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From the Dairy Aisle to Payday Loans: An In-depth Examination of Consumer Economics in the U.S.

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From the Dairy Aisle to Payday Loans:
An In-depth Examination of Consumer Economics in the U.S.

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Economics

by

Nicole Golden

Dissertation Committee:
Professor Matthew Harding, Chair
Associate Professor Yingying Lee
Associate Professor Damon Clark

2024

DEDICATION

To my family, my peers/friends, and my professors. I am truly grateful for their support.

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ACKNOWLEDGMENTS

I wish to extend my sincere gratitude and appreciation to all individuals who have provided support and made valuable contributions to the successful completion of this dissertation.

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VITA

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ABSTRACT OF THE DISSERTATION

From the Dairy Aisle to Payday Loans:
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Nicole Golden

Doctor of Philosophy in Economics

University of California, Irvine, 2024

Professor Matthew Harding, Chair

This dissertation undertakes a comprehensive investigation into consumer economics within the United States, spanning diverse realms, from the dairy aisle and the domain of payday loans. The first chapter delves into the impact of migration on consumer behavior, specifically focusing on dairy and plant-based milk consumption. Utilizing Nielsen consumer panel data, the research discerns a trend wherein individuals who undergo migration exhibit an increase in expenditures on dairy milk, accompanied by a corresponding decrease in expenditures on plant-based milk. Notably, the destination of migration elucidates approximately half of the variations observed in dairy milk expenditures, whereas it only accounts for seventeen percent of the variations in plant-based milk expenditures. These findings suggest a substantial convergence in dairy milk expenditures towards the average level prevalent in the destination state. The second chapter transitions from tangible commodities to financial products, specifically examining extended payment plans associated with payday loans and their implications for financial health. Leveraging the comprehensive coverage offered by Clarity payday loan data, the study illuminates the positive impact of these extended payment plans on various facets of borrowers' financial well-being. This impact is evident in metrics such as the amount past due, original charge-off, delinquency rate, and the rate of charge-off or debt-in-collections. The third chapter extends the inquiry by investigating the heterogeneous

treatment effects of extended payment plans over time and across individuals with varying income volatility, as defined by the income coefficient of variation. The research reveals that the treatment effect exhibits variation across different years without a discernible pattern. Individuals with income coefficients of variation ranging from the first quartile to the median level appear to derive the most benefit from these plans. However, the treatment effect is either small or non-existent for individuals with income coefficients of variation beyond the third quartile. In summary, this dissertation contributes to the understanding of consumer economics by analyzing data pertaining to both tangible and intangible products, ranging from milk consumption to payday loan borrowing in the United States. The findings not only shed light on dietary-related policies, especially the policy for the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC), but also hold relevance for policy considerations in the realm of financial products.

Chapter 1

Got Milk? Analyzing Milk Consumption Patterns in the Context of U.S. Migration

Abstract

This paper exploits a natural experiment in the U.S. among households who have moved to another state to study how migration affects dairy and plant-based milk consumption. Using Nielsen Consumer Data to measure outcomes, I find that after moving to a new state, on average, (i) the movers have increased their dairy milk expenditures by 1.2%, whereas the plant-based milk expenditures have decreased by 1.5%; and (ii) the new destination explains about 53% of the differences in dairy milk expenditures and only about 17% for plant-based milk expenditures. These results imply a more considerable convergence for dairy milk expenditures toward the destination state's average level. In contrast, plant-based milk expenditures have only slightly converged toward the average level in the households' new states.

Keywords: dairy milk, plant-based milk, migration, geographic variation, demand, preferences, Nielsen Homescan data

JEL Codes: D12, I12, L66

1.1 Introduction

Dairy milk consumption in the United States has exhibited a consistent and noteworthy declining trend spanning the past seven decades. According to Stewart and Kuchler (2022), the daily per capita consumption of dairy milk in the U.S. decreased from 0.96 cups to 0.49 cups between 1970 and 2019, reflecting a substantial nearly 50% reduction. On average, the decline for each decade amounted to 12.45% [1]. The surge in plant-based milk (later referred to as "plant milk") consumption may contribute to this phenomenon, despite its considerable price premium [2]. The increasing adoption of plant milk can be attributed to factors such as being lactose-free, serving as a nutrient substitute for dairy milk, and the promotion of its health and environmental benefits, as well as animal welfare considerations. The COVID-19 pandemic has further accelerated the shift towards plant-based foods, as evidenced by the findings in Loh et al. (2021) that many individuals preferred plant options during the pandemic. A report in Association (2022) indicated a substantial 20.7% increase in plant-based food sales in terms of dollars from 2019 to 2020.

Understanding how consumers allocate their expenditures between animal-based and plant milk carries significant economic implications, particularly for formulating effective policy recommendations in the realm of dietary policies, such as the Special Supplemental Nutrition

[1] Stewart and Kuchler (2022) reported the US daily per capita consumption of dairy milk as 0.96 cups, 0.84 cups, 0.78 cups, 0.69 cups, 0.62 cups, and 0.49 cups for the years 1970, 1980, 1990, 2000, 2010, and 2019, respectively.

[2] According to Panescu and Voss (2022), plant milk experienced an 87% overall price premium compared to dairy milk on a gallon-for-gallon basis in 2022. For instance, if a gallon of whole milk averages $4.44 (USDA, 2022), a gallon of plant milk would cost approximately $8.30.

Program for Women, Infants, and Children (WIC). While extensive research has been conducted on estimating the demand for animal-based and plant milk, there remains a gap in understanding precisely how households allocate their expenditures between these two categories and how their spending patterns are influenced by local environmental factors.

This paper uses dairy and plant milk as an example to answer these types of questions. Specifically, the main objectives of this study are: (1) to uncover expenditure patterns for both dairy and plant milk among households who have moved to another state and those who have not; (2) to learn how the new local environment affects household's expenditures for dairy and plant milk. I use Nielsen Consumer data for this study since it contains consumer characteristics and weekly milk purchases. Nielsen updates households' state-level Federal Information Processing Standard (FIPS) code annually, which allows us to identify movers. The outcome variable is the logarithm of quarterly expenditures per person for dairy and plant milk.

The first econometric strategy exploits the fact that households move randomly[3]. This randomness allows the use of the difference-in-differences (DiD) model to identify milk expenditure patterns among movers (treated group) and non-movers (control group).

The second econometric strategy also uses the difference-in-differences model. It creates a new predictor, "size of move"[4] to measure the percentage change of milk expenditures due to moving to another state. "Size of move" measures the difference between the milk expenditures in the movers' new state and the original state. This empirical strategy difference-in-differences depends on how the environment, including milk supply, milk (or farm) regulation, taxes, and movers' peers, changes discretely when households move. If the new environment is the main drive for the milk purchases, say a household moves from state 1 to state 2, we should see a jump in the household's milk purchases to a level that of the

[3]In Section 3.1, I use a logit model to show that households indeed move at random.
[4]More detailed explanation about its construction is given in Section 4.

consumers in state 2. However, if milk purchases are only driven by household characteristics, such as their milk preferences and personal experiences, we should not expect a jump in the movers' milk purchases.

The results from the first difference-in-differences model show that, after households move to a new state, there is a 1.2% increase in dairy milk expenditures and a 1.5% decrease in plant milk expenditures. These results are surprising. It is known that dairy milk consumption has decreased at an average rate of 1% per year during the 2000s. Moreover, during the 2010s, it is decreasing at a 2.6% rate per year (USDA, 2021). In the meantime, Plant Based Foods Association (2020) found that compared with a small 0.1% sales growth in dairy milk, plant milk has experienced a 5% growth in 2019.

The fact that people are increasingly choosing plant milk motivates the second econometric strategy. The results from the second difference-in-differences model show that the new destination explains about 53% of the differences in dairy milk expenditures but only about 17% for plant-based milk expenditures. These results imply a more considerable convergence for dairy milk expenditures toward the destination state. However, its expenditures have only slightly converged toward the average level in the households' new states for plant milk.

This paper relates to several works on plant milk related topics in economics. First, there is vast literature comparing the nutritional values between dairy and plant milk. Vanga and Raghavan (2018) compared the nutritional values among various dairy and plant milk, and they concluded that soy milk might be the best dairy milk alternative in the human diet. Astolfi et al. (2020) did a similar analysis by comparing forty-one elements from multiple dairy and plant milk samples, and the authors also found that soy milk was the best alternative for human health. These works show that plant milk is gaining more popularity and thus motivate the need to study plant milk related literature.

Second, this paper relates to willingness to pay (WTP) in plant milk. Falkdalen (2017) used household scanner data in Sweden in 2011. It was estimated that the WTP for plant milk is 32% higher than the average milk price. A recent study by Yang and Dharmasena (2021) focused on soy, almond, and rice milk. Among the three, soy milk had the highest own-price elasticity. Consumers were not very sensitive to price changes due to inelastic demand. It also found that soy milk was a substitute for all four types of dairy milk[5]. The three types of plant milk were also complements of each other. This study adds to the WTP literature showing that if we use a natural experiment by separating the movers and non-movers, dairy milk is still the dominant type consumed in the U.S.

Third, some papers discuss food's environmental impacts. One of the factors that consumers choose plant milk is environmental sustainability. Poore and Nemecek (2018) compared the environmental impacts of various food products by compiling data covering 38,700 farms and 1600 processors. The finding showed that even for just the lowest-impact animal-based products, their environmental impacts typically exceeded those of plant-based products. McClements et al. (2019) looked at just dairy and plant milk products. They revealed that dairy milk had much higher greenhouse gas (GHG) emissions, land use, and water use than all types of plant milk on a per-liter basis. Among plant milk, almond and rice milk required much higher water use than soy milk and oat milk, and the land use was slightly higher for the latter two. These findings suggest great environmental benefits of consuming more plant milk, but the benefits largely depend on the type of plant milk chosen. I intend to use my findings to potentially shed light on environment-related federal and state food policies since these findings reveal geographic variations.

Finally, this paper relates to the literature on determinants of a household's choice of dairy and plant milk. Boaitey and Minegishi (2020) show that parental dairy consumption patterns can impact their children's dairy milk choices. An increasing number of children grow up in a household with more plant milk consumption. This phenomenon may be due to parents'

[5]The types of dairy milk include whole milk, 2% milk, 1% milk, and fat-free milk.

perception of animal welfare and food sustainability. This study may be extended in the future to study how parents influence children's milk choices if they move to a new destination.

1.2 Background on Dairy and Plant Milk in the U.S.

In the 1990s, one of the most acclaimed advertising campaigns, "Got Milk?" won the hearts of Americans of all ages and encouraged the consumption of milk. Or, more specifically, dairy milk. This event makes dairy milk one of the most commonly consumed beverages in the U.S. However, U.S. per capita consumption of dairy milk has been trending downward steadily since the 2000s (USDA, 2021). A recent report by (Cessna et al., 2021) states that dairy milk consumption has been decreasing at an average rate of 1% annually during the 2000s. It decreases at an even faster rate (2.6%) per year during the 2010s. In the meantime, the plant milk market has emerged and expanded quickly. Statista (2022) estimated that the global plant milk has about $21 billion market value in 2021, with a $3.1 billion market value in the U.S. Using 2019 IRI retailer data, Plant Based Foods Association (2020) found that compared with a small 0.1% sales growth in dairy milk, plant milk has experienced a 5% growth in 2019. Of course, plant-based foods are not just limited to the milk industry. There are also plant-based alternatives for meat, cheese, and yogurt. All types of plant-based foods combined totaled 11.4% in 2019, compared with a small 2.2% growth in all foods (Plant Based Foods Association, 2020).

There are several driving forces of the increasing demand for plant milk. First, people may choose plant milk over dairy milk for lactose intolerance or protein allergy reasons (Gerliani et al., 2019). Second, from a nutritional perspective, plant milk is an excellent source of macronutrients and micronutrients vital to human health[6], and it has lower calories and fat in general. Plant milk can be classified into five general categories: cereal-based,

[6]For dairy and plant milk nutrient comparison, see Appendix A.1.

legume-based, nut-based, seed-based, and pseudo-cereal-based (Sethi et al., 2016). Take soy milk as an example; it contains a good amount of proteins, vitamins, and minerals (Vanga and Raghavan, 2018). Third, plant milk is designed as functional drinks[7] that not only satisfy our desire for good taste but also nutritional needs. The emerging flexitarian lifestyle also influences plant-based food consumption. Other factors that make people choose plant milk are environmental sustainability and farm animal welfare (Boaitey and Minegishi, 2020). This trend motivates me to study the expenditures of the two types of milk.

1.3 Data

1.3.1 Nielsen Consumer Panel

This paper uses Nielsen Homescan Consumer Panel data from 2004 to 2019 to measure household-level milk purchases measured in expenditures. The panel is representative of the whole U.S. population[8]. Each household scans all their grocery purchases daily. The purchased quantities and prices for each household are recorded at the Universal Product Code (UPC) level. This research cannot analyze milk purchases at the individual level since each purchase is recorded at the household level.

Each year, Nielsen surveys the household's demographic characteristics, such as age, income, education, marital status, household composition, and geographic location. By taking advantage of variations in the panel over time, this study can uncover movers and non-movers at state level[9].

[7]By (USDA, 2010) definition, "(f)unctional foods are designed to have physiological benefits and/or reduce the risk of chronic disease beyond basic nutritional functions, and may be similar in appearance to conventional food and consumed as part of a regular diet."

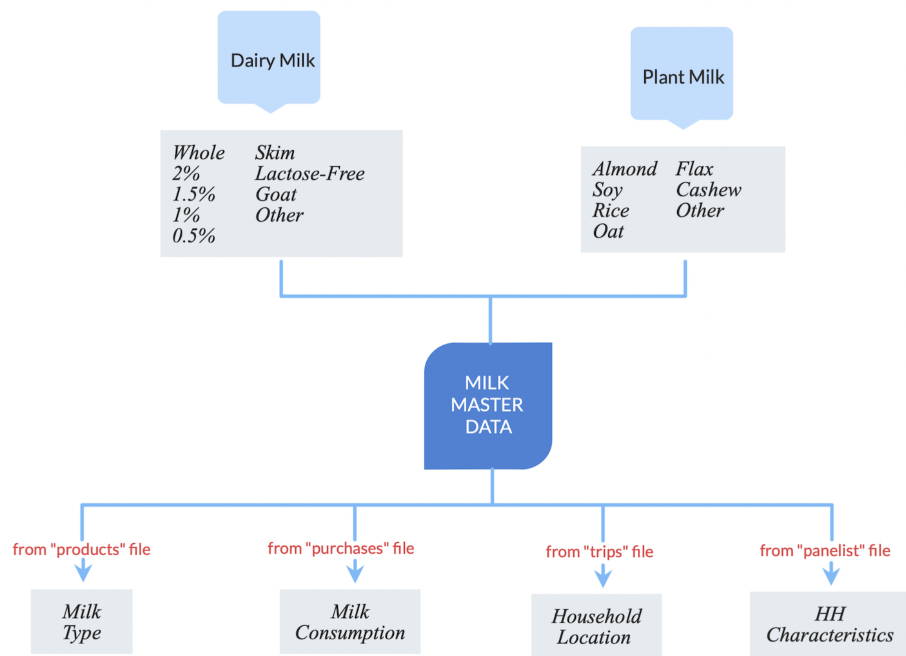
[8]Nielsen samples all 51 states and major markets, except for Alaska and Hawaii. The panelists are demographically balanced and geographically dispersed. Each panelist is assigned a unique projection factor such that each purchase is projectable to the entire U.S.

[9]The data also allows me to find movers and non-movers at county level and zip code level. The concern

1.3.2 Sample Construction

Four types of data files are used to construct sample data. The "products" file helps identify each type of dairy and plant milk[10]. Figure 1.1 shows a complete list of types of milk. Each year has a "purchases" file that records each household's weekly milk purchases. Using the total prices paid and total units, one can construct the outcome variables, which will be explained later in more detail. Each year's "trips" files record exact purchase dates, which use each Saturday as the end of each week. The dates make it possible to aggregate the data at a quarterly level for the difference-in-differences analysis. They can also be aggregated at weekly, monthly, or annual levels, and they will be used for some other type of analysis later.

Figure 1.1: Data Manipulation to Obtain Master Milk Data



Notes: This data manipulation process is plotted based on her analysis.

The critical data in identifying migrants are the "panelist" files. Each state has a unique

is that, at such a micro level, the data could be very noisy, and there is minor variation in milk purchases.

[10]Between 2006 and 2007, only soy, rice, and oat milk were identified in Nielsen data. In 2008, almond milk data was added to the data. Flax milk is not identified until the year 2011. Cashew milk has been found in the data since the year 2014.

two-digit FIPS state code. By comparing the FIPS state code of the households from year to year in the data, one can identify movers and non-movers. This study defines "mover" as those households who have moved only once during the whole 16 years[11]. Since the movers' geographic location is recorded only once a year, their exact migration time cannot be identified. To avoid mismeasurement issues, I have to exclude the year of the move from the sample data[12]. These files also contain household characteristics such as household income, household size, presence of children, and race. The variables age, education, and employment status are recorded separately for male and female household heads. For this analysis, I use the household head's average age, highest education level, and highest employment status among both genders. Figure 1.1 illustrates a general workflow of the data manipulation process.

1.3.3 Outcome Variables

The main outcome variables are household-level quarterly milk expenditures per person for dairy and plant milk. First, we adjust the milk expenditures to 2019 dollars using the consumer price index for urban consumers. Then we calculate the milk expenditures per person by dividing household expenditures by the total number of persons in a household. In the main specification, the outcome variable is taken logarithm of quarterly milk expenditures. We take logarithm form because the dairy and plant milk expenditures are skewed to the right. After the log transformation, the expenditure distributions become more normally distributed.

[11] Some households who have moved more than once move between two or more states. This study excludes these types of movers to ensure the analysis is more stable.

[12] To clarify: The main analysis is aggregated at a quarterly level. Data for households who moved in 2006 is excluded since it is the base year; data for households who moved in 2019 is also excluded since we cannot observe purchases in 2020. Households who moved at any period in 2007 are defined as movers in 2008 at quarter 1; same for years between 2008 and 2018. That means between 2006 quarter 1 and 2007 quarter 4, we only observe non-movers; between 2008 quarter 1 and 2019 quarter 4, we can observe both movers and non-movers.

1.3.4 Summary Statistics

For each household, I report summary statistics for their characteristics in Table 1.1. The table reports the mean and standard error for each household characteristic for the mover and non-mover groups. In general, there are some differences between the two groups, but they are not too far from each other. For example, the movers are more likely to be white (non-Hispanic), have higher income, be older, and have higher education; meanwhile, movers have a smaller family size, a slightly lower employment rate, and a smaller ratio of children who are under 18 years old. The two groups' mean marriage rates are identical in the sample.

In addition, Table 1.1 shows ratios of households who reside in a region or move to another region in the U.S. Again, there are some differences between the two groups, but the ranks of ratios for the four regions are the same. For example, most people move to the South region, and most non-movers reside in the South. The second most popular region people move to is the Midwest, followed by the West and Northeast regions. Same for the non-movers: the second most populous region is in the Midwest region, followed by the West and Northeast regions. For the milk purchases, we can see from Table 1.1 that dairy and plant milk are also similar among movers and non-movers. Based on these summary statistics, we can conclude that the movers and non-movers are generally comparable, and thus we can proceed using difference-in-differences models.

1.4 Empirical Strategy: Milk Consumption Patterns

This section examines changes in milk purchases after households move to another state. First, I will conduct an event study to identify the milk purchase before and after moving. Next, we will plot parallel trends with raw data. These trends help visualize the average milk expenditures among movers and non-movers over time. We will then estimate a difference-in-

Table 1.1: Household Summary Statistics

	(1) Movers	(2) Non-Movers
	Demographic Characteristics	
Household Income	$72,086.92	$70,812.92
	($222.62)	($36.67)
Household Size	2.47	2.72
	(0.019)	(0.003)
Age	49.98	49.10
	(0.304)	(0.049)
College	0.40	0.34
	(0.023)	(0.030)
Employed	0.56	0.58
	(0.008)	(0.025)
Race: White Non-Hispanic	0.81	0.78
	(0.011)	(0.002)
Married	0.65	0.65
	(0.017)	(0.003)
Children	0.270	0.364
	(0.044)	(0.081)
	First Observed Residence	
Northeast	18.1	16.8
Midwest	22.7	25.5
South	36.7	38.4
West	22.5	19.3
	Milk Purchases	
Log(Expenditure) of Dairy Milk	0.40	0.36
Log(Expenditure) of Plant Milk	0.54	0.50
Quantity of Dairy Milk	3.84	3.82
Quantity of Plant Milk	3.48	3.44
Number of Households	4,777	185,230

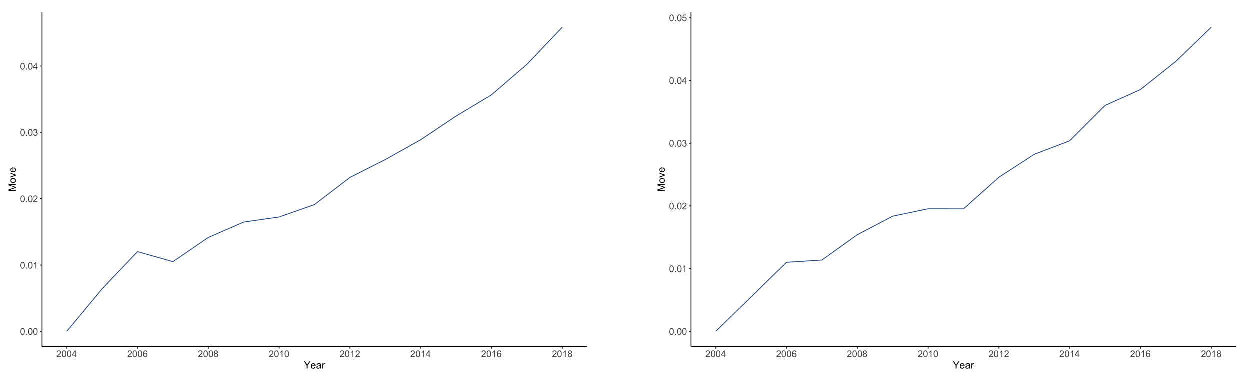
Notes: All household characteristics are measured during the first year in the sample. Household income and milk expenditures are adjusted to 2019 dollars using the consumer price index for urban consumers. The movers are defined as those who have moved only once from 2004 to 2019. Non-movers include those households who have never moved during the sample period. The difference is statistically different from zero at a 1% significance level for all demographic characteristics.

differences model, which shows the effect in the long run. The first differences model will then be used to study the short-term effects.

