The Unintended Consequences of

Interest Rate Caps on Small Dollar Loans

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Abstract

Interest rate caps on small-dollar loans could make it unprofitable for lenders to serve the market, restricting small-dollar loan access for borrowers and exposing them to unregulated alternatives with greater financial stress. This study leverages a randomized controlled trial (RCT) implemented by a fintech lender in California and its Utah bank partner to assess these effects. Findings show no impact on loan take-up, and the caps lead borrowers to over-borrow from larger, unregulated loans when they restrict the small-dollar loan access. Without the interest rate cap, high-risk borrowers self-select into small-dollar loans, and the access to small-dollar loans can reduce their default rates. Heterogeneity analysis reveals greater benefits for financially fragile borrowers, especially low-income and underserved groups. Evidence shows that interest rate caps on small-dollar loans prevent borrowers from replicating favorable repayment schedules with larger loans, leading them to delay prepayment at a higher cost.

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I. Introduction

Interest rate caps are among the most controversial regulations implemented to balance credit access and consumer protection in the consumer credit market (Temin and Voth, 2008; Maimbo and Henriquez, 2014; Cuesta and Sepúlveda, 2021). In the United States, state governments enact varying interest rate regulations, ranging from no cap in Utah to a maximum annual percentage rate (APR) as strict as 17% in Arkansas. Most interest rate caps are typically applied to small-dollar loans, with maximum interest rates allowed up to a specific loan size level.[1] This can make it unprofitable for lenders to serve in the market of small-dollar loans and exit the market (Cuesta and Sepúlveda, 2021; Bolen et al., 2022; Cherry, 2024), which in turn would cause borrowers to borrow from unregulated alternatives and ultimately lead to credit misallocation.

This misallocation can increase financial stress for borrowers, especially when they resort to unregulated larger alternatives that often come with higher interest payments. This issue is particularly concerning for underbanked and financially vulnerable populations that rely on smaller loans for short-term liquidity needs. Therefore, it is vital to understand who becomes exposed to these unregulated larger alternatives (selection effect) due to interest rate caps on small-dollar loans, how this exposure impacts their financial stress (treatment effect), and constraints that drive this outcome. This understanding is essential for both studying borrower behaviors and informing effective policy.

This paper analyzes the impact of such distortions on borrower behaviors through a randomized controlled trial (RCT) conducted by a fintech lender in California in partnership with a bank in Utah between 2018 and 2019, which involved implementing different interest rate regulation regimes for borrowers in California. The findings in this paper indicate that imposing interest rate caps on small-dollar loans can increase financial stress among borrowers by pushing them toward larger alternatives due to the restriction on small-dollar loan access.

[1] Based on the National Consumer Law Center 2018 fact sheet (see appendix A), forty-six states have interest rate caps in place, and twenty-eight states apply interest rate caps only up to specific loan sizes. For example, Alabama has an interest rate cap that applies to loans of $2,000 or less, Virginia and California have an interest rate cap only for loans of less than $2,500, and New Jersey has an interest rate cap that applies to loans of $50,000 or less.

During the experiment, borrowers in California who applied for loan offers with the same interest rates were processed using a shared underwriting algorithm approved by the bank partner. Those who received offers exceeding $2,600 were randomly divided into two loan groups. One group, originated by this fintech lender, is regulated under California law, which effectively mandates that loans be above $2,500.[2] This is due to the interest rate caps that apply to loans below $2,500 in California, making it unprofitable for the fintech lender to provide such loans. The other group originates from a Utah bank, which allows loans as low as $500 since Utah has no interest rate caps. Consequently, access to small-dollar loans ranging from $500 to $2,500 was made possible due to the absence of interest rate restrictions on small-dollar loans under Utah state law.

My findings suggest that borrowers take out loans regardless of whether small-dollar options are available. However, high-risk borrowers disproportionately prefer small-dollar loans when accessible, and this access significantly reduces their likelihood of default—particularly among lower-income individuals and those in financially fragile areas. Lenders also benefit from improved loan performance under these conditions.

Further evidence indicates that borrowers face constraints that prevent them from replicating the favorable repayment schedules of small-dollar loans by immediately prepaying larger loans. As a result, they delay prepayment, which extends their repayment periods and exposes them to higher cumulative payments over time, exacerbating financial stress. This, in turn, reduces the profitability of larger loans for lenders.

Due to potential endogeneity issues, assessing the effect of interest rate caps through restrictions on small-dollar loan access is challenging. Thus, analyzing borrowers' repayment in different states with various interest rate regulations would not be sufficient to isolate the selection of small-dollar loans and the treatment of small-dollar loan access. Karlan and Zinman (2009) suggest that isolating empirical selection and determining causal impact requires comparing the performance of different borrower groups who opt for identical

[2] Because California's interest rate cap applies to loans of less than $2,500 during the time this fintech lender operates in the state, the lender is hesitant to offer loans in the range of $2,500 to $2,600, as it may attract government scrutiny. Therefore, the minimum loan amount this fintech can originate for borrowers in California is $2,600.

financial contracts. In this setting, endogeneity may stem from the regulatory process itself and from unobserved borrower characteristics. For instance, political and economic forces can drive both interest rate regulations and market equilibrium shifts (Benmelech and Moskowitz, 2010; Bircan and Saka, 2021). In response to these regulatory changes, lenders might adjust their credit supply strategies across states (Smolyansky, 2019; Akey et al., 2021).

Moreover, borrowers with unobserved biases (Kuchler and Pagel, 2021; Carvalho et al., 2024; Jorring, 2024; Leland, 1968) and limited credit access may favor specific credit products (Higgins et al., 2024; Sumit et al., 2024; Beaman et al., 2023), making it hard to distinguish between unobserved heterogeneity and supply frictions without exogenous credit supply variations in loan applications. Finally, identifying treatment effects requires behavioral changes between comparable groups of borrowers. This is challenging to study in natural experiments, as shifts in credit supply can also alter the composition of borrowers who take out loans.

Therefore, to address these empirical challenges, I found it essential to utilize the data generated by the RCT. This enables me to compare the ex-post repayment behavior of ex-ante identical borrowers facing the same loan contract. These borrowers chose their contracts from a different menu of options regarding small-dollar loan access under various regulatory regimes. Therefore, their selection for small-dollar loans with differing repayment behaviors allows me to study selection and treatment simultaneously.

For the loan application analysis in the experiment, I find no effect of limited access to small-dollar loans—caused by the interest rate cap—on loan take-up rates. Although high-quality borrowers with better access to market credit are more likely to withdraw when small-dollar loans are unavailable, this suggests that withdrawal decisions are less driven by the randomized assignment of small-dollar loan access under different interest rate regulation regimes.

Moreover, borrowers in both groups exhibit similarly high take-up rates of around 80%, regardless of whether their offers include small-dollar loans. This indicates that applicants who proceed with their loan applications likely face market frictions or have limited access to alternative credit, making them more reliant on the offered loans. This

finding is consistent with the balance test of originated loans, where borrowers in both groups have an average VantageScore of approximately 560, and about 20% have bankruptcy flags.[3]

Additionally, I find that a significant portion of borrowers choose to take small-dollar loans when they are available. Specifically, about 40 percent of borrowers opt for loans under $2,600 in the group with access to small-dollar loans. Furthermore, the probability of default decreases for loans exceeding $2,600 within this group. This reduction in default probability is associated with borrowers who self-select into loans below $2,600, indicating potential advantageous selection on small-dollar loans due to the absence of interest rate caps.

In the main analyses, I find that the absence of interest rate caps on small-dollar loans reduces the probability of default among high-risk borrowers. In other words, by using the randomized assignment of interest rate cap absence as an instrumental variable—which isolates the effect of small-dollar loan access—we demonstrate that borrowers who opt for small-dollar loans experience a lower probability of default. Notably, both the default rate and the rollover default rate decrease by approximately 30 percent among borrowers with small-dollar loan access in comparison to those without. These findings highlight the potential unintended negative effects of interest rate caps on small-dollar loans, namely, that they can lead borrowers into greater financial stress by forcing them into larger loans.

In a further analysis, I examine the heterogeneous effects of small-dollar loans across different demographic regions using the machine-learning inference approach proposed by Chernozhukov et al. (2020), hereafter referred to as CDDF. The CDDF method allows me to remain agnostic about borrowers' characteristics ex ante, while the algorithm identifies the characteristics that most accurately predict heterogeneous treatment effects. The method's sample-splitting feature also helps me mitigate overfitting concerns in subgroup analyses.

The results show that borrowers with high financial fragility benefit the most from the absence of interest rate caps on small-dollar loans. The effects are typically more pronounced among borrowers with lower monthly incomes and those from geographical

[3] According to a FICO report, the average US credit score was 710 between 2018 and 2019. The FICO model defines credit scores as "poor" and "very poor" when below 600. This is also consistent with observations that many marketplace lenders, such as LendingClub and Prosper, require borrowers to have a FICO score above 600 even before submitting their applications on their platform, which explicitly excludes borrowers with FICO scores below 600.

areas with lower medium incomes, higher poverty rates, larger Hispanic populations, lower housing prices, and lower education attainment (high school or college). Access to small-dollar loans, even with the same interest rates and terms, can alleviate financial stress for these borrowers.

To investigate the underlying mechanisms, I analyze the prepayment and default decisions of borrowers in both groups to gain a better understanding of the constraints that contribute to higher default rates among those taking out larger loans. I find that borrowers who took out loans exceeding $2,600 in the group without access to small-dollar loans exhibit a greater likelihood of prepayment over time. This finding suggests that borrowers cannot replicate the repayment schedule of small-dollar loans through immediate prepayment when they take larger loans, so they choose to delay their prepayments. This indicates that borrowers may experience short-term prepayment constraints and postpone their prepayments until these constraints are more likely to ease, which aligns with the initial borrowing incentive.

I further find that borrowers who took out loans exceeding $2,600 in the group without access to small-dollar loans are more likely to default over time than those who have access. This indicates that delayed prepayments among borrowers without small-dollar access could lead to increased financial stress over time. This is particularly relevant when considering the large payment amount due each period, which results from the non-negotiable loan contracts they are bound by from the beginning.

Finally, I analyze loan profitability across both groups. In practice, if interest rates remain sufficiently high and partial repayments occur before default, larger loans—even with some defaults—can be more profitable than smaller loans that are fully repaid. However, assuming a required 20% return on capital for investors and lending costs of $75 per originated loan, small-dollar loans benefit borrowers while also enhancing lender profitability. By optimizing loan sizes, lenders can improve average returns by approximately 75% through lower default rates and reduced losses. These findings suggest that facilitating access to small-dollar loans can create a win-win scenario for both lenders and borrowers.

Related Literature. This paper contributes to several branches of the existing literature. First, it extends the body of research on interest rate regulation (Bodenhorn, 2007; Temin and Voth, 2008; Benmelech and Moskowitz, 2010; Zinman, 2010; Rigbi, 2013; Fekrazad, 2016; Melzer and Schroeder, 2017; Ferrari, Masetti, and Ren 2018; Cuesta and Sepúlveda 2021; Lukongo and Miller 2022; Cherry 2024). Most of these studies find that binding interest rate regulations negatively impact credit access, and much of this work also employs natural experiment methodologies and primarily examines credit access as the main outcome. In contrast, this study is the first study that utilizes loan-level data with a randomized controlled trial (RCT) to directly investigate the effects of interest rate caps on borrowers' financial stress through its restriction on credit access under different regulatory regimes. Doing so provides a sharper setting to isolate the underlying selection effects and treatment effects that could take place at the same time in the market, subject to the interest rate regulation changes.

Furthermore, this paper contributes to the literature on information asymmetry in the consumer finance market. Building on the pioneering studies of Jaffee and Russell (1976) and Stiglitz and Weiss (1981), which first demonstrated how adverse selection leads to credit rationing, subsequent research has explored various dimensions of asymmetric information's impact on credit markets (De Meza and Webb, 1987; De Meza and Webb, 2001; Einav and Finkelstein, 2011). While a rich body of empirical work has robustly documented adverse selection effects (Ausubel, 1991; Dobbie and Skiba, 2013; Edelberg, 2003, 2004; Stroebel, 2016), few studies have identified advantageous selection in credit markets. Notably, Einav et al. (2012) and Marco and Fabrizio (2022) find evidence of advantageous selection into large loans within the auto loan and marketplace lending sectors. In contrast, this study provides the first evidence of advantageous selection into smaller loans in the consumer credit market, which is driven by borrowers' constraints to replicate favorable repayment schedules associated with smaller loans by immediate prepayment out of unregulated larger loans due to the legal bindings.

More broadly, this paper contributes to the literature on borrowers' default decisions and interventions aimed at reducing default. A key debate in this literature

concerns whether borrowers default primarily due to liquidity constraints—as evidenced by Gross, Notowidigdo, and Wang (2014), Fuster and Willen (2017), Ganong and Noel (2020), and Indarte (2023), who find that mortgage defaults and household bankruptcy filings are largely driven by a lack of liquidity—or insolvency, where borrowers with liquidity still choose to default because they anticipate being unable to repay the full loan over its lifetime, as shown in Dobbie and Song (2020) for credit card defaults. Many studies examine the effects of interventions for distressed borrowers on their likelihood of default, including extending loan maturities to reduce monthly payments (Ganong and Noel, 2020; Aydin, 2024), reducing principal owed (Ganong and Noel, 2020), lowering interest rates (Dobbie and Song, 2020; Castellanos et al., 2024; Aydin, 2024), and introducing forbearance programs (Aydin, 2024). However, there is limited evidence on interventions that can be implemented ex ante to prevent overborrowing and encourage advantageous selection, thereby substantially reducing future defaults—an area that this paper aims to address.

Finally, this paper contributes to the literature on credit intervention evaluations. While most studies in this field assess the impact of expanding access to microloans (Karlan and Zinman, 2010; Banerjee, Karlan, and Zinman, 2015; Meager, 2019), our research examines a different dimension of credit expansion—access to loans significantly smaller than those typically available under existing regulatory frameworks. Unlike Gharad, Karlan, and Osman (2024), which focus on the impact of large enterprise loans on small business success, this paper instead examines financial stress among households. By integrating machine learning methods (Chernozhukov et al., 2020) with a randomized controlled trial (RCT), we identify both significant treatment effects and heterogeneous effects. Our findings indicate that size restrictions imposed by interest rate regulations can have unintended consequences, disproportionately harming low-income borrowers and those in financially fragile areas—the very populations these regulations are designed to protect.

The remainder of this paper is organized as follows: Section II describes the institutional background, Section III describes the experiment setting and data, Section IV

describes the results, Section V interprets the results and discusses the potential mechanisms, and Section VI concludes them.

II. Institutional Background

A. Interest rate regulation in the consumer credit market

As part of the anti-usury law, the state government regulates the interest rate caps in the consumer credit market. Over one-third of states apply the interest rate caps, particularly for small-dollar loans up to a few thousand dollars, primarily due to numerous problematic lending practices in this sector, such as those found in pawnshops, vehicle title loans, and payday loans.[4] These loans often feature high interest rates, small principal amounts, short repayment periods, and may involve wage garnishment or require collateral at significant discounts. At the same time, these loans are also easy to access and serve a general purpose, which typically fits the urgent demands.

The controversial nature of these credit products attracts public attention and leads to increasingly stringent regulations over time. Interest rate caps, as one of the most common interest rate regulations, aim to limit lender exploitation and prevent the abuse of market power in loan pricing. These regulations also seek to protect consumers from exploitation arising from their behavioral biases.

However, these regulations could inadvertently reduce access to the consumer credit market and prompt many mainstream lenders—including banks, marketplace lenders, and public financial companies—to withdraw from the market due to the relatively high cost of lending, legal compliance, or further exercising their market power by serving larger loans only.

