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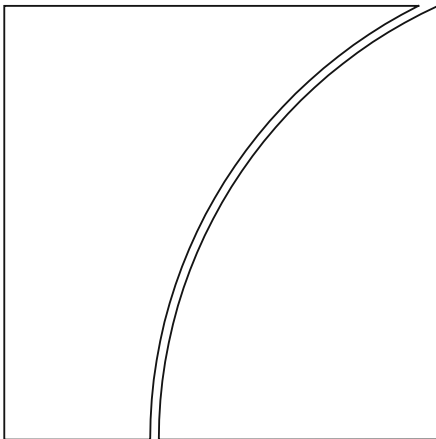
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Privacy regulation and fintech lending

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Abstract

Consumers dislike sharing data with fintechs, but greater access to data can improve loan market outcomes through better screening. We study how the California Consumer Privacy Act (CCPA), which grants users control over and mitigates concerns about sharing their data, affects fintech lending. After the CCPA's introduction, fintechs' loan rates decline relative to those of other lenders. In addition, rate dispersion across fintech loans increases, fintechs deny more applications, and they make greater use of nontraditional credit scoring models, whereas their default rates decline by more than those of other lenders. These results are consistent with an improved screening process enabled by additional data. Mortgage originations by fintechs also increase, suggesting that well-designed privacy regulation may enhance financial inclusion.

JEL Codes: G21, G23, G28.

Keywords: Data privacy, data sharing, fintech, privacy regulation, CCPA, mortgages.

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1 Introduction

The market share of fintech lenders has increased rapidly in many countries. These lenders frequently use nontraditional data and machine learning to screen applicants and price borrowers. Better access to data can therefore foster the growth of fintechs and promote competition in the financial sector, thereby benefiting borrowers. Individuals from traditionally underserved groups, including minority and low-income applicants, stand to benefit in particular, as credit scores often inaccurately reflect their creditworthiness.

There is mounting evidence, however, that consumers dislike sharing their personal data. Concerns include price discrimination, data abuse, unethical advertising, and fraud. Moreover, consumers care about whom they share their data with. For a representative sample of U.S. households, [Figure 1](#) documents that consumers have significantly less confidence in fintechs than in other financial institutions to safely handle their data and protect them from data abuse or misuse. These patterns partly reflect concerns about fintechs' use of technology and the sharing of their personal data.¹

Regulators designing privacy protection rules therefore face a challenging trade-off. Limiting or even prohibiting the collection and use of personal data protects consumers' privacy, but may come at the cost of reducing the availability and quality of data-intensive services, especially to those who need it most. At the same time, the absence of a regulatory framework that addresses privacy concerns may impede fintechs' development. Consumers might be reluctant to share data or engage with fintechs altogether, as they are concerned about privacy violations. Facing legal uncertainty, fintechs may be reluctant to use personal data. In designing privacy regulation, regulators must strike the right balance between protecting users' privacy and promoting the growth of data-intensive firms like fintechs.

To investigate the effects of privacy regulation on the provision of financial services, and in particular on fintech lending, this paper studies the California Consumer Privacy Act (CCPA). Introduced in 2020, the CCPA constitutes a landmark change in the design of privacy regulation. By

¹For example, three-quarters of consumers believe that fintechs are more likely to sell their personal data than other firms ([IDX \(2021\)](#)). Moreover, a long-standing literature highlights barriers to consumers' trust in machine learning models and algorithmic decision-making, see [Glikson and Woolley \(2020\)](#) and [D'Acunto and Rossi \(2023\)](#) for discussions.

giving California residents control over their data and thus mitigating concerns about sharing data, it protects consumers' privacy without restricting information collection outright. For example, individuals can prevent firms from selling their personal information or request that firms delete the data after their use.²

To investigate the effects of the CCPA on loan markets, our analysis uses loan-level data on residential mortgages from the Home Mortgage Disclosure Act (HMDA) database from 2018 to 2021. Since 2018, the publicly available HMDA data provide a wealth of information on lenders, applicants, and loan terms, including loan rates. We estimate regressions with data on individual mortgages and compare fintechs with other nonbank lenders. The CCPA, introduced in 2020, acts as the treatment for borrowers in California, while borrowers in neighboring states constitute the control group.

We first investigate the effects of the introduction of the CCPA on loan pricing. Exploiting the fact that privacy concerns are more salient with respect to fintechs, we hypothesize that the marginal benefit of privacy regulation that assuages concerns about sharing data is greater for fintechs. If users become more willing to share data, the availability of additional information could allow fintechs to better screen applicants and offer loans at more favorable rates relative to other lenders.³ In addition, reduced legal uncertainty may enable fintechs to use personal data more intensively.

We find that the CCPA significantly reduced rates on mortgages originated by fintechs relative to other nonbanks in California. In particular, loan rates declined by around 7 basis points (bps) (or 9% of the standard deviation of rates) more for fintechs. There are no discernible differences in the evolution of fintech loan rates compared to other nonbanks before the CCPA's introduction in 2020.

To examine the mechanism, we first focus on applicants from traditionally underserved groups. In particular, for minority and low-income applicants, traditional credit scores provide an inaccurate picture of their future creditworthiness (Blattner and Nelson, 2024; Di Maggio et al., 2022).

²Survey evidence shows that the majority of Californians have already exercised their CCPA rights, see Consumer Action and Consumer Federation of America (2021): California Consumer Privacy Act (CCPA) Survey.

³Alternative data used for screening in the mortgage market include financial data, such as on-time rental, utility or telecommunications payments, as well as non-financial data, such as educational institution or social media activity. Section 2.3 provides detailed information on the use of alternative data in mortgage lending.

Therefore, the relative decline in fintechs' loan rates because of greater availability or better use of additional information should be larger for these applicants. Consistent with a greater role for screening with alternative data, we find that the relative impact of the CCPA on fintechs' loan rates is larger in economic magnitude for borrowers from traditionally underserved groups.

Further analyses provide evidence consistent with improved screening. First, we find that the introduction of the CCPA has led to greater dispersion in interest rates among fintech loans compared to other nonbanks. This could reflect more individualized pricing because of a more precise signal about applicants' quality (Jansen et al., 2025; Babina et al., 2025). Second, the share of denied loan applications increases for fintechs compared to nonbanks in California after the introduction of the CCPA, which may suggest an improvement in fintechs' ability to screen out low-quality applicants. Third, complementary evidence from loans purchased by government-sponsored enterprises (GSEs) shows that default rates decline by relatively more for fintechs than for other nonbank lenders in California after the CCPA introduction, even when we control for borrowers' credit scores.

Fourth, we find tentative evidence that fintechs in California process more applications using nontraditional credit scores after the introduction of the CCPA. Whereas direct information on lenders' use of data is difficult to obtain, the use of nontraditional credit scores in processing applications can serve as a proxy for greater reliance on alternative personal data. Among mortgages not sold to GSEs by the end of the year, we find a substantial increase in our proxies for the use of nontraditional credit. Moreover, the decline in interest rates among fintech loans post-CCPA is stronger among lenders that in general rely more on nontraditional credit scores in processing mortgage applications.

Turning to quantities, we find that, after the introduction of the CCPA, loan applications to fintechs compared to other nonbanks increase significantly in California relative to neighboring states. Moreover, fintechs originate more mortgages in California after the introduction of the CCPA. Thus, the CCPA not only improved loan terms but may also have expanded access to credit along the extensive margin. Consistent with a financial inclusion channel, we find the effects of the CCPA on fintech loan rates to be stronger in areas where banks had a smaller footprint.

The analysis faces the identification challenge that any observed change in loan outcomes could be because of unobservable factors at the lender or borrower level. For example, a change in financial conditions that affects fintechs and other lenders differently could be reflected in the rates they charge. Likewise, fintechs could serve tracts with higher income growth over the sample period, which could result in different interest rate trajectories.

We address this challenge in different ways. For one, our analysis focuses only on the set of counties that lie on the border of California with its neighboring states, which have been found to be comparable along observable characteristics.⁴ To further account for differences in borrower characteristics, our regressions include a battery of loan- and borrower-level controls, interacted with the California and Post-CCPA dummies. Moreover, we include time-varying fixed effects. Borrower tract \times time fixed effects absorb any observable and unobservable differences in tract characteristics over time, including applicants' income, demographic structure, or credit demand. Lender type \times time fixed effects control for time-varying observed and unobserved heterogeneity in lender characteristics, for example, funding conditions or regulation. Our results remain robust across specifications.⁵

Our findings have implications for the policy debate on how to regulate the use of personal data. Personal data lie at the heart of the digital economy. By allowing lenders to better assess the riskiness of borrowers (Berg et al., 2022), the use of data can, for example, promote financial inclusion (Philippon, 2020), reduce the need for collateral (Gambacorta et al., 2022; Cramer et al., 2025), or spur entrepreneurship (Ahnert et al., 2025). At the same time, consumers value their privacy and are concerned about the abuse and misuse of data (Armantier et al., 2021; Lin, 2022; Tang, 2022; Aldasoro et al., 2024). Lenders, on the other hand, may restrict their use of personal data when there is legal uncertainty. These considerations pose a trade-off for policymakers, who need to balance gains in efficiency from greater use of data with the protection of users' right to privacy. Our results suggest that privacy protection legislation can mitigate this trade-off by enhancing users' control over data and increasing transparency and accountability in their use, consistent with survey-level evidence obtained in Athey et al. (2017) and Armantier et al. (2025).

⁴We find that borrower characteristics are statistically similar between fintechs and other lenders in our sample.

⁵In further tests, we show that our results are not explained by a shift toward refinancing loans, the Covid-19 pandemic, local house price developments, or competition effects between fintechs.

To the extent that the CCPA makes users more willing to share data, it enables fintech lenders to offer lower rates, potentially by improving their ability to better screen with data.

