	-0.135**	-0.159**
	(0.007)	(0.010)	(0.008)	(0.018)	(0.015)	(0.011)	(0.010)	(0.067)	(0.049)	(0.058)	(0.057)
Mortgage In California * Bank	-0.019***	0.007	0.015*	-0.021	-0.027*	0.019*	0.029***	-0.119	-0.137	-0.131	-0.131
	(0.007)	(0.009)	(0.009)	(0.016)	(0.014)	(0.011)	(0.011)	(0.255)	(0.240)	(0.207)	(0.213)
After the California Consumer Privacy Act * Bank	-0.043***	0.057***	0.063***	0.021	0.023*	0.076***	0.071***	-0.004	0.002	-0.171***	-0.137***
	(0.005)	(0.009)	(0.010)	(0.016)	(0.014)	(0.011)	(0.011)	(0.056)	(0.044)	(0.038)	(0.033)
Caucasian	0.056***	0.056***	0.050***	0.061***	0.091***	0.055***	0.043***				
	(0.001)	(0.008)	(0.011)	(0.014)	(0.012)	(0.009)	(0.011)				
Male	-0.003***	-0.006***	-0.012***	-0.000	-0.008***	-0.009***	-0.015***				
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)				
Age	-0.009***	-0.013***	-0.016***	-0.012***	-0.024***	-0.013***	-0.015***				
	(0.000)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)				
Joint ownership	0.054***	0.025***	0.028***	0.049***	0.077***	0.016*	0.018*				
	(0.001)	(0.007)	(0.010)	(0.013)	(0.011)	(0.008)	(0.010)				
Median Family Income Ratio	0.000***	-0.001***	-0.001***	-0.002***	-0.002***	-0.001***	-0.001***				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
Lender Credit Score Model Type	-0.002***										
	(0.000)										
Lambda (selection correction)		-0.752***	-0.781***	-0.971***	-1.544***	-0.663***	-0.652***				
		(0.136)	(0.191)	(0.250)	(0.215)	(0.161)	(0.182)				
Lender - County - Year Variables (see Table 3)	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County * Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.179	0.743	0.3	0.754	0.306	0.737	0.271	0.627	0.616	0.675	0.648
Number of Observations	1,676,160	1,016,942	982,034	318,447	303,439	698,383	678,474	12,487	12,487	16,596	16,596

The table reports regression estimates of the spread or cost/value of conforming mortgages on the indicated variables and fixed effects. The variable definitions are in Appendix Table A.1. Robust standard errors clustered at the tract level are listed in parentheses below the coefficient estimates. *** p<0.01, ** p<0.05, * p<0.1.

Table 11. The impact of the California Consumer Privacy Act on bank approval, rate and spread, by census tract median family income (MFI) ratio, for refinancing purposes

Mortgages for Refinancing in California versus Border Counties	1st Stage - *All*	2nd Stage - *Approved*						*Credit Quantity*			
		All		MFI Ratio < 1		MFI Ratio >= 1		MFI Ratio < 1		MFI Ratio >= 1	
Dependent Variable	Approval	Rate	Spread	Rate	Spread	Rate	Spread	Volume	Number	Volume	Number
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Mortgage In California * After the California Consumer Privacy Act * Bank	0.033***	0.043***	0.054***	0.072***	0.119***	0.033**	0.033***	-0.180**	-0.183***	-0.127*	-0.161**
	(0.009)	(0.013)	(0.011)	(0.024)	(0.019)	(0.015)	(0.012)	(0.071)	(0.050)	(0.071)	(0.065)
Mortgage In California * Bank	-0.029***	-0.021*	-0.005	-0.042*	-0.060***	-0.017	0.011	-0.255	-0.243	-0.187	-0.102
	(0.009)	(0.012)	(0.010)	(0.023)	(0.018)	(0.014)	(0.011)	(0.215)	(0.197)	(0.188)	(0.200)
After the California Consumer Privacy Act * Bank	-0.049***	0.093***	0.074***	0.045**	0.016	0.110***	0.087***	-0.122**	-0.003	-0.242***	-0.128***
	(0.006)	(0.012)	(0.012)	(0.022)	(0.017)	(0.013)	(0.011)	(0.057)	(0.048)	(0.056)	(0.041)
Caucasian	0.062***	0.040***	0.045***	0.071***	0.095***	0.028**	0.035***				
	(0.001)	(0.011)	(0.013)	(0.020)	(0.016)	(0.012)	(0.011)				
Male	-0.007***	-0.009***	-0.016***	-0.009***	-0.017***	-0.010***	-0.017***				
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)				
Age	-0.009***	-0.004**	-0.006***	-0.008**	-0.013***	-0.003	-0.005***				
	(0.000)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)				
Joint ownership	0.055***	-0.008	0.019*	0.038**	0.073***	-0.026**	0.005				
	(0.001)	(0.009)	(0.011)	(0.018)	(0.014)	(0.011)	(0.009)				
Median Family Income Ratio	0.000***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
Lender Credit Score Model Type	-0.002***										
	(0.000)										
Lambda (selection correction)		-0.293*	-0.605***	-0.964***	-1.463***	-0.036	-0.408**				
		(0.169)	(0.205)	(0.321)	(0.257)	(0.198)	(0.168)				
Lender - County - Year Variables (see Table 3)	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Lender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County * Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.181	0.689	0.266	0.704	0.261	0.68	0.243	0.63	0.65	0.669	0.668
Number of Observations	1,097,454	655,276	635,654	195,541	187,313	459,639	448,242	9,742	9,742	13,370	13,370