For example, in the wake of increased household financial stress following the 2008 financial crisis, public interest in improving access to consumer credit was renewed. The Federal Deposit Insurance Corporation (FDIC) launched a two-year pilot program in 2008 to assess whether banks could profitably offer affordable small-dollar loans as alternatives

[4] See appendix A, state by state interest rate cap applied to the unsecured term loans in the consumer credit are listed.

to high-cost credit products like payday loans and fee-based overdraft protection (Herrmann and Tescher, 2008). The program ended unsuccessfully, with limited bank participation due to the unsustainability of small-dollar loan lending under interest rate caps.[5]

Similarly, due to the undersupply of small-dollar loans and rising household financial stress during the onset of COVID-19 in 2020, several regulatory agencies—including the Federal Reserve, FDIC, NCUA, and OCC—tried to encourage more bank participation to address these needs by issuing a joint statement on more favorable treatment under the Community Reinvestment Act (CRA) for small-dollar lending. Since then, six bank lenders have entered the market, including Regions Bank, Truist, Wells Fargo, Bank of America, Huntington Bank, and U.S. Bank.[6] This suggests that credit availability in this market can also be influenced by financial regulations in general, which may require joint efforts beyond state governments to address.

Meanwhile, the small-dollar loan market could be an essential source for borrowers to smooth consumption over short-term liquidity demand. Several studies on household financial fragility highlight that many U.S. households are liquidity-constrained and financially vulnerable. Research indicates that over one-quarter of households cannot come up with $2,000 within 30 days, with an additional 19% relying on methods like selling possessions or taking payday loans (Lusardi, Schneider, and Tufano, 2011; Hasler, Lusardi, and Oggero, 2018; Balyuk and Williams, 2021). The $2,000 benchmark represents everyday unexpected expenses—such as major car repairs, medical co-payments, legal fees, or home repairs—and reflects the average amount of friends and family transfers during periods of income loss (Lusardi et al., 2011; Balyuk and Williams, 2021).

Therefore, the complex nature of interest rate regulation, especially the interest rate cap, requires more rigorous examination to assess its effects on borrowers' behaviors and

[5] Lenders in the small-dollar loan market can face significant fixed costs, such as subscription to alternative data service for algorithmic underwriting, applications evaluations, financing loan originations, processing payments, reporting to credit bureaus, and collecting on delinquent accounts (Chen and Elliehausen, 2020). Most of these costs do not scale proportionately with loan amounts, for example, a $594 loan requires a 103.54% rate to be viable, while a $2,530 loan can break even at a 36% rate (Chen, Elliehausen, and Wicks, 2018).

[6] Trusts, Pew. "Affordable Credit Poised to Save Consumers Billions." *Pew Trusts, May* 15 (2023).

lenders' profitability. This will better balance credit access and consumer protection in the market.

B. Fintech Lender and Bank Partnership

The FinTech lender in my study operates an online platform specializing in the consumer credit market and has provided personal installment loans across the US since the early 2010s. Its loan product amounts between $500-$5000 based on the most recent updates, repayment terms ranging from 9 to 18 months, and a fixed Annual Percentage Rate (APR[7]). The loan amount range can vary by state due to state-level regulations. Our FinTech employs an advanced underwriting algorithm incorporating alternative data sources to determine the maximum loan amount and maturity, a method distinct from the income share calculations typically used by payday lenders (Dobbie and Skiba, 2013).

In 2017, our FinTech formed a strategic partnership with state-chartered banks from Utah. This alliance combines Fintech lender's sophisticated algorithms with the financial backing of the bank partners to originate loans. Because any interest rate is allowed as long as both party agreed in the contract in Utah and the state law is applied based on where the loans are originated, the bank partner can export its lending practices across states, enabling our FinTech to offer consistent interest rates in California for the experiment. Additionally, our FinTech acquires over 95% of the participation rights in these loans within two to three days of origination, providing a limited incentive to alter the underwriting algorithms since our FinTech will ultimately service the loans and collect repayments.

To evaluate the effects of these adjustments, our FinTech, in conjunction with one of its banking partners, conducted a randomized controlled trial (RCT) in California from September 1, 2018, to October 31, 2019. During this period, a new credit product was introduced to our FinTech lender's online platform. The subsequent sections will explore the specifics of this experiment and discuss its implications for the accessibility of small-dollar loans.

[7] APR is anonymized for privacy, and it is a flat rate between 100% and 200% for all borrowers from California, and the rates can vary across states.

III. Data and Setting

A. Loan Application and RCT

When applying for a loan through our FinTech lender's online platform, a borrower begins by providing sufficient information for the firm to access her creditworthiness and bank account details. The firm then evaluates her maximum loan amount eligibility using complex data inputs, such as monthly income, a soft credit check from Clarity, and bank transaction data from Plaid. A shared underwriting algorithm is used for all applicants, approved at the bank partner's discretion, with the only variation being the minimum loan amount that can be originated. Our FinTech usually verifies monthly income using the last 30 days of bank transactions. If transaction data is insufficient, the borrower must submit pay stubs for further verification. The amount the borrower wishes to finance is optional and does not influence the algorithm's output.

Thanks to the automated underwriting system, lending decisions are typically made within the same or next business day. Eligible borrowers are notified of these decisions and the loan offers via email. The primary function of the algorithm is to determine the maximum loan amount and set the maturity date based on the borrower's repayment capacity. The standard minimum loan amount is typically $2,600, and borrowers cannot negotiate this minimum or the loan's maturity terms.

This process was modified during the experimental phase described in Figure 1. In the experiment, our FinTech randomly assigned eligible borrowers to one of two different loan products. To facilitate this, applications were randomly divided into two groups, as shown in Figure 1. Only borrowers with a monthly income of at least $4,000 were considered for the experiment. Those earning less than $4,000 were automatically placed in the group with small dollar access and excluded from the experimental conditions. Importantly, borrowers were not made aware of the ongoing experiment or the specific income criteria used for eligibility.

Borrowers proceed to apply through the same online system with randomized assignment to a specific loan product at the beginning of the application. This early stage of the application process is crucial as it determines the disclosure of the actual lender's

identity and details regarding the delegation of loan servicing and collection. These disclosures are vital since borrowers must sign the agreement before submitting their applications, a prerequisite for commencing the underwriting process.

During the experiment, one group is assigned to a constrained credit product, which has a loan range of $2,600 to $4,500, while the other group is assigned to a unconstrained credit product with a broader range of $500 to $4,000. Entering a desired loan amount during the application process is optional which is explicitly stated, and the range of available loans is only displayable when borrowers attempt to specify their desired loan amount. As a result, borrowers can become aware of the differences in available ranges only if they actively enter an amount or search on the website for more product details in California. Generally, they receive information about the standard product as presented on the online portal. Once applications are submitted, they are processed using a shared algorithm to determine the maximum loan amount each borrower qualifies for. The key distinction in the underwriting process is the different minimum limits set by the two credit products.

The constrained credit product within this framework, which offers a narrower range of loans without access to small-dollar options, is designated as the 'constrained group.' [8] Conversely, the 'unconstrained group' consists of loans granted under the unconstrained credit product, which includes options for small-dollar loans. Hence, the experimental treatment is defined as the access to borrow within the small-dollar loan range of [$500, $2600]. This opportunity is available to the small-dollar accessible group but absent in the small-dollar inaccessible group.

Once the application is approved, the borrower will receive an email detailing the range of available loans, the assigned maturity, and the repayment schedule. Depending on the maximum loan amount i determined by the algorithm, the borrower i will be informed of the loan range. If she is in the small-dollar accessible group, the range will be [$500, $\$max_i$]; for others, it starts from [$2600, $\$max_i$]. The borrower cannot negotiate

[8] There is only one observation in my sample with a taken loan size of over $4000 in the constrained group during the experiment, so I don't consider the $500 difference in the upper limit between the two groups as part of the treatment.

repayment terms beyond selecting an amount within the approved range. Therefore, the repayment amount will be predetermined and calculated based on the loan amount taken and the maturity.

Borrowers in the constrained group cannot select loans below $2,600. If such a borrower is approved for a maximum loan of less than $2,600 but more than $500, she will receive a rejection letter via email—this restriction does not apply to the unconstrained group. Additionally, suppose a borrower in the constrained group qualifies for a loan larger than $2,600 but wishes to borrow less. In that case, she must either decline the offer or accept the minimum $2,600 and return the excess amounts after signing the contract.

However, borrowers must adhere to the scheduled repayment plan for $2,600, regardless of whether they return part of the loan immediately after origination. This approach only benefits the borrower in terms of reduced accrued interest on the outstanding balance. As such, early prepayment effectively shortens the loan's maturity due to the fixed minimum payment amount required for each period.[9] Appendix Section B illustrates the trade-off of prepayment under a fixed payment schedule. In my study, fewer than ten borrowers choose to immediately return the portion they don't need before the first payment cycle, and most borrowers choose to make prepayments later.

Similarly, if the borrower makes payments less than the required amount, interest will continue to accrue daily until the loan is paid in full. Consequently, borrowers may need to continue making payments beyond the initially scheduled maturity date. At the same time, a payment lower than scheduled could lead to a reduction in FICO scores due to the credit report being sent to the three credit bureaus.

A sample of the final contract offer is illustrated in Figure 2. After loan origination, borrowers receive the contract offer via email, where they can review details, including the lender information, Annual Percentage Rate (APR), finance charge, amount financed, total payment amount, and the corresponding payment plan. The typical payment plan specifies an amount due for each payment before each due date. If borrowers choose to immediately

[9] Changing the repayment plan requires an additional contract with smaller amount in practice, which is illegal for borrowers in the constrained group due to the interest rate regulation in California during the experiment. This type of contract structure is also common for marketplace lending, such as LendingClub.

return the principal, the loan can be paid off on day one. Importantly, there is no pre-payment penalty for paying off the loan early.

During the experiment, because the access to small-dollar loans in the constrained group is enabled by the absence of interest rate regulation associated with Utah state law, it created a perfect RCT for me to study how interest rate caps can impact borrower through their restriction on small-dollar loan access.

B. Sample Selection and Balance Check

I have access to the lender's transaction records for all originated loans in California from 2017 to 2021, with loan outcomes retrieved as of November 8, 2021. Since the experiment was conducted between September 1, 2018, and October 31, 2019, I have at least 24 months of repayment transaction observations following the last day of loan origination within the experiment.

The dataset includes over 35,000 unique customers, approximately 84,000 granted loans, and a total loan amount of about $170 million. However, the experiment specifically resulted in 10,318 unique customers, 14,948 granted loans, and a total granted amount exceeding $40 million, subject to the $4,000 income threshold. The data provides detailed information about borrowers, including verified monthly income, loan amount taken, loan maturity, interest rate, product name, mailing address zip code, and delinquency status.

Due to customer privacy regulations, I cannot collect specific demographic information about households associated with unsecured loan accounts from our FinTech lender. To address this limitation, I used the borrowers' mailing addresses and the ACS 2020 5-year census data to construct demographic information about borrower neighborhoods. While these demographic proxies are noisy, they still offer valuable insights into estimating heterogeneous effects, especially related to the area where they come from.

To construct my final sample, I applied additional filters to focus on borrowers who qualified for maximum loans of $2,600 or more and whose first-time loans originated during the experiment. This approach allows me to compare loan performance among comparable first-time borrowers who were unfamiliar with the products ex-ante in both

groups. The final sample consists of 1,837 observations for first-time borrowers in the constrained group and 3,943 observations for first-time borrowers in the unconstrained group. From this point onward, I refer to first-time borrowers simply as "borrowers" or “households”.

Table 1 presents the balance test for the approved application assignment to two groups to confirm the random assignment in the RCT. The results indicate that the randomization was successful. There is no statistically or economically significant difference in the observables I can examine from our FinTech lender between two groups: monthly income, offer amount and maturity, and borrowers' characteristics based on their mailing address ZIP code. The average applicant has a monthly income of about $6000. The borrowers in the application are more likely to come from areas with a high fraction of Hispanics at 40%, and those areas also have high school graduating rates at 84% but low college graduating rates at 33%. In contrast to CA census data, I find that borrowers in the application are from areas with relatively lower median incomes and a lower percentage of college graduates. As for approved loans, borrowers in both groups are provided with similar offers before loan origination. The average maximum loan amount is about $2800 with determined maturities of about 10 months in both groups. This shows that underwriting algorithms issue comparable contract offers for both groups.

As an additional test, I find that the rate of loan approval and the probability of take-up does not change regarding the assignment in the experiment, as illustrated in Figure 3. Applicants in both groups have a similar rate of about 30% with a loan approval of at least $2,600, and the difference is economically small and insignificant within the 95% confidence interval (Panel A).

Panel B gives the ITT effect measured by loan take-up rate. Conditional on receiving loan offer at least $2,600, borrowers in both groups have almost the same take-up rate. About 80% of applicants choose to take up the loan offer regardless of the assignment, and the difference is economically small and insignificant within 95% confident interval. The consistent high taken up rate between two groups also suggests that

the borrowers may have limited alternative options.[10] This is consistent with Bhutta, Skiba, and Tobacman (2015), where they find that subprime borrowers often shop (unsuccessfully) for traditional credit just before taking out an expensive loan.

Such test is important since high quality borrowers could be more likely to take up a loan when small dollar loan becomes accessible in the unconstrained group. Such sorting could lead to bias in the estimation of the treatment effects. Hence, the consistent high take up rate in both group with respect to the treatment address such concerns.

To compare the borrowers in both groups, summary statistics for borrowers who take loans in the experiment are presented in table 2. We find a substantial selection of loan amounts in the unconstrained group. Compared with the average loan amount of $2,930 in the constrained group, the average loan amount in the unconstrained group is $2,560, and it is smaller than the constrained group by $370 on average. The difference is both economically large and statistically significant. Moreover, the originated loan amount for both group are smaller than the offer amount, which implies that borrowers are more likely to be rational given the high interest rate and they already choose to take small amount in the assigned group. At the same time, the difference in monthly income, offer amount, maturity, sampled bankruptcy flag and sampled vantage score at the individual level and geographic characteristics are both small and insignificant for both groups. The lower FICO score around 560 and high percentage of bankruptcy flag around 20% in both groups is consistent with observation about the high take up rate maybe related to limited credit access from other lenders.

A further comparison between the statistics for approved offers in table 1 and originated loans in table 2 shows that applicants with higher monthly income are more likely to take up loans. And applicants are more likely to withdraw their offers when their approved offers have shorter maturities, though the differences are economically small and

[10] Our FinTech lender also has a referral program customers could sign up for free. The referral program helps customers find more affordable credit options int the market, including those with interest rates lower than 36% from other non-partner lenders. If the consumer qualifies for another product, our FinTech lender helps ensure they have access to better alternatives. However, our FinTech lender found that less than 2% of the customers who participated in the referral program qualified for better alternatives or decided to take the alternatives.

statistically insignificant. And due to the random assignment in two groups, such customer attrition are similar between two groups, which lead to balanced panels for both approved offers and originated loans in two groups.

With comparable borrowers assured by the balance check in the experiment and originated loan data originated for both groups, I am able to study the questions in the following sections.

