Regulating Credit: Effects on Market Structure, Lender Technologies, and Credit Access

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Abstract

I show that price regulation reduces access to affordable credit by altering the number and composition of lenders in a market. I focus on state-level enforcement of interest rate limits and oversight measures, such as licensing and examinations, in the U.S. nonbank personal loan market. I find that these regulations unintentionally lead lenders with advanced screening technologies to exit the market. Remaining lenders rely more heavily on traditional credit scores to screen borrowers and possess less information about borrower default risk. The exit of these more informed lenders raises prices and reduces credit availability for subprime borrowers and those without credit scores. The regulations and resulting lender exits negatively impact loan performance, borrower outcomes, and financial inclusion. I develop a structural lending model to isolate the effects of shifting lender composition and changes in market power from interest rate caps, examining their impact on prices, loan quantities, and lender profits. The model incorporates consumers with heterogeneous preferences and costs, lenders with varying screening technologies, and adverse selection. Model results show that interest rate caps and increased oversight disproportionately disadvantage borrowers with low default risk who appear risky based on conventional credit scoring methods. Counterfactual simulations suggest that modest adjustments, such as raising the rate cap from 21% to 28% and reducing fixed regulatory costs by 45%, could improve credit access for subprime borrowers.

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1 Introduction

Access to affordable, fairly priced credit is crucial for fostering financial security, economic growth, and social equity. However, millions of Americans rely on high-cost financial services like payday loans, check cashing, and pawnshops. These alternatives often carry significantly higher costs than mainstream financial products, which can lead to financial instability or trap individuals in cycles of debt, furthering financial instability (Carrell and Zinman, 2014; Melzer, 2011; Campbell et al., 2012; Skiba and Tobacman, 2008). This reliance on expensive credit disproportionately impacts low-income households and minority communities, deepening financial inequality and limiting wealth-building opportunities (Baradaran, 2015; Stegman, 2007; Charron-Chénier, 2020). Given the U.S.'s well-developed financial system, the continued exclusion of these groups from more affordable services raises important questions about the barriers they face in accessing fair credit (Barr, 2008; Blank and Barr, 2009).

The ongoing debate over barriers to affordable credit has fueled interest in how regulation might expand access to fairly-priced loans. For example, regulatory policies may have the potential to improve credit access by incentivizing institutions to adjust their practices if barriers like limited branch locations, high fees, or complex application processes restrict access. (Célerier and Matray, 2019; Davidson, 2018). However, I argue that well-intentioned regulations can unintentionally limit credit access by driving out lenders with advanced screening technologies, disproportionately affecting borrowers with lower credit scores and limited credit histories.

A central question in this debate about regulation's role in expanding credit access is whether high interest rates reflect borrowers' true risk or if they result from excessive markups aimed at less sophisticated borrowers. A common regulatory response to high interest rates is to impose interest rate caps, which presents a straightforward economic trade-off: if caps are set below the default-adjusted cost of credit, borrowers could lose access to credit entirely. Conversely, if high rates are driven by markups, caps could reduce prices without limiting access (Cuesta and Sepúlveda, 2021). Consistent with prior work on these regulations, I show that interest rate caps directly exclude the highest marginal-cost borrowers from the market. I also find that enforcing these limits requires regulatory oversight, with higher oversight improving compliance with rate caps. I depart from prior work by focusing on the impact of these regulations on the structure of the market. While prior work on rate caps often assumes a fixed market structure, I find that these regulations unintentionally reduce credit access for subprime (those with credit scores below 660) and thin credit file (those less than one year of history or fewer than three accounts credit bureaus) borrowers by driving out lenders with advanced screening technologies. Both rate caps and oversight reduce lender profits, leading to exits. Lenders using advanced screening technologies are the most likely to exit, as they experience the largest declines in profit following regulation. I then examine the redistributive effects of these policies, as the impact on different risk groups remains unclear both qualitatively and quantitatively.

I study the effects of price regulation and oversight in the U.S. nonbank personal loan market, which provides an ideal setting due to state-level variations in regulations and detailed data on loan outcomes. Personal loans play a crucial role in providing credit to individuals with low incomes and low credit scores, as they offer a more affordable alternative to higher-cost credit options. In 2022, the total U.S. personal loan market reached nearly $365 billion. From 2015 to 2016, state-level regulatory events in New York, Vermont, Connecticut, and Colorado led to the sudden enforcement of interest rate caps in nonbank markets in these states. Rate limits were accompanied by additional oversight measures, such as state licensing and regulatory examinations, potentially increasing fixed regulatory costs of operating in these markets. The state-level events were triggered by surprise court rulings and lawsuits and were unexpected by market participants. As a result, they provide plausibly exogenous shocks to the regulatory environment in the nonbank sector.[1] I use a staggered difference-in-difference design around these events to estimate the effects of interest rate caps and heightened oversight on credit access, pricing, and loan performance. Given the limited presence of traditional banks in this market, my analysis focuses exclusively on the nonbank sector.[2]

These state-level events result in reduced loan quantities and adjustments in pricing. As interest rate limits are enforced, some loans that would have been made in the absence of a cap become unprofitable and total nonbank credit supply to declines by 10%. The restrictions on high-interest rate loans also reduce average interest rates by 8%. The largest declines in both loan quantities and prices occur among subprime borrowers, indicating that the costs and benefits of interest rate limits disproportionately affect those with poor credit scores and low incomes. However, the decline in average interest rates is primarily driven by changes in borrower composition. As interest rate limits are enforced, risky borrowers are rationed out of the market. After adjusting for changes in the composition of borrower risk, I find that interest rates increase by 1.1 percentage points for observationally identical borrowers, an increase of 5%. Importantly, the absence of pre-trends in these estimates supports the view that these state-level events represent plausibly exogenous shocks to nonbank regulation from the perspective of both nonbank lenders and borrowers.

Changes in credit access and pricing partly stem from the regulations' impact on market structure. In addition to the direct impact of rate limits, these regulations have the secondary effect of reducing lender profits which lead to lender exits. In particular, lenders using advanced screening technology are more likely to exit the market. These lenders serve riskier populations and face heightened regulatory scrutiny, making them particularly vulnerable to profit declines following regulation. To show these results, I first demonstrate significant heterogeneity in non-bank screening models prior to regulation—some lenders rely heavily on credit scores, while others use alternative data or models. I quantify this reliance on credit bureau data by examining R-squared values from lender-level regressions of interest rates on credit bureau data. Lenders that are less dependent on credit bureau data charge lower interest rates to observationally similar borrowers and experience lower delinquency rates, consistent with these lenders possessing better information about borrower default risk. My difference-in-difference estimates suggest that 2.3 (21%) of lenders exit treated markets, with the reduction in lenders at the county level almost entirely driven by the exit of these "informed" intermediaries. The departure of informed lenders reduces competition and has redistributional impacts across borrower groups, especially in segments where public credit scores are less informative about borrower risk.

The enforcement of limits and the resulting lender exits negatively impact loan performance, financial outcomes, and financial inclusion. Delinquency rates rise within borrower risk categories, as the exit of lenders with superior screening models results in a less-creditworthy borrower pool. Subprime borrowers in affected states face increased bankruptcy rates, more accounts in collections, and a greater reliance on payday loans and pawnshops, suggesting that restricted access to affordable loans drives borrowers toward high-cost alternatives and financial distress. Financial inclusion also declines, measured by a reduced percentage of adults with a credit score. The decline in financial inclusion suggests that informed lenders play a crucial role in helping previously excluded borrowers gain access to the mainstream financial system.

[1] Several media reports confirm the sudden and unexpected timing of these events in New York, Connecticut, and Vermont (https://www.venable.com/insights/publications/2022/02/fighting-the-fix-states-challenging-occ-and-fdic) and Colorado (https://katten.com/colorado-establishes-safe-harbor-for-bank/fintech-lending-programs). Accessed October 22, 2024. Legal scholars also confirm the plausible exogeneity of these events (see Honigsberg et al. (2017) and Horn and Hall (2017)).

[2] As a robustness check, I investigate changes in bank lending and substitution between nonbank and bank credit in Appendix H.

Building on my reduced-form results, I estimate a structural lending model that includes a rich supply-side and incorporates adverse selection between lenders. Motivated by my findings on changing market structure and heterogeneous lender screening models, the structural model also accounts for lender entry/exit and includes lenders with varying screening technologies. The model serves four main purposes. First, it assesses the impact of regulation on financial inclusion where two regulatory changes—interest rate limits and increased oversight—occur simultaneously. I use the model to disentangle the effects of each change. Second, the model isolates the roles of changing lender market power, shifts in lender composition, and interest rate caps on prices, loan quantities, and lender profits. Third, it helps gauge distributional consequences for borrowers with different levels of risk. Finally, the model allows me to quantitatively evaluate how credit access changes under counterfactual policies.

On the supply side, I model competing nonbank lenders with varying screening technologies that offer differentiated loans. Informed lenders use advanced screening tools to set individualized prices based on each borrower's default risk and price sensitivity, while uninformed lenders set pooled prices according to the distributions of these characteristics within a credit score category. Consequently, informed lenders are able to offer rates more aligned with each borrower's probability of default, making these lenders an important source of credit for low-risk borrowers who may appear risky under conventional credit scoring. Uninformed lenders may face adverse selection if informed lenders "cream skim" these low-risk borrowers. To adjust for an adversely selected borrower pool, uninformed lenders use a posterior distribution reflecting the distribution of characteristics of borrowers who *accept* their offers to set interest rates. The degree of adverse selection between lenders depends on the dispersion of default costs within a credit score group. In markets where credit scores reveal less information about borrower costs, informed and uninformed lenders develop different expectations about borrower default risk, resulting in substantially different interest rate offers. To capture equilibrium changes in market structure due to regulation, I also model the entry and exit of informed lenders.

Regulation is modeled through interest rate limits and fixed regulatory costs, mirroring the changes observed in my reduced-form setting. Interest rate limits cap the maximum rates lenders can offer, with lenders continuing to extend loans if the optimal rate falls below the cap or if lending remains profitable at the capped rate. Lenders do not offer loans if it is not profitable to do so under the cap. Thus, while interest rate limits may reduce prices in markets where lenders have market power, they can also restrict credit access. My model allows for partial compliance with caps, aligning with patterns observed in the data. Regulatory oversight is modeled as a fixed operating cost that lenders must incur to operate in the market, consistent with the forms of oversight observed in my setting. Both the interest rate caps and the fixed oversight cost decrease lender profitability and can lead to equilibrium exits.

I model demand using a discrete-choice framework with heterogeneity, following Berry et al. (1995) and Nevo (2000). Consumers with varying preferences for loans, default costs, and price sensitivities select from a menu of loans offered by heterogeneous lenders. Allowing for borrower heterogeneity enables me to capture realistic consumer substitution patterns and the redistributive effects of policies (see Buchak et al. (2024); Wong et al. (2019); Stroebel and Vavra (2019)), as well as adverse selection between lenders and borrowers. The equilibrium involves interest rates set by lenders with different screening technologies, consumer choices, and informed lender entry decisions. Lenders maximize profits and enter a market if profitable, while consumers make optimal loan choices to maximize their utility.

I estimate supply and demand separately, using variation in state interest rate limits to identify price sensitivity and obtain exogenous price variation. State-specific interest rate caps create differences driven by political economy factors unrelated to loan demand.[3] As a result, some lenders offer identical loans

[3] States have different *levels* of interest rate limits, which were relatively static over this period, unlike the enforcement events I study.

at different prices across states. This variation informs my estimates of price elasticity, aligning with the existing literature (e.g., Buchak et al. (2024) and DeFusco and Paciorek (2017)). Optimal lender pricing and loan losses allow me to identify lender-level marginal costs, comprising both default costs and lender-specific operational costs.

Estimates of lender loan losses indicate adverse selection between lenders. Informed lenders attract safer borrowers by offering lower rates to low-risk individuals. As a result, their realized default costs are lower than the expected costs implied by the unconditional distribution of default within a credit score. Uninformed lenders are thus left with a riskier pool of borrowers, resulting in greater loan losses than the unconditional distribution of default costs suggests. To account for this selection, uninformed lenders set higher prices. This form of adverse selection is particularly evident in the subprime market, where credit scores reveal less information about default cost. Consequently, the exit of informed lenders has a larger effect on prices and loan quantities in subprime segments than in prime markets where "cream skimming" is less pronounced.

I estimate moderate to large fixed costs from regulatory oversight, which contribute to lender exits. Higher fixed costs are correlated with greater interest rate cap compliance, highlighting the role of regulatory oversight in promoting adherence to these regulations. To estimate these fixed costs, I use the prices, market shares, price elasticities, and lender marginal costs to estimate lender profits across different market configurations. I combine these profits with observed lender entry and exit decisions from my difference-in-difference specification to estimate fixed costs, which are consistent with levels reported in industry reports and contribute to the exit of some lenders.[4] As an out-of-sample validation, I assess model performance following price regulation implementation, finding that the model accurately predicts both bunching at interest rate limits and changes in loan quantities.

The model shows that interest rate limits, rather than fixed regulatory costs, are the primary driver of declining credit access. As in prior work (Cuesta and Sepúlveda, 2021), I find rate limits directly exclude the riskiest borrowers from the market. Importantly, however, these regulations have the secondary effect of reducing lender profits, leading to lender exits. Rate caps and changes in market structure reduce total loan quantity by 10% and increase rates by 5% on average. However, these aggregate results mask significant heterogeneity in the impact across different borrower groups. I decompose changes in prices and quantities by both public (credit score) and private (unobserved default cost) risk types. Low risk borrowers experience reduced credit availability across all credit scores following regulation, as the exit of informed lenders leads to higher prices and diminished access now that these borrowers are pooled with high-risk individuals.

Risky borrowers with subprime credit scores face reduced access and higher prices as a result of these regulations, driven by increased market power and lender exits. In contrast, high-risk borrowers with prime credit scores experience little change in access but benefit from lower prices due to rate caps. Risky borrowers of all credit scores also also benefit from the shift of safer borrowers to uninformed lenders following the exit of informed lenders. This shift toward uninformed lending weakens the cream-skimming effect and allows uninformed lenders to offer lower pooled prices. Lower pooled prices benefit high-risk consumers who now receiver lower interest rate offers from uninformed lenders. In summary, borrowers who appear risky based on conventional credit scores but are intrinsically low-risk suffer under interest rate limits and increased oversight, while those who seem creditworthy but are more likely to default ben-

These levels were mostly set between the 1980s and early 2000s. As a result, the factors driving the level of state interest rate limits are unlikely to be correlated with loan demand during the 2013-2018 period. See Elliehausen et al. (2021) for a discussion of these limits.

[4] U.S. Department of Treasury: "Assessing the Impact of New Entrant Non-bank Firms on Competition in Consumer Finance Markets," Accessed on October 22, 2024. https://home.treasury.gov/system/files/136/Assessing-the-Impact-of-New-Entrant-Nonbank-Firms.pdf

efit. These findings highlight the uneven impact of interest rate limits and oversight, reducing access for low-risk borrowers while benefiting higher-risk ones.

I estimate the effects of alternative regulatory policies on credit access and pricing, focusing on different interest rate caps and fixed regulatory costs. Raising the interest rate cap from 21% to 28%, along with reducing fixed regulatory costs by 45%, improves credit access for subprime borrowers. Higher limits and lower fixed costs allow lenders to earn greater profits, thereby reducing informed lender exits. The presence of more informed lenders is especially beneficial for less risky borrowers with subprime credit scores who rely on these lenders for fairly priced credit. A moderate cap of 28% also reduces markups for a number of consumers while minimizing the number of loans that are unprofitable under the cap. Under this policy, credit access for subprime borrowers increases by 7.8%. However, the benefits of this policy mostly accrue to borrowers with greater default risk, as the benefits of rate caps for less risky subprime borrowers are reduced by the fact that even more lenient rate caps can lead to the exit of some informed lenders.

Additionally, I examine a scenario where regulations prohibit the use of advanced screening technologies, such as machine learning and AI algorithms. Regulators may consider restricting these technologies due to concerns about consumer harm for certain groups. Banning advanced screening technologies would require lenders to charge a pooled price within each credit score group. This regulation would benefit high-risk borrowers, who would receive lower rates by being pooled with low-risk borrowers, but would reduce access and increase prices for low-risk borrowers who previously received lower interest rates due to technologies accurately identifying them as low risk. Credit access declines most sharply for underrepresented minorities, as credit scores reveal less information about default for these borrowers.

My paper relates to four broad strands of literature. First, I contribute to the literature on financial regulation in consumer credit markets. My work is most closely related to Cuesta and Sepúlveda (2021), who analyze the effects of interest rate limits in Chile and find that these limits primarily harm credit access and overall welfare. I extend this with by showing the equilibrium adjustment of lenders to these regulations - lenders with advanced screening technologies exit impacted markets. These exits result in significant redistributive effects. Several other studies examine the impact of interest rate limits and generally find negative effects on credit access, though many focus exclusively on the payday lending market or a single lender (Bodenhorn, 2007; Temin and Voth, 2008; Benmelech and Moskowitz, 2010; Zinman, 2010; Rigbi, 2013; Fekrazad, 2020; Melzer and Schroeder, 2017). Most of these studies similarly find negative effects of interest rate limits on credit access, though many focus exclusively on the payday lending market or a single lender. In contrast, I examine the effects on borrowers while also assessing how interest rate limits interact with market structure and lender technologies. I focus on the national personal loan market, which features much lower interest rates than the payday loan market. Additionally, I allow for lax compliance with regulations and I explore the equilibrium redistributive effects of interest rate limits within a model of lending competition.

A number of papers investigate the effects of regulatory policies that restrict the use of information in credit markets. For instance, Nelson (2018) and Agarwal et al. (2015) study the 2009 CARD Act, which limited credit card lenders' ability to adjust interest rates based on new information about borrowers. Liberman et al. (2018) examine the equilibrium effects of information deletion in Chile's credit market, analyzing a natural experiment in which credit bureaus were required to stop reporting defaults for 2.8 million individuals. In a related line of inquiry, Babina et al. (2024) and He et al. (2023) study the impact of open banking, a policy enabling customers to share their financial transaction data across providers. Buchak et al. (2018) explore regulatory differences between banks and shadow banks, showing that traditional banks reduced credit supply in markets where regulatory pressure increased, while shadow banks—using different informational tools—partially filled these gaps. Two studies, Honigsberg et al. (2017) and Danisewicz and Elard (2023), directly examine the first regulatory event in my analysis, which impacted borrowers in New York, Connecticut, and Vermont, finding that credit supply in subprime markets declined and personal bankruptcies increased. Building on these findings, I highlight the endogenous supply-side response to regulation, demonstrating how price caps and regulatory oversight can limit the adoption of advanced screening technologies. By focusing on the redistributive effects across borrower risk types, I show that these regulations have different impacts based on borrower characteristics, revealing unintended consequences of regulatory policies on credit access and borrower outcomes.

Second, my paper advances the literature on information and credit scoring in consumer credit markets. Einav et al. (2013) and Adams et al. (2009) highlight the role of credit scoring in reducing adverse selection in the auto industry. Recent work by Chatterjee et al. (2023), Blattner and Nelson (2021), Blattner et al. (2021), and Blattner et al. (2022) examines the design and inherent disparities within consumer credit scoring systems. Keys et al. (2010, 2012) and Rajan et al. (2015) argue that securitization incentives impaired lender screening efforts. Additionally, a substantial body of research focuses on the use of alternative credit scoring data and models by fintech nonbanks (Berg et al., 2020; Di Maggio et al., 2022; Ghosh et al., 2022; Bartlett et al., 2022; Berg et al., 2022; Fuster et al., 2022). Relative to this literature, I examine the equilibrium effects of lender entry and exit, especially of those using advanced screening technologies. My findings show that borrowers who appear risky by conventional credit scoring methods but have low intrinsic risk are disadvantaged by policies that drive informed lenders out of the market. Conversely, borrowers who appear creditworthy but are higher-risk benefit from pooled pricing once informed lenders exit, as they face lower interest rates than would be assigned under more accurate risk assessment.

My paper also relates to the literature on lender competition in markets with adverse selection and lender screening (Crawford et al., 2018; Broecker, 1990; Yannelis and Zhang, 2023; Petersen and Rajan, 1995; Jansen et al., 2022; Hauswald and Marquez, 2003; Mahoney and Weyl, 2017; Matcham, 2024). I extend this literature by analyzing a setting characterized by adverse selection among lenders with varying screening technologies. My findings reveal the equilibrium effects on credit prices and access as more informed lenders exit the market, illustrating how the departure of these lenders impacts both credit availability and pricing structures for different borrower risk profiles.

Finally, my work contributes to the literature on the effects of access to expensive credit (Allcott et al., 2022; Melzer, 2011; Morse, 2011; Bhutta et al., 2015; Skiba and Tobacman, 2008; Adams et al., 2009; Fonseca, 2023). I show that a reduction in the supply of moderately priced credit has adverse effects on financial outcomes and financial inclusion, particularly for underserved borrowers. My findings further suggest that access to high-cost credit supports market entry, ultimately lowering costs for certain borrower segments by fostering competition.

The remainder of the paper is organized as follows. Section II describes the U.S. personal loan market and data. Section III explains the identification strategy. Section IV reports the reduced form analyses. Section V introduces the structural empirical model of the U.S. nonbank personal loan sector and its estimation. Section VI uses the model to evaluate the effects of regulation and consider counterfactual regulatory policies. Section VIII concludes.

2 Setting and data

I examine how interest rate caps and increased regulatory oversight affect market structure and credit access in the U.S. nonbank personal loan market. I draw on data from two main data sources: one of the major U.S. credit bureaus and a credit monitoring website. These data sources provide me with a comprehensive view of the personal loan market and allow me to estimate these regulations' impact on lender and borrower behavior.

2.1 Setting: U.S. nonbank personal loan market

The U.S. personal loan market is particularly well-suited for studying the effects of regulation on credit access due to two key factors. First, its regulatory environment offers plausibly exogenous variation in regulation: state-level events result in the unexpected enforcement of interest rate caps and increased oversight standards, the levels of which vary by state. Second, this market includes lenders who employ alternative data and advanced underwriting algorithms to originate and price loans. The presence of varying screening models allows me to estimate how regulation affects the use of advanced technologies in the market and the resulting implications for credit access across risk types.

The personal loan market is also a particularly good setting in which to study the impact of regulation on underserved groups because these loans provide an affordable alternative to high-cost credit options. Often used to consolidate high-interest credit card debt or as a buffer against unexpected income shocks, personal loans offer considerably lower interest rates than payday loans. For instance, personal loans generally start at $1,000, have terms of at least 12 months, and carry interest rates ranging from 4% to 60% APR. In contrast, payday loans are typically smaller (under $1,000), have shorter terms (usually less than 12 months), and carry much higher APRs, often exceeding 150%. Payday loans also operate under a distinct regulatory framework and are not subject to the regulatory changes examined in this study.

The U.S. unsecured personal loan market has grown substantially over the past decade, with nonbanks dominating this growth.[5] Personal loan balances rose from $50 billion in 2010 to nearly $365 billion by 2022. In 2015, nonbanks—including both online and traditional firms—accounted for 40% of personal loan originations, increasing to 51% by 2020. Nonbanks are particulalry active in certain segments, especially in subprime markets where they originate over 70% of loans (see Elliehausen and Hannon (2024), Elliehausen et al. (2021), and Johnson et al. (2023) for more on bank and nonbank market segmentation).[6] Due to the limited presence of banks in this market, my analysis focuses solely on the nonbank sector, specifically unsecured personal loans with fixed interest rates.[7]

2.1.1 Nonbank regulation

The regulatory environment of the nonbank personal loan market provides plausibly exogenous variation in regulation: state-level events lead to the unexpected enforcement of rate limits and increases in regulatory oversight, with significant variation across states. Each state imposes its own regulations on nonbank lenders, creating substantial compliance costs for those operating across multiple states. Consequently, some lenders engage in regulatory arbitrage to bypass state requirements. A sudden crackdown on these practices led to unexpected enforcement of state regulations in certain states, which I leverage in my empirical design.

[5] Following Buchak et al. (2018), nonbanks are defined as nondepository institutions.

[6] I classify subprime loans as those issued to borrowers with credit scores below 660, while prime borrowers have scores of 660 or higher, following FICO's classification.

[7] As a robustness check, Appendix H explores changes in bank lending and any substitution effects between bank and nonbank credit.

Personal loan regulation in the U.S. revolves around interest rate limits and regulatory oversight. Interest rate limits impose caps on the maximum amount of interest that lenders can charge and vary significantly by state. Some states impose limits as low as 7% APR, while others have no restrictions. Violations can lead to substantial fines and revoked licenses. Regulatory oversight includes licensing and examination requirements. Most states require nonbanks to secure licenses to operate within their jurisdictions. Nonbank lenders operating in multiple states must obtain multiple licenses, a costly and time-consuming process involving extensive documentation. Many states also require periodic compliance examinations conducted by the state regulator. Noncompliance with state regulations can result in enforcement actions like cease-and-desist orders or fines. Licensing costs across states range from $1 million to $30 million, which may limit business growth and increase the fixed expenses of operating in a market.[8] A detailed summary of state-specific rate limits and oversight components is in Appendix C. Further details on nonbank regulation in personal loan markets are also provided in Elliehausen and Hannon (2024).

The costs associated with state compliance have driven many nonbanks to evade state regulations by partnering with banks. Unlike nonbanks, which are subject to a patchwork of state regulations, banks operate under a more uniform regulatory framework. Their banking charters allow them to circumvent most state consumer finance laws, including state interest rate limits and oversight requirements. Additionally under the valid-when-made doctrine, all loans that were "valid" when they were originated have historically been considered valid over the lifecycle of the loan.[9] By relying on their bank partners to originally issue their loans, nonbanks have typically been able to use their partners' banking charter and the valid-when-made doctrine to evade state law. Nonbanks use their bank partner originate loans and immediately buy the loans from the partner-bank. Because the partner-bank was not subject to state laws, the loans are "valid-when-made" and traditionally remained valid over the loans' lifecycles. It is important to note that banks entering these arrangements typically specialize in nonbank partnerships and do not originate personal loans directly to consumers. They are also usually located in states with lax regulators, such as Utah.[10]

A typical bank partnership operates as follows: (1) Borrowers apply for a loan through the nonbank's website; (2) The nonbank evaluates the application, makes the approval descision, and determines the interest rate using its own underwriting model; (3) Instead of directly originating the loan, the nonbank routes the loan through its partner bank; and (4) The bank originates the loan and sells it back to the nonbank within two to three business days. Since these loans are originated by banks, they are granted federal preemption of state regulations. Nonbanks are therefore able to use the bank's charter to bypass various state-specific requirements—such as interest rate limits, licensing mandates, examinations, and state oversight—engaging in what is effectively regulatory arbitrage.[11] The structure of these partnerships is illustrated in Figure C.1. More details on these partnerships can be found in Appendix C.

2.1.2 Information and credit scoring in the personal loan market

In U.S. consumer credit markets, traditional underwriting has heavily relied on credit scores derived from data provided by nationwide consumer reporting agencies.[12] These credit scores are intended to predict

[8] U.S. Department of the Treasury Report https://home.treasury.gov/sites/default/files/2018-08/A-Financial-System-that-Creates-Economic-Opportunities—Nonbank-Financials-Fintech-and-Innovation.pdf, Accessed October 27, 2024

[9] See Levitin (2021) for more details on the valid-when-made doctrine.

[10] Most nonbanks enter partnerships with banks located in states that have high or no interest rate ceilings, as federal regulations allow a bank to charge the interest rates permitted in its home state. Loans originated through these bank partnerships can be issued at higher interest rates when the bank partner is located in a state with a high rate ceiling.

[11] Brookings Institute Report: https://www.brookings.edu/blog/up-front/2021/06/21/bank-regulators-true-lender-rule-undercuts-bank-regulatory-protections-and-shelters-predatory-lending/, Accessed October 27, 2024

[12] The three credit bureaus in the U.S. are Equifax, Experian, and TransUnion.

the likelihood of default but are estimated to misclassify risk for around 30% of consumers, potentially restricting these borrowers' access to credit.[13] Approximately 45 million Americans lack credit scores altogether, which further limits credit access. To address these gaps, many lenders have begun adopting alternative data sources, such as bank account data and reunt/utility payments, and advanced algorithms, including machine learning and artificial intelligence, to assess default risk. Nonbank lenders in the personal loan market are particularly active in experimenting with these models. Unlike traditional linear models based on credit scores, these advanced approaches enable lenders to identify complex patterns in borrower characteristics and behavior, offering a more nuanced assessment of repayment probability. As a result, these models can enhance credit access by providing higher approval rates and potentially lower costs for borrowers who are low-risk but appear high-risk under conventional scoring models. These models may also improve credit availability for consumers with thin credit files or no credit scores, expanding access in riskier market segments. Additionally, advanced screening models could allow lenders to evaluate demand elasticity which may enable them to target less price-sensitive borrowers with higher rates. Major nonbank lenders like Upstart and LendingClub emphasize their reliance on alternative credit scoring methods in their public communications, including their websites and 10-K filings. They position these models as supplements or replacements for traditional credit scores. Industry reports also describe the widespread use of machine learning in the personal loan market, underscoring the role of alternative models in expanding access and improving risk assessments.[14] For a detailed discussion on both traditional and alternative credit scoring models, including their benefits and potential concerns, refer to Appendix B.

2.2 Data

I use two main data sources to evaluate the impact of regulation on credit access: a major U.S. credit bureau and a credit monitoring website. The credit bureau data provides a random sample of personal loans originated across the United States. This data set also includes comprehensive information on borrower outcomes and loan performance. Because the credit bureau data does not include lender identities I combine this dataset with data from a credit monitoring website, which provides lender names and allows me to conduct lender-level analysis. I supplement these datasets with detailed state regulatory data and specific lender characteristics, enabling an in-depth evaluation of how the enforcement of interest rate caps and regulatory costs affect various lender types.

2.2.1 Credit bureau

My primary dataset comes from one of the three main U.S. credit bureaus and provides a comprehensive view of the U.S. consumer credit market. This dataset includes detailed information on all major credit products and allows me to follow borrowers and loans over time. The dataset is a 10% random sample covering the years 2013 to 2018. For this study, I focus on unsecured installment loans issued by nonbanks during this period. I calculate interest rates based on loan terms, scheduled payments, and origination amounts, excluding loans with interest rates below 4% or above 100% and those with balances under $500 or terms shorter than 12 months. Appendix D provides further details on the data cleaning process.

Because I am interested in the effects of regulation on borrowers with different risk types, I present summary statistics for prime (credit scores over 660) and subprime (credit scores below 660) borrowers

[13] Research showing that conventional credit scores misclassify risk for about 30% of consumers (Albanesi and Vamossy, 2019).

[14] FinRegLab: https://finreglab.org/wp-content/uploads/2023/12/FinRegLab$_2021-09-16_{Research-Report_The-Use-of-Machine-Learning-for-Credit-Underwriting_Market-and-Data-Science-Context.pdf}$, Accessed October 27, 2024

separately. Subprime borrowers generally receive less favorable terms on loans than prime borrowers, as illustrated in columns (1) and (2) of Table 1. On average, subprime borrowers pay higher interest rates (27% vs. 20%), receive smaller loan amounts ($4,926 vs. $6,787), and have shorter loan terms (33 months vs. 37 months). They also have lower incomes ($30,321 vs. $37,878) and shorter credit histories (149 months vs. 181 months). These differences underscore the challenges faced by subprime borrowers, who typically encounter higher borrowing costs and have less established credit profiles than their prime counterparts.

2.2.2 Credit monitoring website

I combine my primary dataset with a credit monitoring website that provides lender names, as the credit bureau data does not include lender identities. This website offers free access to credit score monitoring, credit reports, and identity protection tools for its 16 million users. When users log into their accounts, the website retrieves their information from a credit bureau, enabling me to observe the lender identities for their entire history of originated loans. I successfully match 9.6% of the website data with the credit bureau dataset, which is consistent with the credit bureau's 10% coverage of the U.S. population. Details about the matching algorithm and results, as well as summary statistics of the matched loans and borrowers, are provided in Appendix D. The characteristics of the matched subsample closely resemble those of the full samples. By merging these two datasets, I can conduct analysis at the lender level.

I demonstrate that this website offers a representative sample of borrowers. First, the website has a large user base, with over 16 million users as of 2021. Furthermore, a TransUnion study indicates that more than one half of Americans were enrolled in at least one credit monitoring service by 2021, suggesting that users of this website resemble the average American. To validate the representativeness of the data, I show summary statistics for loans issued to prime and subprime borrowers on the website, in columns (3) and (4) of Table 1. The same data cleaning process is applied to this dataset as was applied to the credit bureau data. The comparison shows that borrowers from the credit monitoring website share similar observable characteristics—such as interest rates, loan terms, and credit scores—with those in the broader credit bureau data. Notably, subprime borrowers are slightly overrepresented on the website (63% versus 55% in the credit bureau data), likely reflecting their motivation to improve their credit scores. Additionally, borrowers from the website tend to originate slightly larger loans on average. Overall, the credit monitoring website provides a dataset that is comparable to that of the broader American borrower population based on observable characteristics.

2.2.3 Other data sources

To assess how interest rate limits and regulatory costs impact lenders over time, I assemble a dataset on state-level regulations and oversight across four key areas of nonbank regulation, as to my knowledge no comprehensive dataset currently exists. First, I gather information on state interest rate limits from 2013 to 2018 to examine how these caps influence credit availability and pricing. Second, I create a dataset on state nonbank licensing by collecting data from state regulator websites and the Nationwide Multistate Licensing System (NMLS), a registry covering non-depository financial service licensing across participating states, to explore how lenders respond to state licensing requirements. Third, I compile a dataset of enforcement actions taken by state attorneys general against consumer finance companies, as these actions are a primary tool for regulating nonbanks and addressing violations of laws, unsound practices, and fiduciary breaches. Lastly, I collect information on lenders using bank partnerships for loan origination, allowing me to identify which lenders were directly affected by regulatory changes. This hand-collected dataset provides a detailed view of the regulatory landscape that nonbank lenders navigate.

There is significant variation in nonbank regulatory costs and requirements across states, as shown in Table C.11. The data suggests relatively lax enforcement, with many lenders violating state interest rate limits and licensing mandates. Panel (a) shows average interest rate caps for a $2,000 loan with a 24-month term, with caps averaging 32% APR. About 10 states had no limits on interest rates during this period. Panel (b) highlights state licensing requirements, where only 4% of loans were made by licensed lenders in 2014, increasing modestly to 24% by 2018. The low share of licensed lenders reflects exceptions in licensing, lax enforcement, and the use of bank partnerships to avoid regulation. Panel (c) reports enforcement actions, with 1,100 to 1,500 actions issued annually, and a standard deviation of 64 to 87 across states, indicating variability in enforcement. Panel (d) focuses on bank partnerships, showing that while a large share of loans (49% in 2014, 53% in 2018) were originated through partnerships, only 4% to 7% of lenders used such models.

3 Empirical strategy

I use a staggered difference-in-difference design centered around state-level events that resulted in the sudden enforcement of state regulations estimate their effects on market structure and credit access. In particular, these events challenged the ability of lenders to use the bank partnerships described in Section 2.1.1. The challenges were triggered by surprise court rulings and lawsuits and were unexpected by market participants, providing plausibly exogenous shocks to the regulatory environment in the nonbank personal loan sector.

3.1 State regulatory challenges to nonbank-bank partnerships

I use state challenges to the nonbank-bank partnership model as a source of plausibly exogenous variation in nonbank regulation. These partnerships allows nonbanks to bypass state regulations and have faced legal challenges in several states. These state-level challenges had two effects: (1) they enforced interest rate caps, limiting the rates nonbank lenders could charge borrowers within a given state, and (2) they increased fixed regulatory costs by requiring lenders to obtain licenses, undergo periodic examinations, and comply with state oversight. Although these challenges directly targeted nonbank lenders using the bank-partnership model, I treat all nonbanks in affected states as part of the treatment group. I do so for two reasons. First, regulators discussed these challenges around efforts to prevent the evasion of state laws, likely signaling to all nonbank lenders that state enforcement would intensify. Second, I empirically observe that nonbank lenders using traditional origination models also adjusted their lending practices to comply with state regulations following these challenges. Table A1 provides an overview of the regulations and oversight nonbank lenders faced in the four affected states: New York, Connecticut, Vermont, and Colorado.

Below, I describe the state challenges used in my empirical design and discuss their validity as exogenous shocks to nonbank regulation.

3.1.1 New York, Vermont, Connecticut:

In May 2015, a surprise court ruling called into question the ability of nonbanks to use a bank partner to avoid state regulation and oversight in New York, Vermont, and Connecticut. A judge in the U.S. Court of Appeals for the Second Circuit ruled in the case of *Madden v. Midland Funding* that entities could not charge interest rates higher than state usury limits if they were not national banks. This decision challenged the "valid-when-made" doctrine, which typically allows loans originated by national banks to retain their original terms even when sold to third parties, impacting nonbank lenders' ability to enforce higher interest rates across state lines. The *Madden v. Midland Funding* decision, which applied to New York, Connecticut, and Vermont, reshaped how nonbank personal loan lenders operated in these states. Lenders expressed significant concerns about the potential impact of this decision on their operations (Knight, 2017). In response, several personal loan lenders halted lending in affected states, adjusted their practices to comply with state regulations, and sought state licenses (Horn and Hall, 2017).

The unexpected nature of the *Madden v. Midland Funding* decision and the fact that it was made by a single judge in the Second Circuit suggests that this ruling can be treated as an exogenous shock to nonbank regulation—one that was unlikely to be influenced by factors associated with nonbank loan demand or supply.[15] The ruling was confined to the Second Circuit, creating a sudden regulatory shift in these states while offering a natural set of treatment and control states for analyzing the decision's effects.[16] The *Madden v. Midland Funding* decision has also been used as an exogenous shock to regulatory environments in other academic work, including Honigsberg et al. (2017), Conti-Brown (2019), and Danisewicz and Elard (2023). For a more detailed analysis of the case and its impact on credit in these states, see Honigsberg et al. (2017).

3.1.2 Colorado:

In 2017, a similar event occurred in Colorado. The Administrator of the Uniform Consumer Credit Code filed a lawsuit against Avant and Marlette Funding, two nonbanks using the bank partnership model in Colorado. This lawsuit alleged that these nonbank personal loan lenders violated state law by lending without a license and exceeding the state interest rate limit. This action signaled that state regulators in Colorado would prosecute lenders violating state laws and regulations, prompting other lenders to alter their operations in Colorado.[17] The lawsuit was settled in 2021, requiring both companies to obtain state lending licenses, face heightened regulatory oversight, and cap their interest rates at Colorado's limit.

The unexpected nature and timing of this event suggests that it is a plausibly exogenous shock to nonbank regulation in Colorado (Horn and Hall, 2017). Although nonbank-bank partnerships had been under scrutiny in several states, the timing and geographic scope of this lawsuit were unexpected for market participants.[18] Further evidence that this event was not driven by loan demand or local economic conditions is provided in Appendix F.

3.2 Empirical specification

I use a staggered difference-in-difference design around state challenges to nonbank-bank partnerships to estimate the effects of price regulation on market structure and borrower outcomes. I implement a

[15] Manatt: https://www.manatt.com/insights/newsletters/financial-services-law/madden-litigation-sputters-out-with-settlement, Accessed October 22, 2024

[16] Industry reports confirm that lending in jurisdictions outside of New York, Connecticut, and Vermont was not impacted. https://www.krcl.com/insights/five-years-later-madden-v-midland-funding-llcs-limited-impact-on-the-valid-when-made-doctrine, Accessed October 22, 2024

[17] The FinReg Blog: https://sites.duke.edu/thefinregblog/2021/02/02/continuing-uncertainty-after-colorado-compromise-the-limited-impact-of-the-avant-marlette-settlement-on-true-lender-risk-for-nonbank-bank-partnerships/. Accessed on October 22, 2024

[18] In this podcast, experts discussed the Avant and Marlette settlement, emphasizing how the lawsuit disrupted nonbank regulation by challenging the bank partnership model, causing a regulatory shock to lending practices. They highlighted how the decision unsettled the existing framework, forcing lenders to rethink strategies: https://provoke.fm/what-the-avant-marlette-co-ag-settlement-means-for-the-future/, Accessed on October 22, 2025

stacked regression estimator following Cengiz et al. (2019) to address concerns about biased estimates due to treatment effect heterogeneity, as highlighted by Baker et al. (2022). For each regulatory event, I construct event-specific datasets by pairing each treated state with all never-treated states. These event-specific datasets are stacked in relative time to estimate the average treatment effect across events using a single set of treatment indicators. Estimating coefficients on treatment indicators allows me to confirm the absence of pre-trends, supporting the parallel trends assumption. The main specification is as follows:

$$y_{i,t,s,g} = \alpha + \sum_{r=-4}^{5} \beta_r \mathbb{1}[t - L_s = r] + \theta X_{i,t,g} + \gamma_{s,g} + \psi_{t,g} + \varepsilon_{i,t,s,g} \tag{1}$$

where i denotes the borrower, loan, or county in state s in quarter t, and g represents the specific stacked dataset. L_s is the quarter in which a regulatory event occurred in state s, and $\mathbb{1}[t - L_s = r]$ is an indicator variable equal to 1 if state s is r quarters away from the regulatory event in quarter t. $X_{i,t,g}$ represents a set of borrower or loan controls, which are interacted with both time and dataset fixed effects. The terms $\gamma_{s,g}$ and $\psi_{t,g}$ are state-dataset and calendar time-dataset fixed effects, respectively. This approach leverages strict criteria for control units and mitigates concerns about using previously treated units as comparisons. As a result, it is more robust to heterogeneous treatment effects than the standard staggered difference-in-difference model. I also estimate the model using the Callaway and Sant'Anna (2021) estimator as a robustness check, finding similar results.[19] Standard errors are clustered at the state level, and I apply the Bell-McCaffrey degrees-of-freedom adjustment due to the small number of treated states (McCaffrey and Bell, 2003).

Estimating the effect of these regulatory shocks on credit access requires that the shocks are exogenous to borrower demand, lender supply, and local economic conditions. These assumptions are also discussed in Section 3.1. The identifying assumptions of this design are twofold: (1) state challenges to bank-partnership models affect lending in treated states only through their impact on nonbank regulatory oversight, and (2) in the absence of these challenges, nonbank lending would have followed similar trends in both treated and non-treated states. The first assumption is plausible because these regulatory challenges specifically targeted nonbank origination models, which allowed lenders to circumvent state laws. Other credit sources, such as banks, payday lenders, and pawnshops, operate under different regulatory frameworks and were unaffected by these changes.

