Assessing the Impacts of State Regulations on the Usage of Alternative Financial Services

by

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Abstract

Are regulations on the payday loan effective? Do people switch to other forms of expensive credit such as pawnshop loans because of such regulations? In this study, we aim to find the answers to these two questions through exploring state-level variations in regulations on payday loans and other alternative financial services. Using FDIC's panel survey data and Google Trends data, we find that although the strict payday loan ban is less effective in the short run due to enforcement issue created by loopholes such as the online payday loans, it is effective in the long run as the law enforcement agency increases enforcement effort. We also find evidence that the regulations on payday loans induce the users of payday loans to switch to pawnshops when we restrict our study to the respondents who use exclusively either payday loans or pawnshops before and after the regulations.

Thesis Supervisor: Joseph Farrell
Title: Professor of Economics

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Chapter 1

Introduction

1.1 Motivations & Overview

Like traditional forms of credit such as bank loans or credit card, the payday loan gives people an opportunity to access the money that they don't possess at the moment of borrowing, with a cost. Unlike the traditional credits, the payday loan is unique in its extremely high annual percentage rate of interest, typically 400% APR or even more [1], and despite the skyrocketing high cost, annually there are approximately 12 million Americans use the payday loans according to Pew Charitable Trust[2]. Who are these 12 million people and why are they willing to borrow at such high cost? According to Pew Trust's 2012 survey study, people who don't college education, who are home renters, who are divorced or separated, who are low-income earners, and who are African American are more likely to borrow payday loans, and they do so due to unexpected expenses. Does the benefit justify the high cost? Some researchers claim the answer is yes, and yet others disagree (Skiba and Tobacman, 2009; Morgan, Strain and Seblani, 2012; Carrell and Zinman, 2014).

Nevertheless, the Consumer Financial Protection Bureau (CFPB)'s study suggests that majority of payday borrowers it tracked rolled over or re-borrowed payday loans

[1] `http://www.paydayloaninfo.org/facts`

[2] `http://www.pewtrusts.org/en/research-and-analysis/issue-briefs/2015/07/cfpb-proposal-for-payday-and-other-small-loans`

in less than a month [3], and repeatedly we saw headlines on the news that people incurred enormous amount debt just with a tiny amount of initial borrowing[4]. According to Pew's survey study, 3 in 4 people think payday loans need to be regulated, and yet there are no federal level regulations on payday loans and the payday lenders can legally charge high-interest rate well above 300% APR in many states. Ever since the 2008 financial crisis, several states have adopted certain forms of payday loan regulations [5], and CFPB in 2016 issued a proposal for a federal level payday loan regulation[6]. As new regulations on payday loans gradually roll out in many states and possibly soon nationwide, we want to understand what are the impacts of the regulations introduced at state level on the usage of payday loans and other alternative financial services. In particular, we pose the following question:

Are regulations on the payday loan at the state level effective and do people switch to other expensive credit such as pawnshop loans because of such regulations?

To answer this question, we begin by conducting extensive research on the past literature and on the available data sources. The publicly available micro level data on payday loans are scarce and mainly survey based due to the sensitive nature of the private financial information. We decide to use the Federal Deposit Insurance Corporation (FDIC)'s National Survey of Unbanked and Underbanked Households, which is a biannual panel survey data covering years from 2009 to 2015, as our primary data source. In addition, we use Google Trends data on the search terms such as "Payday loans" or "Pawnbrokers" as our secondary data source. Using the information from National Conference of State Legislature, we identify various states in which the regulations were introduced between the year 2009 and 2015. Then we construct multiple treatment groups by the types of regulations and a control group consisting of multiple states where no regulation was introduced prior to 2015.

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[3] `http://www.paydayloaninfo.org/facts`

[4] `http://www.star-telegram.com/news/local/article9528494.html` and other sources

[5] `http://www.paydayloaninfo.org/state-information` New Hampshire 2009, Arizona 2010, Montana 2010, Colorado 2010, Arkansas 2011

[6] `https://www.consumerfinance.gov/about-us/blog/we-want-hear-public-about-payday-loans/`

Under the Difference in Differences framework, we propose two variations of difference-in-differences model: first, we introduce an additional interaction term so that the model can take into account of the possibility of a delayed treatment; second, we conditionally partition the dataset based on the survey response and then create a new dependent variable which under the DD framework should capture the diversion ratio[7]. Then with a baseline DD model and two variations of DD model, we estimate the policy impact across various treatment groups.

First, we find that people with college education and older people are less likely to use payday loans, pawnshops, and check-cashing services. Second, we find evidence that individuals who are currently unemployed are more likely to use payday loans, pawnshops, and check-cashing services in the past 12 months. Third, we have mixed results regarding the effectiveness of payday loan regulations: (1) for states that introduced strict interest caps on payday loans, we find that the interest cap induces a decrease in payday loan use in the long run but not in the short run and it also induces a decrease in pawnshop use in the long run; (2) for the state (Colorado) where the payday loan was not banned but instead was transformed into the long-term loan, there is a decrease in payday loan borrowing in the short run as a result of such regulation and the regulation has no effect on the usage of pawnshop loans or check-cashing; (3) for state (Arkansas) that repealed the Check-Casher Act and hence outlawed payday loans and other expensive check-cashing services, the regulation resulted in a reduction in the usage of payday loan and check-cashing service in the long run but not the short run, and the regulation increases the usage of the pawnshops; (4) for the state (Mississippi) that reenacted the Check Casher Act which itself is a protection for payday loan industry, the [de]regulation increases payday loan use in the short run and decreases the usage of check-cashing service in the long run; (5) overall, the restrictive regulation on payday loan regulation induces nearly 16%

[7] In Industrial Organization, the Diversion Ratio is formally defined as "the fraction of sales gained by product 1 from a small reduction in the price of product 1 that come at the expense of product 2" (Farrell and Shapiro, 2008). In our case, although we don't observe a price decrease in pawnshop loans, we do observe the payday lenders are forced out of business, and we loosely call the substitution from payday loans to pawnshop loans that arises from regulation as the diversion ratio.

increase of pawnshop use within the subpopulation of people who uses either payday loan or pawnshops but not both, which translates to 16% diversion from payday loan uses to pawnshop uses due to regulation.

In the remaining part of this chapter, we formally introduce the definition of payday loans and other alternative financial services. In the next chapter, we discuss previous literature on payday loans. In chapter 3, we provide a detailed description of data. In chapter 4, we discuss the models and estimation methods. In chapter 5, we discuss the regression results in various settings in detail and potential problems associated with the results. In chapter 6, we conclude the study, discuss the policy implications of our study, and suggest some directions for the future research.

1.2 Description of Payday Loans and Other Alternative Finances

1.2.1 Payday Loans

Payday loans are short term small amount loans that are typically under $500, depending on the different state limits. In order to borrow a payday loan, the borrower must give the lenders access to his/her checking account either through writing a postdated personal check or by authorizing the lender to debit the account electronically with the principal amount borrowed plus a fee. The loan terms are typically for two weeks and come due on the borrower's next payday. The charges for a $100 loan typically ranges from $10 to $30, which translates to a nearly 400% annual percentage rate of interest. The payday loans sometimes come with different features depending on the state-level regulation. For example, most commonly, the payday loan are structured to be paid off in a lump-sum payment and usually borrowers have the option to rollover the loan by paying off only the interest charges. In other cases, the payday loans are structured to be an installment loan that can be paid off over a longer time period.[8]

1.2.2 Alternatives to Payday Loans

The term "**Alternative Financial Service** " (hereafter referred to as AFS) is a blanket term used to describe a wide range of financial services that are provided not by the federally insured banks [9]. The loan products such as payday loan, pawnshop, rent-to-own service, check-cashing service, and auto-title loan are all considered as AFS.

The **Pawnshop loan** is a short term and secured loan product. A pawnshop owner (lender) typically take certain valuable physical possessions from the borrower as the collateral. The borrower at the pre-designated repayment date has to return the borrowed amount plus a fee, and if the borrowers are unable to do so, the lending agreement will give the pawnshop the right to possess the pawned items. The size of the pawnshop loan is typically a fraction of the value of possessed items. The APR for pawn loan can range from 12% to 300% according to FDIC.[10] The mechanism of the **auto title loan** is similar to the pawnshop loan, with the pawned possession being the clean car title of the borrower.

The **Rent-to-Own** (RTO) service provides the customer the option to purchase expensive customer items such as large items of furniture and household appliances under the rental-purchase agreement. The customer gets the item from the RTO service provider for use and pays the provider weekly or monthly payment, and the customer has the option to return the item or purchase the item. Like payday loans, the RTO is controversial for its high APR. If the consumers eventually decide to purchase the RTO item instead, they will end up paying many times of the nominal price of the item, which translates to APR as high as more than 200% (Anderson and

[8] The definition of payday loans is provided by Consumer Financial Protection Bureau. For more information, refer to `https://www.consumerfinance.gov/askcfpb/1567/what-payday-loan.html`

[9] `https://www.fdic.gov/bank/analytical/quarterly/2009_vol3_1/altfinservicesprimer.html`

[10] `https://www.fdic.gov/bank/analytical/quarterly/2009_vol3_1/altfinservicesprimer.html`

Jackson, 2011).

The **Check-Cashing service** is a broader term which can include many financial services involving personal checks, such as the payday loans and money orders. Check cashing has a simple working mechanism: the check-cashing customers have checks made to them, and for reasons such as they don't have a bank account or they don't want to wait for the checks to clear, they go to the check casher, present their checks, and the check casher verifies the check, and them give them the amount money in the check minus a fee[11]. Although the Check cashing service has such a simple mechanism, there are many complications. The check cashers have to bear the risk of returned checks and the borrowers have to pay an expensive fee for using such service (consider the cost of payday loans for example).

The **bounced checks** and **bounced check protection**: the bounced check is often used to describe the check that has Non-sufficient funds (NSF) and hence cannot be honored by the depository institutions. Many banks now offer services such as bounce protection or overdraft protection, under which the checks with NSF will no longer be bounced but instead the banks will charge the account holder an NSF fee. According to a 2010 study by Marc Anthony Fusaro, an average bounce protection per check is $26 in 2007, and the implicit interest rate of such program is extremely high, and there are instances that the calculated APR can be as high as 7700%. As of the time of Fusaro's study, 85% banks offer overdraft protection transfer, 78% banks offer overdraft protection line-of-credit, and 43% banks offer bounce protection. (Fusaro, 2010)

[11] `http://smallbusiness.chron.com/checkcashing-business-work-39894.html`

Chapter 2

Literature Review

There have been a variety of studies on payday loans and other alternative financial services, which can be roughly divided into three broad categories. The first category consists of articles claiming that payday loan hurts customers for reasons including but not limited to the high APR (annual percentage rate), the high proportion of its customers with multiple loan rollovers, and its propensity to target vulnerable demographics. The second types of research articles claim that payday loan benefits customers for reasons including but not limited to the fact that payday lenders help people to get access to the otherwise not available credits that can be used to cope with people's financial distresses. Often time these two types of articles directly study the impacts of payday loan regulations on people's credit borrowing behavior and their general financial well-being. In contrast, the third type of articles focuses on the behavioral aspects of payday borrowers or on the characteristics of payday lending practices, which often do not offer clear stances on whether the payday loans are beneficial or detrimental.

Currently, there is hardly any consensus on the impacts of payday loan regulations on the financial well-being of those who are (or potentially would be) affected. On the one hand, some researchers argue that payday loan access can decrease people's well-being. For example, Carrell and Zinman in their 2008's study find that payday loan access can worsen the performance of military personnel, especially for those who are young and lack of financial sophistication. Skiba and Tobacman in their 2009 study suggest that through worsening the households' cash flow position, the access to payday loans induces more bankruptcy filings. On the other hand, other researchers find evidence that supports the opposite argument. For example, Morgan, Strain and Seblani in their 2012 study find a correlation between payday loan ban and decrease in Chapter 13 bankruptcy rates. Nevertheless, in the same study, they also find robust evidence that the banks' overdraft income increased and the number of returned checks increased following the payday loan ban, which suggests that payday loan regulations can have impacts on other forms of credit.

Several other studies have assessed the impacts of payday loan regulations on the usage of payday loans and other alternative financial services such as the pawnshops and the bank account overdrafts. According to Robert Shapiro 2011's review paper "*The Consumer and Social Welfare Benefits and Costs of Payday Loans: A Review of the Evidence*", technically, or rather desperately, instead of taking payday loans, the people in need of credit can write checks that won't be able to be covered by their bank account. However, this act will incur the so-called "overdraft" fees or "bounced-check" fees that cost \$25 to \$35, which are more expensive than the typical payday loans. Moreover, additional consequences of taking repeated overdrafts include, but are not limited to, bank account closure, lowered credit score and even legal inconveniences. According to another paper published in 2003 by Stegman and Faris (*Payday Lending: A Business Model that Encourages Chronic Borrowing*), among the reasons explaining people's demand for payday loans, avoiding overdrafts is a frequently cited concern.

Zinman in his 2010 study on the effect of Oregon interest cap on payday loans also employed a difference-in-differences design, using neighboring state Washington as the control group. Using his survey design before and after the payday interest cap, he finds a decrease (30%) in likelihood of recent payday loan borrowing in the treatment state relative to the control state and that the interest cap resulted in people's switch to "incomplete and plausibly inferior substitutes", especially the checking account overdrafts. He also finds that the respondents reported an increase in difficulty of getting a short-term loan as a result of the interest cap on payday loans. Zinman suggests that his study possibly measures only the transitory effect of the regulation, and our study complements his study by looking at longer term impacts of various types of regulations.

Similar to Zinman's finding, Melzer and Morgan in their 2015 paper *Competition in a Consumer Loan Market: Payday Loans and Overdraft Credit* discuss the substitution relationship between payday loans and overdraft credits. In this paper, they find that in the absence of payday credit and payday lenders, the depository institutions have lowered the price (5%) on the charge of the overdraft credit program, and in the meantime they are also 8% less likely to offer the "bounce protection", under which they automatically cover overdrafts up to a credit limit, and those who still offer the bounce protection lower the permissible credit limit. They conclude, "price per unit of credit limit actually increases when payday lenders are forced to exit, consistent with a decline in competition."

In addition, the refund anticipation loan (RAL) is another alternative to payday loans. According to Wikipedia, RAL is a short-term consumer loan in the United States provided by a third party against an expected tax refund for the duration it takes the tax authority to pay the refund. The loan term was usually about two to three weeks, related to the time it took for the U.S. Internal Revenue Service to deposit refunds in electronic accounts. The loans were designed to make the refund available in as little as 24 hours. They are secured by a taxpayer's expected tax refund and designed to offer customers quicker access to funds. In the 2014 paper *Payday Lending Regulation and the Demand for Alternative Financial Services* by Galperin and Weaver, they conclude that "the behavioral component is stronger than the rational-strategic component of demand for payday loans: we find that prohibition of payday loans results in about a 5 percent drop in the demand for RALs."