1.4.1 Migration Patterns: How and Why Migrants Move

To visualize migration patterns for each state, Appendix A.2 shows the migration maps for the top 10 most populous states in the U.S. We can see that households do move across the country, though most often they tend to move to nearby states or region[13]. Figure 1.2 plots separate time series plots for movers who either consume dairy or plant milk. We can observe that each year, there is a steady migration across the U.S., and the migration trend is very similar among dairy and plant milk consumers.

Figure 1.2: Movers Time Series



(a) Dairy Milk (b) Plant Milk

Notes: The y-axis is the accumulative fraction of movers between the years 2004 and 2019.

Before conducting an event study, one concern is that households may not move randomly. If the household's decision to move is significantly influenced by, for example, their income or education level, the difference-in-differences results may not be valid since there is an endogeneity issue. I estimate a logit model to confirm that the move over time is close to random to validate the model. The binary logistic regression model follows the specification in Walker and Duncan (1967):

[13]Florida appears to be a trendy state for migrants. This phenomenon may be due to its appealing weather, scenery, and fair cost of living. Website such as My Life Elsewhere states that the U.S. is 5.8% more expensive than Florida. In terms of just milk price, Florida is more expensive. I have calculated Florida's milk price index and found that its overall milk price is higher than the U.S. average price (See Appendix A.9).

$$Prob\{Ever\_Move_{it} = 1|X_{it}\} = \frac{1}{1 + exp(-X_{it}\beta)} \tag{1.1}$$

where $Ever\_Move_{it}$ is a binary outcome variable equal to one if a household has moved, and equal to zero otherwise, X_{it} is a set of household characteristics including age level, education level, income level, having children or not, race, marital status, and employment status.

Appendix A.3 presents both coefficients and average marginal effects[14] from the logit model. A few coefficients are significant, but most of the results are not. This at least provides some evidence that households do move randomly.

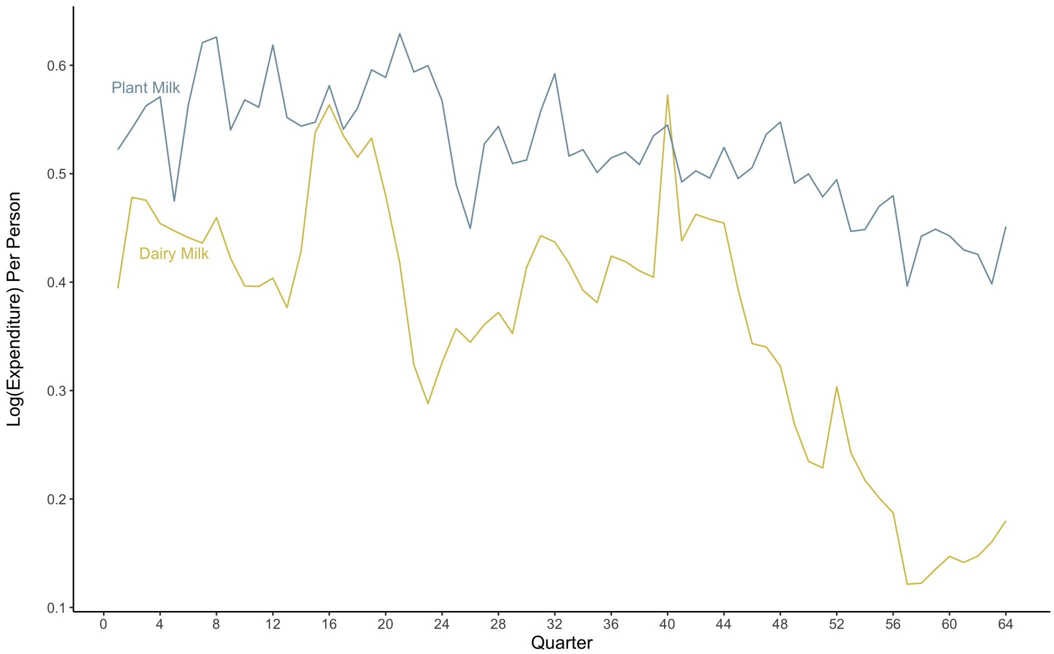
1.4.2 Parallel Trend

Various reports and many news media have reported that dairy milk sales have been trending downwards since the 2000s (USDA, 2021). I use Nielsen data and plots Figure 1.3 to demonstrate this overall trend. We can see that the dairy milk expenditures have decreased drastically over time, whereas the plant milk expenditures have been (at least) steady over time. This trend is consistent with the current findings.

However, in a difference-in-differences setting, a fundamental assumption requires no time-variant household-specific unobservables among the movers and non-movers. This assumption is the parallel trend assumption. Figure 1.4 compares the parallel trend for both dairy and plant milk. The trend for dairy milk somewhat exists (though some points do intersect), and then there is a divergence starting from quarter 57 (or year 2018 Q1). The trend for plant

[14]Marginal effects at mean (MEMs) give very similar results as average marginal effects (AMEs), hence the MEMs are not presented in the table. The marginal effects are defined as $\frac{\partial P}{\partial X_j} = F'(X'\beta)\beta_j = \Lambda(X')\beta[1 - \Lambda(X'\beta)]\beta_j = \frac{e^{X'\beta}}{1+e^{X'\beta}}\beta_j$. The MEMs are defined as $\frac{\partial P}{\partial X_j} = F'(\bar{X}\beta)\beta_j$, and the AMEs are defined as $\frac{\partial P}{\partial X_j} = \frac{\sum F'(\bar{X}\beta)}{n}\beta_j$

Figure 1.3: General Trend for Dairy and Plant Milk

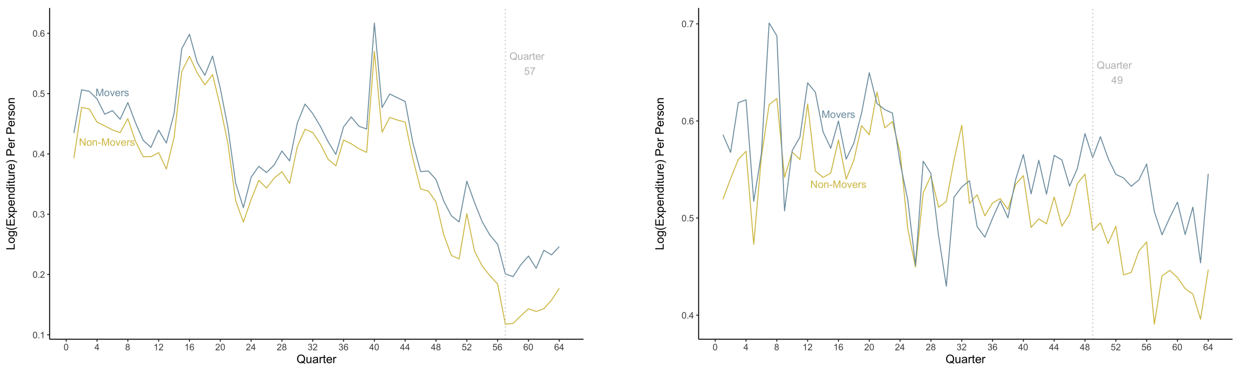


Notes: The x-axis is the accumulative quarters over the years 2004 and 2019 (64 quarters in total), and the y-axis is the outcome variable: logarithm of quarterly expenditure per person for each type of milk.

milk is not very obvious. There are multiple periods in the lines that intersect for movers and non-movers. There is a sharp divergence between movers and non-movers from quarter 49 (2016 Q1), and this divergence is much more significant than dairy milk.

Note that this parallel trend is plotted with raw data. In this case, the parallel trend assumes that the only control group is non-mover. This assumption does not hold here since people have moved at different periods in the sample. The difference-in-differences are comparisons between movers and non-movers, early movers and late movers, and late movers and early movers. Thus showing the comparison with only non-movers is not enough.

Figure 1.4: Parallel Trend for Dairy and Plant Milk



(a) Dairy Milk (b) Plant Milk

Notes: The x-axis is the accumulative quarters over the years 2004 and 2019 (64 quarters in total), and the y-axis is the outcome variable: logarithm of quarterly expenditure per person for each type of milk. The gray dashed line marks some unusual trend. For dairy milk, before quarter 57 (2018 Q1), the general trend is downward, then there is an uptick after that. For plant milk, before quarter 49 (2016 Q1), the general trend is almost monotonic, then it goes downward.

1.4.3 Event Study

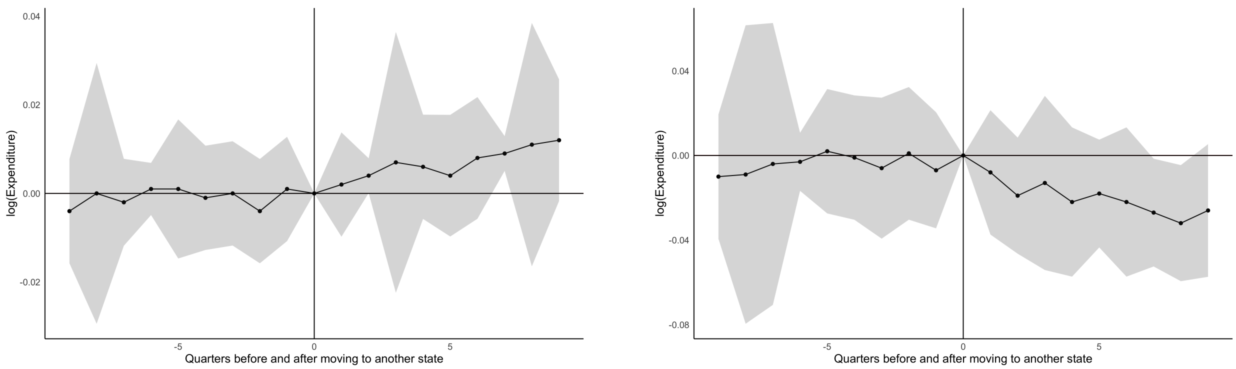
In the earlier section, we have seen evidence that the move occurs randomly across time. Moreover, the parallel trend gives us a visualization of the general trend for milk expenditures. Next, we can use an event study to estimate and plot the post-move effects.

I estimate the following event study model for household i for period t:

$$ln(y)_{it} = \alpha_i + \tau_t + \sum_{r=\underline{m}, r\neq -1}^{\overline{m}} \beta_r \cdot I_{it} + X'_{it}\Gamma + \epsilon_{it} \quad (1.2)$$

where $ln(y)_{it}$ is the log quarterly milk expenditures per person for household i in quarter t, α_i and τ_t are household and time fixed effect respectively, I_{it} is an indicator variable set equal to one if household i in quarter t is r quarters after it has moved to another state, X_{it} is a set of controls for household characteristics. The household characteristics specifications

Figure 1.5: Event Study for Milk Expenditures



(a) Dairy Milk (b) Plant Milk

Notes: The x-axis is the move's relative time (at a quarterly level). For example, 0 indicates the quarter of the move, -1 the quarter before the move, and 1 the quarter after the move. The data of the moving year is excluded to avoid mismeasurement issues. For example, if a household moved in 2006, "the quarter of the move" is defined as 2007 Q1.

are the same as in Appendix A.3. The error term ϵ_{it} captures unobservables.

Additional indicators corresponding to "outside the event window"[15] are also added, which helps fully capture the dynamic effects of the treatment. By conditional on household fixed effects and quarter-specific shocks, we assume that all households that are r quarters away from moving to another state are identical. Here we allow $|\underline{m}| = \overline{m} = 8$, which includes 2 years of pre-move and post-move sample data. The specification also includes an indicator variable +9 that captures all periods more than 8 quarters from moving to another state; for similar reasons, indicator -9 captures all periods more than 8 quarters before the move. Event study helps visualize the effect of moving to another state on milk expenditures and checking that all pre-trend event time, $\sum_{r=-9}^{r=-2}$, are equal to zero. The coefficients of post-trend event time, $\sum_{r=0}^{r=9}$ visualized the evolution of the treatment effect.

Figure 1.5 are the plots for the event study with 95% confidence intervals. The pre-move coefficients are close to zero, though some standard errors appear to be significant. After the move, there was a 0.8% increase in expenditures for dairy milk and a 0.1% decrease for plant

[15]This design draws inspiration from Harding and Rapson (2019).

milk. The p-value from the joint significance test of the pre-move event time estimates is 0.0073 for dairy milk and 0.12 for plant milk. The p-value for the plant milk is only weakly significant; this still lends some evidence that there are only minor differences between the movers and non-movers before the move. The plots suggest a clear pattern: before the move, there is little evidence of divergence in expenditures for both types of milk. However, after households move to a new state, they increase their dairy milk expenditures and decrease plant milk expenditures. We need to turn to the difference-in-differences model to quantify the exact expenditure changes.

1.4.4 Difference-in-Differences

The difference-in-differences model compares milk expenditures across households and time relative to when they move. We use the difference-in-differences model because we have data for the control group (non-movers) and the treated group (movers). In addition, we can observe data at least two years before the treatment for the movers. The model specification is as follows:

$$ln(y)_{it} = \alpha_i + \tau_t + \beta D_{it} + X'_{it}\Gamma + \epsilon_{it} \tag{1.3}$$

where D_{it} is an indicator variable which equals to one if household i has moved to another state in quarter t. The difference-in-differences specification is the same as Equation 1.2, except that all the coefficients before the move (r < 0) are normalized to zero and the coefficients after the move (r $\geq$ 0) are collapsed into one. β is our coefficient of interest, which uncovers the average treatment effect on the treated households (ATT), where $ATT = E[\beta|D = 1]$.

Table 1.2 column (1) – (3) are the results for dairy milk, and column (4) – (6) are for plant milk. The effect for dairy milk is only 5% (not statistically significant) if we do not control for the number of children and race in the model. When we do control for these additional variables, however, the effect more than doubles: 1.2% (and statistically significant at 5% level) of increase in dairy milk expenditures after the move. This result makes sense since there will be more milk consumption if a family has many children. Besides, dairy milk is still the more popular type consumed among households with children, and the price for dairy milk, in general, is lower than plant milk[16]. These facts all make dairy milk a naturally popular choice. In addition, the household characteristics in this model include all levels for each variable. This additional information should give us more precise estimates[17]. There may also be cultural differences at play. For example, different races may have different milk consumption habits. If we control for the "race" factor too, it should give us a more convincing estimate.

On the other hand, we see a 1.5% decrease in plant milk expenditures (statistically significant at 10% level) on average after the move. The estimates are the same even when not controlling for the number of children and race. These results are surprising since dairy milk sales are trending downward, but dairy milk is consumed more here based on our estimates. One may argue that this decrease in plant milk expenditures could be because the households have lower income or education, but it has been proven not the case (See Table 1.1). The movers' characteristics (i.e. higher income and education) suggest that movers should consume more plant milk since it has higher prices (see Appendix A.9) and fits a healthier and more sustainable lifestyle.

Appendix A.4 gives difference-in-differences results using movers data only. The estimate for dairy milk is the same as using a full sample. This result may be because dairy milk data is a popular type of milk (i.e., its consumption is more stable at the national level), and it has

[16]For price comparisons between dairy and plant milk, see Appendix A.9

[17]For the results from the earlier logit model (see Appendix A.3), each variable is put into smaller groups. For example, the variable "income" has 20 levels in the data. I have to group them so that I can fit the logit model results in one table.

Table 1.2: Milk Expenditures After Move. Difference-in-Differences Estimates.

	Dairy Milk			Plant Milk		
	(1)	(2)	(3)	(4)	(5)	(6)
Post move	0.005	0.012**	0.012**	-0.015*	-0.015*	-0.015*
	(0.007)	(0.006)	(0.006)	(0.008)	(0.008)	(0.008)
Age	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes	Yes	Yes
Marital Status	Yes	Yes	Yes	Yes	Yes	Yes
Employment	Yes	Yes	Yes	Yes	Yes	Yes
Children		Yes	Yes		Yes	Yes
Race			Yes			Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Household FEs	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	HH	HH	HH	HH	HH	HH
Households	188,028	188,028	188,028	73,536	73,536	73,536
Observations	3,323,626	3,323,626	3,323,626	434,264	434,264	434,264

Notes: The household characteristics here use full levels from sample data, instead of just putting them into sub-groups. For example, there are 9 levels of "age": 1 signifies households under 25 years old, 2 signifies households between 25-29 years old, and so on. Including all levels for each variable is to ensure the precision of the difference-in-differences estimates. The model includes time fixed effects and household fixed effects. The standard errors are clustered at the household level. *** Significant at 1% level.** Significant at 5% level.* Significant at 10% level.

a large number of households and observations, so even using just movers data, the estimate is very close (identical in this case) to the estimate using the whole sample. However, if we use only movers data for plant milk, the estimate becomes very small: a 0.6% decrease only in its expenditures (and not significant). The reason may be due to a considerable reduction in households and observations. Such a decrease in sample size may well affect our estimate.

To conclude, these results reveal one truth: even though dairy milk sales have been decreasing over the years, it is still the dominant type of milk consumed in the U.S. Another way to interpret it is that people's preferences for dairy milk are persistent at the U.S. national level, and it is not easy to change from dairy to plant milk. In Section 1.5, we will address regional milk preferences, and we will see that people's milk preferences may adjust to a new region after the move. However, their preferences do not change at the national level here because they become negligent or nonexistent when we average the effects.

1.4.5 First Differences

It is also interesting to see the first differences model's short-term treatment effects. As mentioned earlier, the first quarter of the move is not the quarter right after the move[18] but the first quarter of the following year after a household moved. To estimate the short-run effects, I define the following first differences model:

$$dln(y)_{it} = \tau_t + \beta D_{it} + X'_{it}\Gamma + \epsilon_{it} \tag{1.4}$$

where $dln(y)_{it} = ln(y)_{i,t} - ln(y)_{i,t-1}$. The term α_i from Equation 1.3 is dropped from the differencing since these household characteristics are time-invariant.

Table 1.3 presents the first-differences results. Same as before, column (1) – (3) are the results for dairy milk, and column (4) – (6) are for plant milk. The estimates for dairy milk vary between 0.6% and 0.9%. All of them are significant at least at a 5% level. The overall effect for dairy milk expenditures is reduced to half compared to the difference-in-differences estimates: just a 0.6% increase if we add all control variables. This result means that the immediate increase after the move in dairy milk expenditures is only half the size compared to the long-term change. There may be several reasons. First, when households just moved, they may need time to adjust to the local environment (such as finding the right grocery stores). This move may disrupt their shopping record. Second, the household in the sample may have more children (or have more people in the household in general) in the long run, thus dairy milk consumption should be higher in the longer term.

After the move, there is a more significant reduction in plant milk expenditures: a 2%

[18] At the beginning of the move, the households may need time to explore new surroundings to find their regular grocery stores for shopping, and their shopping record may not be as accurate.

Table 1.3: Milk Expenditures After Move. First Differences Estimates.

	Dairy Milk			Plant Milk		
	(1)	(2)	(3)	(4)	(5)	(6)
Post move	0.009***	0.005**	0.006**	-0.020**	-0.019***	-0.020**
	(0.003)	(0.002)	(0.002)	(0.007)	(0.005)	(0.005)
Age	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes	Yes	Yes
Marital Status	Yes	Yes	Yes	Yes	Yes	Yes
Employment	Yes	Yes	Yes	Yes	Yes	Yes
Children		Yes	Yes		Yes	Yes
Race			Yes			Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Household FEs	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	HH	HH	HH	HH	HH	HH
Households	188,028	188,028	188,028	73,536	73,536	73,536
Observations	3,323,626	3,323,626	3,323,626	434,264	434,264	434,264

Notes: The household characteristics here use full levels from sample data, instead of just putting them into sub-groups. For example, there are 9 levels of "age": 1 signifies households under 25 years old, 2 signifies households between 25-29 years old, and so on. Including all levels for each variable is to ensure the precision of the difference-in-differences estimates. The model includes time fixed effects and household fixed effects. The standard errors are clustered at the household level. *** Significant at 1% level.** Significant at 5% level.* Significant at 10% level.

decrease (statistically significant at a 5% level) compared to just a 1.5% decrease in the difference-in-differences model. The magnitude of the change is much smaller than dairy milk (25% change for plant milk, compared to 50% change for dairy milk). These results imply that changes in plant milk expenditures among movers are gradual but not drastic, whether in the short term or long term. We can see that pattern in Figure 1.4 figure (b). I suspect that the decrease in plant milk expenditures may be related to the availability of different types of plant milk or just the general availability of plant milk. For example, between 2006 and 2007, only soy, rice, and oat milk were available in Nielsen data. Almond milk data was available only until 2008. Flax milk was identified in 2011, and Cashew milk was found in 2014. Smaller availability could limit our plant milk sample size in terms of the total number of movers (or households) and observations[19].

[19]The evidence of the limited plant milk availability is evident when we compare the number of plant milk consumers in Appendix A.3 and Table 1.3. There are 4762 movers for dairy milk but only 2732 for plant

Same as in the difference-in-differences model, we provide first-differences estimates but use movers data only. The results are presented in Appendix A.5. Dairy milk has a larger effect: a 1.4% increase (significant at 1% level). However, this effect is very close to the difference-in-differences estimate using the whole sample. Again, I would argue that this may be because dairy milk is a well-accepted type of milk, so the estimate is more stable using the full sample or just movers data. Again, the estimate for plant milk is small (just 0.3%) and insignificant. The reason might be the smaller sample size and lesser plant milk availability.

To conclude, the general trend for dairy and plant milk still conforms to results from the difference-in-differences model. These estimates again imply that dairy milk is still the dominant type consumed in the U.S., and people are not changing their milk preferences as easily.

1.4.6 Heterogeneous Effects

Differences-in-differences and first differences give an overall effect. To take a closer look at the effects among households of different backgrounds (e.g., different income levels, education, and age), we need to get heterogeneous effects. I estimate Equation 1.2 by interacting I_{it} with the same household characteristics as in Appendix A.3. Table A.6.1 in Appendix A.6 shows that the increase in dairy milk expenditures is mostly driven by the people who are between 50 and 64 years old (the "midH" group), whose families have no children living in the households, or people who earn a lower income. People under 49 years old group (the "young" and "midL" groups), on the other hand, are lowering their dairy milk consumption. The decrease in plant milk expenditures is mostly driven by the "college" group (those who have had some college education or completed college education). They consume less maybe because this group needs time to earn a higher income to pick up a new lifestyle since plant milk is more expensive than dairy milk. The "college" group recorded in the Nielsen data

milk. Dairy milk has 55% more households and more than 6 times observations than plant milk.

also includes those exposed to but have not completed a college education. The inclusion of such a group of people may also have influenced the plant milk estimates.

I then estimate Equation 1.3 and 1.4 by interacting D_{it} with the same set of household characteristic variables. Table A.7.1 and Table A.7.2 in Appendix A.7 present the heterogeneous treatment effects from the difference-in-differences model. Table A.8.1 and Table A.8.2 in Appendix A.8 are heterogeneous first differences estimates. Note that in these four tables, the base specifications are the same as in Table 1.2 and Table 1.3. That is why their estimates are identical[20].