IV. Results

A. Experiment design

To study whether interest rate caps could cause over-borrowing by restricting small dollar access, I start by measuring the selection of loan amount taken in both groups by collapsing the data based on the month of origination (t) and calculating the fraction of loans N_{kt}(%) for each \$600 loan amount bin (k) level (amount bins measured starting from \$800, e.g., \$800 to \$1,400, \$1,400 to \$2,000, and so on) and compare the fractions between unconstrained group and constrained group for each amount bin. I define a dummy variable T_{kt} equal to one for those loan amount-month pairs in the unconstrained group and zero otherwise. Then, I estimate the following regression:

$$N_{kt} = \beta'_k + \delta'_t + \gamma'_k \beta'_k \times T'_{kt} + \epsilon_{kt} \quad (1)$$

The coefficient of interest is γ'_k, the average percent change in the fraction of loans originated for the eventually selected amounts in the unconstrained group compared with the constrained group. β'_k is the fixed effect of each loan amount bin, and δ'_t is the month of origination fixed effect.

Figure 4 Panel A shows our estimates of the coefficient γ'_k with robust standard errors. The coefficient γ'_{2600} is -38.37 with a standard error of 3.49, and it indicates that there are about 38% fewer borrowers who choose to take the loan at an amount between \$2,600 and \$3,200 in the unconstrained group compared with those from the constrained group. At the same time, γ'_{800}, γ'_{1400} and γ'_{2000} are positive and statistically significant at 9.36 (SE=0.94), 16.62 (SE=1.31), and 13.36 (SE=1.06). It implies that there are

increasing fractions of borrowers who choose to take smaller loans below $2600 because of the access in the unconstrained group.

In contrast, γ'_{3200} and γ'_{3800} are 0.40 (SE=1.97) and -1.38 (SE=1.97), which are both economically small and statistically insignificant. It suggests that borrowers who take loans above $3,200 are less likely to change their decision regardless of the smaller loan access. These results further serve as the placebo test that reinforces our observations that borrowers are rational and prefer to take small loans already, so additional access to the small-dollar loans below $2,600 could influence the borrowers who take loans above the threshold.

A more straightforward unconditional distribution can be seen in Figure 4 Panel B. Some borrowers are taking smaller loans between $800 and $2,600 instead of bunching between $2,600 and $3,200 in the unconstrained group compared with the constrained group.

By the revealed preference argument, the selection into small-dollar loans in the unconstrained group suggests that borrowers could overborrow when the desired amount is not in the available range. Moreover, such a preference could also be seen in the constrained group, given the taken loan amount bunching by the $2,600, where many borrowers qualified for loans above $2,600 still prefer to take loans at the minimum level in the constrained group. Together, they suggest that the interest rate caps could cause overborrowing when they limit the availability of small-dollar loans.

B. Selection and Repayment

Having shown that interest rate caps could cause overborrowing and borrowers choose to take small-dollar loans when it is available, I further ran a test to uncover the quality of the self-selected borrowers by comparing the probabilities of default in both groups for borrowers who take loans, including and above $2600. I estimate the regression with the following specifications:

$$Default_i = \beta_i^k + \delta_i^t + \delta_i^z + \gamma'_k \beta_i^k \times T_i + X_i + \epsilon_i \quad (2)$$

The coefficient of interest γ'_k measures the change of the default rate on average at the loan amount bin (k) level in the unconstrained group compared with the constrained group. I include a granular month of origination fixed effect δ_i^t and ZIP code fixed effect δ_i^z to control for regional risk and time of origination. I also include a vector of control variables observable at origination, X_i. In my baseline specification, X_i includes monthly income for the risk associated with the borrower i's ability to repay.

Riskier borrowers are self-selected to get smaller loans when it is available in the unconstrained. This is particularly true if the loan amount is close to the minimum lending limit. Panel A of Figure 4 shows the estimates of the coefficient γ'_k. The coefficient γ_{2600} is -0.08 (SE=0.02), which implies that the average probability of default in the unconstrained group for the borrowers taking loans between $2,600 and $3,200 is smaller than those from the constrained group by 8% with a standard error equals 0.02. However, the difference is economically small and statistically insignificant for other loan size category γ_{3200} and γ_{3800}, which consistent with previous observations that borrowers are rational and the access to small-dollar loans has limited effect on borrowers who takes loans above the $2,600 threshold.

The lower probability of default in the unconstrained group indicates that higher default rates are typically associated with borrowers who are compelled to secure loans between $2,600 and $3,200 when access to smaller loans is unavailable.

A similar pattern could be seen in Panel B of Figure 4 for rollover default. The coefficient γ_{2600} is -0.08 (SE=0.02), which implies that the average probability of rollover default in the unconstrained group for borrowers taking loans between $2600 and $3200 is smaller than those from the constrained group by 8% with a standard error 0.02. And the difference is economically small and statistically insignificant for γ_{3200} and γ_{3800} where loans are originated at preferred levels. This suggests that the borrower's default probability is less likely to be driven by the availability of refinance in the unconstrained group after taking smaller loans.

The result suggests that borrowers who are overborrowing due to the interest rate caps on small-dollar loans are typically associated with borrowers under greater stress and frequently choose to default when overborrowing.

C. Treatment effect of small-dollar loan access

To further progress and establish causal relationships, I use the random assignment to the unconstrained group as an instrumental variable to identify the impact of interest rate caps on borrowers' default decisions through small-dollar loans. More specifically, I estimate the following regression:

$$I[size < \$2600]_i = \gamma T_i + X_i + \delta_i^t + \delta_i^z + \epsilon_i \quad (3)$$

$$Default_i = \beta^{IV} I[size < \$2600]_i + X_i + \delta_i^t + \delta_i^z + \epsilon_i \quad (4)$$

Where T_i is a dummy variable for the borrower i with one if the borrower is assigned to the unconstrained group, and $I[size < \$2600]_i$ is a dummy variable 1 for the borrower i chooses to take a loan of less than \$2,600, and 0 otherwise. I include the month of origination fixed effect δ_i^t , and ZIP code fixed effect δ_i^z to control for risk over time and other sources of heterogeneity in some specifications. I also include monthly income to control the risk associated with the borrower i's ability to repay.

The coefficient of interest β^{IV} measures the impact of accessing a loan below \$2600 on the borrower's probability of default in the unconstrained group compared to the borrowers in the constrained group. A significant and negative β^{IV} implies that borrowers who take small-dollar loans choose to default less.

Table 3, columns 1 reports result of equation (3), the first stage regression in 2SLS. The point estimate γ is negative and significant, confirming the previous findings about selection, and about 40% of borrowers in the unconstrained group choose to take loans below \$2,600 when it is accessible.

Table 3, columns 2-3 report the OLS estimates of equation (4) and I find negative and significant estimates for β as -11% and -12% for default and rollover default, indicating that borrowers in the unconstrained group have about 11% to 12% lower probability of default compared with these from the constrained group.

Table 3, columns 4-5 report the 2SLS results, and I find even bigger effects of small dollar loan access at -28% and -31% for default and rollover defaults. It implies that borrowers who typically benefit from the small dollar loan access are these 40% of borrowers in the unconstrained group who choose to take small dollar loans.

The results show that the absence of interest rate caps could indeed contribute to decreasing borrower's financial stress through the small dollar loan access since there are borrowers in the unconstrained group choose to take smaller loans and they typically benefit in terms of lower financial stress measured by the lower probability of default.

D. Heterogeneous Effect Using Machine Learning

In this section, I further follow the method from Bryan, Karlan, and Osman (2024) and investigate the heterogeneous effects of access to small-dollar loans using the machine learning approach proposed by Chernozhukov et al. (2020) (CDDF). This method enables the detection of significant heterogeneity in treatment effects based on observable factors and helps determine the effects across different subgroups. Ultimately, it allows me to describe which covariates are most associated with this heterogeneity.

To estimate heterogeneity in the treatment effect, we first split the sample into a "training set" and a "testing set." Throughout, we use 50/50 splits. Using the training set only, we train a machine learning (ML) method to generate a "control" effect $\mathrm{B}(Z_i)$ (i.e., the expected outcome for firms with covariates Z if they were assigned to control) and predicted treatment effect $S(Z_i)$, where Z_i denotes the full set of covariates used to predict heterogeneity for the subject i. In my study, I include both individual monthly income and Zipcode Characteristic illustrated in table 1.

With the estimates $\mathrm{B}(Z_i)$ and $S(Z_i)$ in hand, we then undertake two analyses using the testing set. First, we estimate the regression:

$$Y_i = \alpha \times X_i + \beta_1 \times T_i + \beta_2 \times T_i \times S(Z_i) + \epsilon_i \quad (5)$$

where X_i is a set of covariates that includes $\mathrm{B}(Z_i)$ and T_i is an indicator for the treatment group. Our primary use for this specification is to test the null hypothesis of no

heterogeneity $\beta_2 = 0$.[11] Second, we split the testing sample into quartiles of predicted treatment effect using $S(Z_i)$ and estimate the regression:

$$Y_i = \alpha \times X_i + \sum_{j=1}^{4} \gamma_j \times T_i \times 1(S_i \in I_j) + \eta_i \quad (6)$$

where I_j is the set of loans in the jth quartile. γ_j measures the "sorted group average treatment effect" (GATES) for each quartile and is the key measure that we use to understand how treatment effects differ across well-defined groups.

The heterogeneous effect of small-dollar loan access is illustrated in Table 4, column 2. The Panel A column 2 shows the heterogeneous effect on default. We fail to reject the hypothesis $\beta_2 = 0$. However, Panel B column 2 shows a stronger heterogeneous effect on rollover default given $\beta_2 = 0.43$ (SE=0.30). And based on the GATES in Panel B, the rollover default for the most affected quantile (γ_1) is less than that for the least effected quantile (γ_4) by 0.11 (SE=0.07). It suggests that some of the heterogeneous effect of treatment is later realized due to the option to refinance.

To better characterize the individuals who benefit the most from access to the small dollar loans, I further compare the baseline characteristics of the most affected quantile and the least affected quantile. The characteristics of the most affected quantile and the difference between the most affected quantile and the least affected quantile for different characteristics are listed in Panel C and Panel D for both default and rollover default.

It turns out that borrowers who benefit the most from the small dollar loan access are individuals with lower monthly income and those from regions with lower medium income, lower housing prices, more people under the poverty line, more Hispanic population, and less educational attachment (with higher or college degree). It is consistent with areas associated with the demographics of financially fragile populations.[12]

[11] $\beta_2 = 0$ is a joint test for whether no heterogeneity or the ML prediction $S(Z_i)$ does not capture that heterogeneity.

[12] Hasler, Lusardi, and Oggero (2018) shows that financially fragile population are mainly associated with lower income (typically at income levels below the $50,000 mark), lower the education attainment, minority ethnicity, and unemployment status.

In summary, we find heterogeneous effects are typically stronger for rollover default, and borrowers with lower monthly incomes and coming from regions with high financial fragility typically benefit from the access to small dollar loans in the unconstrained group. This suggests that an interest rate cap causes financial stress for borrowers who could be better off without it.

E. Impact on Loan Return

This section addresses the costs of interest rate caps on small-dollar loan access for Fintech lenders. Though lenders benefit from better overall loan performance, small-dollar loans could be less profitable overall due to the fixed origination cost. Hence, the impact on loan profitability is ambiguous.

To estimate the net return on loans originated in the experiment, we made two assumptions. First, we assume the cost of capital is about 20% per year. Our Fintech lender was a private company that relied mainly on its investors to finance and lend during the experiment. We used the APR for fair credit borrowers from LendingClub on Jan 8, 2019, as the base required rate of return for capital from private investors.

Second, I assume the lending cost is $75 per loan, which is comparable to the cost of origination, including underwriting, servicing, reporting to the credit bureau, and collection in delinquency. We calculate the return on loans by discounting all payments made on these loans (including the cost of lending) back to the origination date and dividing the result by the original loan amount.

Figure 7 illustrates the distribution returns for loans in two groups. In Panel A, the return for loans ending with default increases in the group with access to small-dollar loans. Similarly, for roller default loans in Panel B, we find the increasing rate of return for loans in the group with small-dollar loan access. This suggests that the advantageous selection of risky borrowers for small-dollar loan access improves the rate of return for a loan that either ends in default or defaults after refinance. At the same time, we find the increasing rate of return for payoff loans in Panel C, which implies that access to small-dollar loans also improves the net returns for payoff loans.

To better understand the reason for the increasing rate of return, we compare the returns of loans originated in both groups with the results presented in Table 5. Column 1 shows that the average return in the group with access to small-dollar loans is 26% higher than in the other group. Columns 2 and 3 reveal that this difference is primarily driven by loans below $3,000 in both groups, and the rate of return is increasing by 40% in the unconstrained group. Repeating the IV regressions in 4, access to small-dollar loans increases the average loan return by 73%, suggesting that the improved performance of small-dollar loans compensates for the more significant loan amounts that originated in the group without small-dollar access.

In summary, small-dollar loans also contribute to an increasing rate of return on loans, which benefits the lender. This is particularly noteworthy given that the return calculation already incorporates a one-time lending cost of $75 for each loan origination.

V. Interpretation

So far, my empirical results indicate that borrowers who prefer small-dollar loans are associated with high default risk. This revealed preference suggests the presence of unobserved information influencing risky borrowers' decision-making. In this section, we explore the nature of this unobserved information.

In theory, borrowers could reduce loan sizes through immediate prepayment. However, this is challenging for the constrained group in practice. Their repayment contracts impose fixed payment amounts that remain unchanged regardless of prepayments. In contrast, borrowers in the unconstrained group who take small-dollar loans have greater flexibility. As a result, the over-borrowing in the constrained group may lead to heightened financial stress over time, further increasing their incentive to delay prepayment over time.

To investigate this interpretation, I track the timing of first-time prepayments and missed payments for borrowers with loans over $2,600 in both groups. Differences in prepayment and delinquency behaviors provide a clearer understanding of the decision-making processes of borrowers holding large loans without access to small-dollar loans.

Figure 8 illustrates the first-time prepayment behavior of borrowers with loans over $2,600 in both groups, categorized by maturities of 9 months (Panel A), 12 months (Panel B), and 15 months (Panel C). The plots show that constrained borrowers with larger loans increasingly make prepayments over time across all maturities. This suggests that, rather than prepaying immediately, they tend to do so later, indicating that their prepayment constraints are gradually resolved.

Similarly, Figure 9 presents the first-time missed payment behavior of borrowers with loans over $2,600 in both groups, categorized by maturities of 9 months (Panel A), 12 months (Panel B), and 15 months (Panel C). The plots indicate that constrained borrowers with larger loans face an increasing probability of missing payments over time, suggesting cumulative financial stress.

The increasing likelihood of both first-time prepayments and missed payments within the constrained group indicates that borrowers encounter diminishing prepayment constraints over time, yet simultaneously endure escalating financial stress due to the costs associated with deferred prepayments. This duality may further incentivize borrowers to retain surplus loan amounts rather than opting for immediate prepayments, especially considering the relatively substantial fixed payment obligations characteristic of the constrained group. Consequently, the propensity for borrowers to select small-dollar loans may be indicative of underlying, unobserved prepayment constraints.

Collectively, these findings imply that interest rate caps may exacerbate financial stress among borrowers by limiting their capacity to balance immediate liquidity needs against the costs of postponed prepayments, particularly since the advantageous repayment structures associated with small-dollar loans are not replicable. This issue is especially pertinent in the context of this study, as borrowers with low monthly incomes often experience significant income volatility and negative financial shocks (Farrell, Greig, & Yu, 2019), and the interest rate caps that limit small-dollar loan access could make borrowers worse off both due to mistakes and misfortune (Carvalho, Olafsson and Silverman 2024).

It is important to acknowledge that multiple mechanisms may concurrently influence these outcomes, and a comprehensive analysis of these underlying factors extends beyond the scope of this paper. Future research endeavors would benefit from a more detailed examination of these potential mechanisms to enhance our understanding of the interplay between interest rate regulations and borrower financial well-being.

