The Effect of Payday Loan Extended Payment Plans on Financial Health: A Synthetic Difference-in-Differences Approach [*†]

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Abstract

Payday loans are long seen as predatory lending. Many states have taken steps to limit or completely ban payday loan access. Some states have passed extended payment plans to prevent consumers from falling into "debt traps." To the author's best knowledge, this paper is the first to study these laws' effects on individual financial health. Using the synthetic difference-in-differences method, I find that, on average, these laws reduce the total loan past due amount by $25, and it decreases the charge-off amount by $49. These laws also reduce delinquency rate by about 2.9% and decrease charge off or debt in collections rate by about 2.7%.

Keywords: Household finance, consumer finance, payday loans, extended payment plans

JEL Codes: D12, D14, G2

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[†]Researcher(s) own analyses calculated (or derived) based in part on data from Clarity Services Inc. The conclusions drawn from the Clarity data are those of the researcher(s) and do not reflect the views of Clarity. Clarity is not responsible for, had no role and was not involved in analyzing and preparing the results reported herein.

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1 Introduction

Poor financial health is prevalent in the U.S. According to Tescher and Silberman (2021), about two-thirds of individuals are not doing financially well, half of the Americans are just financially coping (i.e., struggling with some aspects of their financial lives), and one-fifth of the population is financially vulnerable (i.e., struggling with all aspects of their financial lives). One of the common signs of poor financial well-being is loan delinquency. A report by Braga et al. (2019) finds that three years after their first delinquency, those consumers are more likely to have subprime credit scores than those who do not have any delinquent debts[1].

One type of loan that is incredibly invasive to financial health is a payday loan. This type of loan is described as "predatory" for its high annual interest rates (APRs). Some states have completely banned payday loans to deter their negative financial impacts. Nunez et al. (2016) finds that most payday loan borrowers have bad or very bad credit scores (which leads to limited access to traditional cheaper loans from banks). About 64% used payday loans or cover regular expenses, and 80% used them to cover emergency bills (Nunez et al., 2016). Many studies (for example, Di Maggio et al. (2020) and Miller and Soo (2020)) found that, even with the presence of policies that help reduce the cost of traditional banking and have increased usage of traditional banking, there is no evidence that borrowers reduce the use of payday loans[2]. In addition, most researchers found no evidence of payday loans improving borrowers' financial situations (such as paying a mortgage, rent, utility bills, or improving credit scores (See Melzer (2011), Bhutta (2014), Bhutta et al. (2015), and Melzer (2018)).

Since many borrowers still heavily use payday loans for practical reasons, the states may need to pass laws to provide more financial protections related to payday loans. One research on this type of law by Wang and Burke (2022) studies the effect of information disclosure on payday loan volumes in Texas and similar but stricter city ordinances in Austin and Dallas. The state requires information disclosure for consumers taking out payday loans starting in January 2012. The disclosure requires lenders to

[1]The statistics for the shares of consumers with subprime credit after three years is staggering: between 24% to 59% of consumers have subprime credit if they have had one delinquency, and between 31% to 72% if they have had more than one delinquency.

[2]The reasons are multiple folds. First, This may be because, in some situations, a credit card cannot be used to pay for some types of payments (such as child support, rent, and loans from family). Second, Current policies are not effective because the traditional financial system may still charge individuals high fees, and alternative financial service (AFS) users are reluctant to take to the harsh consequences (such as high overdraft fees, lower credit scores, involuntary bank account closures, and no credit for up to 5 years. Another reason is that these individuals may not spend enough time searching for the best terms since payday loans are quick and convenient.

compare the cost of payday loans with other credit products, and they must present to borrowers their likelihood of renewal in simple to understand terms. This study shows that a statewide disclosure led to a significant and persistent decline (about 13%) in loan volume for the first six months after the law.

Another consumer protection measurement raised by the Consumer Financial Protection Bureau (CFPB) is the payday loan extended payment plans[3]. Among the states where payday loans are legal, fifteen states[4] have opted for this policy that allows consumers to repay their outstanding payday loans in multiple installments at no extra charge. The state laws may vary in the extended payment plans availability, but all states mandate that the "lenders shall offer" an extended payment plan to consumers in this policy[5]. This type of law is yet to be studied. This paper is the first attempt to study the effect of these extended payment plans on payday loan borrowers' financial health. Specifically, I study different financial well-being measurements, including the amount past due, original charge-off amount, delinquency rate, and charge-off or debt in collections rate. The treatment is a binary variable, whether or not the state has passed the extended payment plans. I also use borrowers' characteristics relevant to payday loan borrowing behavior as covariates.

This study uses proprietary Clarity[6] payday loan data to uncover the effect of extended payment plans on borrowers' financial health. Clarity records different financial health related variables such as amount past due and delinquency at both individual and state levels. It also includes relevant borrower characteristics such as age, income, and housing status. I use the Consumer Financial Protection Bureau report on extended payment plans and narrow the list of states that have passed such laws(CFPB, 2022a). Then I search through each state's legislature or financial department websites for the extended payment plan legal clauses[7] to find the exact passing date for each state[8].

[3]Sometimes it is referred to as an "offramp."

[4]These states are Alabama, Alaska, California, Delaware, Florida, Idaho, Indiana, Louisiana, Michigan, Nevada, South Carolina, Utah, Washington, Wisconsin, and Wyoming (CFPB, 2022a).

[5]For more details, see Section 2.2.

[6]Clarity Services is a subsidiary of Experian. It specializes in alternative financial services data. Its data source is collected from various financial service providers: online small-dollar lenders, online installment lenders, single payment lenders, line of credit, storefront small-dollar lenders, auto title, and rent-to-own. For more detail, see `https://www.clarityservices.com`

[7]For the exact legal clause, see ALA. CODE 5-18A-12c; ALASKA STAT. 06.50.550; 10 CAL. FINANCIAL CODE 23036(b); 5 DEL. CODE ANN. 2227(8) & 2235A(a)(2); FLA. STAT. 560.404(21)-(22); IDAHO CODE 28-46-414; IND. CODE 24-4.5-7-401; La. Stat. Ann. 9:3578.4.1; MICH. COMP. LAWS 487.2155 Sec. 35; NEV.REV. STAT. 604A.5026-5027; S.C. CODE ANN. 34-39-280; UTAH CODE ANN. 7-23-403(7); WASH. REV. CODE 31.45.084; WIS. STAT. 138.14(11g); and WYO. STAT. ANN. 40-14-366.

[8]See Appendix C for the list of states and law passing dates.

Using these treated dates, we can create the treatment variable. The final data for this study are aggregated at the state level.

The Two way fixed effect (TWFE) difference in difference (DiD) model is used as a baseline model. The main method uses Synthetic DiD (SDiD) model. It fits this setting since the data is at an aggregated state level and is balanced. The main findings suggest that, on average, the treated states have \$25 less amount past due and \$49 less charge-off amount after passing these laws. In addition, there is a reduction of 2.9% for the delinquency rate and a 2.7% decrease for the charge-off or debt in collections rate. All results are robust and significant.

This paper relates to several works on payday loan related topics in economics. The earlier works generally focus on the effect of access to payday loans on financial health. Using the National Survey of America's Families (NSAF), Melzer (2011) found that access to payday loans leads to hardships in paying mortgages, rent, and utility bills. Some researchers found no effect of these loans on financial well-being. For example, Bhutta (2014) and Bhutta et al. (2015) found that payday borrowing had little to zero effect on credit scores, new delinquencies, and other measures of financial health.

Recent researchers have started to analyze how easier (and cheaper) access to traditional credit affects alternative borrowing. For example, Di Maggio et al. (2020) analyzed the effect of banks being banned from practicing the reordering of transactions from "high-to-low" for their overdraft fees[9]. After banks stop practicing high-to-low reordering, consumers experience improved financial health. Specifically, consumers decreased their payday loan borrowing after the ban because traditional credit became cheaper than alternative ones. Hence this ban increases access to traditional banking (which in return increases credit scores and overall financial well-being). In Miller and Soo (2020), it analyzed the effect of removal of Chapter 7 bankruptcy flag[10] on payday borrowing. By linking traditional credit data from Experian and alternative credit data from Clarity Services, they found that flag removals increase the use of alternative credit products such as subprime installment loans.

There are also attempts to study the effect of payday loan laws that aim to protect borrowers. For

[9]High-to-low transaction reordering increases banking overdraft fees significantly. For example, a customer has only \$400 in his checking account balance. On a particular day, he wants to withdraw a \$50 first to cover an electric bill, a \$50 for the groceries, and then a \$500 bill for rent. The typical overdraft fee for each transaction is \$35. Under a chronological transaction ordering, only one overdraft incurs, and by the end of the day, his account balance = $\$400 - \$50 - \$50 - \$500 - \$35 = -\$235$. However, under the high-to-low transaction reordering, each transaction is ordered from the highest to the lowest. So the number of overdrafts incurred under this rule is 3, and by the end of the day, his account balance = $\$400 - \$500 - \$35 - \$50 - \$35 - \$50 - \$35 = -\$305$.

[10]The Fair Credit Reporting Act requires credit bureaus to remove Chapter 7 bankruptcy flags from individual credit reports after ten years.

example, in January 2022, Texas mandated disclosure for consumers taking out payday loans[11]. In the meantime, the cities of Austin and Dallas applied stricter supply restrictions through city ordinances. Wang and Burke (2022) found that statewide and city ordinances significantly declined payday loan borrowing.

2 Background on Payday Loans

Payday loan[12] is one form of small-dollar loans[13], which is usually repaid in a single payment on the borrower's next payday, or other receipts of income (CFPB, 2022b). The typical loan limit is $500, and the typical annual percentage rate (APR) is between 300% to 500%. In comparison, the APRs on credit cards only range between 12% and 30%.

Despite their high APRs, payday loans are still popular for quick cash. To illustrate, I have collected payday loan descriptions from 11 large payday loan lenders' websites[14] and conducted a simple text analysis. Appendix A illustrates the results. We can see that "cash, quick, fast, easy" are some of the most significant features. Payday loans are also described to cover "unexpected" or "emergency bills."

2.1 Payday Loan Protection Laws in the U.S.

Because of their high APRs and the consequence of "debt traps," Payday loans are long seen as predatory loans. As a result, many states have passed laws to battle bad debts caused by these loans. There are four main categories of regulation on payday loans: (1) prohibitions (i.e., altogether banning payday loans); (2) price caps (e.g., Some states limit payday loan APR to 36%); (3) contract requirements (e.g., Some states may restrict the number of rollovers or renewals); and (4) disclosures (e.g., Texas required payday loan information disclosures in summer 2011).