We can see that some results are consistent with the event study results in Appendix A.6. For example, in Table A.7.1 in Appendix A.7, the difference-in-differences estimates show that younger households (who are under 49 years old) are consuming less dairy milk, while people who are between 50 and 64 years old, have no child in the household, and have lower income, increase their dairy milk consumption. These results conform to the results presented in Appendix A.4, where the estimates are obtained using movers data only. We can also see that households with children under 12 years old also consume more dairy milk, and people with children above 12 years old or those who have a graduate education also tend to decrease their dairy milk consumption. These differences arise maybe because the difference-in-differences model uses all periods, whereas the event study only includes a year before and after the treatment. The short-term heterogeneous effects presented in Appendix A.8 are very similar to Appendix A.7 in terms of signs (increasing or decreasing) for each sub-group.

The estimates for plant milk are more different than the standard difference-in-differences results. In Table A.7.1 in Appendix A.7, it appears households who have children above 12 years old and are black consume less after the move. Households consume more plant milk if they have no children, have a high school degree, or have medium to high-level income. Right after the move, the immediate effect is that people under 34 years old, between 50-64 years

[20] I listed the base specifications here again just for a reference.

old, black and Asian, decreased plant milk consumption. On the other hand, households between 35-49 years old, who have no children, have a high school degree, or are white, increase their plant milk consumption (See Appendix A.8). These results are more different compared with Appendix A.4. These estimates vary more than dairy milk using different models because the plant milk sample size is small, and some varieties of plant milk appear in the market (thus in the data) later. That is why the estimates in plant milk vary more often if we change the models.

Overall, these results lend some evidence that a new lifestyle (i.e. healthier and more sustainable) is emerging among younger and more educated households, as reported in the news. However, some estimates are not very consistent, especially among plant milk. This motivates me to study milk consumption among households in different regions since regional consumption may be more consistent and stable. In Section 1.5, we are going to estimate geographic variations in milk consumption, instead of just getting average effects at the national level.

1.4.7 Robustness Checks

We also perform a placebo test[21] to support the claim that the unobservables do not affect the results. For the difference-in-differences placebo test, I follow the following procedure:

1. Use only the data that came before the treatment went into effect (i.e., before households moved to another state).

2. Randomly assign a fake treatment period. Here, the fake treatment is assigned 2 quarters before the real treatment.

3. Estimate the same difference-in-differences model as in Section 1.4.4, but create a new

[21] This method is widely used. For example, Cheng and Hoekstra (2013) adopts this same method: They performed inference using placebo estimates from pre-castle doctrine (pre-treatment only) data.

treatment variable equal to one if the households are in the treated group and zero otherwise.

4. If there is no "effect" for the fake treatment (where there should not be one), there is evidence to support the claim that there is some effect on the expenditures after the move. The parallel trend assumption would also hold.

Table 1.4: Placebo Test Results

	Dairy Milk		**Plant Milk**	
	DiD	FD	DiD	FD
Placebo Treatment	0.004	0.004	-0.017	-0.012
	(0.005)	(0.006)	(0.012)	(0.013)
Time FEs	Yes	Yes	Yes	Yes
HH FEs	Yes	Yes	Yes	Yes
Clustered SEs	HH	HH	HH	HH
Observations	3,263,218	3,263,218	424,055	424,055

Notes: I assigned fake treatments 6 quarters before the actual treatment in this placebo test. The model includes time fixed effects and household fixed effects. The standard errors are clustered at the household level. *** Significant at 1% level.** Significant at 5% level.* Significant at 10% level.

Table 1.4 shows the placebo test results. After I drop all data after the actual treatment and then pretend that the treatment occurred two quarters earlier, I find no difference-in-differences effect. For example, both difference-in-differences and first differences are 0.4% for dairy milk. The estimate is close to zero and not statistically significant. The plant milk estimates appear to be slightly larger: between 1.2% and 1.7% of decrease, but both results are not statistically significant. One may still question the robustness of the estimates at this point. At the beginning of the study, I used a logit model to prove that the households move across states at random. The covariates included in these models are very related to the milk consumption behavior and should explain the consumption variations well. Another concern is the confounding issue. I cannot think of other confounders that could affect milk consumption (at least given the scope of the data availability). I would conclude that these estimates are robust and can explain the average milk consumption at a national level.

1.5 Empirical Strategy: How Current Environment Affects Milk Consumption

Section 1.4 studies expenditure patterns for both types of milk. After moving to a new state, we have learned that households increase their dairy milk expenditures and decrease plant milk expenditures. How much of these variations are due to the current environment exactly? This section explains these geographic variations using the same empirical strategy but with some modifications. As a convention, we will first conduct an event study to identify the milk expenditures before and after the move. We will then estimate a difference-in-differences model, which shows the effect in the long run.

1.5.1 Event Study

As usual, we start this section by defining an event study model. For household i for period t, the event study model is specified as follows:

$$ln(y)_{it} = \alpha_i + \tau_t + \sum_{r=\underline{m}}^{\overline{m}} \theta_r \cdot I_r \cdot \Delta_i + X'_{it}\Gamma + \epsilon_{it} \tag{1.5}$$

where $ln(y)_{it}$ is the log quarterly milk expenditures per person for household i in quarter t, α_i and τ_t are household and time fixed effect respectively, I_r is an indicator variable set equal to one if household i in quarter t is r quarters after it has moved to another state, X_{it} is a set of controls for household characteristics. The error term ϵ_{it} captures unobservables. The quarter of the move is indexed by 0. The coefficient θ_{-1} on the last quarter (before the move) is normalized to zero. The standard errors are clustered at the household level.

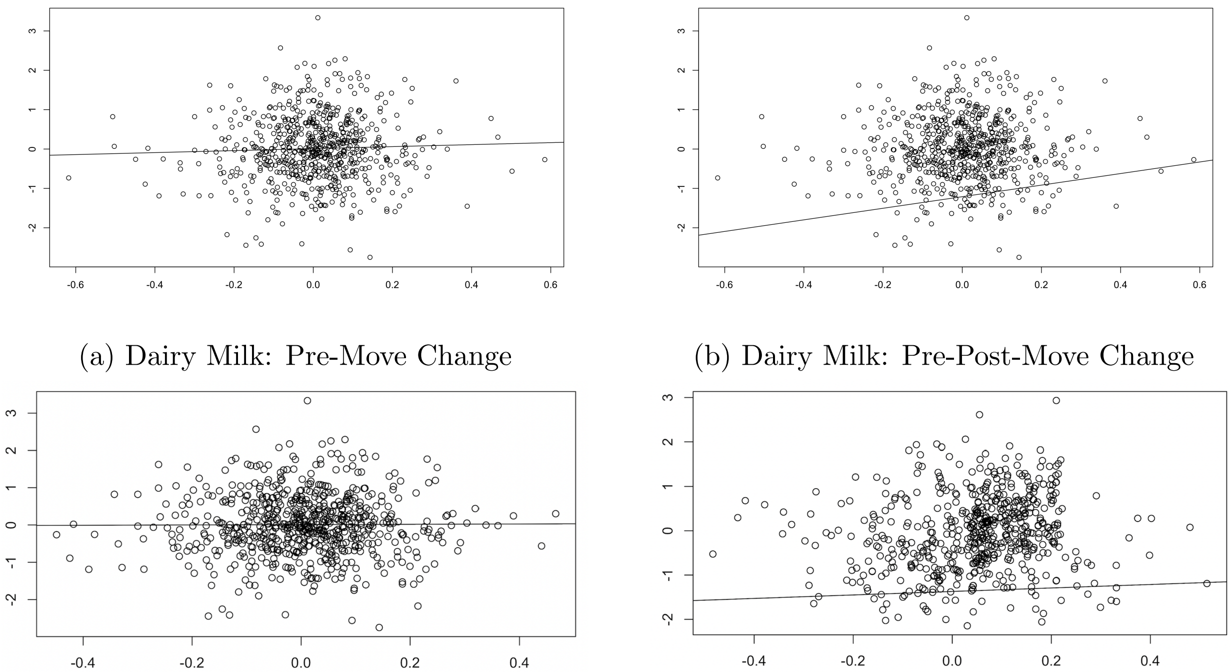
Term $\Delta_i = \bar{y}_{N,i} - \bar{y}_{O,i}$ is the size of the move[22]. It measures the share of the average difference between the movers' new state and the original state due to the current environment. This study follows this procedure to obtain the variable "size of the move": Use non-movers data only to compute state-level milk expenditure averages. First, average milk expenditures across households and quarters for each state (using sample weights). Then, average expenditures across all quarters. We can think of this as the expenditures of self-regressing on expenditure differences of others who are in their destination states or origin states. As in Section 1.4.3, additional indicators corresponding to "outside the event window" are also added.

The coefficients θ_r measures how much milk expenditures converge towards the new states' average. If movers' milk expenditures are not changed, the coefficient θ_r is zero. If movers' milk expenditures converge towards the new states, θ_r equals one. In reality, θ_r would be between 0 and 1. It measures the percentage difference in milk consumption between the new state and the original state.

One assumption needed for the event study is that the pre-move trend in milk expenditures is uncorrelated with the size of the move. We provide evidence by scatter plots. In Figure 1.6, plot (a) shows the pre-move changes for dairy milk, where the x-axis is the average size of move, the y-axis is the pre-move changes in expenditures, which is the difference of expenditures between the last quarter before the move and 3 quarters before the move ($y_{-1} - y_{-3}$). The slope is 0.2541 with a standard error of 0.2469, which is not significant. Plot (b) is for the post-move changes for dairy milk, where the x-axis is still the average size of move, the y-axis is the pre-post-move changes in expenditures, which is the difference of expenditures between the first quarter after the move and last quarter before the move ($y_1 - y_{-1}$). The slope is 1.4705 with a standard error of 0.2257. The result is significant at the 1% level. For plant milk, plot (c) has a slope of 0.0447 with a standard error of 0.2602, which is not significant. Plot (d) gives a slope is 0.3949 with a standard error of 0.1961. The result is significant at

[22]The empirical strategy is from Finkelstein et al. (2016). It shows how the coefficient measures the share of variation explained by the location.

Figure 1.6: Changes in Milk Expenditures by the Size of Move



(a) Dairy Milk: Pre-Move Change

(b) Dairy Milk: Pre-Post-Move Change

(c) Plant Milk: Pre-Move Change

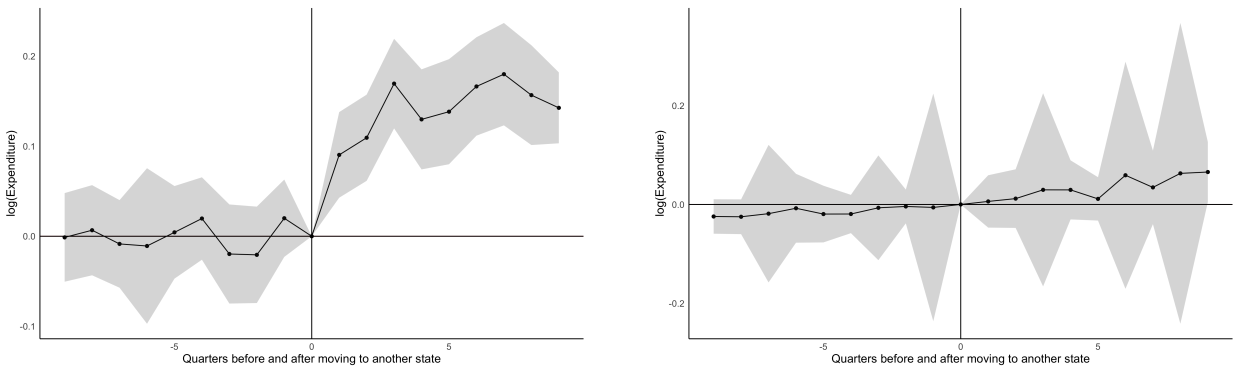
(d) Plant Milk: Pre-Post-Move Change

Notes: For scatter plots (a) and (c), the x-axis is the size of move, and the y-axis is the log expenditure differences between one quarter before the move and three quarters before the move (event time -1 and event time -3). For scatter plots (b) and (d), the x-axis is the size of move, and the y-axis is the log expenditure differences between one quarter after the move and one quarter before the move (event time 1 and event time -1).

the 5% level. Although there may be a slight pre-trend (but not statistically significant) before the move, they are much smaller compared to the post-trend after the move. This lends some evidence that The event study assumption holds.

Once we have proved that the trends in mover's expenditures are unlikely correlated with the "size of move," we can estimate the Equation 1.5 and visualize the milk expenditure changes pre-move and post-move. Figure 1.7 plots the results from Equation 1.5. The black dots connected with a black line represent all the coefficients estimated from the event study model. The shaded gray area is the estimated confidence interval. The center 0 is the time of the move. To its left, it is the pre-move trend; to its right, it is the post-move trend. For dairy and plant milk, the pre-move trends appear to be flat and close to zero (although

Figure 1.7: Event Study for Milk expenditures (Size of Move)



(a) Dairy Milk (b) Plant Milk

Notes: The x-axis is the move's relative time (at a quarterly level). For example, 0 indicates the quarter of the move, -1 the quarter before the move, and 1 the quarter after the move. The data of the moving year is excluded to avoid mismeasurement issues. For example, if a household moved in 2006, "the quarter of the move" is defined as 2007 Q1.

some estimates tend to have larger confidence intervals than others). After the move, there is a bigger upward jump for dairy milk and a smaller upward trend for plant milk. These results imply that people tend more adopt more dairy milk consumption based on the current environment than plant milk. In Section 1.5.2, we are going to quantify such milk expenditure variations due to the local environments.

1.5.2 Difference-in-Differences

We begin this section by defining a difference-in-differences model:

$$ln(y)_{it} = \alpha_i + \tau_t + \beta \cdot \Delta_i \cdot D_{it} + X_{it}'\Gamma + \epsilon_{it} \tag{1.6}$$

where D_{it} is an indicator variable which equals one if household i has moved to another state in quarter t. The difference-in-differences specification is the same as Equation 1.5.

Table 1.5: Change in Milk Expenditures After Move. Difference-in-Differences Estimates

	Dairy Milk (1)	**Plant Milk** (2)
$\Delta \cdot$ *Post move*	0.534*	0.173**
	(0.169)	(0.076)
Time Fixed Effects	Yes	Yes
Household Fixed Effects	Yes	Yes
Clustered SE	HH	HH
Movers	4,762	2,732
Observations	148,786	22,484

Notes: The outcome variable is Log(Expenditure). Δ_i is the difference in the average logarithm of milk expenditures between the new state and the original state. The sample data includes movers who have moved only once to another state. The model includes time fixed effects and household fixed effects. The dependent variable is the logarithm of milk expenditures. Standard errors are clustered at the household level. The coefficients are significant at 1% level. *** Significant at 1% level.** Significant at 5% level.* Significant at 10% level.

Table 1.5 shows the estimates for Equation 1.6 using all periods of data. For dairy milk, we can see about 53% (significant at 10% level) of the new state minus the original state difference in the expenditure changes after the move. For plant milk, the expenditure changes are only about 17% (significant at 5% level). These results imply a more considerable convergence for dairy milk expenditures toward the destination state's average level. In contrast, plant milk expenditures have only slightly converged toward the average level in the households' new states. This variation may be reasonable since, in Section 1.4.4, we see that dairy milk is still the dominant type of milk consumed in the U.S. Another reason is that there are more movers (more observations) among dairy consumers than plant consumers since plant milk is a more recent product.

The results again are estimated at a national level. We have seen the overall trend using all data from all periods in the previous and this section. We know that movers increase their dairy milk expenditures but decrease plant milk expenditures after the move. Households tend to adopt more dairy milk consumption behaviors in the new state than plant milk. At this point, one might be curious about comparing specific regions and seeing their milk consumption behavior, given that the regional economy and culture can be vastly different.

Table 1.6: Dairy Milk Purchases After Move (Movers Between Midwest and Every Other Region). Difference-in-Difference Estimates.

	Origin: Midwest			**Destination: Midwest**		
	West	Northeast	South	West	Northeast	South
	(1)	(2)	(3)	(4)	(5)	(6)
Post move	0.013	0.127**	0.080***	-0.016	-0.020	-0.034*
	(0.023)	(0.127)	(0.017)	(0.035)	(0.041)	(0.020)
Age	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes	Yes	Yes
Marital Status	Yes	Yes	Yes	Yes	Yes	Yes
Employment	Yes	Yes	Yes	Yes	Yes	Yes
Children	Yes	Yes	Yes	Yes	Yes	Yes
Race	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Household FEs	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	HH	HH	HH	HH	HH	HH
Households	195	53	502	147	65	286
Observations	5,948	1,503	16,609	4,194	2,074	8,547

Notes: The outcome variable is Log(Expenditure). These estimates are re-estimated for Equation 1.3 using data for each region. All household characteristic specifications are the same as in 1.3. The model includes time fixed effects and household fixed effects. The standard errors are clustered at the household level. *** Significant at 1% level.** Significant at 5% level.* Significant at 10% level.

In Table 1.6 and Table 1.7, I present results for Equation 1.3 using data for each specific region. For each table, columns (1) - (3) are the estimates for households who move from Midwest to West, Northeast, or South. Columns (4) - (6) are results for those who move from the opposite direction: from West, Northeast, or South to the Midwest. Here is the rationale for why I use Midwest as the base region (or as a reference): Multiple sources point out that Midwest has the lowest plant milk sales volume (Good Food Institute, 2020) (The Good Food Institute, 2020) (Ipsos Retail Performance, 2022). In this case, it may be more interesting to see how movers from Midwest to the other regions change their dairy and plant milk consumption. Likewise, it is worth investigating how households who move from relatively higher plant milk consumption regions[23] to a low consumption region (Midwest)

[23]Using Nielsen data, I was able to show that the level of plant milk expenditures matches the map shown

change their milk consumption.

Looking at households who move from Midwest to the other regions, they all increase dairy milk expenditures (1.3%, 12.7% [significant at 5% level], and 8% [significant at 1% level] respectively). The increases are substantial for the Northeast and South regions. Moreover, if people from other regions move to the Midwest, they appear to decrease dairy milk consumption (1.6%, 2%, and 3.4% [significant at 10% level] respectively). The changes in columns (4) - (6) are much smaller than the changes in columns (1) - (3) on average. These estimates show that dairy milk is still the dominant type in the U.S., and people are not decreasing that much dairy milk expenditure even moving to a new environment. In an overall picture, one can interpret these results for dairy milk as follows: People who migrate from a lower plant milk consumption region or dairy milk dominant region (Midwest in this case) to a higher plant milk consumption region may still maintain their old consumption behavior. That is to say, if their original dairy milk consumption is high, they will continue to consume more dairy milk even after moving to a region where dairy milk is less prevalent. This also works the other way around: Households who move from a higher plant milk consumption region or less dairy milk dominant region (in this case, every region other than the Midwest) to a lower plant milk consumption region may persistently consume less dairy milk. A downside of these estimates is that the number of households dropped drastically once dividing the data by regions. Hence, we need to treat these estimates with precaution but use them as a reference.

The plant milk estimates are more interesting. In Table 1.7, households who move from the Midwest to other regions increase their plant milk expenditures (6.4%, 64.4% [significant at 5% level], and 0.9% respectively). The increase is the smallest for the South. Furthermore, it is the other way around if people move from other regions to the Midwest: they all decrease their plant milk consumption (9.1%, 32.7%, and 2.4%, respectively). One may argue that

in Good Food Institute (2020). Midwest has the lowest average log(expenditure): 0.492 (sd = 0.643), followed by South 0.494 (sd = 0.631), Northeast 0.509 (sd = 0.654), and West 0.533 (sd = 0.663).

Table 1.7: Plant Milk Purchases After Move (Movers Between Midwest and Every Other Region). Difference-in-Difference Estimates.

	Origin: Midwest			**Destination: Midwest**		
	West	Northeast	South	West	Northeast	South
	(1)	(2)	(3)	(4)	(5)	(6)
Post move	0.064	0.644**	0.009	-0.091	-0.327	-0.024
	(0.052)	(0.182)	(0.040)	(0.071)	(0.466)	(0.036)
Age	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes	Yes	Yes
Marital Status	Yes	Yes	Yes	Yes	Yes	Yes
Employment	Yes	Yes	Yes	Yes	Yes	Yes
Children	Yes	Yes	Yes	Yes	Yes	Yes
Race	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Household FEs	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	HH	HH	HH	HH	HH	HH
Households	108	27	272	72	29	147
Observations	966	186	2,129	443	134	1,221

Notes: The outcome variable is Log(Expenditure). These estimates are re-estimated for Equation 1.3 using data for each region. All household characteristic specifications are the same as in 1.3. The model includes time fixed effects and household fixed effects. The standard errors are clustered at the household level. *** Significant at 1% level.** Significant at 5% level.* Significant at 10% level.

Midwestern households who move to other regions increase plant milk consumption because there is more variety of plant milk. Another way to see these results is that, although dairy milk is a dominant type of milk in the U.S., people could adopt a new eating style and local culture if their environment changes. In this case, households start to drink more plant milk if they move to the West, Northeast, or South. Of course, the percentage change varies from region to region. Same as in the dairy milk estimates, the limitation is that the sample size becomes too small once we limit the data to a specific region. We need to interpret these results with precaution and only use them at best as reference.

1.6 Conclusions and Discussions

This paper exploits a natural experiment in the U.S. among households who have moved to another state to estimate how migration affects dairy and plant milk consumption. I merged multiple data files related to milk types, milk purchases, household locations, and characteristics from Nielsen Consumer Data to get two main findings. First, after moving to a new state, households increased their dairy milk expenditures by 1.2%, whereas the plant milk expenditures decreased by 1.5%. The second finding shows that the new destination explains about 53% of the differences in dairy milk expenditures and only about 17% for plant-based milk expenditures. A trivial finding is that people have a persistent dairy milk consumption behavior: if their original dairy milk consumption is high, then their dairy consumption will remain high even when moving to another region; and it is the same the other way around. On the other hand, households appear to pick up local plant milk consumption behavior. If they move from a region where plant milk is less prevalent, they could increase plant milk consumption; and if they move from a region where plant milk is more popular, they may reduce plant milk consumption. Overall, I conclude that dairy milk is still the dominant type consumed in the U.S., thus it is not easy for consumers to switch their preferences to plant milk. From the geographic variation point of view, the local environment has a more considerable influence on dairy milk consumption than plant milk. These findings bear significance in shaping more impactful policy recommendations related to food, particularly for programs like the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC), as well as the National School Lunch and School Breakfast Programs.

