# Privacy regulation and fintech lending

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October 2023

**Abstract**

Consumers dislike sharing data with fintechs but better access to data can improve loan market outcomes. We study how the California Consumer Privacy Act (CCPA), which grants users control over and mitigates concerns about sharing data, affects bank and fintech lending. Difference-in-differences estimations show that the CCPA increases mortgage applications to fintechs relative to banks in California. Further evidence suggests that applicants' greater willingness to share data improves fintechs' screening process: they engage in more individualized pricing, deny more applications, and increase their use of non-traditional data. In turn, they offer lower loan rates, in particular to traditionally under-served groups.

*JEL Codes*: G21, G23, G28.

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

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# 1 Introduction

Over the last decade, the market share of fintech lenders has increased rapidly in many countries (Buchak et al., 2018; Cornelli et al., 2020). These lenders usually use non-traditional data and machine learning to screen and price borrowers (Berg et al., 2022). Better access to data hence holds the potential to foster the growth of fintechs and promote competition in the financial sector. Individuals from traditionally under-served groups, including minority and low-income applicants, stand to benefit in particular, as credit scores oftentimes inaccurately reflect their creditworthiness (Di Maggio et al., 2022).

There is mounting evidence, however, that consumers dislike sharing their personal data (Goldfarb and Tucker, 2012; Tang, 2022). Concerns range from price discrimination to data abuse, unethical advertising, and financial fraud (Chen et al., 2021; Lin, 2022; Prince and Wallsten, 2022; Bian et al., 2023). Moreover, consumers value with whom they share their data. For a representative sample of U.S. households, Figure 1 documents that consumers have significantly lower confidence in fintechs than in banks to safely handle their data and protect them from data abuse or misuse (Armantier et al., 2021). These patterns in part reflect users' concerns about fintechs' use of technology and the sharing of their personal data.[1]

Regulators designing privacy protection regulation hence face a challenging trade-off. Limiting or even prohibiting the collection of personal data protects consumers' privacy, but may come at the cost of reducing the availability and quality of data-intensive services (Acquisti et al., 2016). At the same time, the absence of a regulatory framework that addresses privacy concerns can also impede fintechs' development. Consumers might be

[1] For example, three-quarters of consumers believe that fintech companies are more likely to sell their personal data than other firms (link). 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.

reluctant to share data or engage with fintechs altogether, as they are concerned over privacy violations (Chen et al., 2023). In designing privacy regulation, regulators hence need to strike the right balance between protecting users' privacy and promoting the growth of fintechs.

This paper focuses on the effects of the California Consumer Privacy Act (CCPA) on bank and fintech lending. Introduced in 2020, the CCPA constitutes a landmark change in the design of privacy regulation. By giving California residents control over their data and thus mitigating concerns over sharing them, it attempts to protect consumers without generally restricting information collection. For example, individuals can prevent firms from selling their personal information or request that firms delete the data after their use (Camhi and Lyon, 2018). Recent survey evidence shows that the majority of Californians have already exercised their CCPA rights.[2]

The CCPA differs from other types of privacy regulation that typically limit firms' ability to collect information.[3] It also differs from open banking, which aims to facilitate access to data, rather than protect privacy per se.[4] By now, most other states consider introducing legislation in the spirit of the CCPA, and it serves as U.S. Congress' model to create a federal privacy protection regulation (Mulligan et al., 2019). Understanding the CCPA's impact on loan market outcomes and access to credit can yield important insights on the benefits of similar legislation outside of California.

[2]See Consumer Action and Consumer Federation of America (2021): California Consumer Privacy Act (CCPA) Survey.

[3]For example, a key principle of the the European Union's General Data Protection Regulation (GDPR) is that firms must minimize their data processing activities, eg use data only for the purpose for which they were initially collected (Liu et al., 2020). Similar to policies such as bankruptcy flag removal, the GDPR hence effectively prevents the collection and use of data. Since data are valuable, such regulation can reduce access to and increase the cost of credit (Liberman et al., 2019; Jansen et al., 2022; Johnson, 2022).

[4]Open banking mandates financial institutions to share their proprietary data with third parties, including fintech lenders, if users give their consent. The need to share data, however, can discourage incumbents from acquiring and storing data in the first place (Babina et al., 2022). It can also increase market power to the detriment of consumers (He et al., 2023), or distort banks' credit allocation (Goldstein et al., 2022).

To investigate the effects of the CCPA on loan markets, our analysis uses data on residential mortgages from the Home Mortgage Disclosure Act (HMDA) database from 2018 to 2021. HMDA provides a wealth of information on lenders, applicants, and loan terms. We classify lenders into fintechs and banks, including 'shadow banks', following Fuster et al. (2019).[5] For identification, we estimate difference-in-differences regressions with individual borrower data collapsed to the lender–tract–year level.[6] The CCPA, introduced in 2020, acts as treatment for tracts in California, while tracts in the neighboring states constitute the control group.

We first investigate the effects of the introduction of the CCPA on loan applications. Leveraging on the fact that privacy concerns are more salient towards fintechs (see Figure 1, as well as Armantier et al. (2021) and Chen et al. (2023)), we hypothesize that the marginal benefit of privacy regulation that assuages concerns about sharing data is higher for fintechs. Consistent with this argument, we find that after the introduction of the CCPA loan applications to fintechs compared to banks increase significantly in California, relative to neighboring states. In terms of magnitude, loan applications to fintechs increase by about 14% after the introduction of the CCPA. This implies an increase in fintechs' market share of 2 percentage points (pp).

Second, we study the impact of the CCPA on interest rates on approved mortgages. In principle, an increase in demand for fintech loans due to better privacy regulation could lead to an increase in the rates they charge. On the other hand, if users become more willing to share data and thus apply to fintechs, the accrual of additional information

[5]We investigate differences between fintechs, banks, and shadow banks in more detail below.

[6]We also estimate application-level regressions, mitigating concerns about selection effects among applicants within tracts.

could allow fintechs to better screen applicants.[7] This would lower the risk of their borrower pool and result in lower rates.

We find that the CCPA reduced loan rates by around 8 basis points (or 13% of the standard deviation) on mortgages originated by fintechs relative to banks in California. As traditional credit scores provide an inaccurate picture of the future creditworthiness of applicants with thin credit histories (Blattner and Nelson, 2021; Di Maggio et al., 2022), the CCPA should especially benefit applicants from traditionally under-served groups. Restricting the sample to tracts with a higher share of 'thin credit file' applicants, ie minority and low-income applicants, we find the negative effect of the CCPA on fintechs' loan rates to be significantly stronger. For example, in tracts with a high share of minorities the CCPA has reduced fintechs' loan rates by 12 basis points relative to banks - a third more than in the full sample. Taken together, these results suggest that the privacy protection offered by the CCPA made applicants more willing to apply to and share data with fintechs, thereby improving fintechs' screening process.

We provide evidence in support of the argument that the CCPA has improved fintechs' screening abilities. We first show that, after the introduction of the CCPA, the dispersion in interest rates increases by relatively more for fintechs. Greater rate dispersion is consistent with more individualized pricing due to a more precise signal about applicants' quality (Babina et al., 2022; Jansen et al., 2022). Second, we show that the share of denied loan applications increases for fintechs compared to banks in California after the introduction of the CCPA. The relative increase in denial rates suggests an improvement in fintechs' ability to screen out low-quality applicants. Third, we find that fintechs in California process significantly more mortgage applications with data beyond

[7] Alternative data used for screening in the mortgage market range from financial data, like on-time rental, utility or telecommunications payments; to 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.

standardized credit scores after the introduction of the CCPA. While direct information on lenders' use of different types of data is difficult to obtain, the use of non-standardized credit scores in processing applications proxies a greater reliance on alternative personal data (Babina et al., 2022). The relative increase in fintechs' use of non-standardized credit scores is in line with our argument that the CCPA increases applicants' willingness to share data, thereby improving fintechs' screening process.

These effects increase in magnitude when we restrict the sample to loans not sold to government sponsored enterprises (GSEs). Mortgages sold to GSEs carry an implicit guarantee that lowers the credit risk held by the investor (Buchak et al., 2022; Fuster et al., 2023). In addition, not all alternative data can be used in GSEs' automated underwriting systems. Lenders' incentives to collect and use additional data to screen applicants could hence be lower for GSE loans, even if repeated interactions between originators and GSE imply reputational concerns that provide lenders with an incentive to accurately screen GSE loans (Agarwal et al., 2012; Keys et al., 2012; Deku et al., 2022).[8] Consistent with greater incentives to screen mortgages not sold to GSEs with alternative data, we find that the CCPA's impact on fintechs' relative interest rates, rate dispersion, denial rates, and use of non-standardized credit scores is larger in magnitude for non-GSE loans. This exercises also addresses the concern that on-balance sheet loans, which are more frequent among banks, could differ in unobservable characteristics from GSE loans, including in terms of compliance costs (Gupta et al., 2023).[9]

Our results raise the question of whether the CCPA has improved access to credit. We find that although denial rates increase, fintechs also originate more mortgages in

[8]Recent evidence suggest that lenders screen mortgage applicants and price their risk independently from the GSEs' requirements (Bosshardt et al., 2023).

[9]The CCPA has likely increased compliance costs, and Gupta et al. (2023) argue that is has done so more for banks. However, our findings that the CCPA has a positive effect on applications to fintechs, as well as fintechs' interest rate dispersion, denial rates, and the use of non-traditional data, are inconsistent with explanations based on compliance costs alone.

California after the introduction of the CCPA. Consequently, their market share in loan originations increases in the post-CCPA period.

The analysis faces the common identification challenge that any observed change in loan applications or rates could be due to unobservable factors at the lender or borrower level. For example, fintechs could serve tracts with higher income growth over the sample period, leading to an increase in applications. Likewise, a change in financial conditions that affects fintechs and banks differently could be reflected in the rates they charge.

We address this challenge in different ways. For one, our analysis focuses only on the set of tracts within counties that lie on the border of California with its neighboring states. As has been shown in a large literature, border counties are similar along many observable characteristics, mitigating concerns about selection effects and omitted variable bias (Allegretto et al., 2017). Indeed, in the border sample we find no discernible difference in the evolution of loan applications to or rates on loans by fintechs compared to banks prior to the introduction of the CCPA in 2020 (ie, there is no evidence of differential pre-trends). In addition, we show that the average fintech and bank applicant have comparable observable characteristics in border tracts before the CCPA was introduced.

We further include granular time-varying fixed effects. Tract*time fixed effects absorb any observable and unobservable differences in tract characteristics over time, including applicants' income, demographic structure, or credit demand. They also control for potential differences in the severity of the Covid-19 pandemic and associated movement restrictions across tracts. In essence, we exploit only within-tract variation and compare applications to different lenders from individuals in the same tract and the same year. In addition, we include lender type*time fixed effects to control for time-varying observed and unobserved heterogeneity in lender characteristics, for example funding conditions or regulation.

We find that our results are robust to the inclusion of granular time-varying fixed effects. Together with the absence of any differential pre-trends, this finding mitigates concerns that the CCPA was introduced because of the rise of fintech lenders in California border counties, or that our findings reflect differences in applicant characteristics across or within tracts.

We investigate a number of alternative explanations for our findings. First, we control for the local severity of the Covid-19 pandemic. If movement restrictions limited applicants' ability to visit a bank branch, applications to fintechs could have increased. However, an increase in demand should have put upward pressure on interest rates charged by fintechs. We find that our main results remain qualitatively unaltered when we control for the severity of Covid-19. Moreover, controlling for the potential increase in demand and attendant upward pressure on rates during Covid-19 leads to a larger negative effect of the CCPA on interest rates charged by fintechs relative to banks. We also show that our results are not due to the uptick in mortgage refinancing during the Covid period. Second, we address the concern that the decline in the interest rate offered by fintechs could be due to an improvement in the quality of fintech applicants within tracts. As applications increase, higher-quality applicants could decide to apply more to fintechs, allowing them to offer lower rates irrespective of any change in their screening ability. Yet we find no significant change in various measures of the quality of applicants to fintechs vs. banks with the introduction of the CCPA. Further, directly controlling for the quality of the applicant pool leads only to a modest decline in the magnitude of the estimated effect of the CCPA on interest rates by fintechs.[10]

Our results are robust to a wide range of alternative specifications. They are unaffected when we exclude applicants of age 62 and above from the sample, ie applicants

[10] The absence of selection effects is consistent with Armantier et al. (2023), who in a representative survey of U.S. consumers find no systematic correlation between individuals' relative distrust in fintechs and characteristics reflecting default risk, such as income, education, or their self-assessed credit score.

that could have been more affected by Covid-19 related restrictions; they are present both among purchase and refinance loans; and they remain robust to the inclusion of a large set of tract-level applicant controls or when we estimate applicant-level regressions and directly control for applicant characteristics.

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) or reduce the need for collateral (Gambacorta et al., 2022). At the same time, consumers value their privacy and are concerned about the ab- and misuse of data (Armantier et al., 2021; Tang, 2022; Lin, 2022). These considerations pose a trade-off for policy makers, which need to balance improving efficiency through greater use of data with protecting users' right to privacy. Our results suggest that privacy protection legislation that enhances users' control over data and increases transparency and accountability in their use can mitigate this trade-off. As the CCPA makes users more willing to share data, it enables lenders to better screen with data and offer lower rates, enhancing the scope of financial services.