A. Precautionary Motive

More credit-constrained Borrowers typically have limited liquidity and more incentive to save. This could explain why borrowers still choose to borrow when small-dollar loans are unavailable in the constrained group, especially when the APR is high and above 100%.

The prefixed payment schedule in the contract from the constrained group imposes a trade-off between a significant decrease in savings and fewer future payments. Addressing this could be challenging when facing lower-income and large-income volatility associated with adverse shocks. Therefore, keeping the money in the savings account until the uncertainty is resolved in the future can be a dominating solution. Present Bias

This observation is not unique; it can be traced back to findings about the "credit card debt puzzle." Gross and Souleles (2002) found that some households hold high-interest credit card debt and low-return liquid savings that could be used to pay down those debts. Many follow-up works interpret such findings favorably as related to the precautionary motive (Fulford 2015; Gorbachev and Luengo-Prado 2019; Cohen-Cole and Morse 2010; Cohen-Cole and Morse 2010; Telyukova 2013).

In this case, the selection into the small-dollar loan in the unconstrained group can serve as a screen device to distinguish borrowers with high precautionary motives when taking larger loans.

B. Present Bias

Because saving data is unavailable in this study, I cannot explore how borrowers relocate their savings. Therefore, borrowers could also choose to consume excess credit

because of the immediate gratification. This could be typically true, given that borrowers in my study are from areas associated with lower education attainment.

Kuchler and Pagel (2021) show that present bias typically fails to stick to self-set debt paydown plans. In this case, borrowers could suboptimally delay their immediate prepayment and fail to stick to their payment plan later.

The selection of these borrowers for small-dollar loans in the unconstrained group also suggests that they are sophisticated, present-biased borrowers who prefer to take smaller loans to stay thrifty (O'Donoghue and Rabin, 1999). Hence, small-dollar loan access could serve as a discipline device to alleviate borrowers' immediate gratification.

C. Financial Stress

Carrell and Zinman (2014) show that expensive loans could impact borrowers' work performance using Military Personnel data. This implies that borrowers in my study could experience declines in work performance due to the high interest rate charged by Fintech lenders. Kaur et al. (2025) also find a similar pattern in India, where liquidity constraints could also impact workers' productivity, and alleviating liquidity constraints and financial concerns could improve their outputs. Then, in my study, restricting small-dollar loan access in the constrained group can expose borrowers to work performance deterioration because of the financial concerns associated with more considerable loan amounts and the demanding repayment schedule.

Therefore, borrowers could apply the unused portion of the loan to the payment and only start making prepayments when the outstanding balance decreases or positive income shocks arrive, which could contribute to fewer financial concerns.

In this case, selection into small dollar loans is a crucial way to avoid the more significant negative impact on work performance induced by financial concerns.

VI. Conclusion

In this paper, I use an RCT conducted by a fintech in California, together with its bank partner from Utah, to study the impact of interest rate caps on borrowers' financial stress through the potential restriction on small dollar loan access.

In the US, anti-usury laws at the state level frequently apply interest rate caps to small dollar loans in the personal loan market. On the one hand, these laws could prevent lenders from abusing market power in loan pricing and protect consumers from exploitation arising from borrowers' behavioral biases. On the other hand, these laws restrict small-dollar loan access for borrowers since many lenders find it unprofitable to serve in that market and choose to exit.

My study shows that interest rate caps on small-dollar loans could cause borrowers to overborrow from larger and unregulated amounts and thereby expose them to more significant financial stress. The access to the small dollar loans in the absence of interest rate caps would typically benefit borrowers with lower monthly incomes and those from areas characterized by high financial fragility populations.

My further analysis of the borrowers' prepayment and missing payment behaviors over time suggests that borrowers can't replicate the repayment schedule associated with small dollar loans from unregulated larger loans by immediately returning the unused portion in prepayment. Instead, borrowers choose to delay their prepayments and are simultaneously exposed to greater financial stress due to a longer payment period with the more considerable payment amount due.

These results shed new light on the role of small dollar loans access, which is less studied in the previous study about interest rate regulation and intervention that could contribute to less default ax-ante. This justifies the ongoing efforts for regulators to improve interest rate regulation and to advocate for better policy.

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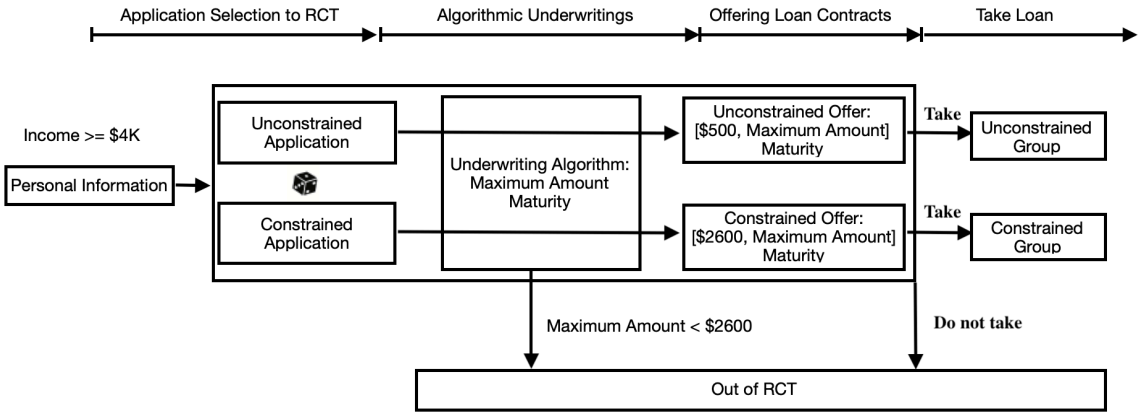
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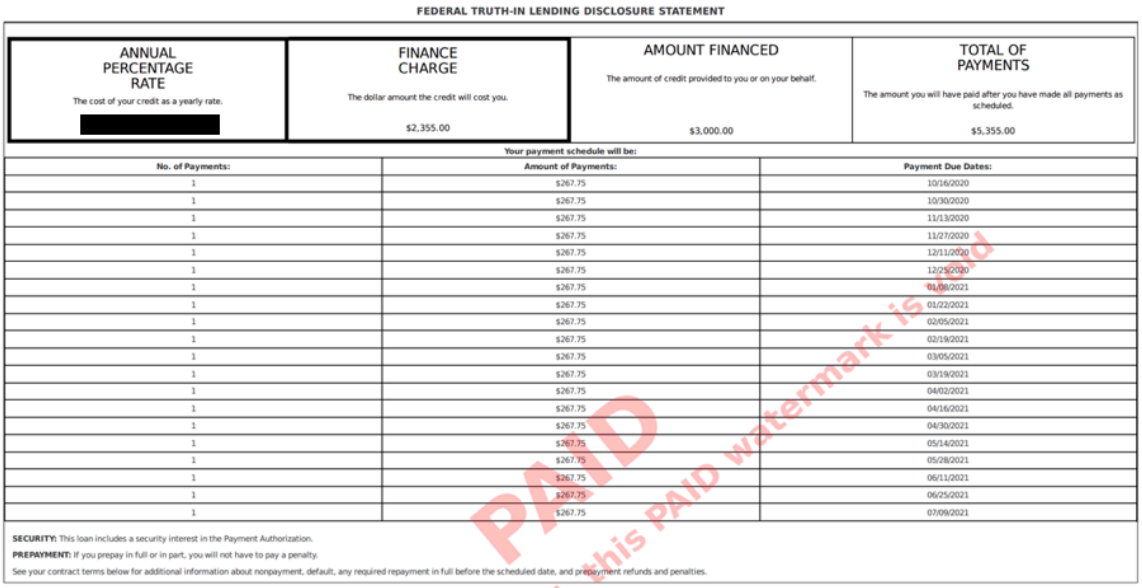
Figures

Figure 1: Experimental Design



Note: The random assignment process consists of four steps. The first step involves collecting bank transactions, verifying income, making soft credit inquiries from borrowers, and selecting borrowers based on a verified monthly income threshold of $4,000 into the RCT. The second step is the randomized assignment of applications to either an unconstrained or constrained group for underwriting. A shared underwriting algorithm, approved by the bank partner, determines the maximum amount of loan and maturity approved for both groups, except for the minimum amount in the unconstrained group. Therefore, applications with an approved maximum amount below $2600 in the unconstrained group are dropped from the RCT. The third step is the loan offers rendered to the borrowers associated with either unconstrained or constrained groups. Borrowers can't negotiate maturity and can only choose from the range of loans approved for each group; more specifically, borrowers in the unconstrained group can choose a loan from the range [$500, Maximum Amount], and borrowers from the constrained group can choose a loan only from the range [$2600, Maximum Amount]. Borrowers who accepted loan offers will be selected as borrowers in my study.

Figure 2: The Loan Offer Contract



FEDERAL TRUTH-IN LENDING DISCLOSURE STATEMENT

ANNUAL PERCENTAGE RATE	FINANCE CHARGE	AMOUNT FINANCED	TOTAL OF PAYMENTS
The cost of your credit as a yearly rate.	The dollar amount the credit will cost you.	The amount of credit provided to you or on your behalf.	The amount you will have paid after you have made all payments as scheduled.
[redacted]	$2,355.00	$3,000.00	$5,355.00

Your payment schedule will be:

No. of Payments:	Amount of Payments:	Payment Due Dates:
1	$267.75	10/16/2020
1	$267.75	10/30/2020
1	$267.75	11/13/2020
1	$267.75	11/27/2020
1	$267.75	12/11/2020
1	$267.75	12/25/2020
1	$267.75	01/08/2021
1	$267.75	01/22/2021
1	$267.75	02/05/2021
1	$267.75	02/19/2021
1	$267.75	03/05/2021
1	$267.75	03/19/2021
1	$267.75	04/02/2021
1	$267.75	04/16/2021
1	$267.75	04/30/2021
1	$267.75	05/14/2021
1	$267.75	05/28/2021
1	$267.75	06/11/2021
1	$267.75	06/25/2021
1	$267.75	07/09/2021

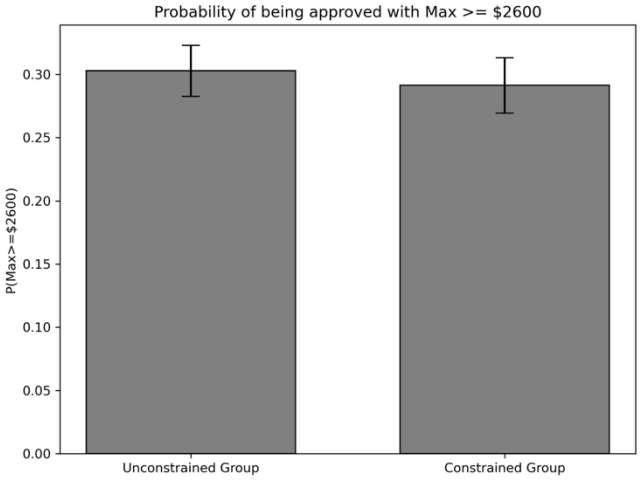
SECURITY: This loan includes a security interest in the Payment Authorization.
PREPAYMENT: If you prepay in full or in part, you will not have to pay a penalty.
See your contract terms below for additional information about nonpayment, default, any required repayment in full before the scheduled date, and prepayment refunds and penalties.

PAID
This PAID watermark is fake!

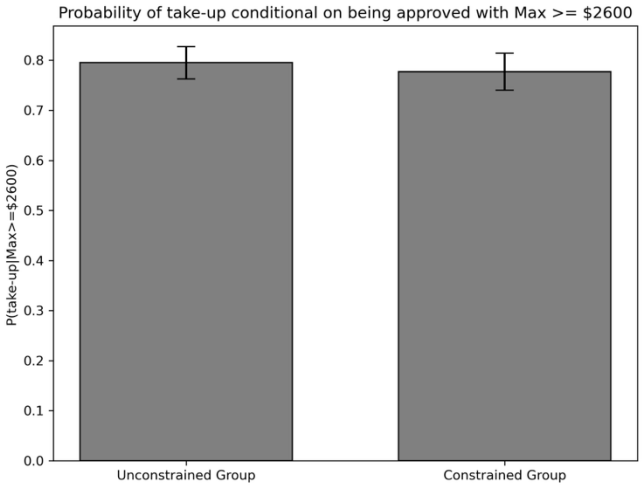
Note: After the loan origination, borrowers will receive a contract offer through email, and they will be able to learn about the offer's details, including information about the lender, Annual Percentage Rate (APR), financial charge based on the APR, amount financed, total payments and number of payments with amounts and each due date.

Figure 3: Approval and take-up Rate

Panel A: Application Approval Rate



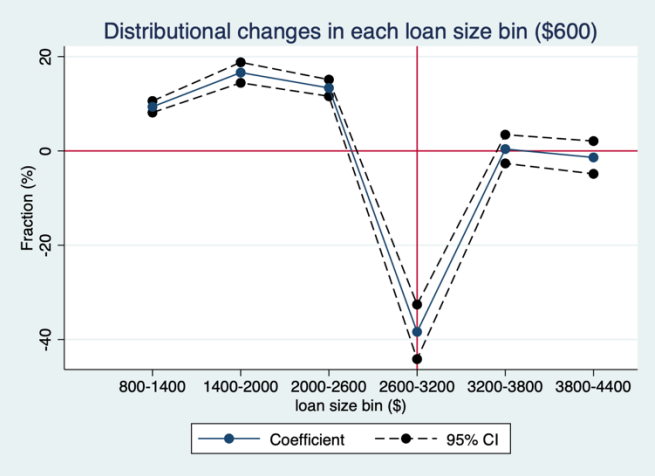
Panel B: Loan Take-up Rate



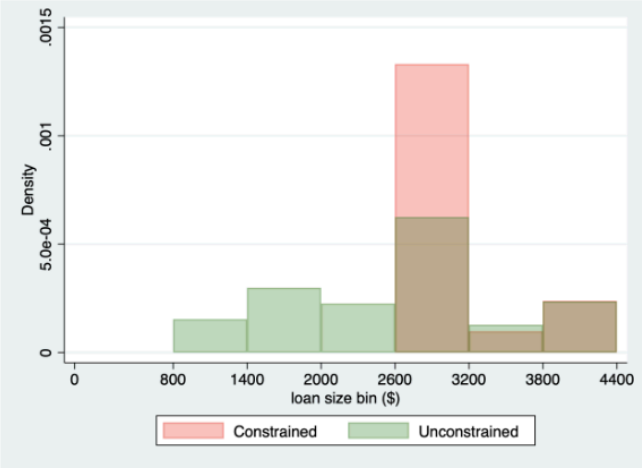
Note: This figure presents the application approval rate with the offer $max_i >= \$2600$ for the applicant i (Panel A) and the loan take-up rate conditional on being approved $max_i >= \$2600$ for the applicant i (Panel B). Each bar plots the mean outcomes among borrowers in each group along with 95% confidence intervals.

Figure 4: The selection of loan amount in both groups

Panel A: Estimation of the coefficient γ'_k with 95% Confident Interval



Panel B: Unconditional distribution of originated loan amount in the experiment



Note: Panel A shows the estimates of the coefficients from the equation:

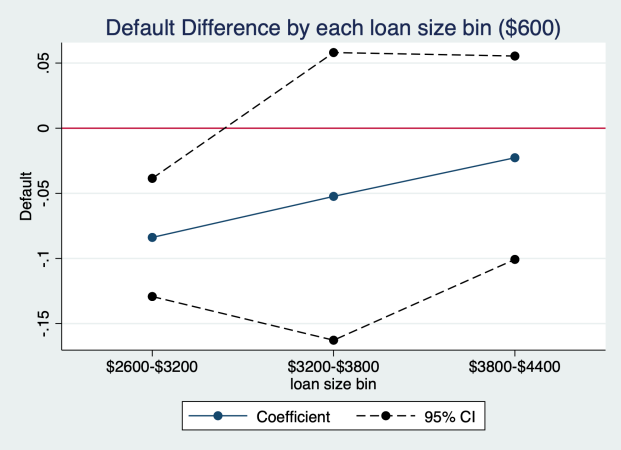
$$N_{kt} = \beta'_k + \delta'_t + \gamma'_k \beta'_k \times T'_{kt} + \epsilon_{kt} \quad (1)$$

Where γ'_k is the average change in the fraction (%) for each loan at the loan amount bin (k) level in the unconstrained group compared with the constrained group.