There are several limitations to this study. Nielsen data only covers some major markets and a few Census Region levels in the U.S.[24]. This sampling method may limit interpretations of the study since plant milk may not be broadly available in smaller cities. Even if it is

[24] Nielsen data sample is stratified into 61 geographic areas in total, including 52 major markets and 9 remaining Census Divisions in the U.S.

available, its higher price (than dairy milk) may limit households from choosing it. Future study could focus on just metropolitan areas defined by USDA[25] since in this case, both dairy and plant milk will be appropriately represented. Another limitation is that there may be recording errors in Nielsen data since it is self-recorded. Einav et al. (2010) demonstrated that such errors[26] could be present and have shown some correction methods. I could learn from this paper and use the correction methods to correct potential recording errors.

[25]USDA provides Market Groups data which defines 26 metropolitan areas in the U.S. See https://www.ers.usda.gov/webdocs/DataFiles/52760/qfahpd1codebook.xls?v=349.5QFAHPD-1–Codebook for its definitions.

[26]Einav et al. (2010) describes the potential recording errors in Nielsen data as follows, "First, there are potential concerns about sample selection. Because of the time commitment, households who agree to participate in the sample might not represent the population of interest. Second, households who agree to participate in the sample might record their purchases incorrectly." Since Einav et al. (2010) was published in 2010, I suspect that Nielsen is aware of such an issue and has been adjusting its data collection method over the years to minimize such errors.

Chapter 2

Got Money? Investigating the Impact of Payday Loan Extended Payment Plans on Financial Well-being

Abstract

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

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

JEL Codes: D12, D14, G2

2.1 Introduction

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

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

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

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

borrowers' financial situations (such as paying a mortgage, rent, utility bills, or improving credit scores (See Melzer (2011), Bhutta (2014), Bhutta et al. (2015), and Melzer (2018)).

Since many borrowers still heavily use payday loans for practical reasons, the states may need to pass laws to provide more financial protections related to payday loans. One research on this type of law by Wang and Burke (2022) studies the effect of information disclosure on payday loan volumes in Texas and similar but stricter city ordinances in Austin and Dallas. The state requires information disclosure for consumers taking out payday loans starting in January 2012. The disclosure requires lenders to compare the cost of payday loans with other credit products, and they must present to borrowers their likelihood of renewal in simple to understand terms. This study shows that a statewide disclosure led to a significant and persistent decline (about 13%) in loan volume for the first six months after the law.

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

loans are quick and convenient.

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

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

[5]For more details, see Section 3.2.2.

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

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

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

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

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

[8]See Appendix B.3 for the list of states and law passing dates.

delinquencies, and other measures of financial health.

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

There are also attempts to study the effect of payday loan laws that aim to protect borrowers. For example, in January 2022, Texas mandated disclosure for consumers taking out payday loans[11]. In the meantime, the cities of Austin and Dallas applied stricter supply restrictions through city ordinances. Wang and Burke (2022) found that statewide and city ordinances significantly declined payday loan borrowing.

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

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

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

2.2 Background on Payday Loans

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

Despite their high APRs, payday loans are still popular for quick cash. To illustrate, I have collected payday loan descriptions from 11 large payday loan lenders' websites and conducted a simple text analysis. Appendix B.1 illustrates the results. We can see that "cash, quick, fast, easy" are some of the most significant features. Payday loans are also described to cover "unexpected" or "emergency bills."

2.2.1 Payday Loan Protection Laws in the U.S.

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

Appendix B.2 figure (a) illustrates a map of each state's payday loan laws, including legal status and price caps. As of the end of 2020, thirteen states have laws in place that explicitly

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

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

ban payday loans[14]. Nine states have laws that limit payday loan APRs to 36%. This low-interest rate is considered an effective ban since below 36% APRs are not profitable, which would eventually drive all payday lenders to shut down their business[15]. Appendix B.2 figure (b) is an example of contract requirements. This map considers prohibited and effective-ban states that do not allow payday loans. Looking at only states where payday loans are legal, most states do not allow rollovers except for Texas and Nevada.

2.2.2 Extended Payment Plan Laws for Each State

Among the states where payday loans are legal, some have passed extended payment plan laws to help alleviate the repayment burdens. Consumers may choose these extended payment plans to pay back their outstanding payday loans in installments at no extra charge (CFPB, 2022a). The typical features[16] of extended payment plans may include:

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

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

Allowable Fees: Fourteen states require no additional charge for the extended payment plans[17].

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

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

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

[16] For more details, see CFPB (2022a) or Appendix B.3 for more details.

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

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

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

Appendix B.2 figure (c) plots the map for each state that has passed the extended payment plan laws. Appendix B.3 lists detailed extended payment plans for each state. By the end of 2020, fifteen states that require lenders to provide extended payment plans. The rest of the fourteen states where payday loans are legal do not have any extended payment plan laws passed[18].

2.3 Clarity Credit Data

This paper uses a novel dataset from Clarity Services, Inc. (later referred to as "Clarity"). Clarity is a subsidiary credit reporting agency of Experian that specializes in providing underwriting services and information to lenders who offer alternative credit products such as payday loans[19]. Like traditional credit bureaus, lenders using Clarity's underwriting services report each loan applicant's information to Clarity for verification purposes. Clarity then tracks each borrower's tradeline activity. These tradelines are very similar to traditional credit reports, which include account types, balances, delinquencies, and repayment histories. This information is valuable to lenders for assessing an applicant's default probabilities.

Clarity data includes over 60 million borrowers and covers more than 70% of non-prime

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

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

consumers in the U.S. One caveat is that Clarity data only contains loan records of who uses its underwriting services. Despite this, Clarity may be the best existing coverage of payday loan behavior in the U.S. In addition, Clarity data has more online payday lending recorded than storefront payday lending. Appendix B.4 shows these differences.

2.3.1 Sample Construction

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

Given Clarity's sampling frame, only these five states had data before the extended payment plan laws were rolled out: Delaware, Florida, Louisiana, Nevada, and Utah. Table 2.1 presents each treated state's treated date, the quarter being treated, and the total treated quarters. First, the quarters are aggregated for the six years, i.e., from 2015 to 2020. The quarters range between one to twenty-four. Then the treated quarter is assigned based on three months after the treated date. For example, if the law was effective on 2016-07-01 for Utah, then I assume the actual effect takes effect after three months, which is on 2016-10-01. That said, the (aggregated) quarter being treated for Utah is quarter 8. This works the same for the other four states. The time period is aggregated at a quarterly level for a few reasons. The first reason is that a smaller time period (e.g., in months) would lead to many missing periods because some states may have yet to record data. Another reason is that measurements in quarters may be more accurate since it may take some time for the new laws to take effect.

Table 2.1: States that Passed Extended Payment Plans between 2015-2020

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

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

2.3.2 Outcome Variables

The outcome variables are related to each borrower's financial health. I use four variables to measure an individual's financial health after the law: (1) **Total amount past due**. This value is the total amount of payments (adjusted to 2020 dollars) due based on delinquency. This value includes late charges and fees (if applicable) that are past due. (2) **Original charge-off**. This variable is the original amount charged off due to loss by the lender. (3) **Delinquency rate**. It is the delinquency rate of loans for each borrower [20]. (4) **Charge-off or debt-in-collections rate**. This variable is the ratio of charge-off or debt-in-collections. If a borrower does not pay the debt after 150 or more days, debtors will put this debt in collections and keep collecting the remaining debts. If the debts are still not fully collected after about six months, debtors will put it in charge-off, e.g., selling the debt to a debt collector and letting them collect the rest. These are common measures based on multiple papers, and Consumer Financial Protection Bureau (CFPB) reports (Nunez et al., 2016). One thing to note is that because most people repay their loans on time, most values for each outcome will be zero. Appendix B.5 gives histograms for the outcome variables.

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

2.3.3 Summary Statistics

Table 2.2 reports summary statistics for my sample. I present mean and standard error for each variable for the control and treated states. The table also provides p-values computed using the paired t-test for the difference in means between these two groups. There are some differences between the two groups, but the difference is not substantial.

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

2.4 Empirical Strategy

2.4.1 Event Study

I employ the event study framework for staggered adoption following Sun and Abraham (2021) to motivate this research. The event study helps visualize the treatment effect once the treatment is "switched on" (i.e., once the extended payment plans become effective). It is possible to visually show the treatment effect in an SDiD setting (which will be presented later). However, event study is a common practice, and Clarke et al. (2023) proposed the event study method presented by Sun and Abraham (2021) as a good alternative for the staggered adoption setting.

Table 2.2: State Summary Statistics

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

Notes: The five treated states are Delaware, Florida, Louisiana, Nevada, and Utah. See Table 2.1 for the exact treated dates. The fourteen control states (the donor pool) are Hawaii, Illinois, Iowa, Kansas, Kentucky, Minnesota, Mississippi, Missouri, Nebraska, North Dakota, Oklahoma, Rhode Island, Tennessee, and Texas. The mean and SD for outcome variables are calculated using pre-treatment data. For all dollar values, the numbers are adjusted to 2020 dollars using the consumer price index for urban consumers. The table reports the mean ratios for pay frequency, housing status, delinquency rate, and charge-off or debt-in-collections. The p-values are from the t-test for the mean differences between the control and treated groups. Note that the sample size is small because it is aggregated at the state level. At an individual level, there are 2,498,231 observations for the control units and 360,453 observations for the treated units.

The event study follows the below model:

$$y_{it} = \alpha_i + \beta_t + \sum_{g} \sum_{r \neq -1} \mu_{g,r} \left(\mathbf{1}(G_i = g) \times event\_time_{it}^{r} \right) + \epsilon_{it} \tag{2.1}$$

The outcome variable y_{it} is at the state i and quarter t level. State and quarter fixed effects are represented by α_i and β_t. Each treated cohort is indicated by g, where $g = \{1, 2, ..., 5\}$. Since the five states are treated at five different periods, $G_i = 5$. The binary indicator $\mathbf{1}(G_i = g)$ equals 1 if G_i corresponds to that specific treated cohort. The variable $event\_time^r_{it}$ is time relative to the law adoption time, which is restricted between $[-6, 6]$. Here, $r = -1$ is omitted, which is standard in the event study literature since it makes it easier to visualize the treatment effect of "switching on" the laws and study the pre-existing trends in the outcomes. The interaction term $\mathbf{1}(G_i = g) \times event\_time^r_{it}$ gives a coefficient $\mu_{g,r}$ for each cohort interacted with a different $event\_time^r_{it}$[21].

Figure 2.1 presents event study results for each outcome variable. After a state adopted the extended payment plans, all financial outcomes have improved: we can see a significant decrease in each measurement. One should note that we cannot simply interpret the results from this event study as causal effects but as a simple comparison of outcomes pre-treatment and outcomes post-treatment. To quantitatively measure the actual treatment effect, we will use the SDiD model in the following subsection to measure these treatment effects.

2.4.2 Synthetic Difference-in-Differences

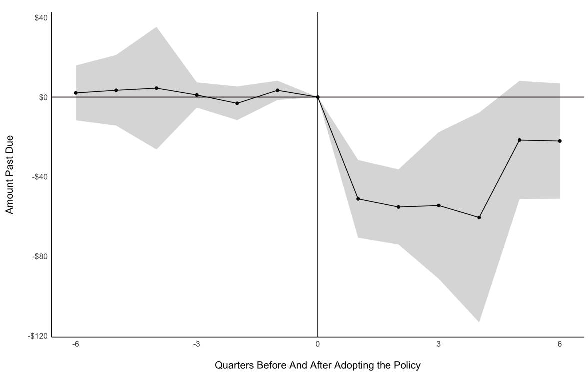
To uncover the causal effect of these extended payment plans on borrowers' financial health in states where they have passed these laws, I employ the SDiD model following Arkhangelsky et al. (2021) and Clarke et al. (2023). The SDiD model is defined as follows:

$$\hat{\tau}^{SDiD} = \underset{\mu,\alpha,\beta,\tau}{\operatorname{argmin}} \left\{ \sum_{n=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - \tau D_{it})^2 \hat{w}_i \hat{\lambda}_t \right\} \tag{2.2}$$

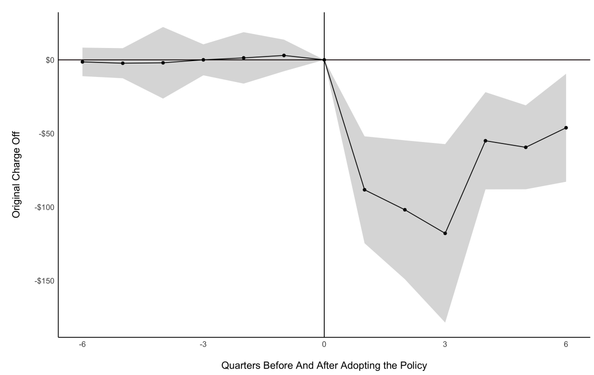
[21] Here is a straightforward process of this event study: For each treated cohort g and each $event\_time$, we estimate a treatment effect. For example, when $g = Delaware$, we obtain a treatment effect for each $event\_time$ except for when $r = -1$. Do the same for the other treated state. Then get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

Our interest of parameter is τ, which identifies the average treatment effect on the treated. The outcome variable Y_{it} is related to a borrower's financial health; it can be the total amount past due, total charge-off amount, delinquency rate, or charge-off or debt-in-collections rate. μ is the intercept. α_i and β_t represent the state and quarter fixed effects. D_{it} is the binary treatment variable. It equals 1 if a state has passed the extended payment plan laws, and it equals 0 otherwise. I set the treatment variable as binary for two reasons. First, the extended payment plans are composed of a set of features. As seen in Section 3.2.2, each state has some variations for these features. It would make sense to study all features as a whole instead of separate ones. In addition, all five treated states require no additional charge for the extended payment plans. This feature directly affects borrowers' repayment behavior, crucial to studying financial health.

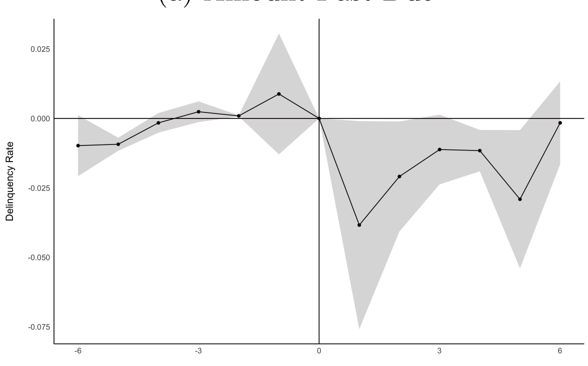
Figure 2.1: Event Study for Financial Health Variables



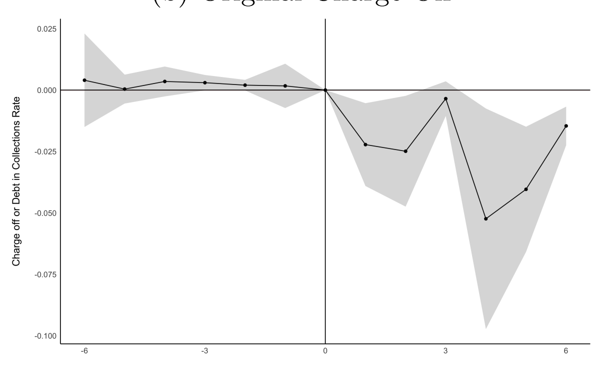
(a) Amount Past Due



(b) Original Charge-Off



(c) Delinquency Rate



(d) Charge-Off or Debt-In-Collections Rate

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

Note that in Equation 2.2, there are two types of weights: the unit weights $\hat{w}_i$ and the time weights $\hat{\lambda}_t$. The fourteen untreated states specified in Table 2.2 act as donor units. By applying both unit and time weights on the donor units, SDiD generates a synthetic control version of the treated unit.

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

$$\hat{w} = \underset{w_0, w}{\operatorname{argmin}} \parallel \bar{\mathbf{y}}_{pre,treat} - (w_0 + \mathbf{Y}_{pre,control}\mathbf{w}) \parallel^2 + \xi^2 T_{pre} \parallel \mathbf{w} \parallel_2^2 \tag{2.3}$$

such that $\sum_{i=1}^{N_{control}} w_i = 1$ and $w_i \geq 0 \; \forall \; i$. Here, $\bar{\mathbf{y}}_{pre,treat}$ is the mean outcome pre-treatment for the treated states. w_0 is the intercept, which allows the treated unit and the synthetic control to have a different level. $Y_{pre,control}$ is the outcome for control units before treatment. $\mathbf{w}$ is a $N_{control} \times 1$ vector. T_{pre} is the total pre-treatment periods. The term $\parallel w \parallel_2^2$ is a squared $l2$ norm (or Euclidean norm)[22].

The extra ξ term in equation 2.3 is a regularization parameter, which is identified by the following:

$$\begin{aligned} \xi &= (N_{treat} \cdot T_{post})^{1/4}\hat{\sigma}, \quad & \text{with } \hat{\sigma}^2 &= \frac{1}{N_{control}(T_{pre}-1)} \sum_{i=1}^{N_{control}} \sum_{t=1}^{T_{pre}-1} (\Delta_{it} - \bar{\Delta})^2, \\ \Delta_{it} &= Y_{i(t+1)} - Y_{it}, & \text{and } \bar{\Delta} &= \frac{1}{N_{control}(T_{pre}-1)} \sum_{i=1}^{N_{control}} \sum_{t=1}^{T_{pre}-1} \Delta_{it} \end{aligned} \tag{2.4}$$

$N_{control}$ and N_{treat} are the total number of control units and treated units correspondingly. T_{pre} and T_{post} represent the total pre-treatment and post-treatment periods. Δ_{it} is the first

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

difference in outcomes, and $\bar{\Delta}$ is the mean for the first differences. $\hat{\sigma}$ is the standard deviation of first difference Δ_{it}. The regularization parameter ξ is chosen to match the size of the first difference for untreated units in the pre-treatment period, multiplied by a theoretically motivated term $(N_{treat} \cdot T_{post})^{1/4}$. If both ξ and w_0 are zero, then Equation 2.3 would become the weights for synthetic control model discussed in Abadie (2021) where $N_{treat} = 1$.

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

$$\hat{\lambda} = \underset{\lambda_0, \lambda}{\operatorname{argmin}} \parallel \bar{\mathbf{y}}_{post,control} - (\lambda_0 + \boldsymbol{\lambda} \mathbf{Y}_{pre,control}) \parallel^2 \tag{2.5}$$

such that $\sum_{t=1}^{T_{pre}} \lambda_t = 1$ and $\lambda_t \geq 0 \; \forall \; t$. Note that $\bar{\mathbf{y}}_{post,control}$ is the mean outcome for the control group after the treatment. λ_0 is an intercept, which allows the pre- and post-treatment periods to have different levels. $\boldsymbol{\lambda}$ is a 1 by T_{pre} row vector[23].

The data needs to satisfy certain requirements to run the SDiD model. First, it needs to be a balanced panel, where each variable for each unit has no missing values for each period. For the individual level data, many borrowers are not observed for some quarters, which makes it impossible to run the SDiD model. Since I intend to study the average treatment effect for the treated states instead of for the treated individuals, it is more appropriate to aggregate the data at the state level[24]. The SDiD model also requires at least two pre-treatment periods off of which to determine control units (It is satisfied for the payday loan data here).

In the DiD model, the covariates are added directly into the model; in the SC model, the covariates are included to get close matches between treated and synthetic control units.

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

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

However, the SDiD covariate adjustments are pre-processed to ensure they remove the impact of changes in covariates from outcomes before obtaining synthetic controls [25]. Appendix B.6 explains that we must first run a two-way fixed effect (TWFE) model by regressing outcomes on all predictors where all data comes from pre-treatment periods. Then we apply the SDiD model on residual outcomes where the estimates obtained from the TWFE model to all data (including treated units)[26].

In practice, obtaining the treatment effect will require extra steps since the treatment here involves differential timing. To illustrate, the matrix D in Equation 2.6 below shows how each state passed the extended payment plan laws at different periods. All of the control states are combined in the first column vector. The vector's values are denoted as 0 and are labeled with the corresponding quarters. For example, the treatment switches on for Delaware at quarter 17, so the value switches from 0 to 1 at quarter 17. For Florida, the value switches from 0 to 1 in quarter 20.

The SDiD model cannot handle matrix D because we do not have a clear definition for the pre-treatment period or a control unit. To solve this, we can delete columns (or units) in matrix D and decompose D into five smaller block matrices, each with control states and one treated state only. This way, we can apply a simple two-by-two DiD model for each small block matrix. To illustrate, the matrix $D_{Delaware}$ in Equation 2.7 is for control states and Delaware, where all values for control states are 0, and values for Delaware switch from 0 to 1 at quarter 17. Similarly, we can construct a small block matrix for other treated states.

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

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

$$D = \begin{array}{c} \begin{array}{cccccc} Control\ States & Delaware & Florida & Louisiana & Nevada & Utah \end{array} \\ \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \mathbf{1} & \vdots & \vdots \\ & & & & & \mathbf{1} \\ & & & & \mathbf{1} & \\ & \mathbf{1} & & & & \\ & & \mathbf{1} & & & \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \mathbf{1} & \mathbf{1} & \mathbf{1} & \mathbf{1} & \mathbf{1} \end{bmatrix} \end{array} \tag{2.6}$$

$$
D_{Delaware} = \begin{bmatrix} \textit{Control States} & \textit{Delaware} \\ 0 & 0 \\ 0 & 0 \\ \vdots & \vdots \\ & \\ & \\ & \\ & \mathbf{1} \\ & \\ \vdots & \vdots \\ 0 & \mathbf{1} \end{bmatrix} \tag{2.7}
$$

After running weighted SDiD models separately for each treated state, we get five different average treatment effects on the treated (ATT). In order to get a final treatment effect for all treated states, we need to re-weight each state's ATT by their treated periods following Clarke et al. (2023). For example, based on Table 2.1, the total treated quarters for all five states are 65. The weight is $\frac{8}{65}$ for Delaware ATT, $\frac{5}{65}$ for Florida ATT, and so on. Appendix B.6 explains the complete algorithm for estimating ATT using SDiD with staggered adoption.

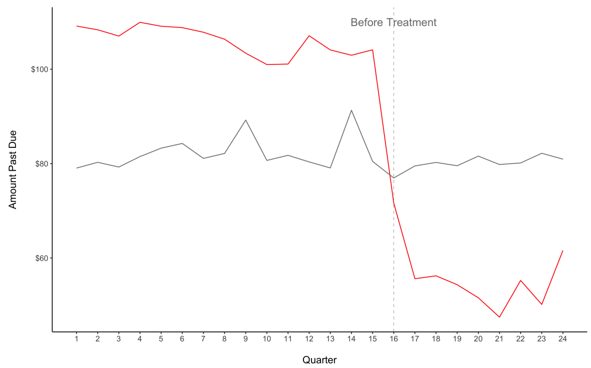
2.4.3 Impact of Extended Payment Plans on Financial Health

Figure 2.2 shows each treated state's ATT for the outcome variable amount past due. The treatment effect for each state could vary a lot, but the overall treatment effect is negative. This result means that after passing the extended payment plans, each treated state has reduced past due amounts for payday loans. For the other three outcome variables, the ATTs have very similar trends (see Appendix B.7).