Appendix B.1a illustrates a map of each state's payday loan laws, including legal status and price

[11]The disclosure requires lenders to compare the cost of payday loans with other credit products and present the likelihood of renewal in easier-to-understand terms.

[12]In some states, a payday loan is referred to as deferred deposit, deferred presentment loans, cash advance loans, and check loans.

[13]Common small-dollar loans may include payday loans, auto title loans, rent-to-own (RTO), and pawn loans.

[14]These payday lenders are Ace Cash Express, Advance America, Cash Central, Cash Store, Check City, Check into Cash, Check n' Go, DirectPaydayLoans, Money Tree-California, My Payday Loan, Oasis Payday Loans, and PaydayChampion.

caps. As of the end of 2020, thirteen states have laws in place that explicitly ban payday loans[15]. Nine states have laws that limit payday loan APRs to 36%. This low-interest rate is considered an effective ban since below 36% APRs are not profitable, which would eventually drive all payday lenders shut down their business[16]. Appendix B.1b is an example of contract requirements. This map considers prohibited and effective-ban states that do not allow payday loans. Looking at only states where payday loans are legal, most states do not allow rollovers except for Texas and Nevada.

2.2 Extended Payment Plan Laws for Each State

Among the states where payday loans are legal, some have passed extended payment plan laws to help alleviate the repayment burdens. Consumers may choose these extended payment plans to pay back their outstanding payday loans in installments at no extra charge (CFPB, 2022a). The typical features[17] of extended payment plans may include:

Installments: Most states offer consumers a chance to repay payday loans in three or four installments instead of in one payment. This is the most salient feature of extended payment plans.

Plan Length: Some states determine a minimum repayment term, typically between 60 to 90 days.

Allowable Fees: Fourteen states require no additional charge for the extended payment plans[18].

Frequency of Use: Most states limit the extended payment plan to once every 12 months.

Consumer Eligibility: Some states may only allow consumers to take an extended payment plan if they have reached a threshold of rollovers.

Disclosures: Some states may require lenders to either disclose the availability of an extended payment plan before lending the loans or require lenders to notify consumers about these plans upon default.

[15] These states are: Arizona, Arkansas, Connecticut, District of Columbia, Georgia, Maryland, Massachusetts, New Jersey, New York, North Carolina, Pennsylvania, Vermont, and West Virginia.

[16] These states are Colorado, Maine, Montana, New Hampshire, New Mexico, Ohio, Oregon, South Dakota, and Virginia.

[17] For more details, see CFPB (2022a) or Appendix C for more details.

[18] Michigan allows lenders to charge consumers $18.69 through 2025 to extend their payment plans.

Appendix B.1c plots the map for each state that has passed the extended payment plan laws. Appendix C lists detailed extended payment plans for each state. By the end of 2020, fifteen states that require lenders to provide extended payment plans. The rest of the fourteen states where payday loans are legal do not have any extended payment plan laws passed[19].

3 Clarity Credit Data

This paper uses a novel dataset from Clarity Services, Inc. (later referred to as "Clarity"). Clarity is a subsidiary credit reporting agency of Experian that specializes in providing underwriting services and information to lenders who offer alternative credit products such as payday loans[20]. Like traditional credit bureaus, lenders using Clarity's underwriting services report each loan applicant's information to Clarity for verification purposes. Clarity then tracks each borrower's tradeline activity. These tradelines are very similar to traditional credit reports, which include account types, balances, delinquencies, and repayment histories. This information is valuable to lenders for assessing an applicant's default probabilities.

Clarity data includes over 60 million borrowers and covers more than 70% of non-prime consumers in the U.S. One caveat is that Clarity data only contains loan records of who uses its underwriting services. Despite this, Clarity may be the best existing coverage of payday loan behavior in the U.S. In addition, Clarity data has more online payday lending recorded than storefront payday lending. Appendix D shows these differences.

3.1 Sample Construction

The Clarity panel data used in this research range from January 1st, 2015, to December 31st, 2020. It records two main categories of information. First, there is a set of loan applicant's characteristics, which include age, net monthly income, pay frequency, housing status, months at address, state, zip code, inquiry received date, and inquiry type. Each individual has a unique ID. The second category includes each borrower's (who has opened a loan account) repayment history. The information may

[19] These states are Hawaii, Illinois, Iowa, Kansas, Kentucky, Minnesota, Mississippi, Missouri, Nebraska, North Dakota, Oklahoma, Rhode Island, Tennessee, and Texas.

[20] In my sample data between 2015 and 2020, about half of the observations are payday loans, the rest of them are mostly installment loans.

include the account opened date, account and portfolio type, current balance, delinquency status, and other types of account status.

Given Clarity's sampling frame, only these five states had data before the extended payment plan laws were rolled out: Delaware, Florida, Louisiana, Nevada, and Utah. Table 1 presents each treated state's treated date, the quarter being treated, and the total treated quarters. First, the quarters are aggregated for the six years, i.e., from 2015 to 2020. The quarters range between one to twenty-four. Then the treated quarter is assigned based three months after the treated date. For example, if the law was effective on 2016-07-01 for Utah, then I assume the actual effect takes after three months, which is on 2016-10-01. That said, the (aggregated) quarter being treated for Utah is quarter 8. This works the same for the other four states. The time period is aggregated in quarter for a few reasons. The first reason is that a smaller time period (e.g., in months) would lead to many missing periods because some states may have yet to record data. Another reason is that measurements in quarters may be more accurate since it may take some time for the new laws to take effect.

Table 1: States that Passed Extended Payment Plans between 2015-2020

Treated state	Date being treated	Quarter being treated	Total treated quarters
Delaware	2018-12-12	17	8
Florida	2019-07-01	20	5
Louisiana	2015-01-01	3	22
Nevada	2017-07-01	12	13
Utah	2016-07-01	8	17

Notes: The other 11 states that also passed extended payment plans were excluded because our clarity data does not have a pre-treatment record.

3.2 Outcome Variables

The outcome variables are related to each borrower's financial health. I use four variables to measure an individual's financial health after the law: (1) **Total amount past due**. This value is the total amount of payments (adjusted to 2020 dollars) due based on delinquency. This value includes late charges and fees (if applicable) that are past due. (2) **Original charge-off**. This variable is the original amount charged off due to loss by the lender. (3) **Delinquency rate**. It is the delinquency rate of loans for each borrower [21]. (4) **Charge-off or debt in collections rate**. This variable is

[21] A loan is considered delinquent if there is a payment that is past due.

the ratio of charge-off or debt in collections. If a borrower does not pay the debt after 150 or more days, debtors will put this debt in collections and keep collecting the remaining debt. If the debt is still not fully collected after about six months, debtors will put it in charge-off, e.g., selling the debt to a debt collector and letting them collect the rest. These are common measures based on multiple papers, and Consumer Financial Protection Bureau (CFPB) reports (Nunez et al., 2016). One thing to note is that because most people repay their loans on time, most values for each outcome will be zero. Appendix E gives histograms for the outcome variables.

3.3 Summary Statistics

Table 2 reports summary statistics for my sample. I present mean and standard error for each variable for the control and treated states. The table also provides p-values computed using the paired t-test for the difference in means between these two groups. There are some differences between the two groups, but the difference is not substantial.

For the outcome variables, the amount past due and original charge-off are a bit higher among the treated states. On the other hand, the treated states tend to have lower delinquency rates and charge-off or debt-in-collection rates. Compared with people from the control states, borrowers from the treated states tend to be older and have higher income; in terms of housing and income pay, people from the treated states also tend to rent a place or live with friends, reside longer at the current address, and are more likely to be paid biweekly. These variables are collected by the payday loan lenders and are regularly maintained since all information is highly relevant to the business survival; thus the data is highly trustworthy.

4 Empirical Strategy

4.1 Event Study

I employ the event study framework for staggered adoption following Sun and Abraham (2021) to motivate this research. The event study helps visualize the treatment effect once the treatment is "switched on" (i.e., once the extended payment plans become effective). It is possible to visually show the treatment effect in an SDiD setting (which will be presented later). However, event study is

Table 2: Summary Statistics for Control and Treated States

	Control States (N = 336) Treated States (N = 120)				
	Mean		SD		p-value
	Control	Treated	Control	Treated	
Outcome Variables					
Amount Past Due	$40.680	$41.470	$13.564	$14.013	0.017
Original Charge-Off	$116.016	$120.926	$39.672	$41.3067	0.025
Delinquency Rate	6.861	5.887	1.127	1.521	0.010
Charge-Off or Debt-in-Collections Rate	7.563	6.190	1.237	0.552	0.023
Borrower's Characteristics					
Age	43.993	44.034	12.615	13.132	0.139
Net Monthly Income	$3,055.509	$3,143.424	$1,724.401	$1,727.416	0.423
Months at Address	28.624	30.038	10.383	11.098	0.135
Pay Frequency: Biweekly	52.647	59.196	6.157	5.525	0.210
Pay Frequency: Monthly	21.985	20.738	2.575	1.947	0.003
Pay Frequency: Weekly	12.952	12.169	1.350	1.121	0.043
Pay Frequency: Semimonthly	12.293	10.611	1.577	0.690	0.371
Pay Frequency: Annual	0.123	0.287	0.025	0.028	0.240
Housing Status: Rent	56.368	58.187	6.340	5.259	0.011
Housing Status: Own	39.545	38.864	4.204	3.466	0.009
Housing Status: Other	3.072	2.554	0.378	0.228	0.081
Housing Status: Living with Family	0.343	0.144	0.045	0.013	0.029
Housing Status: Living with Friends	0.263	0.306	0.064	0.002	0.000
Housing Status: Living with Parents	0.408	0.225	0.054	0.019	0.520

Notes: The five treated states are Delaware, Florida, Louisiana, Nevada, and Utah. See Table 1 for the exact treated dates. The fourteen control states (the donor pool) are Hawaii, Illinois, Iowa, Kansas, Kentucky, Minnesota, Mississippi, Missouri, Nebraska, North Dakota, Oklahoma, Rhode Island, Tennessee, and Texas. The mean and SD for outcome variables are calculated using pre-treatment data. For all dollar values, the numbers are adjusted to 2020 dollars using the consumer price index for urban consumers. The table reports the mean ratios for pay frequency, housing status, delinquency rate, and charge-off or debt-in-collections. The p-values are from the t-test for the mean differences between the control and treated groups. Note that the sample size is small because it is aggregated at the state level. At an individual level, there are 2,498,231 observations for the control units and 360,453 observations for the treated units.

a common practice, and Clarke et al. (2023) proposed the event study method presented by Sun and Abraham (2021) as a good alternative for the staggered adoption setting.