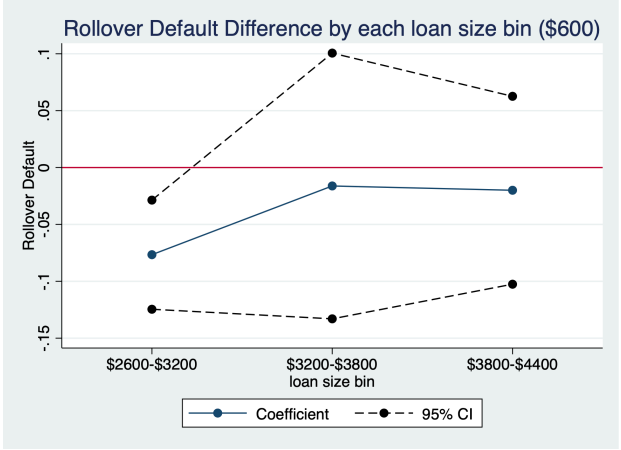
Panel B illustrates the distribution of loans originating at each $600 binned amount starting from $800 between the two groups.

Figure 5: The selection of loan amount in both groups

Panel A: Risk distribution change by group



Panel B: Rollover risk distribution change by group

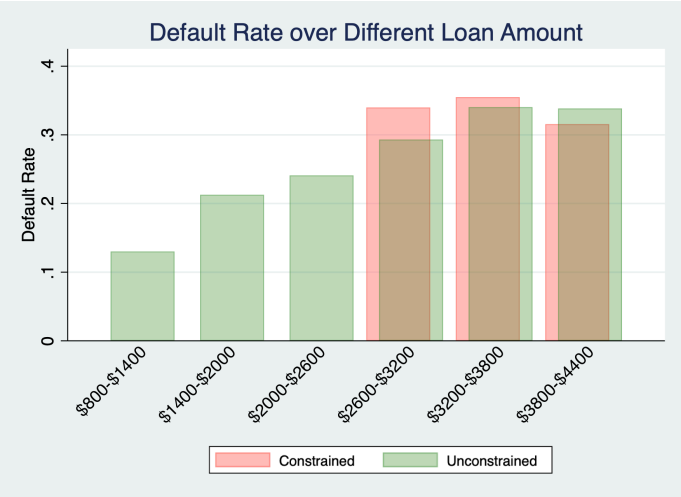


Note: The figure shows the estimates of the coefficients γ'_k from

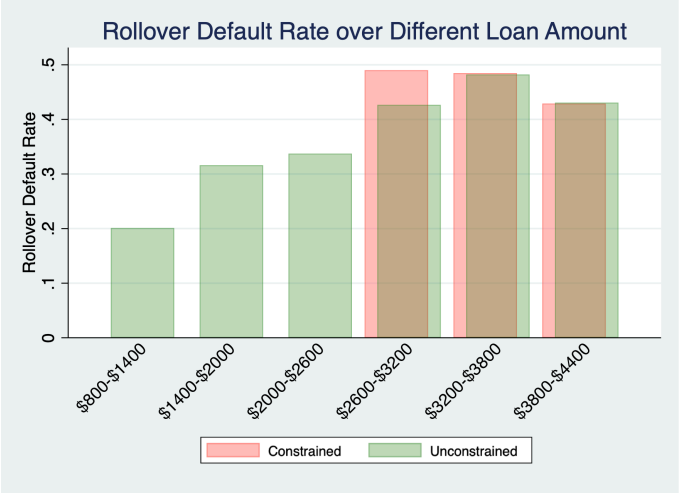
$$Default_i = \beta_i^k + \delta_i^t + \delta_i^z + \gamma'_k \beta_i^k \times T_i + X_i + \epsilon_i \quad (2)$$

The coefficient of interest γ'_k measures the change of the default rate for each loan at the loan amount bin (k) level in the unconstrained group compared with the constrained group. Both first-time default (Panel A) and rollover default (Panel B) are provided.

Figure 6: Distribution of default



Panel A: Distribution of default

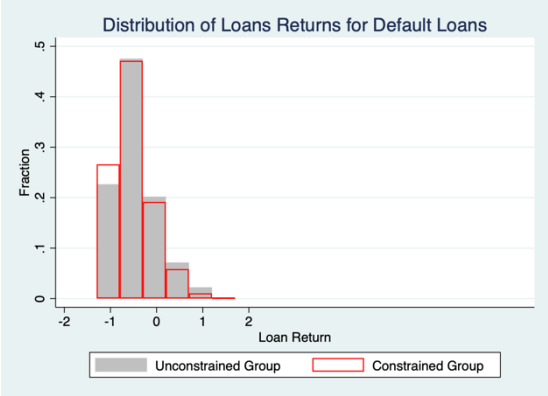


Panel B: Distribution of rollover default

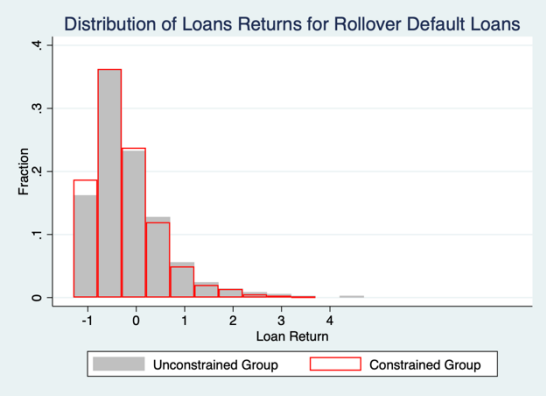
Note: Panel A shows the unconditional probability of defaults for borrowers taken at each loan amount bin for both constrained and unconstrained groups. Panel B shows the unconditional probability of rollover defaults for borrowers taken at each loan amount bin for both constrained and unconstrained groups.

Figure 7: Distribution of Net Returns for Loan in both groups

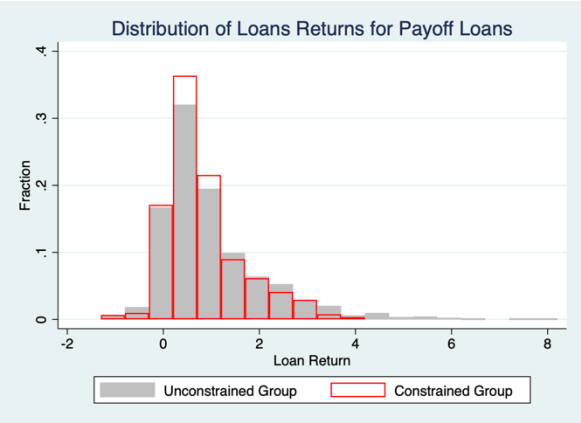
Panel A: Default Loans



Panel B: Rollover Default Loans



Panel C: Payoff Loans



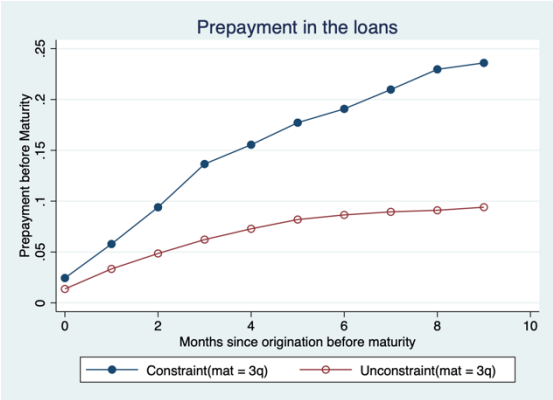
Note: The fixed cost of lending for each loan is 75$ based on the report from the fintech lender, and the required rate of capital from private investors is 20% based on the 2018 require rate of return for loans lend to borrowers with fair FICO score on LendingClub. I first discount all future repayments to the origination date with a 20% APR and define the rate of return as follows:

$$Rate\ of\ Return_i = \frac{Total\ Discounted\ Payment_i - \$75 - amount_i}{amount_i}$$

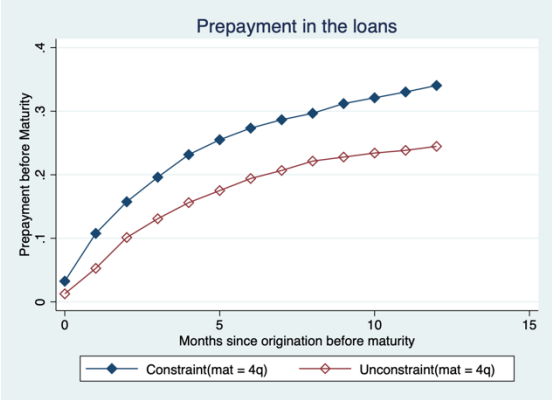
Panel A shows the distribution of the rate of return for loans ending in default, Panel B shows the distribution of the rate of return for loans ending in rollover default, and Panel C shows the distribution of the rate of return for loans ending in payoff. The overall loan rate of return is increasing for borrower's access to the small-dollar loans in the unconstrained group.

Figure 8: First-time Prepayment in both groups for loans above $2600

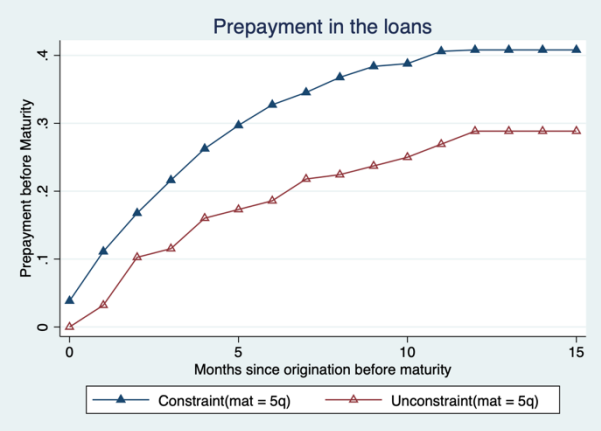
Panel A: Loans with 9 months maturity



Panel B: Loans with 12 months maturity



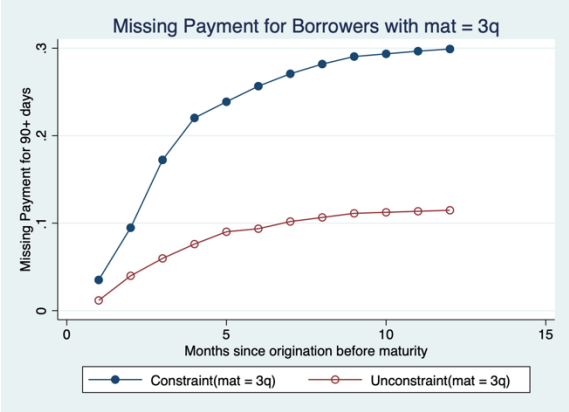
Panel C: Loans with 15 months maturity



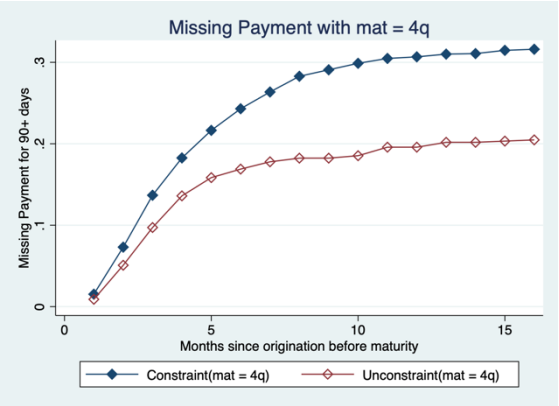
Note: In my study, most borrowers have maturity of up to 9 months, 12 months, and 15 months. So, I plot the cumulative probability of first-time prepayment for the borrowers with this maturity. Panel A shows the cumulative probability of first-time prepayment for borrowers with 9 months of maturity. Panel B shows borrowers' cumulative probability of first-time prepayment with 12 months of maturity. Panel C shows borrowers' cumulative probability of first-time prepayment with 15 months of maturity. So, it suggests that borrowers in the constrained group can't manufacture small-dollar loans by making prepayments immediately, and they can make prepayments later.

Figure 9: First-time missing Payment in both groups for loans above $2600

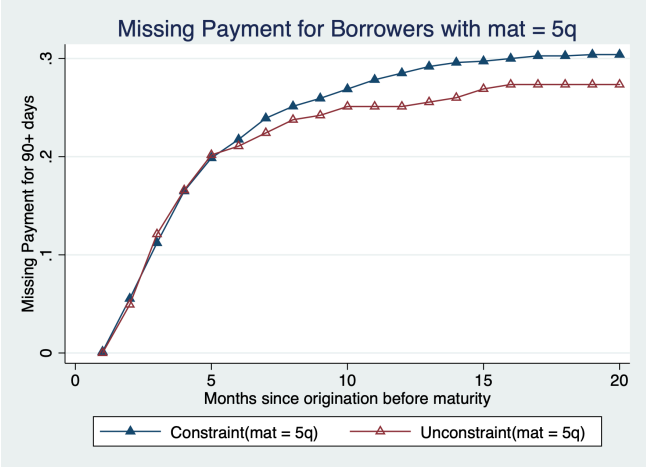
Panel A: Loans with 9 months maturity



Panel B: Loans with 12 months maturity



Panel C: Loans with 15 months maturity



Note: In my study, most borrowers have maturity of up to 9 months, 12 months, and 15 months. So, I plot the cumulative probability of first-time missing repayment for the borrowers with this maturity. Panel A shows the cumulative probability of first-time missing repayment for borrowers with 9 months of maturity. Panel B shows borrowers' cumulative probability of first-time missing repayment with 12 months of maturity. Panel C shows borrowers' cumulative probability of first-time missing repayment with 15 months of maturity. So, it suggests that borrowers in the constrained group can be exposed to greater financial stress over time.

Table 1: Summary Statistics for Offered Loan

	Mean	SD	Mean	SD	*P-value*	CA
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Individual Characteristic					
	Constrained		Unconstrained		(1)=(3)	
Monthly Income ($1000)	5.97	2.64	6.10	2.58	0.06	
Offer Amount ($1000)	3.15	0.64	3.12	0.66	0.36	
Maturity (month)	10.1	2.72	10.0	2.70	0.16	
	Panel B: ZipCode Characteristic					
Median Income ($1000)	82.00	27.73	82.66	28.93	0.37	84.10
Med Value of Housing ($M)	0.57	0.29	0.58	0.29	0.18	0.57
Unemployment Rate (%)	4.22	1.70	4.22	1.70	0.83	4.30
Persons Below Poverty Line	0.12	0.06	0.12	0.06	0.50	0.12
Hispanic	0.40	0.22	0.40	0.22	0.73	0.40
Black	0.07	0.08	0.07	0.08	0.34	0.07
Asian	0.14	0.14	0.15	0.14	0.17	0.16
Foreign-Born Population	0.26	0.11	0.26	0.11	0.30	0.27
High School Grad or Higher	0.84	0.11	0.84	0.11	0.31	0.84
College Grad or High	0.32	0.17	0.33	0.17	0.19	0.35
N	4000+		2000+			

Note: This table shows characteristics for borrowers associated with the loan offers generated in the third step of the RCT. These borrowers include both those who took the loans and those who didn't. Panel A provides the individual-level characteristics, and Panel B provides the zip code characteristics for the area where borrowers come from.