Besides the overdrafts and RAL, some studies have discussed the relationship between the usage of pawnshop and that of payday loans, Skiba and Tobacman in their 2007's paper *Measuring the Individual-Level Effects of Access to Credit: Evidence from Payday Loans* find that an initial payday loan approval encourages almost 9 more payday loans borrowing on average for a given person within twelve months of the initial approval and the payday loan approval causes the short-term pawnshop uses to decrease.

The CPS data has been a popular source for the studies on payday loans. Author Susan Payne Carter in her 2012 paper uses the CPS Unbanked and Underbanked Supplement (the same source as ours) to study the relationships between pawnshop uses and payday loans, in which she finds that people are more likely to use pawnshops and payday loans jointly in the locations where 3 or more rollovers are allowed, which suggests a complementary relationship between payday loans and pawnshop loans. Similarly, Bhutta, Goldin and Homonoff in their 2014 paper *Consumer Borrowing After Payday Loan Bans* use 2009 and 2011 CPS Unbanked and Underbanked Supplement combined with Federal Reserve Bank of New York's Consumer Credit Panel to study the effect of payday loan bans, in which they find such regulations have significantly reduced payday loan usages and increased the usage of pawnshops.

The advantage of our research is that we have used all the available CPS data (from 2009 to 2015) and we have studied various treatment groups with different types of regulations on payday loans. Moreover, we were able to observe the long term effect of the payday loan regulations, which are not included in the discussions in those two papers. Furthermore, the identification in Bhutta et al.'s paper is controversial: for example, the authors identified Montana (ban on Nov 2010) and Arkansas (ban on 2011 March) in their treatment group; however, they use 2009 data as the pre-treatment period and 2011 data as the post-treatment period. This is controversial because the 2011 data were collected in June 2011 asking if the respondents have taken a payday loan or other AFS in the past 12 months, and hence respondents in Montana and Arkansas might not be treated at all when the data were collected.

Some researchers turned to foreign countries that have strict regulation on short-term loan credit. Damon Gibbons has documented the practice and evidence from Japan in his 2012 paper "*Taking on the Money Lending: Lessons from Japan*. Japan has a large number of payday loan borrowers, and the payday lending is coined as the term "Sarakin". In the past, Japan was plagued by loan sharks and Yakuza's brutal loan collection, which gradually led to the increase in maximum sentence for loan sharking (up to 10 years prison and 30 million yen (300,000 USD) fine). In 2006, Japan passed the Money Lenders Law, which was fully implemented in 2010. Among many of its requirement, the law reduced the interest rate cap from 29.2% to 20%, and limits the maximum amount of lending to 1/3 of the borrower's income. Many lenders were forced out of business, not because of the law, but instead because of Lehman Brothers went under and because of the mass reclaiming the overpaid interests. The remaining lenders have changed their business model to adapt to the new law. In addition, the number of payday borrowers dropped from around 11 million to 8 million, and the average consumer debt dropped 50%. Moreover, the number of debtors with at least five unsecured loans has dropped from 2.3 million in 2006 to 440,000 in 2011, which is accompanied by a steady decline in bankruptcies. One thing to notice is that the overall lending activity in the domestic banks and regional cooperative banks has decreased over the same period, which may indicate that restricting payday lending did not lead to the increasing usage of banking credits.

Additionally, there has been very few researches on the topic of online payday loans. Fritzdixon and Skiba in their recent research on online payday loans, *The Consequences of Online Payday Lending*, use fuzzy regression kink design only to find the same problem underlying the payday lending industry: the online payday borrowers are extremely credit constrained, and they suggest that a larger loan may help mitigate their credit problem. Unlike traditional payday loans, the online payday loan market is largely unregulated, and only sporadically we see law enforcement agencies tackle the illegal payday loans made online to the regulated states [1]. In order to study online payday loans, I argue that researchers need more unconventional data sources, such as Google Trends.

Perhaps the most famous study using Google Trends is Carneiro and Mylonakis' study *Google Trends: A Web-Based Tool for Real-Time Surveillance of Disease Outbreaks*, in which they find that "Google Flu Trends can detect regional outbreaks of influenza 710 days before conventional Centers for Disease Control and Preven-

[1] https://www.lawyersandsettlements.com/articles/internet-payday-loans/office-of-attorney-general-state-arkansas-dustin-19164.html

tion surveillance systems". In addition, the Google Trends data tend to have certain predictive powers for economic outcomes. In their study *Predicting the Present with Google Trends*, Choi and Varian suggest that including Google Trends in the seasonal autoregressive model can improve the forecasting results from the models that do not include Google Trends variables, which is particular the case for the retail sale of auto parts and for the Census Bureau's statistics on housing sales. The evidence from existing studies using Google Trends suggests that the Google Trends can be potentially used as a proxy for the real world economics activities. In this study, we will explore and use this aspect of Google Trends data, which can provide us a robustness check for the results from the micro-level Census data.

Chapter 3

Data

3.1 Overview

The existing publicly available data on payday loans and other forms of alternative financial services are extremely limited at micro-level due to the sensitive nature of such data. Several studies mentioned in the literature review were able to obtain the non-public data from payday loan companies and study various aspects of payday loans using those data; however, those studies were limited to rather short time horizons concerning the activities of the studying subjects. Due to the availability of the non-public data and the limitations associated with the already studied data, we need to find alternative data sources that can potentially address these issues.

In this Research, we have two main data sets: (1) Current Population Survey Unbanked and Underbanked Supplement; (2) Google Trends. The CPS supplement has been used in multiple studies regarding the payday loans, as mentioned in the literature review (Carter, 2012; Butta et al., 2014); however, in this research we have the opportunity to exploit the entire supplement ranging from 2009 to 2015, which none of the existing studies has explored. The Google Trends data, on the other hand, is novel in the sense that no researchers have utilized such data for the study of payday loans. In the following sections, we will present a detailed discussion of our Google Trends and CPS Supplement data.

As we discussed in the introduction section, there are yet any regulations on payday loans at the federal level. Since the regulations on payday loans at the state level are not uniform, it is crucial to identify the states in which the regulations are introduced in the time frames that fall into the range of our data.

To achieve this goal, we will mainly use the information from the websites of National Conference of State Legislations (NCSL)[1] and of the Consumer Federation of America (CFA)[2] to identify whether a given state has any regulations on payday loans. This identification will help us to construct the control group and the treatment group, with which we can access the policy impacts of a particular regulation in a given state.

Our identification strategy for the control group is to use available information to find all states where there's no regulation on payday loans or check-cashing services (check-cashing can include payday loan use) prior to 2015. To do so, we use the information from NCSL, CFA, and The Pew Charitable Trust [3], and we identify our control group to be the aggregation of the data from following states:

Alabama, Alaska, California, Florida, Hawaii, Indiana, Iowa, Kentucky, Louisiana, Maine, Michigan, Minnesota, Missouri, Nebraska, New Mexico, Ohio, Oklahoma, South Carolina, Tennessee, Texas, Virginia.

Similarly, use the heterogeneous introductions of regulations at various states, we identify and construct five treatment groups [4].

- The first treatment group consists of Arizona and Montana, where the regulations on payday loans were introduced in late 2010, which effectively capped the allowed annual percentage rate (APR) on a given loan product to less than 36%.

- The second treatment group consists of only the state Colorado, where the regulation was introduced in late 2010. Instead of a strict interest cap on

[1] http://www.ncsl.org/research/financial-services-and-commerce/payday-lending-2014-legislation.aspx

[2] http://www.paydayloaninfo.org/state-information

[3] http://www.pewtrusts.org/en/multimedia/data-visualizations/2014/state-payday-loan-regulation-and-usage-rates

[4] http://www.ncsl.org/research/financial-services-and-commerce/payday-lending-2014-legislation.aspx

payday loans, the regulation included several less extreme measures such as a minimum six-month loan term.

- The third treatment group consists of only the state Arkansas, where the then-governor on March 28, 2011 signed the Act 720 repealing the Check-Cashers Act. This act capped the APR of deferred deposit loans (including payday loans) to be under the state usury limit (17%)[5].

- The fourth treatment group consists of only the state Mississippi, where the then-governor on February 24, signed the bill that reenacted the Mississippi Check-Cashers Act, which reestablished the legal status of deferred deposit loans in Mississippi. In addition, on March 20, 2013, the-governor signed the bill that repealed the repealer of the Check-Cashers Act. We will explore these two related [de]regulations.

- The fifth treatment group consists of multiple states including Idaho, Mississippi, Nevada, Utah, and Wyoming, where in the year 2013 a range of "regulations", such as licensing and reporting requirements, were introduced. We are hoping this pooling will increase the statistical power of our analysis.

3.2 Google Trends

3.2.1 An Overview of Google Trends

According to Google, the Google Trends Data is produced by taking an unbiased sample from the Google search data. [6] The trends data consists of both real time data and non-real time data, which can be traced back to 2004. Once the data are collected, Google classifies them to different topics. During the production of the data, they also took care of complications such as the duplicate searches by eliminating repeated searches by the same person in a short time period.

[5] `http://www.paydayloaninfo.org/state-information/11`

[6] For a detailed documentation, please refer to `https://support.google.com/trends/answer/4355213?hl=en&ref_topic=6248052`

We here emphasize that one should be careful when interpreting the magnitude of trends data. According to Google:

- Each data point is divided by the total searches of the geography and the time range it represents, to compare relative popularity. Otherwise, places with the most search volume would always be ranked highest.

- The resulting numbers are then scaled to a range of 0 to 100 based on a topics proportion to all searches on all topics.

- Different regions that show the same number of searches for a term will not always have the same total search volumes.

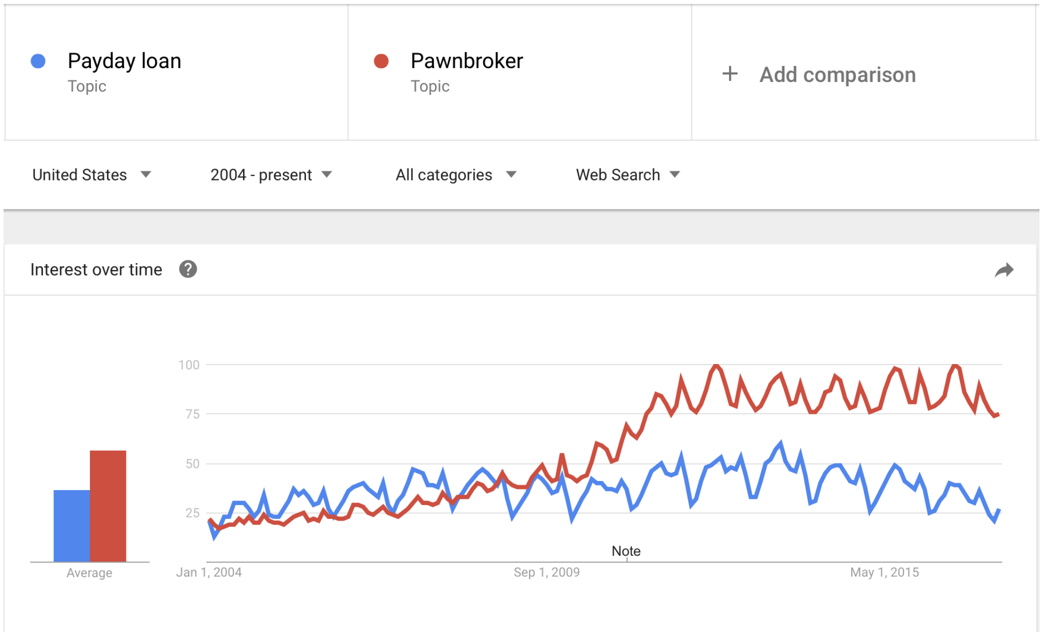
Therefore one should only interpret Google Trends data as a relative measure of the popularity of certain search items that varies when one changes the time spans, geographic locations, and the comparison subjects.

The time series nature of the trends data has made them popular in the studies of disease outbreaks and economic and financial forecasting; nevertheless, there is very few, if not none, researches using the trends data to assess the impacts of certain economic and regulatory policies. In this study, we explore the time series structure of the search data at the aggregate state level and exploit the time series discontinuities at those states around the neighborhood of the time when a certain regulation is introduced. In the following subsections, we present the Google Trends data pertinent to our research. We will fully utilize Google Trends' graphic features.

3.2.2 Google Trends, Payday Loans, and Pawnbrokers

First, at aggregate level (the United States), we obtain the relative trends data of payday loans and pawnbrokers from the Google Trends website [7]

[7] Data source: Google Trends (`www.google.com/trends`)



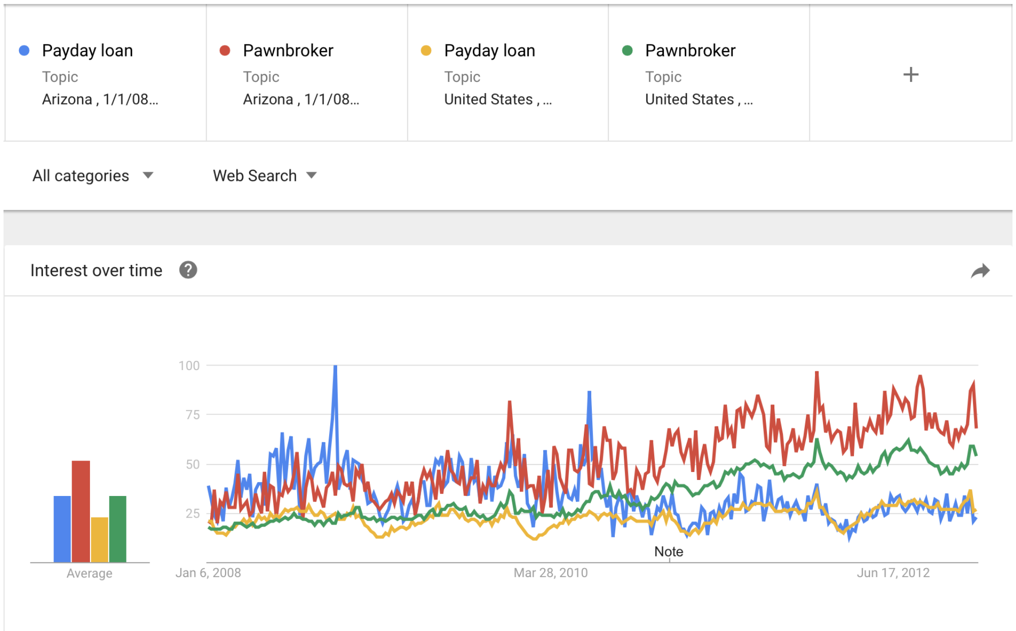
There are several features of the payday loan and pawnbroker trends. At the national level, we can see that the internet searches for both payday and pawnbroker exhibit very strong and consistent seasonal patterns over the entire time period of the available Google Trends data. The "twin-peak" feature, which both trends peak at August and December can arguably be the indication that people tend to borrow at those periods. Moreover, for a relative comparison, the pawnbroker trend has increased dramatically since 2009, while the payday loan trend is rather flat.