**Related literature.** Our paper provides the first empirical evidence on how the CCPA, one of the world's most comprehensive privacy laws, affects fintech lending. It speaks to the growing literature studying 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., 2022). 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, 2018). Europe's General Data Protection Regulation, 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., 2018).[11] Moreover, privacy-conscious consumers have used the GDPR to opt for reporting less data, thereby creating externalities for the remaining consumers and losses for intermediaries (Aridor et al., 2022).

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 banks may endogenously adjust their liabilities once data become open to challengers (Goldstein et al., 2022). Finally, Babina et al. (2022) show that while 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 the CCPA, ie privacy regulation that grants users control over their data and mitigates privacy concerns by explicitly considering differences in privacy preferences. 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 results

[11] A growing literature investigates the effects of the GDPR on firms and finds that it hurts firm performance (see Johnson (2022) for a survey).

suggest that privacy legislation in the spirit of the CCPA can make applicants more willing to share their data and lead to improved loan market outcomes – especially for traditionally under-served groups.[12] We thereby speak to recent work that highlights how alternative data can complement traditional credit scores to foster financial inclusion (Blattner and Nelson, 2021; Di Maggio et al., 2022).

Finally, our paper relates to work studying the rise of fintechs and the attendant effects on banks. 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).[13] In addition, better access to data, notably from payments, can help fintechs compete with banks: fintech lenders can use payments data to obtain information about potential borrowers that compensates for the lack of an existing lending relationship (Ghosh et al., 2021).[14] 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 banks has not explicitly considered the role of privacy preferences or data protection legislation (see Berg et al. (2022) for a survey). We find that in the presence of privacy-sensitive consumers, privacy legislation can spur the growth of fintechs, which could increase the competitive pressure for banks.

The remainder of the paper is organized as follows. Section 2 discusses the evidence on borrowers' preferences for privacy, provides the institutional background on the CCPA, and discusses the role of alternative data in mortgage lending. Section 3 lays out a

[12] These results are consistent with Ali et al. (2022), who theoretically show that consumer control over data can improve consumer welfare.

[13] Note that our setting does not strictly require fintechs to have better technology than banks. Whether consumers have lower trust in fintechs to store and handle their data because fintechs actually use machine learning models to analyze personal data, or because consumers perceive fintechs to do so has the same implications.

[14] Other papers look at privacy preferences, data availability, and firm performance (Begenau et al., 2018; Farboodi et al., 2019; Bian et al., 2022; Canayaz et al., 2022) or the growth of fintechs more broadly (Cornelli et al., 2021).

conceptual framework to derive a set of testable hypotheses on the effects of privacy regulation on banks and fintechs. Section 4 tests the hypotheses with U.S. mortgage data, exploiting the introduction of the CCPA. Section 5 concludes.

# 2 Privacy preferences, the CCPA, and alternative data

This section first shows 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 set the standard for privacy legislation across the U.S. Finally, it discusses the use of alternative data in mortgage underwriting.

## 2.1 Privacy preferences

As more and more economic activity moves online, personal data is turning into an important asset for firms (Acquisti et al., 2016; Jones and Tonetti, 2020). In loan markets, personal data increasingly complement traditional credit scores when lenders screen prospective borrowers (Jagtiani and Lemieux, 2019; Berg et al., 2022). They can be directly collected, eg through loan applications, but also purchased from third-party data aggregators and vendors. Non-traditional data can range from education and employment history (Di Maggio et al., 2022) to rent and utility payments (GAO, 2021) to social network activity or digital footprints (Berg et al., 2020). We discuss the use of alternative data in more detail in Section 2.3.

However, 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 for users' decision 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), which are also commonly reflected in financial fraud complaints (Bian et al., 2023).

Since 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 ab- or misuse. Figure 1 shows that 70% of U.S. households have high trust in traditional financial intermediaries (FI), as opposed to only 30% placing high trust in fintechs. Chen et al. (2023) report a similar pattern for a large sample of countries: survey respondents are significantly less willing to share their data with fintechs than with other FIs.

Taken together, the evidence suggests that consumers have a preference for keeping their personal data private; and that they have lower confidence in fintechs than other lenders to safeguard their personal data.

## 2.2 The California Consumer Privacy Act

The CCPA is a data privacy law covering the state of 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 their personal information, delete it, and to opt-out of its sale (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. By now, many other states consider introducing legislation in the spirit of the CCPA, and U.S. Congress considers it as the blueprint for a federal privacy protection regulation (Mulligan et al., 2019).[15]

The Office of the Attorney General (OAG) in California monitors compliance with the CCPA via enforcement sweeps. If the sweeps uncover practices that go against the CCPA, the OAG sends the company a notice of alleged noncompliance. The company then has 30 days to respond. Violations of the Act entail hefty fines, and there are active cases against Amazon, Zoom, or TikTok, among others.[16]

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 (see Figure 2). Under the CCPA, any consumer can request that her data not be sold or be deleted after transacting with a firm. Therefore, the CCPA decreases the uncertainty around the use of personal information by intermediaries. As highlighted in an impact assessment of the CCPA by the California Department of Justice, if the CCPA increases consumers' trust of data protections it could increase the amount of data that consumers are willing to share with firms.[17] Recent survey evidence confirms that the CCPA makes consumers more willing to share their data (Armantier et al., 2023).

The CCPA is expected to have a stronger impact on applicants' attitudes towards 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 to begin with. Lower trust in fintechs likely arises from users' perception that fintech companies are more likely to sell their personal

[15]In 2021 alone, lawmakers in twenty-seven U.S. states proposed CCPA-like privacy legislation (see 'Which States Will Consider CCPA-Like Consumer Privacy Bills in 2022?' and 'CCPA: Congress' Model for Data Privacy - or Oblivion?'.

[16]See: Data Grail: The Biggest GDPR & CCPA Fines, Analyzed. Appendix Section B.1.3 provides more information on the CCPA and its enforcement.

[17]See Standardized Regulatory Impact Assessment: California Consumer Privacy Act of 2018 Regulations.

data than other firms, as well as a general distrust in opaque machine learning models and algorithmic judgment.[18] It could also reflect that banks are already subject to a variety of regulations that at times include data sharing agreements. Moreover, banks oftentimes have long-lasting relationships with clients, which mitigate concerns that data are misused.

In granting users control over their data, the CCPA differs from other data initiatives and regulations in important aspects. For example, a key principle of the GDPR is that firms need to minimize their data processing activities (Liu et al., 2020). Similar to policies such as bankruptcy flag removal, it hence effectively limits firms' ability to exploit information (Liberman et al., 2019; Jansen et al., 2022; Johnson, 2022). Open banking, on the other hand, 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., 2022), increase market concentration (He et al., 2023), or distort banks' credit allocation (Goldstein et al., 2022).

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 those interviewed had seen the notice of their rights required by the CCPA on websites they visited.[19] Moreover, the majority of respondents had exercised their rights granted by the CCPA. For example, over 50% have asked firms to not share or delete their data. Consistent with these survey results, mortgage lenders often provide didactic and simple explanations of what the law entails for California residents when they apply

[18] Three-quarters of consumers believe that fintech companies are more likely to sell their personal data than traditional firms (link). A long-standing literature highlights barriers to consumer trust in algorithmic decision making (Glikson and Woolley, 2020; D'Acunto and Rossi, 2023).

[19] See the 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.

for a mortgage.[20] 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 (see Figure OA1).

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, it makes consumers more willing to share data, and in particular with fintech lenders (Armantier et al., 2023).

## 2.3 The use of alternative data in mortgage lending

In their decision whether to grant a loan or not, mortgage lenders traditionally rely on standardized credit scores by private providers such as Fico or Equifax, in combination with variables such as the loan-to-value ratio or applicants' debt-to-income ratio. However, lenders increasingly use alternative data to assess individuals' credit-worthiness.

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 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 non-traditional 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 that either do not have a traditional credit score or have an insufficient credit

[20] See the screenshots of mortgage lenders' websites in Figure OA2 and Figure OA3.

history (CFPB, 2017), 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).[21] 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 sell loans to the enterprises, 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 non-traditional data on eg rent, utility, and insurance payments for screening, the information needs to be transmitted manually, which makes the underwriting process for GSE loans more resource-intensive (GAO, 2021). Mortgages not sold to GSEs are hence more likely to benefit from a greater use of alternative data, even if both sellers and buyers in the secondary market value accurate screening, for example because of reputational concerns (Agarwal et al., 2012; Keys et al., 2012; Deku et al., 2022).

[21] Credit scoring firms are increasingly providing alternative credits cores that incorporate non-traditional data. FICO offers UltraFico, but only if a consumer provides access to her 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).

Beyond improving the screening of individual applications, more data could benefit lenders by providing a more comprehensive picture of the state of the local economy. For example, as more individuals apply to fintechs, each fintech benefits from aggregating data from a larger pool of individuals to make more precise inferences on the local environment. It can thus more accurately infer also other applicants' creditworthiness (Ichihashi, 2021; Bergemann et al., 2022).

# 3 Conceptual framework

To guide our empirical analysis, this section presents a simple conceptual framework. It illustrates how privacy protection regulation affects loan markets in the presence of privacy concerns among applicants.[22]

Suppose two types of lenders – banks and fintechs – 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 might request or applicants provide additional information, such as applicants' education history, phone or electricity bills. While 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.[23]

[22]The framework is based on a parsimonious model of the loan market with banks and a fintech that use data to screen applicants. Applicants dislike sharing their data, in particular with the fintech. For details, see the Online Appendix B.2.

[23]Our 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.

Consumers are concerned about the ab- or misuse of data when applying for a loan. Importantly, they are more concerned about sharing their data with fintechs than with banks. These assumptions follow directly from Figure 1 and Figure 2. Some individuals might hence be unwilling to contract with a fintech, or unwilling to share additional data, even for a lower interest rate.

We then 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 to sharing them. This decline is more pronounced for sharing data with fintechs compared to banks, an assumption consistent with the evidence that individuals generally have significantly lower confidence in fintechs to safely handle personal data.

By reducing applicants' disutility from sharing data with fintechs, privacy regulation is expected to increase applications to fintechs compared to banks:

***Hypothesis 1***: The introduction of privacy protection legislation leads to an increase in loan applications to fintechs compared to banks.

The impact of privacy regulation on interest rates is a priori unclear. On the one hand, an increase in applications could increase the price of fintech credit and lead to higher interest rates (demand effect). On the other hand, applicants' greater willingness to share data could enable fintechs to use additional data to improve their screening process (Berg et al., 2020; Di Maggio et al., 2022), thereby filtering out more low-quality applicants and offering lower interest rates (screening effect). If the screening effect dominates, the following is true:

***Hypothesis 2***: The introduction of privacy protection legislation decreases loan rates on loans originated by fintechs compared to banks if the screening effect dominates the demand effect.

A relative decline in fintechs' interest rates hence implies that fintechs experience an improvement in their screening process. A more precise signal about borrowers' quality is commonly associated with more individualized pricing across borrowers (Babina et al., 2022; Jansen et al., 2022), implying greater rate dispersion. In addition, it would allow fintechs to better screen out low-quality applicants, which should lead to an increase in the share of denied applications:

***Hypothesis 3.1***: By enabling better screening through data, privacy regulation increases the dispersion in interest rates across borrowers among fintechs relative to banks.

***Hypothesis 3.2***: By enabling better screening through data, privacy regulation increases the share of denied loan applications by fintechs relative to banks.

Finally, applicants' greater willingness to share data with fintechs implies that fintechs will increase their use of data beyond traditional credit scoring models:

***Hypothesis 3.3***: After the introduction of privacy regulation, fintechs' loan applications processed with non-traditional data increase by more than banks.

We expect these effects to depend on the loan type and borrower characteristics. First, current credit scores do not paint an accurate picture of the future creditworthiness of applicants with thin credit histories (Di Maggio et al., 2022) or for applicants from traditionally under-served groups, including minority and low-income applicants (Blattner and Nelson, 2021). Therefore, and 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 thin file borrowers. Second, alternative data are likely to play a more important role for mortgages that are not sold to the GSEs. Non-GSE mortgages do not benefit from the implicit government guarantee, so lenders have greater incentives to assess applicants' creditworthiness; and lenders have greater leeway in the type of data they can use in originating non-GSE loans (see Section 2.3).

# 4 The CCPA and fintech lending

This section exploits the introduction of the California Consumer Privacy Act in 2020 to test the hypotheses developed in Section 3. We first investigate how the CCPA affects mortgage applications and loan rates. We then analyze the effects of data protection legislation on fintechs' individualized pricing, application denial rates, and use of alternative credit scores.

## 4.1 Data and summary statistics

HMDA provides home mortgage application data, covering the vast majority of applications and approved mortgages in the U.S. The yearly data include the application outcome, loan amount, and, for granted loans, the interest rate. Additionally, they contain detailed information on applicant income, race, and gender, among other items. To classify lenders in HMDA as banks or fintechs 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.[24] In our baseline regressions, we compare fintechs to all other mortgage

[24]See Fuster et al. (2019) for a detailed discussion. We also follow what is standard in the literature to select our sample of mortgages. We focus on conventional mortgages for purchase or refinancing as principal residence; we drop reverse mortgages, those with business or commercial purpose, with interest only or balloon payment, more than one unit. Further, we drop applications with missing applicant age or sex, and open-end line of credits, as well as files that were closed for incompleteness.

lenders, ie banks and shadow banks.[25] We discuss and investigate the role of shadow banks in further detail in Section 4.3.

We collapse the individual applicant data at the lender–applicant tract–year level. In our analysis, we use mortgage applications in counties that lie on the border of California (CA) and its neighboring states Arizona (AZ), Nevada (NV), and Oregon (OR). The sample period covers the years from 2018, the first year for which data on interest rates are available, to including 2021. To eliminate noise stemming from tracts with insignificant amounts of loan applications by a given lender, we restrict our sample to markets where a given lender made at least two loans in each year.