The event study follows the below model:

$$y_{it} = \alpha_i + \beta_t + \sum_{g} \sum_{r \neq -1} \mu_{g,r} \left(\mathbf{1}(G_i = g) \times event\_time_{it}^{r} \right) + \epsilon_{it} \tag{1}$$

The outcome variable y_{it} is at the state i and quarter t level. State and quarter fixed effects are represented by α_i and β_t. Each treated cohort is indicated by g, where $g = \{1, 2, ..., 5\}$. Since the five states are treated at five different periods, $G_i = 5$. The binary indicator $\mathbf{1}(G_i = g)$ equals 1 if G_i corresponds to that specific treated cohort. The variable $event\_time_{it}^{r}$ is time relative to the law adoption time, which is restricted between $[-6, 6]$. Here, $r = -1$ is omitted, which is standard in the event study literature since it makes it easier to visualize the treatment effect of "switching on" the laws and study the pre-existing trends in the outcomes. The interaction term $\mathbf{1}(G_i = g) \times event\_time_{it}^{r}$ gives a coefficient $\mu_{g,r}$ for each cohort interacted with a different $event\_time_{it}^{r}$[22].

Figure 1 presents event study results for each outcome variable. After a state adopted the extended payment plans, all financial outcomes have improved: we can see a significant decrease in each measurement. One should note that we cannot simply interpret the results from this event study as causal effects but as a simple comparison of outcomes pre-treatment and outcomes post-treatment. To quantitatively measure the actual treatment effect, we will use the SDiD model in the following subsection to measure these treatment effects.

4.2 Synthetic Difference-in-Differences

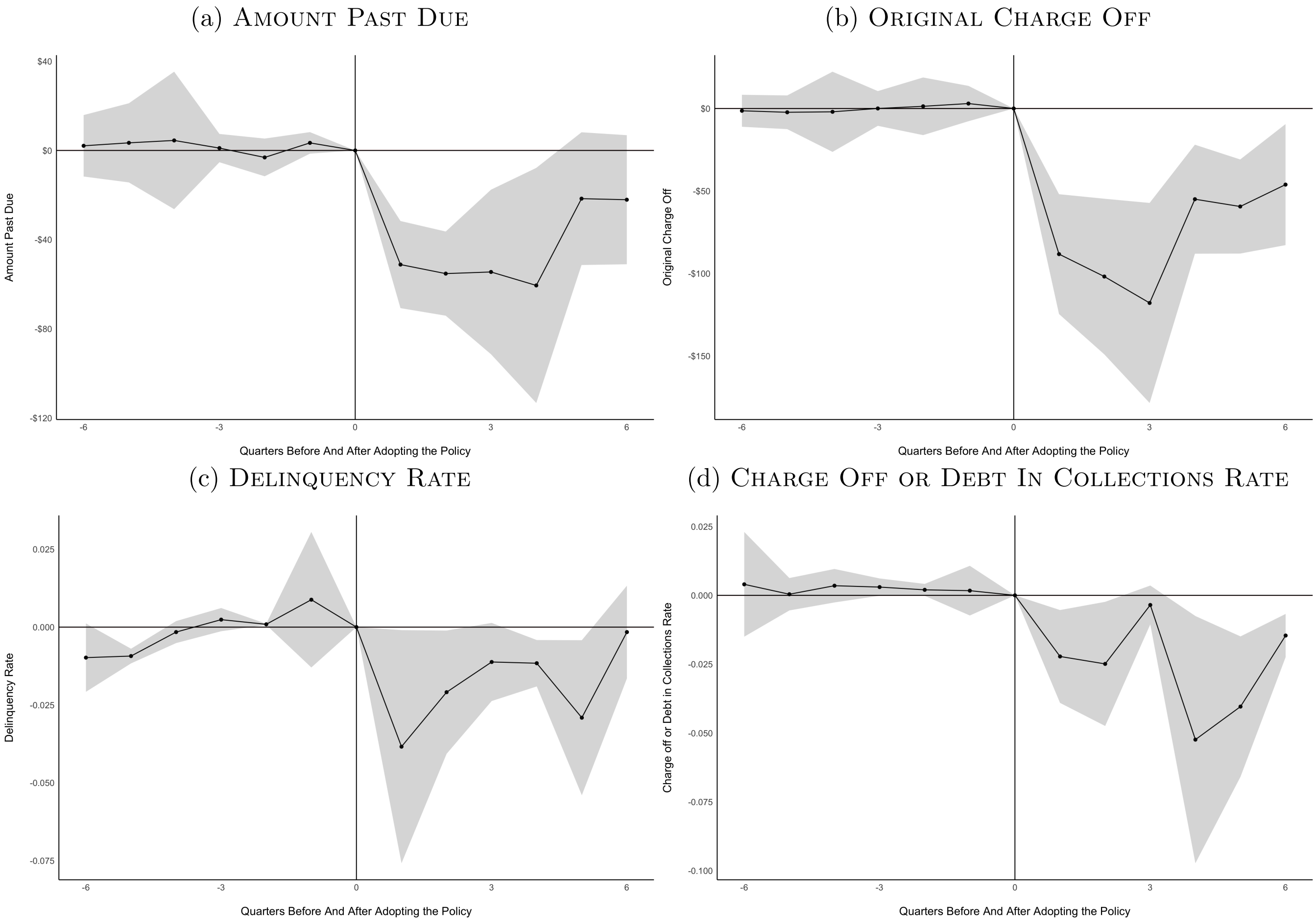
To uncover the causal effect of these extended payment plans on borrowers' financial health in states where they have passed these laws, I employ the synthetic difference-in-differences (SDiD) model following Arkhangelsky et al. (2021) and Clarke et al. (2023). The SDiD model is defined as follows:

$$\hat{\tau}^{SDiD} = \underset{\mu,\alpha,\beta,\tau}{\operatorname{argmin}} \left\{ \sum_{n=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - \tau D_{it})^2 \hat{w}_i \hat{\lambda}_t \right\} \tag{2}$$

Our interest of parameter is τ, which identifies the average treatment effect on the treated. The

[22]Here is a straightforward process of this event study: For each treated cohort g and each $event\_time$, we estimate a treatment effect. For example, when $g = Delaware$, we obtain a treatment effect for each $event\_time$ except for when $r = -1$. Do the same for the other treated state. Then get a mean treatment effect for each $event\_time$.

Figure 1: Event Study For Each Outcome Variable



Notes: The black dot is the estimated effect for each event time. The shaded area is the 95% confidence interval.

outcome variable Y_{it} is related to a borrower's financial health; it can be the total amount past due, total charge-off amount, delinquency rate, or charge-off or debt-in-collections rate. μ is the intercept. α_i and β_t represent the state and quarter fixed effects. D_{it} is the binary treatment variable. It equals 1 if a state has passed the extended payment plan laws, and it equals 0 otherwise. I set the treatment variable as binary for two reasons. First, the extended payment plans are composed of a set of features. As seen in Section 2.2, each state has some variations for these features. It would make sense to study all features as a whole instead of separate ones. In addition, all five treated states require no additional charge for the extended payment plans. This feature directly affects borrowers' repayment behavior, crucial to studying financial health.

Note that in Equation 2, there are two types of weights: the unit weights $\hat{w}_i$ and the time weights

$\hat{\lambda}_t$. The fourteen untreated states specified in Table 2 act as donor units. By applying both unit and time weights on the donor units, SDiD generates a synthetic control version of the treated unit.

The unit weights $\hat{w}_i$ is calculated via constrained least squares on pre-treatment data:

$$\hat{w} = \underset{w_0, w}{\text{argmin}} \parallel \bar{\mathbf{y}}_{pre,treat} - (w_0 + \mathbf{Y}_{pre,control}\mathbf{w}) \parallel^2 + \xi^2 T_{pre} \parallel \mathbf{w} \parallel_2^2 \tag{3}$$

such that $\sum_{i=1}^{N_{control}} w_i = 1$ and $w_i \geq 0 \; \forall \; i$. Here, $\bar{\mathbf{y}}_{pre,treat}$ is the mean outcome pre-treatment for the treated states. w_0 is the intercept, which allows the treated unit and the synthetic control to have a different level. $Y_{pre,control}$ is the outcome for control units before treatment. $\mathbf{w}$ is a $N_{control} \times 1$ vector. T_{pre} is the total pre-treatment periods. The term $\parallel w \parallel_2^2$ is a squared $l2$ norm (or Euclidean norm)[23].

The extra ξ term in equation 3 is a regularization parameter, which is identified by the following:

$$\begin{aligned} \xi &= (N_{treat} \cdot T_{post})^{1/4} \hat{\sigma}, & \text{with } \hat{\sigma}^2 &= \frac{1}{N_{control}(T_{pre}-1)} \sum_{i=1}^{N_{control}} \sum_{t=1}^{T_{pre}-1} (\Delta_{it} - \bar{\Delta})^2, \\ \Delta_{it} &= Y_{i(t+1)} - Y_{it}, & \text{and } \bar{\Delta} &= \frac{1}{N_{control}(T_{pre}-1)} \sum_{i=1}^{N_{control}} \sum_{t=1}^{T_{pre}-1} \Delta_{it} \end{aligned} \tag{4}$$

$N_{control}$ and N_{treat} are the total number of control units and treated units correspondingly. T_{pre} and T_{post} represent the total pre-treatment and post-treatment periods. Δ_{it} is the first difference in outcomes, and $\bar{\Delta}$ is the mean for the first differences. $\hat{\sigma}$ is the standard deviation of first difference Δ_{it}. The regularization parameter ξ is chosen to match the size of the first difference for untreated units in the pre-treatment period, multiplied by a theoretically motivated term $(N_{treat} \cdot T_{post})^{1/4}$. If both ξ and w_0 are zero, then Equation 3 would become the weights for synthetic control model discussed in Abadie (2021) where $N_{treat} = 1$.

We can obtain the time weights $\hat{\lambda}$ by using constrained least squares on the control data:

$$\hat{\lambda} = \underset{\lambda_0, \lambda}{\text{argmin}} \parallel \bar{\mathbf{y}}_{post,control} - (\lambda_0 + \boldsymbol{\lambda}\mathbf{Y}_{pre,control}) \parallel^2 \tag{5}$$

[23]The l2 norm is defined as $\parallel w_2^2 \parallel = \sum_{i=1}^{N_{control}} w_i^2$. Adding this l2 penalty ensures we do not have very large weights, forcing us to use more control units.

such that $\sum_{t=1}^{T_{pre}} \lambda_t = 1$ and $\lambda_t \geq 0 \; \forall \; t$. Note that $\bar{\mathbf{y}}_{post,control}$ is the mean outcome for the control group after the treatment. λ_0 is an intercept, which allows the pre- and post-treatment periods to have different levels. $\boldsymbol{\lambda}$ is a 1 by T_{pre} row vector[24].