I find no indication that the decision to implement these challenges was influenced by local economic conditions or borrower demand. The initial events in New York, Connecticut, and Vermont were triggered by a surprising and controversial ruling by a judge in the Second Circuit Court, making it unlikely that local confounding factors played a role. Similarly, the regulatory challenge in Colorado was unexpected by both borrowers and lenders. To further support the exogeneity of these shocks, I present evidence that these regulatory challenges were not driven by confounding factors. First, media reports and legal studies indicate that market participants were caught off guard by these events, and consumers were likely unaware of the changes.[20] Second, I test whether state-level changes in unemployment rates, earnings, bankruptcy rates, house prices, or default rates can predict these regulatory challenges. The results, detailed in Appendix F, show no evidence that local economic conditions or consumer demand influenced

[19] The Callaway and Sant'Anna estimator handles staggered treatment adoption by estimating group-time specific effects, allowing for heterogeneity in treatment effects. The stacked regression estimator simplifies estimation by pooling data across periods. In my setting, where treatment timing differences are present but may not significantly affect the treatment effect, both methods are suitable.

[20] See Horn and Hall (2017) for a discussion on the unexpected nature of these events and Honigsberg et al. (2017) on consumer awareness.

the timing of these regulatory changes. Furthermore, I find no evidence of pre-trends when I estimate this specification, providing further evidence that the assumption of parallel trends holds.

My results would also be invalid if the Stable Unit Treatment Value Assumption (SUTVA) does not hold.[21] I find no evidence that SUTVA is violated by showing that lenders do not adjust their lending in non-treated states in response to regulatory challenges. For instanc,e this assumption might be violated if lenders might offset reductions in lending in treated states by increasing lending in non-treated states. Such adjustments could lead to higher quantities and lower prices in control states, potentially resulting in an overestimation of the impact of regulatory costs on prices and quantities in the treatment group. To test for this violation, I examine whether lenders who were previously active in treated states increase their lending in non-treated states following regulatory challenges compared to lenders that did not operate in treated states. I find no evidence of such a response. The details of this procedure and the corresponding empirical evidence are provided in Appendix F. This appendix demonstrates that SUTVA holds in my setting.

Lastly, although these regulatory events were officially targeted at lenders using bank partnerships to originate loans, I treat all nonbank lenders in affected states as part of the treated group. I make this decision for two reasons. First, state regulators framed these challenges as efforts to prevent lenders from circumventing state regulations, which signaled to all nonbank lenders that regulators would be enforcing state laws more aggressively. As a result, nonbank lenders, even those not using bank partnerships, may have adjusted their behavior in anticipation of heightened regulatory scrutiny. Second, I observe empirically that nonbank lenders utilizing traditional origination models also modify their lending practices in response to these regulatory challenges.

4 Reduced form results

I use this empirical design to show that interest rate limits and regulatory oversight reduce credit access, alter pricing, and reshape the structure of the lending market. First, I find that loan quantities and prices decrease in treated markets, with the largest reductions observed among subprime borrowers. After adjusting for changes in borrower composition, however, observationally similar borrowers pay higher prices for the same loans following regulation. The price increase likely reflects shifts in market power. Specifically, I find that fewer lenders operate in treated markets, and lenders using advanced screening technology are more likely to exit. The departure of these more "informed" lenders has distributional consequences - it disadvantages borrowers who appear risky based on traditional credit scores but are, in fact, low-risk. Additionally, borrowers in treated states experienced heightened financial distress and reduced financial inclusion, suggesting that borrowers are worse off following the regulatory changes. The absence of pre-trends in my estimates further supports the interpretation of these state-level events as plausibly exogenous shocks to nonbank regulation, affecting both lenders and borrowers.

4.1 Personal loan credit supply

Total personal loan credit declines in treated markets following regulation, with the largest reductions occurring in the subprime segment. Specifically, the dollar amount of originations decreases by 3% in the prime market and by 15.5% in the subprime market, as shown in Panel (a) of Figure 1. In the following subsections, I demonstrate that this decline is driven entirely by a reduction in *nonbank* lending. The

[21] The Stable Unit Treatment Value Assumption (SUTVA) assumes that the outcome for any observation is influenced solely by its own treatment, with no interference from other units' treatments.

majority of this decline results from credit rationing following the enforcement of interest rate limits, which I show using a bunching estimator. Additionally, I find limited substitution toward bank or credit card lending, indicating that borrowers do not offset the reduction in nonbank credit with other forms of mainstream credit. Instead, there is an increase in high-cost alternative borrowing, such as payday loans and pawnshops. These findings underscore the unintended consequences of price regulation and oversight, which limit access to affordable credit for subprime borrowers.

4.1.1 Nonbank credit supply

The decline in personal loan credit is driven entirely by a reduction in nonbank lending. Panel (b) of Figure 1 shows that the dollar amount of originations decrease by 5% among prime borrowers and by 22% among subprime borrowers. A pooled version of this specification, shown in Table A2, indicates that total nonbank personal loan originations decline by 13% across borrowers.

The majority of this decline is the result of loan rationing, as many loans became unprofitable under the interest rate caps.[22] Using a bunching estimator (details in Appendix G), I find that 9.4% of loans were rationed due to interest rate limits (see Table G.1). This finding illustrates the tradeoff between lower prices and reduced credit access, a common outcome in settings with interest rate caps (Cuesta and Sepúlveda, 2021).

4.1.2 Other types of credit

I find little change in other types of mainstream credit, suggesting that borrowers do not compensate for the reduction in nonbank credit by turning to banks or credit cards. Since these regulatory challenges did not directly affect banks or credit card lenders, any observed shifts in these types of lending would reflect borrower substitution or changes in competition.[23] Panel (a) of Figure H.1 shows no significant change in aggregate bank personal loan lending at the county level, and Panel (b) shows no change in credit card borrowing.

To assess the elasticity of substitution between nonbank and bank credit, I use state challenges to bank-partnerships as an instrument for nonbank credit access. Prime borrowers are able to partially substitute with bank credit following these regulatory challenges, with an elasticity of substitution between nonbank and bank credit of 31%. Subprime borrowers are less able to substitute toward bank credit, reflecting the tendency of subprime borrowers to be underserved by traditional financial institutions. Specifically, the elasticity of substitution between nonbank and bank credit for subprime borrowers is marginally significant at 18%, as shown in Table H.1. Neither prime nor subprime borrowers show meaningful substitution toward credit card borrowing.

In contrast to the limited substitution to mainstream credit, borrowing from high-cost alternative lenders increases following regulation. The percentage of residents using payday loans in a county rises by 29%, as shown as shown in Table A3. Similarly, the percentage using pawnshops increases by 23%. With interest rates on payday loans typically exceeding 100%, these findings suggest that borrowers may turn to high-cost credit options when access to nonbank personal loans is restricted.

[22] Interest rate limits in this setting range from 18% to 25%, with an average of 21%.

[23] Note that banks originating personal loans directly to consumers are distinct from banks entering partnerships with nonbanks. Banks in such partnerships typically specialize in these arrangements, are often located in different states, and do not originate loans directly to consumers. For more details, see https://sites.duke.edu/thefinregblog/2020/01/23/the-rise-of-rent-a-charter-examining-new-risks-behind-bank-fintech-partnerships/ (accessed October 29, 2024).

4.2 Personal loan prices

Average interest rates decrease in treated markets, primarily due to the enforcement of interest rate limits. Average prime interest rates decreases by 0.5 percentage points (a 3.8% reduction). Larger reductions occur in the subprime market, where the average rate declines by 1.7 percentage points, a reduction of 7.3%. These changes are show in Panel (a) of Figure 2. Changes in prices are driven entirely by adjustments in the nonbank sector.

4.2.1 Nonbank prices

The decline in personal loan interest rates is entirely due to changes in nonbank pricing. Table A4 shows a 1.5 percentage point (5.7%) decline in nonbank interest rates after controlling for loan size and terms, but *not* for borrower risk. The price reduction is more significant for subprime borrowers, who experience a 3.2 percentage point (11%) decrease in interest rates, compared to a 0.8 percentage point (4%) reduction for prime borrowers. These declines are shown in Panel (b) of Figure 2. In contrast, I find no change in bank interest rates (See Figure H.2). The decline in nonbank interest rates is primarily driven by the enforcement of rate limits - fewer loans over caps are originated following regulation. Using my bunching estimator, I find that interest rate limits reduced prices for 6% of loans, with an average rate reduction of 2 percentage points (6.8%), as shown in Table G.1.

The decrease in average prices is driven by a shift in the composition of borrowers, as interest rate limits ration out the riskiest borrowers from the market. After controlling for changes in borrower risk composition—including credit score, income, debt-to-income ratio, and credit card utilization, I find that average interest rates actually *increase* for similarly risky individuals following price regulation. Figure 3 shows a 1.3 percentage point (which is a 5% increase) rise in interest rates in treated states. A pooled analysis in Table A4 reveals that prime borrowers experience a 0.9 percentage point (3.5%) increase in rates, while subprime borrowers see a 1.4 percentage point (4.8%) increase. This increase in risk-adjusted interest rates post-regulation may be due to shifts in the lending market's structure which I investigate in the following section.

4.3 Structure of personal loan market

Regulations influence both the number and the composition of nonbank lenders in the market.[24] I find that lenders employing advanced screening technologies are more prone to exit the market. To provide evidence of this compositional shift, I first demonstrate heterogeneity in nonbank screening models. I then examine changes in market structure, showing that lenders with superior screening models are more likely to exit post-regulation.

4.3.1 Lender screening models

I demonstrate significant heterogeneity in how nonbank lenders screen borrowers in the pre-regulation equilibrium. Some lenders rely heavily on credit scores to set interest rates, while others do not. To assess lenders' credit scoring models, I calculate $1 - R_j^2$, which represents the fraction of interest rate variation *not* explained by credit bureau data. This measure is derived from regressions of each lender's interest rates on borrower credit scores and other characteristics:

[24] Given limited adjustments and substitution toward bank lending, my analysis centers on the nonbank market.

$$r_i^j = \alpha^j + \beta_0^j\, CreditScore_i + \beta_1^j\, CreditScore_i^2 + \beta_2^j\, CreditScore_i^3 + \boldsymbol{\eta^j X_i} + \gamma_{st}^j + \varepsilon_i^j,$$

where r_i^j is the interest rate for loan i from lender j, and $CreditScore_i$ is the borrower's credit score.[25] To capture non-linear relationships, I include second- and third-order terms for credit score and other borrower observables. Since a significant portion of interest rate variation is driven by macroeconomic factors, I difference out state-quarter fixed effects, allowing R_j^2 values to reflect variation explained specifically by lenders' models. This analysis covers 104 lenders with at least 200 originated loans each, from 2013 to 2016 (pre-regulation).

Lenders with lower $1 - R_j^2$ values rely more heavily on credit bureau data to set interest rates, while those with higher $1 - R_j^2$ values depend less on this data. For instance, lenders with higher $1 - R_j^2$ may incorporate additional factors such as proprietary models or alternative data sources. The $1 - R_j^2$ measure thus helps distinguish lenders using novel screening technologies from those relying on more traditional methods. Appendix E provides further details on this measure and motivation for why it is a good measure of lender screening models. Similar approaches are used in Buchak et al. (2018), Keys et al. (2010), and Rajan et al. (2015) to estimate the portion of interest rate variation not explained by credit scores. Figure A1 presents a histogram of $1 - R_j^2$, illustrating significant variation in lenders' reliance on credit bureau data.

I present evidence that lenders with higher $1 - R_j^2$ values—those relying less on traditional credit bureau data—possess superior information about borrower risk. Here, I highlight the difference between the interest rates on accepted loans (which I observe) and interest rates on offered loans (which I do not observe). Lenders with advanced screening technologies may "undercut" competitors who rely on traditional credit scores by offering low-risk consumers lower rates to attract creditworthy borrowers. Consequently, informed lenders attract a more creditworthy population of borrowers. Therefore, loans originated by these lenders should have lower interest rates and experience lower delinquency rates than those originated by lenders relying more heavily on credit bureau data. All lenders have access to publicly available credit scores, so my predictions regarding interest rates and delinquency rates hold within the same credit score levels - i.e. borrowers who accept loans from lenders with superior screening technologies should receive lower interest rates and have a lower likelihood of delinquency than borrowers with similar credit scores who accept loans from lenders with less advanced screening.

I confirm these predictions by showing that loans issued by informed lenders have lower interest rates and better ex-post performance. Figure 4 illustrates these relationships through binned scatter plots.[26] These findings suggests that lenders who rely less on credit bureau data possess better information about borrower characteristics and can offer lower interest rates to borrowers with lower default risks. By undercutting their competitors, these more informed lenders "win" less risky borrowers within a credit score. Based on this evidence, I classify lenders with above-median $1 - R_j^2$ values as informed and those with below-median values as uninformed. Table A5 further supports this classification, showing that informed lenders set rates 13% lower on average (columns 1 and 2) and their loans are 6.6% less likely to be 60 days delinquent or worse (columns 3–5). Additionally, interest rates set by informed lenders more accurately predict defaults, suggesting these lenders offer interest rates more in line with a borrower's true default risk.

[25] I also include borrower income, debt-to-income ratios, and credit card utilization.

[26] A binscatter plot displays the conditional mean of the dependent variable at each percentile of the independent variable, revealing their relationship. To include control variables, one can first partial out the effects of the controls from both the dependent and independent variables, then generate the binscatter plot with the adjusted data. For further details, see Stepner (2013).

4.3.2 Characteristics of informed versus uninformed lenders

Informed lenders serve a less creditworthy population on average, as shown in Table A8. While both types of lenders offer similar loan sizes and terms, informed lenders serve borrowers with lower credit scores and thinner credit files. Figure A3 confirms this finding, demonstrating that borrowers with lower credit scores and incomes are more likely to borrow from informed lenders. This result suggests that informed lenders play a key role in providing credit to underserved populations. Their importance in riskier market segments likely stem from their ability to differentiate between more and less risky borrowers within a given credit score. Informed lenders are able to distinguish less risky borrowers from those with higher risk. As a result, low-risk borrowers are more likely to obtain offers from informed lenders than from uninformed lenders and also receive lower interest rates conditional on offers. In contrast, uninformed lenders may find it too costly to serve these segments or offer interest rates that are prohibitively high for these borrowers.

Because informed lenders serve riskier populations, they are particularly affected by interest rate limits and increased regulatory oversight. In the pre-regulation equilibrium, informed lenders originate a larger share of loans that exceed state interest rate limits. As a result, rate limits are likely to significantly reduce their profitability. Figure 5 shows that a greater proportion of informed lenders' loans surpass state interest rate thresholds prior to regulation. Furthermore, informed lenders experience higher costs from regulatory oversight. Figure 6 illustrates this point by showing that informed lenders are more likely to encounter state regulator enforcement actions, suggesting they incur higher fixed regulatory oversight costs. These lenders may attract increased regulatory scrutiny due to their use of non-standard credit scoring models, as regulators may want to ensure compliance with fair lending laws. Alternatively, the financial vulnerability of their borrowers could prompt closer oversight from regulators.

4.3.3 Changes in market structure

Interest rate limits and increased regulatory oversight lead to lender exits, driven by a decline in the number of informed lenders. As shown in Figure A2, the number of lenders declines by 21% within five quarters following regulatory challenges to the bank-partnership model. Column (1) of Table 3 confirms this result using a static form of Equation (1). Columns (2) and (3) demonstrate that the decline in the number of lenders is driven almost entirely by the exit of informed lenders. This reduction in lenders aligns with Table 2, which shows a reduction in loans originated above state rate caps post-regulation, an increase in state licensing among lenders, and intensified enforcement actions due to enhanced regulatory oversight. These changes are particularly pronounced for informed lenders, who attract greater regulatory scrutiny and originate more high-interest rate loans in the pre-regulation equilibrium. Consequently, interest rate limits likely reduce lender profitability, while increased oversight (as measured by enforcement actions) likely raise the fixed costs of operation. Both of components of regulation contribute to lender exits. Section 6 further examines these mechanisms through a structural model.

4.4 Ex-post loan and borrower outcomes

Borrowers experience worse loan performance, greater financial distress, and reduced financial inclusion following regulation. These findings suggest that borrowers that the reduction in credit supply and exit of informed lenders negatively impact individuals living in treated states.

4.4.1 Decline in loan performance

Average nonbank delinquency rates rise following regulatory changes within borrower risk groups, indicating that a less-creditworthy subset of borrowers gains credit access post-regulation. As informed lenders with superior insights into borrower default risks exit the market, uninformed lenders increase their market share; however, their limited ability to accurately assess risk leads to a less creditworthy borrower pool. [27] To demonstrate this decline in loan performance, I estimate a difference-in-difference specification using an indicator for whether a nonbank loan originated in quarter t becomes 60 days past due or worse at some point over its lifecycle. The analysis focuses on loans originated just before and after regulatory challenges, tracking their full life cycle and restricting the sample to loans with complete payment data (86% of the sample). I control for measures of observable borrower risk. Control variables include loan size, terms, borrower income, credit score, debt-to-income ratio, credit card utilization, and zip code-quarter and quarter fixed effects to account for local economic conditions influencing borrower default. Subprime loans originated after regulatory changes are two percentage points more likely to experience a missed payment compared to those originated just before regulation, as illustrated in Panel (a) of Figure A4.[28]

I provide further evidence of the in borrower quality post-regulation by showing that loans originated post regulation are less profitable. I calculate loan losses as the ratio of cash returned to cash lent, $\frac{CashReturned_{i,t,s}}{CashLent_{i,t,s}}$, for each loan. I find that average loan profitability declines by 7 percentage points post-regulation, as shown in Panel (b) of Figure A4. Similarly, Table A6 presents estimates from static versions of these regressions and also shows that a larger share of loans required modification post-regulation.[29]

4.4.2 Ex-post borrower outcomes

Borrowers receiving nonbank loans after regulatory challenges have worse outcomes two years after borrowing compared to those who received loans before the regulatory changes. Worse ex-post outcomes are again consistent with a deterioration in screening ability. As informed lenders exit the market, the pool of nonbank borrowers becomes worse. To show this, I track borrowers for two years after loan origination and assess several outcomes: whether the borrower has a bankruptcy flag on their credit report, the growth in their credit score, whether they are small business owners, and the number of accounts in collection. Table A7 shows the results of these regressions. Borrowers receiving loans after regulatory challenges are 1.2 percentage points (10%) more likely to file for bankruptcy, experience 0.8 percentage points (66%) less credit score growth, are 0.5 percentage points (11%) less likely to be small business owners, and have 0.27 (9%) more accounts in collection. These findings suggest that borrowers receiving loans post-regulation are of lower credit quality, consistent with the average pool of borrowers declining as informed lenders exit the market.

4.4.3 Financial distress and inclusion

Borrowers, particularly those with low credit scores, experience increased financial distress and decreased financial inclusion following regulation. These findings suggest that borrowers are worse off following regulatory changes. Specifically, subprime borrowers have more money in collection accounts and are

[27] Furthermore, the increase in average interest rates may suggest that borrowers willing to accept loans at these higher rates may be riskier on average, similar to the mechanism described in Stiglitz and Weiss (1981).

[28] Default rates in this market are high: 52% of subprime loans have at least one missed payment, reflecting the financial vulnerability of borrowers in this segment.

[29] The decline in loan performance holds on *average* across the market. Within individual lenders, however, loan performance remains stable or improves, consistent with a decline in the "cream-skimming" effect as more informed lenders exit the market.

more likely to have at least one account marked as a major derogatory (such as a charge-off, severe delinquency, bankruptcy, or foreclosure). Panel (a) of Figure A5 shows that borrowers in treated states have, on average, \$3,000 (9.8%) more in collection accounts. Panel (b) indicates that these borrowers have 0.04 (6%) more accounts classified as major derogatory. Table A9 confirms these findings using a static empirical design.

Despite the increase in overall financial distress, I do find that interest rate limits and oversight requirements are successful at reducing the number of "debt cycles," which may suggest a role for regulation to improve borrower outcomes. I define debt cycles as the origination of three or more personal loans within a three month period by the same borrower. The decline in debt cycles is notable, as regulators advocates often warn that high-interest loans can trap vulnerable borrowers in "cycles of debt."[30]

However, I show that restricting credit access results in worse outcomes for individuals already engaged in a debt cycle. Borrowers with high loan usage pre-regulation have significantly more accounts past due in the period following regulatory challenges compared to borrowers with low or moderate loan use. Panel (b) of Figure A6 illustrates this finding by showing a 5 percentage point (6%) decline in repeat borrowing following regulatory challenges, where a repeat borrower is defined as someone who originates at least two personal loans within a six-month period. As a result, simply cutting off access to high-interest loans may not improve borrower outcomes.

Finally, I observe a decline in financial inclusion following the exit of informed lenders, measured by the percentage of adults with a credit score. I combine credit bureau data with census population data to estimate the fraction of the adult population with a credit score within each zip code. Figure 7 shows a 0.5 percentage point (0.6%) decline in this fraction following regulatory changes. Even a small decline in the percentage of people with credit scores can have substantial welfare implications, as individuals without credit scores may face challenges in accessing affordable credit, renting properties, or securing employment opportunities. The decline in financial inclusion aligns with the role of informed lenders in providing credit to underserved individuals. These lenders often extend credit to individuals lacking sufficient data to be considered creditworthy by traditional standards. With the exit of these lenders, individuals without credit scores may struggle to access mainstream credit, limiting their ability to build credit histories.

4.5 Additional findings

In this section, I list additional findings that illustrate changes in the personal loan market following regulation. The exit of informed lenders leads to a market-wide increase in the reliance on traditional credit scores for pricing loans (Figure A7), consistent with an increased reliance on credit bureau data following the exit of informed lenders. Credit scores become more predictive of default and interest rates become less predictive of default in unreported tests, also consistent lower screening ability. Furthermore, there is greater standardization in loan contracts and a decline in the predictive power of average interest rates regarding borrower default in treated markets, consistent with a reduction in the amount of information used to originate and price loans (Table A10). Importantly, I also find no evidence that informed lenders violate fair lending laws by setting different interest rates based on race.[31]

[30] For example, the D.C. Attorney General, when advocating for a 24% interest rate cap, argued that loans violating state laws "have a devastating impact on individuals who are in need of an honest and lawful loan. These loans can perpetuate debt cycles, lower credit scores, and drive borrowers to seek more high-cost loans." https://oag.dc.gov/release/ag-racine-announces-nearly-4-million-settlement

[31] In unreported tests, I test for fair lending violations by examining how interest rates evolve based on the racial composition of a zip code. In particular, I use the racial composition of a zip code as a proxy for race.

5 Model

The findings from the previous sections highlight key trade-offs resulting from the enforcement of interest rate limits and increased regulatory oversight. While interest rate limits lead some borrowers to receive lower prices, they also result in other borrowers being excluded from the market. Additionally, these regulatory changes prompt the exit of lenders, potentially increasing the market power of remaining lenders and leading to larger markups. Notably, lenders with advanced screening technologies are the most likely to leave treated states, which may have additional distributional consequences based on borrower default risk. The net effect of these regulations depends on which of these forces prevail in equilibrium.

Building on my reduced-form results, I develop a structural lending model for the nonbank personal loan sector using data from the pre-regulation equilibrium. This model allows me to analyze the effects of enforcing interest rate limits and increasing regulatory oversight on credit access and prices. It incorporates two key features of the nonbank market identified in the reduced-form analysis: variation in lenders' screening technologies and their decisions to enter or exit markets. Additionally, the model accounts for heterogeneous default costs and price sensitivities among borrowers. The model fulfills four primary objectives. First, it assesses the impact of regulation on financial inclusion, considering the simultaneous implementation of interest rate limits and increased oversight. It therefore allows me to disentangle their individual effects on outcomes. Second, the model isolates the roles of changing lender market power, shifts in lender composition, and interest rate caps on loan prices, quantities, and lender profits. Third, it evaluates the distributional consequences of these regulations for different borrower risk types. Finally, the model is used to quantitatively assess how credit access would change under various counterfactual policies.

5.1 Model overview

On the demand side, I employ a discrete-choice framework with heterogeneity, following **?** and Nevo (2000). Consumers with varying preferences for price and quality select from a menu of loans offered by heterogeneous lenders. This approach captures realistic consumer substitution patterns and the redistributive effects of policies (see **?**; **?**; **?**). Heterogeneous price sensitivities are important for analyzing the equilibrium effects of interest rate limits and increased oversight, as this heterogeneity influences which types of consumers alter their borrowing behavior in response to regulation. Borrowers also differ in their default costs and public credit scores. I allow price sensitivities to vary with default costs, introducing adverse selection into my model.

On the supply side, I model competing nonbank lenders with varying screening technologies that offer differentiated loans in the nonbank personal loan market. Motivated by my reduced form evidence on heterogeneity in screening technology, informed lenders set individualized prices based on each borrower's default risk and price sensitivity.[32] In contrast, uninformed lenders lack these tools and set pooled prices based on the average default costs and price sensitivities within a credit score. Uninformed lenders may face adverse selection if informed lenders "cream skim" low-risk borrowers and adjust their interest rates using a posterior distribution that accounts for this selection. The degree of adverse selection between lenders is driven by the dispersion of default costs within a credit score. In markets with high dispersion of default costs within credit scores, informed and uninformed lenders form diverging expectations about a borrower's default cost and offer significantly different interest rates. In these markets, informed lenders will undercut their uninformed competitors to "win" creditworthy borrowers.

[32] Note that here I assume that advanced credit scoring models provide lenders with better information about borrower default costs *and* price sensitivities.

Consistent with my reduced-form results on lender exits, I allow for the entry and exit of informed lenders. I model regulation as interest rate limits and increased regulatory fixed costs, which mirror the regulatory changes studied in my reduced-form setting. Interest rate limits are modeled as caps on the maximum interest rates that lenders can charge. Lenders continue offering loans if the optimal rate is below the cap or if it remains profitable to lend at the capped rate when the optimal rate exceeds the limit. Regulatory oversight is modeled as a fixed cost that lenders must pay to operate in a market.

The equilibrium involves interest rates set by lenders with different screening technologies, consumer choices, and informed lender entry decisions. Lenders maximize profits and enter a market if profitable, while consumers make optimal loan choices to maximize their utility. The timing in my model is as follows: First, lenders realize their fixed cost draw and choose whether to enter a market. Second, entering lenders set interest rates. Third, consumers choose among offered loans and the outside option.

5.2 Demand

Consumers vary in their default costs, price sensitivities, and credit scores. They choose from loans offered by differentiated lenders and an outside option. These heterogeneous consumers are indexed by i. Loans are offered by an endogenous number J nonbank lenders.[33] Consumers apply for loans from all lenders in their consideration set. Screening occurs through interest rates, and borrowers receive offers from all lenders and the outside option. They choose at most one loan from the available offerings. For simplicity, I model only the extensive margin of borrowing, not the consumer's choice of loan amount. Borrowers differ on four dimensions: their observed type (public credit score), unobserved type (unobserved default cost not revealed by credit score), their price sensitivities, and their preferences over loans. I use loan default to recover ex-ante borrower default costs, similar to the approach used in Nelson (2018).[34] Default rates also depend only on borrower types, not on prices or lenders. This assumption rules out moral hazard and is common in the consumer finance literature (Nelson, 2018; Cuesta and Sepúlveda, 2021; Castellanos et al., 2018). A borrower's public type is based on public credit score (cs_i), which is observed by all lenders. Lenders with advanced screening technologies observe a borrower's unobserved type, which fully reveals a borrower's true default cost, δ_i. Informed lenders also observe a borrower's price sensitivity, α_i.

Consumer i makes a discrete choice of firm j's loan from J_i competing lenders, where J_i is the number of lenders in i's consideration set. A borrower's consideration set includes the lenders that originate loans to borrowers with the same credit score and unobserved default cost in a given county-year. I calculate unobserved default cost by determining the fraction of the loan that is not repaid to the lender. Borrowers are classified as high-unobserved cost if their default cost is above the median within their credit score.[35] Loan ijm is characterized by both the interest rate (r_{ijm}) and the loan's quality or convenience (q_j). I define market m at the county-year level and treat borrowers with different observed (public credit score) and unobserved (default cost) types as belonging to distinct markets. For example, a subprime borrower with a high unobserved default cost in county c is in a different market than a subprime borrower with a low unobserved default cost in the same county. This definition of markets, based on both observed and unobserved dimensions of default cost, accounts for the fact that borrowers with different unobserved default costs may face different choice sets and prices. For instance, subprime borrowers with low

[33] I model only competition between nonbank lenders, as my reduced-form results suggest limited substitution to bank lending. See Appendix H for more details on bank lending.

[34] Note that there is no uncertainty in my model—borrowers have default *cost*, not default *probabilities*.

[35] In the data, median default costs range from 1% among the highest credit score borrowers to over 40% among the lowest credit score borrowers.

unobserved default costs are likely to face lower prices from informed lenders than subprime borrowers with high unobserved default costs. Failing to account for these differences in prices could lead to biased estimates of price sensitivity. Each market contains $i = 1, \dots, I_m$ consumers and $j = 1, \dots, J_m$ lenders.

A consumer's indirect utility depends on her interest rate and the quality/convenience of the service provided by her lender:

$$u_{ijm} = -\alpha_i r_{ijm} + q_j + \xi_{jm} + \epsilon_{ijm} \tag{2}$$

where the consumer's indirect utility is declining in the interest rate and α_i is the borrower-specific price sensitivity. r_{ijm} is the interest rate charged to borrower i by lender j in market m. q_j is the lender quality, and ξ_{jm} is a lender market-specific unobservable. q_j can be estimated as a lender fixed effect in the data, while ξ_{jm} is not observable. Borrowers' preferences over lenders also differ idiosyncratically, which is captured in the i.i.d. T1EV borrower-specific utility shock, ϵ_{ijm}. These borrower-specific taste shocks prevent the market from unraveling by obscuring whether a borrower accepts an offer from uninformed lender j because she is of unobserved high-cost type, because she was offered a high rate by informed lenders, or because she has an idiosyncratic preference for lender j (Crawford et al., 2018; Babina et al., 2024).

Interest rate sensitivity is consumer-specific. Consumers' preferences are drawn from a distribution, where the distribution is a function credit score and unobserved type. Specifically, price sensitivity is then:

$$\alpha_i = \bar{\alpha} + \Pi(D_{im}) + \Sigma\nu_i \tag{3}$$

where D_{im} is a vector of consumer i's observable characteristics, which include credit score and unobserved default costs. $\nu_i \sim N(0, 1)$ are i.i.d. shocks. Σ scales these shocks so that borrowers with the same observable characteristics can differ in their price elasticity. Π is a vector describing how α_i depends on observable characteristics. By allowing price sensitivities to vary by measures of default cost, I capture adverse selection between borrowers and lenders. Understanding the correlation between default costs and price sensitivities is important for evaluating the effects of interest rate limits and oversight on borrower outcomes—interest rate limits may reduce markups charged to borrowers with low price elasticities, bringing prices more in line with marginal costs, but may reduce access for borrowers with high default costs.

Among the loans offered and the outside option u_0, the borrower chooses the loan with the highest indirect utility. Given the characteristics of loans offered in market m (including interest rate and quality) and demand parameters $\theta_d = \{\alpha, \Pi, \Sigma\}$, the set of borrower characteristics, including loan-borrower match utilities ϵ_{ijm}, such that borrowers with these characteristics in market m choose a loan from lender j is:

$$A_{jm}(r_{.m}, q_{.}, \xi_{.m}; \theta_d) = \{D_i, \epsilon_{i0m}, ..., \epsilon_{ijm} | u_{ijm} \geq u_{ikm} \; \forall k\} \tag{4}$$

where $A_{jm}(.)$ denotes the set of demographic characteristics D_i and idiosyncratic shocks ϵ_{im} such that, given loan characteristics $r_{.m}, q_{.}$ and demand parameters θ_d, consumers with those demographics and preference shocks obtain more utility from choosing the loan from lender j than from all other lenders.

Integrating over demographics and shocks yields the market share of lender j offering a loan in market m:

$$s_{i,j,m}(cs_i, \delta_i, \boldsymbol{\nu_i}) = \int \mathbb{1}\{u_{ijm} > u_{ikm} \; \forall k \neq j\} \, dF(\boldsymbol{\epsilon_i}) \tag{5}$$

5.3 Supply

On the supply side, I model competing nonbank lenders with varying screening technologies that offer differentiated loans in the nonbank personal loan market. Lender type is denoted by ϕ_j, where $\phi_j = 0$ represents uninformed lenders and $\phi_j = 1$ represents informed lenders that use advanced technologies to set individualized prices based on each borrower's default risk and price sensitivity. In contrast, uninformed lenders ($\phi_j = 0$) lack these tools and set pooled prices based on the average default costs and price sensitivities within a credit score, cs_i. This modeling choice is similar to the setup of insider and outsider firms in Babina et al. (2024). The distinction between informed and uninformed lenders is motivated by reduced-form evidence in the nonbank personal loan sector, which shows that lenders relying less on credit scores exhibit better loan performance and offer lower interest rates within the same credit score group.

5.3.1 Lender profits

Conditional on entry, firms compete in a differentiated Bertrand structure. Firm j's marginal cost for consumer i is the sum of mc_{jm}, a firm-market specific cost common to all of j's potential borrowers, and firm j's assessment of borrower i's default cost and price sensitivity. Informed lenders observe δ_i and thus accurately assess borrower i's default cost. They also observe α_i and assess i's willingness-to-pay. Uninformed lenders only observe cs_i (the borrower's credit score) and know only the distribution of default costs and price sensitivities within that credit score $dF^{cs}(\delta_i)$.

Uninformed lenders may face adverse selection if informed lenders "cream skim" low-risk borrowers and adjust their interest rates using a posterior distribution that accounts for this selection. The degree of adverse selection between lenders is driven by the dispersion of default costs within a credit score. In markets with high dispersion of default costs, informed and uninformed lenders form diverging expectations about a borrower's default risk, resulting in significantly different interest rates. Consequently, uninformed lenders update their beliefs about borrower default costs to account for adverse selection. Specifically, uninformed lenders use the posterior distribution $d\tilde{F}_j^{cs}(\delta_i)$, incorporating the likelihood that higher-cost borrowers will accept their offers, to estimate costs. Informed lenders offer lower interest rates to borrowers with low δ_i, making these low-cost borrowers more likely to accept their offers. As a result, the pool of borrowers accepting offers from uninformed lenders is more costly than the average default cost for that credit score suggests. Uninformed lenders anticipate this and adjust their interest rates to reflect the higher risk.

Firms set prices to maximize profits. Informed lender j's profit for borrower i with credit score cs_i and default risk δ_i in market m is as follows:

$$\Pi_{i,j,m} = \max_{r_{i,j,m}} \underbrace{s_{i,j,m}(cs_i, \delta_i, \boldsymbol{\nu_i})}_{\text{Probability of } i \text{ accepting } j\text{'s offer}} (r_{i,j,m} - \underbrace{\delta_i}_{\text{Default cost}} - \underbrace{mc_{jm}}_{\text{Lender marginal cost}}) \quad \text{if } \underbrace{\phi_j = 1}_{\text{Informed}}$$

where $s_{i,j,m}(cs_i, \delta_i, \boldsymbol{\nu_i})$ is the probability of a borrower with credit score cs_i and default cost δ_i accepting lender j's offer from among all offered loans and the outside option, $\boldsymbol{\nu_i}$. This quantity is obtained by integrating the consumer's optimal choice across the utility shock.

In contrast, uninformed lenders set a pooled price within credit score, cs, by integrating over the posterior distribution, $d\tilde{F}_j^{cs}(\delta_i)$:

$$\Pi_{cs,j,m} = \max_{r_{cs,j,m}} \int \underbrace{s_{i,j,m}(cs_i, \delta_i, \boldsymbol{\nu_i})}_{\text{Probability of } i \text{ accepting } j\text{'s offer}} (r_{cs,j,m} - \underbrace{\delta_i}_{\text{Default cost}} - \underbrace{mc_{jm}}_{\text{Lender marginal cost}}) d\tilde{F}_j^{cs}(\delta_i) \qquad \text{if} \quad \underbrace{\phi_j = 0}_{\text{Uninformed}}$$

Informed lender j will offer a loan to borrower i if $\Pi_{i,j,m} \geq 0$. Informed lenders aggregate over all borrowers i to obtain market-specific profit:

$$\Pi_{j,m} = \int_i \Pi_{i,j,m}\, di \quad \text{if } \phi_j = 1$$

Similarly, uninformed lender j will offer a loan to borrowers with credit score cs if the total profit after aggregating over borrowers with credit score cs is positive: $\int_{cs_i} \Pi_{cs,j,m}\, dcs_i \geq 0$. Uninformed lender j's profit in market m is equal to its profit across all its credit scores:

$$\Pi_{j,m} = \sum_{cs} \int_{cs_i} \Pi_{cs,j,m}\, dcs_i \quad \text{if} \quad \phi_j = 0$$

I derive the lender's first-order conditions in Appendix I. I assume that borrower i's default cost δ_i is drawn from the empirical distribution $F(\delta; \Theta^{cs})$, where cs represents the borrower's credit score.

5.3.2 Entry and exit

Motivated by my reduced-form findings on lender exits following regulatory changes, I model the entry and exit decisions of lenders. Specifically, before setting prices, lenders decide which markets to enter. They form expectations about the number of competitors (other lenders) that will operate in the market and use these expectations to estimate their expected profit before deciding whether to enter. I assume that lenders do not know their own quality or marginal costs prior to entering a market. Consequently, all lenders contemplating entry have uniform expectations about potential profits should they decide to enter. In other words, lenders make entry and exit decisions based on their anticipated competitive landscape and potential profitability. In my reduced-form section, I observe little entry or exit among uninformed nonbanks and find that entry and exit are most significant among informed lenders. Therefore, I limit the entry decision to informed nonbanks and treat the number of uninformed lenders as exogenous. This approach is justified for two reasons. First, there is limited variation in the data to estimate the fixed costs for uninformed lenders. Second, estimating fixed costs for only informed lenders allows me to compute counterfactual equilibria.

I model entry and exit as a two-stage game, following Buchak et al. (2024), Buchak et al. (2018), Melitz and Ottaviano (2008), and Syverson (2004). In the first stage, lenders pay a fixed cost to operate in a market. In the second stage, they set prices and compete. The model is similar to the setups in Buchak et al. (2024), Dunne et al. (2013), and Pakes et al. (2007). Each market has J_m potential informed lenders, where the potential lenders face fixed costs to operate in market m. These per-market fixed costs are distributed i.i.d., $f_{j,m} \sim FC(f; \Lambda)$, where Λ parameterizes the distribution FC. Potential entrant j realizes its fixed cost draw $f_{j,m}$ before deciding whether to enter the market.

I write the profit as a function of the number of firms operating and the population of a market. I refer to these variables as state variables s_m and write profit as a function of them, $\pi(s_m)$. A potential entrant's value of entering a market, given the expected profit, is $VE_m = M_e(s_m)\pi(s_m)$, where $M_e(s_m)$ represents the matrix of transition probabilities lenders use to form expectations about the state of market m, s_m, in the period that they choose to enter. $\pi(s_m)$ is a vector of a lender's expected profit when s_m lenders are operating for each value of s_m. Lender j will enter market m if its expected value of entering exceeds the fixed cost.

$$VE_m \geq f_{j,m}: \text{ Enter}$$

$$VE_m < f_{j,m}: \text{ Do not enter}$$

Appendix L contains more details on entry and exit.

5.3.3 Regulation

I model regulation at the state level, where regulation takes the form of interest rate limits and increased regulatory fixed costs, which include licensing, examinations, and oversight. This approach mirrors the regulatory changes studied in the reduced-form section. Interest rates under the enforcement of interest rate limits are denoted as $r^{reg,\phi_j}_{i,j,m}$, while unconstrained interest rates that would have been offered without these limits are denoted as $r^{*,\phi_j}_{i,j,m}$. The interest rate limit in market m is $\bar{r}_m$.

I model informed lender interest rates under the enforcement of interest rate limits as:

$$r^{reg}_{i,j,m} = \begin{cases} r^*_{i,j,m} & \text{if } r^*_{i,j,m} \leq \bar{r}_m, \\ \bar{r}_m & \text{if } \bar{r}_m - \delta_i - mc_{jm} \geq 0 \;\&\; \bar{r}_m < r^*_{i,j,m}, \\ . & \text{if } \bar{r}_m - \delta_i - mc_{jm} < 0 \end{cases}$$

In words, the informed lender offers the optimal interest rate if it is below the market's rate limit. If the optimal rate exceeds the limit but the loan remains profitable at the limit, the lender sets the interest rate at the limit. If the loan is unprofitable at the limit, the lender does not offer the loan. Uninformed lenders set interest rates analogously, using $\frac{E_j[\delta_i \times s_{i,j,m}]}{E_j[s_{i,j,m}]}$ instead of δ_i.

I allow for imperfect compliance with interest rate limits, consistent with observations in the data and empirical evidence of lax enforcement in Section 2.2.3. Figure J.1 illustrates this lax compliance by showing that some lenders continue to originate loans over official limits post-regulation. The level of compliance with rate caps varies across markets. For example, almost no loans are originated over the limit in New York, while a number of loans violate limits in Vermont. I model partial compliance through a regulation parameter, λ_m. This parameter ranges from 0 to 1 and reflects the degree to which regulatory constraints limit a lender's ability to offer loans above the set interest rate caps. For example, the threat of large fines or penalties in markets with strict oversight may result in stronger compliance than in markets where with lighter state oversight. A lender offers the optimal rate, $r^{*,\phi_j}_{i,j,m}$, with probability $1 - \lambda_m$, and the regulated rate, $r^{reg}_{i,j,m}$, with probability λ_m. See Appendix J for more details on modeling partial compliance.

The enforcement of interest rate limits requires state licensing, examinations, and general oversight, which raise the fixed costs of operating in a market. I model these fixed costs as a component of the fixed cost distribution described in Section 5.3.2. In other words, regulatory oversight may increase the fixed costs that lenders must pay to operate in a market. The model also allows regulatory compliance (λ_m) to depend on regulatory fixed costs. Greater oversight and penalties for violating regulations may result in greater compliance.

5.3.4 Equilibrium

Timing in my model is as follows: First, lenders choose whether to enter a market. Second, entering lenders set interest rates. Third, consumers choose among offered loans and the outside option. An equilibrium is a set of interest rates $r_{i,j,m}$ and lenders such that the following hold:

1. (Demand): Consumers maximize utility-taking interest rates and lender characteristics as given. Demand is characterized by consumers' choice of loans.
2. (Supply). Lenders maximize profits by setting rates across all markets in which they operate. Supply is characterized by lenders maximizing profits conditional on entry.
3. (Informed lender entry): Informed lenders enter if it is profitable to do so.