The main outcome variables are the log of the number of applications and the average interest rate on approved mortgages. In addition, we compute the share of denied applications, the dispersion in interest rates across approved mortgages, as well as the share of mortgages that do not use standardized underwriting models.[26]

**Descriptive statistics.** Our final sample contains 900,270 mortgage applications between 2018 and 2021 in 9,723 census tracts in border counties. Collapsed to the lender–applicant tract–year level, we end up with 75,354 observations. Table 1 provides summary statistics for our main outcome variables in 2018 and 2019, ie prior to the introduction of the CCPA. The average lender–tract cell had 5.6 applications. The interest rate charged in the average tract was 4.4%, with a standard deviation of 0.63; the share of denied

[25] While a large literature and several industry reports establish that consumers trust fintechs less than other lenders, we are not aware of any study showing that consumers trust shadow banks less than banks. Lower trust in fintechs is usually linked to consumers' concerns about fintechs' ability to safely store and analyze their personal data, as well as the use of seemingly opaque machine learning models. For our context, what matters is not whether fintechs actually sell more data or rely more on machine learning (although available evidence suggests they do), but that consumers believe that fintechs do so. Similarly, while a large literature suggests that fintech lenders use alternative data to screen borrowers, less is known about shadow banks' use of non-traditional data in the screening process. For these reasons, we separate mortgage lenders into fintechs and banks, with the latter category including shadow banks.

[26] We compute the fraction of mortgages originated using a credit scoring model besides the standard ones Equifax, Experian, FICO, or Vantage Score.

applications equaled 5.2%, while the share of applications processed with data beyond traditional credit scores was 24%. In the average tract, out of all applications, a share of 16.3% was to fintechs, with a standard deviation of 12.2%.

Table 2 provides summary statistics for applicants to banks and fintechs prior to the introduction of the CCPA. In 2018–19, applicants are statistically similar in terms of the observable characteristics gender, race, income, the value of the property, loan-to-income ratios, and loan-to-value ratios. An exception is applicant age, with applicants of age 62 and above being more common among fintech lenders (consistent with Fuster et al. (2019)). Beyond statistical significance, most values are similar in terms of economic magnitude. Overall, these patterns suggest that bank and fintech applicants are economically and statistically comparable in border tracts. As we will further show below, the quality of applicants to fintechs relative to banks within tracts does not change with the introduction of the CCPA.

## 4.2 Empirical strategy and results

In this section, we first test whether the introduction of the CCPA has lead to an increase in loan applications to fintechs compared to banks (Hypothesis 1). We then analyze the CCPA's effect on interest rates (Hypothesis 2). Finally, we investigate the underlying channel (Hypotheses 3.1–3.3).

We estimate variants of the following regression at the lender–tract–year level:

$$\begin{aligned} y_{l,c,t} =& \delta_1\ CA_c \times post_t + \delta_2\ fintech_l \times post_t \\ &+ \delta_3\ CA_c \times fintech_l \times post_t + \theta_{l,c} + \tau_{c,t} + \phi_{l,t} + \varepsilon_{l,c,t}. \end{aligned} \tag{1}$$

The dependent variable $y$ is the log of the number of applications or the average rate charged on approved mortgages by lender $l$ 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 a tract in California and zero otherwise. The dummy *post* takes on a value of one after the CCPA was enacted (ie for 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 otherwise. All regressions include lender–tract ($\theta_{l,c}$) fixed effects that absorb any time-invariant characteristics at the lender–applicant tract level. We hence only exploit variation within each lender-tract cell. Standard errors are clustered at the tract level.[27]

Based on Hypothesis 1, we expect a coefficient of $\delta_3 > 0$, that is, the CCPA should increase consumers' willingness to apply to fintechs relative to banks. Hypothesis 2 instead suggests $\delta_3 < 0$ when the screening effect dominates the demand effect: The introduction of the CCPA is expected to lower rates on loans originated by fintechs relative to banks in California. If instead the demand effect dominates we expect the opposite sign.

*Identification.* Equation (1) faces the common identification challenge that any observed change in applications or rates could be due to unobservable factors, rather than due to the introduction of the CCPA. For example, fintechs could serve tracts with higher income growth over the sample period, leading to an increase in applications. To address this challenge, we include granular time-varying fixed effects at the tract level ($\tau_{c,t}$). These fixed effects absorb any observable and unobservable differences in tract characteristics over time. They hence account for changes common to applicants and borrowers within a tract, such as changes in average income, borrower risk, internet access or demographic structure, and credit demand. 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*time fixed effects, we essentially compare applications to different lenders from individuals in the same tract and year. In addition, we include lender

[27]We show the robustness of our findings to different levels of clustering in the Online Appendix.

type*time fixed effects ($\phi_{l,t}$) to control for changes in observed and unobserved characteristics of each type of lender. These control for eg the effects of changes in the Fed funds rate on funding costs of fintechs or banks, or changes in the regulatory environment.

As explained in Section 4.1, to further tighten identification we restrict the analysis to tracts within counties along the border of California with its neighboring states. Border counties are generally similar along many observable characteristics, mitigating concerns about selection effects and omitted variable bias (Allegretto et al., 2017).[28] Moreover, as we show in Table 2, the characteristics of applicants to fintechs and banks did not differ in an economically or statistically significant way prior to the introduction of the CCPA.

### 4.2.1 The CCPA, loan applications, and rates

Columns (1)–(3) in Table 3 show that loan applications to fintechs increase in California border counties after the introduction of the CCPA. The Online Appendix reports the results for the full sample of tracts. Column (1) includes lender-tract as well as year fixed effects and shows that applications increase in California after the introduction of the CCPA ($\delta_1 > 0$ in Equation (1)). The CCPA hence has a positive effect on loan applications with banks, possibly by also increasing some consumers' willingness to share data with banks. Yet, applications increase by significantly more among fintechs compared to banks ($\delta_3 > 0$), in line with Hypothesis 1.

Column (2) controls for unobservable time-varying applicant tract characteristics by introducing tract*time fixed effects. Comparing lending by fintechs and banks to the same tracts leads to almost identical coefficient estimates. These results are consistent with the argument that applicants in tracts in border counties are comparable in terms of observable and unobservable characteristics. Finally, column (3) introduces lender type*time fixed effects to absorb any time-varying unobservable characteristics for each

[28] We provide evidence consistent with these arguments in Table OA8.

lender type. The coefficient on the triple interaction effect remains positive and significant at the 1% level. In terms of economic magnitude, applications to fintech lenders increase by 14.6% more than to banks in California after the introduction of the CCPA.

How does the increase in applications to fintechs translate into changes in their market share? In the Online Appendix we show that the share of applications to fintechs increases by 2.2 percentage points after the introduction of the CCPA (see Table OA1, column (4)), implying an increase of 13% of the mean. These results suggest that the CCPA has spurred the growth of fintechs.

In columns (4)–(6) we analyze the effects of the CCPA on loan rates, ie Hypothesis 2. Column (4) shows that on average, loan rates in California increase by significantly more after 2020 than in neighboring states. Fintechs in California, however, decrease their interest rate compared to banks. To ensure that the effects are not driven by unobservable time-varying tract or lender type characteristics, columns (5) and (6) tighten identification by adding tract*time and lender type*time fixed effects. Results show that, even after holding all observable and unobservable variation across time at the tract and lender type level constant, rates on fintech-approved mortgages in California decrease by an 7.9 bp (0.10 standard deviations) compared to banks. As we will show below, the effect size increases among traditionally under-served groups.

In sum, Table 3 provides empirical support for Hypotheses 1 and 2. Applications to fintechs, relative to banks, increase by more in California after the introduction of the CCPA, compared to neighboring states. Loan rates on mortgages approved by fintechs decrease by relatively more. The decline in interest rates suggest that the screening effect dominates the demand effect among fintech lenders, which we will investigate in the next section.

**Pre-trends.** Were there any pre-trends across fintechs and banks in applications and interest rates? To this end, we estimate how applications and rates by fintechs in California change compared to banks in each year. 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, ie the year before the CCPA came into effect. Panel (a) shows that there is no discernible difference in the share of applications to fintechs prior to the introduction of the CCPA in 2020. While applications to fintechs and banks evolve similarly between 2018 and 2019, applications to fintechs increase by relatively more in 2020, ie when the CCPA came into effect. The gap persists in 2021, suggesting a lasting effect: individuals know that they are protected by the legislation and they permanently adjust their behavior. Panel (b) shows that there is also no significant difference in the evolution of interest rates prior to the introduction of the CCPA. Yet rates decline by significantly more on mortgages approved by fintechs compared to banks after the introduction of the CCPA in 2020.

#### 4.2.2 Testing the mechanism: rate dispersion, denial rates, and the use of non-traditional data

Privacy legislation in the spirit of the CCPA provides consumers with greater confidence that their data will not be used for unintended purposes, making them more willing to share information with lenders. As a consequence, fintechs could be able to engage in more individualized pricing (Hypothesis 3.1) and better screen out low-quality applicants (Hypothesis 3.2) through greater use of alternative data in their screening process (Hypothesis 3.3).

We test these hypotheses in Table 4, estimating variations of Equation (1). In columns (1)–(2) we test Hypothesis 3.1. The dependent variable is the standard deviation in interest rates across loans within each lender–tract–year cell. Consistent with obtaining a more precise signal from additional data, column (1) shows a significant and positive coefficient on the triple interaction term: the dispersion in interest rates increases by significantly more for fintechs relative to banks in California. Adding tract*time and lender type*time fixed effects in column (2) does not materially affect this conclusion.

To test Hypothesis 3.2, columns (3)–(4) analyze the effects of the CCPA on the share of denied loan applications within each lender–tract–year cell. Column (3) uses lender*tract and time fixed effects, while column (4) adds tract*time and lender type*time fixed effects. Across specifications, rejection rates by fintechs significantly increase after the introduction of the CCPA, relative to banks. Greater rate dispersion and an increase in application denial rates are consistent with improved screening through the use of more data.

Direct information on lenders' use of data in the screening process is difficult to obtain. To test Hypothesis 3.3, we thus focus on the share of mortgage applications processed with non-standardized credit scores. As argued in Babina et al. (2022), the use of non-standardized credit scores proxies lenders' reliance on alternative data or the use of alternative credit scores that require users' consent to use alternative data. Column (5) shows that, conditional on lender*tract and year fixed effects, fintechs in California increase their use of non-traditional data beyond standardized credit scores after the introduction of the CCPA. Column (6) with tract*time and lender type*time fixed effects confirms this finding.

To further provide evidence on our proposed mechanism, we focus on 'thin credit file' applicants, oftentimes traditionally under-served groups (Blattner and Nelson, 2021; 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 especially for thin credit file applicants.

Table 5 estimates Equation (1), but focuses on tracts with a plausibly higher share of thin file applicants. Specifically, we focus on tracts with a high share of minority applicants (columns 1–2), a low tract-to-MSA income ratio (columns 3–4), or lower average applicant income (columns 5–6). For each measure, we focus on tracts below the median and in the bottom quartile of the distribution. Consistent with Blattner and Nelson (2021) and Di Maggio et al. (2022), the results show that the negative effect of the CCPA on rates by fintechs is significantly stronger in tracts with a higher share of thin file applicants compared to its baseline estimate of 7.9 bp.

These findings could imply that the introduction of the CCPA improved access to credit. In the Online Appendix we show that fintechs originate relatively more mortgages after the introduction of the CCPA – despite the increase in denial rates (see Table OA1). This pattern suggests that the CCPA did not only lower the cost of credit, but also improved access to credit.

Finally, we restrict the sample to loans not sold to one of the housing agencies Fannie Mae, Freddie Mac, Ginnie Mae, or Farmer Mac in the respective calendar year. The GSEs limit the types of data that lenders can use in assessing applicants through their automated underwriting system,[29] and mortgages sold to them carry an implicit guarantee that lowers the credit risk held by the investor (Buchak et al., 2022; Fuster et al., 2023). These considerations imply that lenders' incentives to collect and use additional data to screen applicants are likely greater, and the benefits of additional data for fintechs' relative screening ability to be stronger, for loans not sold to the GSEs.[30]

[29]For example, lenders can provide data on rent, utility, and insurance payments when underwriting manually, but cannot use browsing history or educational records.

[30]Note that this does not mean that lenders have no incentive to screen sold mortgages (Bosshardt et al., 2023). For one, as mortgage originators repeatedly interact with GSEs and private investors in the secondary market, they have an incentive to screen their borrowers due to reputational concerns (Agarwal et al., 2012; Keys et al., 2012; Deku et al., 2022). Moreover, guaranteed mortgage backed securities are not completely free of credit risk. In recent years the GSEs have issued a new instrument – credit risk transfer (CRT) bonds – with cash flows explicitly tied to credit losses on agency mortgages (Fuster et al., 2023).

Table 6, columns (1) and (2) show that, among loans not sold to GSEs, rates on fintech-approved mortgages in California decrease by 16.4 to 22.4 bp compared to banks. This effect is significantly stronger than our baseline result. Investigating the channel, we also find coefficient estimates to be larger in magnitude for the dispersion in rates (columns 3–4), the share of denied applications (columns 5–6), and the use of non-traditional credit scores (columns 7–8). These patterns suggest that the benefits of the CCPA on fintechs' screening and offered rates are particularly pronounced among loans where credit risk matters more and lenders have more freedom in the data they use for underwriting. This exercises also addresses the concern that banks are more likely to make on-balance sheet loans that could differ in observable or unobservable characteristics from fintech loans (Buchak et al., 2018, 2022), including in terms of compliance costs (Gupta et al., 2023).