The data needs to satisfy certain requirements to run the SDiD model. First, it needs to be a balanced panel, where each variable for each unit has no missing values for each period. For the individual level data, many borrowers are not observed for some quarters, which makes it impossible to run the SDiD model. Since I intend to study the average treatment effect for the treated states instead of for the treated individuals, it is more appropriate to aggregate the data at the state level[25]. The SDiD model also requires at least two pre-treatment periods off of which to determine control units (It is satisfied for the payday loan data here).

In the DiD model, the covariates are added directly into the model; in the SC model, the covariates are included to get close matches between treated and synthetic control units. However, the SDiD covariate adjustments are pre-processed to ensure they remove the impact of changes in covariates from outcomes before obtaining synthetic controls [26]. Appendix F explains that we must first run a TWFE model by regressing outcomes on all predictors where all data comes from pre-treatment periods. Then we apply the SDiD model on residual outcomes where the estimates obtained from the TWFE model d to all data (including treated units)[27].

In practice, obtaining the treatment effect will require extra steps since the treatment here involves differential timing. To illustrate, the matrix D below shows how each state passed the extended payment plan laws at different periods. All of the control states are combined in the first column vector. The vector's values are denoted as 0 and are labeled with the corresponding quarters. For example, the treatment switches on for Delaware at quarter 17, so the value switches from 0 to 1 at quarter 17. For Florida, the value switches from 0 to 1 in quarter 20.

[24]Another way to understand the weights is: The unit weights $\hat{w}_i$ defines a synthetic control unit using pre-treatment data such that $\bar{y}_{pre,treat} \approx w_0 + Y_{pre,control} \cdot w_{control}$. Similarly, the time weights $\hat{\lambda}_t$ defines synthetic pre-treatment period such that $\bar{y}_{post,control} \approx \lambda_0 + \lambda_{pre} \cdot Y_{pre,control}$.

[25]There are a few missing values for some covariates. They are imputed with mean or mode before aggregating the data.

[26]See Kranz (2022). This paper explains that the results are more stable by pre-processing covariates in the SDiD model in some implementations.

[27]There are two requirements for the covariates: (1) Time-varying. Since all borrowers in the payday loan data are from low-income groups, and the borrowing happened from time to time, there are variations for each predictor across time. (2) Non-collinear. The variables are not collinear based on correlation matrix results.

$$
D = \begin{array}{c}
\begin{array}{cccccc} \textit{Control States} & \textit{Delaware} & \textit{Florida} & \textit{Louisiana} & \textit{Nevada} & \textit{Utah} \end{array} \\
\begin{bmatrix}
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
\vdots & \vdots & \vdots & \mathbf{1} & \vdots & \vdots \\
 & & & & & \\
 & & & & & \mathbf{1} \\
 & & & & & \\
 & & & & \mathbf{1} & \\
 & & & & & \\
 & \mathbf{1} & & & & \\
 & & & & & \\
 & & \mathbf{1} & & & \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
0 & \mathbf{1} & \mathbf{1} & \mathbf{1} & \mathbf{1} & \mathbf{1}
\end{bmatrix}
\end{array}
$$

The SDiD model cannot handle matrix D because we do not have a clear definition for the pre-treatment period or a control unit. To solve this, we can delete columns (or units) in matrix D and decompose D into five smaller block matrices, each with control states and one treated state only. This way, we can apply a simple two-by-two DiD model for each small block matrix. To illustrate, the matrix $D_{Delaware}$ is for control states and Delaware, where all values for control states are 0, and values for Delaware switch from 0 to 1 at quarter 17. Similarly, we can construct a small block matrix for other treated states.

).

$$D_{Delaware} = \begin{array}{c} \begin{array}{cc} \textit{Control States} & \textit{Delaware} \end{array} \\ \left[\begin{array}{cc} 0 & 0 \\ 0 & 0 \\ \vdots & \vdots \\ \\ & \mathbf{1} \\ \\ \vdots & \vdots \\ 0 & \mathbf{1} \end{array}\right] \end{array}$$

After running weighted DiD models separately for each treated state, we get five different average treatment effects on the treated (ATT). In order to get a final treatment effect for all treated states, we need to re-weight each state's ATT by their treated periods following Clarke et al. (2023). For example, based on Table 1, the total treated quarters for all five states are 65. The weight is $\frac{8}{65}$ for Delaware ATT, $\frac{5}{65}$ for Florida ATT, and so on. Appendix F explains the complete algorithm for estimating ATT using SDiD with staggered adoption.

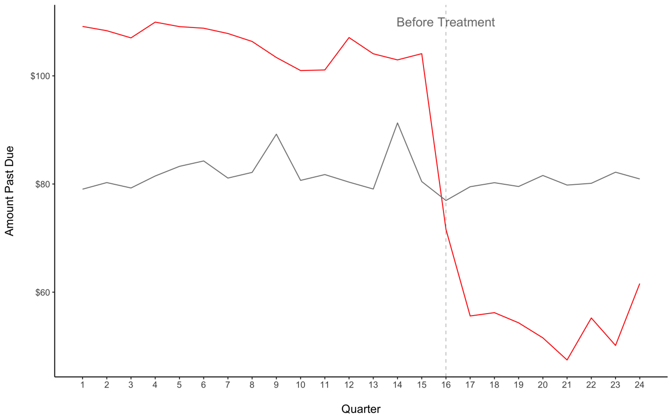
4.3 Impact of Extended Payment Plans on Financial Health

Figure 2 shows each treated state's ATT for the outcome variable amount past due. The treatment effect for each state could vary a lot, but the overall treatment effect is negative. This result means that after passing the extended payment plans, each treated state has reduced past due amount for payday loans. For the other three outcome variables, the ATTs have very similar trends (see Appendix G).

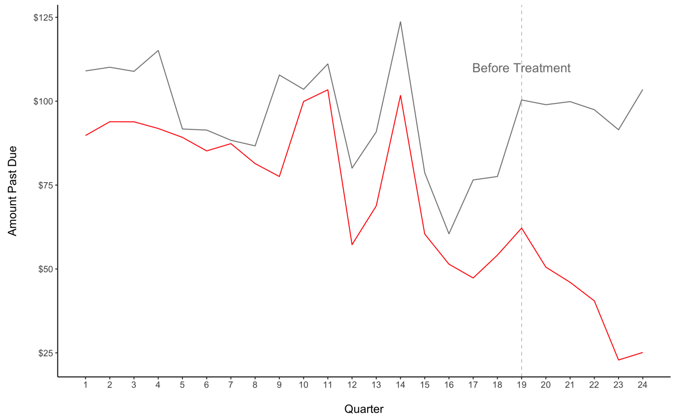
Table 3 presents the results from both DiD and SDiD models. Column (1) and column (3) show

Figure 2: SDiD Plot for Amount Past Due:
ATT for Each Treated State

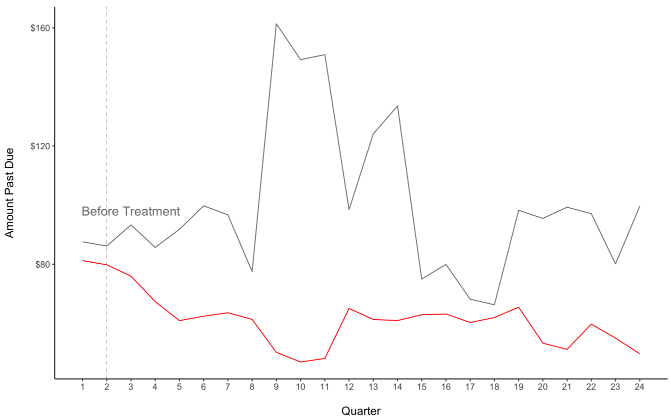
(a) Delaware



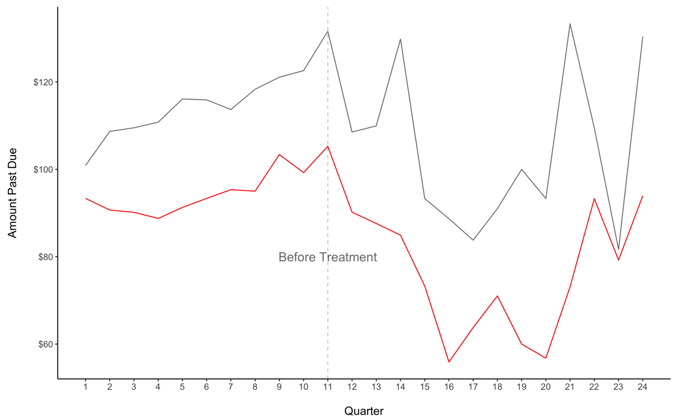
(b) Florida



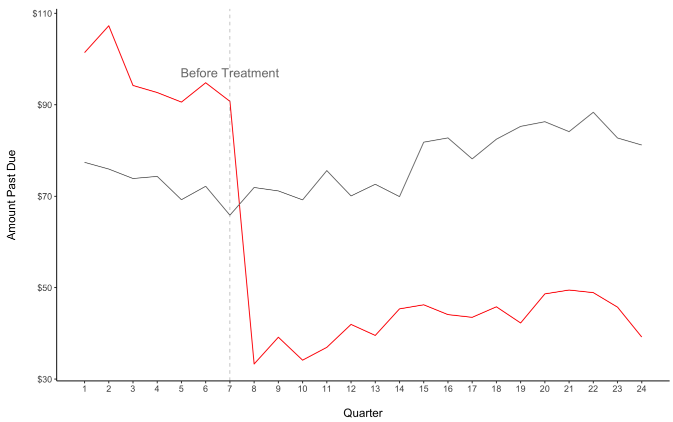
(c) Louisiana



(d) Nevada



(e) Utah



Notes: For each plot, the red line represents the treated state, and the gray line is the synthetic control state. Similar to the parallel trend from DiD model, the SDiD model should also have a parallel trend between the treated and synthetic control states before the treatment.