5.4 Model estimation

I estimate demand, supply, and entry separately. I estimate the model on the data in the pre-regulation equilibrium. I aggregate the loan-level data into market-lender-year observations, focusing on markets not impacted by state challenges to bank-partnership models. This ensures that my estimates are not influenced by regulatory changes. A market is defined as a county-year-consumer type combination. For example, all personal installment loans originated to prime borrowers with high unobserved default costs in county c in 2015 form one market. Unobserved default cost is calculated using default outcomes, specifically as the fraction of the original loan balance not repaid to the lender: $\delta_i = 1 - \frac{CashPaidBack_i}{CashLent_i}$. Borrowers are classified as having high or low unobserved default costs based on whether δ_i is above or below the median within their credit score group. Choice sets consist of the set of realized originations for each market-consumer type category.

To compute adjusted interest rates in a market, I first project out differences due to public credit scores and loan terms. I then adjust each loan's actual interest rate by projecting it on the predicted interest rate to ensure that each loan in the market has the same average borrower credit score and loan size. This adjustment allows for comparison of interest rates across markets and lenders for similarly risky borrowers with the same loan size and terms. I aggregate to the market level by taking the average of these residualized interest rates across lender types.

As in my reduced-form section, I classify lenders based on their screening ability: informed lenders have above-median value of $1 - R^2_j$ from lender-level regressions of interest rates on credit scores, while uninformed lenders have above-median R-squareds. The number of unique lenders J_m per county-consumer type-year represents the typical number of loan offerings available to a borrower from each type of lender.

5.4.1 Demand estimation

My estimation follows the random-coefficients discrete-choice frameworks of Berry et al. (1995) and Nevo (2000). As in their approach, I use aggregate market shares to identify the distribution of consumer preferences for interest rates, once I instrument for price.[36] I exploit variation in state interest rate limits to obtain exogenous price variation and estimate price sensitivity. These limits create differences in prices driven by political economy factors unrelated to loan demand.[37] Specifically, I instrument for price using the interaction between state interest rate limits, $\bar{r}_m$, and an indicator for whether lender j originates

[36] Identifying random coefficients typically requires exogenous variation in choice sets. However, in my model, entry decisions are endogenously determined, partly based on borrower characteristics. I model entry decisions as lenders drawing fixed operating costs from a distribution before choosing to enter a market. This mechanism introduces exogenous variation in entry through random cost draws, ensuring that variation in choice sets is not entirely driven by borrower demand. For instance, a lender may draw different fixed costs when deciding whether to enter two identical markets. These different fixed cost draws may result in entry into the market with the lower cost draw but not the one with the higher cost draw.

[37] Although I estimate my model using data on the pre-regulation equilibrium before the enforcement of interest rate limits, some lenders adhered to these limits in the pre-period as well, generating variation in prices across states even in the absence of formal

loans through a bank-partnership model in market m.[38] In markets where lenders originate loans through the bank partnership model, these lenders are not constrained by interest rate limits.[39] The instrument for price is defined as:

$$z_{jm} = 100 \times \mathbb{1}[(1 - bankpartner_{jm})] + \bar{r}_m \times \mathbb{1}[bankpartner_{jm}]$$

where $bankpartner_{jm}$ is an indicator for whether lender j originates loans through a bank-partnership model in market m. I assume that lenders who are unconstrained by interest rate limits do not originate loans with interest rates over 100%. This choice is motivated by the fact that I observe virtually zero loans with interest rates this high in my data. I interact this instrument with income and credit score to identify the coefficients on the interaction between price sensitivity and credit scores and unobserved default costs.

This price instrument leverages two sources of variation: (1) differences in state interest rate limits, and (2) whether a lender originates loans through a bank-partnership model. State interest rate caps vary by state and constrain direct lenders. Lenders using bank-partnership models are not required to comply with state limits due to the federal preemption of state law afforded to their bank partners. This creates a natural variation in the interest rates faced by borrowers driven by the regulatory environment rather than borrower or market-specific factors. Over time, changes in both state interest rate limits and lenders' origination models provide additional variation, adding to the instrument's ability to isolate the effect of price changes on borrower outcomes. Because these regulatory differences are external to individual borrower demand and market conditions, the instrument is well-suited for identifying the price coefficient. A detailed discussion on the validity of state interest rate limits as an instrument is provided in Appendix K.

To ensure that my demand estimates are representative of the wider population, I demonstrate that my results are robust to two alternative instruments. I conduct this robustness check, as the interest rate limit instruments identify price sensitivity primarily from borrowers receiving interest rate offers near the state interest rate caps, a population that may be riskier than the average consumer. My alternative instruments are: (1) an indicator for whether a lender originates loans through a bank-partnership model post-2015, and (2) Hausman instruments for prices. I also include county fixed effects in these robustness checks. The intuition behind alternative instrument (1) is that in 2015, nonbank lenders using bank-partnership models increased the fees paid to their bank partners due to concerns related to the state challenges discussed in this paper. This increase in fees raised the marginal cost of loans made through the model, generating exogenous price variation. Alternative instrument (2), Hausman instruments, use the price of loans made by the same lender in other markets as an instrument for prices in county c. The rationale is that prices across different markets are likely correlated due to shared marginal cost shocks but less likely to correlate with local demand shocks. Appendix K provides further discussion of these instruments and the price elasticity estimates they imply.

Variation in market shares for a given interest rate across lenders allows me to estimate consumer preferences for non-price attributes $(q_{jt} + \xi_{jmt})$. For example, if Lending Club captures a larger mar-

enforcement. Importantly, state interest rate limits were relatively static during this time, having been mostly established between the 1980s and early 2000s. Unlike the enforcement events I analyze, which occurred more recently, the factors that influenced the original setting of these rate caps are unlikely to correlate with loan demand during the 2013–2018 period. For further discussion of these limits, see Elliehausen and Hannon (2024).

[38] Some lenders originate loans through bank-partnership models in certain states and direct models in others. They are more likely to use bank-partnership models in states with more restrictive regulatory environments. Additionally, lenders adjust their loan origination methods over time, generating variation in lender origination models.

[39] While a number of direct lenders originate loans at or below state interest rate limits, some may occasionally exceed these limits. Lenders using bank-partnership models consistently exceed state interest rate limits in the pre-period.

ket share at a given interest rate, it suggests that borrowers value its convenient application process or customer service. I supplement market share data with demographic information on credit scores and default costs, where default cost is measured as the fraction of a loan that is not paid back to the lender.

The mean $\bar{\alpha} = 1.4$ implies a price elasticity of approximately 4.2, suggesting that borrowers are moderately price sensitive. This estimate is shown in Panel (a) of Table 4. The result indicates that borrowers in the personal loan market are less price sensitive than those in the residential mortgage market, where price elasticities are around 6.6 (Buchak et al., 2024; Koont, 2023). The lower price elasticity may stem from the fact that borrowers often using personal loans to smooth consumption during emergencies or when they have maxed out their credit cards, leading to a higher willingness to pay. The estimate of $\sigma_\alpha^2 = 0.212$ suggests moderate variation in borrower price sensitivity. Panel (b) shows that borrowers with lower credit scores and higher default costs are less price sensitive than those with higher scores and lower costs, consistent with adverse selection. This finding has significant implications for the impact of regulation. Since higher-cost borrowers are less sensitive to price changes than lower-cost borrowers, they may incur higher markups. Thus, interest rate limits may increase the welfare of higher-cost borrowers by reducing excessive lender markups.

I show in Appendix K that these estimates remain robust when using the Hausman instrument or the bank-partnership variable as instruments for price, although my estimates of price elasticity are slightly higher with these alternative instruments. These higher estimates align with the estimates that lower-risk borrowers are more price-sensitive than higher-risk borrowers.

5.4.2 Supply estimation

I estimate the supply-side parameters in three steps. First, I estimate the parameters of borrower default cost distributions. Second, I infer lender-market-specific marginal costs from lender behavior and optimal pricing, conditional on lenders entering a market. Third, I use estimated profits and observed lender entry and exit patterns to estimate the distributions of fixed costs.

Borrower default distributions:
I estimate the distributions of default costs within credit score categories, finding that both average default costs and variances with a credit score are greater in lower credit score buckets. One interpretation of these findings is that there is significant information about default not captured by credit scores, particularly in low credit score groups. This finding is consistent with Einav et al. (2013)'s results that show evidence of significant private information in the subprime auto market. The extent to which credit bureau data reveals borrower default costs influences the degree of adverse selection between lenders. In markets where credit scores provide comprehensive information about borrower default cost, both types of lenders offer similar interest rates and adverse selection between lenders is minimal. Conversely, in environments where credit scores reveal less information about borrower default costs, informed and uninformed lenders offer borrowers significantly different rate offers. As a result, informed lenders are better able to "cream skim" lower-cost borrowers in these markets, leaving uninformed lenders with an adversely selected pool of borrowers.

I use ex-post default outcomes to estimate the distribution of default costs across different credit score categories. Borrowers are divided into 10-point credit score bins, with those possessing thin credit files—defined as having less than two years of credit history or two or fewer accounts—categorized separately. For each credit score category b_{cs}, I estimate the mean and variance of the empirical default cost distributions, denoted as $\delta_{i,b_{cs}} \sim F(\delta; \Theta^{b_{cs}})$. Here, δ_i represents the marginal cost of providing a loan to borrower i, calculated by the formula:

$$\delta_i = 1 - \frac{\text{CashPaidBack}_i}{\text{CashLent}_i}$$

This measure quantifies the loss on the loan. Standard errors are bootstrapped.

Credit scores reveal less information about default costs among lower credit score groups, suggesting the presence of adverse selection between lenders in the subprime market. Panel (a) of Table 5 presents the means and variances of borrower default cost distributions, where borrowers are categorized into six credit score buckets for simplicity. As anticipated, default costs decrease as credit scores improve: borrowers with "excellent" credit scores have average default costs of 3%, whereas those with "very poor" credit scores exhibit average default costs nearing 40%. Additionally, the dispersion of default costs within each credit score category increases as credit scores decline—the variance in default costs is 0.029 for the highest credit score bucket and 0.152 for the lowest. Lower variance in higher credit score groups indicates that credit scores are more informative about borrower credit quality, resulting in similar interest rate offers from both informed and uninformed lenders. Conversely, the higher variances observed in lower credit score buckets lead to more varied loan offers between lenders, highlighting greater asymmetric information between informed and uninformed lenders.

Lender marginal costs:

Lender marginal costs consist of two components: borrower default costs and lender-market-specific marginal costs that reflect origination and funding costs. I begin by estimating marginal costs for informed lenders. Using my demand estimates, I calculate borrower-specific markups and combine these with informed lenders' first-order conditions to compute total marginal costs. Then, using δ_i, I derive the firm-market-specific marginal cost, mc_{jm}, as the difference between total marginal cost and borrower default costs. Next, I estimate marginal cost parameters for uninformed lenders. Unlike informed lenders, uninformed lenders set prices using an updated posterior distribution. I use uninformed lenders' first-order conditions, along with observed prices, acceptance decisions, and default costs, to empirically simulate $d\hat{\tilde{F}}^{cs}$. This procedure allows me to back out mc_{jm} for uninformed lenders.

I use the marginal cost estimates to evaluate the extent of adverse selection between lenders. To do this, I show the default costs for informed and uninformed lenders broken down by subprime and prime borrowers in Panel (b) of Table 5. Column (1) shows $E[\delta_i^j|cs_i]$, the expected default cost for each lender, conditional on borrowers' credit scores. I calculate these values separately for uninformed and informed lenders in both prime and subprime populations, using the default cost distributions estimated in Panel (a). Additionally, I compute the average realized default cost, δ_i^j, for each lender. The difference between $E[\delta_i^j|cs_i]$ and δ_i^j, reported in Column (3), indicates the presence of adverse selection. If uninformed lenders face an adversely selected borrower pool, the realized default costs of borrowers who accept their offers will be higher than the expected default costs implied by the unconditional distribution of default costs for borrowers with similar credit scores.

Marginal cost estimates suggest the presence of adverse selection between lenders, particularly in the subprime market. First, I focus on the default costs of uninformed lenders. Panel (b) of Table 5 shows that for prime borrowers accepting offers from uninformed lenders, there is little difference between $E[\delta_i^j|cs_i]$ and δ_i^j. This is consistent with an environment where credit scores provide most of the necessary information about default cost. However, for subprime borrowers, those accepting offers from uninformed lenders have realized default costs that are 0.4 percentage points higher than expected based on the unconditional distribution of default costs within their credit score. This finding is consistent with uninformed lenders facing an adversely selected pool of borrowers in the subprime market.

In contrast, both prime and subprime borrowers accepting offers from informed lenders exhibit lower realized default costs than their credit scores would suggest. This gap is larger for subprime borrowers, indicating that informed lenders are able to "win" more creditworthy borrowers by undercutting uninformed lenders and offering them lower interest rates. The larger difference between $E[\delta_i^j|cs_i]$ and δ_i^j in the subprime group is also consistent with the finding in Panel (a) of Table 5, which shows greater variation in default costs within lower credit score buckets. In these lower buckets, interest rates offered by informed and uninformed lenders differ significantly, leading a larger share of low-cost borrowers to accept informed lenders' offers.

Finally, in Panel (c) of Table 5, I show that lender-market marginal costs (e.g., costs of funding and origination) are similar for both types of lenders, with uninformed lenders facing marginal costs of 0.88% and informed lenders at 0.85%. These estimates are slightly lower than the estimated origination and financing costs in the mortgage market, which range from 3.5% to 4.5% (Buchak et al., 2024).

Lender fixed costs:

The final step in estimating the supply distribution is to estimate the distribution of fixed costs. Given the limited entry and exit among uninformed lenders in my sample, I restrict the entry decision to informed lenders and treat the number of uninformed lenders in the market as exogenous. Using the demand and supply estimates, I estimate informed lender profits in each market configuration, $\hat{\pi}(s_m)$. Following Pakes et al. (2007), I estimate $\hat{M}_e(s_m)$ using observed transitions to state s_m in my data. I combine estimated profits and estimated transition probabilities to compute $\hat{VE}_m$, a lender's estimated value of entering a market.

Each entrant's expected profit must exceed its fixed cost of entry, and the entry of an additional lender would not be profitable given their fixed costs. I assume fixed costs are drawn i.i.d. from $FC(f;\Lambda)$. The ex-ante probability that lender j enters a market is the probability that its fixed cost is lower than its expected profit:

$$Pr(f_{j,m} \leq \hat{VE}_m) = FC(\hat{VE}_m;\Lambda),$$

where Λ parameterizes the distribution of fixed costs. Note that expected profits are a function of the number of entrants in a market. The number of entrants is binomially distributed, with the probability of success $FC(\hat{VE}_m;\Lambda)$ and n_m representing the number of observed entrants in the market, while N_m represents the total number of potential entrants. The log likelihood of observing a market configuration is:

$$\mathcal{L} = \sum_m \log\left(\binom{N_m}{n_m} FC(\hat{VE}_m;\Lambda)^{n_m}(1 - FC(\hat{VE}_m;\Lambda))^{N_m - n_m}\right).$$

I estimate the fixed cost distribution using maximum likelihood, assuming that fixed costs follow a log-normal distribution, $\log f_{j,m} \sim N(\mu,\sigma^2)$. I estimate this distribution across markets, assuming that the potential number of entrants in each market is identical, $N_m = N$, where N is set to the total number of unique informed lenders—104. See Appendix L for more details on the entry/exit model and estimation.

Table 6 indicates that the mean fixed cost for an informed lender is approximately \$152,124 per market per year. There is moderate variation across markets, with a variance of around \$54,725. The median profit of a lender in a market is roughly \$550,000, suggesting that the mean fixed cost is approximately 27% of the median lender's profit.

5.4.3 Regulation estimation

I simulate interest rate limits by constraining lenders to offer rates at or below the market interest rate cap. If the unconstrained rate exceeds the cap, lenders continue to originate loans at the capped rate as long as it remains profitable. If the loan is not profitable at the interest rate limit, they cease offering the loan. Consequently, markets with higher pre-regulation markups are likely to experience the largest price declines following the enforcement of interest rate limits, while markets with lower markups in the pre-regulation equilibrium likely experience greater reductions in loan quantities. I model lax compliance by allowing lenders to offer loans over the official interest rate limit with probability $(1 - \lambda_m)$. This modeling choice allows me to fit the data, which features imperfect compliance with interest rate limits (see Figure J.1). Markets with greater regulatory constraints, λ_m, experience greater changes following the enforcement of rate caps. I estimate $(1 - \lambda_m)$ from observed changes in the percentage of loans above state limits. See Appendix J.1 for details on the procedure for estimating λ_m and the estimation results.

To estimate the impact of increased oversight on fixed costs, I use the estimated supply and demand parameters to assess how lender profits change after the enforcement of interest rate limits. I recalculate each lender's profits under interest rate limits for each market configuration. I then combine these post-regulation profit estimates with my difference-in-difference estimates of exiting lenders (Table 3) to estimate the fixed cost parameters following regulatory oversight increases. I re-estimate the fixed cost distribution parameters using maximum likelihood, based on the post-regulation profits and lender operating decisions.

Lender profits decline following regulatory changes, with informed lenders experiencing larger changes. Table 7 shows that average lender profits drop by 7% after the enforcement of interest rate limits, with informed lenders experiencing a 15% decline, compared to only 4% for uninformed lenders. This finding is consistent with previous results showing that informed lenders issue more high-interest loans in unregulated environments. Because informed lenders can identify low-cost borrowers within a credit score range and offer interest rates aligned with true default costs, they have greater market share in markets characterized by higher interest rates. Consequently, informed lenders experience significant declines in profit following rate caps.

The fixed regulatory costs of operating in a market also increase following regulatory changes. Panel (b) shows that the mean of the fixed cost distribution rises from approximately \$150,000 to \$224,000—a 49% increase. The variance of the distribution also increases, reaching \$88,412. These estimates suggest that increased oversight raises the fixed costs of operating in a market by an average of \$72,450 annually. I compare my fixed cost estimates to reported costs from lenders, which indicate that my estimates are reasonable. Nonbank lenders report that fixed regulatory costs for state compliance can range from \$1 million to \$30 million annually across all states in which they operate.[40] The average nonbank lender in my sample operates across ten states, suggesting that my estimates of regulatory fixed costs align with those reported by lenders.

I allow compliance with rate caps to vary based on levels of regulatory oversight. I find that markets with greater regulatory fixed costs experience greater compliance. To illustrate this finding, I estimate λ_m separately for each of the four states impacted by regulatory challenges. Then, I analyze how interest rate limits and λ_m affect profits within each market. Using estimated changes in profits alongside observed lender exits in each state estimated through my difference-in-difference specification, I calculate the increase in fixed regulatory costs occurring each state (rather than the average computed previously). States with higher regulatory costs also have higher λ_m values, suggesting that increased regulatory over-

[40] https://home.treasury.gov/system/files/136/Assessing-the-Impact-of-New-Entrant-Nonbank-Firms.pdf

sight and fixed regulatory costs promote compliance. Detailed estimations and the relationship between λ_m and fixed regulatory costs are available in Appendix J.

5.4.4 Model fit

I assess the fit of the model by comparing its predictions to empirical changes following state regulatory challenges. With the exception of λ_m, my model parameters are estimated on the pre-regulation equilibrium, so all tests of model fit except for the percent of loans rationed are out of sample. My model makes several predictions about how prices, quantities, and bunching around interest rate limits evolve in response to the enforcement of interest rate limits and increased oversight costs. I compare these predictions to observed changes in outcomes, which I estimate using a difference-in-difference design and a bunching estimator. Figure 8 presents this comparison. In panels (a) and (b), I compare the effects of interest rate limits observed in the data to those predicted by the model. I use a bunching estimator to estimate the percentage of loans rationed due to interest rate limits and the percentage of loans clustered at the rate caps. Further details on the implementation of the bunching estimator are provided in Appendix G.

The model closely matches the observed number of loans rationed by interest rate limits, as expected. The model slightly overpredicts the degree of bunching at the interest rate limits and the percentage of loans rationed, likely because of less-than-perfect compliance with interest rate limits in the data. However, these differences are relatively small, and the overall alignment between model-predicted and observed changes in bunching and rationing is strong. These findings suggest that the model's predicted markups align with the actual data, validating the accuracy of my supply and demand estimates. In panel (c), I compare model predictions to observed changes in price and quantity across unobserved borrower default costs. I use a difference-in-difference specification to estimate these changes in the data. For price changes, I focus on loans made below the interest rate limits, assuming that contracts below the cap were not directly impacted by the regulations. The model and empirical results align well, both for the overall market and across different borrower risk types, including borrowers with high and low unobserved default costs.

Another implication of my model is that informed lenders capture larger market shares among low-cost borrowers, particularly in markets with greater dispersion in unobserved default costs, such as subprime markets. The intuition behind this result is that informed lenders offer interest rates more closely aligned with actual default costs. In markets with high variation in unobserved default costs, informed lenders offer significantly lower rates compared to uninformed lenders, leading to a larger market share within this population. Conversely, among high-cost borrowers, informed lenders have a smaller share in these markets as uninformed lenders charge a lower price. In markets where credit scores reveal most of the information about default costs, the market shares of informed and uninformed lenders are more balanced since their interest rate offers are similar.

I find that the model matches these predictions by calculating out-of-sample market shares of loans made by informed lenders across four segments: prime-low cost, prime-high cost, subprime-low cost, and subprime-high cost. By "out-of-sample," I refer to the fact that these shares are calculated using data from 2019, a year that was not used for model estimation. I then use my model to predict the share of loans made in these out-of-sample markets and plot the results in Figure 8. The figure confirms that informed lenders have a higher market share in the subprime-low-cost segment and a lower share in the subprime-high-cost segment. In prime markets, the shares between informed and uninformed lenders are more similar, which is consistent with credit scores revealing more information about default costs in this segment.

6 Effects of regulation and counterfactual policies

I use the model to disentangle the effects of interest rate limits and regulatory oversight on borrower outcomes, finding that the decline in credit access is primarily driven by interest rate limits. The exit of informed lenders leads to higher prices and reduced access. Counterfactual policies increasing the rate limit from 21% to 28% and reducing fixed costs by 45% would improve access and lower prices. Finally, banning advanced screening technology would further reduce access for low-risk borrowers, with larger declines for racial minorities due to credit scores revealing less information for these groups.

6.1 Equilibrium effects of regulation

The model reveals that interest rate limits, rather than fixed regulatory costs, primarily drive the reduction in credit access. Consistent with prior research, rate limits directly exclude borrowers with the highest marginal costs. However, they also indirectly reduce lender profits, prompting lender exits and reducing competition. These structural changes result in a 10% decline in total loan quantity and a 5% increase in average rates. These aggregate effects, however, mask substantial differences across borrower groups. By decomposing changes in prices and quantities by both public (credit score) and private (unobserved default cost) risk types, my analysis shows that low-risk borrowers experience decreased credit availability across all credit scores due to the exit of informed lenders, which leads to higher prices and reduced access. I further break down the effects of lender exits, shifts in lender composition, and interest rate limits on credit access for different borrower types.

6.1.1 Contribution of fixed regulatory costs versus interest rate limits to changes in outcomes

The model shows that the decline in credit access is primarily driven by interest rate limits rather than regulatory oversight. I use the model to evaluate the effects of interest rate limits, regulatory oversight, and the combination of both on the number of informed lenders, total loan quantity, prices, and consumer surplus. Specifically, the number of informed lenders decreases by 10.1% when only regulatory oversight increases, 24.8% when only interest rate limits are enforced, and 32% when both are implemented simultaneously. Figure A8 illustrates the changes in informed lenders, loan quantities, prices, and consumer surplus across these three regulatory scenarios. The enforcement of interest rate limits has a larger impact on outcomes compared to increased regulatory oversight. This finding is due to the fact that interest rate limits are binding for 43% of loans made by informed lenders in the pre-regulation equilibrium, resulting in significant declines in profit and lender exits. Increased regulatory oversight has a smaller, but still significant, impact on lender entry and exit. The combination of both interest rate limits and regulatory oversight leads to a 10% decline in quantity, an 8.1% decline in prices, and a 6.2% decline in consumer welfare.

6.1.2 Changes in aggregate outcomes following enforcement of price regulations

Following the enforcement of interest rate limits and increases in oversight, the total quantity of loans originated by uninformed lenders increases by approximately 10%. This rise in uninformed lending is driven by borrowers shifting to uninformed credit as informed lenders exit the market and is illustrated in

Panel (a) of Figure 9. As informed lenders exit the market, a number of borrowers substitute towards uninformed lenders, and uninformed credit rises. In contrast, the quantity of loans from informed lenders declines by nearly 20%, driven by reduced loan profitability under interest rate limits and subsequent market exits. Since informed lenders dominate riskier market segments, they experience more significant reductions in loan volume, as interest rate limits are binding for a larger fraction of their loans. Overall, total loan quantity decreases by nearly 10%, consistent with my reduced-form findings on declining credit supply. Panel (b) of Figure 9 shows similar trends in total profits for uninformed, informed, and all lenders. While total profits decrease, average per-lender profits rise for all borrowers, allowing the remaining lenders in a market to earn non-negative profits as the increased fixed costs of operating in a market.

Average market prices decrease by nearly 8.1%, driven by the enforcement of interest rate limits. This finding is shown in Panel (c) of Figure 9. However, the decline in interest rates is primarily due to a shift in borrower composition, as fewer high-risk borrowers obtain loans. Within each credit score group, average prices increase slightly due to reduced competition, consistent with my reduced form findings. Informed lenders are more constrained by the rate limits, as they have a greater market share in riskier segments of the population. As a result, their average rates decline by about 9.2% in response to the interest rate caps. Meanwhile, uninformed lenders slightly increase their rates following limit enforcement. Since uninformed lenders are less active in market segments constrained by the interest rate limits, they experience smaller price declines from the enforcement of interest rate limits. At the same time, they raise their rates slightly, as they benefit from reduced competition. This reduced competition results in a marginally higher uninformed price.

Average default rates within a given credit score increase following regulation, primarily due to a compositional shift in the borrower pool. The overall borrower pool becomes more costly within each credit score as informed lenders exit. Remaining lenders have lower average screening ability, so the pool of borrowers receiving credit becomes worse on average. Despite the overall rise in defaults, uninformed lenders experience a 0.5% decline in their default rates, as they benefit from a less adversely selected borrower pool after informed lenders exit. In contrast, informed lenders experience a slight increase in default rates, as higher markups attract riskier borrowers who tend to be less sensitive to price.

6.1.3 Decomposition of the effects of lender exits, lender composition, and interest rate limits

I decompose the effects of lender exits, shifts in lender composition, and interest rate limits on loan quantities, prices, and consumer surplus across four borrower segments: prime-high cost, prime-low cost, subprime-high cost, and subprime-low cost. High cost borrowers have above median default costs within their credit score, while low cost borrowers have below median costs within their credit score. To assess the impact of interest rate limits, I simulate changes in quantity, prices, and surplus while holding the number and composition of lenders constant. To evaluate the effects of lender exits, I simulate market outcomes without interest rate limits, keeping the ratio of informed to uninformed lenders stable. Finally, to estimate the impact of shifts in lender composition, I hold the total number of lenders constant but reduce the share of informed lenders by 31%.

Lender exits reduce loan quantities across all borrower groups, as shown in Figure 10. The reduction is more pronounced for less-costly borrowers who are more price sensitive than high-cost borrowers. These low-cost borrowers reduce borrowing more than high-cost borrowers as markups increase due to lender exits. Specifically, lender exits lead to a 15% decline in loan quantity for prime high-cost borrowers, compared to an 8% decline for prime low-cost borrowers. In the subprime group, lender exits result in a

14.1% decline for high-cost borrowers and a 6.2% decline for low-cost borrowers. The light bars in Figure 10 illustrate these changes among borrower risk types. In summary, interest rate limits reduce credit access by increasing lender market power through lender exits.

Next, I show that the changing composition of lenders (i.e. fewer informed lenders) reduces loan quantities for low-risk borrowers but increases access for high-cost borrowers. The exit of informed lenders reduces loan quantities for low-cost borrowers by 5.9% for prime low-cost borrowers and by 9.1% for subprime low-cost borrowers. These borrowers rely on informed lenders to offer interest rates that reflect their true default costs. With fewer informed lenders in the market, these low-cost borrowers experience higher prices and are less likely to accept loan offers. In contrast, prime high-cost borrowers see a 3.9% increase in quantities, while subprime high-cost borrowers experience a 4.8% increase in quantities. This increase is due to the fact that as informed lenders exit the market, low-risk borrowers substitute towards uninformed lenders. This substitution leads to lower pooled prices and encourages more high-cost borrowers to accept loan offers.

Finally, I show the direct impact of interest rate limits on loan quantities. Credit access increases slightly for prime borrowers but declines for subprime borrowers. Interest rate limits lead to small price reductions in prime markets. Although prime borrowers have low default costs, some have low price elasticity and receive high offers from informed lenders. Because these high interest rates are driven by markups rather than default costs, interest rate limits reduce prices for these borrowers without reducing access. Consequently, total loan quantities increase by 0.6% for prime borrowers with low unobserved costs and by 0.3% for prime borrowers with high unobserved costs. The effects of interest rate limits are more pronounced for subprime borrowers, as rate limits are binding for a larger number of loans in this market. Subprime low-cost borrowers see a 4.2% decline in loan quantity due to interest rate limits, while subprime high-cost borrowers face a much larger 22% decline. These declines are due to the fact that interest rate limits render many loans unprofitable in these markets.

In Figure A9, I decompose the effects of lender exits, changes in lender composition, and interest rate limits on prices, highlighting the differential impacts across borrower risk profiles. Lender exits lead to price increases for all risk types, as reduced competition allows remaining lenders to raise markups. The exit of informed lenders causes price increases for borrowers with low unobserved default costs, while prices decline for those with high unobserved default costs. Low-cost borrowers, who previously benefited from more accurate pricing by informed lenders, now face higher prices as these lenders exit the market. Conversely, high-cost borrowers benefit from lower pooled prices offered by uninformed lenders after the departure of informed lenders. Lastly, interest rate limits reduce prices across all borrower groups, with the largest reductions seen among subprime and high-cost borrowers, who are more likely to receive rates above the limits in the absence of regulation.

6.1.4 Changes in outcomes by observed and unobserved borrower type

The aggregate changes in prices, quantity, and welfare mask significant heterogeneity across different borrower groups. To analyze how outcomes change among different risk types, I decompose changes by both public (credit score) and private (unobserved default cost) risk types. I categorize high-unobserved-risk borrowers as those with default costs exceeding the median within their credit score. In contrast, low-unobserved-risk borrowers are those with default costs at or below the median within their credit score.

Regulatory changes affect loan quantities across various credit scores and risk types, as shown in Figure A10. Loan quantities decline most sharply in the subprime market and among borrowers without credit scores, as interest rate limits render loans in these markets unprofitable. Lender exits further reduce quantities as markets become less competitive and markups rise. The increase in markups leads the most price-sensitive borrowers to choose the outside option rather than the offered loans. Low-cost borrowers in both the prime and subprime segments face the most significant reductions in loan quantities due to the exit of informed lenders, as these borrowers receive higher interest rate offers from uninformed lenders. This finding highlights the substantial impact of interest rate limits on financial inclusion and credit access, particularly for borrowers who appear risky based on conventional credit scores but are intrinsically low-risk.

Additionally, the enforcement of interest rate limits leads to a decline in average prices for subprime borrowers and high-cost prime borrowers, due to the direct effect of the interest rate caps on prices. These caps limit the maximum interest lenders can charge, with the most substantial declines occurring in high-cost, price-insensitive markets. In contrast, prices slightly increase for low-cost prime borrowers, who experience increased markups following the exit of informed lenders.

Finally, regulation has varied effects on consumer surplus across borrower risk categories. Consumer surplus declines for low-cost borrowers across all credit scores due to the exit of informed lenders, who previously offered these borrowers low-interest loans aligned with their true default costs. Similarly, high-cost subprime borrowers experience a reduction in consumer surplus, as loan quantities decrease significantly following the enforcement of interest rate caps. In contrast, prime low-cost borrowers see an increase in consumer surplus, as they benefit from substantial price reductions due to interest rate limits with only minor declines in loan quantities. Overall, while interest rate limits may improve outcomes for some borrowers, they reduce access and worsen outcomes for subprime borrowers who are low-risk or lack credit scores, leading to a potential decline in financial inclusion.

In summary, the enforcement of interest rate limits and increased regulatory oversight significantly affect loan quantities, prices, and consumer surplus, with heterogeneous impacts across borrower types. Low-cost borrowers experience the largest reductions in loan quantities and consumer surplus, particularly those with lower credit scores, due to the exit of informed lenders. In contrast, high-cost borrowers see varying effects depending on their risk profiles. The overall decline in average prices across borrower risk types is primarily driven by the enforcement of interest rate limits. Borrowers who appear risky based on conventional credit scores but are intrinsically low-risk suffer under interest rate limits and increased oversight, while those who seem creditworthy but are more likely to default benefit. These findings highlight the uneven impact of interest rate limits and oversight, reducing access for low-risk borrowers while benefiting higher-risk ones.

6.2 Counterfactual policies

Finally, I estimate the effects of counterfactual regulatory policies on credit access and prices, considering various interest rate limits and fixed regulatory costs. I find that an interest rate cap of 28%, combined with reduced fixed regulatory costs, would slightly improve credit access for subprime borrowers.

However, overall access would decline marginally, with most benefits accruing to high-risk subprime borrowers. Even relatively lax interest rate limits lead to the exit of informed lenders, diminishing the benefits of these limits for low-risk borrowers. Additionally, I examine a scenario where regulations prohibit the use of advanced screening technologies, such as machine learning and AI algorithms, which some regulators may seek to restrict due to concerns about consumer harm. My findings suggest that such restrictions would reduce credit access, particularly for low-default-risk subprime borrowers. Banning advanced screening technologies would require lenders to charge a pooled price within each credit score. This regulation would benefit high-risk borrowers, who would receive lower rates by being pooled with low-risk borrowers, but would reduce access and raise prices for low-risk borrowers who previously received lower interest rates due to technologies correctly identifying them as low risk.

6.2.1 Different interest rate limits and fixed costs

I analyze loan quantities, prices, and consumer surplus under various counterfactual regulatory policies, exploring different levels of interest rate limits and regulatory fixed costs. Credit access increases the most with an interest rate cap of 28% (relative to observed caps of 21%) and fixed costs that are 45% lower than observed fixed costs. Higher interest rate limits result in greater lender profits, encouraging the entry of informed lenders. The presence of informed lenders is particularly important for the outcomes of borrowers who appear risky based on conventional credit scoring methods but are intrinsically low-risk. Lower fixed costs also promote lender entry but reduce compliance with interest rate limits. Reduced compliance may lead to higher prices for some borrowers.

To calculate counterfactual outcomes, I use the estimated relationship between fixed costs and compliance with interest rate limits described in Appendix J.1 to estimate lender exits, prices, quantities, and consumer outcomes under different levels of regulatory fixed costs, ranging from \$0 to \$250,000. These fixed costs represent the mean of the regulatory fixed cost distribution per lender-state. I determine the level of fixed costs that maximizes credit access for each potential interest rate limit and calculate the corresponding changes in price and consumer welfare under that level of fixed costs. All changes are measured from the status quo scenario, which assumes no interest rate limit and no regulatory fixed costs.

I determine the level of regulatory costs that maximizes credit access under each potential interest rate limit in Figure J.3. High fixed costs, which increase compliance with rate limits, maximize access under the most stringent interest rate caps. In scenarios with strict rate caps, even low fixed costs result in a large reduction of credit and the exit of informed lenders. Consequently, higher fixed costs reduce prices for more borrowers without causing additional lender exits—a substantial number of lenders exit even under low fixed costs. More moderate levels of fixed regulatory costs are optimal at higher interest rate caps. In these scenarios, moderate rate caps achieve high compliance (lowering prices for borrowers who experience high markups) while minimizing the number of informed lender exits.

I examine how counterfactual policies impact aggregate outcomes in Panels (a), (c), and (e) of Figure 11. Panel (a) shows that loan quantities decline under all interest rate limits with the fixed costs observed in my setting. Under optimal fixed costs, quantities increase slightly under limits of 32 to 34%. The optimal fixed regulatory costs in these scenarios are \$40,000 per lender per state, significantly lower than the observed fixed regulatory costs of \$72,000 that I estimate in my setting. Higher interest rate limits and lower fixed costs allow lenders to earn greater profits, which limit lender exits. They also protect a number of borrowers from high markups while limiting the number of loans that become unprofitable under these limits. Panel (c) shows that average prices are lower with lower interest rate limits, as these limits reduce lender markups and prevent the origination of high-interest loans. Panel (e) shows that total consumer welfare is maximized under an interest rate limit of 28% and fixed costs of \$40,000, as this combination results in the best balance of increased credit access and reduced prices. Next, I show outcomes for subprime borrowers in Panels (b), (d), and (f) of Figure 11. Credit quantities and consumer surplus are maximized under interest rate limits of 28% and fixed costs of \$40,000 per lender-year-state.

Lastly, I show that these benefits mainly accrue to high-cost subprime borrowers. Figure A12 plots changes in outcomes for high- and low-unobserved-cost subprime borrowers. The increase in loan quantity is driven by high-cost borrowers, while consumer surplus rises for both groups, though gains are larger for high-cost borrowers.

In summary, enforcing interest rate caps alongside lower regulatory costs improves credit access and consumer surplus, particularly for subprime borrowers. A 28% interest rate cap, paired with lower fixed costs, increases loan quantities by encouraging more lender entry and reducing markups. The benefits of these regulations primarily improve outcomes for subprime borrowers. However, these benefits primarily accrue to high-risk borrowers, revealing a tradeoff for financial inclusion.

6.2.2 Information restrictions

In recent years, regulatory interest has expanded beyond traditional price controls and regulatory costs to include the oversight of algorithms and artificial intelligence (AI) in lending practices. While much attention remains focused on price regulations, concerns have emerged about the potential unintended consequences of advanced technologies, such as the scoring algorithms lenders use to target less creditworthy borrowers. Regulators worry that these technologies may reduce risk pooling among low-risk borrowers, potentially disadvantaging certain consumers. In this section, I examine the effects of regulatory policies that restrict the use of advanced screening algorithms and data in lending. I consider two different policies: (1) a policy that bans lenders from using technology to determine a borrower's price sensitivity, requiring all lenders to instead make assumptions about borrower price sensitivities based on the distribution of sensitivities within a given credit score; and (2) a policy that prohibits lenders from using technology to determine a borrower's specific price sensitivity *or* default cost, requiring all lenders to set prices based on the distribution of price sensitivities and default costs within a credit score. I also show how these policies impact different races, as the effect of advanced screening technology on minority groups is of interest to regulators.

First, I demonstrate how a ban on these technologies would affect consumer outcomes in the absence of interest rate limit enforcement. Banning the use of price sensitivity data would slightly increase prices and decrease loan quantities for low unobserved cost borrowers, as shown in panels (a) through (c) of Figure 12. Changes are calculated as the differences in outcomes following the regulation of technology (without interest rate limit enforcement or increased oversight) relative to the status quo, where no technology regulation is in place. These borrowers, being less price-sensitive than high-cost borrowers, receive higher markups on average when this technology is banned. Additionally, banning the use of both demand and default cost data results in lower loan quantities and higher prices for low-cost borrowers. Once advanced technology is prohibited, these borrowers receive higher interest rate offers, as they are now pooled with high-cost borrowers. Thus, regulating advanced technology in lending by banning the use of price sensitivity and default cost data increases prices and reduces credit access for low-cost borrowers, as it forces them to be pooled with higher-risk individuals.

Finally, I consider how these regulations interact with borrower race in Figure A13. While I do not directly observe borrower race, I calculate changes in total quantity, average price, and total consumer surplus in zip codes with 75% or more white residents and those with 75% or more Black, Hispanic, or Latino residents. Although I do not account for the potential additional flexibility and triangulation effects discussed in Fuster et al. (2022) on access and pricing for racial minorities, I find that restrictions on lending technology lead to lower access and consumer surplus in zip codes with higher shares of racial minorities. The dispersion in default costs within a credit score is larger in these zip codes, with some borrowers in these areas being less risky than their credit scores suggest. Consequently, these borrowers are adversely affected by regulations that restrict lenders' ability to assess their default risk and price sensitivity accurately.

7 Conclusion

Access to affordable, fairly priced credit is essential for promoting financial security, economic growth, and social equity. Yet despite the U.S.'s advanced financial system, millions of Americans continue to rely on high-cost services like payday loans, check cashing, and pawnshops. My research investigates how regulation affects access to affordable credit, particularly for subprime and low-income individuals. My findings reveal that financial regulation may unintentionally reduce credit supply for underserved groups by driving out lenders with advanced screening technologies. The exit of these lenders disproportionately affects borrowers with lower credit scores and limited credit histories.

I examine the effects of price regulation and regulatory oversight on credit supply, showing that these regulations alter the number and composition of lenders in a market. Analyzing the enforcement of interest rate caps and increased regulatory oversight in the U.S. nonbank personal loan market, I find that 21% of lenders exit impacted markets following regulations. Lenders using advanced screening technologies are more likely to exit. The enforcement of rate caps and the resulting changes in market structure cause loan quantities to decline by 10%, and average prices to fall by 8%, with the largest effects in the subprime market. However, this price reduction is primarily driven by changes in borrower composition—after adjusting for borrower risk, interest rates increase by 5% (1.1 percentage points) for observationally similar borrowers. These regulations also result in negative consequences for loan performance, financial outcomes, and inclusion, particularly for vulnerable borrowers who experience greater financial distress and reduced access to credit.

Building on these findings, I develop a structural lending model that incorporates adverse selection among lenders, lender entry and exit, and varying screening technologies. The model shows that interest rate limits, rather than fixed regulatory costs, are the primary driver of declining credit access. Consistent with prior work, rate limits directly exclude the highest marginal-cost borrowers from the market. Importantly, however, they have the secondary effect of reducing lender profits, thereby leading to lender exits. I also decompose changes in credit quantity and pricing by public (credit score) and private (unobserved default cost) risk types, revealing that low-risk borrowers are most significantly impacted. Lastly, I estimate credit access and pricing changes under counterfactual regulatory policies, finding that an interest rate cap from 21% to 28%, combined with 45% lower fixed regulatory costs, would improve credit access for subprime borrowers.