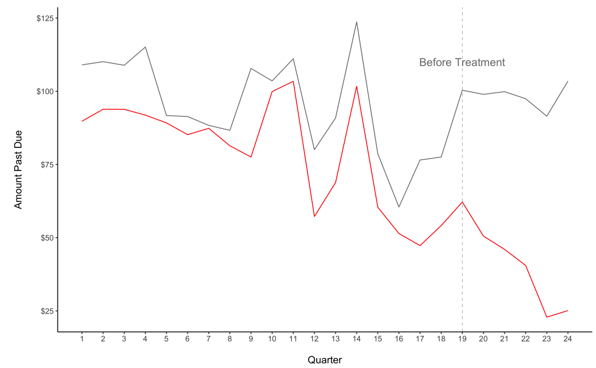
Table 2.3 presents the results from both DiD and SDiD models. Column (1) and column (3) show results using DiD and SDiD without any covariates. Column (2) and column (4) results add covariates to the models. After adding covariates, estimates from both models increased a bit. After passing the extended payment plan laws, on average, the treated states have reduced \$30.53 past due amount using the DiD model and about \$5 less using the SDiD model (\$25.32). The original charge-off amount is reduced by about \$52.84 with the DiD model and \$49.50 with the SDiD model. The DiD model estimates a reduction of 3.08% in delinquency rate after adopting the law and about 2.89% with the SDiD model. For the charge-off or debt-in-collections rate, the DiD estimates a decrease of 3.51%, and the SDiD gives a 2.65% reduction. Overall, the SDiD estimates are smaller than the DiD estimates.

I follow the bootstrap inference algorithm presented by Clarke et al. (2023) to get standard errors. Appendix B.8 shows this algorithm in detail. The main steps are sampling original disaggregated data with replacement. This procedure almost guarantees always having control and treated units in the bootstrap dataset. Then aggregate the data and run the same algorithm presented in Appendix B.6 1,000 times with different bootstrap datasets. Table 2.3 shows that the ATTs are all significant for both DiD and SDiD models. For example, the amount past due ATT is significant at 90% level for SDiD without or with covariates, whereas the DiD is significant at 95% level. After controlling for covariates, the other three outcomes are significant at the 95% level; for DiD model, the original charge-off is more significant (at

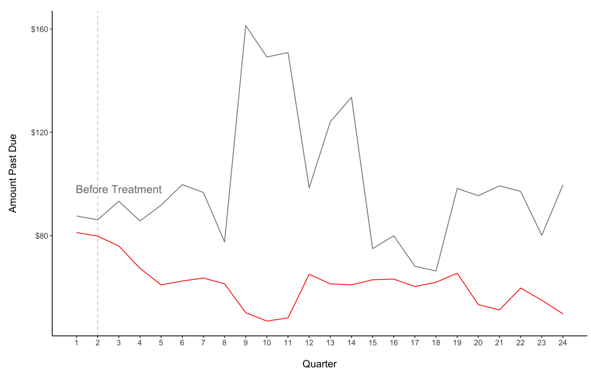
Figure 2.2: Synthetic Difference-in-Differences Plot for Amount Past Due



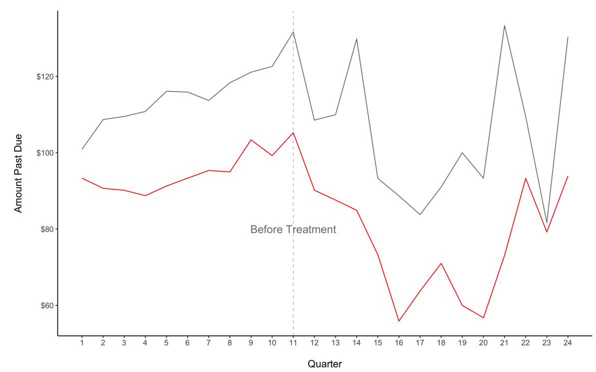
(a) Delaware



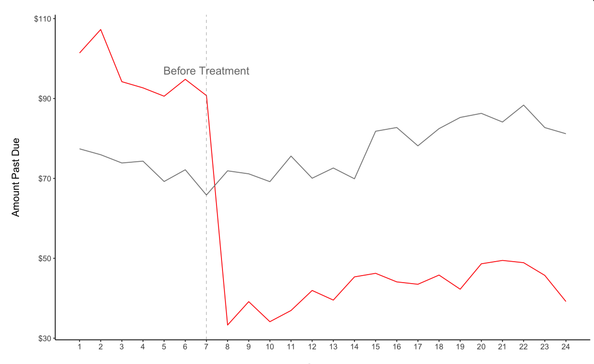
(b) Florida



(c) Louisiana



(d) Nevada



(e) Utah

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

Table 2.3: Average Treatment Effects of Extended Payment Plans on Financial Health

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

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

the 99% level), and the other two outcomes are only significant at the 90% level.

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

2.4.4 Robustness Checks

To check the robustness of the SDiD estimates, I run a placebo test to check if there is a treatment effect or if there are other factors at play. First, I remove the five treated states from the data. Next, randomly select five states and pretend they are the treated states. The sample assigns a treated period for each "fake" treated state using the real treated periods. Then I run the same DiD model as in Section 2.4.2.

Table 2.4 presents results from placebo tests. For the delinquency rate and charge-off or debt-in-collections rate, the effect is close to zero and non-significant. Although the results are not quite zero, the estimates of the amount past due and the original charge-off are minimal relative to the SDiD results in Table 2.3. We can conclude that our estimates from the SDiD model are robust and causal.

2.5 Conclusions and Discussions

This paper exploits a natural U.S. experiment among states that have adopted payday loan extended payment plans. Using the Clarity sub-prime payday loan data, I can estimate these extended payment plan laws' effects on different financial health outcomes. The main findings are that after passing these laws, the treated states, on average, have a reduced amount past due by about \$25 and the original charge-off amount by about \$49. There is also a 2.89% decrease in delinquency rate and a 2.65% reduction in charge-off or debt-in-collections rate. These results are all robust and significant.

These findings are crucial to policies that aim to improve borrowers' overall financial health and are relevant to financial protection bureaus. For example, in 2016, the CFPB proposed a payday loan rule (but it was never implemented) to stop payday debt traps. Under this rule,

Table 2.4: Placebo Test Results

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

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

one of the requirements is that lenders need to disclose whether a borrower can repay the loan and is still able to cover basic expenses and major financial obligations[27]. The findings from this study imply that this payday loan rule may benefit payday loan borrowers, especially those trapped in loan repaying cycles.

There are two main limitations to this study. First, a few treated states must be excluded due to the Clarity sampling frame. Only five treated states are included in this study. If we had pre-treatment data for the other eleven states, we could have obtained a more accurate ATT.

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

Another issue is that the computation process for the SDiD model is somewhat complex and computationally heavy, especially for the staggered adoption setting.

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

Chapter 3

Money Matters? Deciphering the Impact of Payday Loan Extended Payment Plans on Financial Well-being amidst Income Volatility

Abstract

Payday loans are short-term loans that are especially popular among low-income people. However, many borrowers are trapped in debt due to its high annual percentage rate (APR). Several states have passed various laws to protect borrowers who are particularly vulnerable to falling into debt traps. This study analyzes one of these types of laws, the extended payment plans, which allows borrowers to pay back their payday loans in multiple smaller installments without additional fees. The paper Golden (2023) finds that the payday loan extended payment plans help improve borrowers' financial health on average. This paper extends this topic and further explores the heterogeneous treatment effect across time and people of different income volatility, defined by income coefficient of variation. The results show that the treatment effect varies from year to year without a clear pattern. Borrowers between the first quartile and median level of income coefficient of variation appear to experience the most benefit from this type of law; however, the treatment effect is small or non-existent for individuals whose income coefficient of variation is beyond the third quartile.

Keywords: Household finance, consumer finance, payday loans, alternative financial services, financial health, income volatility, extended payment plans, double machine learning.

JEL Codes: D12, D14, G2

3.1 Introduction

Income volatility is trending up in the U.S. Andersen et al. (2015) finds that income volatility has risen since the 1970s. Income volatility affects over half the U.S. population, with over 35 million households experiencing more than 50% change in income in 2010. In recent statistics, estimates from Federal Reserve (2023) suggest that 37% of U.S. households cannot cover a $400 expense with cash or its equivalent in 2022. FDIC (2023) using national survey finds that, in 2021, about 4.5% (or 5.9 million) of American households are "unbanked" [1]. Furthermore, 14.1% (or 18.7 million) American households are "underbanked"[2]. These statistics suggest that income volatility is still prevalent, and many Americans still suffer from poor financial health. The rise of income volatility comes with the macroeconomic background of changing labor markets: a shift from manufacturing to a service economy and a growing gig economy (such as Uber, Lyft, and Instacart part-time jobs). These changes

[1] FDIC (2023) defines that a household is "unbanked" if no one in the household held a checking or savings account at a bank or credit union.

[2] FDIC (2023) defines "underbanked" as the following: The household was banked and in the past 12 months used at least one of the following nonbank transaction or credit products or services that are disproportionately used by unbanked households to meet their transaction and credit needs: (1) Money orders, check cashing, or international remittances (i.e., nonbank transactions); or (2) Rent-to-own services or payday, pawn shop, tax refund anticipation, or auto title loans (i.e., nonbank credit).

lead to job insecurity in some households.

Although income volatility is more common among low-income groups, it is not exclusive but affects a broader spectrum of socioeconomic strata. Hannagan and Morduch (2015) discovers that households below the poverty line experience significant income volatility, and those whose income is from 100 percent of the poverty line up to 300 percent also experience relatively high income volatility. Using the Financial Diaries data that tracks 235 low- and moderate-income households in the U.S., Hannagan and Morduch (2015) finds that a household's income level in the data can lower than $25,000 per year, and it can be higher than $100,000 per year on the higher end. These households could all potentially experience certain levels of income volatility. The statistics suggest that studying income volatility is relevant to low-income earners and those on the higher end.

Income volatility can be divided into four groups: high income and low volatility, high income and high volatility, low income and low volatility, and low income and high volatility. People with low income and high volatility may particularly suffer from poor financial health. Appendix C.1 is a bar plot that shows the counts for the four groups using sample data in 2015. Although there is a high concentration of low income and high volatility, we can also see quite a few high income borrowers who experience high income volatility. Interestingly, the observations are much fewer for both low and high income earners who experience low income volatility.

When people experience income volatility (especially in the negative direction), they may resort to alternative financial services, especially when they do not have access to traditional credit or believe borrowing from a traditional bank would jeopardize their credit. Small-dollar loans are prevalent for their convenience and require no credit check. The common ones include payday loans, auto title loans, and pawnshop loans, among which payday loans have the most shares. Every year, about 12 million Americans take out payday loans (The Pew Charitable Trusts, 2016), which is about 3.6% of the total U.S. population.

Payday loans can have an annual percentage rate (APR) of as high as 500%, much higher than the typical 18% credit card APR. For people who experience volatile income, this loan could be terrible for their finance management because if their next paycheck is much lower than the previous one, they may not be able to pay back on time. If borrowers cannot repay their loans at payday, they can roll over with additional fees. For example, if one borrows $300, he may owe $345 in 14 days, where $45 is the borrowing fee. If he opts for rollover, he pays only the $45 rollover fee at this time. At his next payday, he will pay $300 plus $45 fee that he owes last time. That means the cost of the original $300 loan is doubled after a rollover (from $45 to $90). Despite such high transaction costs, CFPB (2014) finds that 80% of payday loans are not paid back within two weeks, and those loans are either rolled over or followed by another loan.

Despite how invasive the payday loan is, it is still the most popular small dollar loan. CFPB (2021) explains that the borrowers taking out payday loans may be due to either income shocks, such as job loss, or may be due to expense shocks, such as unexpected medical bills. The payday lenders have featured payday lenders' exact needs on their websites. Appendix B.1 in Chapter 2 illustrates the top 45 most utilized words on the top 11 payday lenders' websites. The websites emphasize three key messages to customers: (1) **It is easy to access cash.** The keywords "quick, cash, fast, easy, direct, next, minute, same day, instant, pick up, home, convenient, business day" makes payday loan easy cash, and "credit score" catches customers with low credit scores; (2) **It is safe to use.** The terms "help, short-term, secure" all make the payday loan a safe loan; and (3) **It is for emergency or unexpected expenses.** The terms "unexpected, emergency" make customers believe payday loans are what they need to cover those surprise bills.

Many states have passed extended payment plans to protect payday borrowers from falling into debt traps. This law has various features, such as allowing borrowers to repay in multiple installments without additional fees, loan term disclosure requirements, eligibility, and frequency of use. The extended payment plan varies from state to state, but the goal is to help borrowers repay their loans. The paper Golden (2023) using Clarity data finds that the payday loan extended payment plans help improve borrowers' financial health on average. This paper extends the study and explores the heterogeneous treatment effect of extended payment plans across time and people on borrowers' financial health using the double/debiased machine learning (DML) method. Specifically, I study different financial well-being measurements, including the amount past due, original charge-off amount, delinquency rate, and charge-off or debt-in-collections rate. The treatment is a binary variable, whether or not the individual lives in a state that has passed the extended payment plans. I also use borrowers' characteristics relevant to payday loan borrowing behavior as covariates.

This study uses proprietary Clarity[3] payday loan data. Clarity records different financial health related variables such as amount past due and delinquency. It also includes relevant borrower characteristics such as age, income, and housing status. I used the Consumer Financial Protection Bureau report on extended payment plans and narrowed the list of states that have passed such laws(CFPB, 2022a). Then, I search through each state's legislature or financial department websites for the extended payment plan legal clauses to find the exact passing date for each state[4]. Using these treated dates, we can create the treatment variable. For income volatility, I can derive each borrower's income coefficient of variation. The final data for this study is aggregated at the year level for each individual.

I use double machine learning, specifically the interactive regression model (IRM). I use machine learning methods since they allow us to do causal inference with (1) minimum assumptions about the functional form of our model; and (2) high-dimensional data. The machine learning model could help generate many non-linear transformations of existing

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

[4]See Appendix B.3 in Chapter 2 for the list of states and law passing dates.

variables (such as squared or cubic terms). I find that the treatment effect varies across years, which shows no definite pattern; across people, borrowers who are between first quartile and median income volatility experience the most improved financial health; however, those whose income volatility is above third quartile income volatility may not get improvement in their financial well-being at all.

Current literature focuses on how easier access to traditional credit affects payday lending. Di Maggio et al. (2020) take the "bank the unbanked" approach since about 28.6% US population are either unbanked or underbanked (FDIC, 2023). The authors analyzed the effect of banks being banned from practicing the reordering of transactions from "high-to-low" for their overdraft fees. They found that consumers experienced improved financial health after this law. However, many borrowers are still using payday loans because the traditional financial system may charge them high fees, and the borrowers are reluctant to bear its negative consequences (such as lower credit scores). Miller and Soo (2020) find that after removing the Chapter 7 bankruptcy flag, there is a large increase in access to traditional credit and an increase in credit scores, credit card limits, and approval rates. However, borrowers are not reducing the use of payday loans. Recent research by Chen et al. (2022) finds that payday loans can harm regular expense management (such as paying regular bills), but they also serve as an important cash flow to cover emergency bills. These findings indicate that relying on policies that nudge individuals to borrow from traditional banks alone is insufficient.

Another mainstream literature studies how access to payday loans affects financial health. Melzer (2011) finds payday loan access leads to increased difficulty in paying regular bills such as mortgage, rent, and utility bills. Bhutta et al. (2015) and Bhutta (2014) find that payday loans practically do not affect credit scores or other measures of financial health.

Other literature takes very different approaches and attempts to connect with borrowers' risk tolerance or climate shocks. For example, Wang (2023) discovers that borrowers with higher risk tolerance are more likely to take out payday loans. In Xie et al. (2023), the paper finds that extreme hot and cold days increase payday loan borrowing, especially online payday loan borrowing.

This paper contributes to several topics. First, the study adds to the extensive literature on income volatility. In this case, I study income volatility exclusively on payday borrowers. The Clarity data used in the study covers more than 70% of non-prime consumers in the U.S. Hence, the study gives a better picture of the financial health of US payday loan users. Second, this paper studies intrayear income volatility: older literature discusses long-run trends (such as year-to-year). Third, the dataset in the study includes both low- and high-income borrowers, which presents more interesting results. CFPB (2016) find that not all payday users are low-income earners: 20% of them earn $53,000 per year, one-third are home-owners, and 40% have a 4-year college degree or higher. This paper uses data from borrowers whose net monthly income ranges between zero to ten thousand dollars. Chen et al. (2019) discovers that income volatility among those who earn between $40,000 to $100,000 received little attention, even though this income group has also been experiencing similar income insecurity as low-income groups. The data used in this paper covers both extremely low income (for that month) borrowers and high-income borrowers. Taking 2015 as an example: According to Census, The median personal income is estimated at $30,240, which is $2,520 on average per month (Census, 2023). There are about 56% of individual borrowers whose monthly income is above the median personal income that year [5]. The conclusions would be interesting in uncovering US income volatility patterns for both low- and high-level income groups (which is more representative). Finally, this paper contributes to the extended payment plan literature. Similar literature is done by Wang and Burke (2022), which studies payday loan disclosure rules at the state level in Texas and city level in Austin and Dallas for consumers taking out payday loans. Wang and Burke (2022) found

[5] Between 2016-2020, the percentages of borrowers whose monthly income is above the median personal income that year are 56%, 53%, 44%, 37%, and 37% respectively.

that state and city-level policies significantly declined payday loan borrowing. The paper Golden (2023) finds that the payday loan extended payment plans help improve borrowers' financial health on average.

3.2 Background on Payday Loans

Payday loan[6] is a cash advance loan, which is usually repaid in a single payment on the borrower's next payday or other receipts of income (CFPB, 2022b). It is one type of small-dollar loan[7]. The typical loan limit is $500, and the typical annual percentage rate (APR) is between 300% to 500%. In comparison, the APRs on credit cards only range between 12% and 30%.

3.2.1 Payday Loan Protection Laws in the U.S.

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

[6] A payday loan is also referred to as deferred deposit, deferred presentment loans, and check loans.

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

3.2.2 Extended Payment Plan Laws for Each State

Some states where payday loans are legal have passed extended payment plan laws to help alleviate the repayment burdens. Consumers may choose these extended payment plans to pay back their outstanding payday loans in installments at no extra charge (CFPB, 2022a). The typical features[8] of extended payment plans may include:

> **Installments**: Most states offer consumers a chance to repay payday loans in three or four installments instead of in one payment. This is the most salient feature of extended payment plans.
>
> **Plan Length**: Some states determine a minimum repayment term, typically between 60 to 90 days.
>
> **Allowable Fees**: Fourteen states require no additional charge for the extended payment plans[9].
>
> **Frequency of Use**: Most states limit the extended payment plan to once every 12 months.
>
> **Consumer Eligibility**: Some states may only allow consumers to take an extended payment plan if they have reached a threshold of rollovers.
>
> **Disclosures**: Some states may require lenders to either disclose the availability of an extended payment plan before lending the loans or require lenders to notify consumers about these plans upon default.

The extended payment plans combine categories (3) and (4) mentioned in Section 3.2.1. Appendix B.2 in Chapter 2 Figure (c) plots the map for each state that has passed the

[8] For more details, see CFPB (2022a) or Appendix B.3 in Chapter 2 for more details.

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

extended payment plan laws. Appendix B.2 in Chapter 2 lists detailed extended payment plans for each state. By the end of 2020, fifteen states require lenders to provide extended payment plans. The rest of the fourteen states where payday loans are legal do not have any extended payment plan laws passed[10].

3.3 Clarity Credit Data

This paper uses a novel dataset from Clarity Services, Inc. (later referred to as "Clarity"). Clarity is a subsidiary credit reporting agency of Experian that specializes in providing underwriting services and information to lenders who offer alternative credit products such as payday loans[11]. Like traditional credit bureaus, lenders using Clarity's underwriting services report each loan applicant's information to Clarity for verification purposes. Clarity then tracks each borrower's tradeline activity. These tradelines are very similar to traditional credit reports, which include account types, balances, delinquencies, and repayment histories. This information is valuable to lenders for assessing an applicant's default probabilities.

Clarity data includes over 60 million borrowers and covers more than 70% of non-prime consumers in the U.S. One caveat is that Clarity data only contains loan records of who uses its underwriting services. Despite this, Clarity may be the best existing coverage for payday loan borrowing in the U.S.

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

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

3.3.1 Sample Construction

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

Given Clarity's sampling frame, only these five states had data before the extended payment plan laws were rolled out: Delaware, Florida, Louisiana, Nevada, and Utah. Table 2.1 in Chapter 2 presents each treated state's treated date, the quarter being treated, and the total treated quarters. First, the quarters are aggregated for the six years, i.e., from 2015 to 2020. The quarters range between one to twenty-four. Then, the treated quarter is assigned three months after the treated date. For example, if the law was effective on 2016-07-01 for Utah, then I assume the actual effect takes three months, which is on 2016-10-01. That said, the (aggregated) quarter being treated for Utah is quarter 8. This works the same for the other four states. The time period is aggregated in quarters for a few reasons. The first reason is that a smaller time period (e.g., in months) would lead to many missing periods because some states may have yet to record data. Another reason is that measurements in quarters may be more accurate since it may take some time for the new laws to take effect. The final dataset is aggregated at the year level. For example, for each individual in 2015, we obtained mean values for each variable; for categorical variables, we used the most frequently appeared values for each individual. The final sample data contains 4,205 borrowers residing in control states and 1,584 borrowers living in treated states with 5,789 observations.

3.3.2 Outcome Variables

The outcome variables are related to each borrower's financial health. I use four variables to measure an individual's financial health after the law: (1) **Total amount past due**. This value is the total payments (adjusted to 2020 dollars) due based on the delinquency record. This value includes late charges and fees (if applicable) that are past due. (2) **Original charge-off**. This variable is the original amount charged off due to loss by the lender. (3) **Delinquency rate**. It is the delinquency rate of loans (in percentage) for each borrower [12]. (4) **Charge-off or debt-in-collections rate**. This variable is the percentage of charge-off or debt-in-collections. If a borrower does not pay the debt after 150 or more days, debtors will put this debt in collections and keep collecting the remaining debt. If the debt is still not fully collected after about six months, debtors will put it in charge-off, e.g., selling the debt to a debt collector and letting them collect the rest. These are common measures based on multiple papers and Consumer Financial Protection Bureau (CFPB) reports (Nunez et al., 2016).