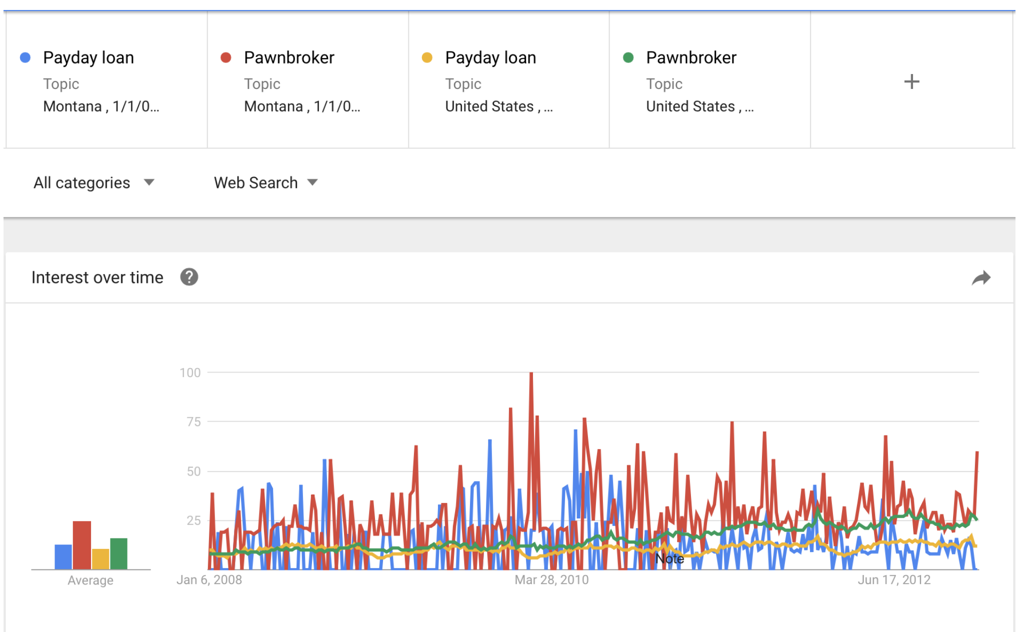
Second, there are significant variations in the trends data at the state level. From the Google Trends website, we collect two sets of data:

1. Payday loan trends at pawnbroker trends at the state level (for the state in the treatment groups) and national level, with the time range from 2008 January to 2013 January. (In some cases the five-year neighborhood of the introduction of the regulation)

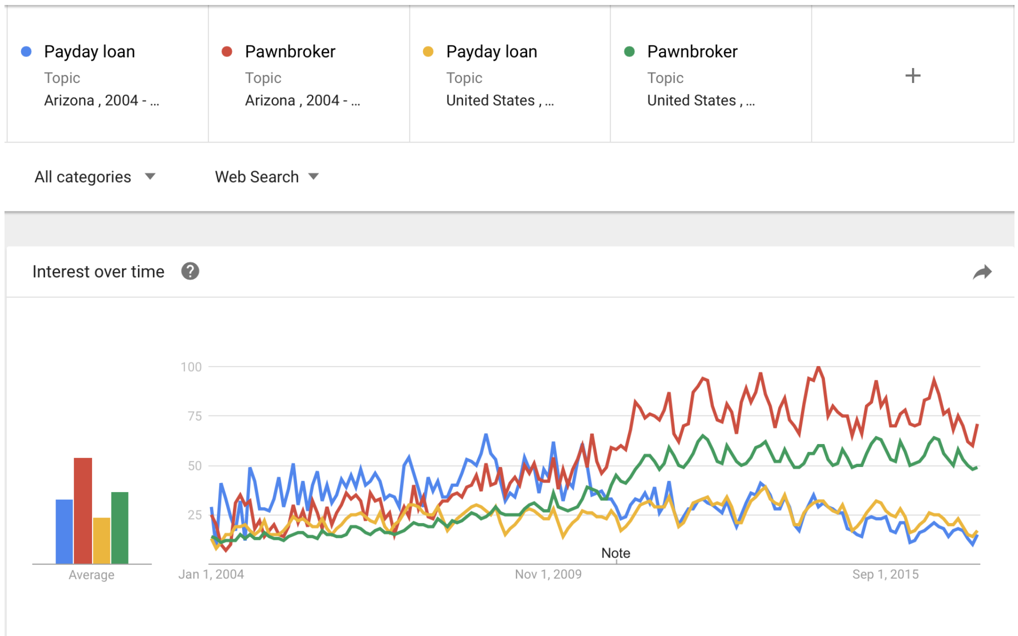
2. Payday loan trends at pawnbroker trends at the state level (for the state in the treatment groups) and national level, with the time range from 2004 January to 2017 March.

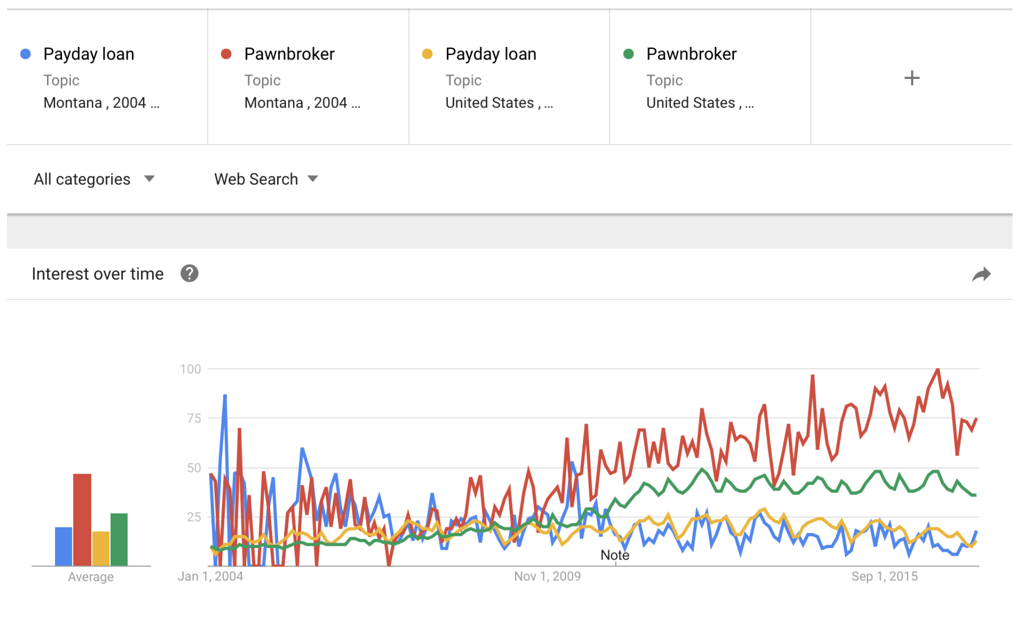
When downloading these trends under the same data frame, Google Trends will automatically adjust the data to the same scale so one can compare the relative popularity.[8] Here we give several examples of the trends data.





[8]Data source: Google Trends (`www.google.com/trends`)





The reason why we collect these two sets of data is due to the availability of Google Trends, for which if the trends have a time range for more than 5 years we can only obtain the monthly data, whereas the trends will have higher frequencies for a shorter time period (≤ 5 years). We will conduct econometric analysis on the data with shorter time periods due to the high frequency for such data. The trends with a longer time period, while available only at the monthly frequency, can be used to understand the evolution of people's search behavior from a macro-perspective.

Moreover, for the Google Trends data, we will use the national trends as the control group and treatment state trends as treatment groups. There are two reasons why we use the national trends instead of the combined trends of states without regulations. First, Google allegedly improved their geographic assignment algorithm at 2011 January, which in some cases introduced significant time series discontinuities at states level; however, the national level is unaffected by this improvements. Second, at the national level, since the Google Trends measures the relative popularity of the search and since in the majority of the states there are no regulations on payday loans, we may be able to assume the regulations in individual treatment states will have little effect on the national trends. In the results section, we will discuss the potential bias caused by using the national trend as the control group.

3.3 Current Population Survey

3.3.1 Overview and Data Description

The existing publicly available data for payday loans and other forms of alternative financial services are extremely limited, especially at the micro-level. Past studies have largely used the proprietary data obtained from payday lenders to study the payday loans; nevertheless, they were limited by both geographical and temporal factors. The Federal Deposit Insurance Corporation (FDIC) in 2009 launched the biannual survey in partnership with the U.S. Census Bureau's Current Population Survey (CPS) to assess the inclusiveness of the banking system, particularly the unbanked and underbanked population [9]. This CPS supplement measures a wide range of demographic and economic characteristics of the survey population, and among those, we are particularly interested in the variables that measure the use of certain alternative financial services.

We obtained the complete panel dataset covering the years from 2009 to 2015 from FDIC official website [10], and from the survey questionnaires, we identify the variables

[9] Source: `https://www.fdic.gov/householdsurvey/2009/index.html`

[10] `https://www.economicinclusion.gov/downloads/index.html`

that are most pertinent to our discussion. Unfortunately, the variables that are vital to our discussion are not available for the year 2009. Therefore, we will restrict our discussion to the year 2011, 2013, and 2015:

1. **bank_status**: a categorical variable which measures the banking status of the correspondent. 1 = unbanked, 2 = underbanked, 3 = fully banked, 4 = status unknown.

2. **year**: panel time variable, indicating the time when a specific entry is recorded. This variable takes value 2011, 2013, 2015.

3. **state**: the identifier for the state in which the respondent resides.

4. **educgrp**: the categorical variable indicating the education status of the respondent.

5. **agegrp**: the categorical variable indicating which age group the respondent belongs to.

6. **empstat**: the categorical variable indicating the employment status of the respondent.

7. **payday_12**: the binary variable indicating whether the respondent has taken a payday loan in the past 12 months.

8. **pawn_12**: the binary variable indicating whether the respondent has used pawnshops in the past 12 months.

9. **cc_12**: the binary variable indicating whether the respondent has used any check cashing service in the past 12 months.

3.3.2 Summary Statistics

In this section, we provide summary statistics for the control variables and mean tables for the payday loan, the pawnshop loan, and the check-cashing services at the state level by year.

The main feature of the mean statistics is that across all years and all states, the mean use of these alternative financial services is very low. In particular, the usages of payday loans and pawnshops are much lower comparing to those of check-chasing across all states and all years. Another interesting feature of the mean table of the payday loans is that in all the states where the payday loans are banned, we can still see the existence of payday loan use. This is not contradictory, as we discussed in the literature review section that people in the states that prohibit payday loans can still access to online payday loans offered from other states or even foreign countries (Fritzdixon and Skiba, 2016). One might be able to use these data to estimate the online or tribal payday loan use.

Second, we see that in our survey population, 3.81% are unbanked, 10.64% are underbanked, and 46.17% are unknown. For the unemployment status, 2.78% of survey population are unemployed and yet 26.60% of the population has no response. For the education status, 34.68% do not have a high school degree, 20.90% have a high school diploma, and 44.42% have some college or have a college diploma.

Third, we discuss the descriptive statistics from the two way tables of control variables against the payday loan usages. Among the people who take payday loans (payday = 1), we see that: first, majority of the borrowers have a high school diploma (31.72%) or have had some college but not college degree (40.36%); second, adults with age from 25 years to 54 years are the majority (69.53%) of the payday loan borrowers; third, majority of the payday borrowers are employed, although there are still substantial fraction of borrowers who are unemployed (7.34%) or not in labor force(26.34%); fourth, there is no payday borrower who is fully banked, and majority of the borrowers are underbanked(90.1%).

Table 3.1: Payday Loan Use, Mean Table

	State	payday2011	payday2013	payday2015	paydayTotal
1	AL	0.0323	0.0304	0.0397	0.0351
2	AK	0.0177	0.0191	0.0139	0.0172
3	AZ	0.0125	0.0216	0.0108	0.0145
4	AR	0.0064	0.0209	0.0000	0.0086
5	CA	0.0184	0.0190	0.0216	0.0195
6	CO	0.0251	0.0194	0.0162	0.0211
7	CT	0.0021	0.0061	0.0000	0.0032
8	DE	0.0117	0.0083	0.0071	0.0094
9	DC	0.0028	0.0092	0.0083	0.0067
10	FL	0.0244	0.0257	0.0275	0.0258
11	GA	0.0081	0.0124	0.0155	0.0118
12	HI	0.0069	0.0149	0.0069	0.0097
13	ID	0.0419	0.0379	0.0338	0.0378
14	IL	0.0116	0.0253	0.0139	0.0168
15	IN	0.0224	0.0207	0.0192	0.0209
16	IA	0.0180	0.0206	0.0138	0.0181
17	KS	0.0364	0.0262	0.0185	0.0281
18	KY	0.0281	0.0232	0.0275	0.0262
19	LA	0.0181	0.0277	0.0400	0.0309
20	ME	0.0035	0.0077	0.0072	0.0059
21	MD	0.0080	0.0118	0.0124	0.0104
22	MA	0.0043	0.0050	0.0046	0.0046
23	MI	0.0137	0.0190	0.0347	0.0215
24	MN	0.0088	0.0088	0.0077	0.0086
25	MS	0.0138	0.0455	0.0252	0.0269
26	MO	0.0210	0.0283	0.0321	0.0266
27	MT	0.0107	0.0098	0.0025	0.0066
28	NE	0.0159	0.0307	0.0186	0.0216
29	NV	0.0739	0.0481	0.0412	0.0564
30	NH	0.0011	0.0037	0.0000	0.0018
31	NJ	0.0013	0.0068	0.0030	0.0036
32	NM	0.0252	0.0274	0.0418	0.0337
33	NY	0.0017	0.0033	0.0069	0.0037
34	NC	0.0042	0.0142	0.0112	0.0096
35	ND	0.0248	0.0228	0.0133	0.0204
36	OH	0.0240	0.0291	0.0292	0.0272
37	OK	0.0305	0.0491	0.0454	0.0412
38	OR	0.0121	0.0138	0.0159	0.0138
39	PA	0.0077	0.0033	0.0075	0.0061
40	RI	0.0106	0.0131	0.0026	0.0097
41	SC	0.0185	0.0380	0.0195	0.0249
42	SD	0.0339	0.0300	0.0405	0.0338
43	TN	0.0339	0.0399	0.0312	0.0349
44	TX	0.0285	0.0305	0.0372	0.0318
45	UT	0.0312	0.0145	0.0271	0.0247
46	VT	0.0028	0.0017	0.0052	0.0032
47	VA	0.0146	0.0210	0.0103	0.0155
48	WA	0.0326	0.0269	0.0154	0.0257
49	WV	0.0057	0.0044	0.0064	0.0057
50	WI	0.0148	0.0093	0.0120	0.0122
51	WY	0.0291	0.0211	0.0116	0.0211
52	Total	0.0170	0.0192	0.0190	0.0183