More broadly, this work connects to questions surrounding the optimal regulation of advanced credit screening technologies, such as machine learning and artificial intelligence, which I aim to explore in future research. Additionally, while I focused on two relatively exogenous regulatory events, a significant number of laws are passed that impact both banks and nonbanks, many of which are likely influenced by the political economy of state regulations. Understanding the forces driving these regulations and identifying the winners and losers remains a promising area for further inquiry.

References

Adams, William, Liran Einav, and Jonathan Levin. 2009. Liquidity constraints and imperfect information in subprime lending. *American Economic Review* 99:49–84.

Agarwal, Sumit, Souphala Chomsisengphet, Neale Mahoney, and Johannes Stroebel. 2015. Regulating consumer financial products: Evidence from credit cards. *The Quarterly Journal of Economics* 130:111–164.

Albanesi, Stefania, and Domonkos F Vamossy. 2019. Predicting consumer default: A deep learning approach. National Bureau of Economic Research.

Allcott, Hunt, Joshua Kim, Dmitry Taubinsky, and Jonathan Zinman. 2022. Are high-interest loans predatory? theory and evidence from payday lending. *The Review of Economic Studies* 89:1041–1084.

Avery, Robert B, Raphael W Bostic, Paul S Calem, and Glenn B Canner. 1996. Credit risk, credit scoring, and the performance of home mortgages. *Fed. Res. Bull.* 82:621.

Avery, Robert B, Kenneth P Brevoort, and Glenn Canner. 2012. Does credit scoring produce a disparate impact?. *Real Estate Economics* 40:S65–S114.

Babina, Tania, Saleem A Bahaj, Greg Buchak, Filippo De Marco, Angus K Foulis, Will Gornall, Francesco Mazzola, and Tong Yu. 2024. Customer data access and fintech entry: Early evidence from open banking. National Bureau of Economic Research.

Baker, Andrew C, David F Larcker, and Charles CY Wang. 2022. How much should we trust staggered difference-in-differences estimates?. *Journal of Financial Economics* 144:370–395.

Baradaran, Mehrsa. 2015. *How the other half banks: Exclusion, exploitation, and the threat to democracy* Harvard University Press.

Barr, Michael S. 2008. Financial services, savings and borrowing among low-and moderate-income households: Evidence from the detroit area household financial services survey. in *3rd Annual Conference on Empirical Legal Studies Papers*.

Bartlett, Robert, Adair Morse, Richard Stanton, and Nancy Wallace. 2022. Consumer-lending discrimination in the fintech era. *Journal of Financial Economics* 143:30–56.

Benmelech, Efraim, and Tobias J Moskowitz. 2010. The political economy of financial regulation: Evidence from us state usury laws in the 19th century. *The journal of finance* 65:1029–1073.

Berg, Tobias, Valentin Burg, Ana Gombović, and Manju Puri. 2020. On the rise of fintechs: Credit scoring using digital footprints. *The Review of Financial Studies* 33:2845–2897.

Berg, Tobias, Andreas Fuster, and Manju Puri. 2022. Fintech lending. *Annual Review of Financial Economics* 14:187–207.

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. pautomobile prices in market equilibrium, qeconometrica.

Bhutta, Neil, Paige Marta Skiba, and Jeremy Tobacman. 2015. Payday loan choices and consequences. *Journal of Money, Credit and Banking* 47:223–260.

Blank, Rebecca M, and Michael S Barr. 2009. *Insufficient funds: Savings, assets, credit, and banking among low-income households* Russell Sage Foundation.

Blattner, Laura, Jacob Hartwig, and Scott Nelson. 2022. Information design in consumer credit markets. *American Economic Review* .

Blattner, Laura, and Scott Nelson. 2021. How costly is noise? data and disparities in consumer credit. *arXiv preprint arXiv:2105.07554* .

Blattner, Laura, Scott Nelson, and Jann Spiess. 2021. Unpacking the black box: Regulating algorithmic decisions. *arXiv preprint arXiv:2110.03443* .

Bodenhorn, Howard. 2007. Usury ceilings and bank lending behavior: Evidence from nineteenth century new york. *Explorations in Economic History* 44:179–202.

Broecker, Thorsten. 1990. Credit-worthiness tests and interbank competition. *Econometrica: Journal of the Econometric Society* 429–452.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru. 2018. Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of financial economics* 130:453–483.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru. 2024. Beyond the balance sheet model of banking: Implications for bank regulation and monetary policy. *Journal of Political Economy* 132:616–693.

Callaway, Brantly, and Pedro HC Sant'Anna. 2021. Difference-in-differences with multiple time periods. *Journal of econometrics* 225:200–230.

Campbell, Dennis, F Asís Martínez-Jerez, and Peter Tufano. 2012. Bouncing out of the banking system: An empirical analysis of involuntary bank account closures. *Journal of Banking & Finance* 36:1224–1235.

Carrell, Scott, and Jonathan Zinman. 2014. In harm's way? payday loan access and military personnel performance. *The Review of Financial Studies* 27:2805–2840.

Castellanos, Sara G, Diego Jiménez Hernández, Aprajit Mahajan, and Enrique Seira. 2018. *Financial inclusion and contract terms: Experimental evidence from Mexico* National Bureau of Economic Research.

Célerier, Claire, and Adrien Matray. 2019. Bank-branch supply, financial inclusion, and wealth accumulation. *The Review of Financial Studies* 32:4767–4809.

Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer. 2019. The effect of minimum wages on low-wage jobs. *The Quarterly Journal of Economics* 134:1405–1454.

Charron-Chénier, Raphaël. 2020. Predatory inclusion in consumer credit: explaining black and white disparities in payday loan use. in *Sociological Forum*. volume 35. 370–392. Wiley Online Library.

Chatterjee, Satyajit, Dean Corbae, Kyle Dempsey, and José-Víctor Ríos-Rull. 2023. A quantitative theory of the credit score. *Econometrica* 91:1803–1840.

Conti-Brown, Peter. 2019. Can fintech increase lending? how courts are undermining financial inclusion .

Cox, Natalie, Ernest Liu, and Daniel Morrison. 2021. Market power in small business lending: A two-dimensional bunching approach.

Crawford, Gregory S, Nicola Pavanini, and Fabiano Schivardi. 2018. Asymmetric information and imperfect competition in lending markets. *American Economic Review* 108:1659–1701.

Cuesta, José Ignacio, and Alberto Sepúlveda. 2021. Price regulation in credit markets: A trade-off between consumer protection and credit access. *Available at SSRN 3282910* .

Danisewicz, Piotr, and Ilaf Elard. 2023. The real effects of financial technology: Marketplace lending and personal bankruptcy. *Journal of Banking & Finance* 155:106986.

Davidson, Charles. 2018. Lack of access to financial services impedes economic mobility. *Economy Matters: Federal Reserve Bank of Atlanta* .

DeFusco, Anthony A, and Andrew Paciorek. 2017. The interest rate elasticity of mortgage demand: Evidence from bunching at the conforming loan limit. *American Economic Journal: Economic Policy* 9:210–240.

Di Maggio, Marco, Dimuthu Ratnadiwakara, and Don Carmichael. 2022. Invisible primes: Fintech lending with alternative data. National Bureau of Economic Research.

Dunne, Timothy, Shawn D Klimek, Mark J Roberts, and Daniel Yi Xu. 2013. Entry, exit, and the determinants of market structure. *The RAND Journal of Economics* 44:462–487.

Einav, Liran, Mark Jenkins, and Jonathan Levin. 2013. The impact of credit scoring on consumer lending. *The RAND Journal of Economics* 44:249–274.

Elliehausen, Gregory, Simona Hannon, and Thomas W Miller Jr. 2021. A new look at the effects of the interest rate ceiling in arkansas .

Elliehausen, Gregory, and Simona M Hannon. 2024. Fintech and banks: Strategic partnerships that circumvent state usury laws. *Finance Research Letters* 64:105387.

Fekrazad, Amir. 2020. Impacts of interest rate caps on the payday loan market: Evidence from rhode island. *Journal of banking & finance* 113:105750.

FinRegLab. 2020. The use of cash-flow data in underwriting credit.

Fishelson-Holstein, Hollis. 2005. Credit scoring role in increasing homeownership for underserved populations.

Fonseca, Julia. 2023. Less mainstream credit, more payday borrowing? evidence from debt collection restrictions. *The Journal of Finance* 78:63–103.

FRB. 2007. Report to the congress on credit scoring and its effects on the availability and affordability of credit.

Fuster, Andreas, Paul Goldsmith-Pinkham, Tarun Ramadorai, and Ansgar Walther. 2022. Predictably unequal? the effects of machine learning on credit markets. *The Journal of Finance* 77:5–47.

Ghosh, Pulak, Boris Vallee, and Yao Zeng. 2022. Fintech lending and cashless payments. in *Proceedings of Paris December 2021 Finance Meeting EUROFIDAI-ESSEC*.

Gramlich, Edward. 2006. *Building assets, building credit: Creating wealth in low-income communities* Brookings Institution Press.

Hauswald, Robert, and Robert Marquez. 2003. Information technology and financial services competition. *The Review of Financial Studies* 16:921–948.

He, Zhiguo, Jing Huang, and Jidong Zhou. 2023. Open banking: Credit market competition when borrowers own the data. *Journal of financial economics* 147:449–474.

Honigsberg, Colleen, Robert J Jackson Jr, and Richard Squire. 2017. How does legal enforceability affect consumer lending? evidence from a natural experiment. *The Journal of Law and Economics* 60:673–712.

Horn, Charles M, and Melissa RH Hall. 2017. The curious case of madden v. midland funding and the survival of the valid-when-made doctrine. *NC Banking Inst.* 21:1.

Jansen, Mark, Fabian Nagel, Constantine Yannelis, and Anthony Lee Zhang. 2022. Data and welfare in credit markets. *University of Chicago, Becker Friedman Institute for Economics Working Paper* .

Johnson, Mark J, Itzhak Ben-David, Jason Lee, and Vincent Yao. 2023. Fintech lending with lowtech pricing. National Bureau of Economic Research.

Keys, Benjamin J, Tanmoy Mukherjee, Amit Seru, and Vikrant Vig. 2010. Did securitization lead to lax screening? evidence from subprime loans. *The Quarterly journal of economics* 125:307–362.

Keys, Benjamin J, Amit Seru, and Vikrant Vig. 2012. Lender screening and the role of securitization: Evidence from prime and subprime mortgage markets. *The Review of Financial Studies* 25:2071–2108.

Knight, Brian. 2017. Risks to innovative credit posed by emerging regulatory and litigation trends. George Mason University, Mercatus Center.

Koont, Naz. 2023. The digital banking revolution: Effects on competition and stability. *Available at SSRN* .

Levitin, Adam J. 2021. Spurious pedigree of the" valid-when-made" doctrine. *Duke LJ Online* 71:87.

Liberman, Andres, Christopher Neilson, Luis Opazo, and Seth Zimmerman. 2018. The equilibrium effects of information deletion: Evidence from consumer credit markets. National Bureau of Economic Research.

Mahoney, Neale, and E Glen Weyl. 2017. Imperfect competition in selection markets. *Review of Economics and Statistics* 99:637–651.

Maimbo, Samuel Munzele, and Claudia Alejandra Henriquez Gallegos. 2014. Interest rate caps around the world: still popular, but a blunt instrument. *World Bank Policy Research Working Paper* .

Matcham, William. 2024. Risk-based borrowing limits in credit card markets. *Available at SSRN 4926974* .

McCaffrey, Daniel F, and Robert M Bell. 2003. Bias reduction in standard errors for linear regression with multi-stage samples. *Quality control and applied statistics* 48:677–682.

Melitz, Marc J, and Gianmarco IP Ottaviano. 2008. Market size, trade, and productivity. *The review of economic studies* 75:295–316.

Melzer, Brian, and Aaron Schroeder. 2017. Loan contracting in the presence of usury limits: Evidence from automobile lending. *Consumer Financial Protection Bureau Office of Research Working Paper* .

Melzer, Brian T. 2011. The real costs of credit access: Evidence from the payday lending market. *The Quarterly Journal of Economics* 126:517–555.

Morse, Adair. 2011. Payday lenders: Heroes or villains?. *Journal of Financial Economics* 102:28–44.

Nelson, Scott. 2018. Private information and price regulation in the us credit card market. *Unpublished working paper* .

Nevo, Aviv. 2000. A practitioner's guide to estimation of random-coefficients logit models of demand. *Journal of economics & management strategy* 9:513–548.

Pakes, Ariel, Michael Ostrovsky, and Steven Berry. 2007. Simple estimators for the parameters of discrete dynamic games (with entry/exit examples). *the RAND Journal of Economics* 38:373–399.

Petersen, Mitchell A, and Raghuram G Rajan. 1995. The effect of credit market competition on lending relationships. *The Quarterly Journal of Economics* 110:407–443.

Rajan, Uday, Amit Seru, and Vikrant Vig. 2015. The failure of models that predict failure: Distance, incentives, and defaults. *Journal of financial economics* 115:237–260.

Rigbi, Oren. 2013. The effects of usury laws: Evidence from the online loan market. *Review of Economics and Statistics* 95:1238–1248.

Schmukler, S, J Tessada, C Vasquez, and M Vera. 2018. Winners and losers from interest rate ceilings: Quasi-experimental evidence from chile.

Skiba, Paige Marta, and Jeremy Tobacman. 2008. Payday loans, uncertainty and discounting: Explaining patterns of borrowing, repayment, and default. *Vanderbilt Law and Economics Research Paper* .

Stegman, Michael A. 2007. Payday lending. *Journal of Economic Perspectives* 21:169–190.

Stepner, Michael. 2013. Binscatter: Stata module to generate binned scatterplots .

Stiglitz, Joseph E, and Andrew Weiss. 1981. Credit rationing in markets with imperfect information. *The American economic review* 71:393–410.

Stroebel, Johannes, and Joseph Vavra. 2019. House prices, local demand, and retail prices. *Journal of Political Economy* 127:1391–1436.

Syverson, Chad. 2004. Market structure and productivity: A concrete example. *Journal of political Economy* 112:1181–1222.

Temin, Peter, and Hans-Joachim Voth. 2008. Interest rate restrictions in a natural experiment: Loan allocation and the change in the usury laws in 1714. *The economic journal* 118:743–758.

Wong, Arlene, et al.. 2019. Refinancing and the transmission of monetary policy to consumption. *Unpublished manuscript* 20.

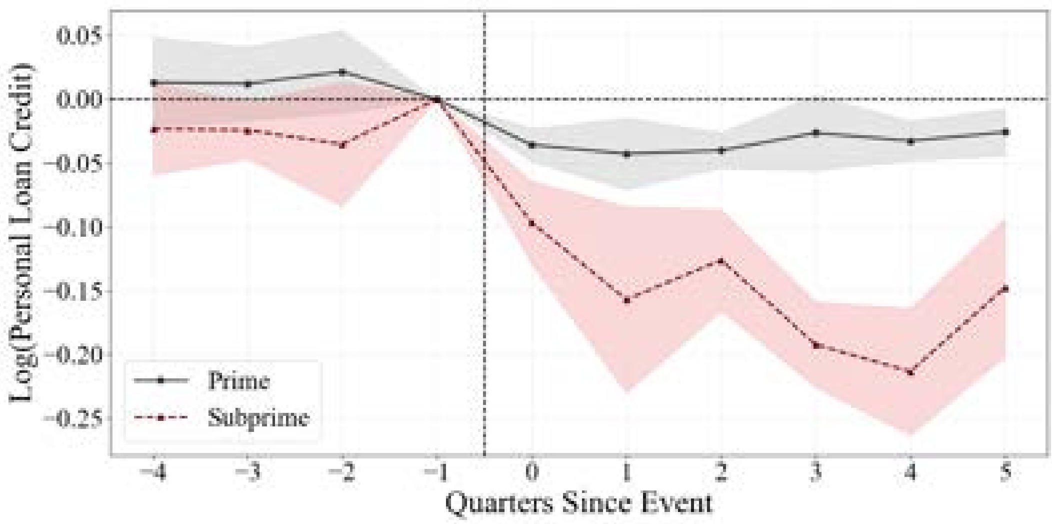
Yannelis, Constantine, and Anthony Lee Zhang. 2023. Competition and selection in credit markets. *Journal of Financial Economics* 150:103710.

Zinman, Jonathan. 2010. Restricting consumer credit access: Household survey evidence on effects around the oregon rate cap. *Journal of banking & finance* 34:546–556.

Figure 1: Personal loan credit quantity around regulatory changes

This figure shows results from the following regression: $y_{c,t,g} = \alpha + \sum_{r=-4}^{5} \beta_r \mathbb{1}[t - L_c = r] + \phi\psi_{c,g} + \gamma_{t,g} + \varepsilon_{c,t,g}$ where c represents county c in quarter t, and g denotes the specific stacked dataset. L_c is the quarter in which a state regulatory challenge occurred for county c. $y_{c,t,g}$ is the log of total personal loan originations (measured in dollars). Relative quarters around challenges are denoted by $\mathbb{1}[t - L_c = r]$, which is an indicator that takes the value of 1 if county c experienced a challenge r quarters from t. $\psi_{c,g}$ are zip code-dataset fixed effects, and $\gamma_{t,g}$ are calendar time-dataset fixed effects. Panel (a) shows results for the total personal loan market (both nonbanks and banks) while Panel (b) shows results for the nonbank personal loan market. Standard errors are clustered at the state level. *Source:* Credit bureau data.

Panel (a): Personal loan quantity (nonbanks and banks)



Panel (b): Personal loan quantity (nonbanks only)

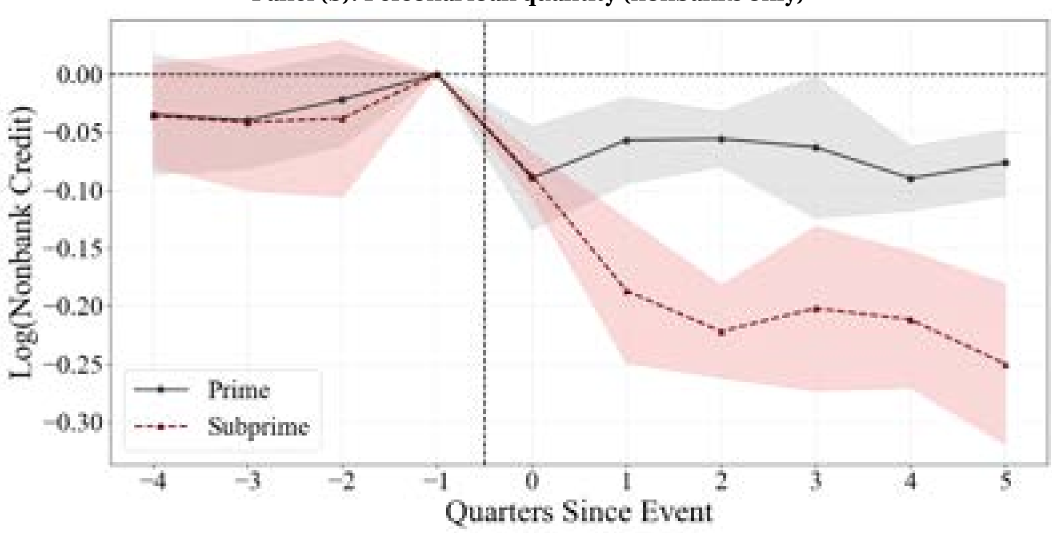
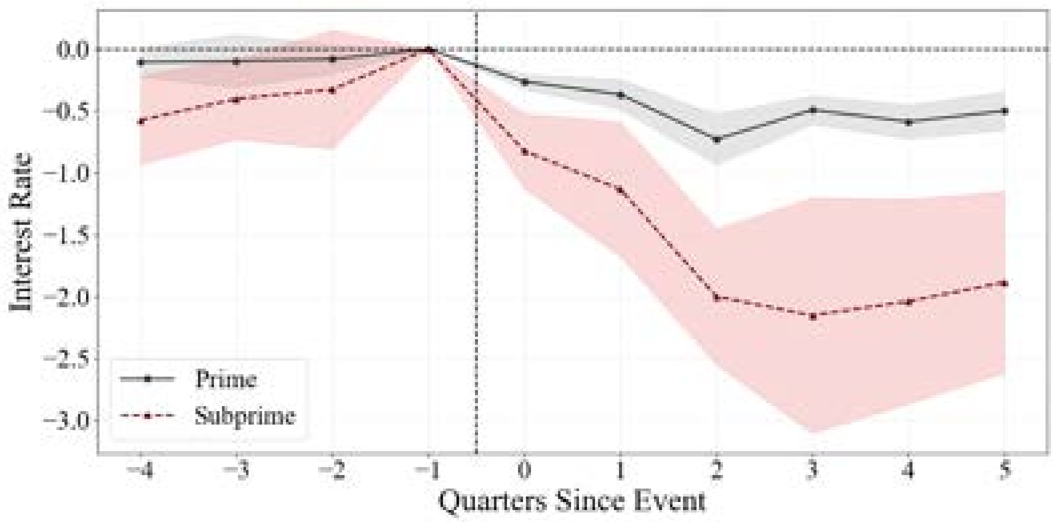


Figure 2: Personal loan prices around regulatory changes

This figure presents results from the following regression: $y_{i,t,z,g} = \alpha + \sum_{r=-4}^{5} \beta_r \mathbb{1}[t - L_z = r] + \theta X_{i,t,g} + \phi\gamma_{z,g} + \psi_{t,g} + \varepsilon_{i,t,z,g}$, where $y_{i,t,z,g}$ is the loan interest rate for borrower i in zip code z and quarter t in dataset g. The indicator $\mathbb{1}[t - L_z = r]$ marks quarters relative to a regulatory challenge in z. Borrower controls $X_{i,t,g}$ interact with time-dataset fixed effects $\psi_{t,g}$, while $\gamma_{z,g}$ provides zip code-dataset fixed effects. Panel (a) shows results for all personal loans (both nonbank and bank), controlling for loan size and terms. Panel (b) shows results for nonbank loans only.
Source: Credit bureau data.

Panel (a): Personal loan interest rates (nonbanks and banks)



Panel (b): Personal loan interest rates (nonbanks only)

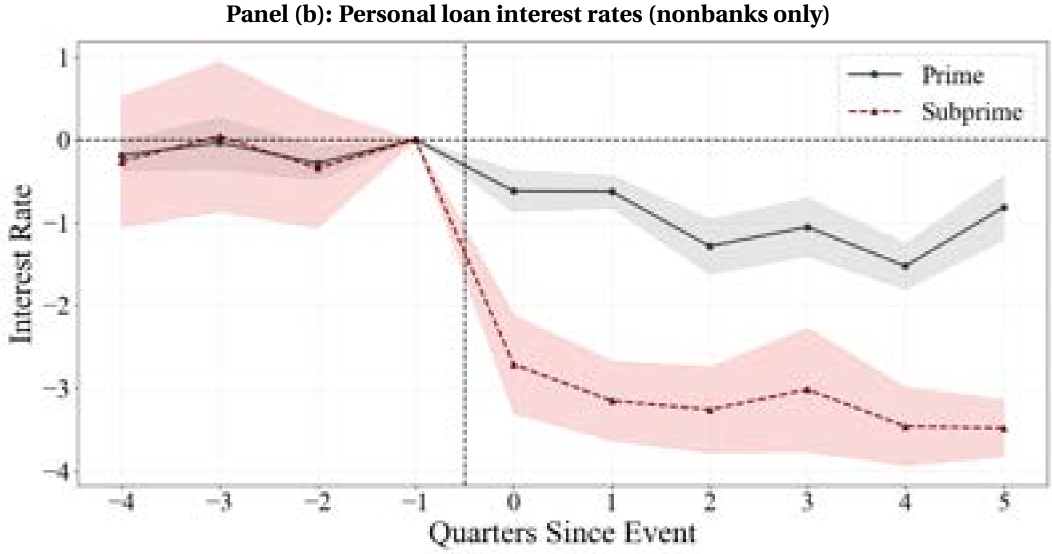


Figure 3: Risk-adjusted nonbank interest rates around regulatory changes

This figure presents results from the following regression: $y_{i,t,z,g} = \alpha + \sum_{r=-4}^{5} \beta_r \mathbb{1}[t - L_z = r] + \theta X_{i,t,g} + \phi \gamma_{z,g} + \psi_{t,g} + \varepsilon_{i,t,z,g}$, where $y_{i,t,z,g}$ is the loan interest rate for borrower i in zip code z and quarter t in dataset g. The indicator $\mathbb{1}[t - L_z = r]$ marks quarters relative to a regulatory challenge in z. Borrower controls $X_{i,t,g}$ interact with time-dataset fixed effects $\psi_{t,g}$, while $\gamma_{z,g}$ provides zip code-dataset fixed effects. Notably, I control for observable measures of borrower risk - including credit score, income, debt-to-income ratio, and credit card utilization - in this regression.*Source:* Credit bureau data.

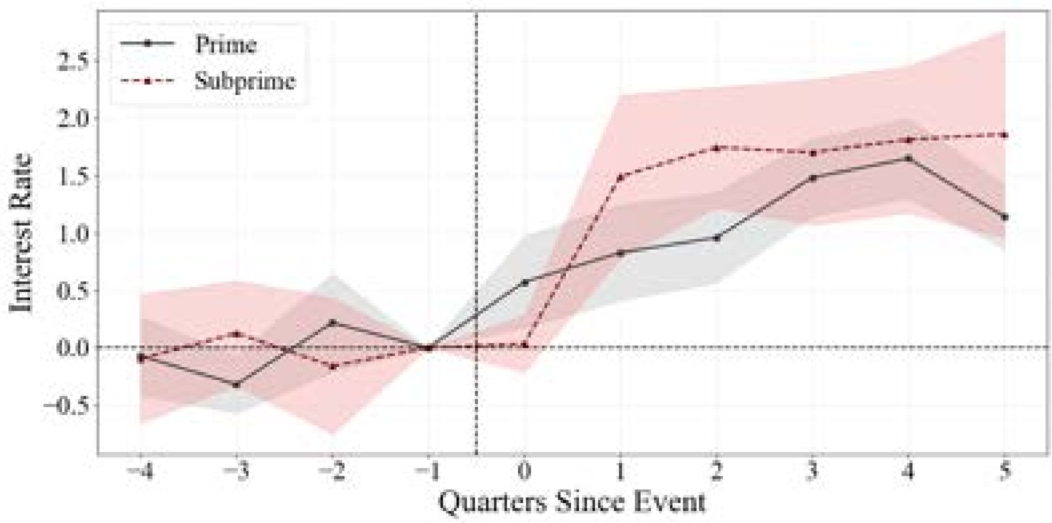
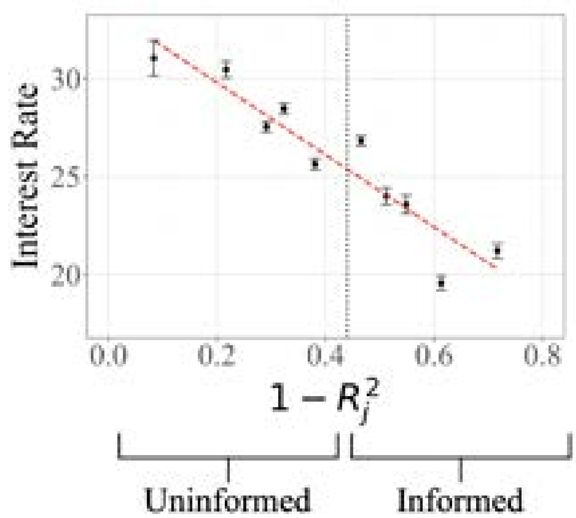


Figure 4: Lender-level interest rates and delinquency rates by use of credit scores

This figure presents binned scatterplots of lender-level interest rates and delinquency rates plotted against lender-level R_j^2 from the following regression: $r_i^j = \alpha^j + \beta_1^j \text{CreditScore}_i + \eta X_i + \gamma_{st}^j + \varepsilon_i^j$, where, r_i^j is the interest rate charged on loan i by lender j; CreditScore_i is the credit score of borrower i at the time the loan was originated; X_i is a vector of control variables, including borrower characteristics (e.g., income, debt-to-income ratio) and loan characteristics (e.g., loan amount, loan term); and γ_{st}^j represents state-year-quarter fixed effects, controlling for time and location-specific factors that could influence interest rates. R_j^2 measures the proportion of variation in interest rates explained by credit scores and serves as a proxy for a lender's use of information. In panel (a), average lender interest rates—adjusted for borrower credit scores and loan size—are plotted against R_j^2. In panel (b), average lender 60-day delinquency rates—also adjusted for borrower credit scores and loan size—are plotted against R_j^2. The 60-day delinquency rate is defined as the percentage of loans originated by a lender that become 60 days delinquent or worse at least once during their lifecycle. These statistics are calculated at the lender-year level, with each observation in year t including all loans originated by the lender in that year. Each dot on the scatter plot represents 16 observations, and error bars show the 95% confidence interval. *Source:* Credit bureau and credit monitoring website.

Panel (a): Interest rates



Panel (b): Delinquency rates

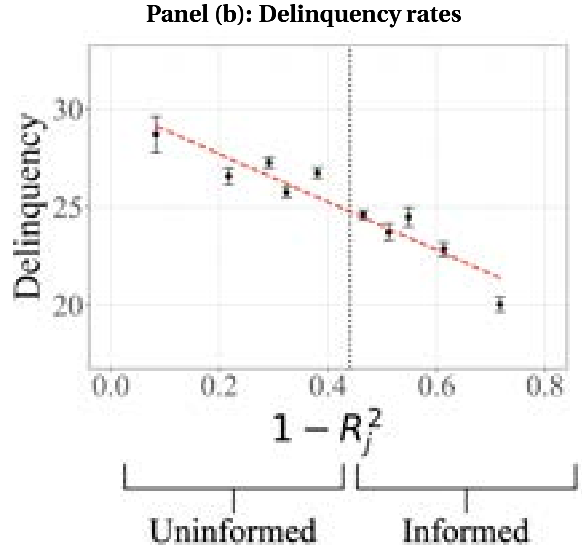
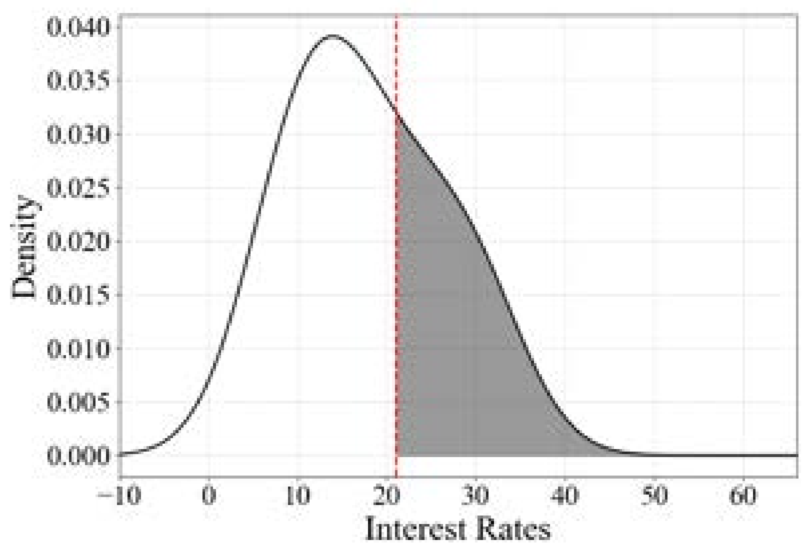


Figure 5: Densities of interest rates for informed lenders and uninformed lenders

This table shows density plots of interest rates for informed lenders and uninformed lenders. I plot interest rates for loans originated from 2013-2015, which corresponds to the pre-period in my empirical setting. The dashed black line is at 21%, the average interest rate limit implemented in the state events that I study. The shaded red area indicates the densities of interest rates that would violate state interest rate limits post-enforcement. Panel (a) plots interest rates for informed lenders and panel (b) plots interest rates for uninformed lenders

Panel (a): Informed lender interest rates



Panel (b): Uninformed lender interest rates

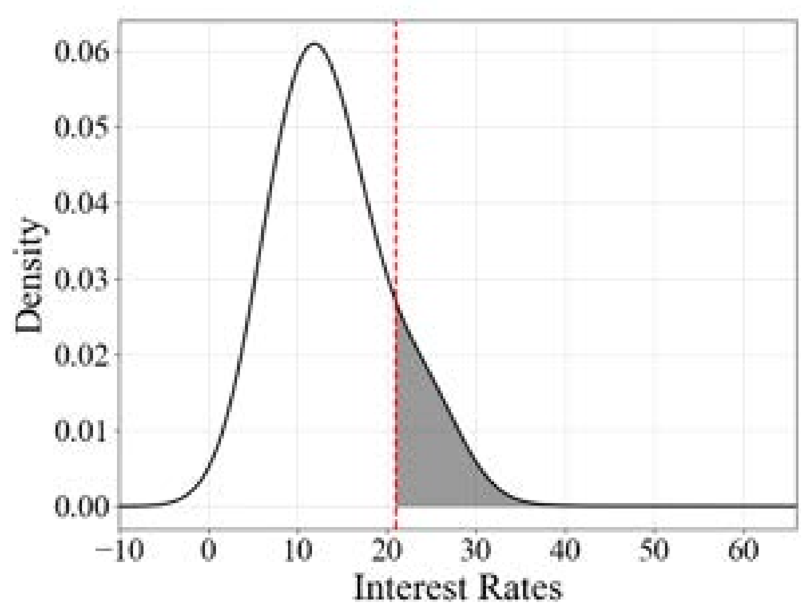


Figure 6: Lender-level probability of enforcement action rates by use of credit scores

This figure shows a binned scatterplot of the lender-level probability of enforcement action in a year plotted against lender-level R_j^2 from the following regression: $r_i^j = \alpha^j + \beta_1^j \text{CreditScore}_i + \eta X_i + \gamma_{st}^j + \varepsilon_i^j$, where r_i^j is the interest rate charged on loan i by lender j; CreditScore_i is the credit score of borrower i at the time the loan was originated; X_i is a vector of control variables, such as borrower characteristics (e.g., income, debt-to-income ratio) and loan characteristics (e.g., loan amount, loan term); and γ_{st}^j is a set of state-year-quarter fixed effects, controlling for time and location-specific factors that could influence interest rates. R_j^2 measures the amount of variation in interest rates that can be explained by credit scores and serves as a proxy for a lender's use of information. I plot the probability of enforcement action in a given year against R_j^2. These statistics are calculated at the lender-year level. Each dot on the scatter plot represents 16 observations, and error bars show the 95% confidence interval. *Source:* Credit bureau and credit monitoring website.

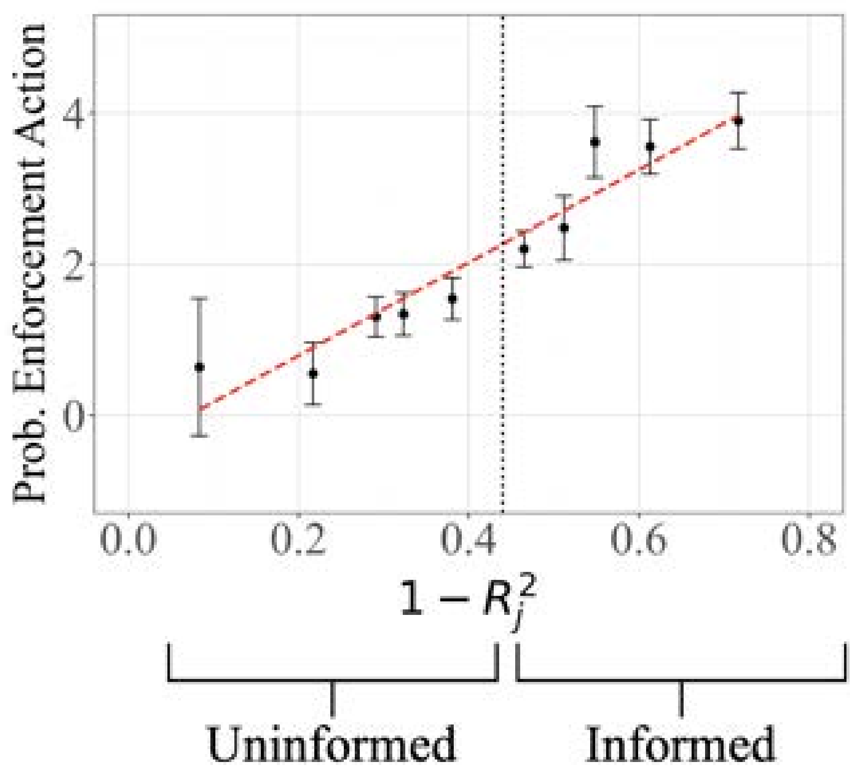


Figure 7: Financial inclusion: Percent of adult population with a credit score

This figure shows results from the following regression: $y_{z,t,g} = \alpha + \sum_{r=-4}^{5} \beta_r \mathbb{1}[t - L_z = r] + \gamma_{z,g} + \psi_{t,g} + \varepsilon_{z,t,g}$, where z represents zip code z in year t, and g denotes the specific stacked dataset. L_z is the quarter in which a state regulatory challenge occurred for zip code z. $y_{z,t,g}$ is the percent of the population 18 years or older in a zip code that has a credit score. I calculate this percentage by merging the credit bureau with data on zip code populations. Relative quarters around challenges are denoted by $\mathbb{1}[t - L_z = r]$, which is an indicator that takes the value of 1 if zip code z experienced a challenge r quarters from t. $\boldsymbol{\psi_{z,g}}$ are zip code-dataset fixed effects, and $\boldsymbol{\gamma_{t,g}}$ are calendar time-dataset fixed effects. Standard errors are clustered at the state level. Standard errors are clustered at the state level. *Source:* Credit bureau data and U.S. Census Bureau.

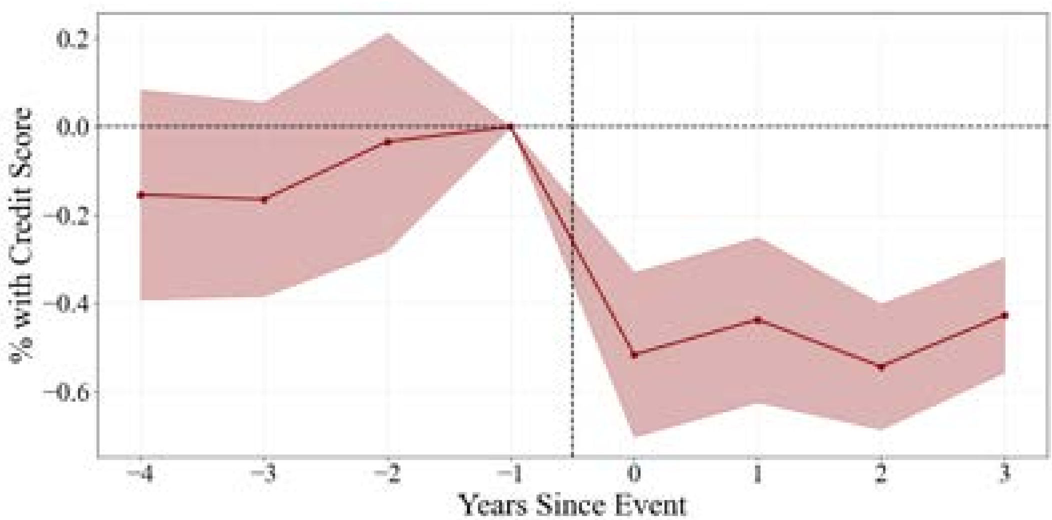
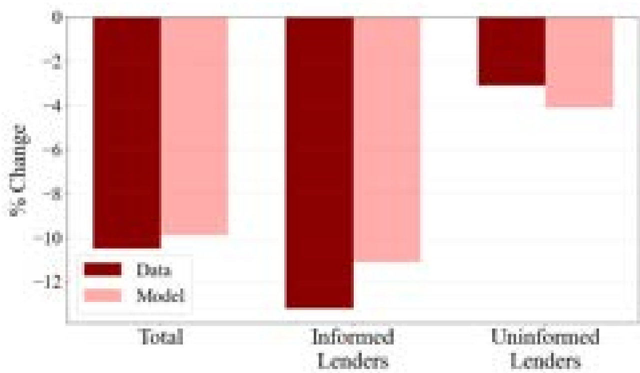


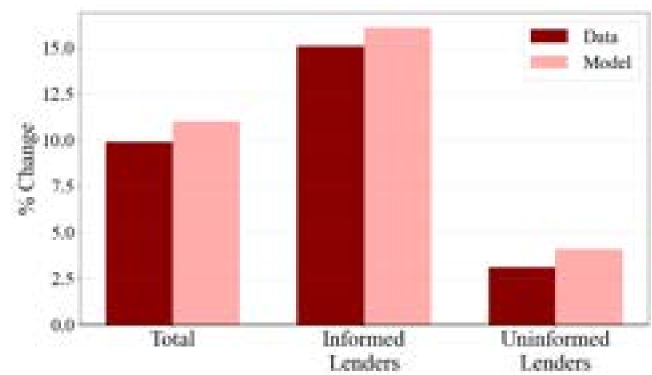
Figure 8: Model fit - Empirical versus model changes around regulatory challenges

This figure shows actual versus model predicted changes in prices, bunching around interest rate limits, and changes in quantity following state regulatory changes. Light red bars represent empirical changes in the data, while dark red bars represent predicted changes from the model. Panel (a) shows the % of loans rationed due to interest rate limits, panel (b) shows the amount of bunching at state interest rate limits, and panel (c) shows changes in price and default by borrower type. High risk borrowers have have above median default costs within their credit score while low risk borrowers have below median default costs within their credit score. Empirical changes are estimated from a bunching estimator in panels (a) and (b) and difference-in-difference estimates in panel (c). *Source:* Credit bureau data and credit website data.