All in all, results in Table 4, Table 5, and Table 6 are consistent with the channel in our conceptual framework: with the introduction of the CCPA, fintechs' screening ability improves thanks to individuals' greater willingness to share data. This results in more individualized pricing and a greater share of denied applications. In consequence, fintechs can offer lower loan rates compared to banks, especially to thin credit file applicants.

## 4.3 Alternative explanations and robustness tests

This section provides a series of tests to examine alternative channels and the robustness of our findings. In particular, we investigate the role of applicant quality, the Covid-19 pandemic, and shadow banks.

**Quality of the applicant pool.** A possibly confounding factor is that the quality of the pool of *applicants* changes as the number of applications increases, thereby affecting the interest rate. For example, fintechs could have a larger footprint in tracts with higher-quality applicants on average. An increase in applications from these tracts would then improve the quality of fintechs' applicant (and hence borrower) pool, so that they can offer lower rates. In our regressions, any such differences in the average quality of applicants or borrowers across tracts are absorbed by tract*time fixed effects. A second possibility, however, is that even within a census tract, as applications increase, higher-quality applicants decide to apply more to fintechs. Tract*time fixed effects would not absorb this variation.

The public HMDA data does not provide applicants' credit score, the most common measure of applicant quality. Instead, we must rely on proxy variables, a caveat that should be kept in mind when interpreting our results. Specifically, we use the log of applicant income, the log of the loan-to-income (LTI) ratio, the log of the loan-to-value (LTV) ratio, and a dummy that takes on a value of one if the debt-to-income (DTI) ratio is below 36%.[31] Finally, we compute a composite measure of applicant quality ('risk PCA') by taking the first principle component of log income, the log of the LTI ratio, and the log of the LTV ratio. It explains a sizeable 52% of the variances of the variables.

Table 7 estimates variants of Equation (1) and shows that there was no statistically or economically significant change in applicant quality among fintechs vs. banks when the CCPA was introduced. In particular, for each measure of quality, which we use as dependent variables in columns (1)–(5), the coefficient on the triple interaction term is statistically and economically insignificant. In columns (6)–(8) we directly control for the quality of the applicant pool in our regressions by including the mean and standard

[31] Albanesi et al. (2022) show a positive correlation between income and credit scores. Fuster et al. (2021) show that the loan-to-income ratio is highly correlated with ex-post default, making loan-to-income ratios a standard measure of risk (Mayer et al., 2009). The cut-off value of 36% for the debt-to-income ratio, ie that household spend less than 36% of their gross monthly income on total debt service, is generally considered as a positive factor in assessing household risk in mortgage applications. To eliminate extreme values, we winsorize each continuous variable at the $5^{th}$ and $95^{th}$ percentile in each year. Since information on LTI, DTI, and LTV ratios is not available for all applications, the sample size of our lender-tract-year sample declines from around 75,000 to around 68,000.

deviation of each risk measure in each lender-tract-year cell as controls. Results show only a modest decline in the magnitude of the estimated effect of the CCPA on interest rates by around 9% (or 1.1 bp from column (6) to column (8)). The (insignificant) change in the average quality of applicants across lenders within tracts hence explains only a small fraction of the magnitude of our estimated effects of the CCPA on interest rates.

Results in Table 7 suggest that there was no systematic selection of higher-quality applicants with fintechs. The absence of selection effects is consistent with Armantier et al. (2023), who show that in a representative survey of U.S. consumers there is no correlation between individuals' relative distrust in fintechs and characteristics such as income, education, or their self-assessed credit score.

**Covid-19 and demand effects.** The outbreak of Covid-19 in 2020 led to severe restrictions on movements. Voluntary restrictions or lockdown measures could have increased applications to fintechs, as applicants were unable to visit bank branches. Such an increase in demand could put upward pressure on interest rates charged by fintechs. To account for the severity of Covid-19 at the local level and its impact on loan applications and loan rates, we use four measures that vary at the county level: workplace mobility and transit mobility (both from Google Mobility Trends), as well as Covid cases and deaths per capita. We create time-varying measures by setting the values for these variables to zero in 2018 and 2019, and to their actual realization (averaged across days) in each county in 2020 and 2021. We then interact these measures, which vary at the county-year level, with the *fintech* dummy and include them as controls in Equation (1).

Table 8 shows that controlling for the severity of the Covid-19 pandemic does not materially affect our estimates. For applications (columns 1–3) we still obtain a highly significant positive coefficient on the triple interaction term $CA \times fintech \times post$. For rates (columns 4–6), the coefficient remains negative and significant, and even increases in absolute value. Controlling for the potential demand-induced upward pressure on rates due to Covid-19 leads to a larger negative effect of the CCPA on interest rates charged by fintechs relative to banks. These results suggest that the positive (negative) impact of the CCPA on applications (rates) among fintechs is not explained by differences in the local severity of the Covid-19 pandemic and associated restrictions on movements.

To further address the concern that some of our results are explained by the stark increase in mortgage refinancing during Covid, Table OA2 shows that the results on rate dispersion, denial rates, and other credit score models are present also among purchase mortgages only.[32] We further confirm in Table OA3 that our results hold for mortgages originated in California only, addressing the concern that results are explained by Covid-19 restrictions and policies in California that differed from those in the neighboring states.

**Shadow banks.** Our baseline analysis compares fintechs to other mortgage lenders, including banks and shadow banks. As explained in Section 4, several studies show that consumers trust fintechs less than other lenders and that fintechs use alternative data to screen borrowers. To the best of our knowledge, no such consistent evidence exists for shadow banks.[33] For these reasons, it is a priori unclear whether the CCPA – by granting users control over their data – makes consumers more or less willing to apply to and share data with shadow banks relative to banks. Likewise, should applications increase, for loan rates it is unclear whether the screening effect (use of more data to screen borrowers) dominates the demand effect (increased demand for mortgages) for shadow banks.

To examine these aspects, Table 9 shows results for Equation (1) when we restrict the sample to fintechs and shadow banks only. Column (1) shows that applications to fintechs

[32]The concern could be that fintechs were more likely to do refinancing during Covid-19, for example streamline refinancing, so that there could be changes in the composition of purchase vs refinance borrowers within tracts that affect average borrower quality.

[33]For example, Buchak et al. (2018, 2022) show that while the growth of shadow banks in the mortgage market is largely driven by regulatory arbitrage, the growth of fintechs is in equal parts due lighter regulation and the use of different information in processing applications.

increase by 11% relative to shadow banks, compared to 14.6% for the full sample. This pattern suggests that applications to shadow banks increased by slightly more than those to banks. Columns (2)–(5) investigate the relative strength of the screening vs demand effect. The negative coefficient for rates in column (2), which is larger in magnitude than our baseline estimate, suggests that the demand effect dominates the screening effect for shadow banks. Consistent with this interpretation, the estimated coefficients for rate dispersion, denied applications, and the use of alternative data in columns (3)–(5) suggest that shadow banks' screening does not improve by the same amount as that of fintechs. In sum, these results suggest that the CCPA made consumers more willing to apply to fintechs relative to banks as well as shadow banks. Moreover, fintechs could make better use of the available data to screen applicants.

**Further robustness tests.** In Table 10, we show that applications to fintechs increase and rates decline both among purchase as well as refinance mortgages, which addresses concerns about second homes or out-of-state applicants. Results remain unaffected when we exclude applicants of age 62 and above from the sample, ie applicants that could have been more affected by Covid-19 related restrictions. They also remain robust when we include a large set of applicant characteristics as controls at the lender–tract–year level (eg the average age, gender or race composition, as well as income levels or loan-to-income ratios); or control for tract-level house prices.

The Online Appendix provides additional tests. We confirm our results when we run the baseline specification leaving one border state out at a time (Table OA4). These exercises ensure that our results are not spuriously driven by movements in the control group. We also ensure that our result are robust to different levels of clustering (Table OA5); and when we include all tracts beyond just those in border counties (Table OA6). Finally, we show that our main results also hold in applicant-level regressions, in which we control for applicants' LTI ratio, LTV ratio, log income, age, sex, race, ethnicity, and debt to income ratio, as well as the log of the loan amount, log of the property value, a dummy for whether the loan was refinanced or not, and a dummy for whether the loan was sold or not (Table OA7).

# 5 Conclusion

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

This paper shows that the 2020 California Consumer Privacy Act is successful in mitigating the trade-off. The CCPA's philosophy is to grant consumers control over their data, thereby reducing their privacy concerns. In turn, it makes users more willing to share their information. Comparing fintechs to banks in counties along both sides of the California border in a difference-in-differences setting shows that the introduction of the CCPA increases fintechs' market share by 2 pp. Further evidence is consistent with fintechs' greater use of alternative data in processing applications, which improves their screening ability and leads to lower interest rates for consumers, and in particular for traditionally under-served segments of the population.

Our results have implications for the policy debate on how to regulate the use of personal data. They suggest that a privacy protection legislation that enhances users' control over data can protect users privacy while still providing firms with access to data. The CCPA can hence be seen as a successful regulatory initiative that holds important lessons for other U.S. states and countries designing or implementing privacy legislation.

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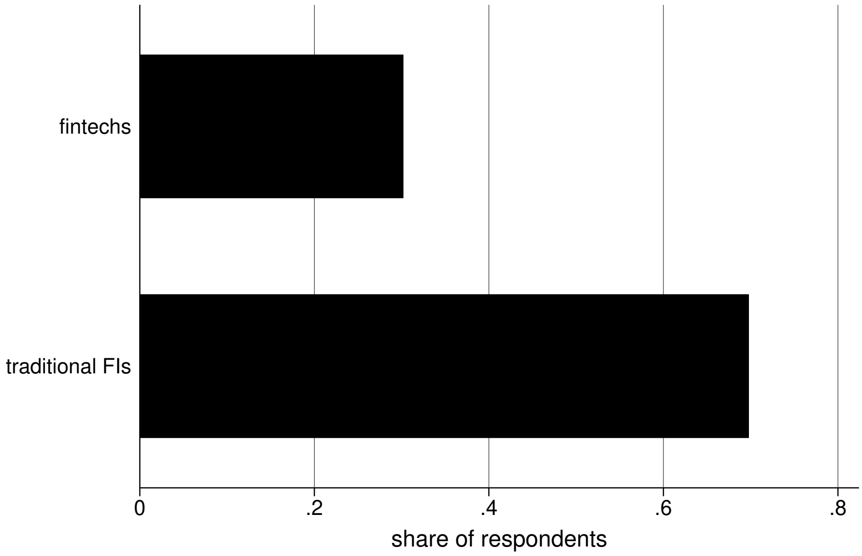
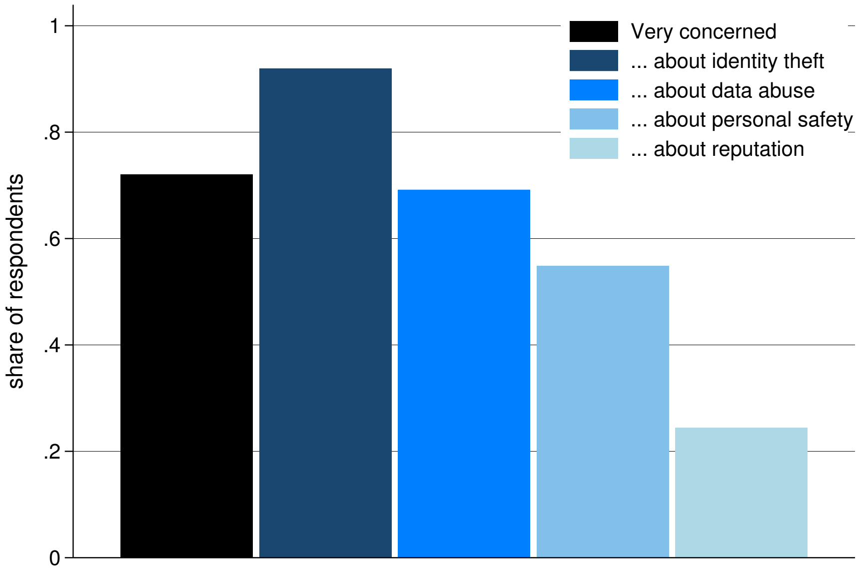
# A Figures and tables

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



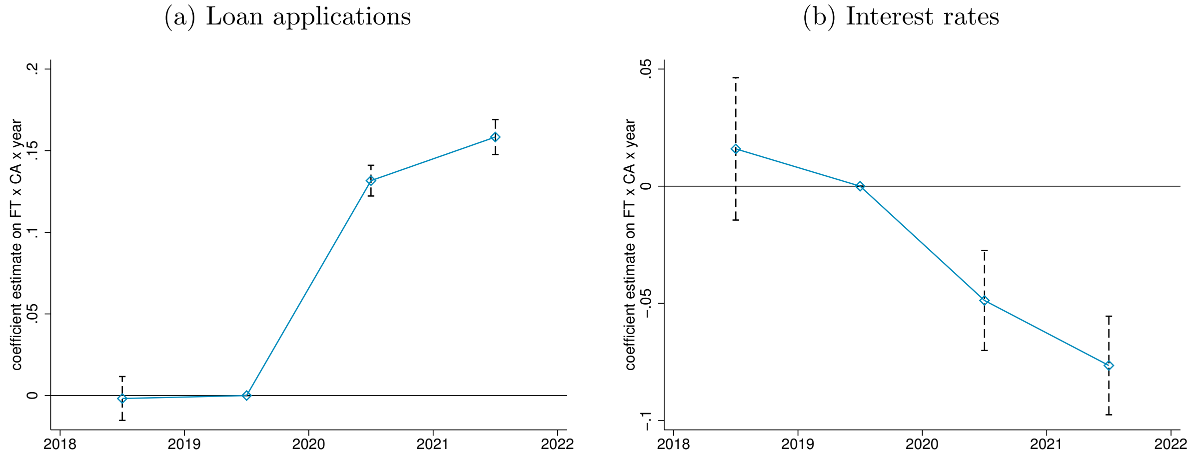

This figure shows the share of respondents reporting "high trust" in counterparties, based on a representative sample of 1,361 U.S. households in September 2020 that were part of the Survey of Consumer Expectations (SCE) of the Federal Reserve Bank of New York. Respondents place 'high trust' with a counterparty 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 that 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 that 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 – coefficient estimates**




This figure plots the coefficient estimates (blue line) and 95% 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 $\beta_k$ indicates the evolution of applications to or interest rates of 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. Panel (a) shows the coefficient estimates for loan applications, panel (b) for interest rates on approved mortgages. All regressions include tract*year fixed effects. Standard errors are clustered at the tract level.