Table 3: AVERAGE TREATMENT EFFECTS OF EXTENDED PAYMENT PLANS ON FINANCIAL HEALTH

	DiD		SDiD	
	(1)	(2)	(3)	(4)
Outcome Variable:				
Amount Past Due	−27.5022**	−30.5277**	−24.4931*	−25.3166*
	(12.7551)	(14.1838)	(14.4660)	(13.8418)
Original Charge Off	−49.2900***	−52.8416***	−40.0734**	−49.4988**
	(18.2468)	(17.1973)	(18.7904)	(19.9673)
Delinquency Rate	−0.0250*	−0.0308*	−0.0117**	−0.0289**
	(0.0139)	(0.0180)	(0.0546)	(0.0136)
Charge Off or Debt in Collections Rate	−0.0326*	−0.0351*	0.0211*	−0.0265**
	(0.0195)	(0.0212)	(0.0109)	(0.0135)
Observations	456	456	456	456
Controls:				
(Baseline)				
Age		Y		Y
Income		Y		Y
Months at address		Y		Y
Housing Status		Y		Y
Pay Frequency		Y		Y
State and Quarter Fixed Effects	Y	Y	Y	Y

Notes: The standard error for the SDiD model is obtained by bootstrap with 1,000 iterations. For the estimation results, *** means 99% significance level, ** means 95% significance level, and * means 90% significance level.

results using DiD and SDiD without any covariates. Column (2) and column (4) results add covariates to the models. After adding covariates, estimates from both models increased a bit. After passing the extended payment plan laws, on average, the treated states have reduced \$30.53 past due amount using DiD model and about \$5 less using the SDiD model (\$25.32). The original charge-off amount is reduced by about \$52.84 with DiD model and \$49.50 with the SDiD model. The DiD model estimates a reduction of 3.08% in delinquency rate after adopting the law and about 2.89% with the SDiD model. For the charge-off or debt in collections rate, the DiD estimates a decrease of 3.51%, and the SDiD gives a 2.65% reduction. Overall, the SDiD estimates are smaller than the DiD estimates.

I follow the bootstrap inference algorithm presented by Clarke et al. (2023) to get standard errors. Appendix H shows this algorithm in detail. The main steps are sampling original disaggregated data with replacement. This procedure almost guarantees always having control and treated units in the bootstrap dataset. Then aggregate the data and run the same algorithm presented in Appendix F 1,000 times with different bootstrap datasets. Table 3 shows that the ATTs are all significant for both

DiD and SDiD models. For example, the amount past due ATT is significant at 90% level for SDiD without or with covariates, whereas the DiD is significant at 95% level. After controlling for covariates, the other three outcomes are significant at the 95% level; for DiD model, the original charge-off is more significant (at the 99% level), and the other two outcomes are only significant at the 90% level.

The estimated differences between the two methods arise due to the model settings. The DiD model essentially uses the same weights across units and time. Moreover, it assumes parallel trends. SDiD works differently. It does not just compare the raw outcomes between the treated and control units. Instead, it uses unit and time weights in a basic TWFE model, which makes the TWFE model "local." In terms of units before treated periods: the regression put more weights on control units that are more similar to the treated units; In terms of time for control units: the regression focuses more on pre-treatment periods that are more similar to the post-treatment periods. These weights make the estimator more robust. Therefore, SDiD captures more outcome variations than both DiD and SC models, reducing the estimator's variance.

4.4 Robustness Checks

To check the robustness of the SDiD estimates, I run a placebo test to check if there is a treatment effect or if there are other factors at play. First, I remove the five treated states from the data. Next, randomly select five states and pretend they are the treated states. The sample assigns a treated period for each "fake" treated state using the real treated periods. Then I run the same DiD model as in Section 4.2.

Table 4 presents results from placebo tests. For delinquency rate and charge off or debt in collections rate, the effect is close to zero and non-significant. Although the results are not quite zero, the estimates of the amount past due and the original charge off are minimal relative to the SDiD results in Table 3. We can conclude that our estimates from the SDiD model are robust and causal.

5 Conclusions and Discussions

This paper exploits a natural U.S. experiment among states that have adopted payday loan extended payment plans. Using the Clarity sub-prime payday loan data, I can estimate these extended

Table 4: Placebo Test Results

	SDiD Placebo Test	
	(1)	(2)
Outcome Variable:		
Amount Past Due	0.3779	0.3218
	(0.9401)	(0.4370)
Original Charge Off	−2.0309	−2.2471
	(1.5546)	(2.8075)
Delinquency Rate	−0.0069	−0.0061
	(0.0115)	(0.0150)
Charge Off or Debt in Collections Rate	−0.0019	−0.0010
	(0.0017)	(0.0010)
Observations	336	336
Controls:		
(Baseline)		
Age		Y
Income		Y
Months at address		Y
Housing Status		Y
Pay Frequency		Y
State and Quarter Fixed Effects	Y	Y

Notes: The fake (randomly sampled) states are Oklahoma, Texas, Missouri, Kentucky, and Nebraska. The standard error for the SDiD model is obtained by bootstrap with 1,000 iterations.

payment plan laws' effects on different financial health outcomes. The main findings are that after passing these laws, the treated states, on average, have a reduced amount past due by about \$25 and the original charge-off amount by about \$49. There is also a 2.89% decrease in delinquency rate and a 2.65% reduction of charge-off or debt in collections rate. These results are all robust and significant.

These findings are crucial to policies that aim to improve borrowers' overall financial health and are relevant to financial protection bureaus. For example, in 2016, the CFPB proposed a payday loan rule (but it was never implemented) to stop payday debt traps. Under this rule, one of the requirements is that lenders need to disclose whether a borrower can repay the loan and is still able to cover basic expenses and major financial obligations[28]. The findings from this study imply that this payday loan rule may benefit payday loan borrowers, especially those trapped in loan repaying cycles.

[28] Under this rule, the full requirement includes (1) Full-payment test: lenders are required to disclose whether a borrower can repay the loan, and still able to cover basic expenses and major financial obligations. (2) Principal-payoff option for certain short-term loans: The borrower may obtain a short-term loan up to \$500 without the full-payment test if the loan allows the borrower to repay in time. (3) Less risky loan options: Loans with less risk to borrowers do not require the full-payment test or the principal-payoff option. (4) Debit attempt cutoff: This cutoff applies to short-term loans with an APR over 36% that includes an authorization for the lender to access the borrower's checking or prepaid account (CFPB, 2017).

There are two main limitations to this study. First, a few treated states must be excluded due to Clarity sampling frame. Only five treated states are included in this study. If we had pre-treatment data for the other eleven states, we could have obtained a more accurate ATT. Another issue is that the computation process for the SDiD model is somewhat complex and computationally heavy, especially for the staggered adoption setting.

For future studies, we could study similar topics using a double machine learning model on disaggregated data (e.g., we can study the heterogeneous treatment effects of extended payment plans on financial health for different levels of income volatility). That way, we could fully utilize the individual-level information and get more interesting results.

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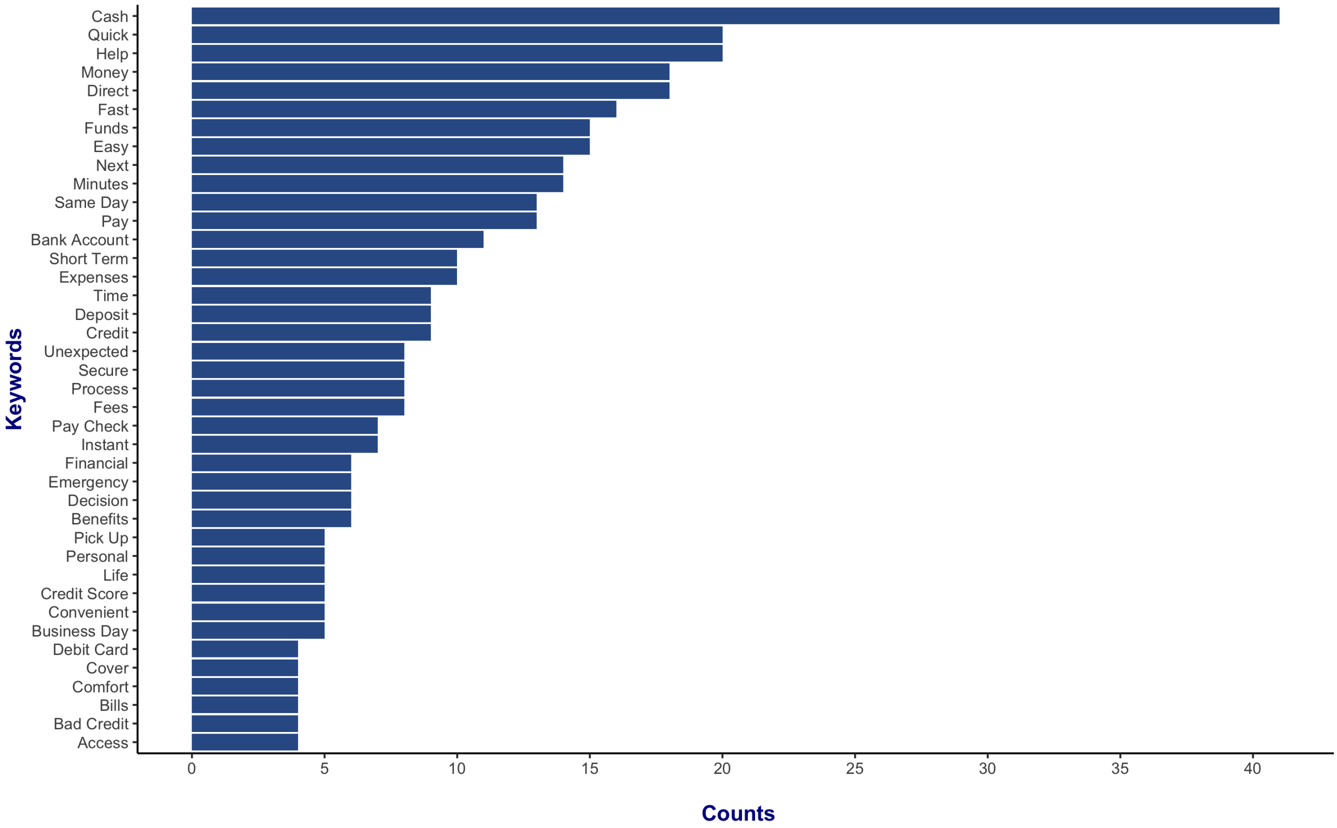
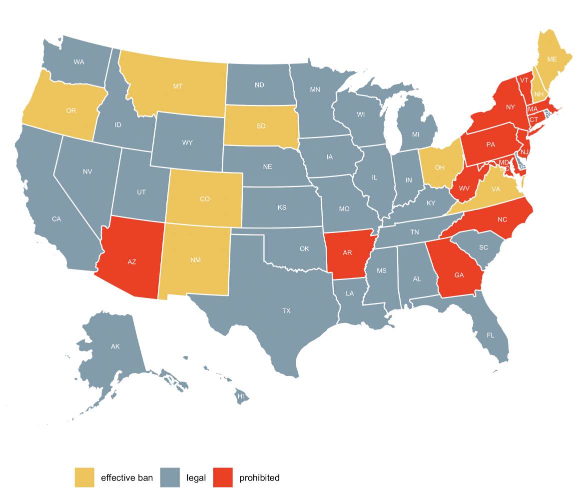
A Appendix: Payday Loan Features

Figure A.1

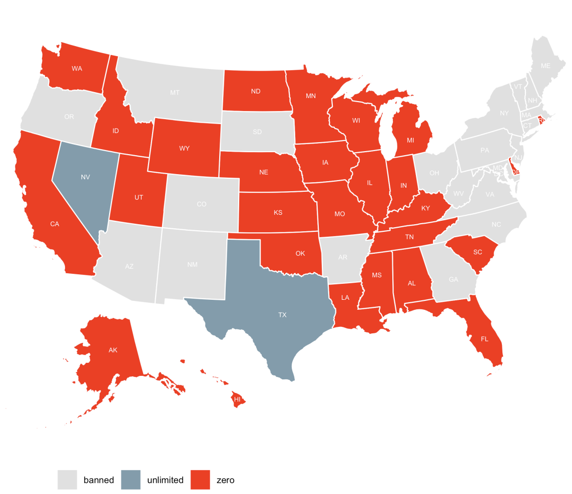


B Appendix: Payday Loan Laws in the U.S.