Table 3.2: Pawnbroker Use, Mean Table

	State	pawn2011	pawn2013	pawn2015	pawnTotal
1	AL	0.0474	0.0350	0.0369	0.0394
2	AK	0.0387	0.0234	0.0418	0.0343
3	AZ	0.0520	0.0476	0.0233	0.0406
4	AR	0.0470	0.0772	0.0414	0.0546
5	CA	0.0190	0.0197	0.0133	0.0176
6	CO	0.0337	0.0340	0.0184	0.0308
7	CT	0.0200	0.0097	0.0074	0.0137
8	DE	0.0088	0.0165	0.0047	0.0105
9	DC	0.0194	0.0107	0.0083	0.0129
10	FL	0.0297	0.0207	0.0167	0.0228
11	GA	0.0511	0.0272	0.0295	0.0366
12	HI	0.0104	0.0150	0.0000	0.0090
13	ID	0.0379	0.0358	0.0394	0.0378
14	IL	0.0161	0.0218	0.0102	0.0162
15	IN	0.0194	0.0303	0.0192	0.0231
16	IA	0.0169	0.0207	0.0161	0.0182
17	KS	0.0378	0.0290	0.0185	0.0296
18	KY	0.0338	0.0377	0.0275	0.0335
19	LA	0.0203	0.0253	0.0272	0.0248
20	ME	0.0316	0.0272	0.0144	0.0264
21	MD	0.0181	0.0203	0.0104	0.0174
22	MA	0.0158	0.0151	0.0046	0.0118
23	MI	0.0235	0.0253	0.0193	0.0229
24	MN	0.0195	0.0302	0.0115	0.0220
25	MS	0.0392	0.0375	0.0252	0.0322
26	MO	0.0238	0.0327	0.0264	0.0277
27	MT	0.0708	0.0688	0.0311	0.0513
28	NE	0.0260	0.0221	0.0070	0.0199
29	NV	0.0515	0.0356	0.0304	0.0404
30	NH	0.0138	0.0149	0.0081	0.0129
31	NJ	0.0151	0.0109	0.0075	0.0114
32	NM	0.0308	0.0396	0.0275	0.0314
33	NY	0.0111	0.0232	0.0069	0.0139
34	NC	0.0350	0.0404	0.0209	0.0328
35	ND	0.0230	0.0305	0.0229	0.0254
36	OH	0.0216	0.0299	0.0111	0.0212
37	OK	0.0555	0.0468	0.0436	0.0487
38	OR	0.0304	0.0309	0.0218	0.0281
39	PA	0.0169	0.0192	0.0075	0.0152
40	RI	0.0318	0.0213	0.0026	0.0218
41	SC	0.0294	0.0685	0.0177	0.0379
42	SD	0.0440	0.0286	0.0152	0.0323
43	TN	0.0485	0.0348	0.0265	0.0365
44	TX	0.0602	0.0549	0.0328	0.0504
45	UT	0.0251	0.0193	0.0181	0.0210
46	VT	0.0083	0.0067	0.0000	0.0053
47	VA	0.0214	0.0236	0.0103	0.0189
48	WA	0.0434	0.0297	0.0277	0.0343
49	WV	0.0342	0.0419	0.0321	0.0353
50	WI	0.0180	0.0117	0.0105	0.0138
51	WY	0.0340	0.0306	0.0116	0.0259
52	Total	0.0285	0.0283	0.0189	0.0256

Table 3.3: Check Cashing Use, Mean Table

	State	cc2011	cc2013	cc2015	ccTotal
1	AL	0.0797	0.0776	0.1013	0.0887
2	AK	0.0779	0.0577	0.0952	0.0755
3	AZ	0.0894	0.0406	0.0629	0.0657
4	AR	0.1073	0.1222	0.0805	0.1021
5	CA	0.0758	0.0560	0.0601	0.0647
6	CO	0.0531	0.0530	0.0624	0.0549
7	CT	0.0335	0.0386	0.0392	0.0365
8	DE	0.0499	0.0429	0.0495	0.0473
9	DC	0.0471	0.0561	0.0652	0.0561
10	FL	0.0757	0.0636	0.0541	0.0653
11	GA	0.0820	0.0803	0.1001	0.0868
12	HI	0.0572	0.0502	0.0323	0.0478
13	ID	0.0755	0.0714	0.0695	0.0722
14	IL	0.0746	0.0620	0.0609	0.0663
15	IN	0.0713	0.0589	0.0479	0.0603
16	IA	0.0626	0.0562	0.0599	0.0597
17	KS	0.0893	0.0799	0.0780	0.0830
18	KY	0.0702	0.0925	0.0685	0.0778
19	LA	0.0820	0.1333	0.0981	0.1031
20	ME	0.0749	0.0581	0.0433	0.0621
21	MD	0.0580	0.0406	0.0559	0.0508
22	MA	0.0429	0.0416	0.0401	0.0415
23	MI	0.0745	0.0473	0.0847	0.0680
24	MN	0.0492	0.0486	0.0403	0.0472
25	MS	0.1172	0.1129	0.0643	0.0913
26	MO	0.0765	0.0692	0.0606	0.0696
27	MT	0.0962	0.0858	0.0510	0.0720
28	NE	0.0638	0.0794	0.0932	0.0766
29	NV	0.1162	0.1131	0.0891	0.1078
30	NH	0.0403	0.0432	0.0544	0.0444
31	NJ	0.0629	0.0637	0.0392	0.0560
32	NM	0.0810	0.0848	0.0915	0.0870
33	NY	0.0740	0.0687	0.0720	0.0717
34	NC	0.0961	0.0688	0.0642	0.0778
35	ND	0.0742	0.0528	0.0952	0.0740
36	OH	0.0667	0.0600	0.0605	0.0626
37	OK	0.0764	0.0846	0.0835	0.0813
38	OR	0.0393	0.0480	0.0616	0.0486
39	PA	0.0551	0.0481	0.0334	0.0468
40	RI	0.0471	0.0374	0.0317	0.0404
41	SC	0.0963	0.0987	0.0796	0.0918
42	SD	0.1066	0.0599	0.0835	0.0845
43	TN	0.1031	0.0467	0.0768	0.0762
44	TX	0.1175	0.1027	0.0822	0.1020
45	UT	0.0544	0.0554	0.0747	0.0614
46	VT	0.0704	0.0626	0.0504	0.0619
47	VA	0.0529	0.0364	0.0562	0.0484
48	WA	0.0590	0.0537	0.0723	0.0612
49	WV	0.0706	0.0788	0.0771	0.0756
50	WI	0.0508	0.0386	0.0464	0.0454
51	WY	0.0867	0.0709	0.0579	0.0728
52	Total	0.0725	0.0640	0.0660	0.0678

Table 3.4: Education Frequency Table

	peducgrp		
	count	frequency (%)	cumulative frequency(%)
No high school diploma	75551	34.67917	34.67917
High school diploma	45535	20.90133	55.5805
Some college	46008	21.11844	76.69894
College degree	50763	23.30106	100
Total	217857	100	

Table 3.5: Age Frequency Table

	pagegrp		
	count	frequency (%)	cumulative frequency(%)
15 to 24 years	7214	4.511654	4.511654
25 to 34 years	24842	15.53625	20.04791
35 to 44 years	27183	17.00032	37.04822
45 to 54 years	31408	19.64264	56.69087
55 to 64 years	30731	19.21925	75.91012
65 years or more	38519	24.08988	100
Total	159897	100	

Table 3.6: Employment Frequency Table

	pempstat		
	count	frequency (%)	cumulative frequency(%)
Employed	96455	44.27446	44.27446
Unemployed	6047	2.775674	47.05013
Not in labor force	57395	26.34526	73.39539
Unknown	57960	26.60461	100
Total	217857	100	

Table 3.7: Banking Frequency Table

	bank_status		
	count	frequency (%)	cumulative frequency(%)
Unbanked	8309	3.81397	3.81397
Underbanked	23183	10.64138	14.45535
Fully banked	85774	39.3717	53.82705
Unknown	100591	46.17295	100
Total	217857	100	

Table 3.8: Education, Payday

	count	frequency(%)	sub frequency(%)	category frequency(%)
payday = 0				
No high school diploma	12075	10.27	10.46	97.58
High school diploma	31743	27.01	27.51	97.89
Some college	33279	28.31	28.84	97.46
College degree	38290	32.58	33.18	99.22
Total	115387	98.17	100.00	98.17
payday = 1				
No high school diploma	299	0.25	13.89	2.42
High school diploma	683	0.58	31.72	2.11
Some college	869	0.74	40.36	2.54
College degree	302	0.26	14.03	0.78
Total	2153	1.83	100.00	1.83
Total				
No high school diploma	12374	10.53	10.53	100.00
High school diploma	32426	27.59	27.59	100.00
Some college	34148	29.05	29.05	100.00
College degree	38592	32.83	32.83	100.00
Total	117540	100.00	100.00	100.00

Table 3.9: Age, Payday

	count	frequency(%)	sub frequency(%)	category frequency(%)
0				
15 to 24 years	5028	4.28	4.36	97.48
25 to 34 years	18214	15.50	15.79	97.11
35 to 44 years	19431	16.53	16.84	97.53
45 to 54 years	22306	18.98	19.33	97.98
55 to 64 years	22503	19.14	19.50	98.57
65 years or more	27905	23.74	24.18	99.29
Total	115387	98.17	100.00	98.17
1				
15 to 24 years	130	0.11	6.04	2.52
25 to 34 years	543	0.46	25.22	2.89
35 to 44 years	493	0.42	22.90	2.47
45 to 54 years	461	0.39	21.41	2.02
55 to 64 years	327	0.28	15.19	1.43
65 years or more	199	0.17	9.24	0.71
Total	2153	1.83	100.00	1.83
Total				
15 to 24 years	5158	4.39	4.39	100.00
25 to 34 years	18757	15.96	15.96	100.00
35 to 44 years	19924	16.95	16.95	100.00
45 to 54 years	22767	19.37	19.37	100.00
55 to 64 years	22830	19.42	19.42	100.00
65 years or more	28104	23.91	23.91	100.00
Total	117540	100.00	100.00	100.00

Table 3.10: Employment Status, Payday

	count	frequency(%)	sub frequency(%)	category frequency(%)
0				
Employed	70243	59.76	60.88	98.01
Unemployed	4632	3.94	4.01	96.70
Not in labor force	40512	34.47	35.11	98.62
Total	115387	98.17	100.00	98.17
1				
Employed	1428	1.21	66.33	1.99
Unemployed	158	0.13	7.34	3.30
Not in labor force	567	0.48	26.34	1.38
Total	2153	1.83	100.00	1.83
Total				
Employed	71671	60.98	60.98	100.00
Unemployed	4790	4.08	4.08	100.00
Not in labor force	41079	34.95	34.95	100.00
Total	117540	100.00	100.00	100.00

Table 3.11: Banking Status, Payday

	count	frequency(%)	sub frequency(%)	category frequency(%)
0				
Unbanked	7339	6.243832	6.360335	97.17956
Underbanked	21103	17.95389	18.28889	91.58096
Fully banked	85774	72.97431	74.33593	100
Unknown	1171	.9962566	1.014846	100
Total	115387	98.16828	100	98.16828
1				
Unbanked	213	.1812149	9.893172	2.820445
Underbanked	1940	1.650502	90.10683	8.419043
Fully banked	0	0	0	0
Unknown	0	0	0	0
Total	2153	1.831717	100	1.831717
Total				
Unbanked	7552	6.425047	6.425047	100
Underbanked	23043	19.60439	19.60439	100
Fully banked	85774	72.97431	72.97431	100
Unknown	1171	.9962566	.9962566	100
Total	117540	100	100	100

Chapter 4

Model

4.1 Baseline Difference-in-Differences Model

The panel data setting and the identification of control group and treatment group gives the possibility of using *Difference in Differences* to estimate the causal effects of various regulations. We drew inspiration from Card-Kruger's study of the causal effect of increasing minimum wage on the employment (Card and Kruger, 1993). In addition to the simple comparison of the difference in means before and after the treatment, we also introduce various control variables including age, employment status, and education level. We have the following baseline model:

$$y_{ist} = z'_{i,s,t}\beta + state'_{i,t}\pi + year'_{i,s}\Lambda + \theta(Post \times Treat)_{i,s,t} + \epsilon_{i,s,t}$$

in which

- $y_{i,s,t}$ is the dummy variable indicating whether the respondent i in state s and time t has used a given form of alternative financial services (including payday loans, pawnshops, and check-cashing services)

- $z'_{i,s,t} = [1, \text{agegrp}, \text{empstat}, \text{educgrp}]_{i,s,t}$ is the row vector consists of constant and control variables

- $state'_{i,t} = [\text{state}_2, \cdots, \text{state}_N]_{i,t}$ is the row vector of the collection of dummy variables that controls for the state level variations

- $year'_{i,s} = [\text{year2013}, \text{year2015}]_{i,s}$ is the row vector of the collection of dummy variables that controls for the time fixed effects

- $Post_{i,s,t}$ is the dummy variable indicates whether a given respondent i in state s and year t is in the post-treatment period

- $Treat_{i,s,t}$ is the dummy variable indicates whether a given respondent i in state s and year t is in the treatment group

The coefficient of interest is θ, which estimates the causal effect of a given regulation.

The basic idea of difference-in-differences in our case is an intuitive one: before the introduction of regulations on payday loans, there were no regulations in the states in both control group and treatment group, so we can estimate the difference in the mean usages of payday loans for the control group and treatment group. In a counterfactual world where the regulation is *not* introduced for the treatment group in the post-treatment period, we should expect the difference in mean usages between the control group and treatment group to be the same in the post-treatment period as in the pre-treatment period. With the treatment (payday loan regulations) actually being introduced to the treatment group, if we observe that the difference in mean usages of payday loans in the post-treatment period is different from that difference in the pre-treatment period, then we arguably can attribute this difference as the effect of regulation (Bertrand, 2002).