Table 1: **Summary statistics**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| applications | 29215 | 5.648 | 6.999 | 2 | 181 |
| log(applications) | 29215 | 1.436 | .675 | .693 | 5.198 |
| interest rate | 29215 | 4.395 | .63 | 1.875 | 6.16 |
| other CS model | 29215 | .24 | .346 | 0 | 1 |
| sd(int rate) | 29215 | .515 | .437 | 0 | 2.21 |
| share denied | 29215 | .052 | .115 | 0 | .818 |

This table reports summary statistics for the main variables at the lender–tract–year level for the years 2018 and 2019, ie before the introduction of the CCPA. The interest rate is multiplied by 100.

Table 2: **Balancedness in applicant characteristics**

| | *banks* | | *fintechs* | | *mean diff.* |
|---|---|---|---|---|---|
| | mean | sd | mean | sd | t |
| share female | 0.25 | (0.26) | 0.25 | (0.26) | -1.19 |
| share Black or African Am. | 0.03 | (0.11) | 0.03 | (0.11) | -0.29 |
| income (in USD th) | 123.11 | (1528.74) | 104.14 | (45.37) | 0.83 |
| property value (in USD th) | 383.67 | (133.77) | 386.14 | (140.66) | -1.12 |
| loan-to-income ratio | 0.03 | (0.01) | 0.03 | (0.01) | 0.19 |
| loan-to-value ratio | 0.77 | (0.14) | 0.77 | (0.11) | -1.43 |
| share age 62+ | 0.17 | (0.25) | 0.20 | (0.26) | -7.00 |
| N | 24,789 | | 4,426 | | 29,215 |

This table reports summary statistics for applicant characteristics in 2018 and 2019 at the lender–tract–year level. The sample is split into banks and fintechs. The column *mean* denotes the mean and *sd* the standard deviation of each variable in each subgroup; *mean diff.* reports the t-value of a test for the statistical significance of the difference in means.

Table 3: **The CCPA, loan applications, and loan rates**

| VARIABLES | (1) applications | (2) applications | (3) applications | (4) rate | (5) rate | (6) rate |
|---|---|---|---|---|---|---|
| CA x post | 0.120*** | | | 0.141*** | | |
| | (0.011) | | | (0.008) | | |
| fintech x post | 0.273*** | 0.284*** | | 0.067*** | 0.057*** | |
| | (0.014) | (0.014) | | (0.011) | (0.011) | |
| CA x fintech x post | 0.133*** | 0.134*** | 0.146*** | -0.083*** | -0.080*** | -0.079*** |
| | (0.020) | (0.021) | (0.021) | (0.015) | (0.015) | (0.015) |
| Observations | 75,354 | 75,354 | 75,354 | 75,354 | 75,354 | 75,354 |
| R-squared | 0.763 | 0.790 | 0.791 | 0.889 | 0.904 | 0.904 |
| Lender*Tract FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Time FE | ✓ | - | - | ✓ | - | - |
| Tract*Time FE | - | ✓ | ✓ | - | ✓ | ✓ |
| Lender*Time FE | - | - | ✓ | - | - | ✓ |

This table reports results for Equation (1) at the lender-tract-year level. The dependent variable is the log of the total number of applications in columns (1)–(3) and the average interest rate on approved mortgages in columns (4)–(6). 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 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. Lender*time FE denote time-varying fixed effects at the lender type level. Standard errors are clustered at the tract level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: **Interest rate dispersion, denial rates, and credit scoring models**

| VARIABLES | (1)<br>sd(int rate) | (2)<br>sd(int rate) | (3)<br>denied | (4)<br>denied | (5)<br>alt CS | (6)<br>alt CS |
|---|---|---|---|---|---|---|
| CA x post | -0.069*** | | 0.003* | | -0.034*** | |
| | (0.007) | | (0.002) | | (0.004) | |
| fintech x post | -0.028*** | | -0.008** | | 0.022*** | |
| | (0.010) | | (0.003) | | (0.003) | |
| CA x fintech x post | 0.111*** | 0.093*** | 0.010** | 0.011** | 0.028*** | 0.029*** |
| | (0.013) | (0.014) | (0.005) | (0.005) | (0.005) | (0.005) |
| Observations | 75,354 | 75,354 | 75,354 | 75,354 | 75,354 | 75,354 |
| R-squared | 0.535 | 0.592 | 0.550 | 0.599 | 0.770 | 0.796 |
| Lender*Tract FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Time FE | ✓ | - | ✓ | - | ✓ | - |
| Tract*Time FE | - | ✓ | - | ✓ | - | ✓ |
| Lender*Time FE | - | ✓ | - | ✓ | - | ✓ |

This table reports results for Equation (1) at the lender-tract-year level. The dependent variable is the dispersion in interest rates in columns (1)–(2); the share of denied loan applications in columns (3)–(4); and the share of mortgages that do not use standardized credit scoring (CS) models in columns (5)–(6). 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 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. Lender*time FE denote time-varying fixed effects at the lender type level. Standard errors are clustered at the tract level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: **Thin credit file borrowers**

| VARIABLES | (1)<br>p50<br>white<br>rate | (2)<br>p25<br>white<br>rate | (3)<br>p50<br>tr income<br>rate | (4)<br>p25<br>tr income<br>rate | (5)<br>p50<br>app income<br>rate | (6)<br>p25<br>app income<br>rate |
|---|---|---|---|---|---|---|
| CA x fintech x post | -0.105*** | -0.119*** | -0.085*** | -0.088** | -0.086*** | -0.090** |
| | (0.023) | (0.036) | (0.024) | (0.037) | (0.024) | (0.044) |
| Observations | 33,065 | 14,213 | 36,942 | 18,748 | 32,947 | 15,675 |
| R-squared | 0.903 | 0.903 | 0.898 | 0.902 | 0.906 | 0.900 |
| Lender*Tract FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Tract*Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lender*Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

This table shows results for Equation (1) at the lender-tract-year level. The dependent variable is the average interest rate on approved mortgages. 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 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. Each column uses a different tract-level measure of the share of thin credit file applicants. Columns (1) and (2) focus on tracts with a low share of white applicants, columns (3)–(4) on tracts with a low tract-to-MSA income ratio, and columns (5)–(6) on tracts with low applicant income on average. For each measure, we focus on tracts below the median and in the bottom quartile of the distribution of minority/tract-to-MSA income/applicant income. Lender*time FE denote time-varying fixed effects at the lender type level. Standard errors are clustered at the tract level. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: **Mortgage loans not sold to GSEs**

| VARIABLES | (1) rate | (2) rate | (3) sd(int rate) | (4) sd(int rate) | (5) denied | (6) denied | (7) alt CS | (8) alt CS |
|---|---|---|---|---|---|---|---|---|
| CA x post | 0.307*** | | -0.131*** | | -0.002 | | -0.056*** | |
| | (0.020) | | (0.019) | | (0.003) | | (0.008) | |
| fintech x post | 0.181*** | | -0.086* | | 0.004 | | -0.017* | |
| | (0.035) | | (0.048) | | (0.005) | | (0.009) | |
| CA x fintech x post | -0.224*** | -0.164*** | 0.183*** | 0.114* | 0.021*** | 0.028*** | 0.056*** | 0.040*** |
| | (0.043) | (0.046) | (0.057) | (0.061) | (0.007) | (0.007) | (0.011) | (0.013) |
| Observations | 34,630 | 34,630 | 18,005 | 18,005 | 34,630 | 34,630 | 34,630 | 34,630 |
| R-squared | 0.820 | 0.861 | 0.617 | 0.720 | 0.629 | 0.695 | 0.660 | 0.723 |
| Lender*Tract FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Time FE | - | - | - | - | - | - | - | - |
| Tract*Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lender*Time FE | - | ✓ | - | ✓ | - | ✓ | - | ✓ |

This table reports results for Equation (1) at the lender-tract-year level for loans not sold to GSEs. The dependent variable is the interest rate in columns (1)–(2); the dispersion in interest rates in columns (3)–(4); the share of denied loan applications in columns (5)–(6); and the share of mortgages that do not use standardized credit scoring (CS) models in columns (7)–(8). 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 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. Lender*time FE denote time-varying fixed effects at the lender type level. Standard errors are clustered at the tract level. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: **The CCPA, loan rates, and applicant quality**

| VARIABLES | (1)<br>DTI < 36pct | (2)<br>LTV ratio | (3)<br>LTI ratio | (4)<br>log(inc) | (5)<br>risk PCA | (6)<br>baseline<br>rate | (7)<br>PCA<br>rate | (8)<br>PCA+other<br>rate |
|---|---|---|---|---|---|---|---|---|
| CA x fintech x post | 0.004 | -0.008 | -0.026 | 0.005 | -0.050 | -0.112*** | -0.107*** | -0.101*** |
| | (0.012) | (0.006) | (0.018) | (0.010) | (0.029) | (0.014) | (0.014) | (0.014) |
| Observations | 68,118 | 68,155 | 68,155 | 68,155 | 68,155 | 68,118 | 68,118 | 68,118 |
| R-squared | 0.549 | 0.693 | 0.631 | 0.777 | 0.651 | 0.901 | 0.903 | 0.908 |
| Lender*Tract FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Tract*Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lender*Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Risk controls | - | - | - | - | - | - | ✓ | ✓ |

This table reports results for Equation (1) at the lender-tract-year level. The dependent variables in columns (1)–(5) are different measures of applicant quality (dummy for low DTI ratio, the log of the LTV ratio, the log of the LTI ratio, the log of income, and the risk PCA). The dependent variable in columns (6)–(8) is the average interest rate on approved mortgages. 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 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 (7) and (8) include the mean and standard deviation of the various risk measures in each lender-tract-year cell as control variables. Lender*time FE denote time-varying fixed effects at the lender type level. Standard errors are clustered at the tract level. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: **Covid, applications, and rates**

| VARIABLES | (1)<br>baseline<br>applications | (2)<br><br>applications | (3)<br><br>applications | (4)<br>baseline<br>rate | (5)<br><br>rate | (6)<br><br>rate |
|---|---|---|---|---|---|---|
| CA x fintech x post | 0.145*** | 0.146*** | 0.140*** | -0.080*** | -0.100*** | -0.100*** |
| | (0.021) | (0.024) | (0.025) | (0.015) | (0.017) | (0.019) |
| fintech × workplace mob | | -0.002 | -0.004 | | 0.008*** | 0.007*** |
| | | (0.003) | (0.003) | | (0.002) | (0.002) |
| fintech × transit mob | | 0.001 | 0.005*** | | -0.002* | -0.001 |
| | | (0.002) | (0.002) | | (0.001) | (0.001) |
| fintech × cases pc | | | 0.058*** | | | 0.014 |
| | | | (0.013) | | | (0.010) |
| fintech × deaths pc | | | -1.258** | | | -0.247 |
| | | | (0.516) | | | (0.434) |
| Observations | 73,554 | 73,554 | 73,554 | 73,554 | 73,554 | 73,554 |
| R-squared | 0.791 | 0.791 | 0.791 | 0.903 | 0.903 | 0.903 |
| Lender*Tract FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Tract*Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lender*Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

This table reports results for Equation (1) at the lender-tract-year level. The dependent variable is the log of the total number of applications in columns (1)–(3) and the average interest rate on approved mortgages in columns (4)–(6). 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 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. *Workplace mob* and *transit mob* stand for an applicant county's workplace mobility and transit mobility indices, taken from Google Mobility Trends. *Cases pc* and *deaths pc* stand for Covid cases per capita and deaths per capita in the county. Values for these variables are set to zero in 2018 and 2019, and to their actual realization (averaged across days) in 2020 and 2021. Lender*time FE denote time-varying fixed effects at the lender type level. Columns (1) and (4) replicate the baseline finding for the smaller sample of tracts in counties with information on the Covid variables. Standard errors are clustered at the tract level. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: **Fintechs vs shadow banks**

| VARIABLES | (1) applications | (2) rate | (3) sd(int rate) | (4) denied | (5) alt CS |
|---|---|---|---|---|---|
| CA x fintech x post | 0.111*** | -0.191*** | 0.120*** | 0.018*** | 0.034*** |
| | (0.025) | (0.017) | (0.016) | (0.005) | (0.005) |
| Observations | 53,334 | 53,334 | 53,403 | 53,403 | 53,403 |
| R-squared | 0.850 | 0.922 | 0.619 | 0.625 | 0.816 |
| Lender*Tract FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Tract*Time FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lender*Time FE | ✓ | ✓ | ✓ | ✓ | ✓ |