Table 2: Summary Statistics for Originated Loan

	Mean	SD	Mean	SD	*P-value*
	(1)	(2)	(3)	(4)	(5)
	Panel A: Individual Characteristic				
	Constrained		Unconstrained		(1)=(3)
Monthly Income ($1000)	6.46	4.00	6.42	2.99	0.71
Offer Amount ($1000)	3.46	0.66	3.49	0.70	0.12
Loan Amount ($1000)	2.93	0.49	2.56	0.91	0.00
Maturity (month)	11.32	2.28	11.30	2.51	0.79
Bankruptcy Flag (sampled)	0.15	0.36	0.19	0.40	0.24
Vantage FICO (sampled)	559	53	564	53	0.29
Default	0.34	0.47	0.27	0.44	0.00
Rollover Default	0.48	0.50	0.38	0.49	0.00
	Panel B: Zipcode Characteristic				
Median Income ($1000)	83.72	27.65	83.73	27.75	0.42
Med Value of Housing ($M)	0.58	0.28	0.57	0.30	0.20
Unemployment Rate (%)	4.12	1.60	4.12	1.60	0.65
Persons Below Poverty Line	0.12	0.06	0.12	0.06	0.31
Hispanic	0.38	0.21	0.39	0.22	0.15
Black	0.07	0.08	0.07	0.09	0.57
Asian	0.15	0.14	0.15	0.15	0.13
Foreign-Born Population	0.26	0.11	0.26	0.12	0.36
High School Grad or Higher	0.84	0.10	0.84	0.10	0.18
College Grad or High	0.33	0.17	0.33	0.17	0.84
N	3943		1837		

Note: This table shows characteristics for borrowers associated with loans originated in the RCT. These borrowers only include those who took the loans. Panel A provides the individual-level characteristics, and Panel B provides the zip code characteristics for the area where borrowers come from.

Table 3: Main Regression

	I[Size<$2600]	Default (OLS)	Rollover Default (OLS)	Default (OLS)	Rollover Default (OLS)
	(1)	(2)	(3)	(4)	(5)
Unconstrained	0.38***	-0.11***	-0.12***		
	(0.01)	(0.02)	(0.02)		
I[Size<$2600]				-0.28***	-0.31***
				(0.04)	(0.05)
Log(Income)	Y	Y	Y	Y	Y
Zipcode FE	Y	Y	Y	Y	Y
MonthYear FE	Y	Y	Y	Y	Y
N	5366	5366	5366	5366	5366

Standard errors in parentheses, *,**,*** represent significance at the 10%, 5% and 1% level, respectively

Note: The table shows estimates for the regression as following:

$$I[size < \$2600]_i = \gamma T_i + X_i + \delta_i^t + \delta_i^z + \epsilon_i \quad (3)$$

$$Default_i = \beta^{IV} I[size < \$2600]_i + X_i + \delta_i^t + \delta_i^z + \epsilon_i \quad (4)$$

Where T_i is a dummy variable for the borrower i with one if the borrower is assigned to the unconstrained group, and $I[size < \$2600]_i$ is a dummy variable 1 for the borrower i chooses to take a loan of less than $2,600, and 0 otherwise. I include the month of origination fixed effect δ_i^t , and ZIP code fixed effect δ_i^z to control for risk over time and other sources of heterogeneity in some specifications. I also include monthly income to control the risk associated with the borrower i's ability to repay.

Table 4: Heterogeneous Effect of Small Dollar Loan Access

	β_1 (ATE)	β_2 (HETERGENEITY)	Group Average Treatment Effects (GATES)			
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A			
Default	-0.11***	0.13	-0.12***	-0.12***	-0.11**	-0.09**
	(0.03)	(0.32)	(0.05)	(0.06)	(0.05)	(0.05)
			Panel B			
Rollover Default	-0.10***	0.43*	-0.14***	-0.12**	-0.09**	-0.04
	(0.03)	(0.30)	(0.06)	(0.06)	(0.05)	(0.05)

Panel C			Panel D		
Default	Bottom GATES GROUP Mean	Difference in Top Group Coef (SE)	Rollover Default	Bottom GATES GROUP Mean	Difference in Top Group Coef (SE)
Monthly Income	6.26	0.42** (0.26)	Monthly Income	6.11	0.82*** (0.24)
Median Income ($1000)	79.29	7.15*** (1.97)	Median Income ($1000)	81.98	5.94*** (2.02)
Med Value of Housing ($M)	0.56	0.07*** (0.02)	Med Value of Housing ($M)	0.56	0.08*** (0.02)
Unemployment Rate (%)	4.12	-0.11 (0.12)	Unemployment Rate (%)	4.18	-0.23** (0.12)
Persons Below Poverty Line	0.13	-0.01*** (0.00)	Persons Below Poverty Line	0.12	-0.01*** (0.00)
Hispanic	0.41	-0.07*** (0.01)	Hispanic	0.39	-0.08*** (0.01)
Black	0.07	-0.01* (0.01)	Black	0.07	0.00 (0.00)
Asian	0.15	0.01 (0.01)	Asian	0.14	0.03*** (0.01)
Foreign-Born Population	0.27	-0.01 (0.01)	Foreign-Born Population	0.26	-0.00 (-0.01)
High School Grad or Higher	0.82	0.04*** (0.01)	High School Grad or Higher	0.84	0.03*** (0.00)
College Grad or High	0.31	0.07*** (0.01)	College Grad or High	0.32	0.07*** (0.01)

Note: This table illustrates the heterogeneous effects of access to small-dollar loans using the machine-learning approach proposed by Chernozhukov et al. (2020) (CDDF). Panel A and Panel B illustrate the heterogeneous effects based on default and rollover default outcomes. Panel C and Panel D demonstrate the difference in characteristics between the most affected quantile and the least affected quantile.

Table 5: Impact of small-dollar loan on loan rate of return

	Return			
	Full Sample (OLS)	Amount < $3000 (OLS)	Amount >= $3000 (OLS)	Full Sample (2SLS)
	(1)	(2)	(3)	(4)
Unconstrained	0.26***	0.40***	0.088	0.73***
	(0.036)	(0.052)	(0.056)	(0.073)
Log(Income)	Y	Y	Y	Y
Zipcode FE	Y	Y	Y	Y
MonthYear FE	Y	Y	Y	Y
N	5366	3136	1941	5366

Standard errors in parentheses, *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Note: This table illustrates the impact of removing the interest rate caps on small-dollar loans on lender's rates of return on originated loans.

Appendix A. State by State analyses for interest rate cap

These summaries are complied by National Consumer Law Center (NCLC) in 2018, and deal only with the provisions of these statutes that apply to unsecured loans by non-bank lenders. They reflect amendments to the statutes effective up through October 2018. All APRs calculated for this report have been rounded to the nearest whole number.

ALABAMA

The Alabama Small Loan Act applies only to loans of less than $1500. Ala. Code §§ 5-18-4(a), 5-18-18. The Alabama Consumer Credit Act applies to loans of any amount. It caps interest and fees only for loans of $2000 or less. The state has no interest rate or fee cap for a $10,000 consumer installment loan, other than a prohibition of unconscionable loan terms. §§ 5-19-3(e), 5-19-16, 8-8-5.

ALASKA

The Alaska Small Loans Act applies to loans of up to $25,000. Alaska Stat. §§ 06.20.010(a), 06.20.230(a). It allows 36% on the balance up to $850, and 24% on the remainder over $850 but not exceeding $10,000, and any rate on remainder over $10,000. § 06.20.230. Taking these blended rates into account, the APR for a $10,000 5-year loan is 25%.

The Alaska Installment Loans Act applies to loans of up to $10,000. § 45.45.080(b). It allows $6 per $100 per year, and appears to allow this to be a discount interest calculation. § 45.45.080(b). But it adds that the resulting simple interest rate cannot exceed 11.8%, so the Small Loans Act allows a higher APR.

ARIZONA

The Arizona Consumer Lenders Act applies to loans of less than $10,000. Ariz. Rev. Stat. Ann. §§ 6-601(7), 6-602(B). It allows 36% on the first $3000 and 24% on the remainder.§ 6-632(A). It also allows a fee of 5% of the principal, capped at $150. § 6-635(A)(4). § 6-632 states that the lender can collect finance charges on this fee. With these elements, a $10,000 loan can have an APR of 30%.

A second statute, § 44-1205, allows the contract rate but applies only to loans of $5,000 or less. In addition, it does not apply to loans subject to the Arizona Consumer Lenders Act. § 44-1205(A).

In 2018, Arizona enacted Ariz. Rev. Stat. Ann. §§ 41-5601 to 41-5612, establishing a "Regulatory Sandbox Program" under which businesses can apply to the attorney general for permission to test "innovative" loan products and other financial services without complying with licensure requirements. The statute requires any consumer loans made under this program to comply with §§ 6-114, 6-632, 6-635(a)-(c), and 6-637, which include

the interest rate cap, the restrictions on fees, and a number of other consumer protections. § 41-5605(B)(3).

ARKANSAS

Amendment 89, § 3 of the Arkansas Constitution limits the interest rate on loans to 17%.

CALIFORNIA

The California Finance Lenders Law limits the interest and fees that can be charged for loans of less than $2,500, but does not limit the interest or fees for loans above that amount. Cal. Fin. Code §§ 22203, 22303. However, the statute does prohibit unconscionable loan terms. §§ 1670.5, 22302.

COLORADO

The Colorado Consumer Credit Code applies to loans of up to $75,000 (and to any loan secured by land). Colo. Rev. Stat. § 5-1-301(15). For a supervised loan, defined by § 5-1-301(47) as one with a rate of more than 12%, 36% is allowed on the first $1,000, 21% on the amount between $1,000 and $3,000, and 15% on the remainder. Applying these split rates produces an APR of 20% for a $10,000 5-year loan. In the alternative, the statute allows the lender to charge 21%. § 5-2-201(2). The statute also allows an alternate rate based on an acquisition charge of 10% of amount financed plus a monthly installment account charge, but this is allowed only for loans of $1000 or less, so is irrelevant here. § 5-2-214. Colorado's payday loan law, Colo. Rev. Stat. §§ 5-3.1-101 to 5-3.1-123, allows 45% interest plus a number of fees that add up to a maximum APR of about 175%, but does not apply to a loan of more than $500.

CONNECTICUT

After recent amendments, Conn. Gen. Stat. § 36a-558(d) now provides that a small loan between $5,000 and $15,000 cannot carry an APR (defined by § 36a-555(2) to incorporate the TILA definition) greater than 25%. (It also provides that the APR cannot exceed 36% as defined by the Military Lending Act if the loan is under $5,000.)

DELAWARE

Delaware's Licensed Lenders Law, Del. Code Ann. tit. 5, §§ 2229, 2237, allows any interest rate agreed to by the parties. No provision in the statute limits the size of the loans to which it applies.

DISTRICT OF COLUMBIA D.C.

Code § 28-3301 allows an interest rate of 24% and appears to apply to a loan of any size. In addition, it is possible to read § 28-3301(e)(2) as allowing one point. A second licensing

statute applies to loans of up to $25,000, but exempts a variety of lenders. §§ 26-910, 26-912(a)(5). Without or without points, the maximum allowable APR for a $10,000 loan, rounded to the nearest whole number, is 24%.

FLORIDA

The Florida Consumer Finance Act allows 30% on the first $3000 of principal, 24% on the next $1000, and 18% on the amount over $4,000, plus a $25 credit investigation fee. Fla. Stat. § 516.031(1), (3). This law applies to loans of $25,000 or less. §§ 516.01(2), 516.031(1). Applying these split rates produces an APR of 24% for a $10,000 5-year loan. In 2018, Florida amended § 560.404 to allow payday installment loans ("deferred presentment installment transactions") at a 208% APR, but since the loan amount is limited to $1000 this amendment does not affect the loans studied in this report.

GEORGIA

The Georgia Industrial Loan Act, which allows 10% per annum as a discount interest calculation plus a number of fees, applies only to loans of $3000 or less. Ga. Code Ann. § 7-3-8. For loans not governed by the Industrial Loan Act, § 7-4-2(a)(1)(A) allows any rate set by contract, but subject to § 7-4-18, which caps this at 5% per month (60% per year). The fees allowed by §§ 7-3-14 and 7-3-15 do not apply to a loan greater than $3000. §§ 7-3-14, 7-3-15.

HAWAII

For a precomputed loan with a term greater than 48 months, Hawaii's Financial Service Loan Companies law allows a lender to charge a 24% APR, calculated according to the Truth in Lending Act. The statute also allows a discount interest calculation, using rates of 14% and 10½%, but only for loans of 48 months or less. Haw. Rev. Stat. § 412:9-302.

IDAHO

The Idaho Credit Code allows any rate agreed to by the parties, with no limit other than unconscionability. Idaho Code §§ 28-45-106, 28-42-201(1).

ILLINOIS

The Illinois Consumer Installment Loan Act, 205 Ill. Comp. Stat. Ann. § 670/15(a), provides that the APR cannot exceed 36%. § 670/15d(5) allows a $25 document preparation fee "in addition to the charges authorized by this Act." The statute does not include a definition of APR, but since the document preparation fee would be treated as part of the finance charge to compute the APR under Truth in Lending rules, a reasonable interpretation would be to require it to be included as part of the 36% interest. For a $10,000 five-year loan the APR, rounded to the nearest whole number, is 36% regardless of how this $25 fee is treated. The Illinois payday installment loan law, 815 Ill. Comp. Stat. Ann.

§ 122/2-5, which allows much higher APRs, applies only to loans of 180 days or less (with a minimum of 112 days).

INDIANA

Indiana's Consumer Credit Code applies to loans of all sizes. For a supervised loan, defined by Ind. Code § 24-4.5-3-501 as one with a rate of more than 25%, the statute allows either 1) 36% actuarial on the first $2,000 of principal, 21% on the next $2,000, and 15% on the remainder; or 2) 25%. § 24-4.5-3-508(2). These amounts are to be adjusted for inflation, but 750 Ind. Admin. Code 1-1-1 shows no change as of July 1, 2018. The statute was amended in 2018 but in ways that do not affect the analysis of the APR allowed for a $10,000 five-year loan. Applying the split rates to this loan produces an APR of 23%, less than the alternate 25% rate.

IOWA

Iowa's Regulated Loan Act applies to loans of up to $50,000, which is adjusted for inflation. Iowa Code § 537.1301. It allows 36% on the first $150, 24% on the remainder up to $300, 18% on the remainder up to $700, and 12% on the amount above $700. But the regulator has adopted a rule for loans of $10,000 or less, allowing 36% on the first $3,000, 24% on the remainder up to $8,400, and 18% on the remainder up to $10,000. Iowa Admin. Code r. 187-15.13 (as amended effective July 1, 2017). The statute does not allow any fees on top of these interest rates. These split rates produce an APR of 29% on a $10,000 loan. A second Iowa statute, the Industrial Loan Law, Iowa Code §§ 536A.1 to 536A.32, applies to loans of up to $50,000, which is adjusted for inflation. §§ 536A.3 (incorporating § 537.1301(15)). The statute allows 10% per hundred per year, which may be calculated as discount or add-on interest. § 536A.23(1)(a)(1). In addition, the lender may charge $1 per $50 of the note, up to $120. § 536A.23(1)(b). These calculations produce an APR of 32%. A third Iowa statute, the Iowa Consumer Credit Code, also applies to loans of up to $50,000, which is adjusted for inflation. § 537.1301 (incorporating a threshold in the Truth in Lending Act). It allows an interest rate of 21% actuarial. § 537.2401(1). An application fee of the lesser of 10% of the amount financed or $30 is allowed, but only if the lender is a bank, savings and loan association, credit union, or savings bank. § 537.2501(1)(j).