Panel (a): Change in quantity from rationing



Panel (b): Bunching at interest rate limit



Panel (c): Change in price and quantity by borrower type

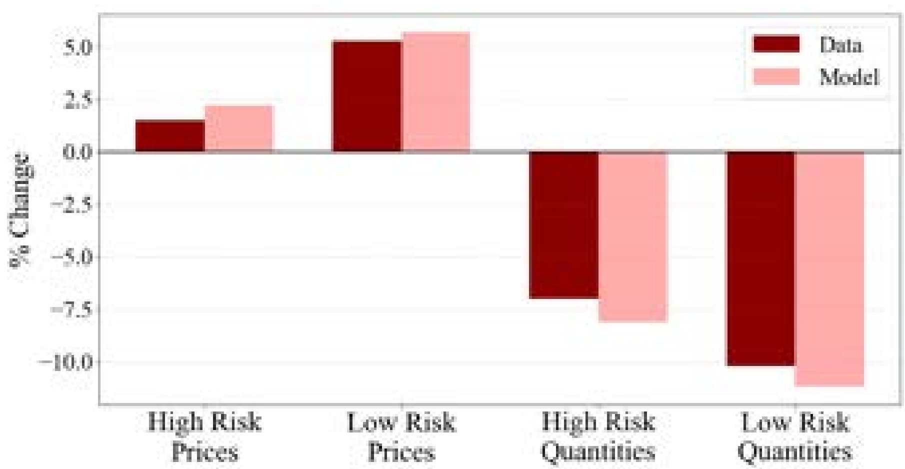


Figure 9: Changes in outcomes following interest rate limits and increased oversight

This figure shows changes in aggregate and lender-specific outcomes under the observed regulatory changes in my setting, which include the enforcement of interest rate limits and increased regulatory costs. Changes are calculated as percentage shifts from the status quo (no interest rate limits and no regulatory fixed costs). Panel (a) presents changes in quantities, Panel (b) shows changes in profits, Panel (c) displays changes in prices, and Panel (d) illustrates changes in default rates. The lightest bars represent changes for uninformed lenders, the medium bars represent changes for informed lenders, and the darkest bars represent market-level changes. *Source:* Credit bureau and credit website data.

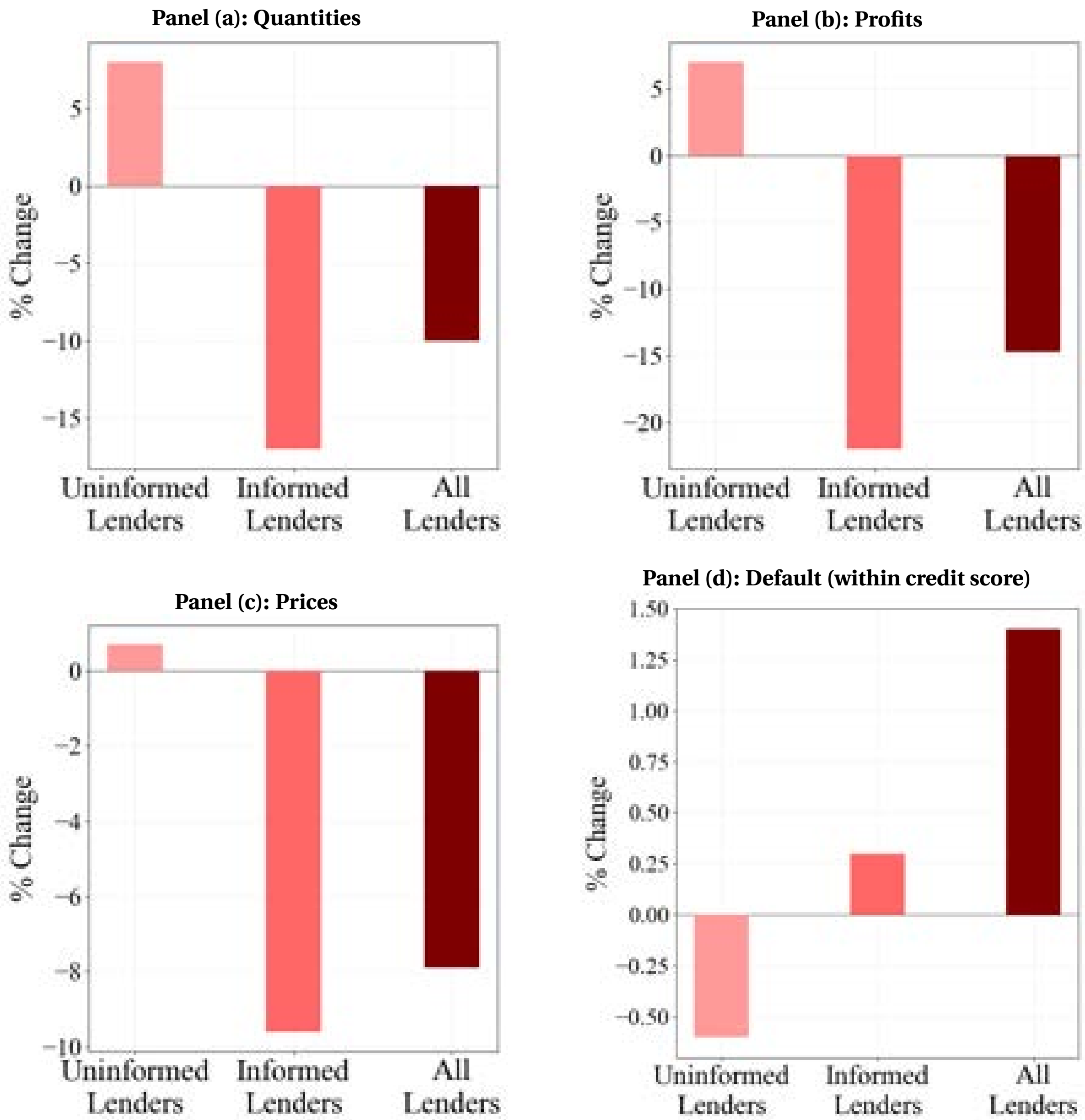


Figure 10: Decomposition - Quantities

This figure decomposes the effects of lender exits, changing lender composition (informed lenders exiting), and interest rate limits on total quantity. Changes are computed from the status quo of no interest rate limits or regulatory fixed costs. The lightest bars illustrate how lender exits impact prices. To calculate this, I use my model to simulate a scenario where 21% of lenders exit the market, while holding the proportion of informed and uninformed lenders constant. The medium bars represent the effect of changing lender composition. To compute this, I hold the total number of lenders fixed but reduce the proportion of informed lenders by 31%. The darkest bars depict the impact of interest rate limits. For this calculation, I hold both the number and composition of lenders constant but enforce interest rate limits. Panel (a) shows results for prime borrowers with low unobserved default costs. Panel (b) presents results for prime borrowers with high unobserved default costs. Panel (c) displays results for subprime borrowers with low unobserved default costs, while Panel (d) shows results for subprime borrowers with high unobserved default costs.

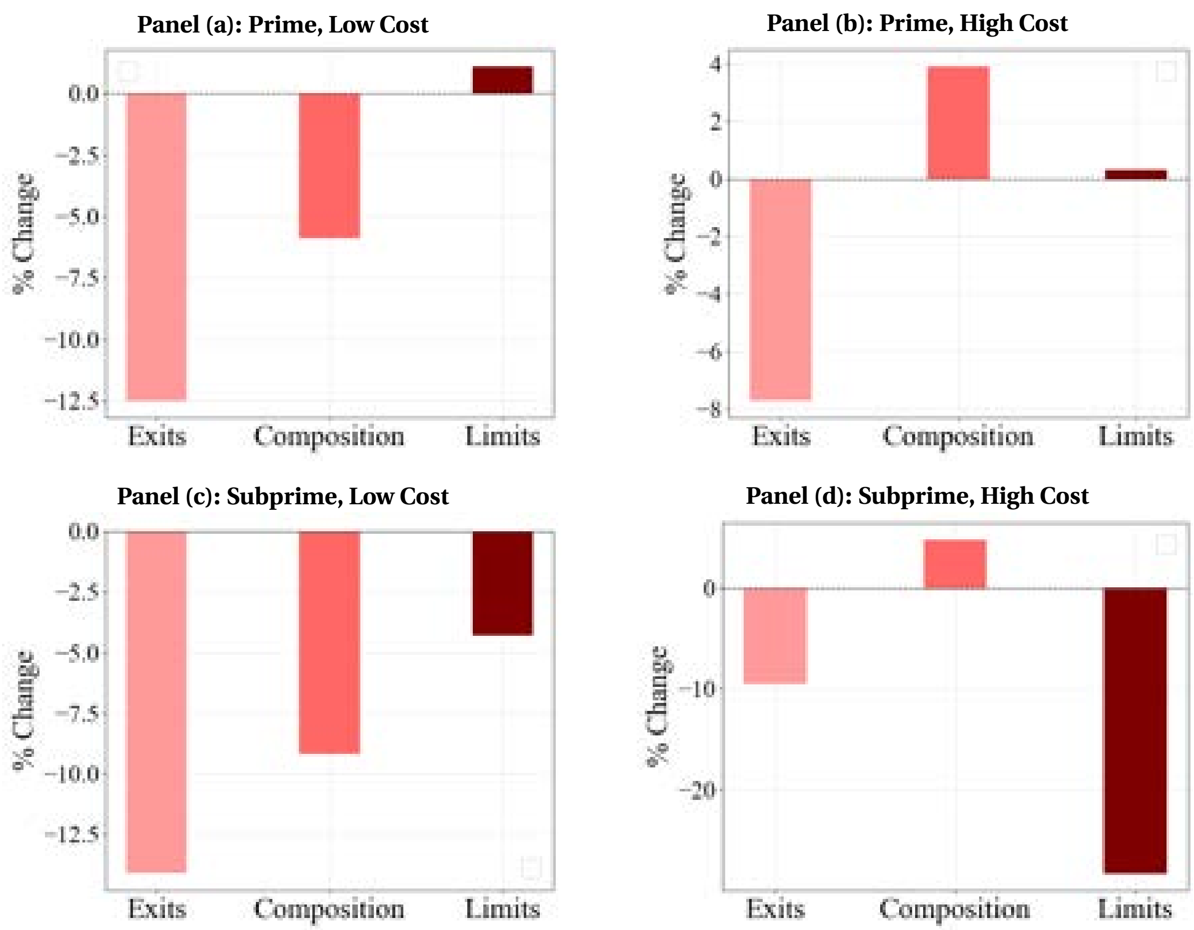
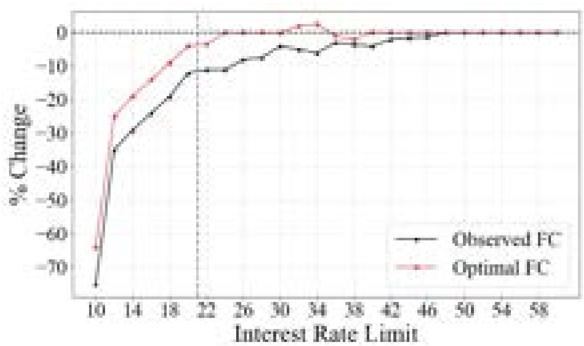


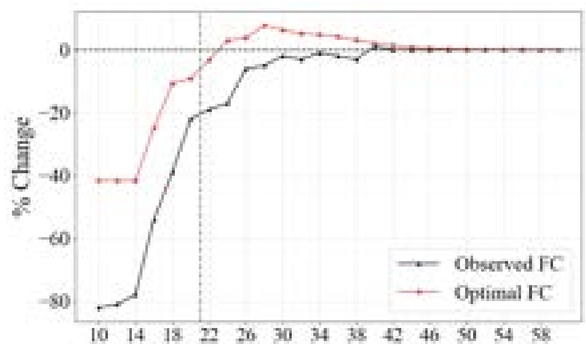
Figure 11: Counterfactuals: Interest rate limits and fixed costs

This figure illustrates changes in quantity, prices, and consumer surplus under varying levels of interest rate limits and fixed costs. All changes are shown relative to the baseline scenario, which assumes no interest rate limits and no fixed costs. Panels (a), (c), and (e) present the results for the entire population of borrowers, while panels (b), (d), and (f) focus on subprime borrowers specifically. The solid black line represents outcomes under the observed fixed costs, while the dashed red line shows the effects of optimal fixed costs, where I calculate outcomes under the level of fixed costs that result in the greatest quantity of credit for each limit. A vertical dashed line at 21% marks the observed interest rate limit in this setting. *Source:* Credit bureau and credit website data.

Panel (a): Change in Quantity - All Borrowers



Panel (b): Change in Quantity - All Subprime



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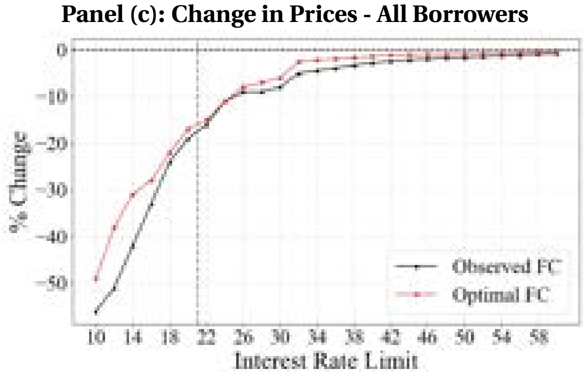
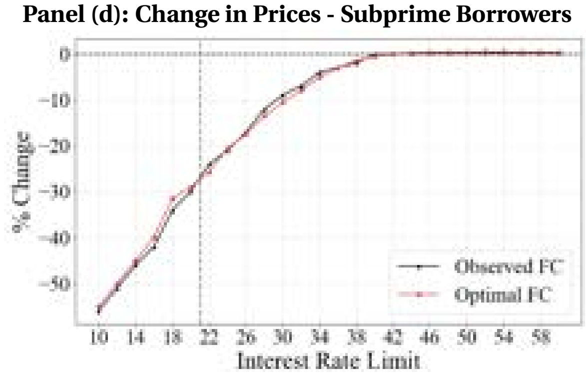
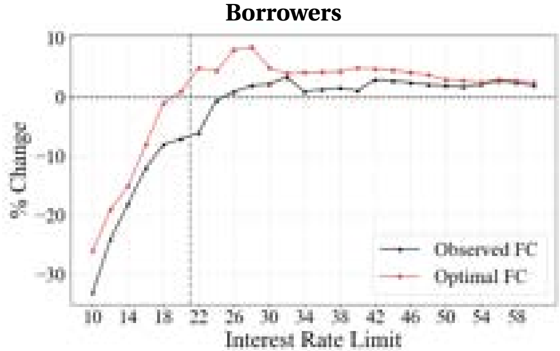
Panel (c): Change in Prices - All Borrowers



Panel (d): Change in Prices - Subprime Borrowers



Panel (e): Change in Consumer Surplus - All Borrowers



Panel (f): Change in Consumer Surplus - Subprime Borrowers

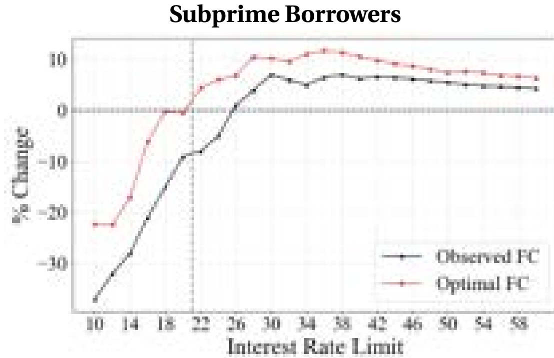


Figure 12: Counterfactual: Regulating algorithms and technology

This figure shows changes in quantities, prices, and consumer surplus under two counterfactual policies that restrict the use of advanced screening technologies: (1) a ban on using borrower demand elasticity information and (2) a ban on all borrower-specific information (i.e., all lenders behave as uninformed). Borrowers are divided into four groups: prime-low, prime-high, subprime-low, and subprime-high unobserved default cost. Dark bars represent outcomes after banning demand elasticity technologies, while light bars show outcomes after banning all borrower-specific technologies. Changes are calculated as percentage deviations from the status quo. Panel (a) shows changes in quantities, Panel (b) in loan prices, and Panel (c) in consumer surplus. *Source:* Credit bureau and credit website data.

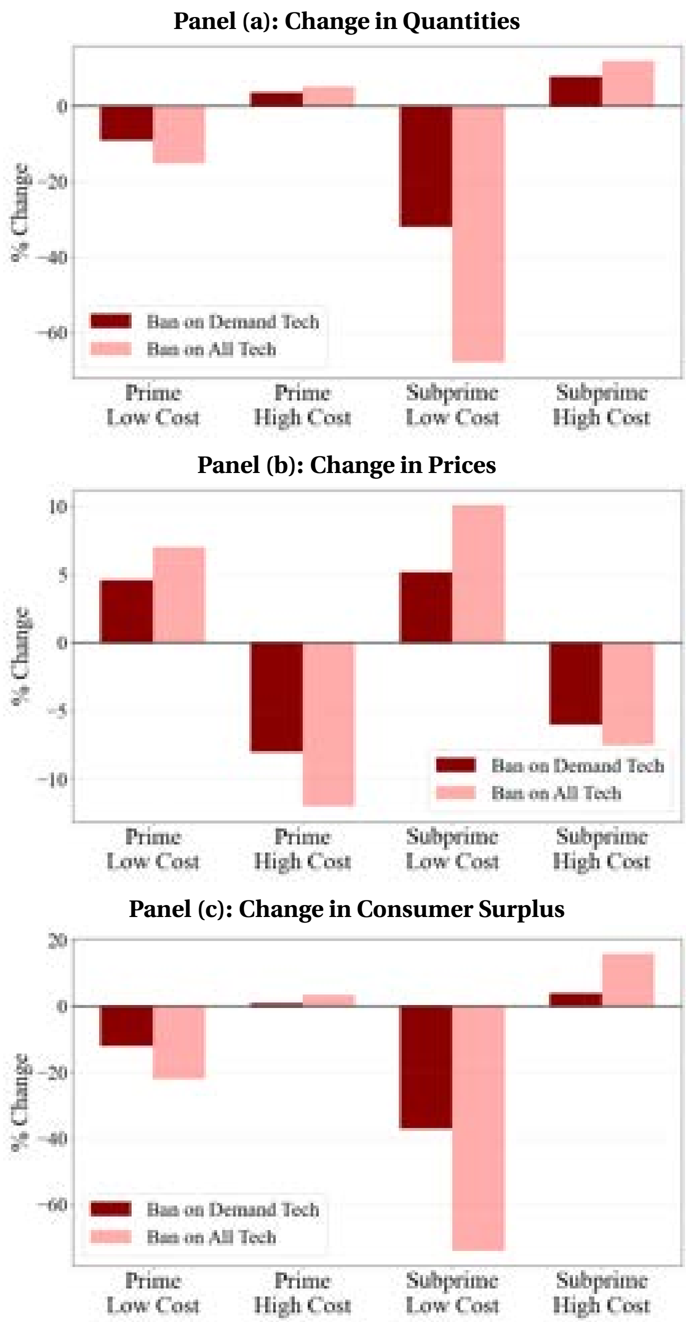


Table 1: Summary Statistics

This table presents summary statistics for the main datasets used in the analysis, which consist of nonbank unsecured personal loans originated between 2013 and 2018. Columns (1) and (2) provide loan-level summary statistics from the credit bureau dataset, while columns (3) and (4) present statistics from the credit monitoring website. The table reports means, with standard deviations in parentheses. *Source:* Data from the credit bureau and credit monitoring website.

	Credit Bureau		**Credit Monitoring Website**	
	(1)	**(2)**	**(3)**	**(4)**
	Subprime	**Prime**	**Subprime**	**Prime**
APR	27	20	26	19
	(8)	(9)	(9)	(14)
Loan Amount	4,926	6,787	5,110	7,040
	(3,468)	(4,500)	(4,393)	(4,952)
Terms (Months)	33	37	34	39
	(15)	(13)	(15)	(13)
Credit Score	561	664	549	659
	(39)	(46)	(41)	(42)
Income	30,321	37,878	-	-
	(10,294)	(13,093)	-	-
Length of Credit History (Months)	149	181	-	-
	(86)	(96)	-	-
Number of Observations	604,206	1,097,044	335,815	529,442

Table 2: Lender-level Regulatory Costs and Compliance around Regulatory Changes

This table presents the results from the following regression: $y_{j,s,t,g} = \alpha + \beta\,\text{Post}1[t - L_s \leq 0] + \theta X_{j,t,g} + \gamma_{t,g} + \xi_{j,g} + \eta_{s,g} + \varepsilon_{j,s,t,g}$, where observations are at the lender-state-quarter level. This regression is the static version of Equation 1, with Post1$[t - L_s \leq 0]$ indicating whether state s enacted a regulatory challenge prior to or during quarter t. L_s is the quarter when state s enacted the challenge. As in Equation 1, a stacked regression estimator is used, where g identifies the dataset. All regressions include state, lender, and quarter fixed effects, as well as a fixed effect indicating whether a lender originates loans through a bank-partner model. Dependent variables in columns (1) and (2) are indicators for whether lender j originates loans over the interest rate cap in state s during quarter t. Dependent variables in columns (3) and (4) are indicators for whether lender j is licensed in state s during quarter t. Dependent variables in columns (5) and (6) are indicators for whether lender j is subject to an enforcement action in state s during quarter t. Lenders are classified as "informed" if they have above-median measures of unexplained variance in interest rates, and "uninformed" if they have below-median measures. Standard errors are clustered at the state level. *Sources:* Credit website, state regulatory agency websites, National Multistate Licensing System.

	Loans Above State Cap		**Licensed Lender in State**		**Prob(Enforce. Action)**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	Informed	**Uninformed**	**Informed**	**Uninformed**	**Informed**	**Uninformed**
Post * Treated	-0.187***	-0.086**	0.074**	-0.016	0.017***	-0.002
	(0.0001)	(0.0002)	(0.0001)	(0.049)	(0.005)	(0.007)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Y-Variable Mean	0.452	0.232	0.084	0.108	0.003	0.002
Observations	11,969	10,792	10,287	10,792	11,870	10,928
Adjusted R-squared	0.3751	0.2026	0.026	0.002	0.066	0.008

*Clustered (State) standard errors in parentheses, Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3: Lender Entry/Exit Around State Challenges

This table shows results from the regression: $y_{s,t,g} = \alpha + \beta Post1[t - L_s \leq 0] + \gamma_{t,g} + \eta_{s,g} + \varepsilon_{s,t,g}$, where observations are at the lender-state-year level. This regression is a version of Equation 1, where $Post1[t - L_s \leq 0]$ is an indicator for whether state s enacted a regulatory challenge prior to or during quarter t. L_s is the year in which state s enacted the challenge. As in Equation 1, I implement a stacked regression estimator, where g identifies the dataset. All regressions include state and year fixed effects, as well as a control for the number of lenders that originate loans through bank partnerships. The dependent variable is the number of nonbank lenders operating in state s during quarter t. Column (1) shows results for all lenders, column (2) shows results for uninformed lenders, and column (3) shows results for informed lenders. Lenders are classified as informed or uninformed based on whether they are above or below the median in terms of unexplained variation in interest rates. Standard errors are clustered at the state level. *Source:* Credit website.

	All Lenders	**Uninformed Lenders**	**Informed Lenders**
	(1)	**(2)**	**(3)**
	Number Operating	**Number Operating**	**Number Operating**
Treated×Post	-2.7***	-0.75	-2.1***
	(0.41)	(1.3)	(0.56)
County FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Online and Bank Partner Controls	Yes	Yes	Yes
Mean of Y-Variable	13.1	6.5	6.6
Observations	67,656	67,656	67,656
Adjusted R-squared	0.76	0.70	0.75

Note: Standard errors clustered at the state level are in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Demand Estimates

This table presents estimated demand parameters. Consumer preferences are given by the equation $\alpha_i = \bar{\alpha} + \Pi(D_{imt}) + \Sigma\nu_i$ where $\bar{\alpha}$ is the mean price sensitivity, Π represents the mapping between demographic characteristics, and Σ scales random shocks. α_i is the borrower's price sensitivity, reflecting the decline in utility from a 1% increase in interest rate. Panel (a) shows the average estimate, while Panel (b) shows how sensitivity varies with borrower credit score and unobserved default risk. *Log(CreditScore)* represents the log of credit scores, and *High unobserved cost* indicates borrowers above the median unobserved default cost. Standard errors are bootstrapped. *Source:* Credit bureau data and credit website data.

Panel (a): Mean Preference Parameters

Parameter	Estimate
$\bar{\alpha}$	1.46
	(0.097)
σ^2_α	0.212
	(0.014)

Panel (b): Demographic-Preference Relationships

	α_i
Log(CreditScore)	0.162
	(0.097)
High unobserved cost	-0.071
	(0.009)

Table 5: Supply Parameters

This table presents estimated supply parameters. Panel (a) shows means and variances of empirical default distributions by borrower credit score bucket b, estimated from payment history data, where $\delta_i = 1 - \frac{CashPaidBack_i}{CashLent_i}$. Standard errors are bootstrapped. Panel (b) presents average default costs for uninformed and informed lenders: Column (1) reports expected default costs $E[\delta_i^j|cs_i]$, Column (2) shows realized lender default costs δ_i^j, and Column (3) shows the difference. Standard errors are in parentheses. Panel (c) provides estimates of lender-specific marginal costs (mc_{jm}), reflecting origination and funding costs. Standard errors are bootstrapped. *Source:* Credit bureau data and credit website data.

Panel (a): Borrower Default Cost Distributions

	(1)	**(2)**
	$\mu_{mc,b}$	$\sigma^2_{mc,b}$
b_5 = Excellent: 781 to 850	0.033	0.029
	(0.001)	(0.002)
b_4 = Good: 661 to 780	0.071	0.034
	(0.0001)	(0.0002)
b_3 = Fair: 601 to 660	0.093	0.047
	(0.0003)	(0.001)
b_2 = Poor: 500 to 600	0.143	0.075
	(0.0002)	(0.0004)
b_1 = Very Poor: 300 to 499	0.397	0.167
	(0.001)	(0.004)
b_0 = Thin File: $\leq$1 year or $\leq$3 accounts	0.161	0.197
	(0.011)	(0.015)

Panel (b): Lender Default Costs

	(1)	**(2)**	**(3)**
	$E[\delta_i^j\|cs_i]$	δ_i^j	$E[\delta_i^j\|cs_i] - \delta_i^j$
Uninformed Lenders (Prime)	6.93	6.95	-0.02
	(0.05)	(0.12)	(0.13)
Uninformed Lenders (Subprime)	13.1	13.5	-0.4***
	(0.04)	(0.11)	(0.13)
Informed Lenders (Prime)	7.16	6.95	0.21**
	(0.03)	(0.09)	(0.10)
Informed Lenders (Subprime)	13.4	12.9	0.5***
	(0.03)	(0.12)	(0.11)

Panel (c): Lender Marginal Costs (mc_{jm})

	Uninformed Lenders	**Informed Lenders**
mc_{jm}	0.882	0.847
	(0.03)	(0.02)

Table 6: Fixed Cost Parameters

This table shows the estimated fixed cost parameters, including the mean and variance of informed lender fixed costs, as well as the number of potential entrants. The mean and variance are calculated using a maximum likelihood estimation procedure described in Section 5. *Source:* Credit bureau data and credit website data.

	Value
μ	152,124
	(3,452)
σ^2	54,725
	(959)
N	104

Table 7: Changes in Profits and Fixed Costs Following Regulatory Changes

Panel (a) shows percent changes in profits after enforcing interest rate limits, based on demand and supply estimates. Standard errors are bootstrapped. Panel (b) estimates the fixed cost distribution post-oversight using profits and lender exits (Table 3). Standard errors are bootstrapped. *Source:* Credit bureau and credit website data.

Panel (a): Changes in Profit

	% Change in Profit
All lenders	-7.2%
	(0.14%)
Uninformed lenders	-4.1%
	(0.23%)
Informed lenders	-15.2%
	(0.01%)

Panel (b): Post-Oversight Fixed Cost Distribution

μ	σ^2
224,320	78,412
(9,834)	(3,451)

Figure A1: Histogram of lender-level R-squared from regressions of interest rates on credit scores

This figure shows a histogram of one minus the lender-level R_j^2 values, calculated as $1-R_j^2$ from the following regression: $r_i^j = \alpha^j + \beta_0^j \,\text{CreditScore}_i + \beta_1^j \,\text{CreditScore}_i^2 + \beta_2^j \,\text{CreditScore}_i^3 + \eta^j X_i + \gamma_{st}^j + \varepsilon_i^j$, where r_i^j represents the interest rates on loans originated by lender j, and CreditScore_i is the credit score of borrower i at the time of loan origination. The regression includes third-order terms of credit score and other observable variables to capture non-linear relationships between credit bureau data and interest rates. A substantial portion of the variation in interest rates is driven by nationwide macroeconomic factors, which are not attributed to lenders' models. To account for this, state-quarter fixed effects are differenced out, and the R_j^2 values are calculated excluding these fixed effects. *Source:* Credit bureau and credit monitoring website.

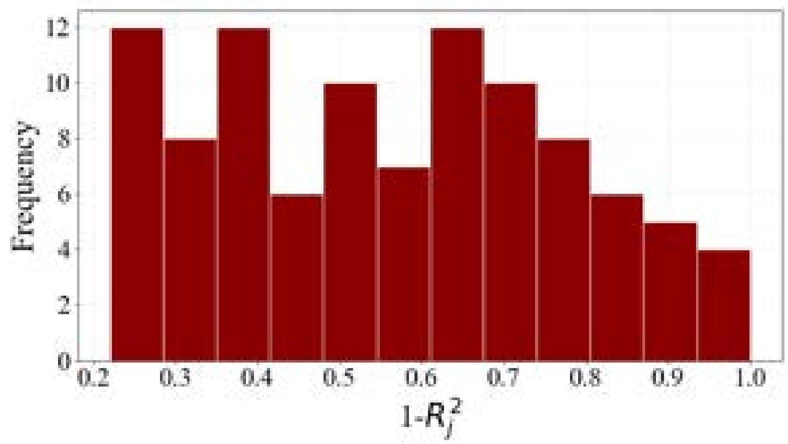


Figure A2: Lender exits around regulatory changes

I use the model to decompose the effects of interest rate limits versus regulatory oversight on borrower outcomes. The model shows that the decline in credit access is primarily driven by interest rate limits rather than regulatory oversight. I decompose changes in prices and quantities by both public (credit score) and private (unobserved default cost) risk types, finding that low-private-risk borrowers experience reduced credit availability across all credit scores. The exit of informed lenders leads to higher prices and diminished access for these borrowers.

I then analyze counterfactual regulatory policies. Increasing the interest rate limit from 21% to 28% and decreasing fixed costs by 43% would lead to increased credit access and lower prices. Finally, I investigate the effects of regulation that bans the use of advanced technology. Banning advanced screening technologies would require lenders to charge a pooled price within each credit score. This regulation would benefit high-risk borrowers, who would receive lower rates by being pooled with low-risk borrowers, but would reduce access and raise prices for low-risk borrowers who previously received lower interest rates due to technologies correctly identifying them as low risk. Declines in outcomes are greater for racial minorities, such as Black, Hispanic, and Latino individuals.

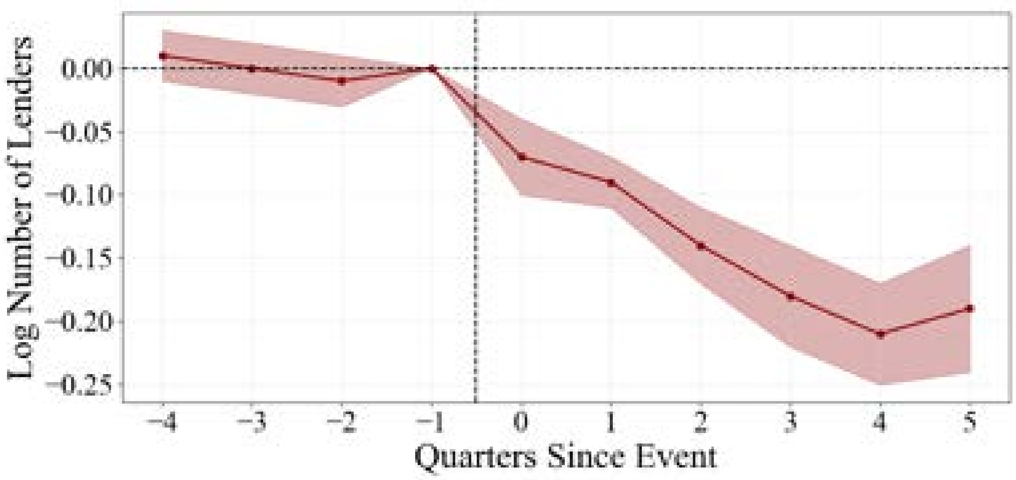


Figure A3: Characteristics of borrowers obtaining loans from informed versus uninformed lenders

This table shows densities of credit score, number of accounts in credit bureaus, and income for with loans from uninformed versus informed lenders, where I classify lenders as informed and uninformed based on the $1 - R_j^2$ measure from lender-level regressions of interest rates on credit bureau data. Panel (a) shows credit scores, panel (b) shows number of accounts in credit bureaus, and panel (c) shows income (as estimated by the credit bureau). Values are taken as of time of loan origination. *Source:* Credit bureau and credit monitoring website.

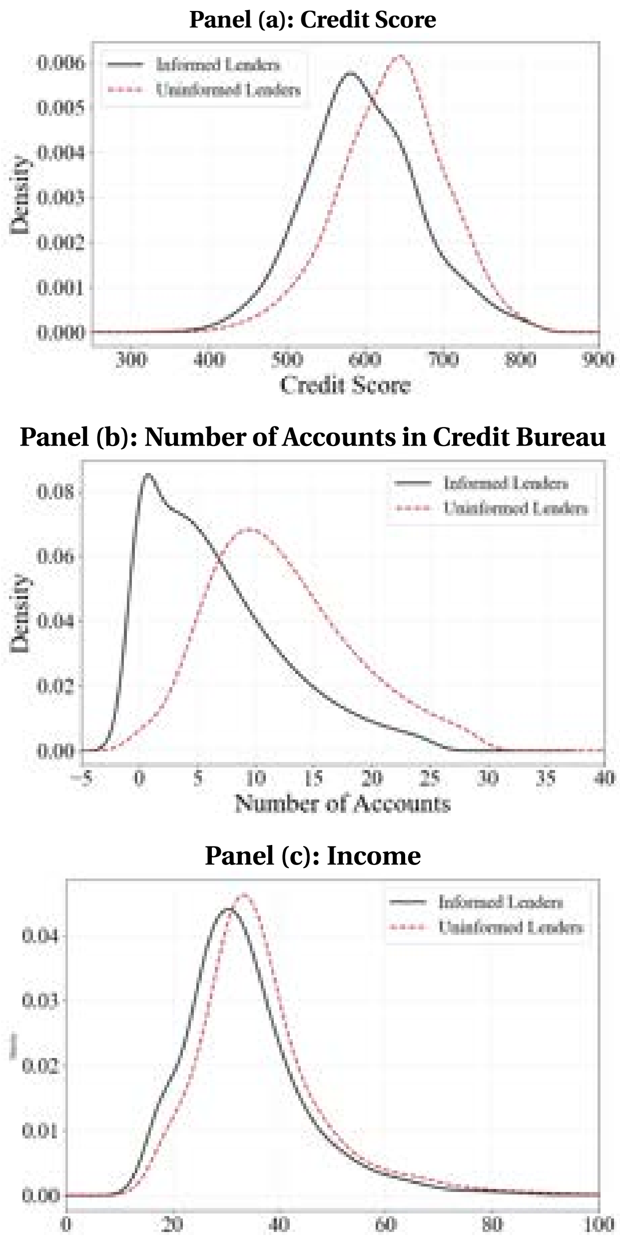
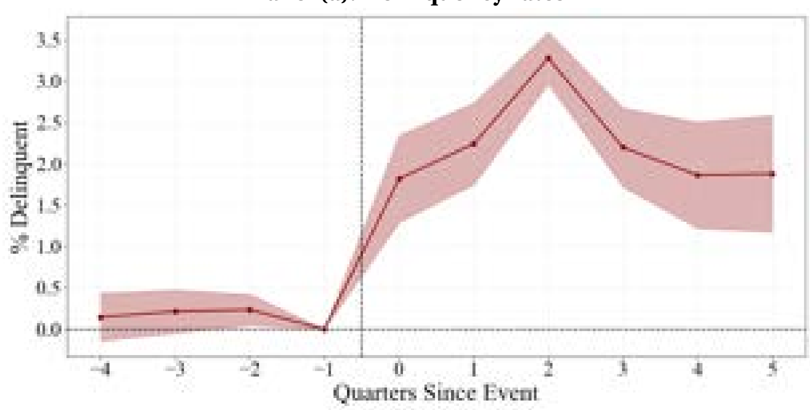


Figure A4: Nonbank loan performance around state challenges

This figure shows results from the following regression: $y_{i,t,z,g} = \alpha + \sum_{r=-4}^{5} \beta_r \mathbb{1}[t - L_z = r] + \theta X_{i,t,g} + \phi\gamma_{z,g} + \psi_{t,g} + \varepsilon_{i,t,z,g}$, where i represents borrower i, living in zip code z in quarter t. g denotes the specific stacked dataset. L_z is the quarter in which a state regulatory challenge occurred for zip code z. Relative quarters around challenges are denoted by $\mathbb{1}[t - L_z = r$, which is an indicator that takes the value of 1 if zip code z experienced a challenge r quarters from t. $X_{i,t,g}$ are a set of borrower controls for borrower i in calendar-quarter t in dataset g. Note that these controls are interacted with dataset and time fixed effects. $\psi_{z,g}$ are zip code-dataset fixed effects, and $\gamma_{t,g}$ are calendar time-dataset fixed effects. In Panel (a), $y_{i,t,z,g}$ is an indicator for whether a loan to borrower i, originated in quarter t in zip code z, enters 60 days or worse delinquency at least once over the loan's lifecycle. In Panel (b), $y_{i,t,z,g}$ is the return on the loan originated by borrower i, calculated as $\frac{\text{CashReturned}_{i,t,z,g}}{\text{CashLent}_{i,t,z,g}}$. Standard errors are clustered at the state level. *Source:* Credit bureau data.

Panel (a): Delinquency rates



Panel (b): Return on loans

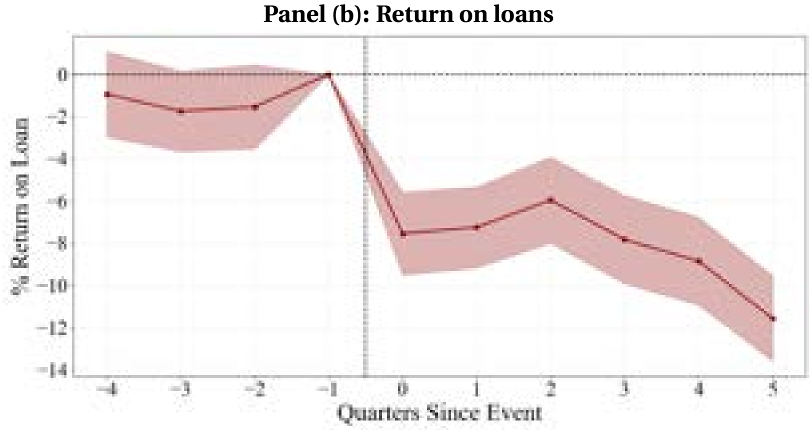
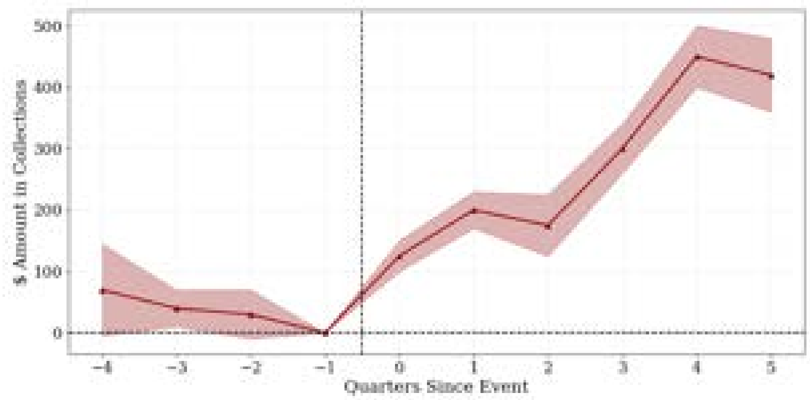


Figure A5: Financial distress around state challenges

This figure presents results from the following regression: $y_{i,t,z,g} = \alpha + \sum_{r=-4}^{5} \beta_r \mathbb{1}[t - L_z = r] + \theta X_{i,t,g} + \phi\gamma_{z,g} + \psi_{t,g} + \varepsilon_{i,t,z,g}$. In this equation, $y_{i,t,z,g}$ represents the outcome variable for borrower i living in zip code z during quarter t in dataset g. The term $\mathbb{1}[t - L_z = r]$ is an indicator function that equals 1 if zip code z experienced a regulatory challenge r quarters from t, where L_z is the quarter when the challenge occurred. $X_{i,t,g}$ are a set of borrower control variables for borrower i in calendar-quarter t in dataset g. Note that these controls are interacted with dataset and time fixed effects. $\gamma_{z,g}$ are zip code-dataset fixed effects, and $\psi_{t,g}$ are calendar time-dataset fixed effects. In Panel (a), $y_{i,t,z,g}$ is the logarithm of the total dollar amount a borrower has in collection accounts. In Panel (b), $y_{i,t,z,g}$ is the total number of derogatory accounts for borrower i. Derogatory accounts include charge-offs, foreclosures, accounts 120 days past due or worse, or bankruptcies. Standard errors are clustered at the state level. *Source:* Credit bureau data.