Related literature. Our paper provides evidence on how the CCPA, one of the world’s most comprehensive privacy laws, affects fintech lending. It speaks to the growing literature on the consequences of data-sharing policies for loan markets and financial inclusion.

One strand of the literature focuses on policies that restrict information sharing. [Dobbie et al. \(2020\)](#) show that bankruptcy flag removal leads to economically large increases in affected borrowers’ credit limits and borrowing. However, by limiting lenders’ access to relevant information, bankruptcy flag removal can have large distributional effects across borrowers and create both winners and losers, with ambiguous welfare effects ([Liberman et al., 2019](#); [Jansen et al., 2025](#)). Similarly, the U.S. Card Act, which limited credit card lenders’ discretion to adjust interest rates in response to new information, reduced prices for high-risk consumers but increased them for others ([Nelson, 2025](#)). Europe’s General Data Protection Regulation (GDPR), which follows the key principle that firms need to minimize their data collection and processing activities, has decreased venture investments in data-related firms ([Jia et al., 2021](#)). Moreover, privacy-conscious consumers have used the GDPR to share less data, thereby creating externalities for the remaining consumers and losses for intermediaries ([Aridor et al., 2023](#)).

Other papers study the consequences of open banking, which allows customers to share their bank account history with third parties such as fintech lenders, but does not target data privacy per se. Improving fintechs’ access to previously unavailable data can result in better screening and loan market outcomes, especially for riskier borrowers ([Nam, 2022](#)). Yet open banking can have unintended negative consequences. If fintechs have a sufficiently superior screening technology, open banking could allow them to achieve market power beyond that of banks, resulting in lower borrower welfare ([He et al., 2023](#)). It can further hamper the efficient allocation of credit, as better-informed banks may reduce lending once data become open to their competitors ([Goldstein et al., 2022](#)). Finally, [Babina et al. \(2025\)](#) show that although open banking can spur fintech venture capital investments and innovation, it can discourage intermediaries’ data production, as they reap fewer benefits from collecting data.

Our paper examines the effects of privacy regulation that grants users control over their data and mitigates privacy concerns, and explicitly considers differences in privacy preferences across lenders. The setting thus differs from studies on the effects of policies that limit lenders' information set or have the goal to facilitate data sharing.

Our paper also relates to work studying the rise of fintechs and the attendant effects on other lenders. Important drivers behind fintechs' rising footprint in the U.S. mortgage market are an increased regulatory burden on banks and fintechs' superior technology with faster processing times (Buchak et al., 2018; Fuster et al., 2019). In addition, better access to data, notably from payments, can help fintechs compete with other lenders: fintech lenders can use payments data to obtain information about potential borrowers that compensates for the absence of an existing lending relationship (Ghosh et al., 2025).⁶ Fintechs competing for payments can also disrupt information spillovers from banks' payments to their lending services (Parlour et al., 2022). Most of the literature studying the rise of fintechs and their competition with other lenders has not explicitly considered the role of privacy preferences or data protection legislation (see Berg et al. (2022) and Bogaard et al. (2024) for surveys). We find that in the presence of privacy-sensitive consumers, privacy legislation can spur the growth of fintechs, which could increase the competitive pressure on other lenders.

2 Privacy preferences, the CCPA, and alternative data

This section first discusses evidence on consumers' privacy preferences and their willingness to share data. It then provides institutional background on the California Consumer Privacy Act, a comprehensive data privacy law that has set the standard for privacy legislation across the U.S. Finally, it discusses the use of alternative data in mortgage underwriting.

⁶Other papers look at privacy preferences, data availability, and firm performance (Begenau et al., 2018; Farboodi et al., 2019; Bian et al., 2022) or the growth of fintechs more broadly (Cornelli et al., 2021). Gupta et al. (2005) study how privacy regulation affects lenders' compliance cost and lending decisions.

2.1 Privacy preferences

As more and more economic activity moves online, personal data are turning into an increasingly important asset for firms (Acquisti et al., 2016; Jones and Tonetti, 2020). In loan markets, personal data can complement traditional credit scores when lenders screen prospective borrowers (Jagtiani and Lemieux, 2019; Berg et al., 2022). They can be directly collected, for example through loan applications, but also purchased from third-party data aggregators and vendors. Nontraditional data can include borrowers' education and employment history (Di Maggio et al., 2022), rent and utility payments (GAO, 2021), social network activity, and digital footprints (Berg et al., 2020).

At the same time, there is mounting evidence that consumers value their privacy (Goldfarb and Tucker, 2012). For example, Tang (2022) finds that consumers derive utility from withholding information when applying for a loan. Lin (2022) shows that a preference for privacy plays an important role in users' decisions to share data. In a representative survey of U.S. households, around three-quarters of respondents were very concerned about negative consequences when sharing their personal data (see Figure 2). Reasons mentioned by survey respondents include identity theft, personal safety, and reputational concerns (Armantier et al., 2021). More generally, the literature has highlighted concerns including price discrimination, data abuse, unethical advertising, and fraud (Chen et al., 2021; Lin, 2022; Prince and Wallsten, 2022; Bian et al., 2023).

Because financial intermediaries make extensive use of consumer data, an important question is in which counterparties consumers have greater confidence to safely handle their data and protect them from data abuse or misuse. Figure 1 shows that only 30% of U.S. households have high trust in fintechs, as opposed to 70% for other financial intermediaries (FI) such as banks or more established nonbank lenders. Chen et al. (2023) report a similar pattern for a large sample of countries.

2.2 The California Consumer Privacy Act

The CCPA is a data privacy law covering California that went into effect in January 2020. It endows Californians with several rights regarding the personal information that a firm collects about them. In particular, they have the right to know what personal information is being collected, whether it

is being sold, and, if so, to whom. They also have the right to access, delete, or opt out of the sale of their personal information (Camhi and Lyon, 2018). The CCPA applies to all data of California residents, irrespective of whether the firm they transact with is based in California or outside of the state. Many other states are considering similar legislation, and the U.S. Congress has considered the CCPA a blueprint for federal privacy legislation (Mulligan et al., 2019).⁷

Enforcement of the CCPA falls under the jurisdiction of the California Privacy Protection Agency and the Office of the Attorney General (OAG) in California. The agency conducts compliance sweeps and, if relevant, issues notices of alleged noncompliance. Companies then have 30 days to respond, and violations of the Act entail substantial fines: for intentional (unintentional) breaches, businesses may face fines of up to \$7,500 (\$2,500) *per violation*, and are additionally liable to cover up to \$750 per person per incident in damages. For companies with thousands of users, such as many mortgage lenders, potential fines could thus be substantial.

By granting consumers control over their data, the CCPA directly addresses several of the concerns that individuals list when it comes to sharing their data. Under the CCPA, any consumer can request that firms delete their data after a transaction or that it cannot be sold to third parties. Therefore, the CCPA reduces uncertainty about how intermediaries use personal information, from both the consumer and lender sides. As highlighted in an impact assessment of the CCPA by the California Department of Justice, if the CCPA increases consumers' trust in data protections, it could increase the amount of data that consumers are willing to share with firms.⁸

The CCPA is expected to have a stronger impact on applicants' attitudes toward sharing data with fintechs compared to other financial intermediaries. One reason is that, absent regulation, users have significantly lower confidence in fintechs to safely store their data and prevent data abuse. Lower trust in fintechs likely arises from users' perception that fintech companies are more likely to sell their personal data than other firms, as well as from a general distrust of opaque machine learning models and algorithmic judgment. It could also reflect that other lenders are already subject to a variety of regulations that at times include data sharing agreements. Finally, there is evidence that consumers have higher trust in firms and products with which they are more

⁷In 2021 alone, lawmakers in twenty-seven U.S. states proposed CCPA-like privacy legislation.

⁸See State of California Department of Justice: Standardized Regulatory Impact Assessment: California Consumer Privacy Act of 2018 Regulations.

familiar (Guiso and Makarin, 2020), which disadvantages newer fintech lenders.⁹ Consistent with these arguments, evidence from a randomized priming experiment suggests that the CCPA makes consumers more willing to share their data, and in particular with fintechs (Armantier et al., 2025).

However, although the CCPA can make consumers more willing to share data with lenders for a given transaction, it may limit the amount of data that lenders can sell to or buy from third parties. If so, the CCPA may change primarily the composition rather than the volume of data available to lenders. Although it restricts access to passive, third-party data, it increases the supply of active, permissioned data shared directly by borrowers. As we discuss below, the mortgage origination process is predominantly an active data environment, so fintechs may disproportionately benefit from the rise in active sharing, even if the volume of passive data declines.

In granting users control over their data, the CCPA differs from other data initiatives and regulations in important respects. For example, a key principle of the European Union’s General Data Protection Regulation (GDPR) is that firms need to minimize their data processing activities (Liu et al., 2020). Similar to policies such as bankruptcy flag removal, it effectively limits firms’ ability to gather and exploit information (Lieberman et al., 2019; Jansen et al., 2025; Johnson, 2022). Open banking, by contrast, mandates financial institutions to share their proprietary data with third parties, including fintech lenders, if users give their consent. As argued, the requirement to share data can benefit some borrowers, but can also discourage information acquisition (Babina et al., 2025), increase market concentration (He et al., 2023), or distort credit allocation (Goldstein et al., 2022).