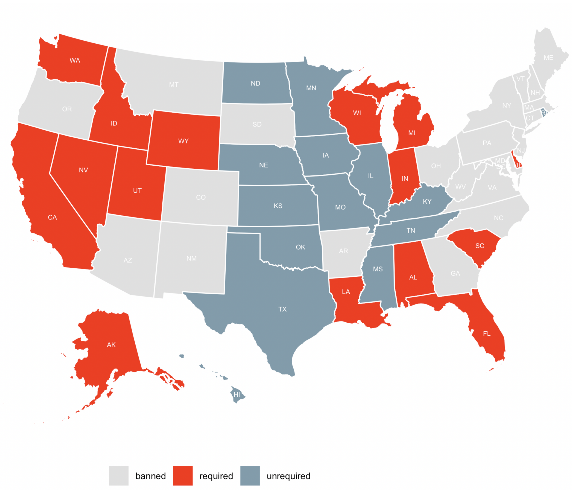
Figure B.1: Map: Payday Loan Laws



(a) Payday Loan Legal Status for Each State by the End of 2020



(b) Rollover Laws for Each State by the End of 2020



(c) Extended Payment Plan Laws for Each State by the End of 2020

Notes: For figure (a), the effective-ban states limit payday loan APRs to 36%. For figures (b) and (c), the gray areas represent those states that ban payday loans. The states that do not allow rollovers are in red, and those that allow rollovers are in blue. Similarly, the red states require extended payment plans, while the blue ones do not.

C Appendix: Extended Payment Plan Laws for Each State

State	Law Effective Date	Installments	Plan Length	Allowable Fees	Frequency of Use	Eligibility	Disclosure
Alabama	2004-01-01	≥ 4	NA	$0	no time limit specified or on notice of inability to pay	loan or rollover threshold	inability to pay or default
Alaska	2010-01-01	NA	NA	$0	no time limit specified or on notice of inability to pay	NA	loan agreement; inability to pay or default
California	2003-01-01	NA	NA	$0	NA	NA	NA
Delaware	2018-12-12	NA	$\geq$ 60 days	$0	NA	loan or rollover threshold	NA
Florida	2019-07-01	NA	$\geq$ 60 days	$0	no time limit specified or on notice of inability to pay	credit or counseling	loan agreement; inability to pay or default
Idaho	2014-07-01	≥ 4	$\geq$ 60 days	$0	once per 12-month	NA	loan agreement
Indiana	2002-01-01	≥ 4	$\geq$ 60 days	$0	no time limit specified or on notice of inability to pay	loan or rollover threshold	loan agreement
Louisiana	2015-01-01	≥ 4	NA	$0	once per 12-month	NA	loan agreement
Michigan	2005-11-28	≥ 3	pay schedule	allow fees	NA	loan or rollover threshold	loan agreement
Nevada	2017-07-01	≥ 4	$\geq$ 60 days	$0	once per 12-month	NA	inability to pay or default
South Carolina	2009-06-16	≥ 4	pay schedule	$0	once per 12-month	NA	loan agreement
Utah	2016-07-01	≥ 4	$\geq$ 60 days	$0	once per 12-month	loan or rollover threshold	loan agreement; inability to pay or default

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Washington	2003-10-01	≥ 3	NA	\$0	no time limit specified or on notice of inability to pay	NA	inability to pay or default
Wisconsin	2013-07-07	≥ 4	pay schedule	\$0	once per 12-month	NA	loan agreement; inability to pay or default
Wyoming	2014-07-01	≥ 4	$\geq$ 60 days	\$0	once per 12-month	NA	NA

Notes: If a feature is labeled as “NA”, it means it is not specified for that state for that feature.

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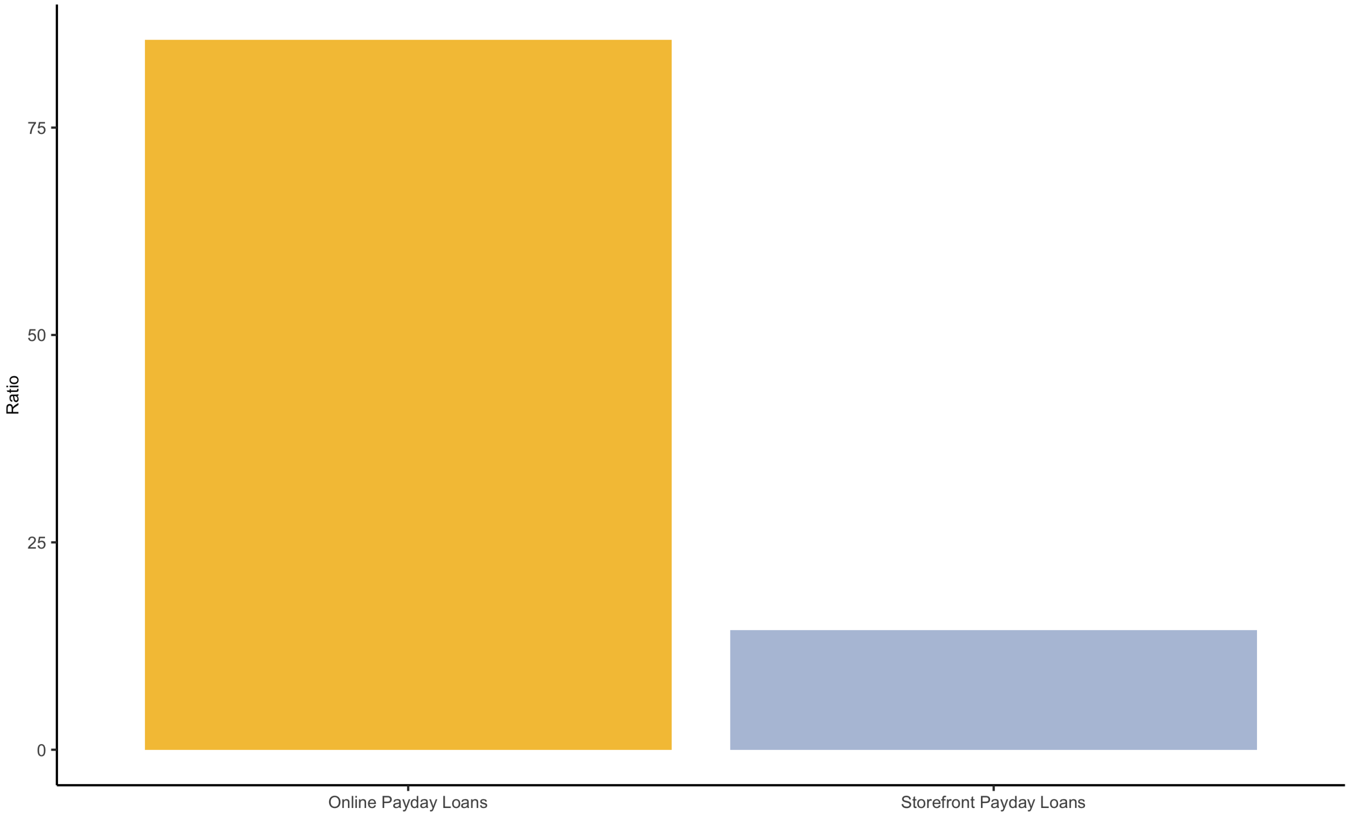
D Appendix: Clarity Online vs Storefront Payday Loans

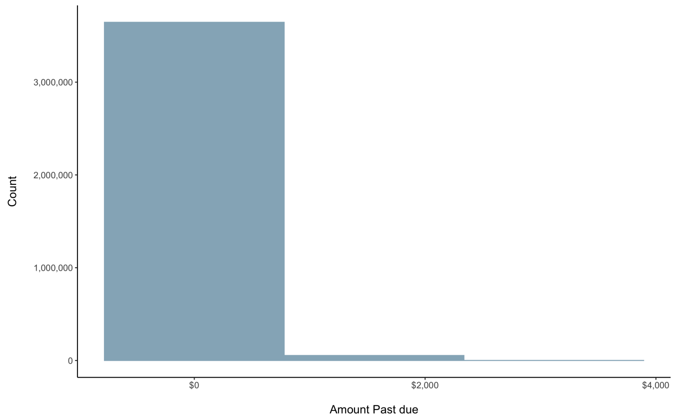
Figure D.1



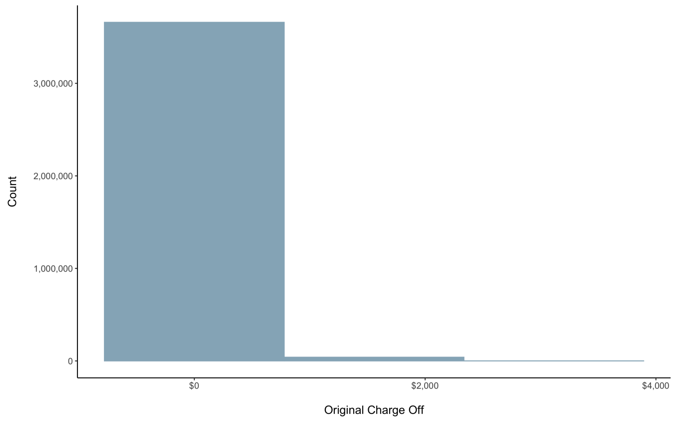
E Appendix: Histogram for Outcome Variables