3.3.3 Income Volatility

We can quantify income volatility in terms of its magnitude, direction, frequency, or combination. The first method is income percentage change (in terms of magnitude and direction), defined as the percentage change compared with income from the previous period. Appendix C.2 panel (a) shows the distribution of income percentage change in 2015 using sample data. We can observe that most income does not change over the year, and non-zero percentage changes are very spread out (even after excluding those more significant than $\pm$ 100% income percentage change). In this case, it does not generate enough variation for our analysis. The second method is to use spikes and dips (in terms of magnitude, direction, and frequency)(see

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

Hannagan and Morduch (2015) and Morduch and Siwicki (2017)). It is a spike if the income is greater than 125% of an individual's mean income and a dip if the income is less than 75%. Appendix C.2 panel (b) displays the distribution of counts for income spikes and dips in 2015, and panel (c) illustrates a random borrower's income spikes and dips. We can see quite a few jumps in this borrower's income. The last common way is the income coefficient of variation (in terms of magnitude) (see Hannagan and Morduch (2015), Morduch and Siwicki (2017), and Wolf et al. (2014)), which is the ratio of the standard deviation of income and mean income. The income coefficient of variation (later referred to as "income CV") is chosen in this study for various reasons: (1) It is aggregated for each individual in each year, which minimizes data entry errors in net monthly income; (2) It is easier to use and interpret since it is continuous; (3) This study focuses on intrayear income volatility in both directions (i.e., income moves up or down) since both positive and negative shocks could affect financial plans in short run or long run.

When estimating the conditional average treatment effect (CATE), the model will be conditional on an income volatility related variable instead of net monthly income. I define income CV using the following formula:

$$income\_CV_{it} = \frac{SD(income_{it})}{Mean(income_{it})} \times 100\% \tag{3.1}$$

The income CV is defined as the standard deviation of a borrower i's net monthly income over a year t expressed as a percentage of the borrower's average monthly income. Income CV is the most common measure of income volatility over time (see Hannagan and Morduch (2015), Morduch and Siwicki (2017), Wolf et al. (2014)). The larger the income CV, the higher the income volatility. The income CV is capped at 100 in my analysis since the income CVs above 100 are rare (see Appendix C.3) and should be removed as outliers.

Appendix C.4 demonstrates a random borrower's income pattern across years. This borrower was chosen because his income CV is at the sample mean of 32%. His average income across all periods is at \$2,543.61, which is about \$500 lower than the sample average. We can observe quite a few ups and downs in his income. For example, his income has decreased to as low as \$291 at period 3, then increased as high as \$5,000 at period 20 and \$4,500 at period 42.

3.3.4 Summary Statistics

Table 3.1 reports summary statistics for my sample. I present mean and standard error for each variable for the control and treated states. The table also provides p-values computed using the paired t-test for the difference in means between these two groups. There are some differences between the two groups, but the difference is not substantial.

For the outcome variables, the individuals who reside in the treated states tend to have slightly higher values than those who live in the control states. Compared with people from the control states, borrowers from the treated states tend to live at the current address longer, are more likely to be paid monthly, and are less likely to be paid weekly. For the rest of the features, the borrowers from the control and treated states are very close to each other. Payday loan lenders collect these variables and are regularly maintained since all information is highly relevant to the business's survival; thus, the data is highly trustworthy.

Appendix C.5 further illustrates the relationship between income CV and each feature. For age, people who are older (especially when older than 70) are less likely to experience high income volatility (i.e., income CV is beyond 75%). For net monthly income, the higher a borrower earns, the less likely one is to experience a high income CV. For months at the current address, the longer a borrower stays at the same place, the less likely they are to experience a high income CV. For pay frequency, borrowers of each pay frequency are all

Table 3.1: Borrower Summary Statistics in 2015

	Control States (N = 4,205) Treated States (N = 1,584)				
	Mean		SD		p-value
	Control	Treated	Control	Treated	
Outcome Variables					
Amount Past Due	\$20.716	\$23.141	\$3.067	\$2.666	0.019
Original Charge-Off	\$7.108	\$9.106	\$1.909	\$3.051	0.022
Delinquency Rate	12.926	15.150	3.553	5.865	0.017
Charge-Off or Debt-in-Collections Rate	13.252	16.877	3.909	7.467	0.025
Borrower's Characteristics					
Age	45.116	44.330	12.235	12.364	0.890
Income CV	32.653	31.906	15.309	16.845	0.987
Months at Address	27.887	30.271	24.564	23.861	0.175
Pay Frequency: Biweekly	49.902	50.654	5.289	6.284	0.223
Pay Frequency: Monthly	24.326	26.418	2.193	2.485	0.024
Pay Frequency: Weekly	13.292	11.478	1.384	1.009	0.342
Pay Frequency: Semimonthly	12.382	11.267	1.909	0.880	0.242
Pay Frequency: Annual	0.098	0.182	0.019	0.201	0.326
Housing Status: Rent	56.878	57.279	5.891	5.766	0.101
Housing Status: Own	38.998	38.451	4.028	3.991	0.103
Housing Status: Other	3.128	3.290	0.349	0.290	0.071
Housing Status: Living with Family	0.116	0.177	0.044	0.029	0.012
Housing Status: Living with Friends	0.448	0.300	0.067	0.013	0.007
Housing Status: Living with Parents	0.431	0.504	0.045	0.027	0.492

Notes: The five treated states are Delaware, Florida, Louisiana, Nevada, and Utah. See Appendix B.3 in Chapter 2 for the exact treated dates. The fourteen control states are Hawaii, Illinois, Iowa, Kansas, Kentucky, Minnesota, Mississippi, Missouri, Nebraska, North Dakota, Oklahoma, Rhode Island, Tennessee, and Texas. For all dollar values, the numbers are adjusted to 2020 dollars using the consumer price index for urban consumers. The table reports the mean ratios for delinquency rate, charge-off or debt-in-collections, pay frequency, and housing status. The p-values are from the t-test for the mean differences between the control and treated groups. Note that the sample is aggregated at year level. In 2015, there were 4,205 unique borrowers residing in control states and 1,584 borrowers living in treated states.

likely to experience high income volatility, but it is more so for people who are paid monthly. For housing status, borrowers who rent are likelier to have high income volatility.

3.4 Empirical Strategy

3.4.1 Double Machine Learning: Average Treatment Effect

There are two types of DML models mentioned in Chetverikov et al. (2016): partially linear regression model (PLR) [13] and interactive regression model (IRM). This study uses the IRM model because the treatment effects can be fully heterogeneous, and the treatment variable is assumed to be binary.

The IRM model is defined as follows:

$$y = g_0(D, X) + \zeta, \;\; E[\zeta|X, D] = 0, \tag{3.2}$$

$$D = m_0(X) + \nu, \;\; E[\nu|X] = 0. \tag{3.3}$$

Where D is the binary treatment variable - whether an individual lives in a treated or control state. X is a set of borrower features, including age, income CV, months at current address, pay frequency, and housing status. y is the outcome variable related to financial health. Since D is not additively separable, this model is more general than the PLR model.

To avoid over-fitting, the algorithm uses five-fold cross-fitting. For the prediction part, I use a random forest with a maximum depth of 5 and a minimum sample leaf of 2. See Appendix C.6 for the detailed procedure.

[13] The partially linear regression (PLR) model is defined as $Y = D\theta_0 + g_0(Z) + \zeta$, where $E[\zeta|Z, D] = 0$, and $D = m_0 Z + V$, where $E[V|Z] = 0$. In this setting, θ_0 measures the average treatment effect (ATE) of D on potential outcomes.

The average treatment effect (ATE) is identified by:

$$E[g_0(1, X) - g_0(0, X)]. \tag{3.4}$$

Table 3.2 shows the ATE for each year using the DML method. All results are negative and do not appear to have an apparent pattern. For the amount past due, the first year, 2015, is negative but not significant, while ATEs for the rest of the years are significant but vary in magnitude. The ATE is the largest in 2016 and the smallest in 2019. All original charge-off results are significant, with 2017 having the largest effect and 2015 having the smallest effect. Regarding delinquency rate, 2015 has the smallest ATE and is non-significant, while 2018 has the largest ATE. The first two years' results are insignificant for the charge-off or debt-in-collections rate, with 2015 having the smallest ATE. The largest ATE was in 2017. These results are ATEs for each year. To understand the effect of extended payment plans on the financial health of borrowers who experience different income volatility, we need to implement a CATE model as demonstrated in Section 3.4.2.

One thing to note is that the DML model is implemented on aggregated annual data instead of typical cross-sectional data. Theoretically, the DML model used in this study is designed for cross-sectional data [14]. There are a few reasons for doing so. First, we do not observe any policy changes or large economic shocks (except for 2020) that could affect payday loan lending. Hence, we assume the aggregated annual data does not have time-variant elements. Second, we aggregate data by year because each feature can be treated as time-invariant; thus, it will not suffer from omitted variable bias. For the numerical variables, age is the same each year for each individual i; months at the current address have little change for each year and are averaged out for that year; income CV is the same each year for each individual i, yet it still captures income volatility. For categorical variables, pay frequency and housing

[14] There are cases where DML is implemented on panel data. For example, in Microsfot Research (2023), the example used in the study treats orange juice panel data as pooled cross-sectional data.

Table 3.2: Average Treatment Effect Estimates.

Year	Amount Past Due	Original Charge-Off	Delinquency Rate	Charge-Off or Debt-in-Collections Rate
2015	-14.3384	-10.7449*	-0.0018	-0.0040
	(16.5212)	(6.2517)	(0.0069)	(0.0937)
2016	-36.9804**	-24.7282*	-0.0302*	-0.0301
	(15.8768)	(13.5442)	(0.0164)	(0.1198)
2017	-13.4121*	-37.2359*	-0.0171*	-0.0354**
	(7.9385)	(19.1379)	(0.0099)	(0.0162)
2018	-20.9190*	-22.3515**	-0.0326***	-0.0141**
	(11.4829)	(11.3621)	(0.0131)	(0.0073)
2019	-7.8651*	-19.2425*	-0.0063*	-0.0072*
	(4.0563)	(10.5332)	(0.0037)	(0.0038)
2020	-24.9912***	-15.8660***	-0.0121*	-0.0240**
	(9.0751)	(2.9805)	(0.0066)	(0.0101)

Notes: The effect for amount past due and original charge-off are in dollar amount. The effect of delinquency rate and charge-off or debt-in-collections rate are in ratio. There were 5,497 unique borrowers (3,992 in control states and 1,505 in treated states) in 2015, 6,732 borrowers (4,532 in control states and 2,200 in treated states) in 2016, 7,074 borrowers (4,639 in control states and 2,435 in treated states) in 2017, 7,197 borrowers (4,589 are in control states and 2,608 in treated states) in 2018, 7,703 borrowers (5,100 in control states and 2,603 in treated states) in 2019, and 4,354 borrowers (2,979 in control states and 1,375 in treated states) in 2020. Note that there is a 43.48% reduction in borrowers from 2019 to 2020. For the estimation results, *** means 99% significance level, ** means 95% significance level, and * means 90% significance level.

status take the most frequent observation for that year. There are also data limitations. The income is recorded as net monthly income. If we cannot observe enough variations in income within a month, we cannot compute income CV if we want to use monthly-level data (a more granular level).

For 2020 results, special considerations should be taken, given that approximately three-quarters of the year was characterized by the profound disruptions associated with the global pandemic. There is a 43.48% reduction in borrowers from 2019 to 2020 in the Clarity sample data. This decrease is under the confluence of several factors. First, fewer payday loans were approved due to the pandemic when people were losing jobs and experiencing declined incomes. According to CFPB (2022c), payday loan volume declined in 2020 by about 65% from 2019.

Second, federal and local governments implemented stimulus policies and debt relief measures that reduced the need for alternative financial services loans (e.g., payday loans). On March 27, 2020, President Trump signed the CARES Act, a $2.2 trillion economic stimulus bill to help cushion individuals against the negative impact of the pandemic (Congressional Research Service, 2020). In the same month, the Federal Reserve slowly cut the federal funds rate from 1.59% on March 3 to 0.25% on March 16 and further down to 0.09% at the end of the year (FRED, 2023). Some local policies may include tax credits, direct cash payments, and expanded Medicaid. As a result, fewer people took out payday loans to finance their spending. Finally, consumers spent less during the pandemic. Celik et al. (2020) used survey data and discovered that state-mandated economic lockdowns reduced consumer spending during the early stage of the pandemic, and many people still kept their expenses low even when the economies began to reopen. For example, 57% of people's spending is less than their income in 2020, compared to 54% in 2019. The 3% increase is an indicator of better financial health.

Using credit bureau data from February 2020 to August 2021, research by Urban Institute (2022) suggests that several credit health measures improved during the pandemic. These measures include improved overall credit scores and a decreased share of residents carrying past-due debt. Celik et al. (2020) finds that as of August 2020, about 33% of people in America were financially healthy, an increase from June 2019 (29%). The ATEs for all variables in 2020 are negative and significant, and some are considered large. These estimates may be elevated by the federal and local policies and changes in consumer behaviors mentioned above. Hence, these estimates can only be used as references.

3.4.2 Double Machine Learning: Conditional Average Treatment Effect

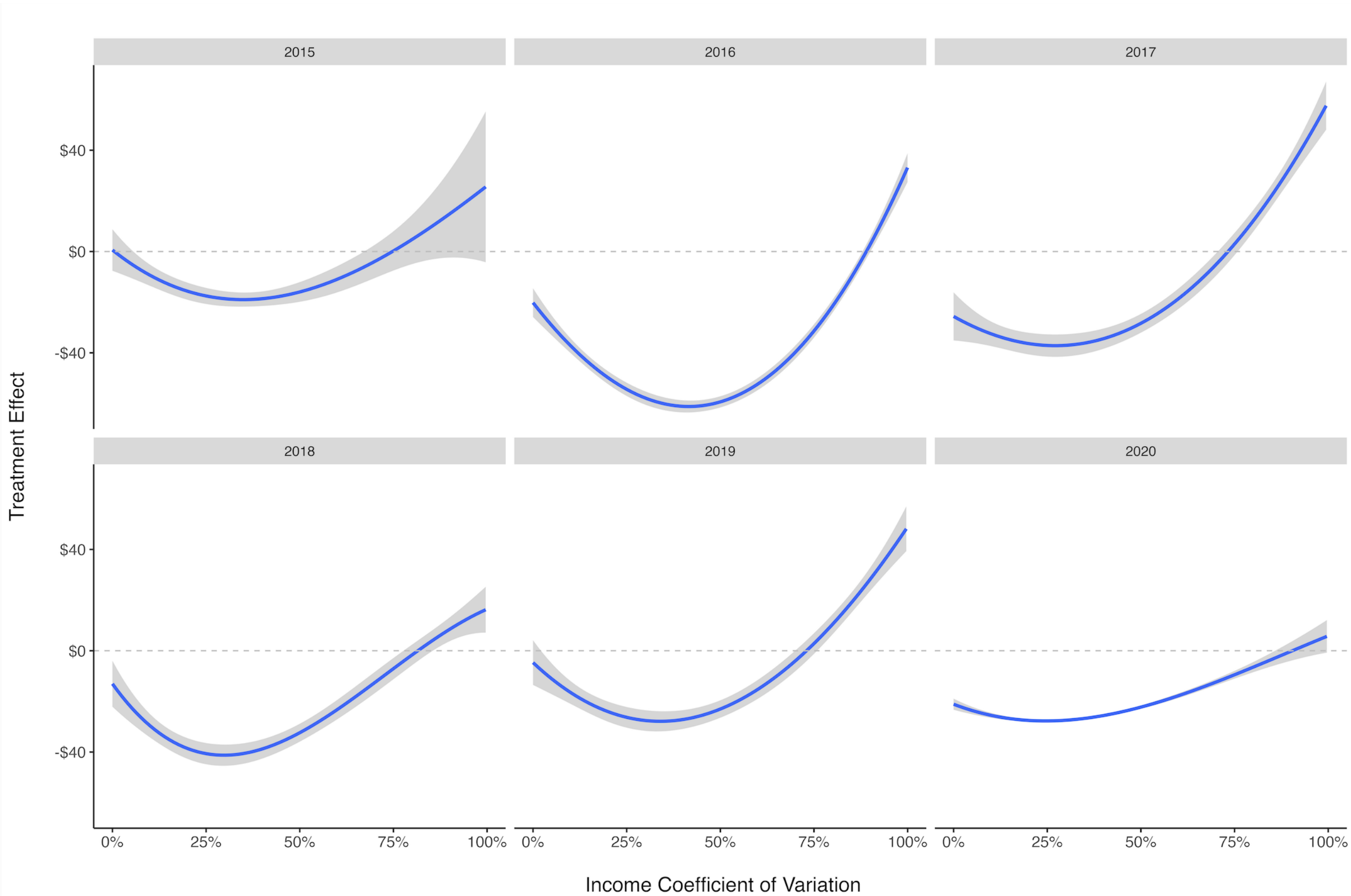
This section explores CATE built on top of Section 3.4.1 for each income volatility level. The CATE is defined as:

$$\theta_0(X) = E[Y(1) - Y(0)|X = x] \tag{3.5}$$

To estimate CATE, we use the best-linear-predictor of the linear score following Semenova and Chernozhukov (2021). We have to define a data frame of basis functions to approximate the target function $g(x)$ with a linear form. Here, we use B-splines with quadratic form and a degree of freedom of 5 using sample code by Microsoft (2023). We use quadratic form because it is the most straightforward way to estimate heterogeneous effects; linear form gives a straight line that cannot capture the non-linearity; and cubic form exaggerates the non-linearity in practice and gives no clear clue of the heterogeneous effect. The degree of freedom is set at 5 (or 3 knots). Higher degrees of freedom would make the estimates too "wiggly" and make it hard to visualize the heterogeneous effects. Since we want to see how different income levels are affected by the extended payment plans, we condition on the variable income CV.

Figure 3.1 shows CATE for different levels of income volatility in each year for the amount past due. We can observe several patterns. First, the overall trend appears to be U-shaped: people who are in between the first quartile and median income volatility benefit the most from this law; borrowers at the first 25th percentile gradually receive more and more treatment effect; people between median and third quartile receive less and less treatment effect until the effect disappears; after the third quartile, people do not seem to receive any treatment effect overall. Second, people whose income volatility is below the 75% percentile generally

Figure 3.1: Conditional Average Treatment Effect Plot for Amount Past Due



Notes: The income coefficient of variation is presented in percentage for easier interpretation.

do receive a reduction in their amount past due because of extended payment plans. Finally, the treatment effect varies from year to year, and there seems to be no apparent pattern (i.e., whether the treatment effect increases or decreases over the years).

Appendix C.7 shows plots for the rest of the outcome variables. Overall, they seem to follow the same U-shape as the amount past due but with some differences. Appendix C.7 panel (a) are heterogeneous treatment effects for the original charge-off. For all years, the treatment effects for borrowers of all income CV levels are positive (under the $0 horizontal line) except for borrowers whose income CV is beyond 75% in 2017 and 2019. The curves are flat, at least for borrowers of below 75% income CV. This may suggest that, unlike the amount past due, people of different income volatility levels experience about the same treatment effect each year. The exceptional results are in 2017 and 2019, where borrowers with lower volatile income (below 50% income CV) experience similar (in 2017) or increasing (in 2019) treatment effect, and borrowers with higher volatile income (beyond 50% income CV) experience from decreased to no treatment effect.

Appendix C.7 panel (b) gives CATE for delinquency rate. Overall, people between the first and third quartile receive positive treatment effects. For 2015, 2018, and 2020, some borrowers before the 25% income CV did not have a positive treatment effect; for the rest of the years, borrowers before the 25% income CV received a positive treatment effect. For most years (except for 2017 and 2020), borrowers between the first quartile and median income CV experience the most reduction in delinquency rate; borrowers between the median and third quartile receive decreased treatment effect; and after the third quartile, borrowers do not get any treatment effect. In 2017 and 2020, borrowers between the median and third quartile received the most treatment effect.

Appendix C.7 panel (c) are heterogeneous treatment effects for the charge-off or debt-in-collections rate. The shapes for each year are more different, possibly due to the combined rates for charge-off and debt-in-collections. For most years (except for 2017), many borrowers below 25% income CV do not receive any treatment effect. Borrowers between the first and third quartiles get positive reductions in the delinquency rate, with the ones between the first quartile and median receiving increasing positive effects and those between the median and third quartile receiving decreasing positive effects. Borrowers on the higher end of income volatility (when income CV ¿ 75%) do not have a reduced delinquency rate. Similarly, all the 2020 results can only be used as references due to the COVID-19 shocks throughout most of the year.

3.5 Conclusions and Discussions

This paper uses a double machine learning method to explore the heterogeneous treatment effect of the payday loan extended payment plans on financial health for borrowers of different income volatility. Using the Clarity sub-prime payday loan data, I can estimate the effects of these extended payment plan laws on different financial health outcomes. The main findings are that this law's treatment effect varies from year to year with no apparent pattern. People whose income volatility is between the first quartile and median levels experience the most benefit from this law.

These findings have a few policy implications. First, the other fourteen states where payday loans are legal could also implement extended payment plans to make repayment more transparent and cheaper, improving borrowers' financial health. Second, people who are at the higher end of income volatility do not benefit from this type of law and may require complementary support, such as job training to have more secure jobs, government monetary assistance, and financial literature training. Finally, the federal and state should monitor and enforce the extended payment plan more effectively. In states where rollovers are allowed, or the extended payment plan needs to be better followed, borrowers may still fall into the debt trap by either rolling over or obtaining new loans.

There are a few limitations of this study. First, the income volatility used in this study is measured by income CV, invariant to scales or absolute changes in income. The disadvantage of income CV is that it does not show the income dynamics over time [15]. In future studies, we can measure income volatility considering its frequency and direction mentioned in Wolf et al. (2014). Second, only five states have recorded data for both pre- and post-treatment.

[15] Consider household A with a net monthly income of \$3,000, \$750, and \$3,000, and household B with a net monthly income of \$3,000, \$2,250, and \$738. The income CV is about 57.7% for both households. However, this measurement of income volatility does not show the direction of the changes: Household A first experiences a large negative income shock but bounces back to the original level quickly, whereas household B experiences a series of income drops.

In reality, fifteen states passed the extended payment plans. Clarity covers more than 70% of non-prime consumers in the U.S., making it the most comprehensive payday loan data available. Future studies could evaluate the effect of extended payment plans on financial health should more comprehensive data be available.