4.2 Difference-in-Differences with Delayed Treatment

In the case of regulating alternative financial services, unlike closing the floodgate with which the water flow would be cut off immediately, the enforcement of regulations is often an issue [1]. During the library research on such issue, we found an interesting

[1] See this example of Arkansas, where the regulation of a strict payday loan ban was put in place in 2011, and yet in 2013 there are still illegal payday lending activi-

case that happened to fall into our treatment state Arizona. Arizona first introduced the interest cap on payday loans on June 30, 2010, which supposed should completely eliminate any payday loan transactions in the state of Arizona; however, from table 3.1, we can see that the rate of payday loans usage actually increased from 2011's 1.25% to 2013's 2.16%. This bizarre phenomenon can explained by three different possible scenarios:

- First case: the regulation never took place, which is not the case in our study
- Second case: the increase is due to the online payday loan offered from other states, which can outskirt the state regulation
- Third case: the regulation is not strictly enforced

Our library study suggests of the second and third scenarios are the most plausible ones. In particular, we found an regulatory document[2] issued by Arizona Department of Financial Institutions in 2013, almost two years after the regulation was first introduced:

The Department has received complaints indicating that Arizona consumers are offered online payday loans or consumer loans by companies that are not licensed by the Department, some of which are located in other states or claim to be owned by Indian tribes, and that charge Arizona consumers an interest rate well in excess of that permitted under Arizona law ⋯ any consumer lender loan that is made by a person who is required to be licensed pursuant to this chapter but who is not licensed is void.

This raises the concern that the true effect of the regulation is delayed until the next period. In addition, in the case of Montana and Mississippi, the new regulations in 2013 are simply the amendment to the regulations in 2011, and therefore one may consider the new amendments also as the delayed treatments. With these observa-

ties in Arkansas.https://www.lawyersandsettlements.com/articles/internet-payday-loans/office-of-attorney-general-state-arkansas-dustin-19164.html

[2]http://www.azdfi.gov/LawsRulesPolicy/Forms/FE-AD-PO-Regulatory_and_Consumer_Alert_CL_CO_13_01%2002-06-2013.pdf

tions, I propose a variation of difference-in-differences model, which can capture the increment effect of the delayed (or additional) treatment under certain assumptions.

Consider the following simplified model, where we just have two groups and no states within each group, and we have three periods, one period before treatment and two periods after treatment:

$$y_{it} = \alpha_0 + z_{it}'\beta + \gamma \cdot Treat_i + \lambda_1 Year2013_t + \lambda_2 Year2015_t$$

$$+\theta_1(Treat_i \times Post_{1t}) + \theta_2(Treat_i \times Post_{2t}) + \epsilon_{it}$$

where z_{it}' is the row vector of all control variables including age, education, and employment status; $Treat_i$ indicates whether the respondent i is in the treatment group; $year2013_t$ is the indicator for year 2013, and $year2015_t$ is the indicator for year 2015; $Post_{1t}$ is the dummy variable that equals 1 if the time period is 2013 or 2015; $Post_{2t}$ is the dummy variable that equals 1 if the time period is 2015. The coefficients we are interested in are θ_1 and θ_2.

Claim: θ_1 is the treatment effect in period 1, and θ_2 is the gross treatment effect of period 1 and period 2.

Proof.

$$\mathbb{E}[y_{it}|z_{it}, Treat_i = 0, Post_{1t} = 0, Post_{2t} = 0] = \alpha_0 + z_{it}'$$

$$\mathbb{E}[y_{it}|z_{it}, Treat_i = 0, Post_{1t} = 1, Post_{2t} = 0] = \alpha_0 + \lambda 1 + z_{it}'$$

$$\mathbb{E}[y_{it}|z_{it}, Treat_i = 0, Post_{1t} = 0, Post_{2t} = 1] = \alpha_0 + \lambda 2 + z_{it}'$$

$$\mathbb{E}[y_{it}|z_{it}, Treat_i = 1, Post_{1t} = 0, Post_{2t} = 0] = \alpha_0 + z_{it}' + \gamma$$

$$\mathbb{E}[y_{it}|z_{it}, Treat_i = 1, Post_{1t} = 1, Post_{2t} = 0] = \alpha_0 + \lambda 1 + z_{it}' + \gamma + \theta_1$$

$$\mathbb{E}[y_{it}|z_{it}, Treat_i = 1, Post_{1t} = 0, Post_{2t} = 1] = \alpha_0 + \lambda 2 + z_{it}' + \gamma + \theta_2$$

This gives us

$$\big(\mathbb{E}[y_{it}|z_{it}, Treat_i = 1, Post_{1t} = 1, Post_{2t} = 0] - \mathbb{E}[y_{it}|z_{it}, Treat_i = 0, Post_{1t} = 1, Post_{2t} = 0]\big)$$

$$-\big(\mathbb{E}[y_{it}|z_{it}, Treat_i = 1, Post_{1t} = 0, Post_{2t} = 0] - \mathbb{E}[y_{it}|z_{it}, Treat_i = 0, Post_{1t} = 0, Post_{2t} = 0]\big)$$

$$= \big(\mathbb{E}[y_{it}|z_{it}, Treat_i = 1, Post_{1t} = 1, Post_{2t} = 0] - \mathbb{E}[y_{it}|z_{it}, Treat_i = 1, Post_{1t} = 0, Post_{2t} = 0]\big)$$

$$-\big(\mathbb{E}[y_{it}|z_{it}, Treat_i = 0, Post_{1t} = 1, Post_{2t} = 0] - \mathbb{E}[y_{it}|z_{it}, Treat_i = 0, Post_{1t} = 0, Post_{2t} = 0]\big)$$

$$= (\alpha_0 + \lambda 1 + z'_{it} + \gamma + \theta_1 - (\alpha_0 + z'_{it} + \gamma)) - (\alpha_0 + \lambda 1 + z'_{it} - (\alpha_0 + z'_{it})) = \theta_1$$

which is the treatment effect for the first period. We also have

$$\big(\mathbb{E}[y_{it}|z_{it}, Treat_i = 1, Post_{1t} = 1, Post_{2t} = 1] - \mathbb{E}[y_{it}|z_{it}, Treat_i = 0, Post_{1t} = 1, Post_{2t} = 1]\big)$$

$$-\big(\mathbb{E}[y_{it}|z_{it}, Treat_i = 1, Post_{1t} = 0, Post_{2t} = 0] - \mathbb{E}[y_{it}|z_{it}, Treat_i = 0, Post_{1t} = 0, Post_{2t} = 0]\big)$$

$$= \big(\mathbb{E}[y_{it}|z_{it}, Treat_i = 1, Post_{1t} = 1, Post_{2t} = 1] - \mathbb{E}[y_{it}|z_{it}, Treat_i = 1, Post_{1t} = 0, Post_{2t} = 0]\big)$$

$$-\big(\mathbb{E}[y_{it}|z_{it}, Treat_i = 0, Post_{1t} = 1, Post_{2t} = 1] - \mathbb{E}[y_{it}|z_{it}, Treat_i = 0, Post_{1t} = 0, Post_{2t} = 0]\big)$$

$$= (\alpha_0 + \lambda 2 + z'_{it} + \gamma + \theta_2 - (\alpha_0 + z'_{it} + \gamma)) - (\alpha_0 + \lambda 2 + z'_{it} - (\alpha_0 + z'_{it})) = \theta_2$$

which is the gross treatment effect. And under certain assumptions, we can find the increment effect

$$\theta_2 - \theta_1 = \big(\mathbb{E}[y_{it}|z_{it}, Treat_i = 1, Post_{1t} = 1, Post_{2t} = 1] - \mathbb{E}[y_{it}|z_{it}, Treat_i = 1, Post_{1t} = 1, Post_{2t} = 0]\big)$$

$$-\big(\mathbb{E}[y_{it}|z_{it}, Treat_i = 0, Post_{1t} = 1, Post_{2t} = 1] - \mathbb{E}[y_{it}|z_{it}, Treat_i = 0, Post_{1t} = 1, Post_{2t} = 0]\big)$$

$$= \big(\mathbb{E}[y_{it}|z_{it}, Treat_i = 1, Post_{1t} = 1, Post_{2t} = 1] - \mathbb{E}[y_{it}|z_{it}, Treat_i = 0, Post_{1t} = 1, Post_{2t} = 1]\big)$$

$$-\big(\mathbb{E}[y_{it}|z_{it}, Treat_i = 1, Post_{1t} = 1, Post_{2t} = 0] - \mathbb{E}[y_{it}|z_{it}, Treat_i = 0, Post_{1t} = 1, Post_{2t} = 0]\big)$$

$\square$

A sufficient assumption (but might not be the necessary) for $\theta_2 - \theta_1$ to be the increment effect is the DD parallel trend assumption. We present additional graphical discussion for this delayed treatment model in the Appendix.

4.3 Difference-in-Differences Model with Decomposed Dependent Variable

First, we introduce some notations to simplify the mathematical discussion:

- PD: the binary variable that equals 1 if the respondent has used the payday loan in the past 12 months and equals 0 if not.
- PW: the binary variable that equals 1 if the respondent has used the pawnbroker in the past 12 months and equals 0 if not.
- Z: be the vector of all control variables in the DD model
- $Post$: the binary variable that equals 1 if the time of the response is after the treatment and equals 0 if before the treatment.
- $Treat$: the binary variable that equals 1 if the respondent is in the treatment group and equals 0 if in the control group.
- $Time$: the factor variable indicates the time periods of a particular response

Second, we decompose the data into 16 mutually exclusive categories according to respondents' usages of pawn shops and payday loans.

Note that if a policy, say prohibiting payday loan, is strictly enforced, then we can not observe in the after period that the payday dummy $PD = 1$. Unfortunately, the possibility that a person in a state where the payday loans are banned can still access to online payday loans from other states without regulation created enforcement issue [3]. Moreover, the remaining 12 cases can be reduced to 6 since the symmetric response will give us the same DD coefficients with only the opposite sign (eg. D_1 and D_8).

To create the policy dummies that can be used to estimate the diversion ratio:

[3] `https://www.lawyersandsettlements.com/articles/internet-payday-loans/office-of-attorney-general-state-arkansas-dustin-19164.html`

Table 4.1: Decomposition

	Before	After	Policy Dummy	Category
Case 1	$PD = 1, PW = 0$	$PD = 0, PW = 1$	D_{1i}	Diversion
Case 2	$PD = 0, PW = 0$	$PD = 0, PW = 1$	D_{2i}	-
Case 3	$PD = 1, PW = 1$	$PD = 0, PW = 0$	D_{3i}	-
Case 4	$PD = 0, PW = 1$	$PD = 0, PW = 0$	D_{4i}	-
Case 5	$PD = 1, PW = 0$	$PD = 1, PW = 1$	D_{5i}	-
Case 6	$PD = 0, PW = 0$	$PD = 1, PW = 1$	D_{6i}	-
Case 7	$PD = 1, PW = 1$	$PD = 1, PW = 0$	D_{7i}	-
Case 8	$PD = 0, PW = 1$	$PD = 1, PW = 0$	D_{8i}	-
Case 9	$PD = 1, PW = 0$	$PD = 0, PW = 0$	D_{9i}	-
Case 10	$PD = 0, PW = 0$	$PD = 1, PW = 0$	D_{10i}	-
Case 11	$PD = 1, PW = 1$	$PD = 0, PW = 1$	D_{11i}	-
Case 12	$PD = 0, PW = 0$	$PD = 1, PW = 0$	D_{12i}	-
Case 13	$PD = 1, PW = 1$	$PD = 1, PW = 1$	D_{13i}	No Response
Case 14	$PD = 0, PW = 0$	$PD = 0, PW = 0$	D_{14i}	No Response
Case 15	$PD = 1, PW = 0$	$PD = 1, PW = 0$	D_{15i}	No Response
Case 16	$PD = 0, PW = 1$	$PD = 0, PW = 1$	D_{16i}	No Response

- First, we partition the date in the before period and after period into 4 mutually exclusive categories. $(1,0),(0,1),(1,1),(0,0)$.
- Second, for a given category, we create the dummy based on the response of the respondent in the before and after period according to the table above.
- Example: to create the policy dummy D_1, if a respondent response is $PD = 1, PW = 0$, then $D_1 = 0$ and if $PD = 0, PW = 1$, then $D_1 = 1$.
- We will test the variable D_1 on our treatment group five, and we will provide a simple justification for why we use this particular treatment group.

Once the variable D_1 is created, we will use regular DD model to estimate the policy effect:

$$D_{1i,t} = Z'_{i,t}\beta + \pi Treat_i + \gamma Time_t + \theta_{Div}(Post \times Treat)_{i,t} + \epsilon_{i,t}$$

and the DD coefficients θ will be the estimation of policy effect (or diversion ratio).

The intuition that difference-in-differences of D_1 variable we created above in the example can capture the diversion ratio is a straightforward one: under the usual DD setting with D_1 as the dependent variable, the DD coefficient captures the difference in the proportion of people using pawn shops but not payday loans between control and treatment group before and after treatment. If the DD coefficient is significantly different from 0, then the policy has caused the θ_{Div} fraction more people to switch to use pawnshops after the treatment.

Chapter 5

Results

All the models for the CPS data in this chapter will be estimated using heteroskedasticity-robust Ordinary Least Squares (OLS), with state and time fixed effects and clustered standard errors at the individual level. The models for the Google Trends data in this chapter will also be estimated using heteroskedasticity-robust OLS.

First, in the following sections, we will present and discuss the results from the CPS data, for five different treatment groups. For the first four treatment groups, we will analyze the effects of different types of regulations or deregulation on the usage of payday loans, pawnshops, and check-cashing services. For the last treatment group, we will estimate the diversion ratio which we discussed in the model section. Also for each baseline model, we will also include a delayed-treatment model which we discussed in the model section 4.2.

Second, in the last section, we will present the statistical results from the Google Trends data for selected states. We will compare and contrast the results from the Google Trends and from the CPS data. In the cases of significant discrepancy, we will propose some possible hypotheses and some further directions of how to test those hypotheses.

Finally, we will conclude this chapter with the discussion of the potential problems which could potentially invalidate the statistical results we obtained. For those potential problems, we will propose possible solutions.

5.1 Arizona and Montana as Treatment Group

We consider the case where we take Arizona and Montana as the treatment group and use a collection of states as the control group which we introduced in the data section. The reason why we pooled Arizona and Montana together is that both states introduced strict interest cap by the end of 2010, which could completely eliminate the payday loan business in those states as the payday lenders claimed[1]. Limiting the annual percentage rate (APR) of payday loans to be under the usury limit at the state level presents us a natural experiment, and if the regulation indeed worked, we should expect a large negative difference-in-differences coefficient. One of the most controversial issues regarding completely outlaw payday loans is that people who don't have access to traditional forms of credit will have to use other forms of expensive alternative financial services (AFS) if the payday loans are not available. Given the extreme nature of regulations in Arizona and Montana, we should expect an increase in pawnshops use as a result of payday loan regulations. Moreover, sometimes people use check-cashing and payday loans interchangeably, and we should expect a negative difference-in-differences (DD) coefficients for the dependent variable being check-cashing service. The estimation results are presented in Table 5.1.