KANSAS

The Kansas Consumer Credit Code applies to loans of $25,000 or less or loans secured by land. Kan. Stat. Ann. § 16a-1-301(17). It allows interest of 36% on the first $860, and 21% on the remainder. § 16a-2-401(2). In addition, it allows a loan fee of the lesser of 2% of the amount financed or $100. § 16a-2-401(6)(b). Taking the split interest rates and the loan fee into account, the maximum APR for a $10,000 loan is 23%.

KENTUCKY

The Kentucky Consumer Loan Companies statute applies to loans of $15,000 or less. Ky. Rev. Stat. Ann. §§ 286.4-420, 286.4-530(1). It allows interest of 36% if the loan is for $3,000 or less, and 24% if the loan is for more than $3,000. § 286.4-530(1). It also allows a credit investigation charge of $1.50 for each $50 or fraction of the principal on the first $2,000. § 286.4-533(4). Putting all these elements together produces an APR of 24% on a $10,000 5-year loan. In addition, the Kentucky Industrial Loan Act, Ky. Rev. Stat. Ann. §§ 286.7-410 to -990, allows $7 per $100 add-on or discount interest for a loan of $7500 or less. This would not apply to a $10,000 loan, but § 286.7-460(4) also allows the rates allowed by § 286.3-215, which is $8 per hundred add-on or discount, as long as the principal does not exceed $10,000. However, the discount interest method cannot be used for a loan in which the consumer receives $10,000, because then the principal would have to be stated as more than $10,000. Regardless of which method of calculating the maximum amount of interest is used, the statute also allows the lender to charge $1 for each $50 or fraction thereof on the first $800. § 286.3-215(2). Putting all this together, the maximum APR for a $10,000 loan under this Act is 22%.

LOUISIANA

Louisiana's Consumer Credit Law allows 36% per year on the first $1400 of the principal, 27% on the remainder up to $4,000, 24% on amount exceeding $4000 but not exceeding $7,000, and 21% on the remainder. La. Rev. Stat. Ann. § 9:3519(A). In addition, § 9:3530 allows a $50 nonrefundable origination fee, which is "not considered a loan finance charge," and a documentary charge of $20. § 9:3530(A), (C). Treating both of these fees as part of the principal for purposes of determining the maximum amount of interest that can be charged, the APR for a $10,000 loan is 27%.

MAINE

Under Maine's Consumer Credit Code, the interest rate is limited to 18% if the amount financed exceeds $8000, and no fees are allowed. (For smaller loans, the statute allows 30% on the first $2000, 24% on the next $2000, and 18% on the remainder). Me. Rev. Stat. Ann. tit. 9-A, § 2-401(2). The statute applies to loans of up to $50,000, which is adjusted for inflation. § 1-301(14).

MARYLAND

The Maryland Credit Grantor Closed-End Credit Provisions allow 24% simple interest. Md. Code Ann., Com. Law §§ 12-1003(a), 12-1005. This law also allows some additional charges but with many exceptions and provisos that make them in applicable to unsecured consumer loans. Maryland's general usury law, Md. Code Ann., Com. Law § 12-103, allows 24% for unsecured loans or those secured by collateral other than real estate. A second Maryland statute, the Maryland Consumer Loan Law—Credit Provisions, allows a variety of interest rate caps. Md. Code Ann., Com. Law § 12-306. Under amendments effective on October 1, 2018, the statute allows 2.75% per month on the first $1,000 and

2% on the rest, for loans of up to $25,000. Applying these split rates to a $10,000 fiveyear loan produces an APR of 25%.

MASSACHUSETTS

For loans of $6,000 or less, a Massachusetts small loan law caps interest at 23% actuarial, plus a $20 administrative fee. Mass. Gen. Laws ch. 140, §§ 96, 100; 209 Mass. Code Regs. § 26.01(a). The state's criminal usury law, Mass. Gen. Laws ch. 271, § 49(e), caps interest at 20% for lenders that are not subject to "control, regulation or examination" by a state agency, where the interest rate would not be regulated by any other law. Since a nonbank lender making a loan for more than $6000 would not be subject to the small loan law, and its interest rate would not be regulated by that law, the criminal usury statute's 20% cap would apply.

MICHIGAN

The Michigan Regulatory Loan Act applies to all loan amounts and allows 25% interest. Mich. Comp. Laws § 493.13 (incorporating § 445.1854). In addition, it allows a loan processing fee of 5% of principal, up to $250 (now adjusted to $300 due to inflation) to be added to the principal for a closed-end loan. §§ 493.13(4), 445.1856(1)(a). Taking these two elements together, the maximum APR for a $10,000 loan is a little bit above 26%. Michigan also has a Credit Reform Act, which also allows a 25% interest rate but allows a slightly lower processing fee, so would result in a lower maximum APR. §§ 445.1854, 445.1856(1)(a).

MINNESOTA

Minn. Stat. § 47.59 (Financial Institution Credit Extension Maximum Rates) applies to all loan amounts. It allows 1) 21.75% on the unpaid balance; or 2) 33% on the first $1,200 and 19% on the remainder. The statute also allows a $25 administrative fee, which may be included in the principal balance on which the finance charge is computed. But this fee is allowed only if loan amount is less than $6,912 (this is the figure adjusted for inflation as of 2018), so cannot be charged for a $10,000 loan. Applying the split rates to a $10,000 five-year loan produces a maximum APR of 21.5%, a little less than the alternate rate of 21.75%, which we round up to 22% for purposes of this report. Minnesota's Consumer Short-Term Loans Act, § 47.601, applies only to loans of $1,000 or less.

MISSISSIPPI

Mississippi's Small Loan Regulatory Law, which applies to loans of any amount, allows a split rate: 36% on the first $1,000; 33% on the remainder up to $2500; 24% on the amount between $2,500 and $5,000; and 14% on the amount over $5,000. These rates can be increased when the federal discount rate is above a certain amount but that is not the case now. Miss. Code Ann. § 75-17-21. It also allows a fee of 4% of the total of payments or $25, whichever is more, if the loan is for $10,000 or less; otherwise the fee is $500. § 75-

17-21(3). Putting these elements together, the maximum APR for a $10,000 loan under this statute is 26%. Mississippi's Installment Loan Law, § 75-67-39, applies to all loan amounts, but allows a lower APR: 7%. The Mississippi Consumer Alternate Installment Loan Act, §§ 75-67-175 to -185 applies only to loans of $4,000 or less, and the Mississippi Credit Availability Act, §§ 75-67-601 to -637, applies only to loans for 12 months or less, so neither applies to a $10,000 5-year loan.

MISSOURI

Missouri's Small Loan Act applies to loans of any size and allows any rate agreed to by the parties. Mo. Rev. Stat. § 408.100.

MONTANA

Montana's Consumer Loan Act applies to loans of any size. Mont. Code Ann. §§ 32-5-102(2)(a), 32-5-103(1). It caps the interest rate at 36% and does not allow any origination fees. § 32-5-301. NEBRASKA Nebraska allows a lender to charge 24% on the principal up to $1,000, and 21% on the remainder. Neb. Rev. Stat. § 45-1024(1). It also allows a lender to charge an origination fee of 7% of the first $2,000 of the original principal and 5% of the remainder, or $500, whichever is less, which can be added to the principal. § 45-1024(5). (The same statutory provision also allows "reasonable expenses incurred in connection with the making, closing, disbursing…of loans," but the regulator has confirmed that these must fall within the $500/7%/5% cap.) The statute applies to loans of up to $25,000. § 45-1025(2). Putting the split rates and the fee together produces a maximum APR of 24% for a $10,000 5-year loan.

NEVADA

The Nevada Installment Loan and Finance Act, Nev. Rev. Stat. §§ 675.010 to 675.490, allows a lender to charge any rate agreed to by the parties, but § 604A.400 prohibits operating as a "high rate loan service," i.e., one that charges more than 40%, without a license, and even with a license limits high-rate loans to 90 days. As a result, for loans longer than 90 days, the APR is capped at 40%.

NEW HAMPSHIRE

New Hampshire allows a lender to charge a 36% APR for closed-end credit, calculated by TILA rules. N.H. Rev. Stat. Ann. § 399-A:16. Under § 399-A:16(I), for purposes of calculating the statutory 36% APR cap, one annual fee of up to $100 and one annual participation fee of up to $100 are to be excluded. However, § 399-A:15(XI) bars these fees for closed-end credit, so it appears that this provision is relevant only for purposes of calculating the statutory APR cap for open-end credit. Accordingly, the cap for a closed-end $10,000 5-year loan is 36%. The statute applies to loans of $10,000 or less. § 399-A:1(XX).

NEW JERSEY

N.J. Stat. Ann. § 17:11C-32 allows any rate agreed to by the parties for any consumer loan by a licensed lender. This law applies to loans of $50,000 or less. § 17:11C-2 But the criminal usury statute, § 2C:21-19, which applies to all loan amounts, makes it a crime to charge more than 30% "notwithstanding any law of this State which permits as a maximum interest rate a rate or rates agreed to by the parties," so the maximum APR for a $10,000 five-year loan is 30%.

NEW MEXICO

New Mexico caps interest rates, but only for loans of $5,000 or less. N.M. Stat. Ann. § 58-15-2(F). There is no cap that would apply to a $10,000 loan, except that the state deceptive practices statute includes a prohibition of unconscionable terms that has been applied to high-rate consumer installment loans.

NEW YORK

The New York Licensed Lender Law allows any contracted rate for any consumer loan under $25,000. N.Y. Banking Law § 351. Nonetheless, New York's criminal usury statute caps the rate at 25%. N.Y. Penal Law § 190.40.

NORTH CAROLINA

The North Carolina Consumer Finance Act applies to loans of $15,000 or less. N.C. Gen. Stat. §§ 53-166(a), 53-168(a). It allows 30% on the first $4000 of principal, 24% on the next $4,000, and 18% on the remainder. § 53-176(a). It also allows a $25 processing fee for a loan up to $2,500. For a loan greater than $2500, it allows a 1% closing fee, up to $40. § 53-176(b). Taking this split rate and the closing fee into account, the maximum APR allowed for a $10,000 5-year loan is 27%. For a loan greater than $10,000, the statute would limit the interest rate to 18%. North Carolina's general statutory provisions regarding interest, which apply to loans of up to $300,000, § 24-1.1(f), allow 16% or 6 percentage points above a T-bill rate, which is currently so low that produces a rate less than 16%. § 24-1.1(a), (c).

NORTH DAKOTA

North Dakota's Money Brokers statute imposes rate caps only on loans of $1,000 or less. N.D. Cent. Code § 13-04.1-09.2(1). The criminal usury statute imposes a 7% cap, but it does not apply to any lending institution regulated by a state agency. § 47-14-09(2)(e).

OHIO

Ohio has several lending laws that limit interest rates: the Small Loan Act, the General Loan Law, and the Consumer Installment Loan Act. However, for loans of $5,000 or more

that have repayment terms of more than a year, lenders can evade the interest rate caps in these statutes by making the loan through a credit services organization, so Ohio is classified as having no cap. (In 2018, the legislature amended Ohio's lending laws to close the credit services organization loophole for certain consumer loans, effective in 2019).

OKLAHOMA

The Oklahoma Consumer Credit Code applies to loans of up to $50,000, adjusted for inflation, and to loans secured by land and private student loans. Okla. Stat. tit. 14A, § 3-104. It allows either 25%, or a set of split rates: 27% per year on that part of the unpaid balance of the principal that is $2,910 or less, 23% on the amount over $2,910 but no more than $6,200, and 20% on the remainder, with no fees. § 3-508A. Applying these split rates produces a maximum APR of 25% for a $10,000 5-year loan. Higher rates are allowed by § 3-508B, but only for loans of $1530 or less.

OREGON

The Oregon Consumer Finance Act applies to loans of up to $50,000. Or. Rev. Stat. § 725.045(1). It allows the greater of 36% APR or 30 percentage points in excess of the discount window primary credit rate (which was 2.25% as of July 9, 2018, so would produce a rate less than 36%). § 725.340(1). As a result, the maximum rate is 36%.

PENNSYLVANIA

Pennsylvania's Consumer Discount Company Act allows 1) discount interest of $9.50 per $100 per year for a loan up to 48 months; if loan is longer than 48 months, it allows discount interest of $9.50 per $100 per year for the first 48 months and $6 per $100 per year for the remainder; or 2) 2% per month. 7 Pa. Stat. Ann. §§ 6213(E), 6217.1. It also allows the lender to charge a service charge of $1.50 for each $50 "or fraction thereof," up to $150. The regulator has indicated that the $1.50 service charge is to be calculated on the total of payments, i.e., the amount financed, the discount interest, and the service charge itself. This statute applies to loans of $25,000 or less. § 6203. Applying both the interest and the service charge produces a maximum APR of 26% for a $10,000 five-year loan.

RHODE ISLAND

The Small Loan Lenders Act, which allows 3% per month on the first $300, 2.5% per month on the remainder up to $800, and 2% per month on the remainder, applies only to loans of $5000 or less. R.I. Gen. Laws §§ 19-14.2-1, 19-14.2-8. Since this Act does not apply, a $10,000 five-year loan is governed by a more general interest rate cap of 21% or the Wall Street Journal prime rate (which was 5% on July 9, 2018) plus 9%. § 6-26-2. As a result, the maximum APR is 21%.

SOUTH CAROLINA

The South Carolina Consumer Protection Code applies to loans of up to $90,000. S.C. Code Ann. § 37-3-104. The statute allows the lender to choose between two alternate rate caps (18% or an add-on rate) for a loan of $600 or less. For a loan of more than $600, however, this law permits the lender to charge any rate that it files and posts. § 37-3-201(2)(b). The only limit is a prohibition of unconscionability. § 37-5-108. South Carolina also has a Consumer Finance Law, but it applies only to loans of $7500 or less. § 34-29-20(a).

SOUTH DAKOTA

Due to a voter initiative, a 36% cap was imposed on loans of any amount, effective Nov. 16, 2016. S.D. Codified Laws § 54-4-44. This rate cap encompasses all charges and fees, including charges for ancillary products and services, so is a tighter cap than in most other states.

TENNESSEE

For a loan of more than $5,000, Tennessee's Industrial Loan and Thrift Companies law allows an interest rate of up to 24%. Tenn. Code Ann. § 45-5-301. In addition, the lender can charge 4% of the total amount of the loan, which can be deducted in advance, plus $2.50 per month (interest and loan charges are not computed on this latter amount). § 45-5-403(a). Putting this interest rate and these fees together, the maximum APR for a $10,000 loan is 26%. The statute appears to apply to a loan of any amount. (For loans of $5,000 or less, the statute provides two alternate, higher caps).

TEXAS

The Texas Finance Code applies to loans regardless of their amount. For a $10,000 loan, the statute allows a $100 administrative fee (added after calculation of interest) plus either a) 30% on the first $3,500, 24% on the next amount up to $7,350, and 18% on the next amount up to $17,500; or b) $18 per $100 per year as an add-on rate for the first $2,100 and $8 per $100 per year on the remainder. Tex. Fin. Code Ann. § 342.201, as adjusted for inflation pursuant to §§ 341.201 to 341.204. The former calculation produces the higher APR for a $10,000 five-year loan: 26%. A separate set of rules known as Subchapter F allows higher finance charges but is applicable only to loans of $1400 or less. § 342.251.