The CCPA also differs from legislation that is specifically targeted at financial institutions, such as the Gramm-Leach-Bliley Act (GLBA). The GLBA covers nonpublic personally identifiable financial information gathered by financial institutions. The CCPA covers a much wider range of information, as it applies broadly to personal information. The CCPA exempts certain types

⁹Three-quarters of consumers believe that fintech companies are more likely to sell their personal data than traditional firms (IDX). A long-standing literature highlights barriers to consumer trust in algorithmic decision making (Glikson and Woolley, 2020; D’Acunto and Rossi, 2023). In the context of the U.S. mortgage market, Buchak et al. (2018) show that nonbanks accounted for over 25% of all mortgage originations already in 2007 (with steady growth since then), whereas Fuster et al. (2019) show that the number of fintechs increased substantially only after 2015. Other nonbank lenders may have longer-lasting relationships with clients than fintechs, which implies greater familiarity and might mitigate users’ concerns that data are misused.

of personal financial information that are subject to the GLBA, but it does not exempt covered companies from CCPA compliance.¹⁰

Were California residents aware of the introduction of the CCPA? According to a survey by the Consumer Action and Consumer Federation of America (2021), around 70% of respondents had seen the notice of their rights required by the CCPA on websites they visited.¹¹ Moreover, the majority of respondents had exercised their rights granted by the CCPA. For example, over 50% have asked firms to delete or not share their data. Consistent with these survey results, mortgage lenders often provide clear and plain-language explanations of what the law entails for California residents when they apply for a mortgage. In the Online Appendix we further show that Google searches for the CCPA in California increased steeply in late 2019 and remained elevated for most of 2020.

Overall, the CCPA gives consumers control over their data and provides them with greater confidence that their data will not be used for unintended purposes. Accordingly, the evidence suggests that it makes consumers more willing to share data, and in particular with fintech lenders. Additionally, the CCPA could reduce legal uncertainty and thereby make data-intensive fintechs in California more willing to use consumers' data, not just for technological but also for legal reasons. Both channels may reinforce each other: as consumers become more willing to share their data, lenders may become more willing to ask for and use personal data.

2.3 The use of alternative data in mortgage lending

In their decision whether to grant a loan, mortgage lenders traditionally rely on standardized credit scores by private providers such as FICO or Equifax, combined with application variables such as the loan-to-value ratio or applicants' debt-to-income ratio. However, lenders increasingly use alternative data to assess individuals' creditworthiness.

Alternative data can take various forms. They can include financial data, such as consumers' bank account transactions or their on-time rental, utility, and telecommunications payments data. The data can also be of a non-financial nature, for example applicants' educational institution or

¹⁰The CCPA exemptions apply to data "collected, processed, sold, or otherwise disclosed pursuant to the GLBA".

¹¹See Consumer Action and Consumer Federation of America (2021): California Consumer Privacy Act (CCPA) Survey. The survey queried 1,500 adults in California about their awareness of and experience with the CCPA.

the degree earned, as well as shopping habits and social media activity (GAO, 2021). Some lenders also use applicants' geolocation and the time of day of the application in assessing credit risk (Hiller and Jones, 2022).

Evidence shows that nontraditional data can significantly improve default prediction (Berg et al., 2020). For example, consumers' telco, pay-TV and utility payment history correlates strongly with future positive mortgage payment performance in the U.S. (Andrew Davidson & Co, 2023). The inclusion of these data is particularly useful for individuals who either do not have a traditional credit score or have an insufficient credit history (CFPB, 2017; Hair et al., 2025), which disproportionately includes lower-income and Black households (Choi et al., 2022). Fintech mortgage lenders already use such alternative data in assessing applicants. For example, Di Maggio et al. (2022) find that traditional credit scores are a good predictor of performance for loans funded by banks, but not helpful for differentiating borrowers of the fintech lender Quicken Loans.

An important obstacle to the wider use of alternative data in credit scoring is that it oftentimes requires consumers to opt in to its collection and use (Bradford, 2023).¹² Opting in to data collection requires that individuals believe that their data are safe and trust that they will not be abused for other purposes such as debt collection efforts or targeted advertising (GAO, 2021).

Another obstacle to underwriting with alternative data is that the GSEs currently restrict the types of data their automated underwriting system (AUS) processes. To be able to sell loans to GSEs, lenders must meet their underwriting and documentation requirements. To facilitate the origination of conforming loans, the GSEs provide lenders with access to their AUS, which have specific requirements on the types of data that lenders can feed into them. When lenders use nontraditional data for screening, the information needs to be transmitted manually, which makes the underwriting process for GSE loans more resource-intensive (GAO, 2021).

¹²Credit scoring firms are increasingly providing alternative credit scores that incorporate nontraditional data. FICO offers UltraFICO, but only if a consumer provides access to their checking, savings, or money market accounts. Experian offers Experian Boost, which relies on utility or telecom accounts, but also requires users to give their consent to the use of alternative data (Hiller and Jones, 2022).

3 Conceptual framework

To guide our empirical analysis, this section presents a simple conceptual framework. Suppose two types of lenders – one of which is a fintech – compete for privacy-conscious consumers. Before offering a loan, lenders must analyze personal data to screen applicants. These data can be standard, such as an individual’s credit score or proof of income. But lenders may ask for additional information, or applicants provide it, such as applicants’ education history, phone or electricity bills. Although more data improves the screening process for both types of lenders, the marginal benefit is likely larger for the fintech, either because fintechs are better at extracting a precise signal from a given amount of data or because they have access to less data initially.¹³

Consumers are concerned about the abuse or misuse of data when applying for a loan. Importantly, they are more concerned about sharing their data with fintechs than with the other lender. Some individuals might therefore be unwilling to contract with a fintech, or unwilling to share additional data, even for a lower interest rate.

Consider the introduction of a CCPA-like privacy legislation, which provides consumers with greater control over their data. Such legislation reduces concerns about the abuse and misuse of data and hence decreases consumers’ dislike of sharing them, consistent with the findings in [Athey et al. \(2017\)](#) and [Armantier et al. \(2025\)](#). This decline is more pronounced for sharing data with fintechs, an assumption that directly follows from [Figure 1](#) and [Figure 2](#).¹⁴ As discussed, the CCPA may also reduce lenders’ legal uncertainty about using personal data in screening, prompting lenders to ask for more data.

Applicants’ greater willingness to share data with fintechs as well as reduced legal uncertainty imply that fintechs can increase their use of data to improve their screening process ([Berg et al., 2020](#); [Di Maggio et al., 2022](#)). A more precise signal about borrowers’ quality is expected to lead to more individualized pricing across borrowers ([Babina et al., 2025](#); [Jansen et al., 2025](#)) and greater

¹³Our channel does not hinge on whether fintechs are better at extracting a signal from a given amount of data. The implications of superior technology are discussed in [Berg et al. \(2020\)](#); [Di Maggio et al. \(2022\)](#) and [He et al. \(2023\)](#). In our setting, as long as fintechs have less data ex-ante, the marginal benefit of more data will be greater for them. Better technology would have an amplifying effect, but is not necessary.

¹⁴[Athey et al. \(2017\)](#) find that priming a random sample of survey respondents with reassuring information about privacy protection makes consumers less likely to protect their data privacy. In a representative sample of U.S. households, [Armantier et al. \(2025\)](#) use a randomized priming experiment to show that the CCPA makes consumers more willing to share their data, and in particular with fintechs.

rate dispersion. In addition, it allows fintechs to better screen out low-quality applicants, which would lead to an increase in the share of denied applications. An improvement in fintechs' screening process therefore implies that the quality of the pool of borrowers that fintechs serve increases. In consequence, we expect that interest rates on loans originated by fintechs decline relative to other lenders. Consistent with the idea that the marginal benefit of additional data is greater the lower the initial level of information, we expect the effect of privacy regulation on the interest rate of fintech loans to be stronger among borrowers from traditionally underserved groups. The reason is that current credit scores do not paint an accurate picture of their future creditworthiness.

Finally, by reducing applicants' disutility from sharing data with fintechs, the CCPA might not only make individuals more willing to share data, but also more willing to apply to fintechs. If so, depending on the relative increase in applications and denial rates, overall mortgage originations by fintechs may increase.

4 Data and summary statistics

Our analysis uses publicly available loan-level data collected under the Home Mortgage Disclosure Act for 2018-2021. HMDA covers the vast majority of applications and originated mortgages in the U.S. It contains information on the lender, the application outcome, loan amount, loan program (e.g. conventional, FHA, or VA), borrower income, and borrower demographic characteristics such as census tract, race/ethnicity, and gender. Relative to earlier years, the data fields collected have been expanded since 2018. For mortgages originated in 2018 and later, HMDA includes information on property value, loan-to-value ratio (LTV), debt-to-income ratio (DTI), credit score type, borrower age, and, for approved loans, the interest rate, rate spread, and information on closing costs.

To identify fintechs in HMDA, we follow [Fuster et al. \(2019\)](#), who classify an originator as a fintech lender if they enable a mortgage applicant to obtain a preapproval online. We categorize lenders as banks if they are regulated by the Office of the Comptroller of the Currency (OCC, agency code 1), Federal Reserve System (FRS, agency code 2), the Federal Deposit Insurance Corporation (FDIC, agency code 3), or the Consumer Financial Protection Bureau (CFPB, agency

code 9). Lenders not classified as banks or fintechs constitute the group of other nonbank lenders. In our baseline regressions, we compare fintechs to other nonbank lenders, as differences in the regulatory framework between fintechs and nonbanks are smaller than those between fintechs and banks (Buchak et al., 2018).

For our analysis, we restrict the sample to conventional & conforming home purchase, refinance, and cash-out refinance loans of single-unit principal residences. We drop loans classified as primarily for a business or commercial purpose, open-end lines of credit, with a balloon payment, and reverse mortgages. We keep only those loans secured by a first lien; drop observations with missing loan term or applicant income, age, or sex; as well as those with a missing property state or county code; or those applications classified as “files closed for incompleteness”.