First, the control variables give us some insights regarding who tend to use the alternative financial services. We can infer from the statistically significant results from Table 5.1 that on average the people with college education tend to use fewer payday loans (-2.09%), pawnshop loans (-4.2%), and check-cashing services (-7.32%); on average people who are unemployed use more payday loans (1.22%), pawnshops (6.62%), and check-cashing services (7.37%) in the past 12 months; people who are above age 65 tend to use fewer alternative financial services of all forms we studied. One puzzling result is that we have statistically significant result that people who are unemployed are more likely to get a payday loan. This is puzzling, because in order to get any payday loans, people need to have a job in order to have paychecks to use as collateral. Plausibly this can be explained by that people who take payday loans

[1] https://ballotpedia.org/Montana_Loan_Interest_Rate_Limit,_I-164_(2010)

tend to become unemployed soon. ([one way to test this: we can use payday loan trend to predict unemployment trend use Granger Causality test]).

Second, we interpret the difference-in-differences coefficients in each model in Table 5.1. For payday loans, we see in the baseline model (column 1) that the DD coefficient is negative, extremely small in magnitude, and is not statistically significant. In the delayed treatment model (column 2) for payday loans, we still have negative insignificant DD coefficient, which suggests that the regulation has no significant effect one year after its implementation. The coefficient of DD_lag for payday loans, which measures the total treatment effect (we discussed in section 4.2), is negative, statistically significant and small in magnitude. There are several plausible explanations for the insignificant DD coefficients we observed. On the one hand, although we have a large sample, the actual usage of payday loans is extremely low (See the mean table 3.1) and response rate of the survey is also low for this specific question regarding the payday loan usage in the past 12 months, which means that our effective sample size is still rather small for payday loans. On the other hand, it is possible that the regulation did not have the intended effect, as we have seen in the legal document given in model section that payday lenders could and did circumvent regulations via online payday loans or using Indian tribes as protections. The significant coefficient on DD_lag does support the delayed treatment argument, which suggests that the regulation is effective in the long term (3 years after the original implementation).

Now we consider the DD coefficients for the pawnshops. We anticipated that the strict regulation on payday loans will force some payday loan users to switch to use pawnshops; however, our regression results suggests that fewer people were using pawnshops due to the payday loan regulation(-1.59% for baseline and -1.9% for delayed treatment). This result is similar to a previous study that argued that people use payday loans and pawn shops as complements rather than substitutes (Carter, 2012). In the later section, we will propose an alternative explanation using the decomposition model proposed in section 4.3. As we discussed before, the check-cashing service is a commonly used name for the short term deferred deposit loans, which includes payday loans, and therefore we should expect the regulations on payday loans will cause people to use less check-cashing service. Indeed, from the regression results (column 5 and 6), we see that people use less check-cashing (-2.46%) one year after regulation as a result of the regulation on payday loans.

Table 5.1: Arizona & Montana

	(1)	(2)	(3)	(4)	(5)	(6)
	payday_12	payday_12	pawn_12	pawn_12	cc_12	cc_12
High school diploma	-0.00294	-0.00295	-0.0147***	-0.0147***	-0.0527***	-0.0528***
	(0.00246)	(0.00246)	(0.00314)	(0.00314)	(0.00475)	(0.00475)
Some college	0.0000389	0.0000344	-0.0220***	-0.0220***	-0.0732***	-0.0732***
	(0.00249)	(0.00249)	(0.00308)	(0.00308)	(0.00469)	(0.00469)
College degree	-0.0209***	-0.0209***	-0.0420***	-0.0420***	-0.111***	-0.111***
	(0.00228)	(0.00228)	(0.00288)	(0.00288)	(0.00452)	(0.00452)
Unemployed	0.0122***	0.0122***	0.0662***	0.0662***	0.0737***	0.0737***
	(0.00403)	(0.00403)	(0.00600)	(0.00600)	(0.00744)	(0.00744)
Not in labor force	0.00243	0.00243	0.0193***	0.0193***	0.0137***	0.0137***
	(0.00171)	(0.00171)	(0.00204)	(0.00204)	(0.00289)	(0.00289)
25 to 34 years	0.0158***	0.0158***	0.00336	0.00331	-0.0422***	-0.0422***
	(0.00361)	(0.00361)	(0.00476)	(0.00476)	(0.00779)	(0.00779)
35 to 44 years	0.0114***	0.0114***	-0.00276	-0.00282	-0.0607***	-0.0607***
	(0.00351)	(0.00351)	(0.00462)	(0.00462)	(0.00763)	(0.00763)
45 to 54 years	0.00484	0.00481	-0.00735	-0.00741	-0.0768***	-0.0768***
	(0.00336)	(0.00336)	(0.00456)	(0.00456)	(0.00754)	(0.00754)
55 to 64 years	-0.00187	-0.00188	-0.0250***	-0.0250***	-0.103***	-0.103***
	(0.00329)	(0.00329)	(0.00441)	(0.00441)	(0.00742)	(0.00742)
65 years or more	-0.0124***	-0.0124***	-0.0469***	-0.0470***	-0.133***	-0.133***
	(0.00328)	(0.00329)	(0.00445)	(0.00445)	(0.00748)	(0.00748)
DD	-0.00563	0.000201	-0.0159*	-0.00466	-0.0246**	-0.0218*
	(0.00424)	(0.00561)	(0.00856)	(0.0108)	(0.0103)	(0.0121)
DD_lag		-0.00981*		-0.0190**		-0.00471
		(0.00502)		(0.00919)		(0.0107)
Constant	0.0344***	0.0344***	0.0709***	0.0708***	0.235***	0.235***
	(0.00600)	(0.00600)	(0.00702)	(0.00702)	(0.0108)	(0.0108)
Observations	57685	57685	57647	57647	57858	57858
Adjusted R^2	0.011	0.011	0.029	0.029	0.042	0.042
Clustered SE	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.2 Colorado as Treatment Group

Now, we consider the case where we use Colorado as the treatment group and similarly use a collection of states as the control group which we identified in the data section.

Table 5.2: Colorado

	(1)	(2)	(3)	(4)	(5)	(6)
	payday_12	payday_12	pawn_12	pawn_12	cc_12	cc_12
High school diploma	-0.00360	-0.00359	-0.0136***	-0.0136***	-0.0537***	-0.0537***
	(0.00254)	(0.00254)	(0.00314)	(0.00314)	(0.00483)	(0.00483)
Some college	-0.000401	-0.000399	-0.0203***	-0.0203***	-0.0736***	-0.0736***
	(0.00258)	(0.00258)	(0.00309)	(0.00309)	(0.00477)	(0.00477)
College degree	-0.0225***	-0.0225***	-0.0410***	-0.0410***	-0.112***	-0.112***
	(0.00237)	(0.00236)	(0.00288)	(0.00288)	(0.00458)	(0.00458)
Unemployed	0.0116***	0.0116***	0.0637***	0.0637***	0.0704***	0.0704***
	(0.00410)	(0.00410)	(0.00597)	(0.00597)	(0.00745)	(0.00745)
Not in labor force	0.00166	0.00166	0.0183***	0.0183***	0.0128***	0.0128***
	(0.00175)	(0.00175)	(0.00203)	(0.00203)	(0.00292)	(0.00292)
25 to 34 years	0.0160***	0.0160***	0.00490	0.00491	-0.0448***	-0.0448***
	(0.00372)	(0.00372)	(0.00471)	(0.00471)	(0.00786)	(0.00786)
35 to 44 years	0.0109***	0.0109***	-0.00159	-0.00158	-0.0632***	-0.0632***
	(0.00361)	(0.00361)	(0.00458)	(0.00458)	(0.00772)	(0.00772)
45 to 54 years	0.00392	0.00393	-0.00555	-0.00554	-0.0792***	-0.0793***
	(0.00346)	(0.00346)	(0.00450)	(0.00451)	(0.00762)	(0.00762)
55 to 64 years	-0.00218	-0.00217	-0.0235***	-0.0235***	-0.105***	-0.105***
	(0.00339)	(0.00339)	(0.00435)	(0.00435)	(0.00751)	(0.00751)
65 years or more	-0.0130***	-0.0130***	-0.0446***	-0.0446***	-0.134***	-0.134***
	(0.00339)	(0.00339)	(0.00439)	(0.00439)	(0.00758)	(0.00758)
DD	-0.0113*	-0.00996	-0.00322	-0.00207	0.0122	0.00741
	(0.00647)	(0.00714)	(0.00764)	(0.00874)	(0.00994)	(0.0108)
DD_lag		-0.00388		-0.00330		0.0139
		(0.00787)		(0.00906)		(0.0143)
Constant	0.0359***	0.0359***	0.0686***	0.0685***	0.238***	0.238***
	(0.00608)	(0.00608)	(0.00698)	(0.00698)	(0.0109)	(0.0109)
Observations	56602	56602	56570	56570	56780	56780
Adjusted R^2	0.011	0.011	0.027	0.027	0.042	0.042
Clustered SE	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Unlike the strict interest cap in Arizona and Montana, the regulation on payday loans in Colorado is a rather complicated scheme with a distinct clause that the loan term must be longer than six months with lower interest rate than the typical short term payday loans [2]. If this type of regulation indeed works, we should expect a large negative difference-in-differences coefficient. Similarly, we should expect a decrease of check-cashing service DD coefficients because of the regulation. Given that the payday loans are still available, we should expect either a slight increase in pawnshops use which is caused by the payday loan regulations or no increase in pawnshop uses at all because of the regulation. The estimation results are presented in Table 5.2.

First, similarly as before the coefficients of the control variables suggests that on average the people with college education tend to use fewer payday loans (-2.25%), pawnshops (-4.1%), and check-cashing services (-11.2%); on average people who are unemployed uses more payday loans (1.16%), pawnshops (6.37%), and check-cashing services (7.04%) in the last 12 months; people who are above age 65 use fewer alternative financial services of all forms we discussed.

Second, we interpret the difference-in-differences coefficients in each model in Table 5.2. For payday loans, we see in the baseline model (column 1) that the DD coefficient is negative and statistically significant, which suggests that the regulation on payday loan is effective in the short term. Nevertheless, the difference-in-differences coefficients are not statistically significantly different from 0 for both pawnshops and check-cashing services, which holds for both baseline model and delayed treatment model. This result suggests that the regulation on payday loans in Colorado is effective in the sense that it decreases the usage of payday loans and it does not result in increased usages in pawnshops or check-cashing services. The reduction in the payday loan use without an increase in pawnshop use in Colorado may support the previous study that the people who tend use alternative financial services have an incomplete financial knowledge and are overconfident about their state of knowledge (Robb et al, 2015).

[2] `http://www.paydayloaninfo.org/index.php?option=com_content&view=article&id=3&Itemid=3`

5.3 Arkansas as Treatment Group

Next, we consider Arkansas as the treatment group. Similar to Arizona and Montana, Arkansas repealed their Check Casher Act on March 28, 2011, which effectively capped the Annual Interest Rate to be below the Usury limit (17% APR). If effective, the repeal could completely eliminate the payday loan business in Arkansas and restrict the check cashing service significantly. Indeed in Table 3.1, we see that the payday loan usage in 2015 in Arkansas is 0%, and in Table 3.3, we see a sharp drop in check cashing service from 2013 to 2015. The question now is to what extent can we attribute this decreased usage in payday loans and check-cashing services to the regulation. Another issue we have is that whether the regulation can be strictly enforced, since Arkansas was surrounded by states where the payday loans are legal, which give rise to the possibility that people in Arkansas can access to storefront or online payday loans in the neighboring states.

This is a legitimate concern and the Arkansas attorney general has issued a similar warning in their website [3]. Moreover, the Arkansas Attorney General in 2013 started to prosecute online payday lenders [4], and therefore we should pay extra attention to the results from our delayed-treatment model. We should expect negative DD coefficients for payday loans and check-cashing services. Similarly, due to the extreme nature of the regulation, it is likely that the potential payday loan users had to switch to other forms of unconventional credit such as pawnshops. The results are tabulated in Table 5.3.

As in the case of Arizona, Montana, and Colorado, the coefficients on the control variables suggests that on average people who are above age 65 and people with college education tend to use fewer payday loans, pawnshops, and check-cashing services; on average people who are unemployed are more likely to use these three types of alternative financial services in the past 12 months. For the DD coefficients for payday loans, we see in the baseline model (Table 5.3 column 1) that the DD coef-

[3] https://arkansasag.gov/consumer-protection/money/one/illegal-payday-lending/

[4] https://www.lawyersandsettlements.com/articles/internet-payday-loans/office-of-attorney-general-state-arkansas-dustin-19164.html

ficient is negative, extremely small in magnitude, and is not statistically significant. In the delayed treatment model (column 2) for payday loans, we still have negative insignificant DD coefficient but the coefficient of DD_lag for payday loans, which measures the total treatment effect, is negative, statistically significant at 1% level. If the parallel trend assumption holds, since the DD coefficient is not significantly different from 0, we should interpret the coefficient for DD_lag to be solely the increment effect from the year 2013 to the year 2015. In other words, the regulation is effective but delayed for one period due to enforcement issue. Moreover, we see a similar pattern of the coefficients of DD and DD_lag for check-cashing service as well.

Now we consider the DD coefficients for the pawnshops. The significant positive DD coefficient for payday loan suggests that indeed more people were using pawnshops due to the payday loan regulation (a 2.84% increase for delayed treatment model), which contradicts our findings in the Arizona and Montana case but is consistent with our hypothesis that when payday loans aren't available, the potential payday loan users will have to borrow other forms of expensive unconventional credits. Moreover, since the lagged DD coefficient for the pawnshops is not statistically significant, we can attribute this increase in pawnshop uses to the initial payday loan regulation, which forced all storefront payday loans to shut down [5]. Therefore, we can argue that the increased pawnshop users were once the users of storefront payday loans. We will provide justification for this argument in the later section.