UTAH

Utah's Consumer Credit Code applies to loans of up to $50,000 (adjusted annually for inflation) and to any loan that is secured by the consumer's principal dwelling. Utah Code Ann. § 70C-1-202. The statute allows any interest rate agreed to by the parties, limited only by a prohibition of unconscionable terms. §§ 70C-2-101, 70C-7-106.

VERMONT

Vermont's Licensed Lenders Act applies to any loan other than a commercial loan of $1 million or more. Vt. Stat. Ann. tit. 9, § 2201(h). It allows 1) 24% on the first $1,000 and 12% on the excess over $1,000; or 2) 18% on the whole balance. § 2230(a) (incorporating tit. 9, § 41a(b)(5)). The first option—the split rate calculation—produces an APR of 14% for a $10,000 5-year loan, so the maximum rate for this loan is the second option (18%).

VIRGINIA

The Virginia Consumer Finance Companies law applies to loans of any size. It caps the interest rate at 36%, but only for loans of up to $2500. If the loan is for more than $2500, the lender can charge any rate agreed to by the parties. Va. Code Ann. § 6.2-1520(A).

WASHINGTON

The Washington Consumer Loan Act applies to loans of any size. It allows 25% simple interest, plus a nonrefundable origination fee of 4% of the first $20,000 of the principal and 2% of the remainder, which may be included in the principal balance of the loan. Wash Rev. Code § 31.04.105(1), (2). For a $10,000 5-year loan, this produces an APR of 27%.

WEST VIRGINIA

For a loan that is greater than $2,000 but no more than $10,000, or that is secured by real property, West Virginia's Consumer Credit and Protection Act allows an actuarial interest rate of 27% (18% if the loan exceeds $10,000, and 31% if the loan is for $2,000 or less). W. Va. Code § 46A-4-107. In the alternative, a lender may charge 1) 1% in excess of the 90-day discount rate; 2) 6% add-on interest; or 3) 6% discount interest, provided that the actuarial interest rate does not exceed 15%. §§ 31a-4-30a (made applicable to non-bank lenders by § 46A-3-117), 46A-3-104(1) (incorporating § 47-6-5a). However, all three of these alternative methods produce lower APRs than 27% for a $10,000 five-year loan. § 46A-4-107(2).

WISCONSIN

Wisconsin's Licensed Lenders law applies to loans of any size, and the Wisconsin Consumer Act applies to loans of $25,000 or less. Wis. Stat. §§ 138.09, 421.202. Neither statute places any limit on the interest rate a lender can charge other than a statutory prohibition of unconscionability. §§ 138.09(7)(bp), (k), 422.201(2)(bn)

WYOMING

The Wyoming Consumer Credit Code applies to loans of up to $75,000, and to any loan secured by land or a dwelling. It allows 36% on the first $1000 and 21% on the remainder. § 40-14-348. Applying these split rates to this loan produces an APR of 23%.

Appendix B. Payment Schedule Examples

B.1 Payment Schedule Equation

For credit products in both groups, the repayment is calculated as follows:

$$P = L \times \frac{(\frac{r}{12}) \times (1 + \frac{r}{12})^M}{((1 + \frac{r}{12})^M - 1)}$$

P: Monthly repayment amount

L: Loan amount (principal)

r: Annual percentage rate (APR)

M: Total number of months for loan repayment

Payment Plan under CA regulation regime:

Payment Plan 1:

For example, for a loan contract with L=$2600, r=160%, Maturity = 12, payment frequency is monthly, then the repayment per month is:

$$P = L \times \frac{(\frac{r}{12}) \times (1 + \frac{r}{12})^M}{((1 + \frac{r}{12})^M - 1)} = \$446$$

Then, the monthly repayment plan is

{$446, $446, $446, $446, $446, $446, $446, $446, $446, $446, $446, $446},

when the borrower chooses to make payment for each term as required, the payment is $5352 in total.

B.2 Payment Schedule with Prepayment

Payment Plan 2:

When the borrower only needs $1000, the borrower can make an early prepayment of $1600 immediately since there is no prepayment penalty. The rescheduled monthly repayment plan will become:

$$\$1600+\{\$446, \$446, \$377\},$$

The maturity is shortened to 3 months due to the $1600 prepayment and the scheduled payment of $446 per period, for a total payment of $1269, excluding the immediate prepayment of the unused $1600.

Payment Plan 3:

When the borrower only needs $1000, he chooses to make an early prepayment of $1600 in the 3rd month since he keeps the portion for precautionary reasons. The rescheduled monthly repayment plan will become:

$$\{\$446, \$446, \$1600, \$446, \$446, \$446, \$99\},$$

The maturity is shortened to 7 months due to the $1600 prepayment in the 3rd month and the scheduled payment of $446 per period, for a total payment of $2329, excluding the unused $1600 prepayment in the 3rd month.

In the control group, because the credit product is regulated by California regulation, and $1000 with an APR of 160% can't originate, a prepayment of $1600 can't be used to renew a contract with a $1000 principal and 12 months' maturity. Therefore, borrowers in the control group must follow the $446 monthly payment schedule until the outstanding balance becomes 0, which means early prepayment will effectively shorten the maturity.

Payment Plan under UT regulation regime:

In contrast, borrowers in the treatment group can directly receive a loan offer of $1000 with an APR of 160% since a loan originated by a Utah bank won't be regulated by the California government, even if it is for California residents. Thus, the borrower could have 12 months' maturity, which leads to a lower monthly payment requirement for each term as follows:

$$P = L \times \frac{(\frac{r}{12}) \times (1 + \frac{r}{12})^M}{((1 + \frac{r}{12})^M - 1)} = \$172$$

Then, the monthly repayment plan is

{$172, $172, $172, $172, $172, $172, $172, $172, $172, $172, $172, $172},

when the borrower chooses to make payment for each term as required, for a total of $2064.

Appendix B. Machine Learning for Heterogeneous Effects

B.1 Chernozhukov, Demirer, Duflo, and Fernández-Val (2020)

In this study, I follow the method proposed by Bryan, Karlan, and Osman (2024) to examine the differing effects of access to small-dollar loans that result from the absence of interest rate caps. I employ the machine learning approach developed by Chernozhukov et al. (2020), known as CDDF. This method provides a framework for conducting generic machine learning inference on heterogeneous treatment effects in randomized experiments. One significant advantage of the CDDF approach is its sample-splitting feature, which effectively addresses the out-of-sample validity concerns commonly associated with estimating heterogeneous treatment effects. I apply this methodology to analyze how interest rate caps affect access to small-dollar loans, perfectly aligning with the principles of randomized experiments.

The CDDF method applies to binary treatments. In this context, I designate the group with access to small-dollar loans as the "treatment group" ($T = 1$) and the group without access as the "control group" ($T = 0$). Let Y represent the variable of interest, which is the borrower's financial stress measured by the performance of the loan, while Z signifies the vector of covariates. Given the individuals' characteristics represented by Z, the average treatment effect (ATE) transforms into a conditional average treatment effect (CATE), denoted as $s_o(Z) = E(Y \mid T = 1, Z) - E(Y \mid T = 0, Z)$. In our framework, the conditional treatment effect reflects the changes in an individual's financial stress due to access to small-dollar loans, taking into account the individual's characteristics.

CDDF argues that we can use a generic machine learning method to construct an imperfect estimator $\hat{s}(Z)$ of the CATE $s_o(Z)$, and use this measure to sort observations into groups that are most and least treated, study the average characteristics of the groups,

$$\delta_1 = E[g(Y, Z) \mid G_1] \text{ and } \delta_k = E[g(Y, Z) \mid G_k]$$

where G_1 is the least affected group of observations, G_0 is the most affected group of observations, and $g(Y, Z)$ is the characteristics vector of an observation.

To estimate the parameter of interest, we follow a series of steps. First, we partition the sample into a "testing" sample and a "training" sample. Next, we train a machine learning model using all control variables (Z) to predict the corresponding financial stress of borrowers (Y) only for the treatment group within the training sample. We then apply this model to make predictions on the main sample, which will yield the predicted treatment effects. Following that, we train another machine learning model, but this time focusing only on the control group of the training sample. We then apply this model to make predictions on the testing sample, which will provide the predicted baseline effects. The difference between the predicted treatment and baseline effects gives us our estimated conditional treatment effects. Afterward, we run a weighted ordinary least squares (OLS) regression to compute the group average treatment effects, sorting the observations into the least and most affected groups. Finally, we calculate the average characteristics of the most and least treated groups. To address the randomness introduced by the sample splitting, we repeat the above steps multiple times and then take the medians of the point estimates and p-values.

Before computing the group average treatment effects, CDDF suggests first calculating the best linear predictor (BLP) of the conditional average treatment effects. The BLP takes the form:

$$\begin{aligned} BLP[s_0(Z) \mid S(Z)] &= arg \min_{f(z) \in Span(1, S(Z))} E[s_o(Z) - f(Z)]^2 \\ &= \beta_1 + \beta_2 (S(Z) - ES) \\ BLP[s_0(Z) \mid S(Z)] &= arg \min_{f(z) \in Span(1, S(Z))} E[s_o(Z) - f(Z)]^2 \\ &= \beta_1 + \beta_2 (S(Z) - ES) \end{aligned}$$

The average treatment effects are estimated as β_1 and $\beta_2 = 0$ if there is no heterogeneity or the ML prediction $S(Z)$ does not capture that heterogeneity. Hence, this test is based on a

joint hypothesis that there is heterogeneity and that the ML methods can detect it using our covariates.

B.2 Estimation Procedure

In this section, I outline the setting and in Chernozhukov et al. (2020) (CDDF) and my estimation procedures. I follow Bryan, Karlan, and Osman (2024), applying CDDF in an RCT framework. Given that the CDDF method applies only to binary treatment, I partition the sample into “treatment" ($T = 1$) and “control" groups ($T = 0$), assigning an individual to the treatment group if the individual is randomly assigned to the unconstrained group with access to small-dollar loans and chooses to take loan offers.

Let Y be the variable of interest, and Z be the vector of covariates. Each data point is randomly assigned to a treatment ($T = 1$) or a control group ($T = 0$). The probability of assigning to the treatment group is known to the researcher, denoted as the propensity score $p(Z)$, a function of the observed covariates. Researchers are interested in the heterogeneity of the conditional average treatment effect (CATE).

$$s_o(Z) = E(Y \mid T = 1, Z) - E(Y \mid T = 0, Z)$$

Though it is difficult to construct an unbiased and consistent estimator of the CATE $s_o(Z)$, CDDF argues that we can use a generic machine learning method to build an imperfect estimator $\hat{s}(Z)$ and use this measure to study some properties of the CATE $s_o(Z)$. Before explaining how to build the estimator $\hat{s}(Z)$, I need first to discuss the three components of the CATE that characterize the method:

- The Best Linear Predictor (BLP):

$$BLP[s_0(Z) \mid S(Z)] = arg \min_{f(z) \in Span(1, S(Z))} E[s_o(Z) - f(Z)]^2$$
$$= \beta_1 + \beta_2 (S(Z) - ES)$$

$$BLP[s_0(Z) \mid S(Z)] = arg \min_{f(z) \in Span(1, S(Z))} E[s_o(Z) - f(Z)]^2 = \beta_1 + \beta_2 (S(Z) - ES)$$

β2 = 0 when S(Z) is either a complete noise proxy for $s_o(Z)$or no heterogeneity exists, which means $s_o(Z) = s$. Therefore, rejecting β2 = 0 means that S(Z) is a relevant estimator and that there is heterogeneity $s_o(Z)$.

- Sorted Group Average Treatment Effects (GATE):

$$E[s_o(Z) \mid G_k]$$

where $\{G_k\}_{k=1}^{K}$are non-overlapping intervals that span the support of S with monotonicity restriction that:

$$E[s_o(Z) \mid G_1] \leq \ldots \leq E[s_o(Z) \mid G_K]$$

- Classification Analysis (CLAN):

Once BLP and GATES show the existence of substantial heterogeneity, we can examine the properties of the subpopulation of the most and least affected groups G_1 and G_k. Denote $g(Y, Z)$ as a characteristics vector of an observation. It is interesting to know the average characteristics of the most and least affected groups:

$$\delta_1 = E[g(Y, Z) \mid G_1] \text{ and } \delta_k = E[g(Y, Z) \mid G_k]$$

Given the three elements of the CDDF, the following algorithm is proposed:

Step 1 Split the sample equally into a testing sample *A* and a training sample *B*. So we generate random splits of the sample by S times (e.g., S = 100), each indexed by *i*, denoted as $\{A_i, S_i\}_{i=1}^{S}$. Choose a significant level α.

Step 2 For each split $i = 1,...,S$, we repeat the following steps:

1. Given the testing sample A and the training sample B. The propensity score $p(Z)$ is known by the researcher.
2. Use the training sample *B* to train a machine learning (ML) model. First, predict Y_B by Z_B using only the treatment group of the training sample, which is the treatment effect $TR(\bullet)$. Second, predict Y_B by Z_B using only the control group of

the training sample, which is the baseline effect $B(\bullet)$. Here, we follow Bryan, Karlan, and Osman (2024), focusing on gradient-boosted decision trees (XGBoost) implemented by Chen and Guestrin (2016).

3. Use the two models trained on the training sample to make predictions on the testing sample, the predicted treatment effect and predicted baseline effect are $Y(\hat{T}=1)=TR(Z_A)$ and $Y(\hat{T}=0)=B(Z_A)$.
4. On the testing sample, the difference between the predicted treatment effect and predicted baseline effect can be used as the predictor $\hat{S}(Z)=Y(\hat{T}=1)-Y(\hat{T}=0)$, which $\hat{S}(Z)$ is an estimator for the CATE $s_o(Z)$. CDDF shows that the estimator can be used easily to derive some following components of $s_o(Z)$.
    1. The BLP parameters are estimated by a weighted OLS $Y=\alpha X_1+\beta_1(T-p(Z))+\beta_2(T-p(Z))(\hat{S}(Z)-E[\hat{S}(Z)])+\epsilon$ where the weights in the OLS are $w(Z)=\dfrac{1}{p(Z)(1-p(Z))}$, $X1=\{1,Y(\hat{T}=1),Y(\hat{T}=0)\}$ include a constant, predicted baseline effect, and predicted treatment effect.
    2. The GATE parameters can be estimated by a weighted OLS $Y=\alpha X_1+\sum_{k=1}^{4}(T-p(Z))\times 1(S\in G_k)+\epsilon$. The monotonic groups are sorted by $\hat{S}(Z)$. For example, G_k is the k-quintiles of $\hat{S}(Z)$.
    3. The CLAN parameters are $\hat{\sigma}_k=\hat{E}[g(Y,Z)\,|\,S\in G_k]$ where $g(Y,Z)$ is the characteristics vector of an observation.

Step 3 Based on the sample split in **Step 2**, we report the median of estimated coefficients as our adjusted parameters of interest. More specifically, for the heterogeneity parameter β_1, we have S estimated $\{\hat{\beta}_1^i\}_{i=1}^S$. Given the significant level α, we have S estimated confidence intervals $\{\hat{\beta}_{1,L}^i\ \hat{\beta}_{1,U}^i\}_{i=1}^S$. The final adjusted estimates of $\hat{\beta}_1=Median\{\hat{\beta}_1^i\}_{i=1}^S=Median\{\hat{\beta}_1^i\}_{i=1}^S$, and the final adjusted confidence interval at 2α significant level is $\{\hat{\beta}_{1,L}^i\ \hat{\beta}_{1,U}^i\}=\{Median\{\hat{\beta}_{1,L}^i\}_{i=1}^S, Median\{\hat{\beta}_{1,U}^i\}_{i=1}^S\}$.