The table reports regression estimates of the rate or spread of mortgages for refinancing on the indicated variables and fixed effects. The variable definitions are in Appendix Table A.1. Robust standard errors clustered at the tract level are listed in parentheses below the coefficient estimates. *** p<0.01, ** p<0.05, * p<0.1.

Appendix

Appendix Table A.1. Variable definitions

Variable Name	Unit	Definition
Rate	%	Is the interest rate of the loan
Spread	%	Is the interest rate of the loan minus the comparable prime rate
Approval	1/0	=1 if the mortgage is approved by the lender, =0 otherwise
Volume	log	Is the natural logarithm of the total amount of loans originated by a lender in a specific county and year.
Number	log	Is the natural logarithm of the total number of loans originated by a lender in a specific county and year.
Mortgage In California	1/0	=1 if the mortgage is granted in California, =0 otherwise
After the California Consumer Privacy Act	1/0	=1 if the mortgage is granted after the California Consumer Privacy Act went into effect on January 1, 2020, =0 otherwise
Bank	1/0	=1 if the mortgage is granted by a bank, =0 if the mortgage is granted by a nonbank
Caucasian	1/0	=1 if the mortgage is granted to a Caucasian, =0 otherwise
Male	1/0	=1 if the mortgage is granted to a male, =0 otherwise
Joint	1/0	=1 if the mortgage is granted jointly to a househld, =0 otherwise
Age	1-7	Is a variable with discrete values representing different age groups (From below 25 << 10 << above 74 years old).
First lien	1/0	=1 if the mortgage is secured by a first lien, =0 otherwise
Median Family Income Ratio	-	Is the ratio of the median family income in the tract compared to the median income in the MSA
Avg income (by lender-county-yr)	-	Is the average borrower's income in a lender's portfolio in a specific county and year.
Avg LtV (by lender-county-yr)	-	Is the average loan-to-value ratio in a lender's portfolio in a specific county and year.
Avg term (by lender-county-yr)	-	Is the average loan term (months) in a lender's portfolio in a specific county and year.
Caucasian % (by lender-county-yr)	%	Is the proportion of Caucasians in a lender's portfolio in a specific county and year.
Gender % (by lender-county-yr)	%	Is the proportion of males in a lender's portfolio in a specific county and year.
Age (by lender-county-yr)	1-7	Is mean age group in a lender's portfolio in a specific county and year.
Per-capita COVID-19 Death	-	Is the ratio of COVID-19 total number of deaths in a county-year (CDC) to the county population (Census).
Per-capita COVID-19 Case	-	Is the ratio of COVID-19 total number of active cases in a county-year (CDC) to the county population (Census).
Bank Legal Expenses	-	Legal fees and expenses (Call item RIAD4141)/Total Assets (Call item RCON2170)
Bank Data Processing Expenses	-	Data processing expenses (Call item RIADC017)/Total Assets (Call item RCON2170)
Bank Equity	log	Total equity capital (Call item RCONG105)/Total liabilities plus equity (Call item RCON3300)
Bank Size	log	Total assets (Call item RCON2170).