5.4 Mississippi as Treatment Group

Now, we consider the state Mississippi as the treatment group. Unlike previous cases, Mississippi in 2011 reenacted their Check Casher Act and in 2013 repealed the repealer of the Check Casher Act. In some measure, one could argue that the Check Casher Act established certain rules for the check cashers and hence weed out the unlicensed the AFS lenders. Moreover, the Check Casher Act (Section 75-67-501

[5] `https://arkansasag.gov/consumer-protection/money/one/illegal-payday-lending/`

Table 5.3: Arkansas

	(1) payday_12	(2) payday_12	(3) pawn_12	(4) pawn_12	(5) cc_12	(6) cc_12
High school diploma	-0.00340	-0.00337	-0.0133***	-0.0132***	-0.0523***	-0.0522***
	(0.00249)	(0.00249)	(0.00313)	(0.00313)	(0.00481)	(0.00481)
Some college	0.000187	0.000234	-0.0198***	-0.0198***	-0.0729***	-0.0729***
	(0.00253)	(0.00253)	(0.00308)	(0.00308)	(0.00475)	(0.00475)
College degree	-0.0213***	-0.0213***	-0.0405***	-0.0404***	-0.112***	-0.112***
	(0.00232)	(0.00232)	(0.00287)	(0.00287)	(0.00456)	(0.00456)
Unemployed	0.0119***	0.0120***	0.0628***	0.0628***	0.0727***	0.0728***
	(0.00410)	(0.00410)	(0.00599)	(0.00599)	(0.00757)	(0.00757)
Not in labor force	0.00255	0.00256	0.0193***	0.0193***	0.0125***	0.0125***
	(0.00175)	(0.00175)	(0.00207)	(0.00207)	(0.00294)	(0.00294)
25 to 34 years	0.0157***	0.0157***	0.00641	0.00641	-0.0419***	-0.0419***
	(0.00366)	(0.00366)	(0.00473)	(0.00473)	(0.00787)	(0.00787)
35 to 44 years	0.0115***	0.0115***	-0.00178	-0.00176	-0.0601***	-0.0601***
	(0.00355)	(0.00355)	(0.00457)	(0.00457)	(0.00773)	(0.00773)
45 to 54 years	0.00497	0.00500	-0.00453	-0.00450	-0.0772***	-0.0771***
	(0.00341)	(0.00341)	(0.00452)	(0.00452)	(0.00762)	(0.00762)
55 to 64 years	-0.00198	-0.00195	-0.0229***	-0.0229***	-0.103***	-0.103***
	(0.00333)	(0.00333)	(0.00436)	(0.00436)	(0.00751)	(0.00751)
65 years or more	-0.0126***	-0.0125***	-0.0447***	-0.0447***	-0.133***	-0.133***
	(0.00334)	(0.00334)	(0.00442)	(0.00442)	(0.00758)	(0.00758)
DD	-0.00157	0.00971	0.0160	0.0284*	0.00454	0.0229
	(0.00502)	(0.00767)	(0.0122)	(0.0156)	(0.0171)	(0.0206)
DD_lag		-0.0211***		-0.0230		-0.0344*
		(0.00676)		(0.0148)		(0.0187)
Constant	0.0346***	0.0345***	0.0674***	0.0673***	0.236***	0.235***
	(0.00604)	(0.00605)	(0.00697)	(0.00697)	(0.0109)	(0.0109)
Observations	55928	55928	55896	55896	56103	56103
Adjusted R^2	0.011	0.011	0.028	0.028	0.042	0.042
Clustered SE	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

through 75-67-537) also outlawed the rollover of payday loans, which we discussed in the literature review that it is one of the crucial element in the payday loans that causes the controversial. Nevertheless, the Check Casher Act indeed legitimized the payday loans in Mississippi. The results from difference-in-differences model will suggest which aspect in the [de]regulation has more weight in the policy outcome: on the one hand, the Act, if effective, should reduce the illegal payday lending activities; on the other hand, the legalization of payday loans, if effective, may encourage people to borrow such credit. The results are tabulated in Table 5.4.

As in the previous cases, the coefficients on the control variables suggests that on average people who are above age 65 and the people with college education tend to use fewer payday loans, pawnshops, and check-cashing services; on average people who are unemployed are more likely to use these three types of alternative financial services. Moreover, for the DD coefficients for payday loans, we see in the baseline model (Table 5.3 column 1) that the DD coefficient is positive (1.41% increase) and is statistically significant, which indicates the initial legalization of payday loans in 2011 increases payday loan use. In the delayed treatment model (column 2) for payday loans, we still have positive significant DD coefficient (2.93%) but the coefficient of DD_lag for payday loans, which measures the total treatment effect, is negative and is statistically significant at 1%. As we discussed in model section 4.3, if the parallel trend assumption holds, we can interpret the difference in DD and DD_lag coefficients as the increment effect (-2.33% - 2.93% = -5.26%), which suggests that initially the regulation in the first period increases the usage of payday loans, but in the second period decreases the usage of payday loans. Moreover, the regulations resulted in a -5.36% net decrease for check-cashing service and has no significant effect on people's usage of pawnshops. One plausible explanation for the reduction in check-cashing usage is that the licensing requirements in the Check Casher Act may have weed out illegal lending businesses.

Table 5.4: Mississippi

	(1)	(2)	(3)	(4)	(5)	(6)
	payday_12	payday_12	pawn_12	pawn_12	cc_12	cc_12
High school diploma	-0.00410	-0.00410	-0.0132***	-0.0132***	-0.0517***	-0.0517***
	(0.00253)	(0.00253)	(0.00311)	(0.00311)	(0.00478)	(0.00478)
Some college	-0.000424	-0.000443	-0.0205***	-0.0205***	-0.0715***	-0.0716***
	(0.00257)	(0.00257)	(0.00305)	(0.00305)	(0.00472)	(0.00472)
College degree	-0.0221***	-0.0221***	-0.0402***	-0.0402***	-0.111***	-0.111***
	(0.00236)	(0.00236)	(0.00284)	(0.00284)	(0.00454)	(0.00454)
Unemployed	0.0133***	0.0133***	0.0635***	0.0635***	0.0718***	0.0718***
	(0.00419)	(0.00419)	(0.00597)	(0.00597)	(0.00754)	(0.00754)
Not in labor force	0.00237	0.00237	0.0193***	0.0193***	0.0130***	0.0130***
	(0.00176)	(0.00176)	(0.00205)	(0.00205)	(0.00294)	(0.00294)
25 to 34 years	0.0144***	0.0144***	0.00712	0.00712	-0.0463***	-0.0463***
	(0.00379)	(0.00379)	(0.00466)	(0.00466)	(0.00797)	(0.00797)
35 to 44 years	0.0101***	0.0101***	-0.000198	-0.000189	-0.0657***	-0.0656***
	(0.00368)	(0.00368)	(0.00451)	(0.00451)	(0.00781)	(0.00781)
45 to 54 years	0.00340	0.00341	-0.00299	-0.00299	-0.0815***	-0.0815***
	(0.00354)	(0.00354)	(0.00444)	(0.00445)	(0.00771)	(0.00771)
55 to 64 years	-0.00327	-0.00327	-0.0214***	-0.0214***	-0.109***	-0.109***
	(0.00347)	(0.00347)	(0.00429)	(0.00429)	(0.00760)	(0.00760)
65 years or more	-0.0142***	-0.0142***	-0.0428***	-0.0428***	-0.138***	-0.138***
	(0.00347)	(0.00347)	(0.00434)	(0.00434)	(0.00766)	(0.00766)
DD	0.0141*	0.0293**	-0.00312	-0.000451	-0.0250	0.00999
	(0.00784)	(0.0122)	(0.0106)	(0.0135)	(0.0173)	(0.0222)
DD_lag		-0.0233*		-0.00409		-0.0536***
		(0.0123)		(0.0115)		(0.0186)
Constant	0.0366***	0.0366***	0.0660***	0.0660***	0.239***	0.239***
	(0.00614)	(0.00614)	(0.00693)	(0.00693)	(0.0110)	(0.0110)
Observations	55949	55949	55913	55913	56117	56117
Adjusted R^2	0.010	0.011	0.027	0.027	0.042	0.042
Clustered SE	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.5 2013 Pool and Estimation of Diversion Ratio

Now we pool a group of states that have introduced certain forms of payday loan regulations in 2013, which involves measures such as licensing requirement, loan limits requirement and less strict interest cap. We will use this pool as the treatment group, and the remaining unregulated states as the control group. We estimate the DD model with decomposed data, which we discussed in model section 4.3 should give us estimates of the diversion ratio. Here we only have two periods so we don't need to discuss the delayed treatment effects. One of the reasons why we pooled together all the states is due to the small effective sample size as we discussed in the data section, which is especially important since we are only using a fraction of the data to estimate the diversion ratio.

Recall that the dependent variable D_1 is a dummy variable which equals 1 if the respondent has used pawnshops but not payday loans in the past 12 months, and which equals 0 if the respondent did not use pawnshops but used payday loans in the past 12 months. As we argued in the model section 4.3, the difference-in-differences coefficient for D_1 should measure the fraction of people changed from payday loan use to pawnshop use (or vice versa if negative DD coefficients) due to the regulation on payday loans.

First, we can see from Table 5.4 that the DD coefficient for payday loan and check cashing services are both negative (-1.18% and -1.35% respectively) and statistically significant at 1% level. We can argue that the licensing requirements or reporting requirement may have reduced illegal lending activities by those who were not licensed. However, the DD coefficient for unpartitioned data for the pawnshops is extremely small in magnitude and is not statistically significant. One may stop here and argue that the difference-in-differences estimation suggests the regulation on payday loans has little or none effect on the usage of pawnshop loans. However, once we condition our analysis on the subsample in which the respondent uses either pawnshops or payday loans but not both, we see a large positive difference-in-differences coefficient for D_1 (+15.9%) which is also statistically significant. We can argue that under the framework of DD model with the D_1 variable we created, on average, more people switched to use pawnshops from payday loans because of the regulation on payday loans.

Table 5.5: 2013 Combined States

	(1) payday_12	(2) pawn_12	(3) cc_12	(4) D_1
High school diploma	-0.00417*	-0.0144***	-0.0507***	-0.0536**
	(0.00248)	(0.00300)	(0.00457)	(0.0263)
Some college	-0.00169	-0.0215***	-0.0700***	-0.134***
	(0.00251)	(0.00295)	(0.00451)	(0.0263)
College degree	-0.0235***	-0.0408***	-0.108***	-0.146***
	(0.00231)	(0.00276)	(0.00434)	(0.0361)
25 to 34 years	0.0139***	0.00548	-0.0429***	-0.0602
	(0.00370)	(0.00444)	(0.00741)	(0.0388)
35 to 44 years	0.00843**	-0.00257	-0.0608***	-0.0671*
	(0.00359)	(0.00430)	(0.00728)	(0.0394)
45 to 54 years	0.00295	-0.00436	-0.0771***	-0.0350
	(0.00347)	(0.00426)	(0.00719)	(0.0394)
55 to 64 years	-0.00487	-0.0233***	-0.102***	-0.118***
	(0.00339)	(0.00410)	(0.00709)	(0.0428)
65 years or more	-0.0151***	-0.0447***	-0.131***	-0.279***
	(0.00339)	(0.00416)	(0.00715)	(0.0493)
Unemployed	0.0152***	0.0639***	0.0740***	0.232***
	(0.00416)	(0.00569)	(0.00719)	(0.0292)
Not in labor force	0.000381	0.0188***	0.0107***	0.155***
	(0.00167)	(0.00194)	(0.00278)	(0.0219)
DD	-0.0118***	-0.000219	-0.0135**	0.159***
	(0.00437)	(0.00424)	(0.00683)	(0.0608)
Constant	0.0395***	0.0691***	0.233***	0.669***
	(0.00606)	(0.00678)	(0.0106)	(0.0645)
Observations	62112	62070	62295	2630
Adjusted R^2	0.012	0.027	0.040	0.102
Clustered SE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.6 Google Trends, Comparison and Discussion

Now we estimate the simple difference-in-differences model using Google Trends data. Unlike the micro-level CPS data, the Google Trends data are long time series and measures the relative popularity of a certain search term in a given period of time. One advantage of using Google Trends data is that one can actually verify the parallel trend assumption in the DD model. If people's search for payday loans is a good proxy for people's actual usage of payday loans, then we can use Google Trends to check whether the parallel trends assumption holds for the micro-level data. Moreover, another advantage of using Google Trends data is that due to their high frequency, we can identify the (almost) exact time when a certain regulation is introduced. We can compare the DD coefficients for CPS data with the DD coefficients for Google Trends data and use Google Trends data as an alternative robustness check. Nevertheless, there are many disadvantages of Google Trends data as well due to that we can not control other unobservable factors.

The regression results are tabulated in Table 5.6 - Table 5.9. First, for Arkansas (Table 5.6), we see a 18.1 point (out of 100) decrease in the relative research popularity of payday loans as the result of the regulation; meanwhile, there is a 4.072 point increase in the search for the pawnshops. Both results are statistically significant. Although the DD coefficient for payday loans estimated using Google Trends data has the same sign as the one suing CPS data, the DD coefficients for the pawnshops have different signs. That is people search of pawnshops increases while the actual usage of pawnshops decreases. One possible explanation is that the increased pawnshop searches are done by people who were previously using payday loans but not pawnshops, and since the payday loans are no longer available, they have to search for alternative credits. This is the same idea as how we created the D_1 variable and estimated the diversion ratio, in which case we did see an increase in people switching from payday loans to pawnshops.

Second, for both Montana and Arkansas, we have negative DD coefficients for both pawnshops and payday loan searches, which suggest that people's searches for these two terms decreased as a result of regulation.

Third, for Mississippi, we estimate both the baseline and lagged models, in which the lag is identified by the exact date when the repealer of the Check Casher Act was repealed. From Table 5.9, we see that DD coefficients for the payday loans and check cashing are not significant for the baseline model, and the DD_lag coefficients are all positive and significant at 1% level. These results suggest that after the repealer was repealed, people's searches for payday loans, pawnshops, and check-cashing all increased as a result. We can also infer from the insignificant DD coefficients that the initial re-enactment of the Check Cashing Act has no effect on people's search behavior.

Although in many cases above, in contrast to the DD coefficients estimated using CPS data, the DD coefficients for payday loans, pawnshops and cc are highly significant, we should also be cautious about the between states variations that we can not take into account using the Google Trends data. Moreover, people who use the internet to search for alternative financial services may be more likely to use online payday loans, and hence the DD coefficients for Google Trend search are estimating the policy impact of payday loan regulations on only online payday loan users, which is a subset of all payday loan users.