Figure E.1: Histogram for Each Outcome Variable

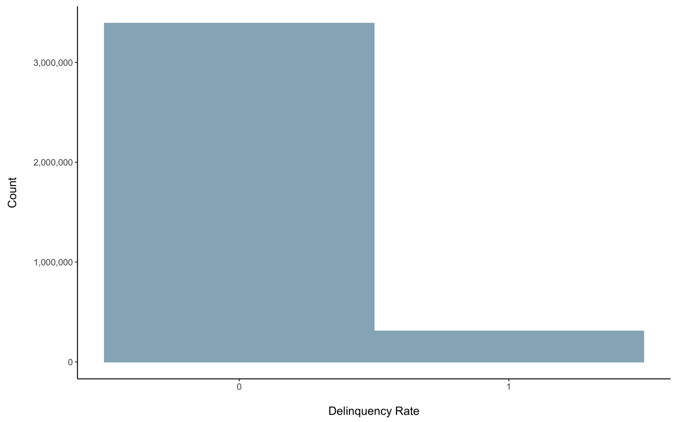
(a) Amount Pat Due



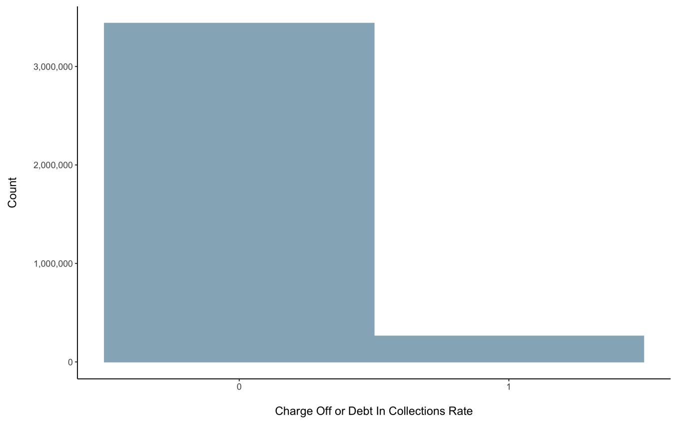
(b) Original Charge Off



(c) Delinquency Rate



(d) Charge Off or Debt in Collections Rate



Notes: For each outcome variable, the most observed value is zero. For outcomes listed from the figure (a) to figure (d), the zero values are 93.95%, 97.07%, 91.66%, and 92.92% of the data.

F Appendix: SDiD with Staggered Adoption: Estimation Algorithm for ATT

Data: Outcome variable $\boldsymbol{Y}$, treatment variable $\boldsymbol{D}$, covariates $\boldsymbol{X}$, and policy adoption $\boldsymbol{A}$[29].

Result: Point estimate $\widehat{ATT}$ and each adoption-specific values $\hat{\tau}_a^{sdid}$, $\hat{w}_a^{sdid}$, and $\hat{\lambda}_a^{sdid}$ for every $a \in \boldsymbol{A}$.

The algorithm procedure follows Clarke et al. (2023).

For each $a \in A$:

1. Run a TWFE regression $Y_{it} = \alpha_i + \beta_t + X_{it}\gamma + \epsilon_{it}$ where $D_{it} = 0$
2. Obtain residuals $\tilde{Y}_{it} = Y_{it} - \hat{Y}_{it}$ where $\hat{Y}_{it} = X_{it}\gamma$ for all D_{it}.
3. Subset $\boldsymbol{Y}$ and $\boldsymbol{D}$ to units who are pure controls and who first adopt extended payment plans in period $t = a$.
4. Compute regularization parameter ζ, unit weights $\hat{w}^{sdid}$, and time weights $\hat{lambda}^{sdid}$.
5. Compute SDiD estimator via weighted DiD regression:

$$\hat{\tau}^{SDiD} = \underset{\mu,\alpha,\beta,\tau}{\operatorname{argmin}} \left\{ \sum_{n=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - \tau D_{it})^2 \hat{w}_i \hat{\lambda}_t \right\} \tag{6}$$

   where Y_{it} is the residual outcome of step 2.

6. Compute ATT across adoption-specific SDiD estimates:

$$\widehat{ATT} = \sum_{for a \in A} \frac{T_{post}^a}{T_{post}} \times \hat{\tau}_a^{sdid} \tag{7}$$

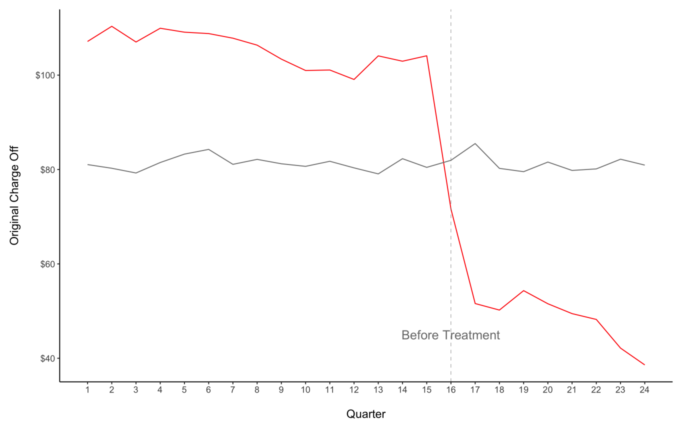
   where T_{post}^a is the total treated periods for each adoption, and T_{post} is the total treated periods for all adoptions.

[29] Each unique adoption period is assigned a value $a \in A$. In this study, A = {1, 2, ..., 5} since there are five unique treated periods.

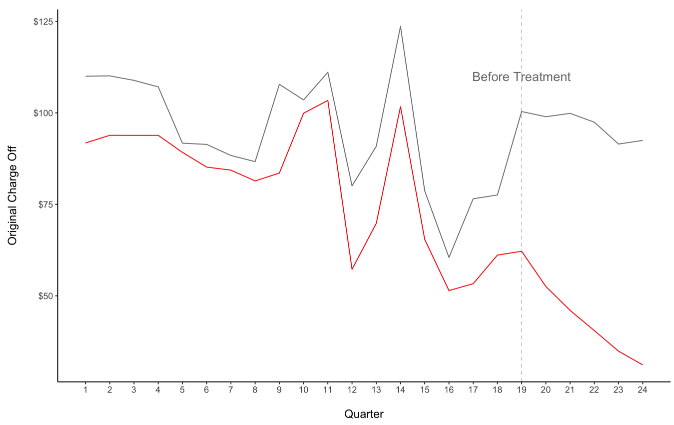
G Appendix: SDiD Plots for More Outcome Variables

Figure G.1: SDiD Plot for Original Charge Off:
ATT for Each Treated State

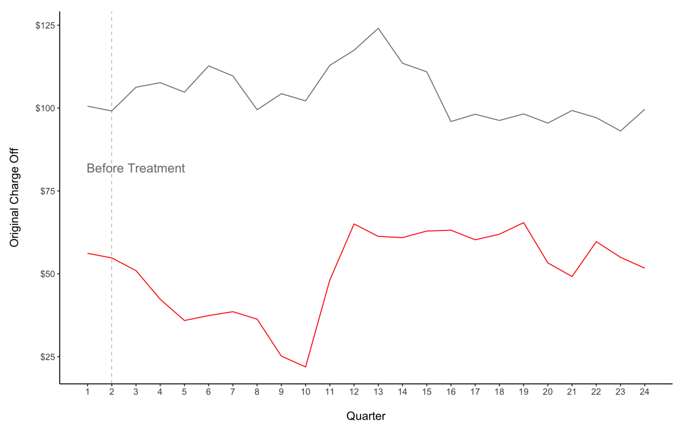
(a) Delaware



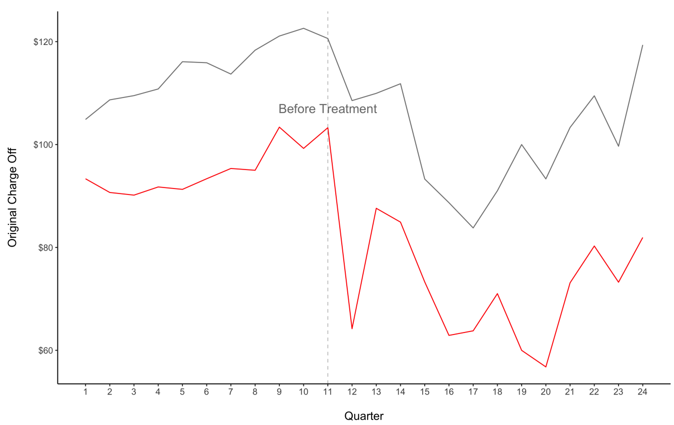
(b) Florida



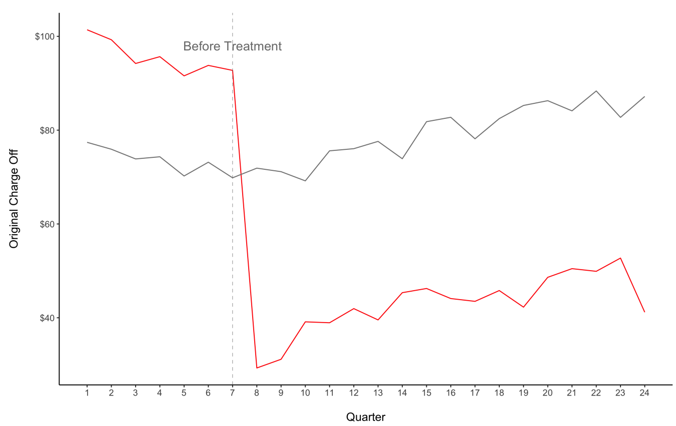
(c) Louisiana



(d) Nevada



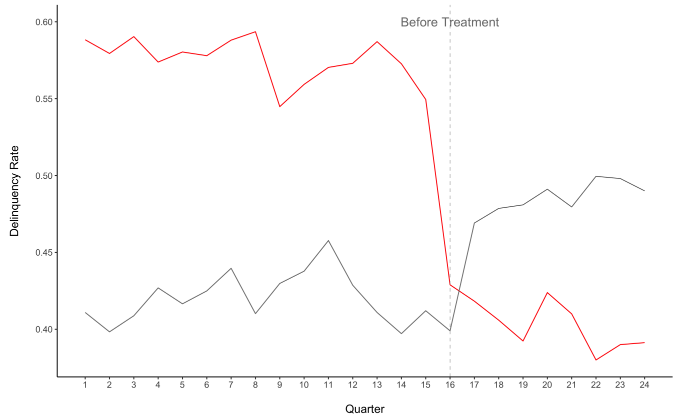
(e) Utah



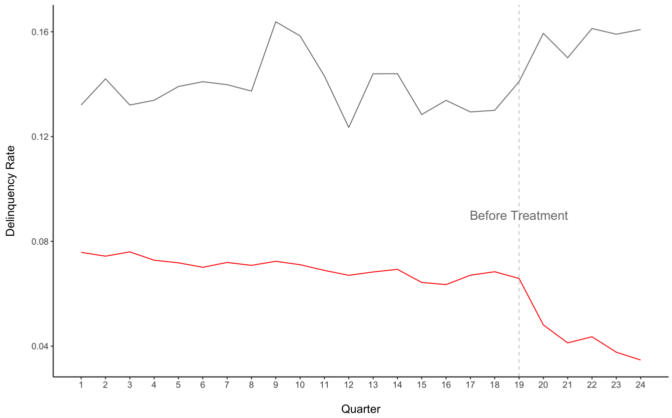
Notes: For each plot, the red line represents the treated state, and the gray line is the synthetic control state.