The table provides the variable definitions.

Appendix Table A.2. The impact of the California Consumer Privacy Act on mortgage rates and spreads for banks versus other financial institutions in California

All Mortgages in California versus Border Counties in 2018-2021				
Dependent Variable	Rate		Spread	
	(1)	(2)	(3)	(4)
After the California Consumer Privacy Act * Bank	0.109***	0.113***	0.106***	0.108***
	(0.003)	(0.003)	(0.002)	(0.002)
Caucasian	0.032***	0.031***	0.018***	0.017***
	(0.001)	(0.001)	(0.001)	(0.001)
Male	-0.011***	-0.010***	-0.013***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.001)
Age	-0.002***	-0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Joint ownership	-0.016***	-0.015***	-0.012***	-0.011***
	(0.001)	(0.001)	(0.001)	(0.001)
Median Family Income Ratio	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Lender Fixed Effects	Yes	No	Yes	No
County Fixed Effects	Yes	No	Yes	No
Year Fixed Effects	Yes	Yes	Yes	Yes
Lender * County Fixed Effects	No	Yes	No	Yes
R2	0.733	0.736	0.277	0.29
Number of Observations	3,586,247	3,581,664	3,478,943	3,474,433

The table reports regression estimates of rate or spread of all mortgages on the indicated variables and fixed effects. Robust standard errors clustered at the county level are listed in parentheses below the coefficient estimates. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A.3. The impact of the California Consumer Privacy Act on mortgage rates and spreads for all financial institutions, and for banks versus other financial institutions with COVID-19 Controls

All Mortgages in California versus Border Counties in 2018-2021				
Dependent Variable	Rate		Spread	
	(1)	(2)	(3)	(4)
Mortgage In California * After the California Consumer Privacy Act	0.037***	0.047***	0.030***	0.042***
	(0.004)	(0.004)	(0.004)	(0.004)
Mortgage In California * After the California Consumer Privacy Act * Bank	0.006	0.005	0.023***	0.022***
	(0.009)	(0.009)	(0.008)	(0.008)
Mortgage In California * Bank	0.025***	0.025***	0.033***	0.033***
	(0.009)	(0.009)	(0.008)	(0.008)
After the California Consumer Privacy Act * Bank	0.095***	0.096***	0.101***	0.102***
	(0.006)	(0.006)	(0.005)	(0.005)
Caucasian	0.014***	0.014***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Male	-0.003***	-0.003***	-0.009***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
Age	-0.006***	-0.006***	-0.010***	-0.010***
	(0.000)	(0.000)	(0.001)	(0.001)
Joint ownership	-0.014***	-0.014***	-0.013***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)
Median Family Income Ratio	-0.001***	-0.001***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	0
Per capita COVID-19 Death in a County	-25.523***		-29.599***	
	(2.777)		(2.868)	
Per capita COVID-19 Case in a County		-0.654***		-0.518***
		(0.060)		(0.054)
Lender Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
R2	0.743	0.743	0.298	0.298
Number of Observations	1,016,943	1,016,943	982,032	982,032

The table reports regression estimates of rate or spread of all mortgages on the indicated variables and fixed effects. Robust standard errors clustered at the county level are listed in parentheses below the coefficient estimates. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A.4. Comparison of the California Consumer Privacy Act and the Nevada Privacy Law