Further, we focus on mortgage applications in counties that lie on the border of California (CA) and its neighboring states Arizona (AZ), Nevada (NV), and Oregon (OR). Border counties are generally similar along many observable characteristics, mitigating concerns about selection effects and omitted variable bias.¹⁵

Our main outcome variable is the interest rate. In addition, we use the dummy *Denied* (0/1) that takes on a value of one if a loan application was denied and zero otherwise. We further define the dummy *Alt CS* (0/1), which takes on a value of one if the application has not been processed with the standard models, i.e. Equifax Beacon, Experian Fair Isaac, FICO Risk Score Classic 04, FICO Risk Score Classic 98, VantageScore 2.0, or VantageScore 3.0. This categorization thus includes the options “More than one credit scoring model”, “Other credit scoring model”, and “Not applicable”. In addition, we define the variables *Alt CS narrow* (0/1) and *Alt CS very narrow* (0/1) that do not include the “Not applicable” and “More than one credit scoring model” options, respectively. We discuss the limitations of these measures below.

At the lender-tract-year level, we compute the dispersion in interest rates across originated mortgages. To study the extensive margin of lending, we calculate the number of applications and originated mortgages at the lender-tract-year level.

¹⁵We report the full list of border counties in our sample in the Online Appendix.

Descriptive statistics. Our final sample contains over 560,000 mortgage originations between 2018 and 2021 in 1,846 census tracts in border counties. [Table 1](#) provides summary statistics for our main variables. Fintechs originate 26.3% of all mortgages. The average interest rate (spread) charged was 3.4% (3.1%), with a standard deviation of 0.81 (0.47). The share of loans processed with nontraditional credit scores was 10.5%, compared to 4.6% for the narrow measure.¹⁶

[Table 2](#) provides summary statistics for applicants to fintechs and other nonbank lenders prior to the introduction of the CCPA. At the loan level, we regress the dummy *Fintech (0/1)* on applicant characteristics, with the control group being other nonbank lenders. In 2018–19, applicants are statistically similar in terms of most characteristics, with applicants of age 62 and above being more common among fintech lenders (consistent with [Fuster et al. \(2019\)](#)). These patterns hold without or with the inclusion of tract×time fixed effects in columns (1) and (2). Beyond statistical insignificance, most coefficient estimates are small in terms of economic magnitude. Overall, these patterns suggest that applicants served by fintechs and other lenders are economically and statistically comparable in border counties prior to the introduction of the CCPA.

5 The CCPA and loan market outcomes

This section exploits the introduction of the California Consumer Privacy Act in 2020 to test the hypotheses developed in [Section 3](#). We first investigate the effects of the CCPA on loan rates. To study the channels, we then focus on borrowers from traditionally underserved groups and explore how the CCPA affects fintechs’ individualized pricing, application denial rates, and use of alternative credit scores. Finally, we analyze the effects on mortgage applications and originations.

¹⁶The Online Appendix provides a detailed overview of the main variables used.

5.1 Empirical strategy

To study the effects of the CCPA on loan market outcomes, we estimate the following regression at the loan level:

$$y_{i(l,c,t)} = \delta_1 CA_c \times Post_t + \delta_2 Fintech_l \times Post_t + \delta_3 CA_c \times Fintech_l \times Post_t + controls_i + \theta_{l,c} + \tau_{c,t} + \phi_{l,t} + \varepsilon_i. \quad (1)$$

The main dependent variable is the interest rate on mortgage i originated by lender l to a borrower in census tract c in year t . The dummy variable CA varies at the state level and takes on a value of one if the property is located in California and zero if it is located in a neighboring state. The dummy $Post$ takes on a value of one in the years after the CCPA was enacted (i.e. for the years 2020 and 2021) and a value of zero in 2018 and 2019. $Fintech$ is a dummy that takes on a value of one if the lender is a fintech and a value of zero if it is another nonbank lender. We compare fintechs to other nonbanks to ensure that results are not explained by differences in regulation.¹⁷ Our main coefficient of interest is δ_3 , which shows the effect of the CCPA on, for example, loan rates on fintech mortgages relative to mortgages originated by other nonbank lenders in California, compared to other states. All regressions include lender \times tract ($\theta_{l,c}$) fixed effects that absorb any time-invariant characteristics at the lender-applicant tract level. We only exploit variation within each lender-tract cell. Standard errors are clustered at the borrower-tract level.

To account for the possibility that fintechs serve different customers than other nonbanks, we control for a large number of loan- and borrower-level characteristics: the loan amount and the property value (both rounded to the nearest \$10k in the public HMDA data), the loan term (in months), the loan program, the LTV ratio (as linear control and bins)¹⁸, the DTI ratio bracket, loan purpose, borrower income, age bracket, race, ethnicity, sex, credit score type, and whether there is a co-applicant. We furthermore control for total loan closing costs relative to the loan

¹⁷The Online Appendix reports results when we include banks in the control group.

¹⁸The combined LTV (CLTV) is directly provided in HMDA, though not for all loans. We therefore calculate the LTV ratio manually, by dividing the (rounded) loan amount by the (rounded) property value. The resulting value is highly correlated with the HMDA CLTV when provided. To construct bins, we group borrowers into those with LTV ratios $< 70\%$, $[70 - 80\%)$, $[80 - 90\%)$, $[90 - 100\%)$, $> 100\%$.

amount.¹⁹ Importantly, we include the interaction terms of all loan- and borrower-level variables with the *California* and *Post* dummies as controls in our regressions.

In addition, we include granular time-varying fixed effects in Equation (1). First, we include tract \times time fixed effects ($\tau_{c,t}$), which absorb any observable and unobservable differences in tract characteristics over time. For example, they control for changes common to applicants and borrowers within a tract, such as changes in GDP growth, internet access, or employment dynamics. They also control for potential differences in the severity of the Covid-19 pandemic and associated movement restrictions across tracts, an issue we revisit below. With tract \times time fixed effects, we essentially compare applications to different lenders from individuals in the same tract and year. Second, we include lender type \times time fixed effects ($\phi_{l,t}$) to control for changes in observed and unobserved characteristics of each type of lender. These control, for example, for the effects of changes in the Fed funds rate on fintechs' or other nonbanks' funding costs, or changes in the regulatory environment.

In essence, Equation (1) is a difference-in-differences-in-differences (DDD) specification. The key identification concern in our empirical strategy is thus that time-varying confounders may develop differently across our treatment and control group. This requires us to find an additional control group that is not subject to the treatment in California but to the time-varying confounders (for example trends affecting fintechs and other nonbank lenders as well as California and other states). In our case, the comparison of fintechs versus other nonbank lenders in California to fintechs versus other nonbank lenders in neighboring states presents such a comparison.

The DDD estimator can be interpreted and computed as the difference between two difference-in-differences estimators (Olden and Møen, 2022). The parallel trend assumption thus requires the difference in loan rates between fintechs and other nonbank lenders to evolve similarly in California relative to neighboring states (i.e. the triple difference). The DDD estimator does not require the loan rate to evolve similarly in California and other states in general pre-CCPA, nor is it required for the loan rate to evolve on a parallel trend for fintechs versus other lenders in all states pre-CCPA. For example, demand for mortgages may increase with the CCPA for all lenders, leading to upward pressure on rates. This demand channel would work against the negative effect of the

¹⁹We winsorize the LTV ratio, loan amount, property value, loan term, and borrower income, as well as closing costs relative to loan amount at the 1st and 99th percentile to reduce the importance of outliers.

CCPA on loan rates through the data/information channel. Our most demanding specification will absorb any such differential trends between fintechs and other lenders or California and other states through time-varying fixed effects.

5.2 Results on loan rates

As laid out in Section 3, an improvement in fintechs’ screening process because of greater data sharing should lead to lower loan rates relative to other lenders. Table 3 estimates variations of Equation (1) and shows the effect of the CCPA on the interest rate charged by fintech lenders versus other nonbank lenders. Column (1), with lender \times tract and year fixed effects, reports a significant and negative coefficient on the triple interaction term, i.e. $\delta_3 < 0$. This finding suggests that fintechs in California decreased their interest rate compared to other nonbanks after the CCPA was introduced compared to developments in other states. Moreover, we find that loan rates went up in California relative to other states ($\delta_1 > 0$). They did so by more for fintechs than other nonbank lenders across all states ($\delta_2 > 0$). These patterns suggest the following: for fintechs in California, the data/information channel dominates the demand channel, leading to lower rates. For non-fintechs, the demand channel dominates the information channel, leading to relatively higher rates.²⁰

Next, we add granular fixed effects. To ensure that the results are not driven by unobservable time-varying tract characteristics, including demand effects, column (2) tightens identification by adding tract \times time fixed effects, which absorb the coefficient on $CA \times Post$. Our estimated coefficients barely change in magnitude or significance. Similarly, when we add lender type \times time fixed effects to control for unobservable factors affecting fintechs and other nonbanks in column (3), δ_3 remains negative, significant at the 1% level, and similar in magnitude to the coefficients obtained in columns (1) and (2). Lender type \times time fixed effects absorb the coefficient on $Fintech \times Post$. These results suggest that observable and unobservable characteristics that vary over time at the borrower tract or lender type level are not systematically correlated with the CCPA’s effect on fintechs versus other lenders in California compared to other states. Finally, column (4) adds our battery of loan- and borrower-level control variables and fixed effects. The coefficient on the triple

²⁰We revisit applications, originations, and credit demand in Table 7.

interaction term and its standard deviation decline in magnitude while the estimate remains highly statistically significant.

In terms of magnitudes, the estimated coefficient on the triple interaction effect in column (4) shows a relative decline of 7 bps (0.09 standard deviations) in the yearly interest rate on fintech mortgages.²¹ Accounting for borrower and loan characteristics reduces the size of the estimated coefficient only modestly.

To assess whether there were any differential pre-trends in interest rates between fintechs and nonbanks, we estimate how rates by fintechs change compared to nonbanks in each year in California compared to other states. [Figure 3](#) plots the coefficient estimates with 90% confidence intervals from Equation (1), in which we replace the *Post* dummy with dummies for each year in the sample. The omitted year is 2019, i.e. the year before the CCPA came into effect. There is no statistically significant difference in the trend in the rate on loans originated by fintechs relative to other nonbanks in California prior to the introduction of the CCPA in 2020, relative to other states. Rates decline, however, by significantly more for mortgages originated by fintechs compared to other nonbanks after the introduction of the CCPA in 2020. The gap persists in 2021, suggesting a lasting effect.²²

5.3 Examining the channel

As discussed in our conceptual framework, the decline in rates on fintech loans could reflect an improvement in fintechs' screening ability. To examine this possibility, we first focus on borrowers from traditionally underserved groups. In a second step, we analyze denial rates and individualized pricing. And third, we provide suggestive evidence on the use of alternative data in loan processing.