This table reports results for Equation (1) at the lender-tract-year level for fintech lenders and shadow banks only. The dependent variable is the log of total applications in column (1); the interest rate in columns (2); the dispersion in interest rates in columns (3); the share of denied loan applications in columns (4); and the share of mortgages that do not use standardized credit scoring (CS) models in columns (5). 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 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 if it is a shadow bank. Lender*time FE denote time-varying fixed effects at the lender type level. Standard errors are clustered at the tract level. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: **Robustness tests**

| VARIABLES | (1)<br>purchase<br>applications | (2)<br>purchase<br>rate | (3)<br>refinance<br>applications | (4)<br>refinance<br>rate | (5)<br>young<br>applications | (6)<br>young<br>rate | (7)<br>controls<br>applications | (8)<br>controls<br>rate | (9)<br>HPI<br>applications | (10)<br>HPI<br>rate |
|---|---|---|---|---|---|---|---|---|---|---|
| CA x fintech x post | 0.092*** | -0.064*** | 0.114*** | -0.071*** | 0.137*** | -0.124*** | 0.140*** | -0.117*** | 0.059** | -0.073*** |
| | (0.035) | (0.023) | (0.042) | (0.020) | (0.022) | (0.017) | (0.022) | (0.013) | (0.027) | (0.021) |
| Observations | 53,972 | 53,972 | 37,418 | 37,418 | 72,441 | 72,441 | 73,767 | 73,767 | 45,547 | 45,547 |
| R-squared | 0.768 | 0.870 | 0.789 | 0.906 | 0.842 | 0.905 | 0.841 | 0.930 | 0.778 | 0.905 |
| Lender*Tract FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Tract*Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lender*Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

This table reports results for Equation (1) at the lender-tract-year level. The dependent variable alternates between the log of the total number of applications and the average interest rate on approved mortgages. 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 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. Lender*time FE denote time-varying fixed effects at the lender type level. Standard errors are clustered at the tract level. Columns (1)–(2) restrict the sample to purchase mortgages, columns (3)–(4) to refinance mortgages. Columns (5)–(6) exclude all applicants of age 62 and above from the sample. Columns (7)–(8) control for a rich set of controls for the average applicant at the lender–tract–year level: the share of female applicants, the share of applicants age 62 and above, the share of black applicants, the share of Hispanic applicants, the share of white applicants, the log of income, the log of the loan amount, the loan-to-income ratio, the share of applications with a debt-to-income ratio below 36%, as well as the fractions of applications that were denied, used an alternative credit scoring model, or are purchase mortgages. Columns (9)–(10) control for the interaction terms of yearly tract-level house price growth with the California dummy as well as the fintech dummy. *** p<0.01, ** p<0.05, * p<0.1.

# B Online Appendix

## B.1 Additional information on the CCPA

### B.1.1 General information

The California Consumer Privacy Act is a law passed in June 2018 that applies to companies handling personal information of California residents. It went into effect in January 2020. It endows Californians with several rights:

- The right to delete personal information collected from them;
- The right to know what personal information a business has collected about them and how it is used and shared;
- The right to opt-out of the sale of their personal information; and
- The right to non-discrimination for exercising their CCPA rights.

Starting in 2023, the law will also include the right to correct inaccurate information and the right to limit the use and disclosure of sensitive personal information.

During our period of analysis, the companies that are subject to the CCPA are those that: Have a gross annual revenue of over $25 million; buy, receive, or sell the personal information of 50,000 or more California residents, households, or devices in one year; or derive 50% or more of their annual revenue from selling California residents personal information.[34]

The scope of what constitutes personal information under the CCPA is broad. For example, an IP address of an individual browsing a website is considered personal infor-

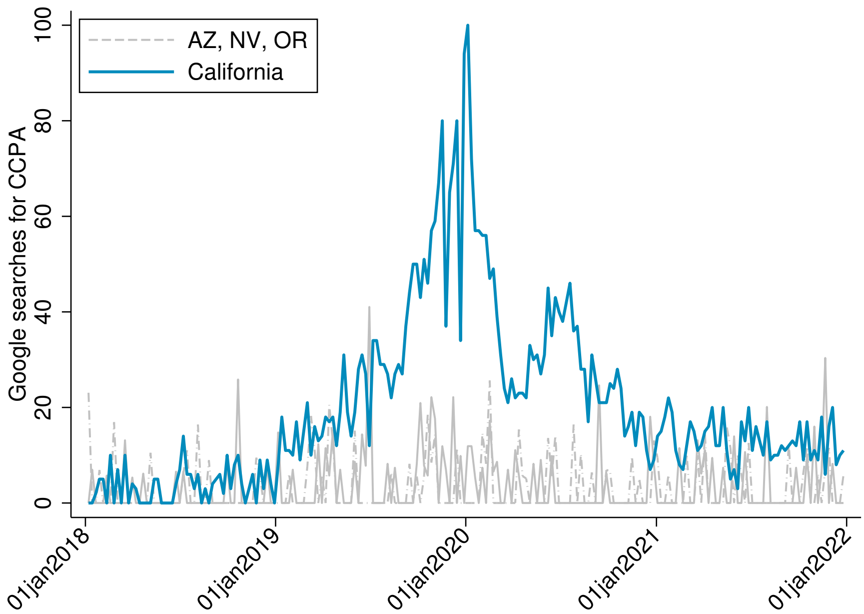
[34] https://cppa.ca.gov/faq.html. Accessed November 25th, 2022. Starting in 2023 to meet the second threshold, businesses must annually buy, sell, or share the personal information of 100,000 or more consumers or households.

mation. Therefore, the CCPA is likely to cover a large proportion of companies, including numerous small- to medium-sized enterprises.[35] Virtually all banks and fintech lenders fall under the CCPA.

### B.1.2 Salience

Google searches for "CCPA" on Google Trends in Figure OA1 suggest that the residents of California were aware of the introduction of the privacy legislation. Google searches for the CCPA in California increased steeply in late 2019 and remained elevated for most of 2020, while trends in Arizona, Nevada and Oregon did not replicate this interest.

Figure OA1: **Internet searches for CCPA**




This figure shows internet searches from Google Trends for 'CCPA' in California and neighboring states over time. The CCPA came into effect in January 2020. Note that Google Trends normalizes the search interest so that the day with the most searches over the period of interest takes the value of 100, and all other dates are with respect to this value. To compare searches across states, series are standardized based on average search frequency in California relative to the other states over the period 01Jan2018 to 31Dec2021, with Washington D.C. serving as benchmark.

[35] https://iapp.org/news/a/new-california-privacy-law-to-affect-more-than-half-a-million-us-companies/. Accessed November 25th, 2022.

Figure OA2 and Figure OA3 provide screenshots of the information on the CCPA consumers can find on mortgage application websites.

### B.1.3 Enforcement

Under the CCPA, individuals can file a consumer complaint with the Office of the Attorney General (OAG). Starting in July 2023, claims can also be filed with the recently founded California Privacy Protection Agency. The Attorney General and the Agency investigate violations, either following a consumer complaint or from their own initiative, and take enforcement actions.[36] Individual suing of a business is limited to data breaches where it is clear the company did not take the necessary measures to protect consumers' data.

The OAG regularly sends companies notices of alleged noncompliance.[37] Once a company is notified of alleged noncompliance, it has 30 days to take the neccesary steps to resolve the noncompliance. If it does not solve the issue that prompted the notice, the Attorney General can engage in civil law procedures. The first enforcement settlement related to the CCPA took place in August 2022 and it concerned the French cosmetics brand Sephora. The investigation found that Sephora was selling consumers' personal information without disclosing it, as well as not complying with opt-out requests. Sephora failed to correct these issues within the 30 days of notification by the OAG. Sephora agreed to settle for $1.2 million in fines and agreed to follow its compliance obligations.[38]

[36] https://cppa.ca.gov/faq.html. Accessed November 25th, 2022.

[37] https://oag.ca.gov/privacy/ccpa/enforcement. Accessed March 24th, 2023.

[38] https://iapp.org/news/a/the-sephora-case-do-not-sell-but-are-you-selling/. Accessed November 25th, 2022.

VIEW MORTGAGE

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# CCPA

## California Consumer Privacy Act Privacy Notice:

This privacy notice supplements the general privacy policy notice of View Mortgage, LLC NMLS# 2185181 which can be found at **https://viewmortgage.com/privacy-policy**. This supplemental privacy policy applies solely to consumers who reside in the State of California ("you"). View Mortgage, LLC adopts this notice to comply with the California Consumer Privacy Act of 2018, as amended ("CCPA") and other applicable California privacy laws. Any terms defined in the CCPA have the same meaning when used in this notice.

The CCPA was passed by the State of California in 2018 and provides California residents with the following rights over their personal information: (a) the right to access, transfer, edit and delete their personal data with a verifiable consumer request; and (b) the ability to opt out of certain data-processing practices. In addition, California residents have the right to: (a) know what information is being collected about them; (b) know if their personal information is sold or disclosed, and to whom; (c) say "no" to the sale of personal information; and (d) equal service and price, even if they exercise their privacy rights under the CCPA.

View Mortgage, LLC does not and will not discriminate in any way against any consumers who choose to exercise their rights under the CCPA.

## What Information We Collect About You:

We may obtain certain personal information (such as name and other contact details) through our Sites. Here are the most common types of information: Contact information (such as name, postal address, e-mail address, telephone number and fax number); Login and access credentials (such as username and password); Information about your property or mortgage loan; Age and gender; Real estate license number.

Figure OA2: This figure displays the CCPA information available in the website from View Mortgage, available at https://www.viewmortgage.com/ccpa.

About Us Education Our Loans Our Offices Partners Payment Portal Start My Loan

## California Consumer Privacy Act

**Open Mortgage is committed to compliance with the new California Consumer Privacy Act (CCPA) and to providing options to Opt-Out. Additionally, Open Mortgage never sells any of your data. That said, it is important to note that CCPA provides exemptions to companies that have consumer data that is necessary to carry out their business. A majority of the data that Open Mortgage collects is exempt from CCPA as it falls under federal privacy laws set out by the Gramm Leach Bliley Act (GLBA) and cannot, as a result, be part of the Opt-Out request. We are GLBA compliant and protect your data to our fullest capability. So, Open Mortgage will receive your Opt-Out request via the option you select, and will work to remove any data that is not exempt.**

**What does that mean?**

That means that if you have applied for a loan from Open Mortgage, we are exempt from removing personal data that was used in the loan process. Personal data that is exempt will include data like your name, phone number, social security number, date of birth, address, employment data, and income data. So while we have to keep that data, we want you to rest assured that Open Mortgage does not engage in the sale of data. Lastly, please keep in mind that data outside the loan process may not be exempt.

**What kind of data is outside the loan process?**

Information that was not collected in your loan application and was collected from marketing activities, promotional activities, information from a non-borrowing spouse, IP addresses, geolocation data through the use of a third-party application, web page tracking, and information collected through a third party like a marketing list.

**To proceed with your request, please be prepared to provide your first and last name, your phone number, your email address, your loan number (if applicable), and the Loan Officer you have been or were working with. Providing this will help us locate your information and validate your request. Open Mortgage may request additional information if your request cannot be validated. You must be a resident of California to be eligible for this request.**

**Click here for the full CCPA privacy policy**

You can fill out and submit this form to request to opt-out.

Figure OA3: This figure displays the CCPA information available in the website from Open Mortgage, available at https://openmortgage.com/ccpa.

## B.2 A parsimonious theoretical framework

This section develops the theoretical framework guiding the empirical analysis. In particular, we generate the hypotheses about loan applications and interest rates charged in a loan market following the introduction of privacy protection regulation.

### B.2.1 Setup

We consider a competitive loan market where potential borrowers are continuously and uniformly distributed along an arc of unit length. Banks and a fintech request data to screen applicants before offering a loan. Fintechs are better at extracting precise information from personal information, but applicants dislike sharing their data with them.

**Applicants.** Applicants are risk-neutral and penniless, but are endowed with a risky investment opportunity that requires one unit of funding. An applicant could be a firm looking for a loan to fund a project, or an individual looking for a mortgage to buy a house. Half of the individuals, called $p_H$, are successful in their investment and get a return $Y$ that allows them to repay. The other half ($p_L$) is unsuccessful so they do not repay. We assume that $Y$ is large enough so that everyone applies for a loan. Applicants are protected by limited liability, and their outside option is normalized to zero.

Applicants are endowed with one unit of personal data and dislike sharing their data with lenders. In line with the evidence in Figure 1, their disutilty from sharing data is higher when they share their data with a fintech than with a bank. We capture this stylized fact by assuming that an applicants' dislike to sharing data with a bank is $s = 1$, while it is $s_F > s$ when sharing data with a fintech. Therefore, $s_F$ denotes the relative dislike of providing data to the fintech vs the bank. Importantly, applicants do not possess the technology to infer their type from their data.

**Lenders.** Two symmetric banks are located at the extremes of the arc, with bank 1 ($B1$) at the beginning and bank 2 ($B2$) at the end. Each applicant regards the lenders as providing services with different convenience levels, which is captured by the distance $x$ between a consumer on the arc and the banks (Thisse and Vives, 1988).