	California Consumer Privacy Act	*Nevada Privacy Law*
Overall	Broader	Narrower
Passed	2018	2019
Effective	2020	2019
Sale definition	The CCPA broadly defines sale as "selling, renting, releasing, disclosing, disseminating, making available, transferring, or otherwise communicating orally, in writing, or by electronic or other means, a consumer's personal information to another business or a third party for monetary or other valuable consideration."	Nevada narrowly defines "sale" as "the exchange of covered information for monetary consideration by the operator to a person for the person to license or sell the covered information to additional persons."
Personal Information	The CCPA's definition of "personal information" casts a wide net, as it includes "information that identifies, relates to, describes, is capable of being associated with, or could reasonably be linked, directly or indirectly, with a particular consumer or household. Personal information includes, but is not limited to, the following if it identifies, relates to, describes, is capable of being associated with, or could be reasonably linked, directly or indirectly, with a particular consumer or household."	Nevada allows consumers to opt-out of the sale of "covered information" collected through a website or online service. Under the law, "covered information" includes: A first and last name; a home or other physical address, which includes the name of a street and the name of a city or town; an electronic mail (email) address; A telephone number; a social security number; an identifier that allows a specific person to be contacted either physically or online; any other information concerning a person collected from the person through the operator's Internet website or online service and maintained by the operator in combination with an identifier in a form that makes the information personally identifiable.
Consumer Rights	The CCPA defines a "consumer" as "a natural person who is a California resident, namely, every individual who is: in California for other than a temporary or transitory purpose/ domiciled in California who is outside the state for a temporary or transitory purpose.	The Nevada Privacy Law defines a "consumer" as "a person who seeks or acquires, by purchase or lease, any good, service, money or credit for personal, family or household purposes from" an operator's Internet website or online service.
"DO NOT SELL"	The CCPA requires businesses that sell personal information to provide a "Do Not Sell My Personal Information" link or button on their websites that enables consumers to opt-out of the sale of their personal information.	There are several differences between the two laws with respect to the right to opt-out of the sale of personal information. Nevada does not require entities to include a "Do Not Sell My Personal Information" button or link on their websites. Instead, it mandates that entities provide consumers with an email address, a toll-free telephone number, or an Internet website to submit verified opt-out requests.
"Opt-In"	Under the CCPA, businesses generally do not need to obtain consumers' opt-in consent. However, where consumers have opted-out of the sale of their personal information, businesses must wait 12 months before they re-engage with those consumers to request that they opt-in to the sale. Moreover, the CCPA has opt-in requirements for the sale of children or minor's information. Specifically, consumers between the ages of 13 and16 must opt-in to the sale of their personal information, and parents or guardians must provide consent for consumers under the age of 13.	Nevada does not require that consumers opt-in to the sale of their personal information.
Consumer request response timeframe	Upon receiving a "verified consumer request," a business has 45-days, with a possible 90-day extension when "reasonably necessary" and by providing notice to the consumer, for a total of 135 days.	Upon receiving a "verified request," an operator has 60-days to respond, with a possible 30-day extension when "reasonably necessary" and by providing notice to the consumer, for a total of 90 days.
Consumer Rights	The CCPA includes the right of access, portability, deletion, or non- discrimination.	Unlike the CCPA, the Nevada Privacy Law does not include the right of access, portability, deletion, or non- discrimination.
Private Right of Action	The CCPA grants a private right of action against an operator.	The Nevada Privacy Law does not establish a private right of action against an operator.
Enforcement & Penalties	The CCPA gives consumers a limited private right of action for certain data breaches, with potential fines ranging from$100 to $750 per consumer per incident, or actual damages. In addition, the California Attorney General may issue an injunction and levy civil penalties of up to $2,500 per violation and up to $7,500 for intentional violations.	The Nevada Privacy Law does not grant consumers a private right of action against an operator. When the Nevada Attorney General, has reason to believe that an operator is violating the law, it may institute a legal proceeding against the operator. If the court finds a violation, it has the authority to impose a civil penalty of up to $5,000 per violation or issue an injunction.
Sources	https://www.cookiebot.com/en/nevada-privacy-law/	https://www.akingump.com/en/insights/blogs/ag-data-dive/new-nevada-privacy-law-takes-effect-in-october-comparison-of

Appendix Table A.5. The impact of the California Consumer Privacy Act on mortgage rates and spreads forfor banks versus other financial institutions, in Arizona and Oregon and in Nevada