Underserved groups. For borrowers from traditionally underserved groups, including minority and lower-income applicants, traditional credit scores provide an inaccurate assessment of future credit risk ([Blattner and Nelson, 2024](#); [Choi et al., 2022](#); [Di Maggio et al., 2022](#)). We expect that the CCPA, by increasing the amount of data available, lowers the interest rate on loans by fintechs

²¹For the average mortgage with an amount of \$311,385 and a typical maturity of 30 years, these lower loan rates amount to a reduction in total interest expenses of approximately \$6,500.

²²We rule out the existence of a linear trend with power analyses following [Roth \(2022\)](#), see Appendix.

especially for such applicants. We thus define underserved borrowers either as borrowers that report their race/ethnicity as Black and/or Hispanic; or as borrowers with an income below the average income of all borrowers in the sample.

Table 4 reports results. The negative effect of the CCPA on rates by fintechs is larger in magnitude for minority borrowers and low-income borrowers. The absolute difference is 3.3 bps for borrowers classified according to race/ethnicity (-0.063 versus -0.096 in columns 1–2). It is 2.6 bps for borrowers classified according to income (-0.051 versus -0.077 in columns 3–4).²³

Denial rates and individualized pricing. To the extent that privacy legislation, in the spirit of the CCPA, provides consumers with greater confidence that their data will not be used for malicious purposes, consumers may become more willing to share information with initially less trusted fintechs. As a consequence, we expect that fintechs can better screen out low-quality applicants and engage in more individualized pricing.

Table 5 first reports results for Equation (1) at the applicant level with the dummy *Denied* as dependent variable. We estimate a parsimonious specification in column (1) and a regression with the full set of controls and fixed effects in column (2). In both columns, denial rates by fintechs significantly increase after the introduction of the CCPA, relative to other nonbanks. In column (2), the probability of denial increases by 1 percentage point (pp), relative to a mean denial rate of 8.5%. The Online Appendix shows that denial rates increase by relatively less among applicants from underserved groups, consistent with fintechs becoming better at identifying higher-quality applicants within this group.

In columns (3) and (4) the dependent variable is the standard deviation in interest rates across loans within each lender-tract-year cell. Column (3) shows a significant and positive coefficient on the triple interaction term: the dispersion in interest rates increases by significantly more for fintechs relative to nonbanks in California. Column (4) again tightens identification by adding tract \times time and lender type \times time fixed effects, as well as including the average of our controls at the borrower and loan level within each lender-tract-year cell as control variables or the median value as a fixed effect. In terms of magnitude, dispersion increases by about 3 bps, or 8% (12%)

²³When we test for whether coefficients statistically differ, we obtain $F(1, 56) = 2.87$ and $Prob > F = 0.096$ for columns (1) and (2) and $F(1, 56) = 2.14$ and $Prob > F = 0.114$ for columns (3) and (4).

of its unconditional mean (standard deviation). These results are consistent with the hypothesis that fintechs obtain a more precise signal from additional data. In support of this interpretation, in Section 6 we show that default rates decline by more for fintechs than for other lenders after the CCPA was introduced.

Suggestive evidence on the use of alternative data. Systematic information on lenders’ use of data in the screening process is difficult to obtain. We therefore cannot directly assess whether the information used by fintechs and other lenders in screening changes as the CCPA is introduced. To proxy the use of alternative data, we examine lenders’ use of nontraditional credit scores in processing mortgages.

As discussed in Section 4, we define the dummy *Alt CS (0/1)*, which takes on a value of one if the application has not been processed with the standard models. Two important caveats need to be kept in mind when interpreting this variable. First, for the option more than one credit scoring model, we cannot disentangle whether this means that the lender used a combination of traditional models or a combination of traditional and nontraditional models. Second, according to CFPB guidelines lenders should select “Not applicable” when the applicant has no credit score. To address the concern that our variable captures an (unobservable) shift in the applicant pool toward those with no credit score, we also use the variable *Alt CS narrow (0/1)* that does not include the “Not applicable” option, as well as the variable *Alt CS very narrow (0/1)* which takes on a value of one when a loan was processed via an “Other credit scoring model” only.

Table 6 shows results from loan-level regressions with the indicator variables *Alt CS (0/1)*, *Alt CS narrow (0/1)*, and *Alt CS very narrow (0/1)* as dependent variables. As discussed, the use of nontraditional data is arguably more important among loans not sold to the GSEs. To proxy for non-GSE loans, we restrict the sample to loans not sold at the end of the calendar year, which likely includes a larger fraction of non-GSE loans.²⁴

For each of the three measures in columns (1)–(3), the coefficient estimate is positive and statistically significant. The coefficient estimates suggest that the share of loans processed with nontraditional credit scores increases by 8.8 pp for the broad, 6.8 pp for the narrow, and 0.5 pp for

²⁴The HMDA data only record whether a loan has been sold by the end of the reporting year. This leads to some measurement error because of the frequent 1–3 month lag between when a loan is originated and when it is sold.

the very narrow measure for fintechs in California post-CCPA, relative to other nonbanks. This compares to mean shares of 19.9%, 13%, and 1% for each measure, respectively.

Next, we examine lender heterogeneity in their ex-ante use of alternative credit scores. We estimate Equation (1), but add an interaction term of the *CA*, *Post*, and *Fintech* dummies with each lender’s average share of loans processed in the pre-CCPA period with the broad, narrow, and very narrow definition of *Alt CS*. A greater ex-ante use of *Alt CS* could indicate that a fintech stands to benefit more from additional data shared by consumers.

Column (4) first confirms the negative effect of the CCPA on fintech loan rates compared to other lenders in California in the smaller sample of non-GSE loans. Columns (5), (6), and (7) then add the additional interaction effects with *Alt CS (pre)* for the broad, narrow, and very narrow measures. They yield negative and statistically significant coefficients for all three measures, suggesting that greater use of *Alt CS* leads to larger rate declines.

Taken together, we tentatively conclude that the CCPA has increased fintechs’ use of alternative credit scores among loans not sold to the GSEs. However, we want to emphasize that this conclusion is subject to strong assumptions on how to interpret the underlying data.²⁵

5.4 Applications and originations

Our results so far suggest that the CCPA, by increasing consumers’ willingness to share data, has benefited borrowers through lower loan rates. We now investigate whether the introduction of the CCPA has affected loan applications and originations, i.e. improved access to credit along the extensive margin.

First, at the loan level, we estimate:

$$fintech_i = \delta_1 CA_c \times Post_t + controls_i + \theta_c + \tau_t + \varepsilon_i. \quad (2)$$

²⁵An alternative way to classify loans kept on balance sheet would be to focus on jumbo loans. However, in our sample less than 5% of all observations are jumbo loans, and less than 4% of all fintech loans are jumbo loans. Moreover, jumbo loans usually require the borrower to have a stellar credit score and a low DTI. The market for jumbo loans is thus a market segment where we do not expect nontraditional data to make a difference, as credit scores get increasingly accurate in predicting borrower default the higher they are. The Online Appendix reports results that show no statistically significant effect of the CCPA on loan rates when we restrict the sample to jumbo loans only, nor is there any systematic evidence that fintechs became significantly more or less likely to originate a jumbo loan relative to other lenders post-CCPA.

The dependent variable is a dummy that takes on a value of one if the originator of mortgage i is a fintech. We estimate the equation once for applications and once for originations. The outcome is a dummy variable, which would suggest using a probit regression, but this would preclude the use of granular fixed effects and come at the cost of not being able to control for confounding factors. We thus estimate a linear probability model.

Second, we estimate Poisson regressions at the lender-tract-year level with total applications or originations in each lender-tract-year cell as dependent variable:

$$y_{l,c,t} = \delta_1 CA_c \times fintech_l \times post_t + controls_i + \theta_{l,c} + \tau_{c,t} + \phi_{l,t} + \varepsilon_{l,c,t}. \quad (3)$$

Table 7 reports results. Loan applications to and originations by fintechs increase in California after the introduction of the CCPA compared to other nonbank lenders. Applications increase by relatively more than originations, reflecting the higher denial rates. Columns (1) and (2) suggest that the relative likelihood that an application is made to a fintech increases by 3.3% and the relative probability that a loan origination is made by a fintech increases by 3% post-CCPA in California compared to other states in the sample. However, in interpreting magnitudes it is important to keep in mind that we estimate linear probability models.

Columns (3) and (4) suggest that in the average lender-tract cell, both applications to and originations by fintechs increase. Expressed in terms of incidence rate ratios (the rate at which an event occurs), which is computed as the exponentiated coefficients, the incidence of an application to or origination by a fintech is 1.078 and 1.066 times higher in California after the CCPA was introduced compared to neighboring states. In interpreting the magnitude of the effects of the CCPA on applications and originations it is important to note that we cannot fully rule out confounding effects of the Covid-19 pandemic. The attendant restrictions on movements could have led to increased applications to fintechs, as applicants were unable to visit branches. By focusing on border tracts and including tract \times time fixed effects, our analysis controls for the severity of the pandemic in each census tract, but cannot fully rule out differential effects between lenders within a tract. We revisit the issue below.