The fintech ($F$) is located at the same distance $x_F$ to all consumers, irrespective of their location on the arc. This assumption captures the idea that fintechs offer online platforms with higher convenience and speed over banks to all consumers, two key drivers behind their rapid growth (Buchak et al., 2018; Berg et al., 2022).[39] We normalize the fintech's distance to all applicants to zero ($x_F = 0$) for simplicity. The analysis remains qualitatively similar for any positive and sufficiently small distance $x_F > 0$.

Lenders have access to a screening technology that returns either a good signal ($\eta_g$) or a bad signal ($\eta_b$). The accuracy of the signal depends on two elements: the technology that each lender type $j = \{B, F\}$ has ($\gamma_j \in (0, 1]$) and the data each lender collects on the borrower ($d_j \in [0, 1]$). Similar to He et al. (2023), we assume that the fintech is better at extracting information from a given amount of data, so $\gamma_F > \gamma_B$, and we normalize its technology to one ($\gamma_F = 1$). Moreover, the screening technology's accuracy is increasing and concave in the amount of data: When there is little data available, more data considerably improves the signal accuracy.[40] When lenders already have a considerable amount of data, an additional unit does not increase accuracy by much.[41]

[39] Chu and Wei (2021) and Vives and Ye (2022) make a similar assumption in a Salop circle.

[40] As our focus is what happens to data and hence interest rates when there is a change in the dislike to sharing data, we employ a screening technologies that yield interior optimal data requested.

[41] Berg et al. (2020) show that even simple, easily accessible data that proxy for income, character, and reputation are highly valuable for default prediction.

More data hence allow the lenders to filter out, among all applicants, a higher proportion of those that would not repay.

The signal is uncorrelated across lenders and has a bad-news flavor: Only applicants that do not repay send bad signals. Good signals can come from both types of applicants. The signal structure is:

$$\Pr(\eta_{j,g}|p_H) = 1, \qquad \Pr(\eta_{j,b}|p_L) = \gamma_j\sqrt{d_j}.$$

With this signal structure, the probability that lender $j$ observes a good signal is:

$$\sigma_j \equiv \Pr(\eta_{j,g}) = \Pr(\eta_{j,g}|p_H)\Pr(p_H)+\Pr(\eta_{j,g}|p_L)\Pr(p_L) = 1\times\frac{1}{2}+\frac{1}{2}(1-\gamma_j\sqrt{d_j}) = 1-\frac{\gamma_j\sqrt{d_j}}{2}$$

Conditional on observing a good signal, the probability of project success is:

$$\Pr(p_H|\eta_{j,g}) = \frac{\Pr(\eta_{j,g}|p_H)\Pr(p_H)}{\Pr(\eta_{j,g})} = \frac{1}{2\sigma_j}$$

Both types of lenders face a perfectly elastic supply of funds at the risk free rate and derive revenue from the interest rate they charge on their loans. We follow Vives and Ye (2022) and assume that the fintech can price discriminate their offers to applicants based on their location in the line thanks to its predictive models (Fuster et al., 2022). Allowing the fintech to price discriminate takes a short-term view on the market dynamics: it assumes that the bank is slow to catch up to fintechs' more advanced technology (Navaretti et al., 2018) and it also assumes that regulation is slow in addressing fintechs' discriminatory practices (Bhutta et al., 2021).

**Timing.** The timing of the game is as follows: First, lenders simultaneously choose the amount of data they request from applicants. Observing each others' data choices, the lenders choose their interest rates: banks first post uniform loan rates, while the fintech moves second and can price discriminate applicants based on their position in the line (Vives and Ye, 2022). The final contract, which consists of a combination of the offered interest rate and requested data $(r(d;x), d)$, is contingent on the applicant qualifying for a loan. If the applicant does not qualify, the lenders withdraw the offer. Applicants then observe the data requested and the interest rate offered by each lender. Considering their position on the arc (ie their relative distance to each lender), they apply to the lender with the offer that maximizes their expected utility.[42] The game concludes as follows: Lenders receive applicants' data and process them to extract the signal. They then extend credit to the applicants that returned a good signal $(\eta_g)$ and disqualify the applicants that returned a bad signal. We focus on equilibria that are symmetric on the banks' choices.

#### B.2.2 Equilibrium

We proceed backwards. An applicant located at position $x \in [0, 1]$ has three choices: either go to bank 1, which is at a distance $x$; go to bank 2, at a distance $1 - x$, or go to the fintech, which is at a distance $x_F$, normalized to zero for expositional clarity.

$$\begin{aligned}
\mathbb{E}[u_s(\ell_{B1}; r_{B1}(d), d_{B1}, x)] &= \frac{1}{2}(Y - r_{B1}(d)) - t_B x - d_{B1} \\
\mathbb{E}[u_s(\ell_{B2}; r_{B2}(d), d_{B2}, x)] &= \frac{1}{2}(Y - r_{B2}(d)) - t_B(1 - x) - d_{B2} \\
\mathbb{E}[u_{s_F}(\ell_F; r_F(d;x), d_F, x)] &= \frac{1}{2}(Y - r_F(d;x)) - s_F d_F
\end{aligned}$$

The expected utility from applying reflects the offered interest rate (which depends on the data requested), the disutility of sharing data (which is greater when applying

[42] Price commitments under screening are as in Kim and Wagman (2015); Burke et al. (2012). Contracts are exclusive, so borrowers cannot apply to two lenders at the same time.

to the fintech), as well as the distance to the lender (which is greater for a bank). The applicant indifferent between a bank and a fintech is located where the expected utility from applying to a bank equals that of applying to the fintech. All else equal, applicants sufficiently close to the endpoints of the line, for whom the disutility from distance is small, contract with the bank. The fintech receives applications from borrowers further away from both banks, ie near the midpoint of the line. While applying to the fintech entails greater disutility from sharing a given amount of data, this disutility is offset by the lower convenience cost.

Individuals' choice of lender gives rise to the demand for each lender. Denote by $\tilde{x}_1$ the position of the borrower indifferent between applying to bank 1 or the fintech whenever the fintech charges the lowest feasible interest rate (that makes it break even), and by $\tilde{x}_2$ the position of the borrower indifferent between applying to lender 2 or the fintech whenever the fintech charges the lowest feasible interest rate.

Proceeding by backwards induction, the fintech sets the interest rate at each location to match the expected utility that applicants get when applying to the bank. Therefore, for each $x \in [\tilde{x}_1, \tilde{x}_2]$, the fintech's interest rate is:

$$\begin{aligned} r_F(d,x) =& r_{B1}(d) + 2x + 2d_{B1} - 2d_F s_F \qquad && \text{if } x \in [\tilde{x}_1, \tilde{x}] \\ r_F(d,x) =& r_{B2}(d) + 2(1-x) + 2d_{B2} - 2d_F s_F && \text{if } x \in [\tilde{x}, \tilde{x}_2] \end{aligned}$$

Banks anticipate the fintech's pricing strategy, take the data choices as given and internalize the effect of their choices on demand.

$$\begin{aligned} \mathbb{E}[\Pi_{Bk}(r_{Bk}(d), d_{Bk}; r_{-j}(d), d_{-j})] &= D_{Bk}(r_{Bk}(d), d_{Bk}; r_{-j}(d), d_{-j})\, \mathbb{E}[\pi_{Bk}(r_{Bk}(d), d_{Bk})] \\ &= D_{Bk}(r_{Bk}(d), d_{Bk}; r_{-j}(d), d_{-j}) \left[ \frac{1}{2} r_{Bk}(d) - 1 + \frac{\gamma_B \sqrt{d_{Bk}}}{2} \right] \end{aligned}$$

The solution to the FOCs that satisfies the SOCs are given by:

$$d^{\star}_{B1} = \frac{\gamma_B^2}{16} \tag{2}$$
$$d^{\star}_{B2} = \frac{\gamma_B^2}{16} \tag{3}$$
$$d^{\star}_{F} = \frac{1}{16s_F^2} \tag{4}$$

At the beginning of the game, the lenders choose the accuracy of their screening technology taking into account the effect that the data requested have on the optimal rates, as well as on the demand: The optimal rates are:

$$\begin{aligned} r^{\star}_B =& 2 - \frac{3\gamma_B^2}{16} - \frac{1}{16s_F}, \\ r^{\star}_F(x) =& 2 + 2x - \frac{\gamma_B^2}{16} - \frac{3}{16s_F}. \end{aligned}$$

In equilibrium, optimal demand ($D_F$) is determined by the relative dislike of providing data to the fintech vs the bank ($s_F$) and the difference in the screening technology ($\gamma_B$):[43]

$$\begin{aligned} D^{\star}_B =& \frac{\gamma_B s_F - 1}{32s_F} \\ D^{\star}_F =& 1 - \frac{\gamma_B s_F - 1}{16s_F} \end{aligned}$$

Lenders' demand for data is a function of each lender's signal accuracy and the dislike to sharing data of the applicants vis-a-vis that lender. In essence, when asking for data, lenders face a trade-off. More data implies greater signal accuracy to screen out the credit-unworthy applicants, and hence lenders can offer a lower interest rate to qualifying applicants. At the same time, asking for more data lowers demand, as sharing data is

[43]Given that in the model, market size is constant, demand to the fintech also represents its market share.

costly for applicants. This trade-off is more pronounced for fintechs, as they have a better screening technology but applicants have a greater dislike for sharing data with them.

#### B.2.3 Introducing privacy protection legislation

We can perform comparative statics exercises to understand how the introduction of privacy legislation affects the loan market. We consider privacy legislation in the spirit of the CCPA, ie legislation that provides consumers with greater control over their data and reduces concerns about the abuse and misuse of data. Such legislation decreases borrowers' dislike to sharing their data. Moreover, we assume that this decrease is greater for sharing data with fintechs compared to banks, consistent with the evidence that individuals generally have lower confidence in fintechs to safely handle personal data.

In equilibrium, the introduction of a privacy protection regulation decreases borrowers' dislike to sharing data with the fintech, $s_F$. It hence increases the relative demand for the fintech In equilibrium, the introduction of a privacy protection regulation decreases borrowers' dislike to sharing data with the fintech ($s_F$). It hence increases the relative demand for the fintech

$$-\frac{\partial D_F^\star}{\partial s_F} = \frac{1}{16 s_F^2} > 0. \tag{5}$$

The increase in demand for the fintech means that the indifferent consumer between banks and fintechs now sits closer to the banks, and hence the range of interest rates offered by the fintech expands, while decreasing the interest rates that the fintech charges relative to banks

$$\left(\frac{\partial r_F^\star}{\partial - s_F}\right) - \left(\frac{\partial r_B^\star}{\partial - s_F}\right) = \left(-\frac{3}{16 s_F^2}\right) - \left(-\frac{1}{16 s_F^2}\right) < 0. \tag{6}$$

The mechanism behind these results is as follows: as borrowers' dislike sharing data with the fintech decreases, the fintech asks for more data, which makes its screening more accurate. The fintech identifies and rejects more of the credit-unworthy applicants. In turn, this improves the quality of the accepted applicant pool, allowing the fintech to offer lower interest rates. Both because borrowers are less concerned about sharing data and because they are charged a lower interest rate, more borrowers apply to the fintech.

In sum, the model generates the following testable hypotheses:

***Hypothesis 1***: The introduction of privacy protection legislation in the spirit of the CCPA leads to an increase in loan applications with fintechs, compared to banks.

***Hypothesis 2***: The introduction of privacy protection regulation in the spirit of the CCPA leads to a decrease in loan rates on loans originated by fintechs, compared to loans originated by banks.

***Hypothesis 3.1***: The introduction of privacy protection regulation in the spirit of the CCPA leads to the fintech offering more individualized pricing and its dispersion in interest rates increases relative to banks.[44]

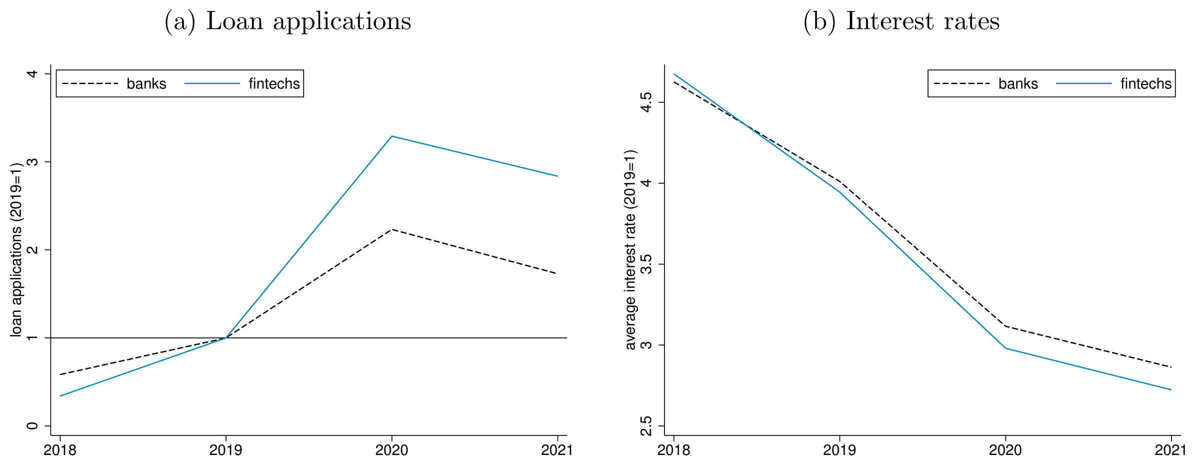
***Hypothesis 3.2***: The introduction of privacy protection regulation in the spirit of the CCPA increases the share of denied loan applications by the fintech by more relative to banks.