All Mortgages in California versus Border Counties in 2018-2021 in	*Arizona and Oregon*				*Nevada*			
Dependent Variable	Rate		Spread		Rate		Spread	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Mortgage In California * After the California Consumer Privacy Act * Bank	0.070***	0.072***	0.038***	0.041***	0.029***	0.029***	0.021***	0.016***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)	(0.006)	(0.006)
Mortgage In California * Bank	0.036***	0.000	0.056***	0.000	0.073***	0.000	0.087***	0.000
	(0.002)	(.)	(0.002)	(.)	(0.004)	(.)	(0.003)	(.)
Mortgage In California * After the California Consumer Privacy Act	0.003	0.000	0.035***	0.032***	0.002	0.002	0.037***	0.041***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.007)	(0.007)	(0.006)	(0.006)
After the California Consumer Privacy Act * Bank	0.034***	0.028***	0.064***	0.054***	0.084***	0.080***	0.088***	0.086***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.007)	(0.007)	(0.006)	(0.006)
Caucasian	0.031***	0.031***	0.017***	0.017***	0.030***	0.030***	0.017***	0.017***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Male	-0.010***	-0.010***	-0.012***	-0.013***	-0.009***	-0.010***	-0.012***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	-0.002***	-0.002***	-0.000	-0.001**	-0.002***	-0.002***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Joint ownership	-0.019***	-0.019***	-0.016***	-0.016***	-0.015***	-0.015***	-0.012***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Median Family Income Ratio	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
Year Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
County * Year Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
R2	0.735	0.736	0.291	0.294	0.736	0.736	0.292	0.295
Number of Observations	4,981,828	4,981,828	4,825,959	4,825,959	3,934,070	3,934,069	3,812,831	3,812,830

The table reports regression estimates of rate or spread of all mortgages on the indicated variables and fixed effects. Robust standard errors clustered at the county level are listed in parentheses below the coefficient estimates. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A. 6. The impact of the California Consumer Privacy Act on bank mortgage log volume or log number, approval, rate and spread, by census tract median family income (MFI) ratio with all fixed effects

Mortgages in California versus Border Counties	1st Stage - *All*	2nd Stage - *Approved*					
		All		MFI Ratio < 1		MFI Ratio >= 1	
Dependent Variable	Approval	Rate	Spread	Rate	Spread	Rate	Spread
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mortgage In California * After the California Consumer Privacy Act	-0.005***	0.042***	0.037***	0.041***	0.034***	0.041***	0.035***
	(0.002)	(0.004)	(0.004)	(0.006)	(0.006)	(0.005)	(0.004)
Mortgage In California * After the California Consumer Privacy Act * Bank	0.002	0.006	0.023***	0.020	0.055***	-0.007	0.007
	(0.007)	(0.009)	(0.008)	(0.017)	(0.014)	(0.011)	(0.010)
Mortgage In California * Bank	-0.016**	0.014	0.021**	-0.014	-0.019	0.027**	0.036***
	(0.007)	(0.009)	(0.009)	(0.015)	(0.014)	(0.011)	(0.010)
After the California Consumer Privacy Act * Bank	-0.037***	0.070***	0.075***	0.036**	0.041***	0.090***	0.083***
	(0.005)	(0.008)	(0.009)	(0.015)	(0.012)	(0.010)	(0.010)
Caucasian	0.056***	0.056***	0.050***	0.064***	0.094***	0.054***	0.044***
	(0.001)	(0.008)	(0.011)	(0.014)	(0.013)	(0.009)	(0.010)
Male	-0.003***	-0.006***	-0.012***	-0.000	-0.008***	-0.009***	-0.015***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Age	-0.009***	-0.013***	-0.016***	-0.012***	-0.024***	-0.013***	-0.015***
	(0.000)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Joint ownership	0.054***	0.025***	0.028***	0.052***	0.079***	0.015*	0.018*
	(0.001)	(0.007)	(0.010)	(0.013)	(0.012)	(0.008)	(0.009)
Median Family Income Ratio	0.000***	-0.001***	-0.001***	-0.002***	-0.002***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lender Credit Score Model Type	-0.002***						
	(0.000)						
Lambda (selection correction)		-0.753***	-0.792***	-1.024***	-1.592***	-0.649***	-0.656***
		(0.137)	(0.192)	(0.254)	(0.220)	(0.162)	(0.181)
Lender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.179	0.743	0.298	0.753	0.305	0.736	0.27
Number of Observations	1,676,160	1,016,943	982,035	318,448	303,440	698,383	678,474

The table reports regression estimates of the spread or cost/value of conforming mortgages on the indicated variables and fixed effects. The variable definitions are in Appendix Table A.1. Robust standard errors clustered at the tract level are listed in parentheses below the coefficient estimates. *** p<0.01, ** p<0.05, * p<0.1.