6 Additional tests

Borrower quality and loan default. The public HMDA data contain no information on applicants’ credit scores or on loan performance. To address these limitations, we use publicly available GSE loan-level data as in [Buchak et al. \(2018\)](#). Similar to our HMDA baseline loan-level regressions, we keep all loans for single-unit properties classified as principal residence originated between 2018–2021 for the purpose of home purchases / refinancing / cash-out refinancing. We drop loans with balloon payment and reverse mortgages. We also drop loans where the seller is identified as “Other” and where the borrower’s credit score is missing. To study loan performance, we categorize a loan as in default if the loan is at least 30 days delinquent a year after origination.²⁶

Before analyzing the role of borrowers’ credit scores and default, it is important to highlight that the GSE and HMDA datasets differ in two important dimensions. First, the most granular geographic unit for the GSE data is the three-digit zip code. We restrict our analysis to zip codes that have any portion in a bordering county, which means that we might be including some mortgages for properties outside of border counties. Consequently, our regressions include zip code fixed effects whereas in HMDA we include census tract fixed effects. Second, the GSEs report the seller of the loan and not the loan originator. We therefore restrict our sample to retail originations, where the seller and the originator are the same, to properly identify nonbank and fintech originators.

We estimate loan-level regressions as in Equation (1). All regressions include as controls the log of the loan amount and of the property value, the LTV ratio, the loan term, whether there is a co-applicant, whether the loan is an adjustable rate mortgage (only present in Freddie Mac data) and fixed effects for the DTI ratio bracket, the GSE that purchased the loan, and the purpose of the mortgage. In addition, we include the borrower credit score in brackets following Experian’s categorization. As above, all controls are interacted with the *California* and *Post* dummies. To control for the timing of the loan origination within-year, the granular fixed effects are at the quarter-year level instead of at the year level.

²⁶The CFPB considers mortgages that are 30-89 days delinquent as early stage delinquencies. In the GSE dataset, we verify whether the mortgage is at least 30 days delinquent one year after origination, and assign a time-invariant indicator to those loans. We therefore control for time since origination implicitly in our definition of default.

Table 8 reports the results. Columns (1) and (2) use the interest rate as the dependent variable, whereas columns (3) and (4) use a dummy that takes on the value of one if the loan is at least 30 days delinquent a year after origination. The results show that interest rates on fintech loans decreased in California by an additional 3.6 basis points more than for other nonbanks after the CCPA was introduced. The magnitude of the effect decreases only slightly when we include the credit score in column (2). Defaults one year after origination also decreased significantly, without or with the credit score included as control (columns 3 and 4). In terms of economic magnitude, defaults on fintech loans declined by 25% of the mean default rate more than for other nonbanks in California post-CCPA.²⁷

Taken together, these results suggest that the decline in interest rates on fintech mortgages post-CCPA is unlikely to be an artifact of imperfectly controlling for borrower quality or risk. Moreover, the fact that we find a decrease in defaults among fintech mortgages post-CCPA is consistent with our argument that the CCPA enabled fintechs to improve their screening ability.

In principle, a relative increase in the quality of the pool of *applicants* to fintechs post-CCPA could also explain why fintechs can offer lower rates. As the public HMDA data do not provide applicants' credit score, we proxy applicant quality with the log of applicant income, the log of the loan-to-income (LTI) ratio, and the log of the loan-to-value (LTV) ratio. In the Online Appendix, we show that there was no statistically or economically significant change in applicant quality between fintechs and other lenders when the CCPA was introduced.

Extensions and robustness. We perform a number of robustness tests to our baseline analysis. As shown in Table 9, our results remain robust when we compare fintechs to banks and when we use the rate spread rather than the interest rate (columns (1) and (2)).²⁸ When we interact the dummies *CA*, *Post*, and *Fintech* with a dummy for purchase loans, we find no differential effect of the CCPA on fintech loan rates between refinance (refi) and purchase loans; nor do we find an

²⁷In unreported regressions, we find that defaults decrease if we use alternative definitions of default, for example 30-day delinquency two years after or anytime after origination. However, although coefficient estimates are always negative, they are not always significant.

²⁸We report results for other outcome variables when we include banks in the Online Appendix. The rate spread is defined as the difference between a loan's interest rate (in terms of annual percentage rate, APR, which incorporates upfront costs) and the average APR on similar-maturity mortgage loans issued to prime borrowers *at the same time*. The rate spread thus incorporates any effects of origination costs, discount points, etc.

economically or statistically significant coefficient on the triple interaction term for the likelihood of an application or loan being for refinancing purposes (columns (3)–(5)). Results also remain similar when we control for the severity of the Covid-19 pandemic or changes in local house prices and their differential effects on fintechs versus other nonbank lenders (columns (6)–(8)). Finally, results remain robust to the inclusion of loan size $\text{bin} \times \text{time}$ fixed effects (column (9)). These results suggest that our headline finding is not explained by a shift in the loan mix toward refinance or larger loans, nor the severity of the Covid-19 pandemic, nor changes in local house prices.

[Table 10](#) assesses heterogeneity in the impact of the CCPA on fintech loan rates across regions. We estimate Equation (1) and interact the dummies *CA*, *Fintech*, and *Post* with the following county-level measures (averaged over the pre-CCPA period): the mortgage market share of fintech lenders, the number of bank branches per capita, the market share of banks, the share of the rural population, and the share of employees in high-tech sectors.²⁹

Column (1) shows that the effect of the CCPA introduction on rates charged by fintechs versus other lenders does not differ economically or statistically with the ex-ante fintech share. This null finding suggests that data-intensive fintechs do not compete more fiercely via price because they are more exposed to a loss of passive data after the CCPA was introduced. Columns (2) and (3) show that the CCPA-induced rate decline among fintechs is stronger where bank branches were scarce or banks’ market share was smaller. These results could suggest that fintechs can compete more effectively where banks’ presence is smaller as users share more data post-CCPA. The patterns also support a financial inclusion mechanism, rather than a bank-retrenchment story. Column (4) shows that the CCPA-induced effect on fintech rates is weaker in more rural counties, which likely have weaker broadband and digital adoption. The privacy-induced data-sharing channel might be muted there. Finally, column (5) reveals that the effect of the CCPA on mortgage rates by fintechs in California is relatively stronger in counties with a higher employment share in high-technology industries. Where data and IT talent are more ample, the channel linking privacy regulation to data usability may thus be stronger. However, the estimated coefficient is statistically not significant.

Finally, the Online Appendix reports coefficient estimates on the triple interaction term in Equation (1) when we compare all states covered in the data (minus California) to each other in

²⁹High-tech industries are those central to the production of digital and advanced technologies, such as electronics, telecommunications, and software.

a pairwise fashion. This results in a total of 1,225 placebo regressions. Nine out of ten regressions yield a coefficient estimate that is smaller than that of California (i.e. has a value closer to zero than -0.076). 7.5% of all regressions yield a coefficient that is statistically significant at conventional levels, and less than 2.5% of all regressions yield a t-value that exceeds the value obtained in our baseline regression for California. Only 11 of the 1,225 placebo regressions result in a larger coefficient estimate that is at least as significant as our estimate obtained for California.

7 Conclusion

Individuals are constantly generating a wealth of personal data. These data contain valuable information about consumers' creditworthiness and their ability to repay. Financial intermediaries, and in particular fintechs, stand to gain from better access to data, with benefits to consumers. Consumers, however, are increasingly concerned that they have lost control over their personal data and worry about the misuse of their personal information. Privacy concerns can deter them from sharing personal data, slowing down the growth of innovative financial companies and eventually limiting the benefits financial innovation brings to consumers. Regulators therefore face a trade-off: effective privacy regulation must protect users' privacy without negating the benefits obtained from intermediaries' access to data.

Our results suggest that the 2020 California Consumer Privacy Act was successful in mitigating this trade-off. The CCPA's philosophy is to grant consumers control over their data, thereby reducing their privacy concerns. In turn, it may have made users more willing to share their information and lenders more willing to use personal data. Comparing fintechs to other nonbank lenders in counties along both sides of the California border we find that fintechs decrease their interest rates by relatively more and we provide evidence consistent with this effect being driven by fintechs' improved ability to screen applicants.

Our results have implications for the policy debate on how to regulate the use of personal data. They suggest that privacy protection legislation that enhances control over data can protect users' privacy while still providing firms with access to data. The CCPA could hence be seen as

a successful regulatory initiative that holds important lessons for other U.S. states and countries designing privacy legislation.