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Appendix A

Chapter 1

A.1 Dairy Milk and Plant-Based Milk: Nutrient Comparison

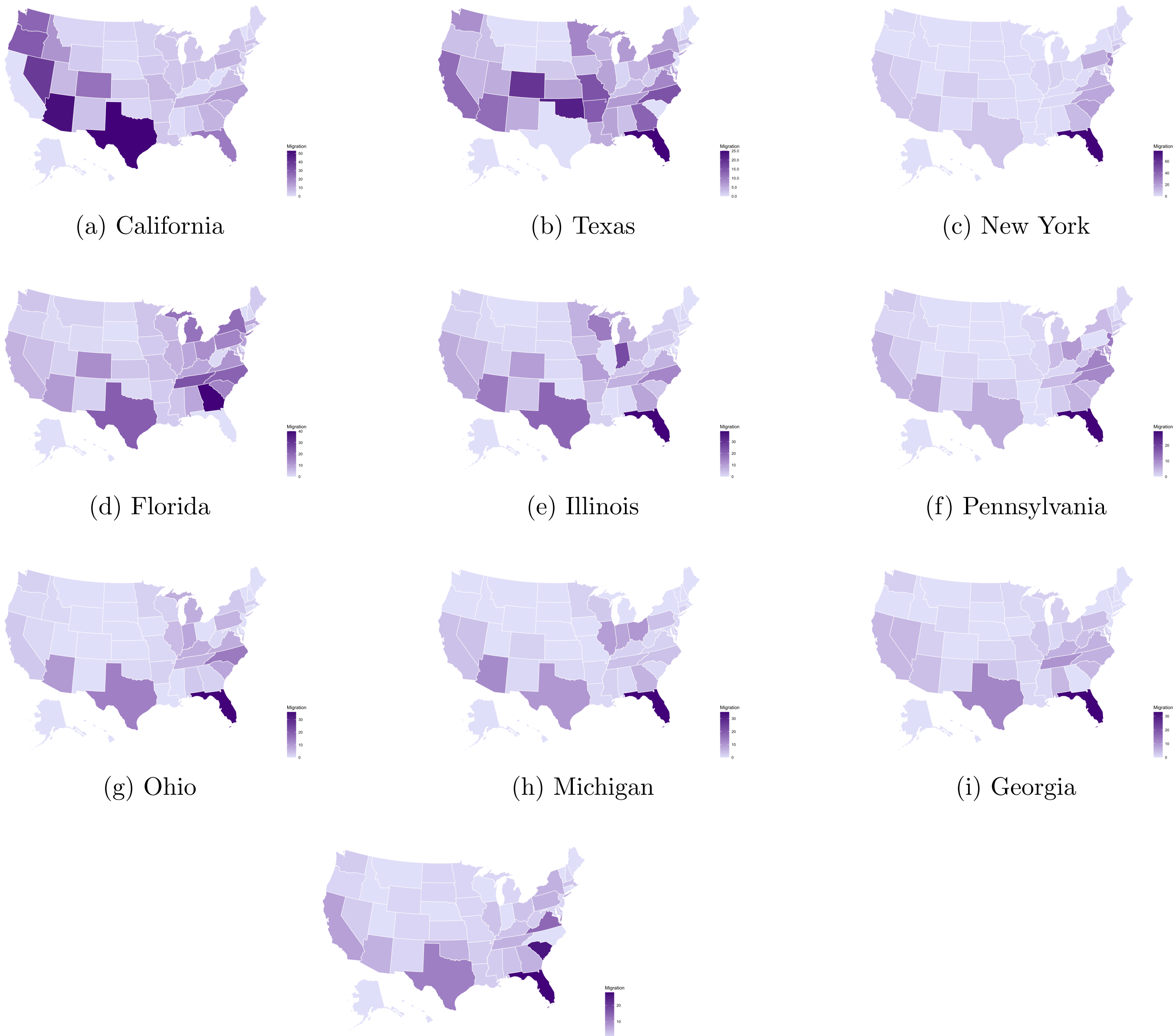
Table A.1.1: Nutritional Profile of Different Types of Milk.

Nutrients	**Whole**	**Skim**	**Soy**	**Almond**	**Oat**	**Coconut**	**Rice**
Calories	150 kcal	80 kcal	80 kcal	30 kcal	90 kcal	40 kcal	120 kcal
Total Fat	8 g	0 g	4 g	2.5 g	1.5 g	4 g	2.5 g
Saturated Fat	5 g	0 g	0.5 g	0 g	0 g	3 g	0 g
Sodium	120 mg	100 mg	75 mg	125 mg	120 mg	45 mg	100 mg
Carbohydrates	12 g	12 g	3 g	1 g	19 g	1 g	23 g
Dietary Fiber	0 g	0 g	2 g	<1 g	2 g	0 g	0 g
Total Sugars	12 g	12 g	1 g	0 g	4 g	0 g	10 g
Added Sugar	0 g	0 g	0 g	0 g	4 g	0 g	0 g
Protein	8 g	8 g	7 g	1 g	2 g	0 g	1 g
Calcium	28%	30%	20%	30%	25%	35%	30%
Folate	3%	3%	10%	-	-	-	-
Iron	1%	1%	6%	2%	2%	2%	4%
Magnesium	6%	7%	8%	2%	-	-	-
Phosphorus	21%	25%	6%	-	-	-	15%
Potassium	9%	10%	7%	2%	8%	6%	1%
Riboflavin	24%	26%	30%	-	10%	-	-
Vitamin A	11%	10%	15%	15%	20%	20%	10%
Vitamin B12	18%	20%	120%	-	10%	35%	25%
Vitamin D	31%	29%	15%	10%	20%	10%	25%
Vitamin E	-	-	-	25%	-	20%	-

Notes: Nutrient data comes from https://totaste.com/got-milk-which-one/. These measures are similar to the results published in Vanga and Raghavan (2018).

A.2 Migration Maps

Figure A.2.1: Migration Maps for Top 10 Most Populous States in the U.S.



(a) California

(b) Texas

(c) New York

(d) Florida

(e) Illinois

(f) Pennsylvania

(g) Ohio

(h) Michigan

(i) Georgia

(j) North Carolina

Notes: The darker the purple, the more people who migrate to that state. The data source is Nielsen.

A.3 Logit Model Results

Table A.3.1: Logit Model to Predict Why Households Move

	Dairy Milk		**Plant Milk**	
	(1)	(2)	(3)	(4)
	Coeffs	AMEs	Coeffs	AMEs
Age (Young)	0.010	0	0.258	0.013
	(0.059)	(0.003)	(0.304)	(0.017)
Age (MidL)	-0.508	-0.015	-0.169*	-0.008
	(0.515)	(0.012)	(0.099)	(0.005)
Age (MidH)	0.183	0.008	-0.181	-0.008
	(0.184)	(0.008)	(0.166)	(0.007)
Age (Old)	-0.140	-0.005	-0.017	-0.001
	(0.308)	(0.010)	(0.135)	(0.006)
Children	-0.080	-0.003	-0.143	-0.007
	(0.053)	(0.002)	(0.178)	(0.009)
No Children	0.058	0.002	0.272	0.014
	(0.098)	(0.004)	(0.167)	(0.009)
Educ(No College)	0.034	0.001	-0.027	-0.001
	(0.218)	(0.008)	(1.065)	(0.047)
Educ (College+)	0.031	0.001	0.163	0.008
	(0.037)	(0.001)	(0.163)	(0.008)
Income (Low)	-0.004	0	-0.278**	-0.012
	(0.049)	(0.002)	(0.101)	(0.004)
Income (Med)	-0.372	-0.011	-0.046	-0.002
	(0.234)	(0.006)	(0.080)	(0.004)
Income (High)	0.065	0.003	0.057	0.003
	(0.147)	(0.006)	(0.131)	(0.006)
Race (White)	-0.104	-0.004*	0.02	0.001
	(0.066)	(0.002)	(0.095)	(0.004)
Race (Black)	-0.018	-0.001	-0.171	-0.007
	(0.039)	(0.001)	(0.152)	(0.006)
Race (Asian)	0.009	0	0.245*	0.011
	(0.068)	(0.002)	(0.128)	(0.005)
Single	0.107***	0.004	0.175	0.009
	(0.037)	(0.001)	(0.117)	(0.006)
Married	-0.065	-0.002	-0.039	-0.002
	(0.054)	(0.002)	(0.125)	(0.006)
Employed	0.078	0.003	-0.231	-0.010
	(0.049)	(0.002)	(0.229)	(0.009)
Unemployed	-0.073	-0.003	-0.166	-0.008
	(0.048)	(0.002)	(0.141)	(0.007)
Non-Movers	183,266	183,266	70,804	70,804
Movers	4,762	4,762	2,732	2,732
Observations	3,323,626	3,323,626	434,264	434,264

Notes: The model uses full sample. The characteristics are from the first year HH moved for movers and are from the first year of the sample for non-movers. The "age(young)" refer to HH $<$ 34 years old, "age(midL)" 35 to 49 years old, "age(midH)" 50 to 64 years old, and "age(old)" $>$ 65 years old. The "children" includes those $\leq$ 18 years old only, and "no children" includes HH who don't have children $\leq$ 18 years old. The "no college" are those who hold a high school degree or lower, and "college+" includes HH who completed some college and beyond. The low-income group are HH who earn $\leq$ \$39,999 annually, median income group earns \$40,000 to \$69,999 per year, and high-income group earns $\geq$ \$70,000 each year. *** Significant at 1% level.** Significant at 5% level.* Significant at 10% level.

A.4 DiD Estimates (Movers Data Only)

Table A.4.1: Dairy Milk Expenditure Patterns After Move. DiD Estimates.

	(1)	(2)	(3)	(4)	(5)	(6)
Base Specification	0.012**					
	(0.006)					
Age: Young		-0.141***				
		(0.028)				
Age: MidL		-0.077***				
		(0.016)				
Age: MidH		0.050***				
		(0.011)				
Age: Old		-0.029*				
		(0.015)				
Children: <12			0.090***			
			(0.029)			
Children: ≥12			-0.124***			
			(0.025)			
Children: Mixed			0.045			
			(0.032)			
Children: None			0.161***			
			(0.026)			
Educ: HS				0.029		
				(0.029)		
Educ: College				0.015*		
				(0.009)		
Educ: Grad				-0.032*		
				(0.015)		
Income: Low					0.037**	
					(0.016)	
Income: Med					0.007	
					(0.014)	
Income: High					-0.009	
					(0.011)	
Race: White						0.011
						(0.008)
Race: Black						0.009
						(0.030)
Race: asian						-0.004
						(0.043)
Households	4,762	4,762	4,762	4,762	4,762	4,762
Observations	148,786	148,786	148,786	148,786	148,786	148,786

Notes: The model uses movers data only. It includes both quarter and HH fixed effects. The standard errors are clustered at a HH level. The age and income groups are defined the same as in Appendix A.3. Children (< 12) refer to children who are under 12 years old, and Children (≥ 12) are for those who are 12 years old or older. Family who has children below and above 12 years old, they are in Children (mixed) group. Family who has no children under 18 years old belong to Children (none) group. The high school group includes those who hold high school degrees or lower. The college group includes those who have some college education or hold a college degree. The grad group includes those who have a post-college education. *** Significant at 1% level.** Significant at 5% level.* Significant at 10% level.

Table A.4.2: Plant Milk Expenditure Patterns After Move. DiD Estimates.

	(1)	(2)	(3)	(4)	(5)	(6)
Base Specification	-0.006					
	(0.013)					
Age: Young		-0.118**				
		(0.055)				
Age: MidL		-0.079**				
		(0.034)				
Age: MidH		0.044*				
		(0.026)				
Age: Old		-0.014				
		(0.035)				
Children: <12			0.024*			
			(0.053)			
Children: ≥12			-0.084			
			(0.046)			
Children: Mixed			0.047			
			(0.067)			
Children: None			0.119**			
			(0.048)			
Educ: HS				0.078		
				(0.055)		
Educ: College				0.002		
				(0.020)		
Educ: Grad				0.001		
				(0.030)		
Income: Low					0.033	
					(0.034)	
Income: Med					0.035	
					(0.029)	
Income: High					-0.020	
					(0.021)	
Race: White						0.023
						(0.019)
Race: Black						-0.098**
						(0.044)
Race: Asian						0.025
						(0.067)
Households	2,732	2,732	2,732	2,732	2,732	2,732
Observations	22,484	22,484	22,484	22,484	22,484	22,484

A.5 First Difference Estimates (Movers Data Only)

Table A.5.1: Dairy Milk Expenditure Patterns After Move. First Difference.

	(1)	(2)	(3)	(4)	(5)	(6)
Base Specification	0.014***					
	(0.038)					
Age: Young		-0.118***				
		(0.017)				
Age: MidL		-0.085***				
		(0.009)				
Age: MidH		0.026***				
		(0.006)				
Age: Old		-0.027***				
		(0.008)				
Children: <12			0.061***			
			(0.016)			
Children: ≥12			-0.058***			
			(0.013)			
Children: Mixed			0.020			
			(0.019)			
Children: None			0.087***			
			(0.013)			
Educ: HS				0.056***		
				(0.010)		
Educ: College				-0.023		
				(0.005)		
Educ: Grad				-0.011***		
				(0.008)		
Income: Low					0.001	
					(0.008)	
Income: Med					-0.042***	
					(0.008)	
Income: High					-0.020***	
					(0.006)	
Race: White						-0.018***
						(0.005)
Race: Black						0.030**
						(0.013)
Race: Asian						-0.156***
						(0.021)
Households	188,028	188,028	188,028	188,028	188,028	188,028
Observations	3,323,626	3,323,626	3,323,626	3,323,626	3,323,626	3,323,626

Notes: The model uses movers data only. It includes both quarter and HH fixed effects. The standard errors are clustered at a HH level. *** Significant at 1% level.** Significant at 5% level.* Significant at 10% level.

Table A.5.2: Plant Milk Expenditure Patterns After Move. First Difference.

	(1)	(2)	(3)	(4)	(5)	(6)
Base Specification	-0.003					
	(0.009)					
Age: Young		-0.030				
		(0.039)				
Age: MidL		-0.067***				
		(0.023)				
Age: MidH		-0.029*				
		(0.016)				
Age: Old		0.018				
		(0.023)				
Children: <12			0.060			
			(0.040)			
Children: ≥ 12			-0.045			
			(0.033)			
Children: Mixed			0.077			
			(0.051)			
Children: None			0.043			
			(0.034)			
Educ: HS				0.126***		
				(0.032)		
Educ: College				-0.074***		
				(0.014)		
Educ: Grad				-0.021		
				(0.021)		
Income: Low					0.066***	
					(0.022)	
Income: Med					0.062***	
					(0.021)	
Income: High					-0.123***	
					(0.015)	
Race: White						-0.050***
						(0.013)
Race: Black						-0.068**
						(0.028)
Race: Asian						-0.097**
						(0.049)
Households	73,536	73,536	73,536	73,536	73,536	73,536
Observations	434,264	434,264	434,264	434,264	434,264	434,264

A.6 Event Study: Heterogeneous Effects

Table A.6.1: Heterogeneous Effects For Dairy Milk

	Age (Young)	Age (MidL)	Age (MidH)	Age (Old)	Children (< 12)	Children (≥12)	Children (Mixed)	Children (None)
Event Time								
-5	-0.011	0.008	-0.002	-0.007	0.006	-0.017	-0.04	0.017
	(0.021)	(0.016)	(0.010)	(0.016)	(0.030)	(0.027)	(0.036)	(0.028)
-4	-0.041*	-0.007	0.009	0	0.007	-0.042	0.012	0.059**
	(0.025)	(0.015)	(0.010)	(0.015)	(0.031)	(0.028)	(0.037)	(0.028)
-3	-0.051**	-0.015	0.017*	-0.011	-0.012	-0.034	0.020	0.054*
	(0.025)	(0.016)	(0.010)	(0.015)	(0.031)	(0.027)	(0.036)	(0.028)
-2	-0.057**	-0.011	0.014	-0.021	0.023	-0.056**	-0.002	0.071**
	(0.025)	(0.016)	(0.011)	(0.016)	(0.031)	(0.028)	(0.037)	(0.029)
-1	-0.045*	-0.004	0.010	0.006	0.025	-0.061**	0.004	0.084***
	(0.025)	(0.017)	(0.011)	(0.017)	(0.034)	(0.030)	(0.040)	(0.031)
0	0	0	0	0	0	0	0	0
1	-0.135***	-0.040**	0.035**	-0.041**	-0.033	-0.020	-0.019	0.038**
	(0.033)	(0.018)	(0.011)	(0.016)	(0.038)	(0.033)	(0.042)	(0.034)
2	-0.103***	-0.054**	0.028**	-0.032*	0.014	-0.049	-0.002	0.062*
	(0.032)	(0.018)	(0.012)	(0.017)	(0.036)	(0.031)	(0.041)	(0.032)
3	-0.107***	-0.045**	0.029**	-0.026	-0.036	-0.007	-0.049	0.024
	(0.035)	(0.019)	(0.012)	(0.017)	(0.038)	(0.032)	(0.041)	(0.033)
4	-0.028	-0.044**	0.021*	-0.005	0.038	-0.056*	0.004	0.077**
	(0.042)	(0.019)	(0.012)	(0.017)	(0.038)	(0.033)	(0.042)	(0.034)
5	-0.006	-0.047**	0.028**	-0.021	0.022	-0.033	-0.022	0.055
	(0.040)	(0.019)	(0.012)	(0.017)	(0.039)	(0.035)	(0.048)	(0.036)

Notes: The model uses full sample. It includes both quarter and HH fixed effects. The standard errors are clustered at a HH level. *** Significant at 1% level.** Significant at 5% level.* Significant at 10% level.

Table A.6.2: Heterogeneous Effects For Dairy Milk (cont.)

	Educ (HS)	Educ (College)	Educ (Grad)	Income (Low)	Income (Med)	Income (High)	Race (White)	Race (Black)	Race (Asian)
Event Time									
-5	-0.006	-0.004	0.022	0.004	0.001	-0.001	0.000	-0.012	0.026
	(0.021)	(0.008)	(0.015)	(0.015)	(0.014)	(0.010)	(0.007)	(0.027)	(0.044)
-4	-0.030	0.012	-0.017	0.010	0.008	-0.001	-0.001	0.005	0.051
	(0.020)	(0.008)	(0.014)	(0.015)	(0.014)	(0.009)	(0.007)	(0.027)	(0.037)
-3	-0.015	0.012	-0.020	0.024	0.021	-0.007	0.001	0.023	0.029
	(0.020)	(0.008)	(0.014)	(0.015)	(0.014)	(0.010)	(0.007)	(0.030)	(0.038)
-2	0.011	0.000	-0.004	0.023	0.018	-0.011	-0.006	0.050*	-0.003
	(0.020)	(0.008)	(0.015)	(0.015)	(0.015)	(0.010)	(0.007)	(0.029)	(0.037)
-1	0.021	0.006	-0.009	0.035**	0.015	-0.008	0.004	0.032	0.013
	(0.021)	(0.008)	(0.016)	(0.016)	(0.015)	(0.010)	(0.007)	(0.031)	(0.039)
0	0	0	0	0	0	0	0	0	0
1	0.016	0.008	-0.029*	0.030*	0.035**	-0.019*	0.001	-0.011	0.053
	(0.022)	(0.009)	(0.016)	(0.017)	(0.016)	(0.011)	(0.007)	(0.033)	(0.043)
2	0.010	0.000	-0.018	0.039**	0.031*	-0.026**	-0.005	0.030	0.026
	(0.023)	(0.009)	(0.017)	(0.017)	(0.016)	(0.011)	(0.008)	(0.034)	(0.046)
3	-0.013	0.005	-0.006	0.015	0.001 -	0.005	-0.001	-0.007	0.060
	(0.023)	(0.010)	(0.016)	(0.017)	(0.017)	(0.011)	(0.008)	(0.032)	(0.045)
4	0.033	0.010	-0.036**	0.029*	-0.009 -	0.003	0.005	-0.008	0.040
	(0.024)	(0.009)	(0.018)	(0.017)	(0.018)	(0.012)	(0.008)	(0.033)	(0.045)
5	0.016	0.013	-0.024	0.035**	-0.013 -	0.001	0.005	0.023	0.027
	(0.022)	(0.009)	(0.017)	(0.017)	(0.017)	(0.011)	(0.008)	(0.036)	(0.040)

Table A.6.3: Heterogeneous Effects For Plant Milk

	Age (Young)	Age (MidL)	Age (MidH)	Age (Old)	Children (<12)	Children (≥12)	Children (Mixed)	Children (None)
Event Time								
-5	0.025	0.060	-0.067***	0.051	-0.017	0.002	-0.188*	-0.036
	(0.051)	(0.043)	(0.024)	(0.043)	(0.080)	(0.065)	(0.101)	(0.067)
-4	0.060	0.068	-0.072***	0.032	0.060	-0.091	-0.045	0.068
	(0.052)	(0.042)	(0.025)	(0.039)	(0.131)	(0.124)	(0.140)	(0.125)
-3	-0.001	0.039	-0.041	0.058	-0.013	-0.050	-0.012	0.050
	(0.051)	(0.043)	(0.027)	(0.041)	(0.068)	(0.053)	(0.099)	(0.056)
-2	-0.007	0.010	-0.034	0.013	-0.009	-0.025	-0.112	0.012
	(0.050)	(0.045)	(0.032)	(0.042)	(0.066)	(0.056)	(0.104)	(0.060)
-1	0.021	0.063	-0.064**	0.011	-0.066	0.020	-0.256**	-0.053
	(0.056)	(0.042)	(0.026)	(0.039)	(0.072)	(0.062)	(0.108)	(0.064)
0	0	0	0	0	0	0	0	0
1	-0.088	0.022	-0.052*	0.049	-0.106	-0.035	-0.029	0.024
	(0.060)	(0.045)	(0.028)	(0.039)	(0.087)	(0.077)	(0.112)	(0.079)
2	-0.065	-0.052	0.001	0.030	0.086	-0.148*	0.018	0.164**
	(0.058)	(0.045)	(0.030)	(0.041)	(0.086)	(0.079)	(0.101)	(0.081)
3	-0.147**	-0.020	0.038	-0.043	0.069	-0.083	0.058	0.105
	(0.063)	(0.043)	(0.029)	(0.044)	(0.072)	(0.063)	(0.125)	(0.066)
4	-0.104	-0.016	-0.013	-0.029	0.093	-0.067	0.141	0.034
	(0.083)	(0.055)	(0.029)	(0.043)	(0.077)	(0.060)	(0.107)	(0.064)
5	-0.022	0.049	-0.046	0.014	-0.034 -	0.024	0.035	0.006
	(0.094)	(0.053)	(0.034)	(0.044)	(0.108)	(0.089)	(0.119)	(0.091)

Table A.6.4: Heterogeneous Effects For Plant Milk (cont.)