Figure G.2: SDiD Plot for Delinquency Rate:
ATT for Each Treated State

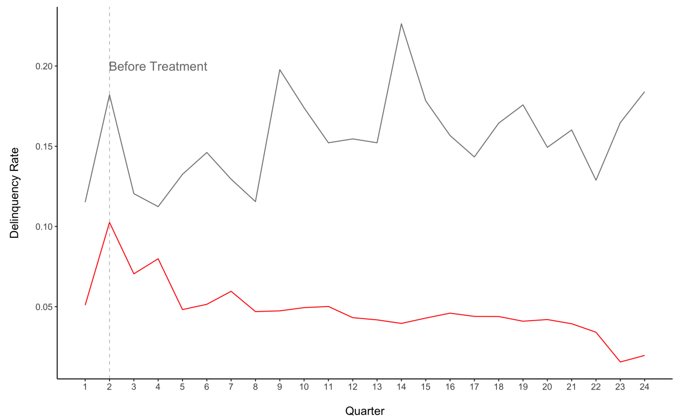
(a) Delaware



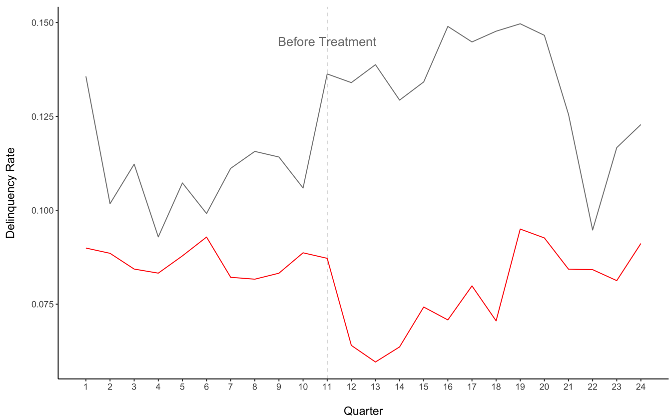
(b) Florida



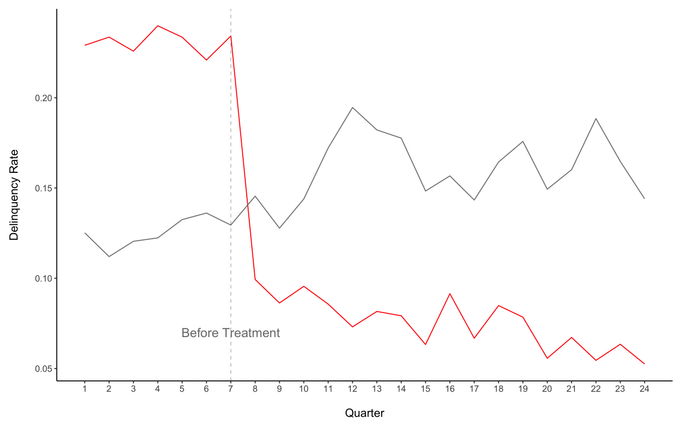
(c) Louisiana



(d) Nevada



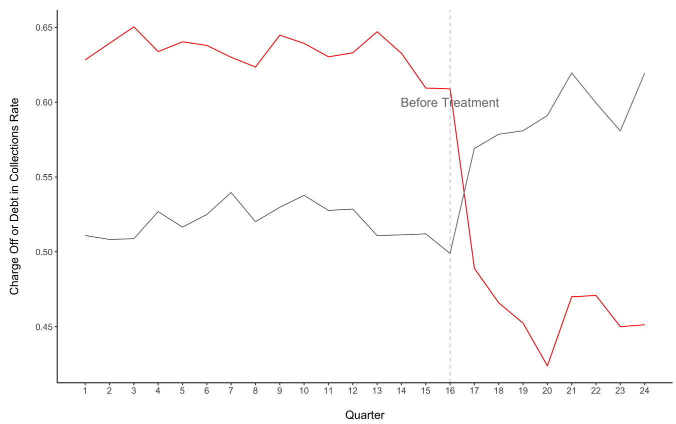
(e) Utah



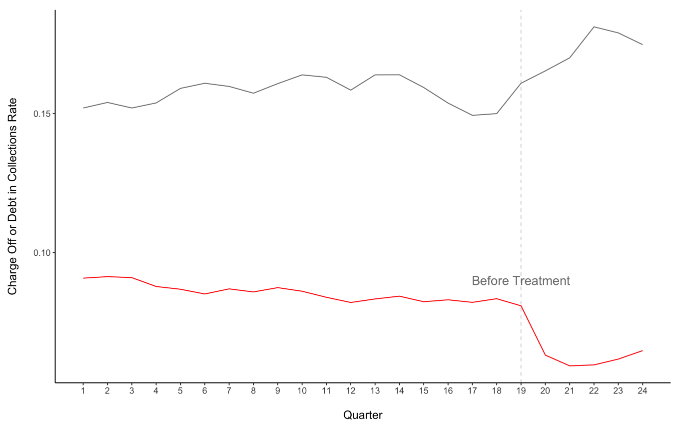
Notes: For each plot, the red line represents the treated state, and the gray line is the synthetic control state.

Figure G.3: SDiD Plot for Charge Off OR Debt in collections Rate: ATT for Each Treated State

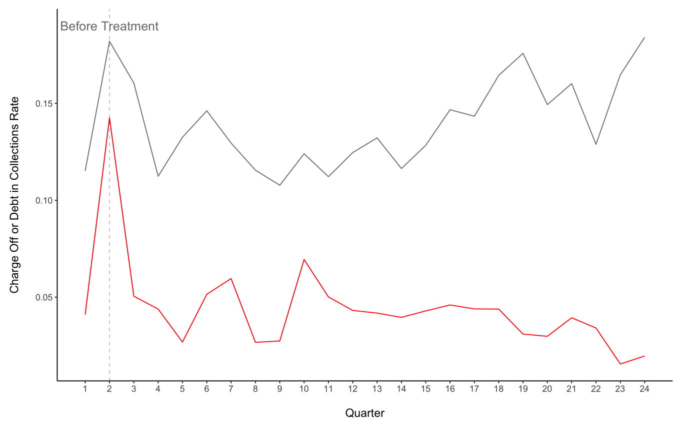
(a) Delaware



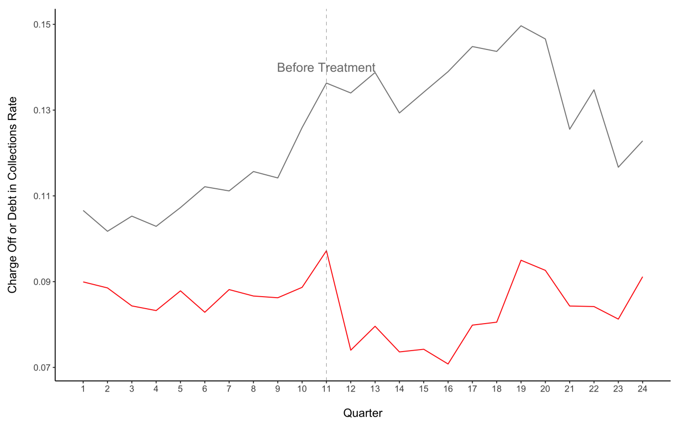
(b) Florida



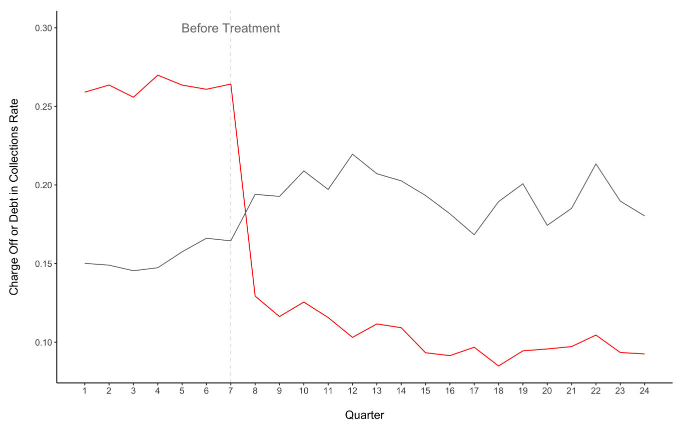
(c) Louisiana



(d) Nevada



(e) Utah



Notes: For each plot, the red line represents the treated state, and the gray line is the synthetic control state.

H Appendix: SDiD with Staggered Adoption: Estimation Algorithm for Variance Using Bootstrap

Data: Outcome variable $\boldsymbol{Y}$, treatment variable $\boldsymbol{D}$, covariates $\boldsymbol{X}$, and policy adoption $\boldsymbol{A}$, and bootstrap iteration B.

Outcome: Variance estimator $\hat{V}^{cb}_{\tau_a}$ for all $a \in A$.

The algorithm procedure follows Clarke et al. (2023).

For $b \leftarrow 1$:

1. Sample N rows of $(\boldsymbol{Y}, \boldsymbol{D})$ with replacement and construct bootstrap dataset $(\boldsymbol{Y}^{(b)}, \boldsymbol{D}^{(b)}, \boldsymbol{A}^{(b)})$.
2. If no treated or control units are in the bootstrap sample, then redo step 1.
3. Compute SDiD estimate $ATT^{(b)}$ following algorithm in Appendix F based on bootstrap data. Generate a vector of adoption-date specific resampled SDiD estimates $\tau_a^{(b)}$ for all $a \in \boldsymbol{A}^{(b)}$.
4. Define estimated variance $\hat{V}^{cb}_{ATT} = \frac{1}{B}\sum_{b=1}^{B}(\widehat{ATT^{(b)}} - \frac{1}{B}\sum_{b=1}^{B}\widehat{ATT^{(b)}})^2$. Estimate adoption-date specific variances for each τ_a^{sdid} estimate as the variance over each $\tau_a^{(b)}$.