Table 5.6: Arizona Google Trends

	(1) payday	(2) pawn
treat	20.77***	15.53***
	(1.204)	(1.076)
time	3.649***	20.82***
	(0.538)	(0.767)
DD	-18.02***	4.072**
	(1.435)	(1.768)
Constant	20.96***	23.12***
	(0.355)	(0.311)
Observations	522	522
Adjusted R^2	0.479	0.671

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

To conclude the result section, we discuss some potential issues that may invalidate

Table 5.7: Montana Google Trends

	(1) payday	(2) pawn
treat	7.662***	16.20***
	(1.497)	(1.641)
time	2.466***	13.51***
	(0.344)	(0.472)
DD	-7.273***	-6.459***
	(1.904)	(2.094)
Constant	12.91***	14.76***
	(0.191)	(0.230)
Observations	522	522
Adjusted R^2	0.059	0.320

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.8: Arkansas Google Trends

	(1) payday	(2) pawn	(3) cc
treat	13.11***	18.39***	9.402***
	(1.502)	(1.420)	(1.849)
time	4.504***	18.11***	10.96***
	(0.416)	(0.579)	(0.345)
DD	-11.22***	-9.249***	-14.16***
	(1.839)	(2.248)	(2.289)
Constant	16.49***	20.28***	15.45***
	(0.238)	(0.360)	(0.225)
Observations	522	522	522
Adjusted R^2	0.163	0.392	0.079

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.9: Mississippi Google Trends

	(1) payday	(2) payday	(3) pawn	(4) pawn	(5) cc	(6) cc
treat	17.70***	17.70***	16.07***	16.07***	17.15***	17.15***
	(2.246)	(2.248)	(2.266)	(2.268)	(2.998)	(3.001)
time	3.647***	3.647***	11.13***	11.13***	10.09***	10.09***
	(0.366)	(0.367)	(0.475)	(0.476)	(0.466)	(0.466)
DD	0.862	-1.526	5.520**	-0.718	-4.608	-8.043**
	(2.392)	(2.497)	(2.511)	(2.590)	(3.211)	(3.302)
DD_lag		5.162***		13.48***		7.424***
		(1.563)		(1.909)		(2.231)
Constant	12.38***	12.38***	18.52***	18.52***	16.50***	16.50***
	(0.306)	(0.306)	(0.417)	(0.417)	(0.406)	(0.406)
Observations	522	522	522	522	522	522
Adjusted R^2	0.498	0.512	0.523	0.589	0.258	0.281

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

the results presented above. First and foremost, in order for the above estimation to be unbiased, we need parallel trend assumption to hold. That is we need that the difference between the mean usages of AFS between control group and treatment group to be constant in all period before the treatment. As we argued before, this assumption can be easily tested on the Google Trends data but unfortunately not on the CPS data. If Google search is a good indicator of the actual usage of AFS, then maybe we can assume the parallel trend assumption in the CPS data. In the literature review, we have seen that Choi and Varian's research indeed suggests that the Google Trends have predictive power for the actual economic variables, and further research can be done on whether there is a strong correlation between Google search and actual credit borrowing.

Second, due to the low usage of AFS, the effective sample size in the CPS data is rather small comparing to the overall CPS sample size. Then all the DD coefficients that are only significant on the borderline are likely to be significant due to pure luck. Moreover, the low response rate in the survey data for the questions related to the usage alternative financial services is another issue that can cause the selection bias. (The issue of which subpopulation are we actually estimating).

Third, unlike Card and Kruger's study of the minimum wage in which the surveys were conducted in the close time neighborhood of the minimum wage hike, our survey data were collected biannually. If some true causal events that happened during the gaps years that systematically caused the decrease in usage of certain alternative financial services, then the DD coefficients will be estimating the causal effects of those events rather than the regulation. Although we have utilized CPS data's panel structure and we have controlled for time and state fixed effect as well as clustered standard errors in our model, to address above concern we may still need higher frequency micro-data.

Chapter 6

Conclusion

Regulations on payday loans have been controversial, and the studies on payday loans and the regulations have often reached results that are inconclusive. It is particularly hard to reach a definite conclusion on whether regulations on payday loans have made people better off or not. On the one hand, people who are against payday loans argue that the payday loans have created debt traps for low-income individuals; on the other hand, the payday loan advocates claim that the payday loans provide the credit constrained people much-needed credit (Zinman, 2010; Morse, 2011). Many payday loan borrowers were extremely credit constrained and they often borrow payday loans for unexpected expenses (Pew, 2012). We have two concerns regarding the payday loan regulations. First, the state-level nonuniform regulations may have created loopholes that invalidate the regulatory efforts in the short term. Second, in the absence of cheaper alternatives to payday loans, the regulations on payday loans may have forced many payday borrowers in need of credit to switch to other expensive credits.

In this study, we construct various treatment groups based on the types of the regulations and then we apply the difference-in-differences model and its variations to the panel Census data and Google Trends data to explore the two proposed hypotheses. Our results suggest that the effect of regulation varies as the types of regulations vary. The first hypothesis that there is a delayed treatment effect due to incomplete enforcement of regulations is supported by the results from Arizona, Montana, and Arkansas. The second hypothesis that the regulation may have forced the users of payday loans to switch to pawnshops is supported by the results from treatment group with multiple combined states restricted to the respondents who use exclusively either payday loan or pawnshops before and after treatment. Arguably, the substitution relationship between payday loans and pawnshops is also supported by the results from the Google Trends data because of their predictive power and high frequency.

The delayed treatment effect from our estimation suggests that in order for the regulations on payday loans to be effective, the policymakers should closely monitor the loopholes such as the availability of online payday loans from other states and increase enforcement effort accordingly. Moreover, the substitution effect from our estimation suggests that when introducing a strict payday loan ban, the policymakers should provide guidance and help to potential payday loan users who may have no option other than using other expensive credits.

In the future, we would like to explore the Google Trends data for various high-cost financial services at the daily frequency at metropolitan level, which is currently unavailable to the public. Moreover, we would like to explore the relationship between online payday loan use and the Google Trends search for payday loans. If the Google Trends data are good proxies for online payday loan use, then like the Google flu trend that predicts disease outbreak, the policymakers and researchers can use Google Trends of various financial services to study people's credit using behavior at much higher frequency than the currently available survey data.

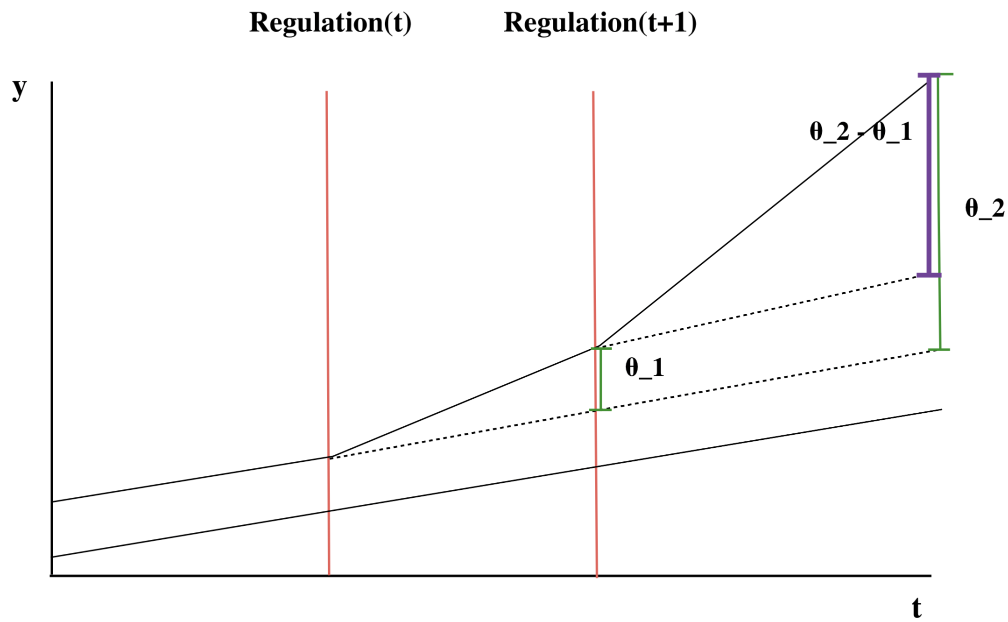
Chapter 7

Appendix

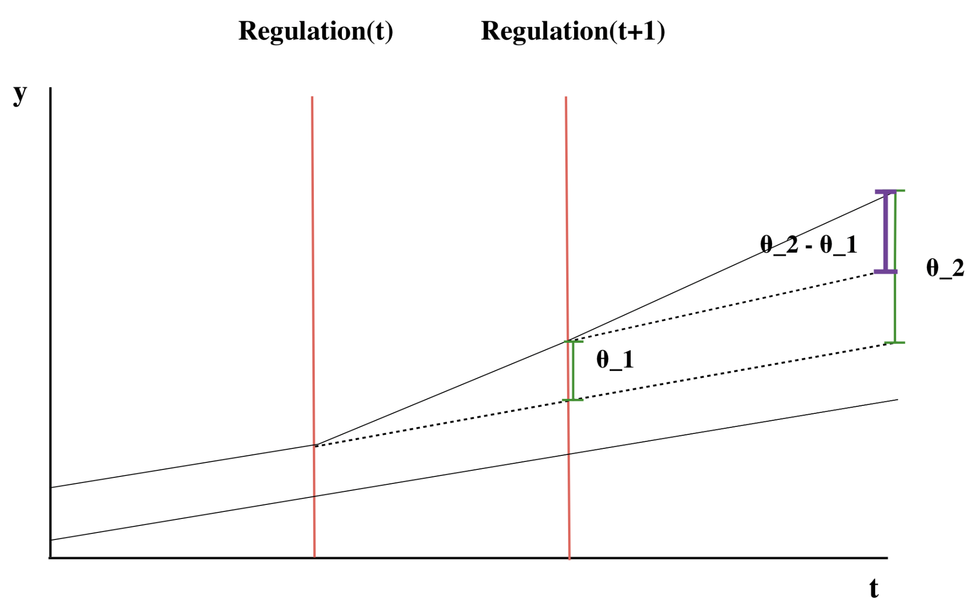
Here we present a graphical approach for the model 4.2. Recall that θ_1 is the treatment effect for the regulation at the first period and θ_2 is the total treatment effect for both period one and period two. In case 1 and case 2, we have that the regulation in period 1 is effective and we observe change θ_1 as the result of such regulation. Then for the second period, the effort of regulation enforcement increases, and we observe a incremental change $\theta_2 - \theta_1$. The difference between case 1 and case 2 is whether the increase in effort changes the slop of the trend. In case 3, we see that there is no treatment effect for the period 1 and the total treatment effect $\theta_2 = \theta_2 - \theta_1$. The no effect in regulation is not unprecedented for payday loan industry. For example, in Ohio, the established Short Term Lender Law was circumvented by payday lenders through using the loophole of another set of law [1]. In case 4, we see that under the parallel trend assumption, $\theta_2 - \theta_1$ continue to measure the increment effect of regulation.

[1] `http://www.nolo.com/legal-encyclopedia/restrictions-payday-lending-ohio.html`

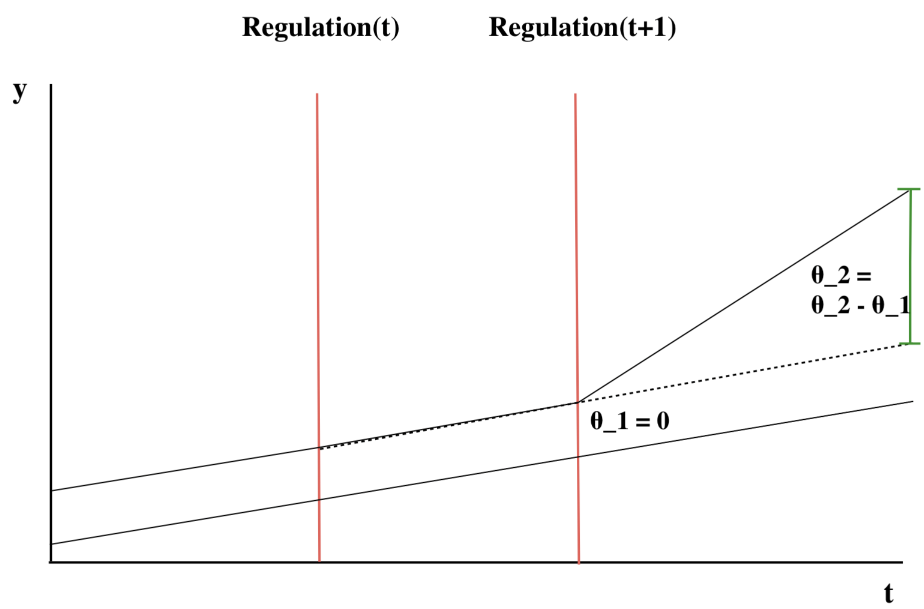
Case 1


Regulation(t)
Regulation(t+1)
y
θ_2 - θ_1
θ_2
θ_1
t

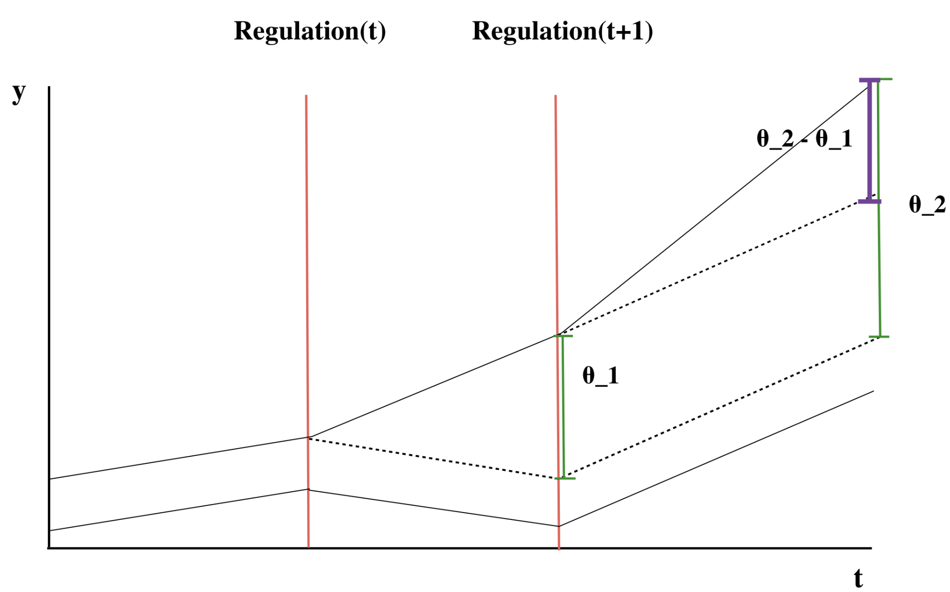
Case 2


Regulation(t)
Regulation(t+1)
y
θ_2 - θ_1
θ_2
θ_1
t

Case 3


Regulation(t)
Regulation(t+1)
y
θ_2 =
θ_2 - θ_1
θ_1 = 0
t

Case 4


Regulation(t)
Regulation(t+1)
y
θ_2 - θ_1
θ_2
θ_1
t

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