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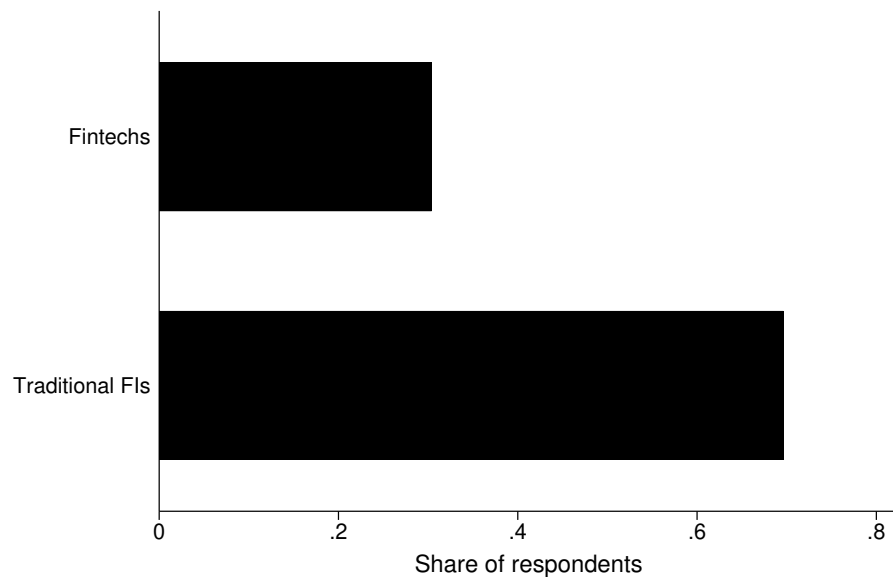
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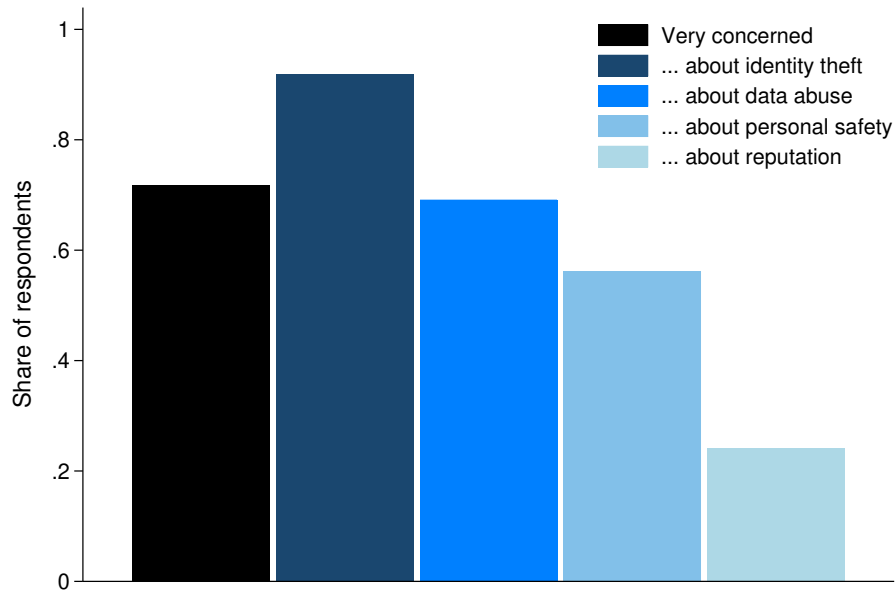
A Figures and tables

Figure 1: Consumers have low trust in fintechs to safeguard their data



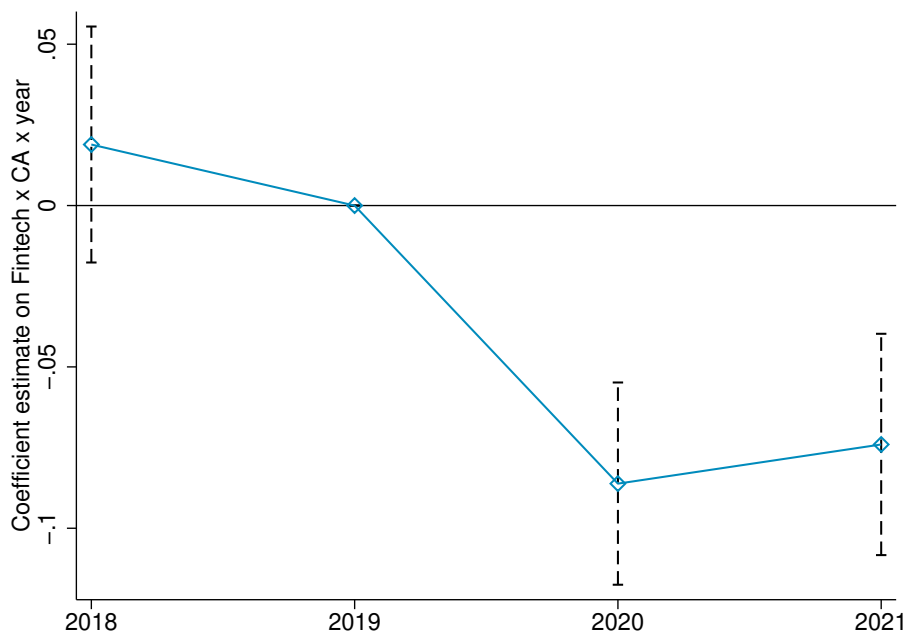
This figure shows the share of respondents reporting “high trust” in counterparties, based on a representative sample of 1,361 U.S. households in September 2020 who were part of the Survey of Consumer Expectations (SCE) of the Federal Reserve Bank of New York. Respondents place “high trust” in a counterparty if they assigned a score of 6 or higher to the question “How much do you trust the following entities to safely store your personal data (that is, your bank transaction history, geolocation or social media data)?”, on a scale from 1 (no trust at all in ability to safely store personal data) to 7 (complete trust). Source: SCE and [Armantier et al. \(2021\)](#).

Figure 2: Consumers are concerned about sharing their data



This figure shows concerns about sharing data online, based on a representative sample of 1,361 U.S. households in September 2020 who were part of the Survey of Consumer Expectations (SCE) of the Federal Reserve Bank of New York. Respondents are “very concerned” about sharing their data online when they assigned a score of 5 or higher to the question “Are you concerned that sharing your personal data could have negative consequences for you?”, on a scale from 1 (not at all concerned) to 7 (extremely concerned). Regarding specific concerns, the numbers provided denote the share of respondents who answered yes to the question “What are you specifically concerned about if your personal data were to become publicly available?”, where specific concerns are identity theft, data abuse, personal safety, and personal reputation. Respondents could answer yes to more than one option. Source: SCE and [Armantier et al. \(2021\)](#).

Figure 3: **Pre-trends in loan rates**



This figure plots the coefficient estimates (blue line) and 90% confidence intervals (gray bars) of the estimated coefficients on the triple interaction term obtained from Equation (1), but with dummies for each year in the sample instead of the *Post* dummy. Coefficient β_k indicates the evolution of interest rates on loans by fintechs in year k before/after the introduction of the CCPA in California. The year prior to the introduction of the CCPA ($k = 2019$) is the omitted category. The regression includes the full set of fixed effects, including lender \times time fixed effects.

Table 1: **Summary statistics**

Variable	Obs	Mean	Std. Dev.	Min	Max	P50
Fintech (0/1)	560337	.263	.441	0	1	0
Interest rate	560337	3.443	.808	2	5.625	3.25
Rate spread	553877	.314	.471	-1	10	.237
Alt CS model broad (0/1)	560337	.105	.307	0	1	0
Alt CS model narrow (0/1)	560337	.046	.21	0	1	0
Income	560337	106.478	65.799	20	755	93
Asian (0/1)	560337	.084	.277	0	1	0
Black (0/1)	560337	.032	.176	0	1	0
Hispanic (0/1)	560337	.209	.407	0	1	0
Female (0/1)	560337	.244	.429	0	1	0
Age below 35 (0/1)	560337	.187	.39	0	1	0
Age above 62 (0/1)	560337	.195	.396	0	1	0
DTI below 36pc (0/1)	560337	.432	.495	0	1	0
LTV ratio	552894	.7	.174	.171	.973	.728
Property value	552894	460.864	174.919	165	3235	435
Loan amount	560337	311.865	112.891	85	595	305
Loan term	560337	335.575	59.276	120	360	360
Cost/amount	560337	.017	.01	0	.043	.015
Loan is ARM (0/1)	560337	.007	.081	0	1	0
Has coapplicant (0/1)	560337	.453	.498	0	1	0
Purchase (0/1)	560337	.334	.471	0	1	0

This table reports summary statistics for borrower and loan characteristics. The interest rate and rate spread are in percent. Income, property value, and loan amount are in USD thousand. The loan term is in months.

Table 2: **Balancedness in applicant characteristics**

VARIABLES	(1) Fintech (0/1)	(2) Fintech (0/1)
Log(income)	0.016 (0.013)	0.014 (0.010)
Female (0/1)	0.006 (0.005)	0.004 (0.005)
Black (0/1)	0.012 (0.010)	0.018 (0.013)
Asian (0/1)	-0.014 (0.024)	-0.011 (0.016)
Age above 62 (0/1)	0.065** (0.031)	0.064** (0.029)
Age below 35 (0/1)	-0.040 (0.030)	-0.038 (0.027)
Has coapplicant (0/1)	-0.016 (0.011)	-0.016 (0.010)
DTI below 36 (0/1)	0.025 (0.017)	0.019 (0.014)
Observations	173,460	173,423
R-squared	0.008	0.051
Tract*Time FE	-	✓

This table reports a balancedness test for applicant characteristics in 2018 and 2019 at the loan level. It regresses the dummy *Fintech (0/1)* on HMDA applicant characteristics. The control group is other nonbank lenders.

Table 3: The CCPA and loan rates

VARIABLES	(1) Interest rate	(2) Interest rate	(3) Interest rate	(4) Interest rate
CA x Post	0.068*** (0.021)			
Fintech x Post	0.096*** (0.015)	0.094*** (0.016)		
CA x Fintech x Post	-0.073*** (0.019)	-0.075*** (0.019)	-0.076*** (0.020)	-0.070*** (0.012)
Observations	560,337	560,212	560,212	551,947
R-squared	0.743	0.747	0.747	0.814
Lender*Tract FE	✓	✓	✓	✓
Year FE	✓	-	-	-
Tract*Time FE	-	✓	✓	✓
Lender*Time FE	-	-	✓	✓
Controls	-	-	-	✓

This table reports results for Equation (1). The dependent variable is the interest rate. The dummy *CA* takes on a value of one if the property is located in a tract in California. The dummy *Post* takes on a value of one in the years after the CCPA was enacted. The dummy *Fintech* takes on a value of one if the lender is a fintech and a value of zero otherwise. Standard errors (in parentheses) are clustered at the borrower-tract level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: **Borrowers from underserved groups**

	(1)	(2)	(3)	(4)
VARIABLES	No minority Interest rate	Minority Interest rate	High inc Interest rate	Low inc Interest rate
CA x Fintech x Post	-0.063*** (0.014)	-0.096*** (0.011)	-0.051*** (0.015)	-0.077*** (0.015)
Observations	410,627	117,220	204,490	320,797
R-squared	0.816	0.838	0.814	0.828
Lender*Tract FE	✓	✓	✓	✓
Tract*Time FE	✓	✓	✓	✓
Lender*Time FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓

This table reports results for Equation (1). The dependent variable is the interest rate. The dummy *CA* takes on a value of one if the property is located in a tract in California. The dummy *Post* takes on a value of one in the years after the CCPA was enacted. The dummy *Fintech* takes on a value of one if the lender is a fintech and a value of zero otherwise. Minority (no minority) refers to borrowers that (do not) report their race/ethnicity as Black and/or Hispanic. High (low) income refers to borrowers with an income above (below) the average income of all borrowers. Standard errors (in parentheses) are clustered at the borrower-tract level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Denial rates and rate dispersion

VARIABLES	(1) Denied (0/1)	(2) Denied (0/1)	(3) Sd(rate)	(4) Sd(rate)
CA x Post	-0.011*** (0.003)		-0.010* (0.005)	
Fintech x Post	-0.024*** (0.003)		-0.020*** (0.007)	
CA x Fintech x Post	0.017*** (0.003)	0.010*** (0.003)	0.032*** (0.009)	0.029*** (0.009)
Observations	788,157	648,291	68,360	67,087
R-squared	0.183	0.540	0.439	0.524
Lender*Tract FE	✓	✓	✓	✓
Year FE	✓	-	✓	-
Tract*Time FE	-	✓	-	✓
Lender*Time FE	-	✓	-	✓
Controls	-	✓	-	✓

Columns (1) and (2) report results for Equation (1). The dependent variable is the dummy *Denied*. Columns (3) and (4) report results at the lender-tract-year level. The dependent variable is the dispersion in interest rates, measured via the standard deviation. The dummy *CA* takes on a value of one if the property is located in a tract in California. The dummy *Post* takes on a value of one in the years after the CCPA was enacted. The dummy *Fintech* takes on a value of one if the lender is a fintech and a value of zero otherwise. Standard errors (in parentheses) are clustered at the borrower-tract level. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: The use of alternative credit scores

VARIABLES	(1) Alt CS (broad)	(2) Alt CS (narrow)	(3) Alt CS (v narrow)	(4) Interest rate	(5) Interest rate	(6) Interest rate	(7) Interest rate
CA x Fintech x Post	0.088*** (0.015)	0.068*** (0.019)	0.005*** (0.002)	-0.053** (0.023)	-0.051** (0.022)	-0.045* (0.024)	-0.039 (0.025)
CA x Fintech x Post x Alt CS broad					-0.194* (0.099)		
CA x Fintech x Post x Alt CS narrow						-0.154*** (0.052)	
CA x Fintech x Post x Alt CS v narrow							-0.145*** (0.044)
Observations	126,530	126,530	126,530	126,407	126,407	126,407	126,407
R-squared	0.690	0.805	0.507	0.811	0.811	0.811	0.811
Lender*Tract FE	✓	✓	✓	✓	✓	✓	✓
Tract*Time FE	✓	✓	✓	✓	✓	✓	✓
Lender*Time FE	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓

This table reports results for Equation (1). In columns (1)–(3) the dependent variables are the dummies *Alt CS*, *ALT CS narrow*, and *Alt CS very narrow* that take on a value of one if a mortgage was processed with a nontraditional credit scoring model. In columns (4)–(7) the dependent variable is the interest rate. The dummy *CA* takes on a value of one if the property is located in a tract in California. The dummy *Post* takes on a value of one in the years after the CCPA was enacted. The dummy *Fintech* takes on a value of one if the lender is a fintech and a value of zero otherwise. Columns (4)–(7) use each lender’s average share of loans processed with alternative credit scoring models in the pre-CCPA period as additional explanatory variables. Standard errors (in parentheses) are clustered at the borrower-tract level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: **Loan applications and loan originations**

VARIABLES	(1) Applications Fintech (0/1)	(2) Originations Fintech (0/1)	(3) Tract Nr of applications	(4) Tract Nr of originations
CA x Post	0.033*** (0.005)	0.030*** (0.005)		
CA x Fintech x Post			0.088*** (0.019)	0.066*** (0.019)
Observations	698,616	600,698	171,537	169,238
R-squared	0.086	0.090		
County FE	✓	✓	-	-
Year FE	✓	✓	-	-
Lender*Tract FE	-	-	✓	✓
Tract*Time FE	-	-	✓	✓
Lender*Time FE	-	-	✓	✓
Controls	✓	✓	✓	✓

This table reports results for Equations (2) and (3). In columns (1) and (2) the dependent variable is the dummy *Fintech* that takes on a value of one if the lender is a fintech and a value of zero otherwise. It is the number of applications and the number of mortgage originations in columns (3) and (4) at the lender-tract-year level. The dummy *CA* takes on a value of one if the property is located in a tract in California. The dummy *Post* takes on a value of one in the years after the CCPA was enacted. The dummy *Fintech* takes on a value of one if the lender is a fintech and a value of zero otherwise. Standard errors (in parentheses) are clustered at the borrower-tract level. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Interest rates and default using GSE loan-level data

VARIABLES	(1) Interest rate	(2) Interest rate	(3) Default	(4) Default
CA x Fintech x Post	-0.035*** (0.005)	-0.035*** (0.005)	-0.003* (0.002)	-0.003* (0.002)
Observations	337,918	337,918	337,918	337,918
R-squared	0.853	0.866	0.012	0.017
Lender*Zip code FE	✓	✓	✓	✓
Zip code*Time FE	✓	✓	✓	✓
Lender*Time FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Credit score	-	✓	-	✓

This table reports results for Equation (1), where instead of census tracts the geographic unit of aggregation is the three-digit zip code. The dependent variable is the interest rate in columns (1) and (2); and a dummy that takes a value of one if the loan is at least 30 days delinquent a year after origination in columns (3) and (4). The dummy *CA* takes on a value of one if the property is located in a tract in California. The dummy *Post* takes on a value of one in the years after the CCPA was enacted. The dummy *Fintech* takes on a value of one if the lender is a fintech and a value of zero otherwise. Columns (2) and (4) include the borrower credit score (in brackets) following Experian's categorization as control variable. Standard errors (in parentheses) are clustered at the borrower location level. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: **Robustness**

VARIABLES	(1) Banks Interest rate	(2) Rate spread	(3) Interest rate	(4) Applications Refi (0/1)	(5) Originations Refi (0/1)	(6) No 2020 Interest rate	(7) Covid Interest rate	(8) House prices Interest rate	(9) Size FE Interest rate
CA x Fintech x Post	-0.041*** (0.008)	-0.064*** (0.016)	-0.052*** (0.014)	-0.000 (0.007)	0.004 (0.006)	-0.051*** (0.015)	-0.054*** (0.012)	-0.069*** (0.017)	-0.069*** (0.013)
Fintech x Post x Purchase			0.013 (0.012)						
CA x Fintech x Post x Purchase			0.029 (0.018)						
Fintech × Workplace mob							0.000 (0.001)		
Fintech × Transit mob							-0.001 (0.001)		
Fintech × Cases pc							0.008* (0.004)		
Fintech × Deaths pc							0.065 (0.159)		
Observations	703,141	545,708	551,947	648,291	552,850	345,187	541,433	551,947	551,947
R-squared	0.807	0.523	0.814	0.302	0.314	0.866	0.813	0.814	0.814
Lender*Tract FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Tract*Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lender*Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓

This table reports results for Equation (1). The dependent variable is the interest rate in columns (1), (3)–(5); and the rate spread in column (2). The dummy *CA* takes on a value of one if the property is located in a tract in California. The dummy *Post* takes on a value of one in the years after the CCPA was enacted. The dummy *Fintech* takes on a value of one if the lender is a fintech and a value of zero otherwise. Column (1) compares fintechs to banks. Column (2) uses the rate spread as dependent variable. Column (3) adds an interaction with a dummy that takes on a value of one for purchase loans. Columns (4) and (5) use a dummy for refinancing loans as dependent variable in the sample of applications and originations, respectively. Column (6) excludes the year 2020 from the sample, whereas column (7) controls for measures of the local incidence of the Covid-19 pandemic interacted with the Fintech dummy. Column (8) interacts the fintech dummy with the county-level house price index, column (9) adds loan size bin×time fixed effects. Standard errors (in parentheses) are clustered at the borrower-tract level. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: **Ex-ante regional characteristics**

VARIABLES	(1)	(2)	(3)	(4)	(5)
	Fintech share Interest rate	Branches p.c. Interest rate	Bank share Interest rate	Rural share Interest rate	High-tech emp Interest rate
CA x Fintech x Post	-0.068*** (0.022)	-0.143*** (0.027)	-0.346** (0.126)	-0.077*** (0.011)	-0.034 (0.044)
Fintech x Post x Measure	-0.001* (0.001)	-0.768*** (0.144)	-0.011*** (0.002)	-0.165*** (0.055)	-0.112 (0.496)
CA x Fintech x Post x Measure	-0.000 (0.001)	0.422** (0.182)	0.009* (0.005)	0.127* (0.073)	-0.552 (0.595)
Observations	551,947	551,872	551,947	551,947	551,947
R-squared	0.814	0.814	0.814	0.814	0.814
Lender*Tract FE	✓	✓	✓	✓	✓
Tract*Time FE	✓	✓	✓	✓	✓
Lender*Time FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓

This table reports results for Equation (1). The dummy *CA* takes on a value of one if the property is located in a tract in California. The dummy *Post* takes on a value of one in the years after the CCPA was enacted. The dummy *Fintech* takes on a value of one if the lender is a fintech and a value of zero otherwise. The variable *Measure* is the pre-CCPA mortgage market share of fintech lenders in each tract in column (1), the number of bank branches per capita in each county in column (2), the mortgage market share of banks in each county in column (3), the share of the rural population in each county in column (4), and the share of employees in high-tech sectors in each county in column (5). Standard errors (in parentheses) are clustered at the borrower-tract level. *** p<0.01, ** p<0.05, * p<0.1.

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