Panel (a): Dollars in Collection



Panel (b): Derogatory Accounts

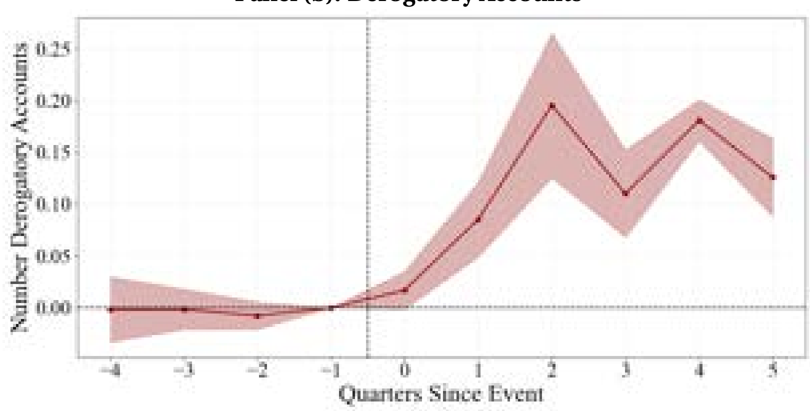
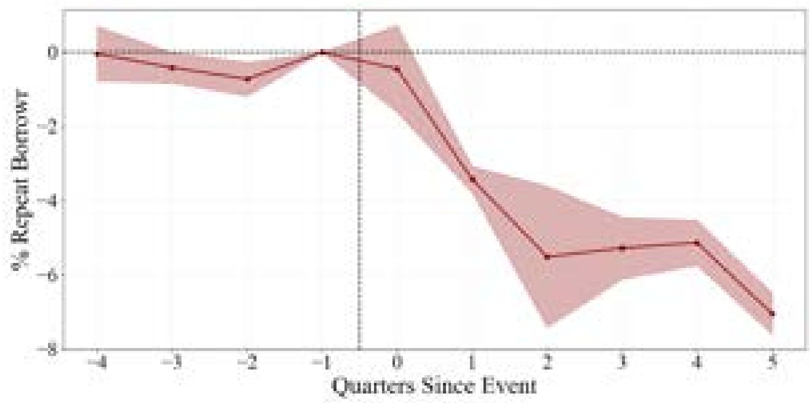


Figure A6: Debt cycles and repeat borrowing

This figure presents results from the following regression: $y_{i,t,z,g} = \alpha + \sum_{r=-4}^{5} \beta_r \, \mathbb{1}[t - L_z = r] + \theta X_{i,t,g} + \phi\gamma_{z,g} + \psi_{t,g} + \varepsilon_{i,t,z,g}$. In this equation, $y_{i,t,z,g}$ is an indicator for whether borrower i originates at least two personal loans within a six-month window, living in zip code z during quarter t in dataset g. The term $\mathbb{1}[t - L_z = r]$ is an indicator function that equals 1 if zip code z experienced a regulatory challenge r quarters from t, where L_z is the quarter when the challenge occurred. $X_{i,t,g}$ represents a set of borrower control variables for borrower i in calendar-quarter t in dataset g. These controls are interacted with dataset and time fixed effects. $\gamma_{z,g}$ are zip code-dataset fixed effects, and $\psi_{t,g}$ are calendar time-dataset fixed effects. Standard errors are clustered at the state level

Panel (a): Debt cycles



Panel (b): Number of Accounts Past Due

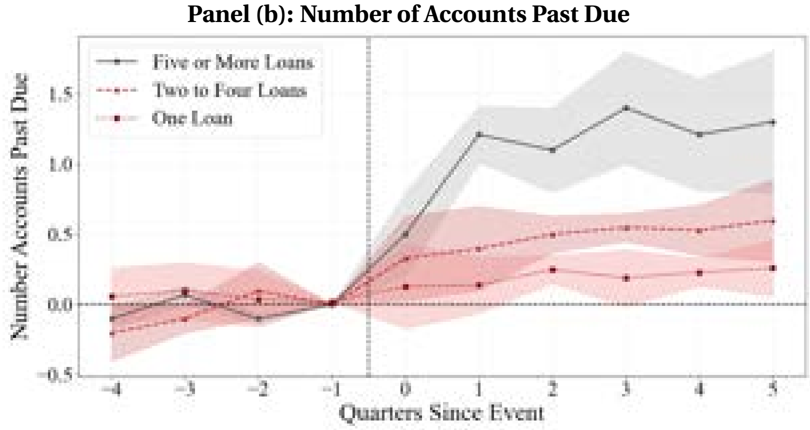


Figure A7: Explanatory value of credit bureau data around state challenges

This figure plots the R-squared from the following regressions: $InterestRate^{Q}_{i,z,t} = \alpha^{Q} + \beta^{Q}\,\text{BureauData}_{i,t} + \gamma^{Q}_{1}\,\text{Amount}_{i,t} + \gamma^{Q}_{2}\,\text{Terms}_{i,t} + \delta_{zt} + \varepsilon_{i,z,t}$, where $InterestRate^{Q}_{i,z,t}$ is the interest rate of borrower i's loan originated in zip code z during quarter t. The regression includes controls for information observable in credit bureaus, including credit score, number of credit inquiries, total debt levels, and prior delinquencies, as well as controls for loan size and terms. We also include zip code-quarter fixed effects. This regression captures the variation in interest rates that can be explained by information observable in credit bureaus. We estimate this regression in each quarter Q from a regulatory event. Treated states are states that experience a regulatory event in quarter Q, while non-treated states are states that never experience a regulatory event for the corresponding calendar quarters. Standard errors are bootstrapped. *Source:* Credit bureau and credit monitoring website.

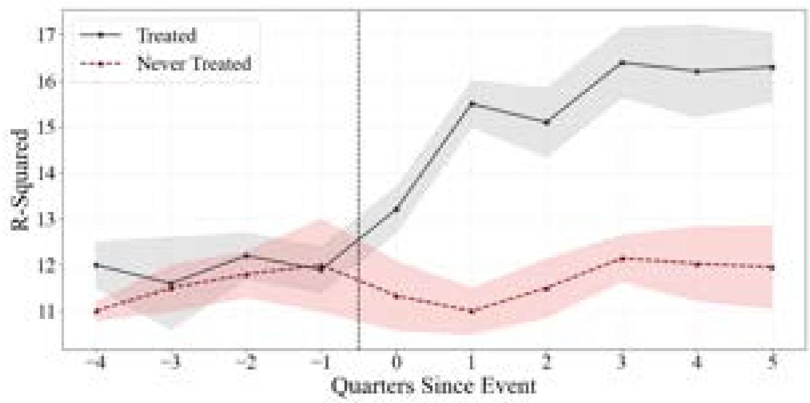


Figure A8: Contribution of fixed regulatory costs versus interest rate limits to changes in outcomes

This figure shows changes in aggregate outcomes relative to the status quo (no interest rate limits and no regulatory fixed costs) under three counterfactual scenarios: (1) increases in regulatory fixed costs only, (2) the imposition of interest rate limits only, and (3) the combination of both. Using my model, I first estimate outcomes with only fixed regulatory costs. I then impose a 21% interest rate limit and, finally, apply both regulatory fixed costs and interest rate limits together. The lightest bars represent the fixed costs scenario, the medium bars represent the interest rate limits scenario, and the darkest bars represent both combined. Panel (a) shows changes in the number of informed lenders, Panel (b) displays changes in loan quantities, Panel (c) shows changes in prices, and Panel (d) illustrates changes in consumer surplus. *Source:* Credit bureau and credit website data.

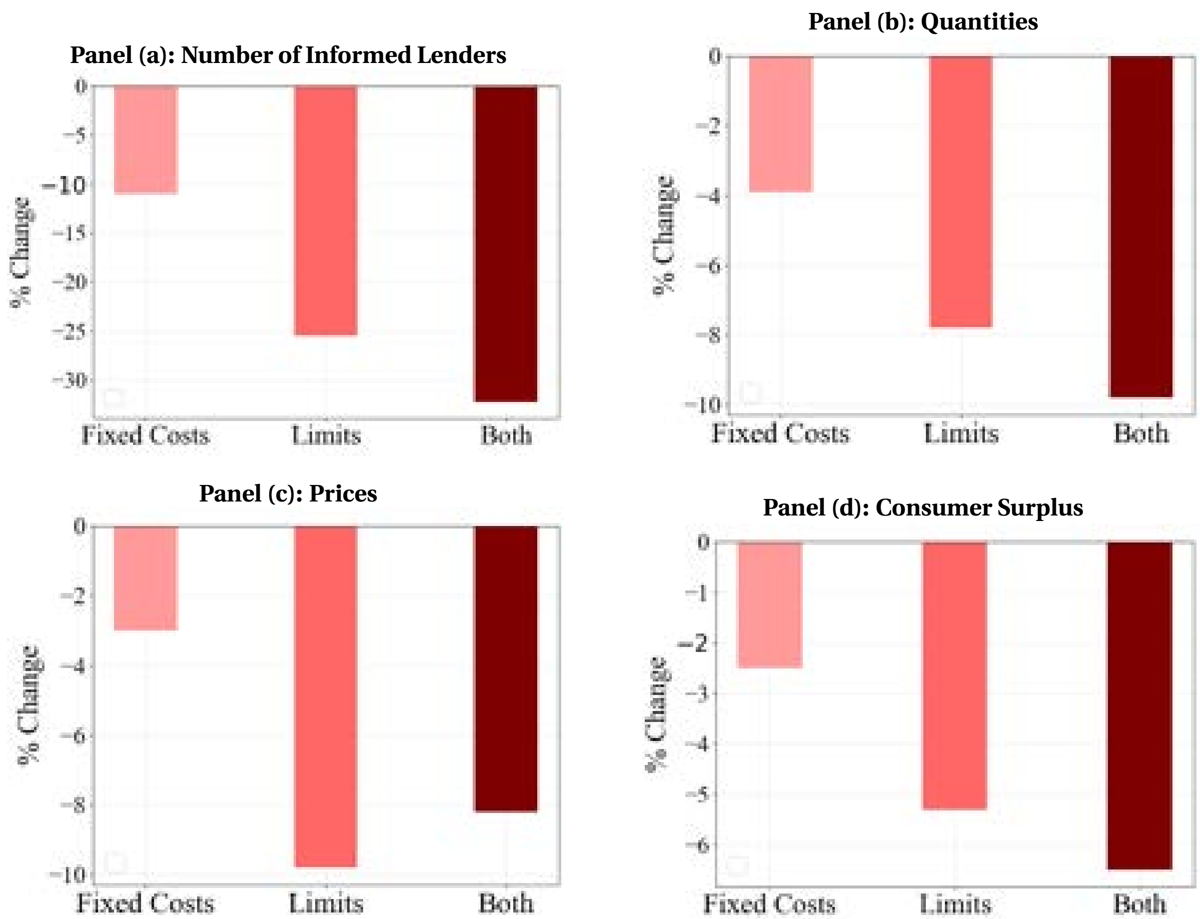


Figure A9: Decomposition - Prices

This figure decomposes the effects of lender exits, changing lender composition (informed lenders exiting), and interest rate limits on prices. Changes are computed from the status quo of no interest rate limits or regulatory fixed costs. The lightest bars illustrate how lender exits impact prices. To calculate this, I use my model to simulate a scenario where 21% of lenders exit the market, while holding the proportion of informed and uninformed lenders constant. The medium bars represent the effect of changing lender composition. To compute this, I hold the total number of lenders fixed but reduce the proportion of informed lenders by 31%. The darkest bars depict the impact of interest rate limits. For this calculation, I hold both the number and composition of lenders constant but enforce interest rate limits. Panel (a) shows results for prime borrowers with low unobserved default costs. Panel (b) presents results for prime borrowers with high unobserved default costs. Panel (c) displays results for subprime borrowers with low unobserved default costs, while Panel (d) shows results for subprime borrowers with high unobserved default costs.

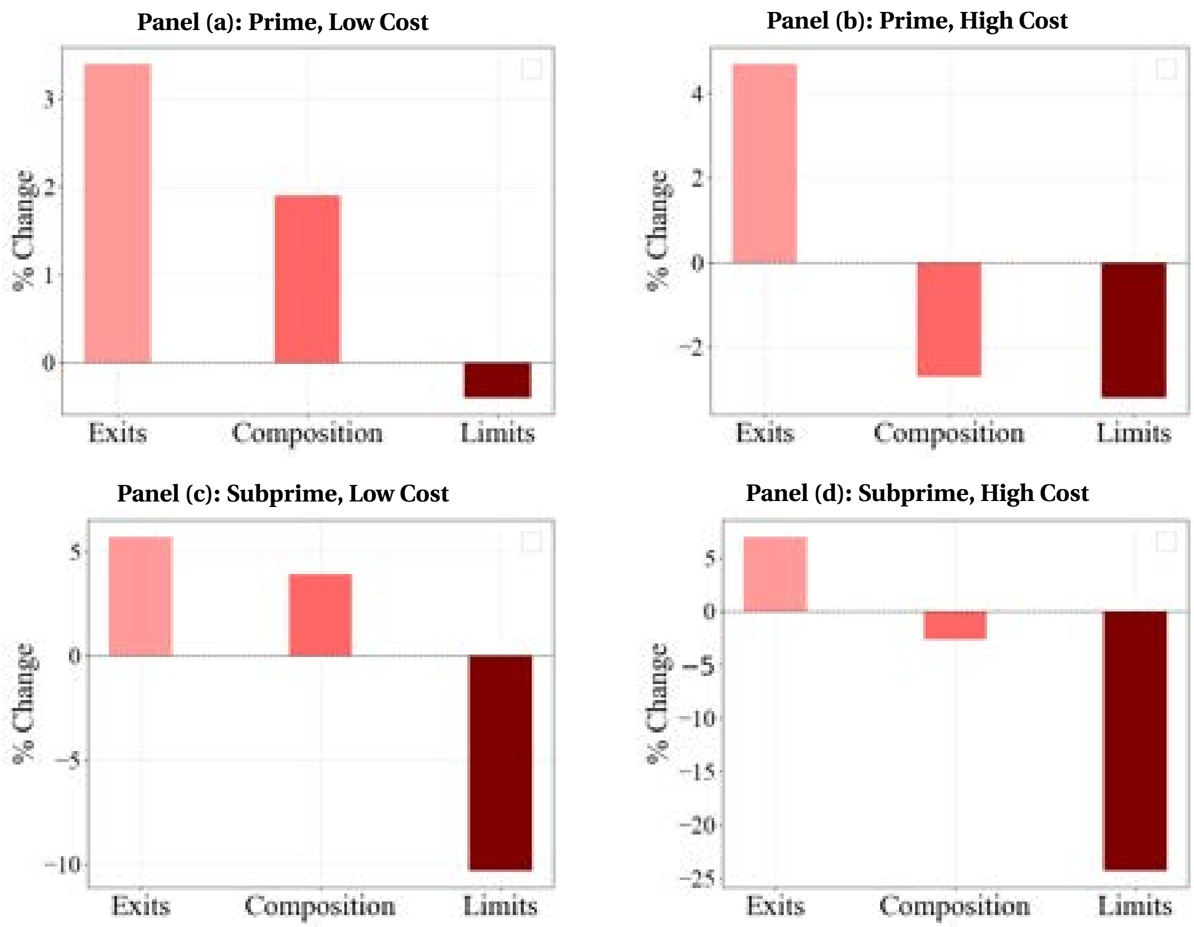
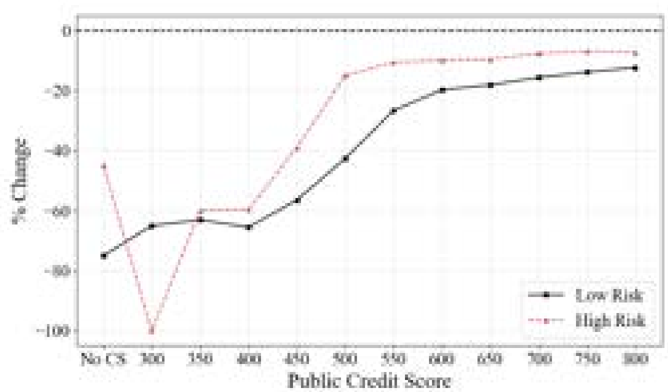


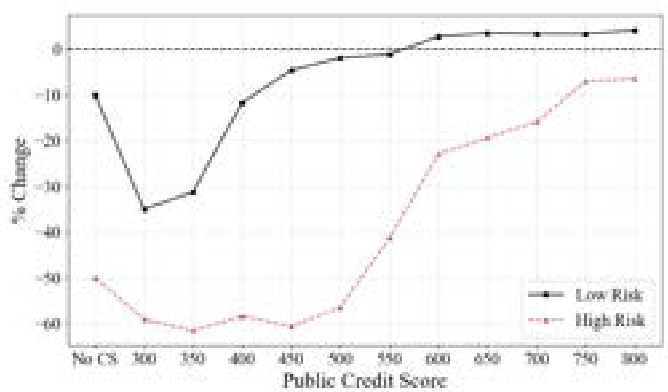
Figure A10: Changes in outcomes across public and private types

This figure shows changes in consumer surplus, loan quantity, and prices for different borrower types under different regulatory policies. I split borrowers into eleven different groups based on their credit score and two groups based on their unobserved default risk. Changes are calculated as percent changes from the status quo. Panel (a) presents changes in prices, Panel (b) shows changes in total loan quantity, and Panel (c) illustrates changes in consumer surplus. Changes are calculated as percent changes from the status quo of no interest rate limits and no fixed costs. Solid black lines show outcomes for low-unobserved default cost consumers and red dotted lines show outcomes for high-unobserved default cost consumers.

Panel (a): Change in Quantities



Panel (b): Change in Prices



Panel (c): Change in Consumer Surplus

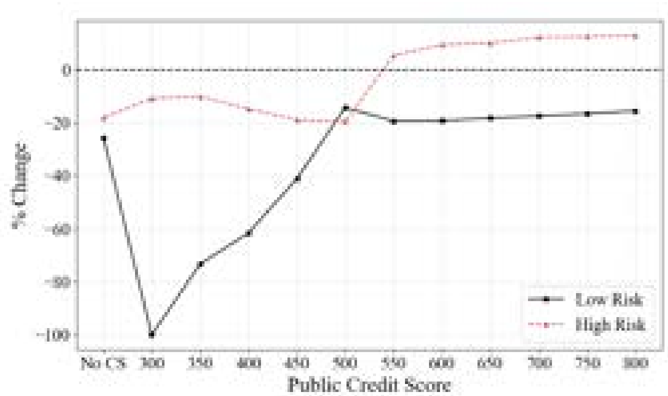


Figure A11: Lax compliance with interest rate limits

This figure illustrates lax compliance with interest rate limits. The figure shows histograms of interest rates in the four quarters following state regulatory changes. Dashed vertical lines indicate each state's interest rate limit. Panel (a) displays New York, panel (b) shows Connecticut, panel (c) shows Vermont, and panel (d) shows Colorado. Source: Credit bureau.

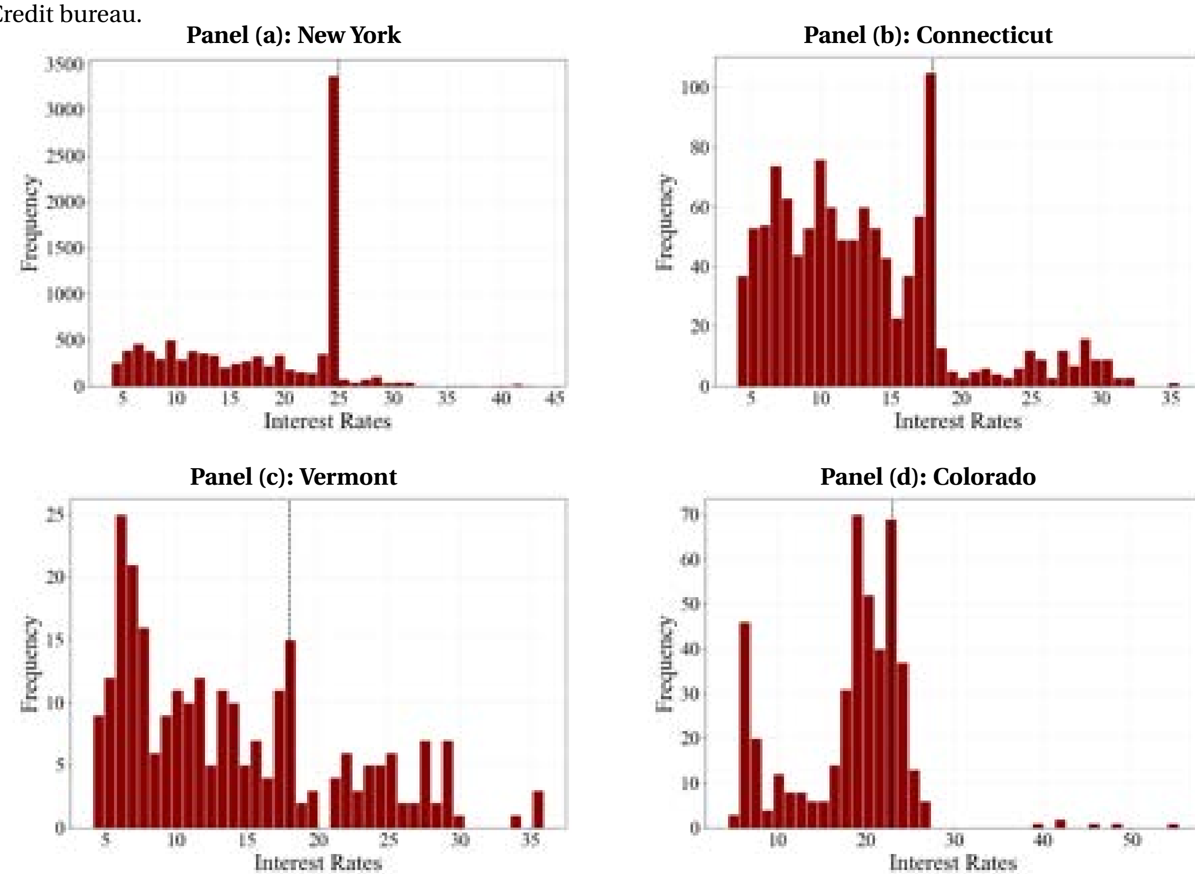
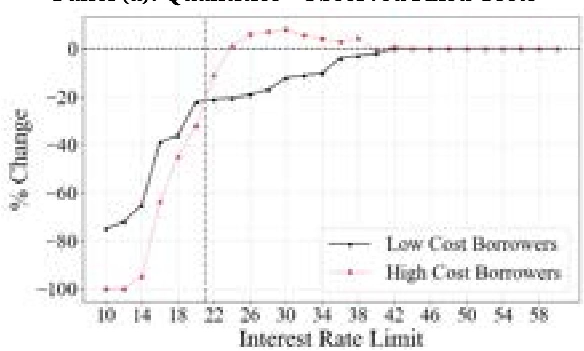


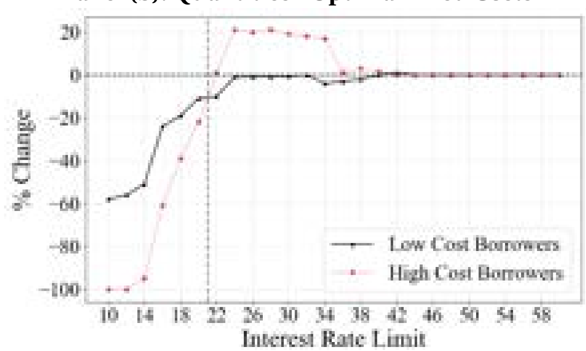
Figure A12: Counterfactual policies - Subprime outcomes by unobserved default costs

This figure illustrates changes in quantity, prices, and consumer surplus under varying levels of interest rate limits and fixed costs, relative to a baseline scenario with no interest rate limits and no fixed costs. Panels (a), (c), and (e) present results for interest rate limits with observed fixed costs (estimated after regulatory changes), while panels (b), (d), and (f) show results under optimal fixed costs, where I calculate the level of fixed costs that would result in greatest credit access within each interest rate limit. Panels (a) and (b) show changes in quantities, panels (c) and (d) show changes in prices, and panels (e) and (f) show changes in consumer surplus. The figure focuses solely on borrowers with subprime credit scores. Black solid lines represent outcomes for borrowers with high unobserved default costs, while red dotted lines show outcomes for borrowers with low unobserved default costs. *Source:* Credit bureau and credit website data.

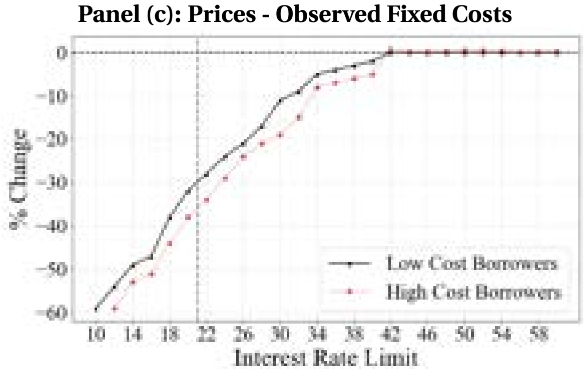
Panel (a): Quantities - Observed Fixed Costs



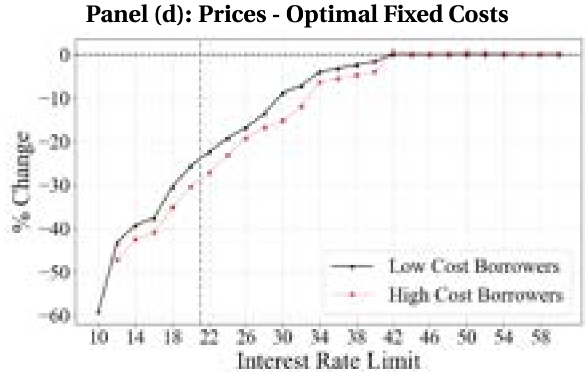
Panel (b): Quantities - Optimal Fixed Costs



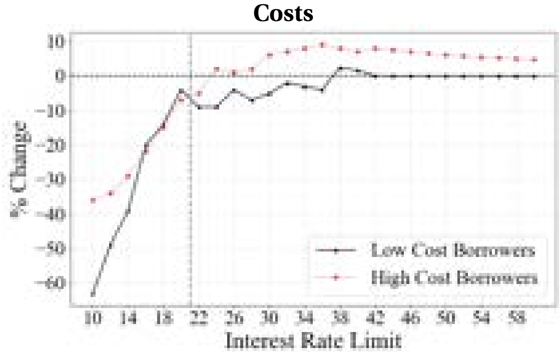
Panel (c): Prices - Observed Fixed Costs



Panel (d): Prices - Optimal Fixed Costs



Panel (e): Consumer Surplus - Observed Fixed Costs



Panel (f): Consumer Surplus - Optimal Fixed Costs

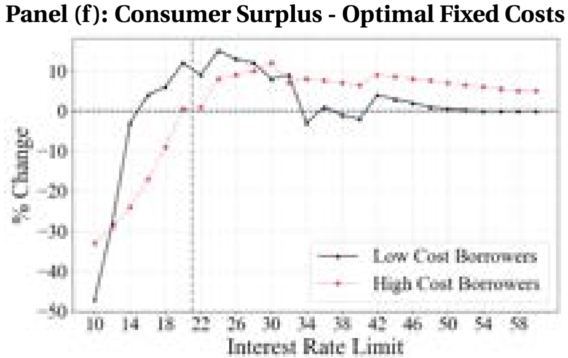
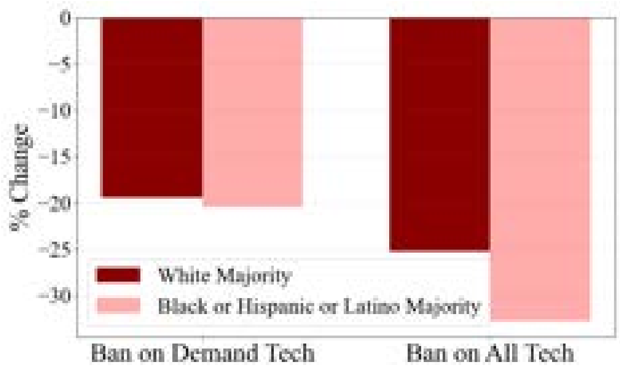


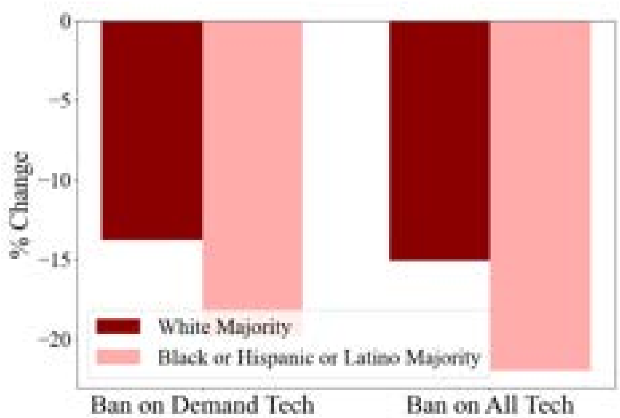
Figure A13: Counterfactual: Race and Regulating Algorithms and Technology

This figure illustrates changes in quantities, prices, and consumer surplus under two counterfactual policies restricting advanced screening technologies: (1) a ban on using borrower demand elasticity information and (2) a ban on all borrower-specific information, where all lenders operate as uninformed. Borrowers are categorized by whether they reside in predominantly white zip codes (75% or more white residents) or predominantly minority zip codes (75% or more Black, Hispanic, or Latino residents). Dark bars indicate outcomes after banning demand elasticity technologies, while light bars represent outcomes after banning all borrower-specific technologies. Changes are expressed as percentage deviations from the status quo. Panel (a) shows changes in quantities, Panel (b) in loan prices, and Panel (c) in consumer surplus. *Source: Credit bureau and credit website data.*

Panel (a): Change in Quantities



Panel (b): Change in Prices



Panel (c): Change in Consumer Surplus

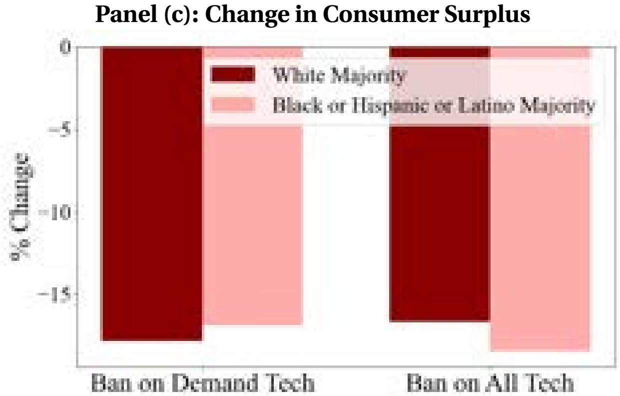


Table A1: State Consumer Finance Laws

This table presents consumer finance laws in states impacted by bank partnership challenges, including civil usury limits, criminal usury limits, and licensing requirements. *Source:* Conference of State Bank Supervisors.

	New York	**Connecticut**	**Vermont**	**Colorado**
Civil Usury Limit	16%	12%	18%	21%
Criminal Usury Limit	25%	36%	NA	45%
Licensing Requirements	Examinations, fair lending certificates, financial statements, annual reports, litigation affidavit	Examinations, financial statement, business plan, annual reports	Examinations, annual reports, financial statements, business plan	Examinations, annual reports, financial responsibility forms

Table A2: Nonbank Quantity Around Regulatory Changes

This table shows results from the following regression: $y_{c,t,g} = \alpha + \beta Post_c \mathbb{1}[t - L_c \leq 0] + \gamma_{t,g} + \eta_{c,g} + \varepsilon_{c,t,g}$, where $y_{c,t,g}$ is log dollar amount of nonbank personal loan originations in county c in quarter t in dataset g. $Post_c \mathbb{1}[t - L_c \leq 0]$ is an indicator for whether county c has experienced a regulatory action in the current quarter or prior quarters. Column (1) shows estimates in the full population of borrowers, Column (2) shows estimates from the subgroup of prime borrowers and column (3) shows estimates from the subgroup of supbrime borrowers. Standard errors are clustered at the state level.*Source:* Author's calculations from 10% random sample of U.S. credit population from credit bureau.

	(1)	**(2)**	**(3)**
	All borrowers	**Prime**	**Subprime**
Post × Treated	-0.129***	-0.052**	-0.223***
	(0.032)	(0.013)	(0.033)
Quarter FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Mean of Y-Variable	11.6	11.7	11.9
Observations	65,889	65,889	65,889
Adjusted R-squared	0.613	0.315	0.564

Table A3: Use of alternative credit sources around regulatory challenges

This table shows results from the following regression: $y_{c,t,g} = \alpha + \beta Post_c \mathbb{1}[t - L_c \leq 0] + \gamma_{t,g} + \eta_{c,g} + \varepsilon_{c,t,g}$, where this specification, $y_{c,t,g}$ represents the outcome variable for county c in year t in dataset g. $Post_z \mathbb{1}[t - L_c \leq 0]$ is an indicator for whether county c experienced a regulatory action in the current year or prior years. Column (1) reports the percentage of individuals in a county with a bank account, column (2) presents the percentage of individuals who used a pawnshop in the past year, and column (3) shows the percentage of individuals who used a payday loan in the past year. Standard errors are clustered at the state level. *Source:* Unbanked/Underbanked Supplement to the Current Population Survey (CPS).

	(1)	**(2)**	**(3)**
	% Banked	**% Used Pawnshop**	**% Used Payday Lender**
Post × Treated	0.003	0.039***	0.038***
	(0.003)	(0.012)	(0.014)
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Mean of Y-Variable	0.950	0.134	0.128
Observations	3,905	3,905	3,905
Adjusted R-squared	0.139	0.469	0.166

Table A4: Interest Rates Around Regulatory Changes

This table presents estimates from the following regression: $y_{i,s,t,g} = \alpha + \beta\,\text{Post}_s\mathbb{1}[t - L_s \leq 0] \times X_{i,s,t,g} + \theta X_{i,t,g} + \gamma_{t,g} + \eta_{s,g} + \varepsilon_{i,s,t,g}$. In this equation, $y_{i,s,t,g}$ represents the interest rate for the loan of borrower i living in state s during quarter t in dataset g. The term $\text{Post}_s\mathbb{1}[t - L_s \leq 0]$ is an indicator variable equal to 1 if state s experienced a regulatory action in quarter t or earlier. $X_{i,s,t,g}$ denotes a vector of loan characteristics, including loan size and terms (in months). In Panel (a), the regressions do not include controls for borrower risk measures. In Panel (b), the regressions incorporate controls for borrower risk—specifically credit score, income, debt-to-income ratio, and credit card utilization. The variables $\gamma_{t,g}$ and $\eta_{s,g}$ represent time-dataset fixed effects and state-dataset fixed effects, respectively. Standard errors are clustered at the state level. *Source:* Author's calculations from a 10% random sample of the U.S. credit population from the credit bureau.

	Without Borrower Risk Controls			**With Borrower Risk Controls**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	All Borrowers	**Prime**	**Subprime**	**All Borrowers**	**Prime**	**Subprime**
	APR	**APR**	**APR**	**APR**	**APR**	**APR**
Post * Treated	-1.523***	-0.806***	-3.198***	1.372***	0.994***	1.464***
	(0.339)	(0.257)	(0.431)	(0.233)	(0.127)	(0.149)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower & Lender FE	No	No	No	Yes	Yes	Yes
Mean of Y-Variable	26.9	20.6	29.7	26.9	20.6	29.7
Observations	1,260,523	389,104	871,418	1,260,523	389,104	871,418
Adjusted R-squared	0.330	0.276	0.272	0.614	0.562	0.597

Table A5: Lender information, interest rates, and delinquency rates

This table shows the results from the following regressions: $y_{i,j,s,t} = \alpha + \beta_1 Unexplained_j + \beta_2 CreditScore_{i,t} + \theta X_{i,t} + \gamma Online_j + \delta_{st} + \varepsilon_{i,j,s,t}$. In this specification, $y_{i,j,s,t}$ represents either the interest rate of loan i originated in quarter t, or an indicator for whether loan i ever enters 60-day delinquency or worse over its life-cycle. *Informed*$_j$ is a binary variable indicating whether lender j is classified as an informed lender based on my measure of unexplained variance in interest rates. *CreditScore*$_{i,t}$ is borrower i's credit score in quarter t, and $X_{i,t}$ represents a vector of additional borrower and loan characteristics, including loan size, loan terms, and borrower income. *Online*$_j$ is an indicator for whether a lender allows borrowers to originate loans entirely online without human interaction. δ_{st} are state-quarter fixed effects. The credit score is scaled by its standard deviation, and standard errors are clustered at the lender level. *Source:* Credit bureau data and credit monitoring website.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
	APR	**APR**	**Delin.**	**Delin.**	**Delin.**
Informed	-0.033**	-0.033***	-0.013**	-0.047***	-0.124***
	(0.017)	(0.010)	(0.006)	(0.006)	(0.009)
Credit Score	-0.028***	-0.095***	-0.087***	-0.086***	-0.087***
	(0.0002)	(0.001)	(0.001)	(0.001)	(0.001)
APR				0.362***	0.208***
				(0.024)	(0.022)
Informed × Rates					0.308***
					(0.030)
Borrower Controls	Yes	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes
Online Lender FE	No	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes
Mean of Y-Variable	0.253	0.253	0.196	0.196	0.196
Observations	60,087	60,087	60,087	60,087	60,087
Adjusted R-squared	0.360	0.362	0.059	0.062	0.073

*Clustered (Lender) standard errors in parentheses, Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A6: Loan Defaults, Returns, and Modifications Around State Challenges

This table presents estimates from the following regression: $y_{i,s,t,g} = \alpha + \beta\,\text{Post}_s \mathbb{1}[t - L_s \leq 0] \times X_{i,s,t,g} + \theta X_{i,t,g} + \gamma_{t,g} + \eta_{s,g} + \varepsilon_{i,s,t,g}$. In this equation, $y_{i,s,t,g}$ is the outcome variable for borrower i's loan, residing in state s during quarter t in dataset g. $\text{Post}_s \mathbb{1}[t - L_s \leq 0]$ is an indicator for whether state s experienced a regulatory action in quarter t or earlier. $X_{i,t,g}$ represents a vector of loan characteristics, including loan size and terms (in months). $\gamma_{t,g}$ and $\eta_{s,g}$ are time-dataset and state-dataset fixed effects, respectively. Standard errors are clustered at the state level. Columns (1) through (3) use an indicator for whether borrower i's loan enters 90-day delinquency or worse as the outcome variable. Columns (4) through (6) use the return on borrower i's loan as the outcome variable, defined as $\frac{\text{CashReturned}_{i,s,t,g}}{\text{CashLent}_{i,s,t}}$. Columns (7) through (9) use an indicator for whether borrower i's loan is modified. Columns (1), (4), and (7) present results for all borrowers; columns (2), (5), and (8) show results for prime borrowers; and columns (3), (6), and (9) display results for subprime borrowers. Standard errors are clustered at the state level. *Source:* Author's calculations from a 10% random sample of the U.S. credit population, derived from credit bureau data.

	Default			**Return on Loan**			**Loan Modification**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
	All	**Prime**	**Subprime**	**All**	**Prime**	**Subprime**	**All**	**Prime**	**Subprime**
Post × Treated	0.012	-0.001	0.035***	-0.067***	-0.073***	-0.056***	0.026***	0.026***	0.041***
	(0.007)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.002)	(0.003)	(0.005)
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State/Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Y-Variable Mean	0.191	0.121	0.258	0.898	0.901	0.896	0.132	0.0657	0.194
Obs.	570,182	208,906	234,456	570,182	208,906	234,456	570,182	208,906	234,456
Adj. R-squared	0.057	0.031	0.060	0.1446	0.123	0.218	0.169	0.105	0.200

Table A7: Borrower outcomes two years from loan origination

This table shows the estimates from the following regression: $y_{i,s,t+8,g} - y_{i,s,g} = \alpha + \beta\,\text{Post}_s \mathbb{1}[t - L_s \leq 0] \times X_{i,s,t,g} + \theta X_{i,t,g} + \gamma_{t,g} + \eta_{s,g} + \varepsilon_{i,s,t,g}$, where $y_{i,s,t+8,g} - y_{i,s,g}$ is the change in the outcome variable $y_{i,s,g}$ two years following loan origination. $\text{Post}_s \mathbb{1}[t - L_s \leq 0]$ is an indicator for whether state s experienced a regulatory action in quarter t or earlier. $X_{i,t,g}$ is a vector of loan characteristics including loan size and terms (in months), while $\gamma_{t,g}$ are time-dataset fixed effects and $\eta_{s,g}$ are state-dataset fixed effects. Standard errors are clustered at the state level. *Source:* Author's calculations from a 10% random sample of the U.S. credit population from the credit bureau.

	(1)	**(2)**	**(3)**	**(4)**
	Bankruptcy	**Credit Score Growth**	**Business Owner**	**# Accounts in Collection**
Post × Treated	0.012***	-0.008**	-0.005**	0.269***
	(0.003)	(0.002)	(0.002)	(0.067)
Time FE x Event FE	Yes	Yes	Yes	Yes
State FE x Event FE	Yes	Yes	Yes	Yes
Y-Mean	0.122	0.012	0.043	2.856
Observations	1,529,999	1,529,999	1,529,999	1,529,999
Adjusted R-squared	0.0418	0.0016	0.0064	0.0307

Table A8: Lender summary statistics - Informed versus uninformed lenders

This table presents lender-level summary statistics for informed lenders (above-median unexplained variance) and uninformed lenders (below-median unexplained variance). Means are reported with standard deviations in parentheses. Interest rates, loan size, terms, and credit scores reflect averages of lender-level means. ”Number of loans” is the average number of loans per lender in each category. ”Online lender” denotes the percentage of lenders offering fully automated online loan origination, and ”Bank partner” indicates the percentage partnering with banks. ”Specialized in underserved” is the percentage of lenders providing at least 10% more credit to underserved borrowers (subprime or thin credit files) than the market average. *Source:* Credit website and credit bureau data.

	Informed Lenders	**Uninformed Lenders**
Interest Rate	24	19
	(7)	(7)
Loan Size	5,386	5,054
	(3,357)	(3,939)
Credit Score	607	621
	(32)	(30)
Number of Loans	14,644	8,110
	(35,015)	(24,695)
Online Lender	0.38	0.28
	(0.49)	(0.45)
Bank Partner	0.41	0.31
	(0.49)	(0.47)
Number of Lenders	52	52

Table A9: Financial distress around regulatory challenges

This table presents the estimates from the following regression: $y_{i,s,t,g} = \alpha + \beta\,\text{Post}_s \mathbb{1}[t - L_s \leq 0] \times X_{i,s,t,g} + \theta X_{i,t,g} + \gamma_{t,g} + \eta_{s,g} + \varepsilon_{i,s,t,g}$. In this specification, $y_{i,s,t,g}$ represents either the logarithm of the dollar amount in collection accounts or the number of severe derogatory accounts (foreclosure, bankruptcy, charge-off, or severe delinquency) for borrower i in state s during quarter t in dataset g. $\text{Post}_s \mathbb{1}[t - L_s \leq 0]$ is an indicator for whether state s experienced a regulatory action in quarter t or earlier. $X_{i,t,g}$ is a vector of loan characteristics, including loan size and loan terms (in months). $\gamma_{t,g}$ represents time-dataset fixed effects, and $\eta_{s,g}$ denotes state-dataset fixed effects. Columns (1) through (3) present the results for the logarithm of the dollar amount in collection accounts, while columns (4) through (6) show the number of severe derogatory accounts. Columns (1) and (4) display results for all consumers; columns (2) and (5) focus on prime consumers; and columns (3) and (6) focus on subprime borrowers. Standard errors are clustered at the state level. *Source:* Author's calculations from a 10% random sample of the U.S. credit population, sourced from credit bureau data.