***Hypothesis 3.3***: The introduction of privacy protection legislation in the spirit of the CCPA implies that the fintech will ask for relatively more personal data than banks.

[44] Babina et al. (2022) relate the use of non-traditional data beyond standardized credit scores to more individualized pricing. Jansen et al. (2022) suggest that a more precise signal about borrowers' quality leads to more accurate pricing and hence greater dispersion in interest rates.

## B.3 Further Figures and Tables

Figure OA4: **Pre-trends**




Panel (a) plots the evolution of loan applications with banks (black dashed line) and fintechs (blue solid line) in California during the sample period. Applications with each lender are standardized to 1 in 2019, the year before the CCPA came into effect. Panel (b) plots the respective interest rates on approved mortgages for banks and fintechs over the sample period.

Table OA1: **The CCPA, fintechs' market share, and mortgage origination**

| VARIABLES | (1) FT mkt share | (2) FT mkt share | (3) FT mkt share | (4) orig FT mkt share | (5) log(orig) | (6) log(orig) |
|---|---|---|---|---|---|---|
| CA x post | 0.033*** | 0.035*** | 0.022*** | 0.026*** | 0.116*** | |
| | (0.005) | (0.005) | (0.006) | (0.008) | (0.011) | |
| fintech x post | | | | | 0.284*** | |
| | | | | | (0.014) | |
| CA x fintech x post | | | | | 0.118*** | 0.129*** |
| | | | | | (0.020) | (0.021) |
| Observations | 6,848 | 6,848 | 6,848 | 6,808 | 75,354 | 75,354 |
| R-squared | 0.506 | 0.508 | 0.513 | 0.493 | 0.753 | 0.783 |
| Tract FE | ✓ | ✓ | ✓ | ✓ | - | - |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | - |
| Controls | - | C | C+A | C+A | - | - |
| Lender*Tract FE | - | - | - | - | ✓ | ✓ |
| Tract*Time FE | - | - | - | - | - | ✓ |
| Lender*Time FE | - | - | - | - | - | ✓ |

Columns (1)–(3) reports results from the following difference-in-differences specification at the applicant tract–year level: $fintech\ market\ share_{c,t} = \beta\ CA_c \times post_t + \theta_c + \tau_t + controls_{c/a} + \varepsilon_{c,t}$. The dependent variable is the share of applications to fintechs in census tract $c$ and year $t$ (ie fintechs' market share). 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 after the CCPA was enacted. Regressions include tract ($\theta$) and year ($\tau$) fixed effects. Census tract-level ($C$) controls include the pre-period values of the minority share, tract-to-MSA income ratio, and the log of the total tract population, all interacted with the post dummy. Applicant-level ($A$) controls, averaged to the tract level, include the pre-period values of the share of female applicants, the share of black applicants, the share of Hispanic applicants, the average interest rate, as well as the log of the average application amount and average applicant income, all interacted with the post dummy. Standard errors are clustered at the tract level. Column (1), with tract and time fixed effects, shows that after the introduction of the CCPA, the market share of fintechs increased by more in California compared to other states (ie, $\beta > 0$). Columns (2) and (3) include a battery of census tract and/or applicant control variables. Across specifications, the estimated coefficient remains positive and economically and statistically significant. In terms of magnitude, the share of applications to fintechs increases by 2.2 percentage points in column (3). The share of loan applications to fintechs was 16.3% with a standard deviation of 12.2%, implying an increase in their market share of 13.5% of the pre-treatment mean. Column (4) replicates column (3), but with the share of mortgages originated by fintechs as dependent variable. Columns (5)–(6) show results for Equation (1). The dependent variable is the log of the total number of originated mortgages. The dummy variable *fintech* takes on a value of one if the lender is a fintech and a value of zero otherwise. *** p<0.01, ** p<0.05, * p<0.1.

Table OA2: **Purchase mortgages only**

| VARIABLES | (1) rate | (2) sd(int rate) | (3) denied | (4) alt CS |
|---|---|---|---|---|
| CA x fintech x post | -0.064*** | 0.097*** | 0.013** | 0.019*** |
| | (0.023) | (0.026) | (0.005) | (0.007) |
| Observations | 53,972 | 32,123 | 53,972 | 53,972 |
| R-squared | 0.870 | 0.670 | 0.637 | 0.772 |
| Lender*Tract FE | ✓ | ✓ | ✓ | ✓ |
| Tract*Time FE | ✓ | ✓ | ✓ | ✓ |
| Lender*Time FE | ✓ | ✓ | ✓ | ✓ |

This table reports results for Equation (1) at the lender-tract-year level for purchase mortgages only. The dependent variable is the interest rate in columns (1); the dispersion in interest rates in columns (2); the share of denied loan applications in columns (3); and the share of mortgages that do not use standardized credit scoring (CS) models in columns (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 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. Lender*time FE denote time-varying fixed effects at the lender type level. Standard errors are clustered at the tract level. *** p<0.01, ** p<0.05, * p<0.1.

Table OA3: **The CCPA, applications, and loan rates — California sample**

| VARIABLES | (1) applications | (2) applications | (3) rate | (4) rate |
|---|---|---|---|---|
| fintech x post | 0.513*** | 0.516*** | -0.063*** | -0.069*** |
| | (0.006) | (0.006) | (0.004) | (0.004) |
| Observations | 259,156 | 259,156 | 259,156 | 259,156 |
| R-squared | 0.764 | 0.799 | 0.907 | 0.921 |
| Lender*Tract FE | ✓ | ✓ | ✓ | ✓ |
| Time FE | ✓ | - | ✓ | - |
| Tract*Time FE | - | ✓ | - | ✓ |

This table shows results for the following equation at the lender-tract-year level: $y_{l,c,t} = \delta\ fintech_l \times post_t + \theta_{l,c} + \tau_t + \varepsilon_{l,c,t}$ for tracts in California only. The dependent variable is the log of the total number of applications in columns (1)–(2) and the average interest rate on approved mortgages in columns (3)–(4). The dummy variable *fintech* takes on a value of one if the lender is a fintech and a value of zero otherwise. The dummy *post* takes on a value of one after the CCPA was enacted. Standard errors are clustered at the tract level. Results show that the main findings obtained in Table 3 also hold for California tracts only. *** p<0.01, ** p<0.05, * p<0.1.

Table OA4: **Excluding individual states**

| VARIABLES | (1) no AZ applications | (2) no AZ rate | (3) no NV applications | (4) no NV rate | (5) no OR applications | (6) no OR rate |
|---|---|---|---|---|---|---|
| CA x fintech x post | 0.142*** | -0.072*** | 0.228*** | -0.084*** | 0.136*** | -0.086*** |
| | (0.021) | (0.015) | (0.036) | (0.027) | (0.022) | (0.016) |
| Observations | 72,863 | 72,863 | 47,189 | 47,189 | 72,197 | 72,197 |
| R-squared | 0.791 | 0.904 | 0.788 | 0.909 | 0.792 | 0.902 |
| Lender*Tract FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Tract*Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lender*Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

This table shows results for Equation (1). The dependent variable alternates between the log of the total number of applications and the average interest rate on approved mortgages. 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 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. Lender*time FE denote time-varying fixed effects at the lender type level. Standard errors are clustered at the tract level. Columns (1)–(2) [(3)–(4); (5)–(6)] exclude all tracts in AZ [NV, OR]. Results show that the findings obtained in Table 3 are not driven by movements in the control group. *** p<0.01, ** p<0.05, * p<0.1.

## Table OA5: **Clustering**

| VARIABLES | (1)<br>T<br>applications | (2)<br>T<br>rate | (3)<br>T*Y<br>applications | (4)<br>T*Y<br>rate | (5)<br>C<br>applications | (6)<br>C<br>rate | (7)<br>C*Y<br>applications | (8)<br>C*Y<br>rate | (9)<br>S*Y<br>applications | (10)<br>S*Y'<br>rate |
|---|---|---|---|---|---|---|---|---|---|---|
| CA x fintech x post | 0.146*** | -0.079*** | 0.146*** | -0.079*** | 0.146*** | -0.079** | 0.146*** | -0.079*** | 0.146** | -0.079*** |
| | (0.021) | (0.015) | (0.021) | (0.015) | (0.041) | (0.029) | (0.048) | (0.025) | (0.064) | (0.019) |
| Observations | 75,354 | 75,354 | 75,354 | 75,354 | 75,354 | 75,354 | 75,354 | 75,354 | 75,354 | 75,354 |
| R-squared | 0.791 | 0.904 | 0.791 | 0.904 | 0.791 | 0.904 | 0.791 | 0.904 | 0.791 | 0.904 |

This table shows results for Equation (1) for tracts in CA border counties. The dependent variable alternates between the log of the total number of applications and the average interest rate on approved mortgages. 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 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. Lender*time FE denote time-varying fixed effects at the lender type level. Standard errors are clustered at the level indicated in the column header, where T is tract, C is county, S, is state, and Y is year. Results show that the findings obtained in Table 3 are robust to different levels of clustering. *** p<0.01, ** p<0.05, * p<0.1.

Table OA6: **All tracts in CA and neighboring states**

| VARIABLES | (1) applications | (2) rate | (3) sd(int rate) | (4) denied | (5) alt CS |
|---|---|---|---|---|---|
| CA x fintech x post | 0.227*** | -0.132*** | 0.065*** | 0.007*** | 0.012*** |
| | (0.011) | (0.007) | (0.006) | (0.002) | (0.002) |
| Observations | 404,536 | 404,536 | 404,536 | 404,536 | 404,536 |
| R-squared | 0.796 | 0.917 | 0.583 | 0.602 | 0.815 |
| Lender*Tract FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Tract*Time FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lender*Time FE | ✓ | ✓ | ✓ | ✓ | ✓ |

This table reports results at the lender-tract-year level for Equation (1) for all tracts in California and neighboring states. The dependent variable is the log of the total number of applications in column (1), the average interest rate on approved mortgages in column (2), the dispersion in interest rates in column (3), the share of denied loan applications in column (4), and the share of mortgages that did not use standardized underwriting models in column (5). 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 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. Lender*time FE denote time-varying fixed effects at the lender type level. Standard errors are clustered at the tract level. Results show that the main findings obtained in Table 3 and Table 4 for border tracts also hold for the full sample of tracts. *** p<0.01, ** p<0.05, * p<0.1.

Table OA7: **Applicant-level regressions**

| VARIABLES | (1) app to FT | (2) app to FT | (3) interest rate | (4) interest rate | (5) interest rate |
|---|---|---|---|---|---|
| CA x post | 0.025*** | 0.021*** | 0.127*** | | |
| | (0.003) | (0.003) | (0.006) | | |
| fintech x post | | | -0.055*** | | |
| | | | (0.005) | | |
| CA x fintech x post | | | -0.058*** | -0.053*** | -0.043*** |
| | | | (0.006) | (0.006) | (0.004) |
| Observations | 674,720 | 674,720 | 595,226 | 595,188 | 595,188 |
| R-squared | 0.017 | 0.036 | 0.513 | 0.524 | 0.658 |
| Tract FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Time FE | ✓ | ✓ | ✓ | - | - |
| Tract*Time FE | - | - | - | ✓ | ✓ |
| Lender*Time FE | - | - | - | ✓ | ✓ |
| Applicant Controls | - | ✓ | - | - | ✓ |

This table reports results at the applicant level. Columns (1)–(2) estimate regressions of the following form: $app\ FT_{i(c,t)} = \beta\ CA_c \times post_t + \theta_c + \tau_t + controls_i + \varepsilon_i$. The dependent variable is a dummy with a value of one if the application of applicant $i$ in census tract $c$ and year $t$ is with a fintech and zero otherwise. Columns (3)–(5) estimate regressions of the following form: $rate_{i(c,t)} = \delta_1\ CA_c \times post_t + \delta_2\ fintech_l \times post_t + \delta_3\ CA_c \times fintech_l \times post_t + \theta_c + \tau_t + controls_i + \varepsilon_i$. The dependent variable is the interest rate on approved mortgages of applicant $i$. 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 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 are clustered at the tract level. To control for applicant characteristics, $controls_i$ include applicants' LTI ratio, LTV ratio, log income, age, sex, race, ethnicity, and DTI ratio, as well as the log loan amount, log of the property value, a dummy for whether the loan was refinanced or not, and a dummy for whether the loan was sold or not. Results show that the main findings obtained in Table 3 also hold in applicant-level regressions. *** p<0.01, ** p<0.05, * p<0.1.

Table OA8: **Applicant characteristics full vs border sample**

| | (1) mean (full sample) | (2) se (full sample) | (3) mean (border sample) | (4) se (border sample) |
|---|---|---|---|---|
| black (%) | .007 | .007 | -.001 | -.001 |
| female (%) | -.027 | -.027 | -.042 | -.042 |
| age 62+ (%) | -.044 | -.044 | -.037 | -.037 |
| white (%) | -.165 | -.165 | -.032 | -.032 |
| log(income) | .298 | .298 | .179 | .179 |
| log(property value) | .481 | .481 | .226 | .226 |
| LTI ratio (%) | .002 | .002 | -.001 | -.001 |
| LTV ratio (%) | -.057 | -.057 | -.027 | -.027 |

For average applicant characteristics at the lender–tract–year level, this table shows the difference in means and associated standard errors between tracts in California and neighboring states. Columns (1) and (2) report values for all tracts, columns (3) and (4) for border tracts. Except for *female*, the difference in applicant characteristics is smaller in border tracts than in the full sample of tracts.