	Log($ in Collections)			**# Accounts Derogatory**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	All	**Prime**	**Subprime**	**All**	**Prime**	**Subprime**
Treated * Post	0.027*	-0.002	0.058**	0.037**	0.024**	0.055**
	(0.015)	(0.010)	(0.022)	(0.016)	(0.011)	(0.024)
Borrower Controls	Yes	Yes	Yes	Yes	Yes	Yes
State and Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Y-Variable	6.83	5.96	7.30	0.616	0.193	1.47
Observations	3,924,598	2,624,964	1,287,946	3,924,598	2,624,964	1,287,946
Adjusted R-squared	0.8054	0.8792	0.7463	0.0060	0.0036	0.0050

Table A10: Shrinkage in distribution of loan terms

This table shows results from the following regression: $\sigma_{z,t,g} = \alpha + \beta Post1[t - L_z \leq 0] + \gamma_{t,g} + \eta_{z,g} + \varepsilon_{z,t,g}$, where $\sigma_{z,t,g}$ is the standard deviation of interest rates, loan amount (in dollars), or loan terms (in months) in zip code z in quarter t in dataset g. $Post1[t - L_z \leq 0]$ is an indicator for whether zip code z has experienced a regulatory action in the current quarter or prior quarters. The first three rows show coefficient estimates, standard errors, R-squareds, number of observations, and the mean of the y-variable for the variation of interest rates. Rows 4-6 show the same information for variation in loan terms (months), and the final three rows show the same information for variation in loan amount (dollars). I run these regressions in three groups of borrowers - subprime, near prime, and prime. Standard errors are clustered at the state level. *Source:* Author's calculations from 10% random sample of U.S. credit population from credit bureau.

	β	**SE**	**R-Squared**	**# of Obs.**	**Y-Mean**
(1) Rates - Subprime	-0.591**	(0.278)	0.279	8,061	6.92
(2) Rates - Near Prime	-0.702***	(0.263)	0.034	8,781	8.15
(3) Rates - Prime	-0.900***	(0.260)	0.035	8,706	8.34
(4) Terms (Months) - Subprime	-1.09***	(0.383)	0.080	8,061	12.6
(5) Terms (Months) - Near Prime	-0.831**	(0.357)	0.083	8,781	12.5
(6) Terms (Months) - Prime	-0.149	(0.339)	0.069	8,706	13.0
(7) Amount ($) - Subprime	-116.3***	(38.27)	0.148	8,061	2,247
(8) Amount ($) - Near Prime	18.3	(56.67)	0.098	8,781	2,421
(9) Amount ($) - Prime	-25.1	(65.02)	0.074	8,706	2,491

B Information in the consumer credit market

The information used to originate and price loans plays a central role in determining which borrowers receive credit and at what price. Underwriting models in the modern consumer credit system heavily rely on credit scores, which are derived from data held by nationwide consumer reporting agencies (credit bureaus). These scores are designed to predict the likelihood that a borrower will default on their debt. As underwriting processes have become increasingly automated over the past few decades, a significant number of lenders have adopted credit scores as a primary tool for assessing borrower risk. In fact, by 2024, an estimated 90% of consumer lending decisions in the United States incorporated credit scores.[41]

However, these "traditional" models that rely on credit scores may not accurately depict credit risk for all borrowers and may exclude millions of Americans, leading some lenders to develop alternative models. Rather than relying primarily on credit scores, these alternative credit scoring models may use cash flow data from bank accounts, utility or rent payments, or advanced machine learning algorithms to assess a borrower's repayment risk. These innovations in credit modeling may lower prices and expand credit access, but some observers have raised concerns about privacy and fair lending violations, leading to additional scrutiny from regulators.[42]

B.1 Traditional credit scoring models

Traditional credit scoring models primarily rely on credit scores to underwrite loans. Credit scores were introduced in the 1950s as the consumer credit market expanded beyond local lending networks. These scores are designed to predict repayment risk and are calculated using a borrower's payment and credit history, as reported to credit bureaus.

Credit scores are a relatively modern development. Before the late 1800s, credit was typically extended by local stores and institutions, with lending decisions based on subjective evaluations—often influenced by factors like racial background, gender, and moral character. As the consumer credit market grew and became more national in scope, lenders needed an objective way to assess the likelihood that a borrower would repay a loan. The first modern credit scores were created in the mid-1950s and gained widespread use in the following decades. Today, credit scores serve as a key indicator of an individual's creditworthiness and are used not only in lending but also in contexts such as rental housing, insurance underwriting, and employment decisions.

The primary purpose of a credit score is to predict the likelihood that a borrower will repay a loan. Factors used in calculating credit scores include payment history, total debt owed, length of credit history, recent credit activity, and the variety of credit accounts (credit mix). In the United States, FICO is the most widely used credit scoring model, with VantageScore as its main competitor. These scores are based on data from the three major credit reporting agencies—Equifax, Experian, and TransUnion—which collect information from voluntary reports by lenders, including credit card issuers, banks, auto lenders, mortgage lenders, and debt collection agencies.

B.1.1 Benefits and concerns related to traditional credit scoring models

The adoption of traditional credit scoring models has been credited with reducing prices and expanding access in the consumer credit market. Credit scores provide lenders with information about applicants

[41] *Source: MyFICO*

[42] Beyond providing information about a borrower's credit risk, alternative models may give lenders additional information about borrowers' elasticity of demand. I abstract from this use in my paper, as my empirical results show evidence of lenders with better information on default risk charging borrowers lower prices than lenders relying primarily on credit scores.

that was previously only accessible to lenders with prior business relationships with those borrowers. Research shows that the use of credit scores has led to lower underwriting costs, reduced default losses, more consistent evaluations of applicants, and increased competition among lenders (FinRegLab, 2020; FRB, 2007; Avery et al., 1996; Fishelson-Holstein, 2005; Chatterjee et al., 2023; Einav et al., 2013; Gramlich, 2006).

The adoption of standardized credit scores may also reduce the risk of disparate treatment and personal bias compared to more subjective underwriting processes. Traditional credit scores are calculated solely from information in a borrower's credit reports and exclude data on age, gender, income, race, religion, or other protected characteristics. As a result, credit scores are generally considered compliant with fair lending standards. Research has found no evidence of disparate impact based on race, ethnicity, or gender (Avery et al., 2012), further suggesting that the use of credit scores may help reduce bias in lending decisions.

Despite their advantages, traditional credit scoring models may exclude a significant number of Americans. Lenders are not required to report information to credit bureaus, and most data come from specific types of lenders, such as mortgage, auto, and credit card providers. As a result, credit bureaus often lack sufficient information on consumers who do not use these types of financial products. This can leave certain groups—particularly young adults, recent immigrants, and minorities—without traditional credit scores, making it difficult for them to obtain credit from mainstream financial institutions. The left cycle of Figure B.14 illustrates how the traditional credit scoring system can perpetuate the exclusion of these borrowers from mainstream credit. The scale of this exclusion is substantial, with an estimated 45 to 60 million Americans either lacking any information in credit bureaus or having files too thin to generate reliable predictions. Blacks, Hispanics, recent immigrants, young borrowers, and lower-income consumers are especially likely to be categorized as "thin file" or "no file."

Credit scores may also be poor predictors of default risk, even for individuals with detailed credit bureau information. Key factors relevant to a borrower's ability to repay, such as income, expenses, and broader financial circumstances, are not included in credit score calculations. Additionally, adverse events like bankruptcies remain on credit reports for seven to ten years, often lowering scores by more than 100 points. This can lead to significant misclassification of default risk, with research showing that conventional credit scores misclassify risk for about 30% of consumers. Even individuals with extensive credit histories ("thick files") may struggle to access credit. Currently, around 80 million U.S. adults have non-prime credit scores, which can result in credit denials or significantly higher interest rates compared to prime borrowers.

B.2 Alternative credit scoring models

Alternative credit scoring models have the potential to more accurately predict default risk and expand credit access for consumers. In recent years, some lenders have adopted these models, leveraging new data sources and advanced algorithms for loan underwriting. Unlike traditional credit scoring models, which typically rely on linear or logistic regressions to predict default, alternative models may employ machine learning or artificial intelligence to uncover more complex relationships between borrower characteristics and repayment behavior.

Alternative credit scoring models often utilize new data sources beyond the traditional credit bureau data. Broadly, the types of alternative data used for modeling credit risk include:[43]

1. *Alternative Financial Data:* This category refers to non-lending financial activities not typically

[43] The Use of Machine Learning for Credit Underwriting

recorded in traditional credit bureau reports, such as inflows and outflows from checking accounts, as well as rent and utility payments. These types of data can provide insights into a borrower's cash flow stability and regular financial commitments, which are important for assessing creditworthiness.

2. *Behavioral Insights in Alternative Financial Data:* This category refers to information about consumer behavior derived from transaction-level financial data, such as the timing, locations, and nature of borrowers' purchases. This data can be used to develop metrics that assess how borrowers manage discretionary spending in response to fluctuations in income, offering insights into their financial resilience and budgeting habits.

3. *Non-Financial Alternative Data:* This category includes information about individuals that is non-financial and not derived from financial data. Examples include a person's social media presence, search histories, and measures of social connectedness. Such data can provide insights into a person's lifestyle, habits, and reliability, which may be indirectly indicative of their creditworthiness.

B.2.1 Benefits and concerns related to alternative credit scoring models

Alternative models may offer lenders a more accurate assessment of a borrower's probability of repayment, leading to higher approval rates and potentially lower costs for some borrowers. These models also enable lending to individuals without credit scores or those with thin credit files. The enhanced precision of these newer models can increase lending in riskier segments of the consumer credit market. For example, VantageScore Solutions reported that its use of machine learning to assess thin file consumers resulted in a 16.6% accuracy improvement for bank card originations and a 12.5% improvement for auto loan originations.[44] Such improvements may be particularly significant for traditionally underserved groups, such as racial minorities and low-income populations. Research indicates that traditional credit scores are less reliable predictors of default for these groups, so the benefits from alternative models might be especially substantial for these borrowers (Blattner and Nelson, 2021).

The right cycle of Figure B.14 illustrates a scenario where alternative credit scoring models could expand credit access. Borrowers with limited information in credit bureaus might be denied loans by lenders relying on traditional credit scoring models. However, if these borrowers apply for a loan from a lender using alternative models, they are more likely to be approved. As they repay their loan, they generate credit bureau data, which can improve their future loan accessibility and potentially reduce the costs of borrowing.

Despite the potential benefits of alternative credit scoring models, these new approaches also raise concerns about accuracy and discrimination. More flexible, opaque machine learning models could have negative effects on populations traditionally subject to discrimination or exclusion. These models can identify a broader number of relationships in the training data, potentially replicating or even amplifying historical disparities. For example, some machine learning models use "latent features" identified by the algorithm from the input data correlations. These latent features may allow the algorithm to infer an applicant's race or gender, making it difficult to diagnose or reduce these issues due to the models' complexity. The increased complexity and use of extensive datasets also raise concerns about privacy, fairness, and data protection. These issues are particularly strong when models incorporate data that may be considered personal or intrusive, or that lack a direct correlation to default risk, such as using social media activity as a proxy for creditworthiness. The complexity and lack of transparency in machine

[44] The Use of Machine Learning for Credit Underwriting

learning models also heighten concerns about the types of data being used.

Figure B.14: Traditional and alternative credit scoring models

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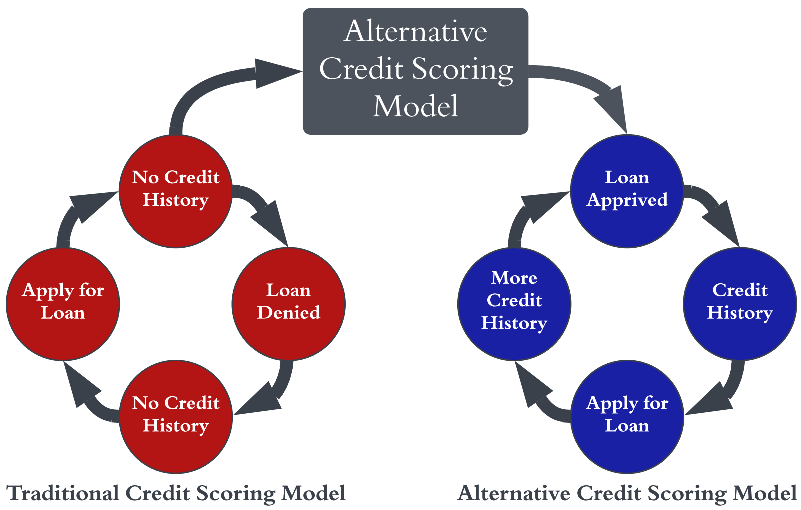


C Overview of personal loans

Nonbanks are primarily regulated at the state level, resulting in variation in regulatory intensity across states and over time, which I leverage in my empirical design. Although nonbanks are subject to many of the same consumer protection laws as banks, they typically do not face the rigorous expectations or periodic examinations imposed by federal regulators on banks.[45] The Consumer Financial Protection Bureau (CFPB) has authority to supervise any nonbank provider of consumer financial services if there is reasonable cause to believe the nonbank poses risks to consumers. However, the CFPB is not the primary regulator for these lenders; state financial regulators hold that role. As a result, nonbanks that lend to borrowers in multiple states must comply with the rules, regulations, and oversight of each state regulator.

C.1 State-Level Regulatory Framework

There is significant variation in rules, regulations, and the intensity of oversight across states, affecting the types of products, fees, and interest rates nonbank lenders can offer consumers. Operating in multiple states requires lenders to adjust pricing and product offerings, which can be costly. Some state financial regulators, such as the New York Department of Financial Services, are well-funded and known for enforcing strict regulatory compliance. In contrast, other states, such as Utah, maintain a more relaxed regulatory environment with less funding and fewer resources to conduct thorough lender examinations.[46] These disparate state regulations have been criticized for increasing lender costs and creating consumer confusion. For instance, one observer noted, "not only do these laws impose significant costs on in-state businesses in terms of direct compliance costs and reduced productivity, but they also escalate expenses for out-of-state businesses that may face multiple and overlapping regulations, leading to consumer confusion."[47] Consequently, nonbank lenders often incur substantial regulatory costs. Some firms report that all-in licensing costs for operating across multiple states range from $1 million to $30 million, not including the opportunity costs associated with time spent on these efforts, which could lead to forgone business opportunities. Beyond these initial expenses, nonbank firms must continuously monitor regulatory requirements in all the states where they operate, pay fees to respective state regulators, and allocate substantial resources to handle multiple state examinations—potentially facing up to 30 different state regulators per year. Critics argue that the state-based regulatory system imposes excessive regulatory costs and restricts nonbank firms, including startups, from innovating and expanding on a national scale.[48].

C.1.1 State Interest Rate Limits

Interest rate regulation is a primary consumer protection tool in this market. Regulators and consumer protection advocates argue that interest rate caps can curb lender market power and reduce exploitation of behavioral biases among borrowers. However, these regulations are controversial; opponents claim that interest rate caps make lending to riskier populations unprofitable. A number of studies have explored this tradeoff between consumer protection and credit access (Cuesta and Sepúlveda, 2021; Maimbo and Henriquez Gallegos, 2014; Rigbi, 2013; Schmukler et al., 2018; Zinman, 2010). Despite mixed

[45] FinRegLab Cash Flow Data in Underwriting
[46] See https://www.csbs.org/50-state-survey-consumer-finance-laws for an overview of various state laws, regulations, and enforcement agencies.
[47] https://www.congress.gov/118/meeting/house/115376/documents/HHRG-118-IF17-20230301-SD021.pdf
[48] U.S. Department of the Treasury: A Financial System That Creates Economic Opportunities Nonbank Financials, Fintech, and Innovation

results, interest rate limits remain a widely implemented consumer protection policy in the United States and globally.

Interest rate limits are straightforward policy tools, yet their implementation in the U.S. is complicated. While there is no general federal law that sets interest rate caps, these limits are determined by state laws based on the borrower's state of residence. There is considerable variation in these limits across states, ranging from as low as 7% APR to no restrictions at all. Non-compliance with state limitations can lead to severe consequences, including forfeiting all profit from the loan and substantial fines. Due to federal preemption, depository institutions can export any interest rate permitted under the laws of their home states, allowing banks to bypass stricter state limits. Despite their ability to export rates, banks tend to focus on creditworthy borrowers, so average bank interest rates remain low. However, this patchwork of interest rate limits often prevents nonbanks, which lack federal preemption, from applying uniform pricing on a national basis.

C.1.2 State Regulatory Oversight and Enforcement

State regulators are primarily responsible for oversight and enforcement of regulations related to nonbanks. This includes managing licensing requirements, conducting periodic examinations, and implementing enforcement actions when necessary. I leverage this cross-state variation in regulatory intensity in my empirical design.

Licensing: Most states require lenders to obtain a license to extend credit to residents within their jurisdiction. These state licensing requirements can significantly hinder a lender's ability to operate across multiple states. Nonbanks often need a license in every state where they offer loans, making the process both costly and time-consuming. To obtain these licenses, companies must submit a comprehensive package of documents, including application information, business plans, policies and procedures, management and organizational charts, surety bonds, and financial statements. Furthermore, key personnel such as officers, directors, and primary owners must provide detailed personal information for background checks, which may include employment histories, financial records, credit reports, and fingerprints.

Examinations: Most states require periodic examinations by state regulators, but the frequency of these examinations varies significantly—some states require annual examinations, while others may not require any.[49] Nonbanks must allocate substantial resources to manage multiple state examinations, potentially facing up to 30 different state regulators annually.[50] During these examinations, state examiners typically require proof of compliance with all pertinent state and federal laws. This includes licensing records, business records, loan contracts, finance charge calculations, compliance with default charges, and adherence to federal laws such as the Gramm-Leach-Bliley Act, the Fair and Accurate Credit Transactions Act, the Fair Credit Reporting Act, and the Equal Credit Opportunity Act. The logistical and financial burden of complying with these examinations across multiple states can be considerable.

Costs can be particularly high for lenders using alternative credit scoring models. During examinations, these lenders are required to provide logs of credit denials, which are scrutinized for potential violations of the Equal Credit Opportunity Act. Regulators must assess whether these models are based on strong, intuitive, and fair relationships between an applicant's behavior and creditworthiness. However, the complexity of these models and their data sources can make it difficult to assess how a model was developed and how it determined a particular applicant's creditworthiness. Lenders using alternative models may therefore find it challenging to establish compliance with a range of regulatory requirements.

[49] See https://www.csbs.org/50-state-survey-consumer-finance-laws for an overview of various state examination requirements.
[50] Nonbank Financials, Fintech, and Innovation

Enforcement Actions: State regulators enforce laws, rules, and regulations through formal enforcement actions against nonbanks operating within their jurisdictions. These actions can include cease and desist orders, written agreements, corrective action directives, removal and prohibition orders, and monetary penalties. These actions often stem from violations of consumer protection laws, including federal consumer financial laws or state laws that prohibit unfair, deceptive, or abusive practices. Some lenders contend that these enforcement actions lead to "regulation by enforcement," where compliance standards become clear only at the conclusion of an examination or following an enforcement action. They argue that this approach makes it challenging and costly for lenders to comply with state laws.

C.2 State Regulatory Data

Interest Rate Limits: To analyze the impact of state interest rate limits on credit availability and pricing for traditionally underserved borrowers, I gather information on state interest rate limits from 2014 to 2018. I use publications from the National Consumer Law Center to determine state interest limits for 2015 and 2018. To fill in the gaps for intervening years (2014, 2016, and 2017), I supplement this data with information gathered from online sources and consumer finance law blogs, allowing me to track changes in interest rate limits over time.

State Licensing: To analyze how lenders respond to state licensing requirements over time, I create a dataset of state nonbank licensing from various sources. First, I scrape state regulator websites to gather publicly available information on licensed lenders. Additionally, I use data from the Nationwide Multistate Licensing System (NMLS), a comprehensive registry for non-depository financial service licensing across participating states. To determine which lenders were licensed from 2014 to 2018, I manually searched the NMLS records, documenting the states in which each lender was licensed each year. To enhance and verify this data, I also submitted information requests to state regulators and received data from Connecticut, Vermont, and Colorado. The final dataset, structured at the lender-state-year level, shows whether a lender was licensed in a specific state each year.

State Attorney General Enforcement Actions: To examine how regulatory costs vary across lenders, I compile a dataset of enforcement actions taken by state attorneys general against consumer finance companies. State regulators use enforcement actions as a primary tool to regulate nonbanks operating within their jurisdictions. These actions are initiated for violations of laws, regulations, final written orders, unsafe or unsound practices, or breaches of fiduciary duty by institution-affiliated parties. The types of enforcement actions include cease and desist orders, written agreements, prompt corrective action directives, removal and prohibition orders, and civil monetary penalties. These actions not only involve direct monetary costs but also require significant time and resources to address, impacting the overall regulatory burden for affected lenders.

To build a database of state enforcement actions over time, a research assistant scraped enforcement data from various state regulator websites, processing over 40,000 enforcement actions. To refine this dataset, the research assistant implemented a two-step classification process using Chat-GPT. The first step identifies whether the actions pertain to a nonbank, and the second step filters out mortgage companies. To ensure accuracy, the assistant manually reviewed 10% of the enforcement orders, finding a 94% agreement rate with the classification algorithm's results. The dataset ultimately includes actions from 41 states. Appendix C provides further details on our data collection procedures and notes the states for which data were missing. This approach ensures an accurate dataset.

Bank-partnership relationships To determine which lenders were directly impacted by the regulatory changes under study, I collected data on whether a lender uses bank partnerships to originate loans.

This information was primarily gathered from the lenders' websites, where those with bank partnerships typically list their associated banks. If a lender did not mention a bank partner or lacked a website, I assumed they did not have a bank partnership. To ensure accurate historical data, I used the Wayback Machine to access archives of lender websites for each year from 2014 to 2018. When a specific year's archive was not available, I used the closest available archive to extract the needed information.

C.3 Constructing Enforcement Action Dataset

In this section, I describe the process for collecting state enforcement action data. Broadly, the categories of entities regulated at the state level include consumer finance companies, banking companies, securities companies, and insurance companies. My focus is on data related to consumer finance infractions. Most infractions fall into one of four categories: fraud violations, license violations, reporting violations, or conduct violations.

For each of the 50 states, we (this work was conducted with the help of a research assistant) identified the relevant state consumer finance regulators. We successfully collected data on consumer finance enforcement actions from 41 of the 50 states. This data was obtained either by scraping the regulator's website or through manual collection. Table C.12 outlines whether we were able to obtain information from each state, the method used to gather the data, and the number of actions collected. After collecting the enforcement orders, we classified them as being directed against either a company or an individual/group of individuals. For enforcement orders involving companies, we further classified them based on whether the respondent entity is: 1) a bank, 2) a nonbank financial company, or 3) a nonfinancial company. This two-step classification process was conducted using the ChatGPT API. We manually verified 1,000 of the orders and found a 94% agreement with the classification decisions.

The final dataset includes the following information: state, year, an indicator for whether a company was involved in the order, an indicator for whether a bank was involved, an indicator for whether a nonbank financial company was involved, and an indicator for whether a nonbank non-financial company was involved. The dataset also includes the names of the companies involved in each order.

Figure C.1: Traditional versus bank-partnership model

This figure compares the traditional and bank-partner models of nonbank loan origination. In the traditional model, a nonbank issues a loan directly to a borrower and is subject to state regulations. In the bank-partner model, the nonbank underwrites the loan, which is originated by a bank partner and sold back to the nonbank within days. This setup places the loan under federal, not state, oversight, enabling nonbanks to bypass state interest rate caps, licensing, and examination requirements. *Source:* Created by author.

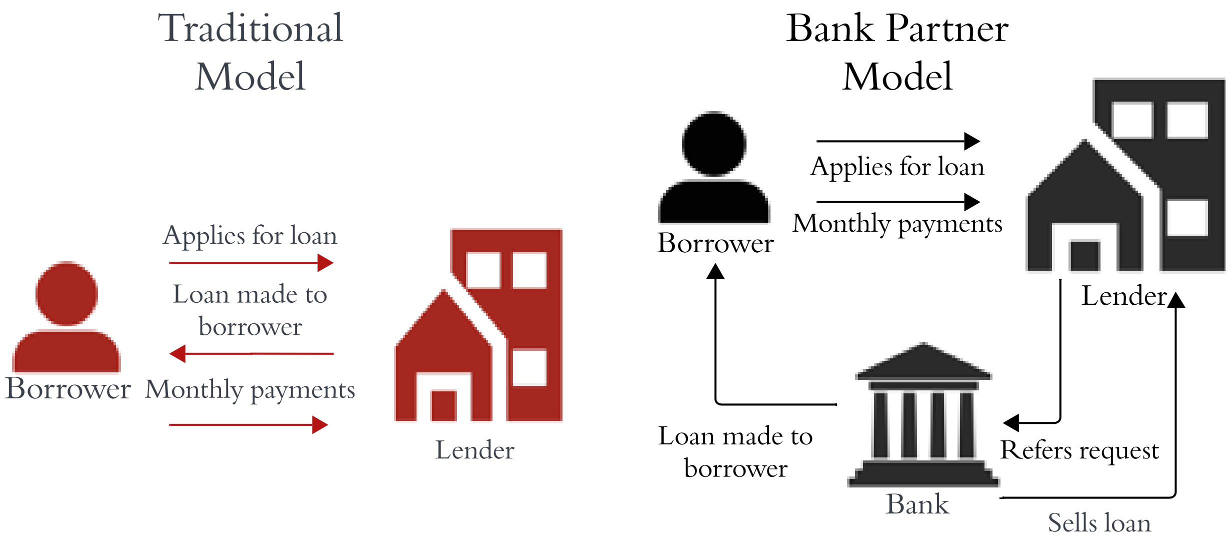


Table C.11: Descriptive Statistics of State Nonbank Regulation

This table provides statistics on state nonbank regulations. Panel (a) shows average interest rate caps, the number of states without caps, and states revising limits from the previous year for $2,000$ loans with a 24-month term. Panel (b) reports the share of loans and lenders licensed per state. Panel (c) presents the average and standard deviation of enforcement actions against consumer finance companies, along with the annual growth rate in these actions. Panel (d) displays the percentage of loans and lenders using bank-partnership models. *Sources:* Regulatory websites, Nationwide Multistate Licensing System, National Consumer Law Center, lender websites.

Panel (a): Interest Rate Limits

	Average Limit	**# States Without Limit**	**# States Revised Limit**
Year: 2014	32.4	11	0
Year: 2015	32.4	11	0
Year: 2016	32.5	10	1
Year: 2017	32.5	10	0
Year: 2018	33.0	9	2

Panel (b): State Licenses

	% Loans by Licensed Lender	**% Lenders Licensed in State**
Year: 2014	4%	4%
Year: 2015	11%	6%
Year: 2016	19%	9%
Year: 2017	23%	11%
Year: 2018	24%	12%

Panel (c): State Enforcement Actions

	Total Enforcement Actions	**SD Across States**	**Avg. Growth Rate**
Year: 2014	1,102	64	0.89
Year: 2015	1,229	69	0.73
Year: 2016	1,360	87	0.56
Year: 2017	1,502	81	0.77
Year: 2018	1,153	82	-0.25

Panel (d): Bank Partnership Origination Model

	% Loans via Bank Partnership	**% Lenders with Bank Partnership**
Year: 2014	49%	5%
Year: 2015	59%	6%
Year: 2016	61%	6%
Year: 2017	60%	7%
Year: 2018	53%	4%

Table C.12: Collection of state enforcement actions

This table contains information about which states had enforcement data, how we collected enforcement data for each state, and the number of enforcement actions per state. *Source:* Collected from state regulatory websites.

State	Status	Collection Type	Observations	State	Status	Collection Type	Observations
AK	COLLECTED	SCRAPING	394	MT	COLLECTED	SCRAPING	206
AL	COLLECTED	SCRAPING	176	NC	COLLECTED	SCRAPING	24
AR	COLLECTED	SCRAPING	1160	ND	COLLECTED	SCRAPING	
AZ	COLLECTED	SCRAPING	7120	NE	COLLECTED	SCRAPING	
CA	COLLECTED	SCRAPING	11320	NH	COLLECTED	SCRAPING	106
CO	COLLECTED	BULK DOWNLOAD	539	NJ	COLLECTED	SCRAPING	130
CT	COLLECTED	SCRAPING	522	NM	COLLECTED	SCRAPING	82
DE	MISSING			NV	COLLECTED	MANUAL	
FL	MISSING			NY	COLLECTED	SCRAPING	324
GA	COLLECTED	MANUAL	13	OH	COLECTED	SCRAPING	
HI	MISSING			OK	COLLECTED	SCRAPING	
IA	MISSING			OR	COLLECTED	SCRAPING	4201
ID	COLLECTED	SCRAPING	535	PA	COLLECTED	SCRAPING	1345
IL	MISSING			RI	COLLECTED	SCRAPING	253
IN	MISSING			SC	COLLECTED	MANUAL	
KS	MISSING			SD	COLLECTED	MANUAL	4
KY	COLLECTED	SCRAPING	1788	TN	COLLECTED	MANUAL	54
LA	MISSING			TX	COLLECTED	BULK DOWNLOAD	3935
MA	COLLECTED	SCRAPING	1178	UT	MISSING		
MD	COLLECTED	SCRAPING	451	VA	COLLECTED	SCRAPING	
ME	COLLECTED	SCRAPING	55	VT	COLLECTED	MANUAL	
MI	COLLECTED	SCRAPING	231	WA	COLLECTED	SCRAPING	3547
MN	COLLECTED	BULK DOWNLOAD	6439	WI	COLLECTED	SCRAPING	1025
MO	MISSING			WV	COLLECTED	MANUAL	3
MS	COLLECTED	SCRAPING	112	WY	COLLECTED	MANUAL	

D Data cleaning

In this section, I describe my initial data cleaning process. First, I use scheduled payment amounts, original loan amounts, and original loan terms to back out interest rates by iteratively solving the non-linear equation:

$$pv \times (1 + rate)^{nper} + \frac{pmt \times (1 + rate \times when)}{rate} \times ((1 + rate)^{nper} - 1) = 0$$

where pv is the original loan amount, $nper$ is the original loan term in months, and pmt is the original scheduled payment.

I then make the following adjustments to my sample:

1. Drop all loans originated by banks
   - My analysis focuses on nonbank loans.
2. Drop all secured loans
   - Secured loans are backed by collateral, such as a car or jewelry, and are subject to different regulations and interest rates than unsecured loans.
3. Drop all loans with terms less than 12 months
   - Loans with terms shorter than 12 months are typically classified as short-term loans and are subject to different rules, regulations, and origination processes.
4. Drop all loans with original balances less than $500
   - Loans with original balances under $500 are generally considered payday loans and are subject to different rules, regulations, and origination processes.
5. Drop all loans with interest rates less than 4%
   - Installment loans usually have interest rates between 5% and 60%. Loans with interest rates below this range likely contain data errors that result in erroneous interest rate calculations.
6. Drop all loans with interest rates greater than 100%
   - Installment loans typically have interest rates between 5% and 60%. Loans with interest rates exceeding this range likely have data errors that result in incorrect interest rate calculations.

Table D.1 shows the number of observations after applying each of the above criteria. The resulting sample includes 1,417,942 unsecured nonbank loans with valid interest rates.

D.1 Dataset Merge

In this section, I describe the process of matching the credit bureau data with the credit monitoring website data. This matching enables me to track loan performance over time, which is observable only in the credit bureau data. Since the credit bureau data represents a random 10% sample of the U.S. credit population, I expect to match approximately 10% of the records from the website data.

To merge the two datasets, I first match all loans with the same origination date, zip code, original loan balance, original loan term, and original loan interest rate. Within these matched loans, I further require that borrowers have credit scores within 15 points of each other. Additionally, I ensure that each loan is uniquely matched to one loan in the other dataset. In total, I match 83,678 loans, representing 9.6% of the original website dataset. Table D.1 provides summary statistics for the merged loans. The characteristics of the merged loans and borrowers closely align with those of the original datasets.

Table D.1: Merged Website and Credit

This table presents summary statistics for prime (VantageScore greater than 600) and subprime (VantageScore less than or equal to 600) borrowers after matching the credit monitoring website data with the credit bureau data. The table reports means, with standard deviations in parentheses. *Source:* Data from credit bureau and credit monitoring website.

	Matched Data	
	Subprime	Prime
	(1)	(2)
APR	30	24
	(9)	(10)
Loan Amount	4,843	6,660
	(3,491)	(4,163)
Terms	37	40
	(14)	(40)
Credit Score	566	655
	(29)	(38)
Income	32,015	36,829
	(10,401)	(12,384)
Length Credit History	153	175
	(86)	(91)
Number of Observations	24,909	58,766

E Theoretical motivation for measure of unexplained variance in interest rates

I provide motivation for why unexplained variance in interest rates may serve as a proxy for lender credit scoring models. Suppose lender j and lender k both operate in a competitive market where they set interest rates for a borrower i based on their respective marginal costs, denoted as $r_{i,h} = mc_{i,h}$ for each lender $h \in [j,k]$. The marginal cost $mc_{i,h}$ depends on the perceived default probability of borrower i and the funding or origination costs associated with the loan from lender h.

Lender j, who relies solely on traditional credit bureau data (cs) and uses a simple linear or logistic regression model, calculates the interest rate based on a more conventional assessment of risk. On the other hand, lender k incorporates additional data points, represented as x, and uses a more complex algorithm f_k to predict the marginal costs and set interest rates. Lenders set interest rates as follows:

$$r_i^j \equiv \tilde{\alpha}^j + \tilde{\beta}^j cs_i + e_i^j, \quad r_i^k \equiv \tilde{\alpha}^k + \tilde{\beta}^k cs_i + \tilde{\gamma}^k f_k(X_i) + e_i^k$$

I observe interest rates and credit bureau data, so I can estimate the following regressions:

$$r_i^j = \hat{\alpha}^j + \hat{\beta}^j cs_i + \underbrace{\epsilon_i^j}_{\text{Error Term}}$$

$$r_i^k = \hat{\alpha}^k + \hat{\beta}^k cs_i + \underbrace{\tilde{\gamma}^k f(X_i) + \epsilon_i^k}_{\text{Error Term}}$$

Assuming that credit bureau data and alternative data are not perfectly correlated (corr$(cs_i, f(x_i)) < 1$), it follows that for borrowers $i \in [1, \ldots, I]$:

$$\text{Var}(\epsilon_i^j) < \text{Var}(\tilde{\gamma}^k f(X_i) + \epsilon_i^k)$$

The above motivation suggests a simple measure for a lender's use of alternative credit scoring models: the R^2 from regressions of a lender's interest rates on credit bureau data. Specifically, for each lender j, I estimate the following regressions for the sample of loans originated by lender j.[51]

$$r_i^j = \alpha^j + \beta_1^j \text{CreditScore}_i + \boldsymbol{\eta X_i} + \gamma_{st}^j + \varepsilon_i^j$$

[51] These regressions are robust to the inclusion of additional credit bureau data, such as the number of inquiries, total debt balances, number of accounts past due, etc.

F Difference-in-difference assumptions

In this section, I provide evidence that the identifying assumptions of my difference-in-difference design hold. First, I show that state challenges to bank partnerships are not driven by local economic conditions or consumer demand. Then, I demonstrate that the Stable Unit Treatment Value Assumption (SUTVA) is not violated in my setting.

F.1 Local economic conditions and consumer outcomes

To support the assumption that nonbank lending would have evolved similarly in treated and non-treated states in the absence of state challenges, I show that these regulatory challenges were *not* driven by confounding factors. Specifically, I test whether changes in state unemployment rates, earnings, bankruptcy rates, house prices, nonbank interest rates, or default rates can predict regulatory challenges. I find no evidence that these changes were driven by local economic conditions or consumer demand.

Specifically, I calculate the growth in explanatory variables over the previous three years:

$$\frac{x_{s,t-1} - x_{s,t-3}}{x_{s,t-3}},$$

where s is a state and t is a year. I use these growth rates as explanatory variables in the following regression:

$$y_{s,t} = \alpha + \frac{x_{s,t-1} - x_{s,t-3}}{x_{s,t-3}} + \gamma_s + \psi_t + \varepsilon_{s,t},$$

where $y_{s,t}$ is an indicator for whether a state enacted a regulatory challenge in year t. I cluster standard errors at the state level.

I find no evidence that local economic conditions, consumer financial distress, or consumer demand drive these changes. Table F.1 shows the results from these regressions where the explanatory variables are the growth in consumer characteristics. Specifically, I investigate whether the growth over the prior three years in the following variables can predict state challenges: the percent of the population classified as subprime, the percent of the population with a bankruptcy flag on their credit report, the percent of the population with at least one account in collections, the percentage of homeowners in foreclosure, the percentage of consumers with credit card utilization above 75%, the percentage of personal loans that are originated by a nonbank, and the percentage of personal nonbank loans in delinquency. The coefficients on these explanatory variables are small and generally not significant, suggesting that changes in consumer characteristics and financial distress do not drive state regulatory challenges.

Table F.2 shows estimates where explanatory variables are growth in per capita income, per capita personal expenditure, unemployment rate, average house price, and average personal income. Again, coefficients are small and insignificant. Taken together, Table F.1 and Table F.2 provide evidence in support of the assumption that nonbank lending would have evolved similarly in treated and non-treated states in the absence of state challenges.

F.2 Stable Unit Treatment Value Assumption (SUTVA)

In this section, I provide evidence in support of the Stable Unit Treatment Value Assumption (SUTVA) — the assumption that the response of lending in a state is only dependent on the treatment it was assigned, and not the treatments of other states. This assumption would be violated if lenders adjusted their lending in non-treated states in response to regulatory changes in treated ones. For example, lenders may offset a decrease in lending in treated states with an increase in non-treated states. This may lead to higher quantities and lower prices in control states, which could result in an overestimate of the effect of regulatory costs on prices and quantities in the treatment group.

I empirically test for the violation of SUTVA and find no evidence of this violation. To test for violations of SUTVA, I calculate the total lending of lender j in state s in quarter t. I restrict my analysis to non-treated states and consider a lender treated if it operated in treated states prior to their state challenges. I then run the following difference-in-difference design:

$$y_{j,s,t,g} = \alpha + \beta 1[t - L_{s_g} \leq 0] \times Treated_{j,s,g} + \psi_{j,g} + \gamma_{t,g} + \eta_{s,g} + \varepsilon_{j,s,t,g}$$

where $y_{j,s,t,g}$ is the log of the total dollar amount of lending for lender j in state s in quarter t in stacked dataset g. $1[t - L_{s_g} \leq 0]$ is an indicator for whether the treated state corresponding to dataset g, s_g, enacted a regulatory challenge prior to or during quarter t. $Treated_{j,s,g}$ is an indicator for whether lender j operated in the treated state s_g prior to regulatory challenges. $\psi_{j,g}$ are lender-dataset fixed effects, $\gamma_{t,g}$ are quarter-dataset fixed effects, and $\eta_{s,g}$ are state-dataset fixed effects.

For example, in the stacked dataset corresponding to New York, the outcome variable includes the total lending of all lenders in never-treated states. $1[t - L_{s_g} \leq 0]$ is an indicator for whether New York has a regulatory challenge in the current or prior quarters, and $Treated_{j,s,g}$ is an indicator for whether a lender operated in New York prior to the regulatory challenge. This allows me to identify whether lenders operating across states change operations in non-treated states following regulatory challenges.

I find no evidence of a SUTVA violation in Table F.3. The coefficient on $1[t - L_{s_g} \leq 0] \times Treated_{j,s,g}$ is small in magnitude and insignificant, suggesting that lenders operating in treated states prior to regulatory challenges do not change their behavior in non-treated states following these challenges. There is no evidence that lenders increase their lending in other states relative to lenders not operating in treated states following regulatory changes.

Table F.1: Consumer characteristics and state challenges to bank-partnership models

In this table, I show the results from the following regression: $y_{s,t} = \alpha + \frac{x_{s,t-1} - x_{s,t-3}}{x_{s,t-3}} + \gamma_s + \psi_t + \varepsilon_{s,t}$, where $y_{s,t}$ is an indicator for whether a state enacted a regulatory challenge in year t. $\frac{x_{s,t-1} - x_{s,t-3}}{x_{s,t-3}}$ represents the growth in an explanatory variable from year $t-3$ to $t-1$. Years (t) include 2010-2018. Explanatory variables are standard deviation scaled. I cluster standard errors at the state level. *Source:* Data from credit bureau.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Challenge	Challenge	Challenge	Challenge	Challenge	Challenge	Challenge
Subprime %	-0.01*						
	(0.00)						
Bankruptcy %		-0.01					
		(0.01)					
Collection Account %			-0.01*				
			(0.01)				
Foreclosure %				-0.01			
				(0.01)			
High CC Utilization %					-0.06		
					(0.04)		
Nonbank Personal Loan %						-0.03	
						(0.02)	
Nonbank Delinquency %							-0.00
							(0.00)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	459	459	459	459	459	459	459
Adjusted R-squared	0.02	0.01	0.02	0.02	0.02	0.01	0.01

Table F.2: Local economic conditions and state challenges to bank-partnership models

In this table, I show the results from the following regression: $y_{s,t} = \alpha + \frac{x_{s,t-1} - x_{s,t-3}}{x_{s,t-3}} + \gamma_s + \psi_t + \varepsilon_{s,t}$, where $y_{s,t}$ is an indicator for whether a state enacted a regulatory challenge in year t. $\frac{x_{s,t-1} - x_{s,t-3}}{x_{s,t-3}}$ is the growth in an explanatory variable from year $t-3$ to $t-1$. I cluster standard errors at the state level. Years (t) include 2010-2018. Explanatory variables are standard deviation scaled. *Source:* Data from credit bureau, Zillow, and U.S. Census Bureau.

	(1)	(2)	(3)	(4)	(5)
	Challenge	Challenge	Challenge	Challenge	Challenge
Per capita GDP	0.02				
	(0.03)				
Per capita personal expenditure		0.04			
		(0.0419)			
Unemployment rate			0.00		
			(0.0120)		
Average house price				0.01	
				(0.0145)	
Average personal income					0.01
					(0.03)
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	459	459	459	459	459
Adjusted R-squared	0.01	0.01	0.01	0.01	0.01

Table F.3: Checking for SUTVA violation

This table shows estimates from the following regression: $y_{j,s,t,g} = \alpha + \beta 1[t - L_{s_g} \leq 0] \times Treated_{j,s,g} + \psi_{j,g} + \gamma_{t,g} + \eta_{s,g} + \varepsilon_{j,s,t,g}$, where $y_{j,s,t,g}$ is the log of the total dollar amount of lending for lender j in state s in quarter t in stacked dataset g. $1[t - L_{s_g} \leq 0]$ is an indicator for whether the treated state corresponding to dataset g, s_g, enacted a regulatory challenge prior to or during quarter t. $Treated_{j,s,g}$ is an indicator for whether lender j operated in the treated state s_g prior to regulatory challenges. $\psi_{j,g}$ are lender-dataset fixed effects, $\gamma_{t,g}$ are quarter-dataset fixed effects, and $\eta_{s,g}$ are state-dataset fixed effects. For example, in the stacked dataset corresponding to New York, the outcome variable includes the total lending of all lenders in never-treated states. $1[t - L_{s_g} \leq 0]$ is an indicator for whether New York has a regulatory challenge in the current or prior quarters, and $Treated_{j,s,g}$ is an indicator for whether a lender operated in New York prior to the regulatory challenge. Standard errors are clustered at the state level. *Source:* Data from credit bureau and credit monitoring website.

	(1)
	Log Originations ($)
Post * Treated	-0.06
	(0.05)
State FE	Yes
Quarter FE	Yes
Lender FE	Yes
Observations	30,498
Adjusted R-squared	0.63

G Bunching estimator

In this section, I describe the bunching estimator I use to estimate the percent of loans that bunch at the interest rate limit and the percent of rationed loans. My approach is similar to that in Cox et al. (2021). First, I make the assumption that if the interest rate cap does not bind for a borrower, then the same loan contract would have been offered with or without the enforcement of the interest rate cap. I also assume that the distribution of loan interest rates is smooth so that the distribution of loans strictly below the cap can be used to estimate the distribution above the cap. I use the difference between the two distributions to estimate the missing mass above the interest rate limit and the extra mass bunched at the limit.

I begin by estimating the distribution $H^0(r)$ of unconditional interest rates from the distribution of interest rates $H^P(r)$ observed in the data. I start from the subsample of loans, S, with interest rates strictly below the limit and recover $H^0(r)$ from the conditional distribution $H^P(r|S)$. Here, I use the assumption that if interest rates in S were optimal for lenders to offer when interest rate limits are not enforced, the same rates will be offered even when interest rate caps are enforced. Because the lender profit maximization problem is concave, the interest rate limit does not move any unconstrained interest rate outside of S into the region strictly below the interest rate limit. This means that the distribution of interest rates in S under enforcement is the same as the conditional distribution without enforcement, so $H^P(r|S) = H^0(r|S)$. Under the assumption that the distribution H^0 is smooth over its domain, I can recover H^0 by extrapolating from the conditional distribution $H^P(r|S)$. I use the difference between the counterfactual and empirical distributions of contracts to estimate the distortion caused by the enforcement.

To estimate the distribution of interest rates in the counterfactual world where state interest rates are not enforced, I restrict my sample to the subset of loans that have interest rates below the interest rate cap. The distribution of interest rates features bunching at intervals of 0.5 percentage points, so I take a nonparametric approach. I first fit flexible polynomials with 0.5 percentage point indicators to the conditional distribution of rates strictly below state interest rate limits: $(r|r < \bar{r_s})$, where $\bar{r_s}$ is state s's interest rate limit. Using the estimated parameters, I predict the distribution of interest rates $(r|r \geq \bar{r_s})$ for $r \geq \bar{r_s}$. I use the observed data to discretize r into bins of 1 basis point and fit the following model using nonlinear least squares:

$$P(R \leq r) = \frac{e^{\eta(r)}}{1 + e^{\eta(r)}}$$

where

$$\eta(r) = P(r) + \delta_1 \left\lfloor \frac{r}{1} \right\rfloor + \delta_2 \left\lfloor \frac{r}{0.5} \right\rfloor + \delta_3 \left\lfloor \frac{r}{0.25} \right\rfloor .$$

$P(r)$ is a polynomial of r with a finite degree, $\lfloor \cdot \rfloor$ is the floor function, and the terms δ_1, δ_2, and δ_3 measure the discontinuous jump in the linear predictor when r reaches, respectively, a round integer interest rate, a multiple of 50 basis points, and a multiple of 25 basis points. I use the estimated coefficients to recover the CDF $P(R \leq r)$ for $r \geq \bar{r_s}$ based on the estimated relationship $\eta(r)$ from loans $r < \bar{r_s}$. I use the difference between the observed and counterfactual distributions to estimate the excess loans bunched at the interest rate limit, the average reduction in interest rates, and the fraction of loans rationed due to the interest rate limits.

Table G.1: Bunching at state interest rate limits

This table presents the estimates from the bunching estimator described in Appendix G. I use the distribution of loans just below the state interest rate cap to predict the counterfactual distribution of loans above the cap that would have existed in the absence of enforcement. By calculating the excess mass at the limit and the missing mass above it, I estimate the percentage of loans that received lower interest rates due to the cap, the average reduction in interest rates, and the percentage of loans that were rationed. Column (1) reports results for all borrowers, column (2) focuses on prime borrowers, and column (3) presents results for subprime borrowers. Standard errors are bootstrapped. *Source:* Author's calculations from a 10% random sample of the U.S. credit population using credit bureau data.

	All Borrowers	Prime	Subprime
	(1)	(2)	(3)
Excess Mass (%)	6.01	4.91	7.18
	(0.091)	(0.857)	(0.473)
Average reduction in interest rate	2.02	2.14	2.28
	(0.173)	(0.212)	(0.218)
Rationed Mass (%)	9.41	3.43	11.1
	(0.312)	(0.011)	(0.091)

H Substitution to bank lending

Next, I investigate whether borrowers offset a decrease in the supply of nonbank credit by turning to bank loans. If borrowers can easily substitute nonbank loans with other types of credit, the welfare impact of a decline in nonbank lending may be mitigated. To explore the elasticity of substitution between nonbank and bank credit, I use state challenges to bank-partnerships as an instrument for nonbank credit access. I estimate the following equations:

$$\log(NonbankCredit_{i,s,z,t}) = \beta_1 Challenge_{s,t} 1[t - L_z \leq 0] + \beta_2 X_{i,s,z,t} + \gamma_t + \mu_z + \epsilon_{i,s,z,t}$$

$$\log(OtherCredit_{i,s,z,t}) = \beta_1 \log(NonbankCredit_{s,t}) + \beta_2 X_{i,s,z,t} + \gamma_t + \mu_z + \epsilon_{i,s,z,t}$$

where $Challenge_{s,t} 1[t - L_z \leq 0]$ is an indicator for whether state s has implemented a regulatory challenge in quarter t or previous quarters, $X_{i,s,z,t}$ is a vector of borrower characteristics, including credit score and income, γ_t are quarter fixed effects, and μ_z are zip code fixed effects.

I find that prime borrowers substitute to bank credit following state challenges, while subprime borrowers are less likely to do so, consistent with subprime borrowers being underserved by mainstream institutions such as traditional banks. Columns (1) and (2) of Table H.1 show that state challenges are strong instruments for the amount of nonbank personal loan balances held by borrowers. Nonbank balances are 7 percentage points lower for prime borrowers and 40 percentage points lower for subprime borrowers following state challenges, with F-statistics around 20. I find that a decline in nonbank credit is associated with a statistically significant increase in bank borrowing for prime borrowers—a 1% decline in nonbank credit leads to a 0.40% increase in bank borrowing for the average prime borrower. The elasticity of substitution is lower for subprime borrowers, and the coefficient is only marginally significant—a 1% decline in nonbank personal loan lending results in a 0.28% increase in bank credit for subprime borrowers. Columns (5) and (6) show no significant change in credit card balances following declines in nonbank credit.

Finally, I investigate how aggregate bank personal loan lending and credit card borrowing evolve following regulatory challenges, finding little change in total bank credit. Since these regulatory challenges did not directly affect banks, any change in bank lending would likely result from borrowers substituting to bank credit and shifts in competition between the two types of institutions. Panel (a) of Figure H.1 shows no significant change in aggregate bank personal loan lending at the zip code level, and panel (b) shows no meaningful change in credit card borrowing. Figure H.2 shows no changes in bank interest rates. Thus, while some borrowers, particularly those with strong credit scores, may offset the reduction in nonbank credit with bank loans, this substitution is not substantial enough to affect market-level quantities and prices.

Table H.1: Substitution to other credit around state challenges

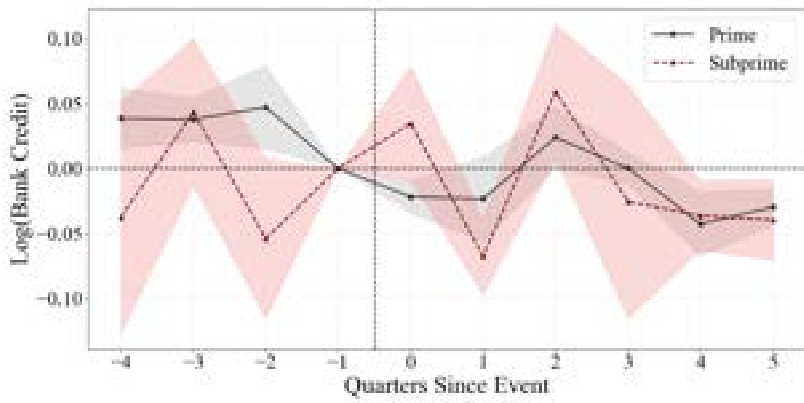
This table shows results from a 2SLS regression where I use state challenges as instruments for supply of nonbank credit. The first stage regression is as follows: $log(NonbankCredit_{i,s,z,t}) = \beta_1 Challenge_{s,t} \mathbb{1}[t - L_z \leq 0] + \beta_2 X_{i,s,z,t} + \gamma_t + \mu_z + \epsilon_{i,s,z,t}$, where $log(NonbankCredit_{i,s,z,t})$ is the log of the nonbank personal loan originations to borrower i in zip code z in quarter t. The second stage is: $log(OtherCredit_{i,s,z,t}) = \beta_1 log(NonbankCredit_{s,t}) + \beta_2 X_{i,s,z,t} + \gamma_t + \mu_z + \epsilon_{i,s,z,t}$. Columns (1) and (2) show the first stage estimates and F-statistics. Columns (3) and (4) show second stage estimates where the outcome variable is the dollar amount of bank personal loan originations. Columns (5) and (6) are second stage estimates where the outcome variable is credit card debt. Standard errors are clustered at the state level. *Source:* credit bureau data.

	(1)	(2)	(3)	(4)	(5)	(6)
	Nonbank		**Bank**		**Credit Cards**	
	Prime	Supbrime	Prime	Supbrime	Prime	Supbrime
State Challenge	-0.07***	-0.40***				
	(0.02)	(0.07)				
Nonbank Credit			-0.31***	-0.18*	-0.08	-0.36
			(0.1)	(0.12)	(0.07)	(0.22)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Quarter & Zip FE	Yes	Yes	Yes	Yes	Yes	Yes
F-Stat	23.4	19.3	-	-	-	-
Observations	15 Million	3 Million	12 Million	3 Million	12 Million	3 Million
Adjusted R-squared	0.022	0.007	0.025	0.014	0.026	0.069

Figure H.1: Bank interest rates around state challenges

This figure presents results from the following regression:
$y_{i,t,z,g} = \alpha + \sum_{r=-4}^{5} \beta_r \mathbb{1}[t - L_z = r] + \theta X_{i,t,g} + \phi\gamma_{z,g} + \psi_{t,g} + \varepsilon_{i,t,z,g}$, where $y_{i,t,z,g}$ is the loan interest rate for borrower i in zip code z and quarter t in dataset g. The indicator $\mathbb{1}[t - L_z = r]$ marks quarters relative to a regulatory challenge in z. Borrower controls $X_{i,t,g}$ interact with time-dataset fixed effects $\psi_{t,g}$, while $\gamma_{z,g}$ provides zip code-dataset fixed effects. This figure shows results for all personal loans (both nonbank and bank), controlling for loan size and terms. *Source:* Credit bureau data.

Panel (a): Bank personal loan quantity



Panel (b): Credit Card Borrowing

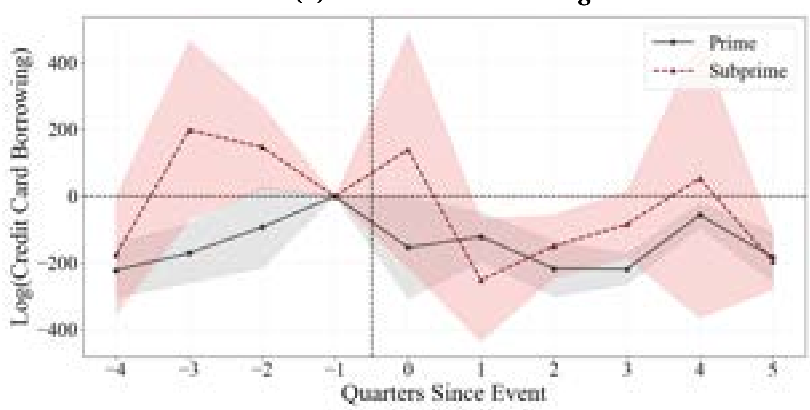
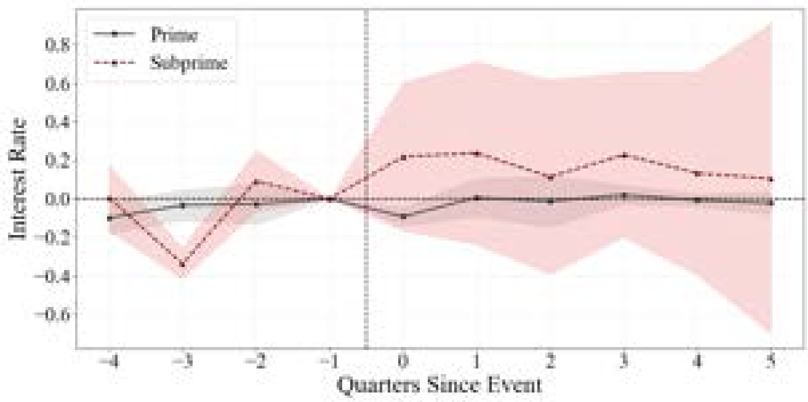


Figure H.2: Bank interest rates around state challenges

This figure presents results from the following regression:
$y_{i,t,z,g} = \alpha + \sum_{r=-4}^{5} \beta_r \mathbb{1}[t - L_z = r] + \theta X_{i,t,g} + \phi\gamma_{z,g} + \psi_{t,g} + \varepsilon_{i,t,z,g}$, where $y_{i,t,z,g}$ is the loan interest rate for borrower i in zip code z and quarter t in dataset g. The indicator $\mathbb{1}[t - L_z = r]$ marks quarters relative to a regulatory challenge in z. Borrower controls $X_{i,t,g}$ interact with time-dataset fixed effects $\psi_{t,g}$, while $\gamma_{z,g}$ provides zip code-dataset fixed effects *Source:* Credit bureau data.



I Lender profit maximization and optimal interest rates

Firms set prices to maximize profits. Informed lender j's profit for borrower i with credit score cs_i and default risk δ_i in market m is as follows:

$$\Pi_{i,j,m} = \max_{r_{i,j,m}} \underbrace{s_{i,j,m}(cs_i, \delta_i, \boldsymbol{\nu_i})}_{\text{Probability of } i \text{ accepting } j\text{'s offer}} (r_{i,j,m} - \underbrace{\delta_i}_{\text{Default cost}} - \underbrace{mc_{jm}}_{\text{Lender marginal cost}}) \quad \text{if } \underbrace{\phi_j = 1}_{\text{Informed}}$$

where $s_{i,j,m}(cs_i, \delta_i, \boldsymbol{\nu_i})$ is the probability of a borrower with credit score cs_i and default cost δ_i accepting lender j's offer from among all offered loans and the outside option, $\boldsymbol{\nu_i}$. This quantity is obtained by integrating the consumer's optimal choice across the utility shock.

In contrast, uninformed lenders set a pooled price within credit score, cs, by integrating over the posterior distribution, $d\tilde{F}_j^{cs}(\delta_i)$:

$$\Pi_{cs,j,m} = \max_{r_{cs,j,m}} \int \underbrace{s_{i,j,m}(cs_i, \delta_i, \boldsymbol{\nu_i})}_{\text{Probability of } i \text{ accepting } j\text{'s offer}} (r_{cs,j,m} - \underbrace{\delta_i}_{\text{Default cost}} - \underbrace{mc_{jm}}_{\text{Lender marginal cost}}) d\tilde{F}_j^{cs}(\delta_i) \quad \text{if } \underbrace{\phi_j = 0}_{\text{Uninformed}}$$

Informed lender j will offer a loan to borrower i if $\Pi_{i,j,m} \geq 0$. Informed lenders aggregate over all borrowers i to obtain market-specific profit:

$$\Pi_{j,m} = \int_i \Pi_{i,j,m} \, di \quad \text{if } \phi_j = 1$$

Similarly, uninformed lender j will offer a loan to borrowers with credit score cs if the total profit after aggregating over borrowers with credit score cs is positive: $\int_{cs_i} \Pi_{cs,j,m} \, dcs_i \geq 0$. Uninformed lender j's profit in market m is equal to its profit across all its credit scores:

$$\Pi_{j,m} = \sum_{cs} \int_{cs_i} \Pi_{cs,j,m} \, dcs_i \quad \text{if} \quad \phi_j = 0$$

Optimal interest rates are found by taking first-order conditions. When $\lambda_m = 0$, optimal interest rates for informed lenders are:

$$r_{i,j,m}^{*,\text{informed}} = \underbrace{\frac{-s_{i,j,m}}{\frac{\partial s_{i,j,m}}{\partial r_{i,j,m}^*}}}_{\text{markup}} + \underbrace{\delta_i}_{\text{borrower default cost}} + \underbrace{mc_j}_{\text{lender marginal cost}}$$

When $\lambda_m = 0$, the first-order condition for the uninformed lender is:

$$r_{j,m}^{*,\text{uninformed}} = \underbrace{\frac{\int s_{i,j,m} \, d\tilde{F}_j^{cs}(\delta_i)}{\frac{\partial s_{i,j,m}}{\partial r_{i,j,m}^*}}}_{\text{markup}} + \underbrace{\frac{\int \delta_i \frac{\partial s_{i,j,m}}{\partial r_{i,j,m}^*} \, d\tilde{F}_j^{cs}(\delta_i)}{\frac{\partial s_{i,j,m}}{\partial r_{i,j,m}^*}}}_{\text{expected borrower default}} + \underbrace{mc_j}_{\text{lender marginal cost}}$$

With regulatory challenges, lenders will set interest rates as follows:

$$
r_{i,j,m}^{\text{reg, informed}} = \begin{cases} r_{i,j,m}^{*,\text{informed}} & \text{if } r_{i,j,m}^{*,\text{informed}} \leq \bar{r}_m \\ \bar{r}_m & \text{if } \bar{r}_m - \delta_i - mc_j \geq 0 \text{ and } \bar{r}_m < r_{i,j,m}^{*,\text{informed}} \\ . & \text{if } \bar{r}_m - \delta_i - mc_j < 0 \end{cases}
$$

$$
r_{j,m}^{\text{reg, uninformed}} = \begin{cases} r_{j,m}^{*,\text{uninformed}} & \text{if } r_{j,m}^{*,\text{uninformed}} \leq \bar{r}_m \\ \bar{r}_m & \text{if } \bar{r}_m - \frac{E_j[\delta_i \times s_{i,j,m}]}{E_j[s_{i,j,m}]} - mc_j \geq 0 \text{ and } \bar{r}_m < r_{j,m}^{*,\text{uninformed}} \\ . & \text{if } \bar{r}_m - \frac{E_j[\delta_i \times s_{i,j,m}]}{E_j[s_{i,j,m}]} - mc_j < 0 \end{cases}
$$

J Partial Compliance with Interest Rate Limits

I observe imperfect compliance with interest rate limits in my setting—some loans are originated over official rate caps even after the regulatory events. Figure J.1 shows the distribution of interest rates post-regulation in each of the affected states, with the vertical dotted lines indicating state limits. Compliance with limits varies across states; almost no loans are originated over the New York limit, while a number of loans exceed Vermont's limit. This finding suggests that regulatory oversight can influence compliance, as violations are fewer in states with the reputation of stricter, better-funded, and larger regulatory agencies.

J.1 Modeling lax compliance

I model partial compliance through a regulatory intensity parameter, λ_m. This parameter ranges from 0 to 1 and reflects the degree to which regulatory constraints limit a lender's ability to offer loans above the set interest rate caps. For example, the threat of large fines or penalties in markets with strict oversight may result in stronger compliance than in markets with lighter state oversight and smaller penalties. A lender offers the optimal rate, $r^{*,\phi_j}_{j,m}$, with probability $1-\lambda_m$, and the regulated rate, $r^{reg}_{i,j,m}$, with probability λ_m.[52] This modeling choice is consistent with regulation operating through the extensive margin of loan origination rather than directly impacting marginal costs. This model of regulation i similar to that of Buchak et al. (2018), who model the regulatory burden on traditional banks following the financial crisis as sometimes preventing a traditional bank from lending to a given borrower altogether through risk constraints, enforcement actions, and the threat of lawsuits. In my setting, this parameter captures the fact that lenders found violating interest rate limits may face consequences such as revoked licenses and large lump-sum fines for violating limits in certain markets.[53]

J.2 Estimating lax compliance

I estimate λ_m using a difference-in-difference estimator that calculates the percent decline in the number of loans originated over state limits following regulatory changes. A 100% decline would indicate perfect compliance with rate limits, while a 0% decline would indicate complete non-compliance. I show these values for each state in Column (1) of Table J.1, which indicates that λ_m ranges from 0.94 in New York to 0.73 in Vermont. These findings align with anecdotal discussions about various state regulators. For example, New York is known for having a large, well-funded, and active financial services agency.[54] On the other hand, Vermont's state regulatory body is relatively small and receives less funding. Thus, the variation in λ_m across markets may be related to state regulatory oversight and costs.

Compliance with interest rate limits, λ_m, is increasing in fixed regulatory costs. To show this relationship, I estimate lender exits following regulation in each state separately (Column (2) of Table J.1). I then use these exit estimates, along with estimated profit changes due to state interest rate limits and the

[52] As described in Section 5.3, $r^{*,\phi_j}_{i,j,m}$ is the optimal interest rate that lender j would charge in the absence of regulation.

[53] Another modeling option would be to represent lax compliance through an increased marginal cost that lenders must pay to regulators to originate loans over the limit. In this case, the lender profit function would be

$$\Pi_{i,j,m} = \max_{r_{i,j,m}} \left[\underbrace{s_{i,j,m}(cs_i, \delta_i, \boldsymbol{\nu_i})}_{\text{Probability of } i \text{ accepting } j\text{'s offer}} \cdot \left(r_{i,j,m} - \underbrace{\delta_i}_{\text{Default cost}} - \underbrace{mc_{jm}}_{\text{Lender marginal cost}} - c_m \mathbb{1}[r^*_{i,j,m} > \bar{r}_m] \right) \right] \quad \text{if } \underbrace{\phi_j = 1}_{\text{Informed}}$$

This profit function would capture the fact that lenders may be required to forgive loan principals and pay additional fines to borrowers for violating limits. However, I find no empirical evidence that lenders set optimal interest rates in this manner, so I model this form of regulation as working along the extensive margin.

[54] https://www.dfs.ny.gov/About$_{U}s$

compliance parameter λ_m to, to estimate regulatory fixed costs across markets. When calculating lender profits, I take into account the size of the markets in each state - lenders operating larger states like New York and Colorado have larger per-state profits than smaller states like Vermont and Connecticut. Using these values, I compute estimated fixed costs post-regulation in each state. Unlike my estimate of regulatory costs in Table 7 which is an average across states, these estimates show the mean of the fixed cost distribution per market.

Table J.2 shows these estimated regulatory fixed costs, calculated as the difference between the pre- and post-regulatory means of fixed cost distributions. Details on fixed cost estimation can be found in Appendix L. States with larger fixed regulatory costs, such as New York, experience greater compliance with interest rate limits. In contrast, states with lower fixed regulatory costs, such as Vermont, experience lower compliance. This finding suggests that greater regulatory oversight may result in increased compliance with state regulations. I show this relationship visually in Figure J.1. While I only have four observations (as there are only four impacted states) there is a clear positive relationship between these variables. I fit a linear line and estimate the relationship between compliance and oversight costs as

$$c(fc) = 2.43 \times 10^{-5} \times fc + 0.286$$

J.3 Counterfactuals with lax compliance

I analyze outcomes under counterfactual policies with varying levels of regulatory fixed costs. I assume that the mean fixed cost parameter impacts compliance according to the relationship estimated above: $c(fc) = 2.43 \times 10^{-5} \times fc + 0.286$. Specifically, higher mean regulatory fixed costs have two effects: (1) fixed costs have a direct effect on lender entry and exit by increasing the level of profit needed for a lender enter, and (2) higher fixed costs lead to stronger adherence to interest rate limits. As before, interest rate limits both lead to a trade-off between reduced markups and credit access and reduce lender profits. Figure J.3 shows the level of fixed costs that results in the maximum level of credit access under each potential interest rate limit for 10% to 60%.

Figure J.1: Lax compliance with interest rate limits

This figure illustrates lax compliance with interest rate limits. The figure shows histograms of interest rates in the four quarters following state regulatory changes. Dashed vertical lines indicate each state's interest rate limit. Panel (a) displays New York, panel (b) shows Connecticut, panel (c) shows Vermont, and panel (d) shows Colorado. *Source:* Credit bureau.

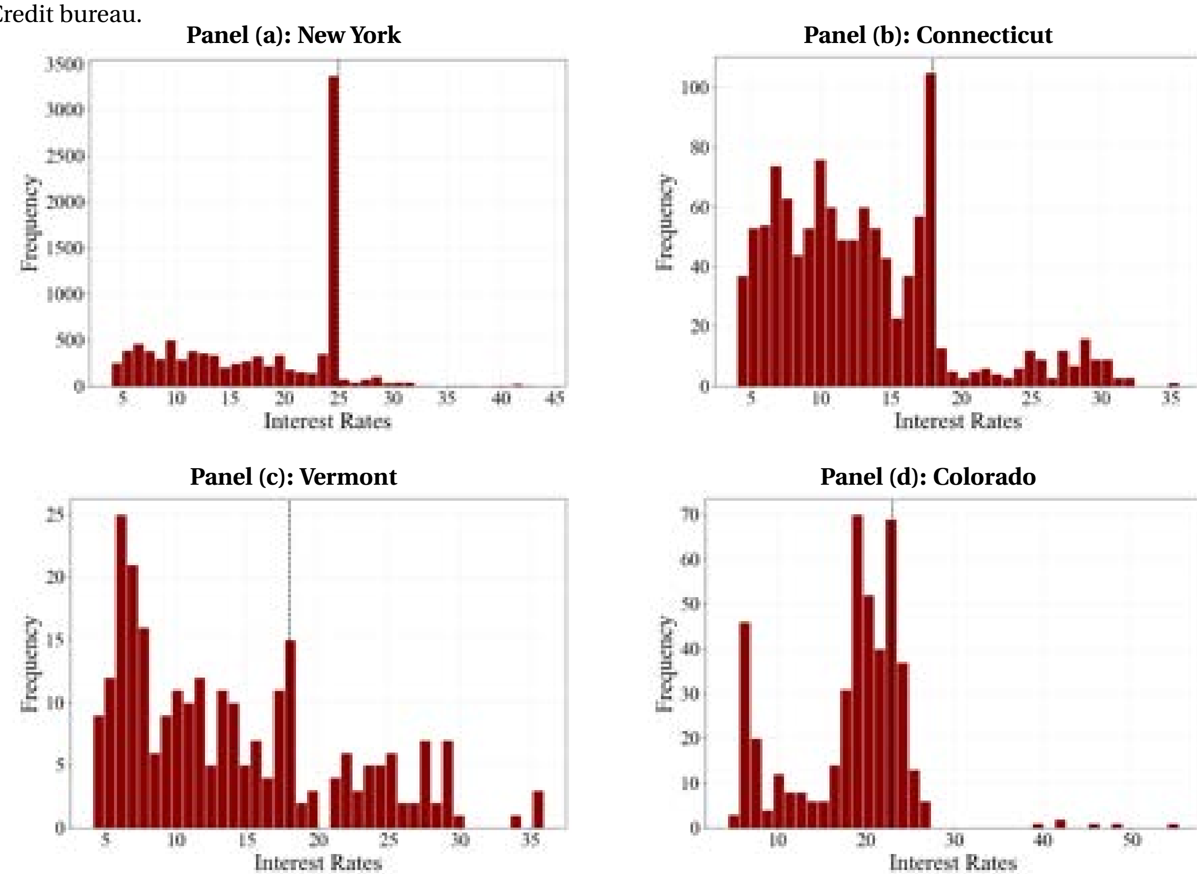


Figure J.2: Correlation between fixed regulatory costs and compliance

This plot shows estimated λ_m values against estimated mean regulatory fixed costs. λ_m values are derived from difference-in-difference estimates as follows: $y^m_{c,t,g} = \alpha^m + \sum_{r=-4}^{5} \beta^m_r \mathbb{1}[t - L_c = r] + \gamma^m_{c,g} + \psi^m_{t,g} + \varepsilon^m_{c,t,g}$, where c represents county c in quarter t, and g denotes the specific stacked dataset. L_c indicates the quarter in which a state regulatory challenge occurred for county c, and $y_{c,t,g}$ is the fraction of loans made over the official interest rate limit. The estimated mean regulatory fixed costs are calculated based on the procedure outlined in Appendix 5.3.2, which uses the estimated λ_m values and additional demand and supply estimates to determine profits in each state. I calculate mean regulatory fixed costs as the difference between pre- and post-regulation fixed costs. *Source:* Credit bureau and credit website.

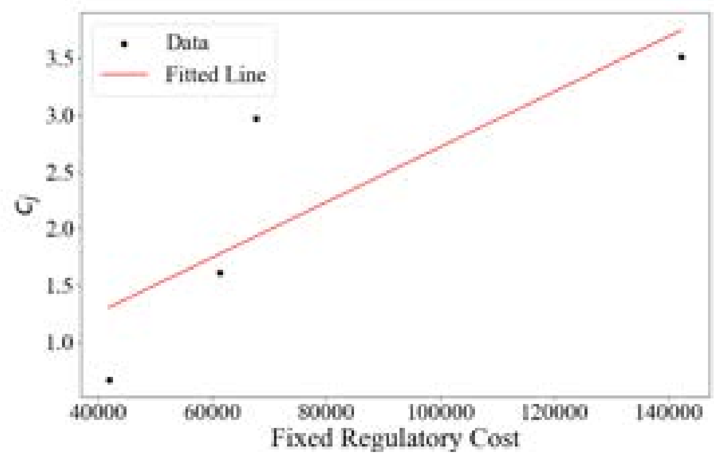


Figure J.3: Optimal fixed costs under various interest rate limits

This figure shows the level of fixed costs that results in the greatest amount of credit quantity under each potential interest rate limit. I calculate counterfactual quantities of credit under fixed costs ranging from \$0 to \$250,000 in 20,000 increments and identify the level that maximizes access for each interest rate limit, from 10% to 60%.

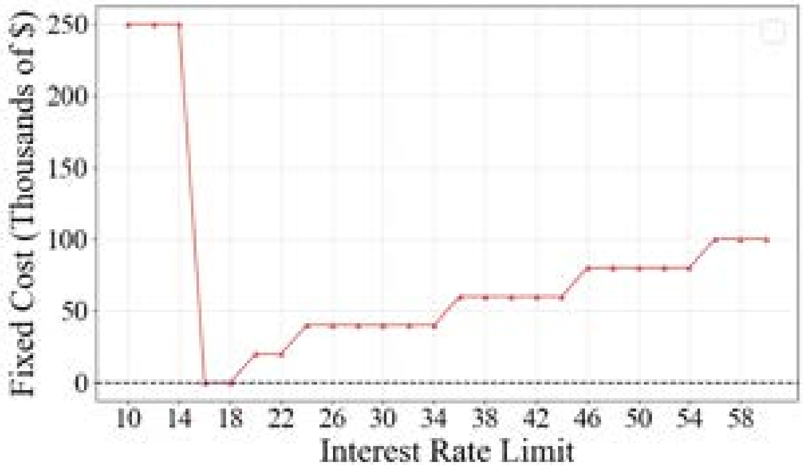


Table J.1: State-level compliance and lender exits following regulation

This table presents estimates of state-level compliance and lender exits following regulation. Estimates are based on the following specification: $y^m_{c,t,g} = \alpha^m + \sum_{r=-4}^{5} \beta^m_r \mathbb{1}[t - L_c = r] + \gamma^m_{c,g} + \psi^m_{t,g} + \varepsilon^m_{c,t,g}$, where c represents county c in quarter t, and g denotes the specific stacked dataset. L_c marks the quarter when a state regulatory challenge occurred for county c, and $y_{c,t,g}$ is either the fraction of loans made over the official interest rate limit or the number of lenders operating in the state. *Source:* Credit bureau and credit website.

	% Change in Loans Over Limit	% of Lenders Exiting
New York	-94.8	-18.5
	(4.98)	(2.41)
Connecticut	-92.5	-29.1
	(4.34)	(2.29)
Vermont	-73.6	-21.4
	(3.88)	(2.29)
Colorado	-87.3	-14.4
	(3.63)	(0.88)

Table J.2: Average regulatory costs by state

This table shows the estimated mean regulatory fixed costs, calculated based on the procedure outlined in Appendix 5.3.2. This procedure uses the estimated λ_m values along with additional demand and supply estimates to determine profits in each state. Mean regulatory fixed costs are calculated as the difference between pre- and post-regulation fixed costs. *Source:* Credit bureau and credit website.

	α_m
Colorado	61,300
	(17,300)
New York	142,200
	(29,900)
Vermont	41,900
	(15,200)
Connecticut	67,700
	(22,600)

K Price Instruments

In this section, I discuss the assumptions around the instrument I use for price—state-level interest rates. I also discuss two alternative instruments, the identifying assumptions of these instruments, and show the robustness of my demand estimates to the use of these two additional price instruments.

Price Instrument: Interest Rate Limits: States have different *levels* of interest rate limits, which were relatively static over this period, unlike the enforcement events I study. These levels were mostly set between the 1980s and early 2000s. As a result, the factors driving the level of state interest rate limits are unlikely to be correlated with loan demand during the 2013-2018 period. See Elliehausen et al. (2021) for a discussion of these limits. State-level interest limits affect the price at which lenders may offer credit in a given state. State interest rate limits typically apply only to non-depository institutions, as banks and credit unions are able to preempt state consumer finance laws. Interest rate caps vary widely by state—some states have no interest rate limits (Utah and North Dakota, for example), while others have relatively low limits (e.g., Maine and Vermont with limits of 18% APR on consumer finance loans). In some cases, loans over certain sizes are exempt from interest rate caps or subject to less stringent limits. In practice, many lenders—even nonbanks—originate loans over the official state interest rate cap. This may be due to lax enforcement and regulatory arbitrage, such as the ability of a nonbank to enter a partnership with a bank to avoid price restrictions. Still, credit prices are impacted by interest rate limits, with more restrictive states experiencing lower limits on average.

State interest rate limits are a valid instrument for prices as long as the interest rate caps are not driven by unobservables that also drive demand. Because interest rate limits are chosen by a democratic political process, demand for higher interest rate limits may be correlated with demand for loans. However, in my setting, this is unlikely. Most interest rate caps were set in the 1990s and remained relatively stable throughout my sample period of 2014-2018, with exceptions in South Dakota and Ohio.

Alternative Price Instrument 1: Hausman Instruments: Hausman instruments (**?**) use the average of the lender's out-of-state rates as an instrument for a lender's rate in state s. These instruments capture the common component of the lender's marginal costs. The Hausman instrument for price assumes that prices in other markets are correlated with the price in the market being studied but are not influenced by local demand shocks. The key identifying assumption is that price variation across markets reflects supply-side factors, such as production costs, rather than local demand conditions. For the instrument to be valid, prices in other markets must not be correlated with unobserved demand shocks in the market of interest. This ensures that the instrument captures exogenous variation in price, isolating the effect of price on the outcome variable.

Alternative Price Instrument 2: Bank-Partnership Model Post-2015: Following the regulatory challenges in 2015, many lenders utilizing the bank-partnership model restructured their agreements with partner banks to make their origination models more resistant to future challenges.[55] These changes increased the marginal cost of providing loans to borrowers post-2015, especially for lenders who continued to use the bank-partnership model. In the wake of the Madden decision, nonbanks were required to pay higher fees to their bank partners in order to maintain these partnerships, exerting additional upward pressure on loan prices. This cost increase was exogenous to local demand conditions, making it an appropriate instrument for price variation. The instrument is valid if the decision to use a bank partnership is correlated with supply-side factors, such as the increased costs imposed by the Madden ruling, but not with unobserved demand shocks. By capturing this exogenous price variation, the instrument allows me to

[55] https://www.jdsupra.com/legalnews/lending-club-makes-big-changes-in-28617/

estimate the price elasticity of demand based on loans that became more expensive after 2015 due to the lender's use of the bank-partnership model.

I compare demand estimates based on three different price instruments to demonstrate the robustness of my estimates of α_i to the choice of instrument. Table K.1 presents similar demand estimates when I use Hausman instruments and an indicator for loans originated under the bank-partnership model post-2015. These alternative price instruments yield slightly lower price elasticity estimates, which may be due to the fact that the variation from the interest rate limit affects borrowers with high-interest loans. These borrowers are typically more risky and, therefore, may exhibit greater price sensitivity.

Table K.1: Demand estimates with alternative instruments for price

This table shows estimated demand parameters. Consumer preferences are given by the equation: $\alpha_i = \bar{\alpha} + \Sigma\nu_i$, where $\bar{\alpha}$ is the mean price sensitivity and Σ scales random shocks. α_i is the borrower's price sensitivity and indicates how much a borrower's utility declines from a 1% higher interest rate. Column (1) shows the average estimate when using state interest rate limits as an instrument for price, column (2) shows the average estimate when using the Hausman instrument as an instrument for price, and column (3) shows the estimate when using an indicator for a loan originated through a bank-partnership model post-2015.

	(1)	(2)	(3)
	State Interest Rate Limit	Hausman Instrument	Post-2015 Bank Partnership Model
$\bar{\alpha}$	-1.71	-1.62	-1.64
	(0.097)	(0.121)	(0.751)
σ^2_α	0.212	0.211	0.266
	(0.014)	(0.037)	(0.015)

L Entry and exit model and estimation details

In this section, I provide additional details about how I model entry and exit and the estimation behind my fixed costs parameters. My approach is broadly based on Buchak et al. (2024), Pakes et al. (2007), and Dunne et al. (2013).

I model entry and exit as a two-stage game in which s_m is a vector of state variables that determine a lender's profit in market m. The variable $\pi(s_m)$ represents the per-lender profits in market m, given the number of operating lenders, population, income, and unemployment rates. The state values in s_m pertain to period two, the period in which entering lenders compete within the market. I assume that lenders do not know their own quality or marginal costs. Consequently, all lenders contemplating entry have uniform expectations about potential profits should they decide to enter. Entry decisions are thus driven by these expected profits for each market m.

Before deciding whether to enter a market, lenders draw a fixed cost $f_{j,m}$ which is private information to the firm and is treated as an i.i.d. draw from a common distribution $FC(f;\Lambda)$. This fixed cost will be paid if they choose to operate. Given expectations about s_m and the expected profits in each of these states, a lender chooses whether to enter a market or not. The value of choosing to enter a market is the firm's expected profit:

$$VE_m = E_s[\pi(s_m)]$$

where the expectation E_s is taken as a firm's perceptions about the future values of the state variables s_m. I will measure the value of entering a market from market-level data on profits, entry/exit rates, and transition rates for the state variables. $M_e(s_m)$ represents the matrix of transition probabilities lenders use to form expectations about the state of market m, s_m, in the period that they choose to enter. Thus, the value of entering can be written as:

$$VE_m = M_e(s_m)\pi(s_m)$$

L.1 Entry/exit estimation

I estimate the profits of lenders operating in different markets using supply and demand parameters and then use my model of entry/exit to estimate the parameters characterizing the distribution of fixed costs. In each market (county), there are two state variables: the number of operating lenders (obtained from my credit bureau), the population (obtained from the U.S. Census Bureau). I estimate entry in the pre-period of my data, which corresponds to the years 2013-2015.

Using my estimated profits and these variables, I estimate the relationship between profits and population. For tractability, I discretize my state variables. n_m, the number of operating lenders, is already discrete. I discretize population into a small number of categories and use the mean of each category as the discrete set of points for evaluation.

Specifically, I take average profits in each market and estimate the following regression:

$$\Pi_{m,state,t} = \alpha + \gamma_n + \beta_1 \text{ population}_m + \xi_{state} + \eta_t + \varepsilon_{m,state,t}$$

to estimate the relationship between profit and number of lenders. Note that I also include state (geographic) fixed effects in this specification. I find that profit linearly decreases with the number of lenders operating in a market. Profit also increases with population. I use these estimated relationships to estimate average profit in each market under each state, s_m, to obtain $\hat{\pi}_m$.

I estimate the transition matrix $\hat{M}_m^e$ from observed transitions between states in the market. This approach is suggested by Pakes et al. (2007). Formally, I assume that lenders must decide each period whether to operate in a market or not. I allow $s_{m,-1}$ to denote the state of market m in period 1, when lenders are deciding whether to enter a market or not in order to compete in period 2. The probability of transitioning from state $s_{m,-1}$ to state s_m is:

$$\hat{M}_e(s_m|s_{m,-1}) = \frac{\sum_{m\in s_{m,-1}} \mathbb{1}[s_m = s_{m,-1}]}{\sum_{m\in s_{m,-1}} \mathbb{1}[s_{m,-1} = s_{m,-1}]}$$

I do this for all states to obtain the full transition matrix $\hat{M}_e$. I combine $\hat{M}_e$ with $\hat{\pi}_m$ to estimate the value of entering a market:

$$\hat{VE}_m = \hat{M}_e(s_m)\hat{\pi}(s_m)$$

I parameterize the fixed cost distribution as a lognormal distribution and will estimate the mean, μ, and variance, σ^2, of the distribution. The log of the probability of observing a market with n_{mt} operating lenders is given by:

$$\mathcal{L}(N_m, n_m, \mu, \sigma^2) = \sum_m \log\left(\binom{N_m}{n_m} FC(\hat{VE}_m; \mu, \sigma^2)^{n_m}(1 - FC(\hat{VE}_m; \mu, \sigma^2)^{N_m - n_m}\right).$$

where N_m is the number of potential entrants and is assumed to be the number of unique nonbank lenders in my dataset - 104. I estimate σ and α, the means of the exponential distributions, using maximum likelihood estimation and bootstrap.