	Educ (HS)	Educ (College)	Educ (Grad)	Income (Low)	Income (Med)	Income (High)	Race (White)	Race (Black)	Race (Asian)
Event Time									
-5	-0.059	-0.054***	0.074*	-0.068*	-0.003	-0.014	0.002	-0.038**	0.035
	(0.076)	(0.020)	(0.039)	(0.041)	(0.038)	(0.025)	(0.050)	(0.019)	(0.129)
-4	0.044	-0.031	-0.040	-0.016	-0.019	-0.026	-0.041	-0.035**	-0.077
	(0.053)	(0.020)	(0.036)	(0.040)	(0.036)	(0.024)	(0.046)	(0.018)	(0.083)
-3	0.045	-0.024	0.006	-0.037	-0.028	0.003	-0.033	-0.019	0.096
	(0.057)	(0.022)	(0.033)	(0.043)	(0.035)	(0.024)	(0.055)	(0.018)	(0.123)
-2	0.062	-0.037*	0.007	-0.045	-0.039	-0.005	-0.001	-0.033*	-0.026
	(0.086)	(0.020)	(0.038)	(0.042)	(0.040)	(0.023)	(0.067)	(0.018)	(0.077)
-1	0.056	-0.057***	0.037	0.009	0.040	-0.053**	-0.002	-0.042**	0.090
	(0.063)	(0.020)	(0.036)	(0.040)	(0.036)	(0.025)	(0.050)	(0.018)	(0.115)
0	0	0	0	0	0	0	0	0	0
1	0.119**	-0.044**	-0.028	0.019	0.023	-0.058**	0.001	-0.043**	0.117
	(0.058)	(0.022)	(0.037)	(0.041)	(0.040)	(0.023)	(0.047)	(0.019)	(0.100)
2	0.032	-0.008	-0.027	0.030	-0.019	-0.02	-0.017	-0.015	0.069
	(0.066)	(0.023)	(0.036)	(0.042)	(0.039)	(0.025)	(0.048)	(0.020)	(0.094)
3	0.065	-0.005	0.024	-0.043	0.029	0.007	0.028	0.004	0.093
	(0.067)	(0.022)	(0.037)	(0.044)	(0.038)	(0.025)	(0.046)	(0.020)	(0.110)
4	0.065	-0.061**	0.075*	-0.014	-0.008	-0.032	-0.083	-0.021	0.120
5	0.053	-0.030	-0.012	0.051	-0.009	-0.050*	-0.048	-0.024	0.039
	(0.065)	(0.026)	(0.043)	(0.042)	(0.054)	(0.028)	(0.070)	(0.021)	(0.111)

A.7 DiD Heterogeneous Effects

Table A.7.1: Dairy Milk Expenditure Patterns After Move. DiD Heterogeneous Effects.

	(1)	(2)	(3)	(4)	(5)	(6)
Base Specification	0.012***					
	(0.006)					
Age: Young		-0.120***				
		(0.029)				
Age: MidL		-0.066***				
		(0.015)				
Age: MidH		0.024**				
		(0.010)				
Age: Old		-0.020				
		(0.013)				
Children: <12			0.050**			
			(0.023)			
Children: ≥12			-0.114***			
			(0.021)			
Children: Mixed			0.037			
			(0.025)			
Children: None			0.139***			
			(0.022)			
Educ: HS				0.023		
				(0.019)		
Educ: College				0.004		
				(0.009)		
Educ: Grad				-0.046***		
				(0.016)		
Income: Low					0.053***	
					(0.014)	
Income: Med					0.020	
					(0.013)	
Income: High					-0.031***	
					(0.010)	
Race: White						-0.003
						(0.008)
Race: Black						-0.005
						(0.030)
Race: Asian						-0.013
						(0.042)
Households	188,028	188,028	188,028	188,028	188,028	188,028
Observations	3,323,626	3,323,626	3,323,626	3,323,626	3,323,626	3,323,626

Notes: The model uses full sample. It includes both quarter and HH fixed effects. The standard errors are clustered at a HH level. *** Significant at 1% level.** Significant at 5% level.* Significant at 10% level.

Table A.7.2: Plant Milk Expenditure Patterns After Move. DiD Heterogeneous Effects.

	(1)	(2)	(3)	(4)	(5)	(6)
Base Specification	-0.015*					
	(0.008)					
Age: Young		-0.072				
		(0.060)				
Age: MidL		-0.037				
		(0.031)				
Age: MidH		-0.006				
		(0.024)				
Age: Old		0.019				
		(0.028)				
Children: $<$12			0.008			
			(0.045)			
Children: $\geq$12			-0.100**			
			(0.039)			
Children: Mixed			0.047			
			(0.049)			
Children: None			0.117***			
			(0.041)			
Educ: HS				0.081*		
				(0.046)		
Educ: College				-0.015		
				(0.018)		
Educ: Grad				-0.022		
				(0.030)		
Income: Low					0.031	
					(0.030)	
Income: Med					0.050*	
					(0.026)	
Income: High					0.045**	
					(0.019)	
Race: White						0.003
						(0.017)
Race: Black						-0.095**
						(0.044)
Race: Asian						-0.023
						(0.066)
Households	73,536	73,536	73,536	73,536	73,536	73,536
Observations	434,264	434,264	434,264	434,264	434,264	434,264

A.8 FD Heterogeneous Effects

Table A.8.1: Dairy Milk Expenditure Patterns After Move. First Differences Heterogeneous Effects.

	(1)	(2)	(3)	(4)	(5)	(6)
Base Specification	0.006**					
	(0.002)					
Age: Young		-0.103***				
		(0.014)				
Age: MidL		-0.085***				
		(0.007)				
Age: MidH		0.049***				
		(0.004)				
Age: Old		-0.043***				
		(0.006)				
Children: <12			-0.015			
			(0.013)			
Children: ≥ 12			-0.005			
			(0.010)			
Children: Mixed			-0.006			
			(0.014)			
Children: None			0.031***			
			(0.010)			
Educ: HS				0.063***		
				(0.008)		
Educ: College				0.003		
				(0.004)		
Educ: Grad				-0.030***		
				(0.006)		
Income: Low					0.013**	
					(0.006)	
Income: Med					-0.013**	
					(0.006)	
Income: High					0.003	
					(0.004)	
Race: White						0.007**
						(0.003)
Race: Black						-0.056***
						(0.010)
Race: Asian						0.183***
						(0.016)
Households	188,028	188,028	188,028	188,028	188,028	188,028
Observations	3,323,626	3,323,626	3,323,626	3,323,626	3,323,626	3,323,626

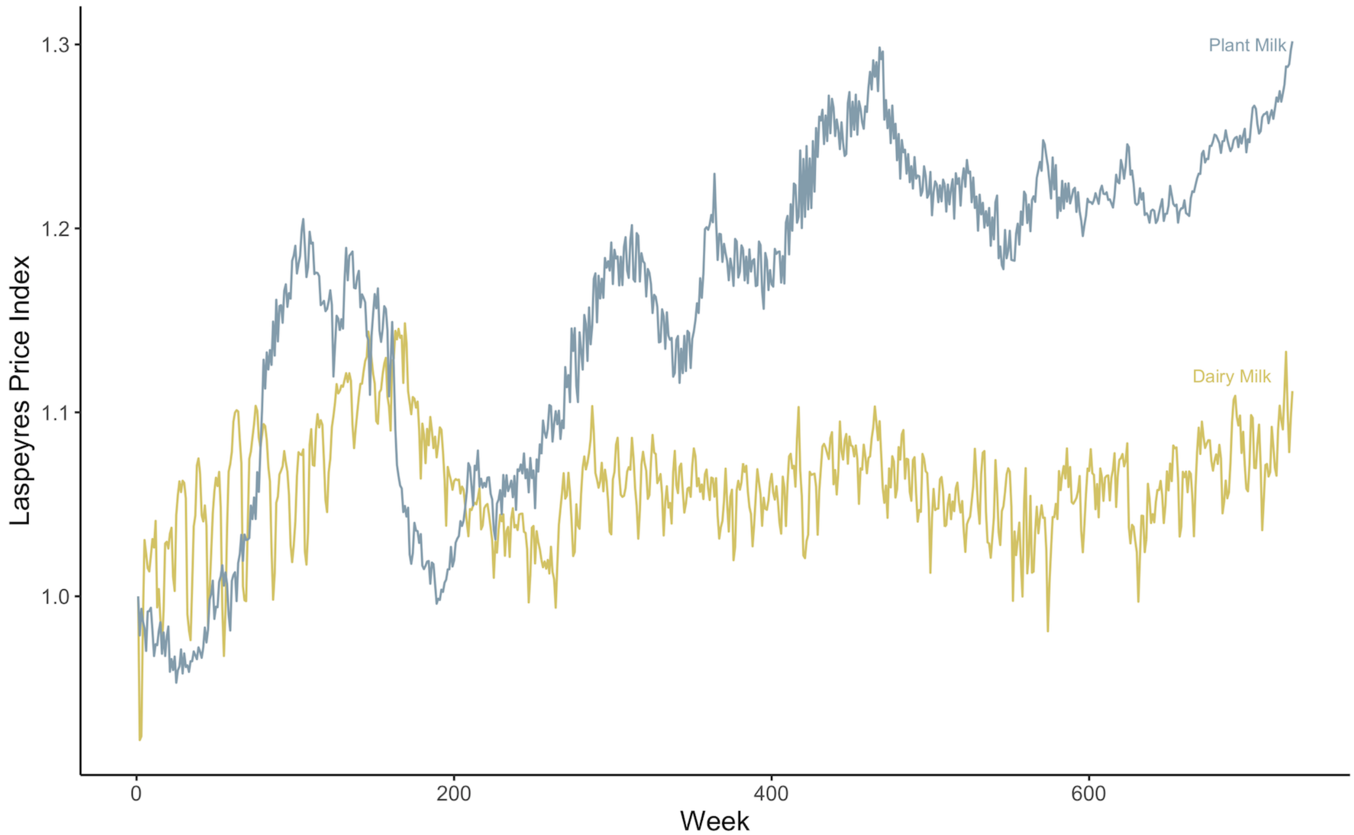
Notes: The model uses full sample. It includes both quarter and HH fixed effects. The standard errors are clustered at a HH level. *** Significant at 1% level.** Significant at 5% level.* Significant at 10% level.

Table A.8.2: Plant Milk Expenditure Patterns After Move. First Differences Heterogeneous Effects.

	(1)	(2)	(3)	(4)	(5)	(6)
Base Specification	-0.020***					
	(0.005)					
Age: Young		-0.078**				
		(0.034)				
Age: MidL		0.049***				
		(0.011)				
Age: MidH		-0.084***				
		(0.018)				
Age: Old		-0.001				
		(0.017)				
Children: <12			-0.003			
			(0.032)			
Children: ≥ 12			-0.012			
			(0.026)			
Children: Mixed			0.052			
			(0.039)			
Children: None			0.054**			
			(0.026)			
Educ: HS				0.087***		
				(0.024)		
Educ: College				0.007		
				(0.009)		
Educ: Grad				-0.014		
				(0.016)		
Income: Low					0.013	
					(0.017)	
Income: Med					0.031	
					(0.017)	
Income: High					0.002	
					(0.010)	
Race: White						0.034***
						(0.008)
Race: Black						-0.113***
						(0.003)
Race: Asian						-0.202***
						(0.005)
Households	73,536	73,536	73,536	73,536	73,536	73,536
Observations	434,264	434,264	434,264	434,264	434,264	434,264

A.9 Price Index

Figure A.9.1: Price Index for Dairy Milk and Plant Milk



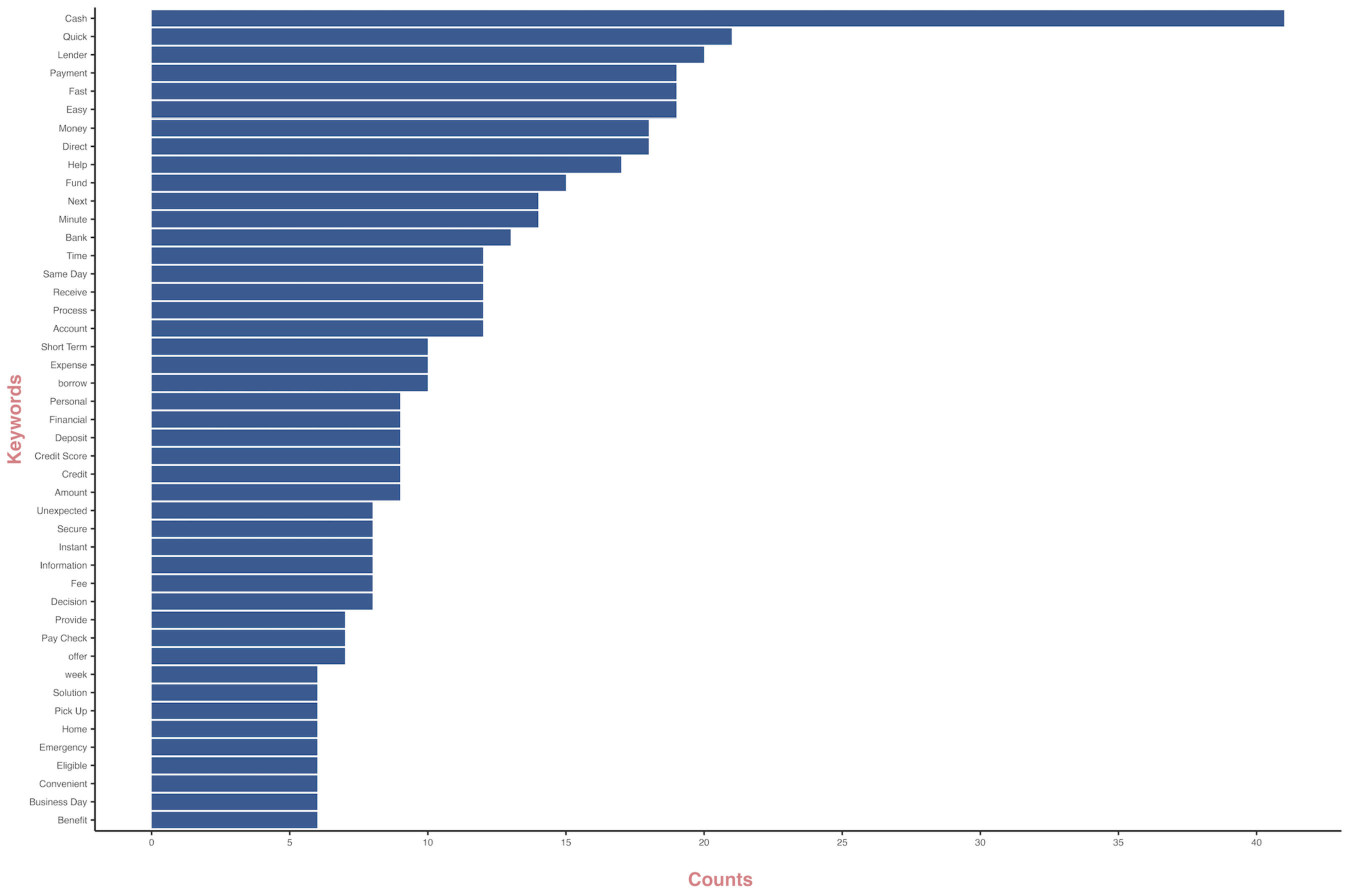
Notes: The data source is Nielsen.

Appendix B

Chapter 2

B.1 Payday Loan Features

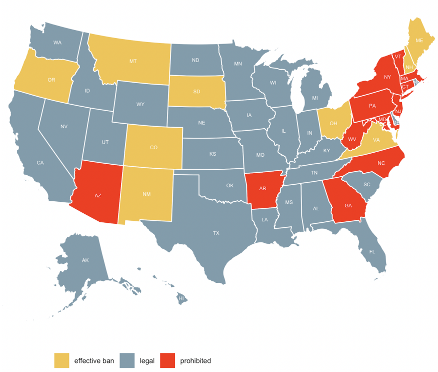
Figure B.1.1: Top 45 Most Utilized Words on Payday Loan Websites



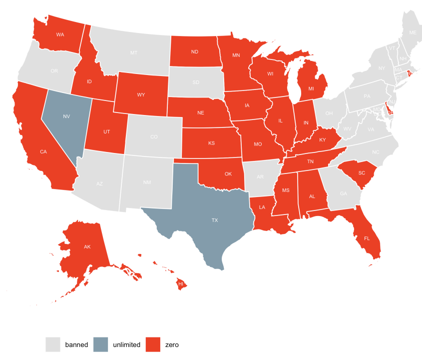
Notes: This is a text analysis of payday loan product descriptions. The text data is collected by the author based on US's 11 largest payday loan lenders' websites (at the time of the research), not from Clarity. These payday lenders are Ace Cash Express, Advance America, Cash Central, Cash Store, Check City, Check into Cash, Check n' Go, DirectPaydayLoans, Money Tree-California, My Payday Loan, Oasis Payday Loans, and PaydayChampion.

B.2 Maps

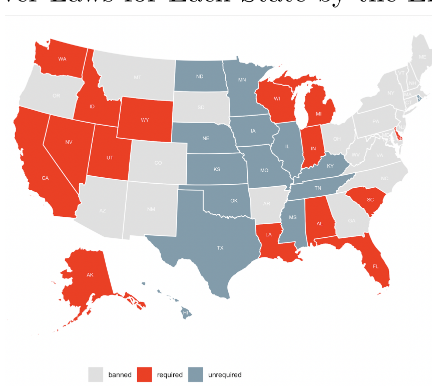
Figure B.2.1: Payday Loan Laws for Each State in the U.S.



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



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



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

Notes: For figure (a), the effective-ban states limit payday loan APRs to 36%. For figures (b) and (c), the gray areas represent those states that ban payday loans. The states that do not allow rollovers are in red, and those that allow rollovers are in blue. Similarly, the red states require extended payment plans, while the blue ones do not. The data is collected by the author based on each state's deferred deposit transaction law, not from Clarity.

B.3 Extended Payment Plans Features

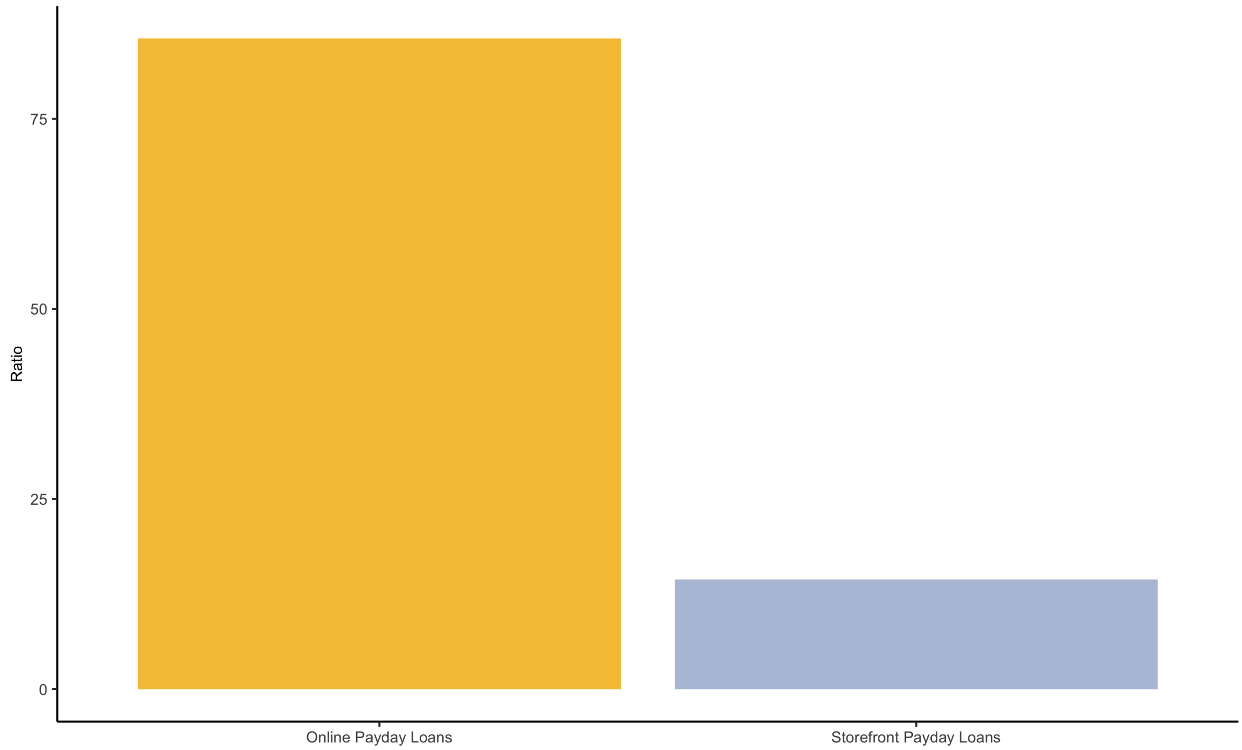
Table B.3.1: Extended Payment Plans Detailed Features for Each State

State	Effective Date	Installments	Plan Length	Allowable Fees	Usage Frequency	Eligibility	Disclosure
AL	2004-01-01	≥ 4	NA	\$0	no time limit specified or on notice of inability to pay	loan or rollover threshold	inability to pay or default
AK	2010-01-01	NA	NA	\$0	no time limit specified or on notice of inability to pay	NA	loan agreement; inability to pay or default
CA	2003-01-01	NA	NA	\$0	NA	NA	NA
DE	2018-12-12	NA	$\geq$ 60 days	\$0	NA	loan or rollover threshold	NA
FL	2019-07-01	NA	$\geq$ 60 days	\$0	no time limit specified or on notice of inability to pay	credit or counseling	loan agreement; inability to pay or default
ID	2014-07-01	≥ 4	$\geq$ 60 days	\$0	once per 12-month	NA	loan agreement
IN	2002-01-01	≥ 4	$\geq$ 60 days	\$0	no time limit specified or on notice of inability to pay	loan or rollover threshold	loan agreement
LA	2015-01-01	≥ 4	NA	\$0	once per 12-month	NA	loan agreement
MI	2005-11-28	≥ 3	pay schedule	allow fees	NA	loan or rollover threshold	loan agreement
NV	2017-07-01	≥ 4	$\geq$ 60 days	\$0	once per 12-month	NA	inability to pay or default
SC	2009-06-16	≥ 4	pay schedule	\$0	once per 12-month	NA	loan agreement
UT	2016-07-01	≥ 4	$\geq$ 60 days	\$0	once per 12-month	loan or rollover threshold	loan agreement; inability to pay or default
WA	2003-10-01	≥ 3	NA	\$0	no time limit specified or on notice of inability to pay	NA	inability to pay or default
WI	2013-07-07	≥ 4	pay schedule	\$0	once per 12-month	NA	loan agreement; inability to pay or default
WY	2014-07-01	≥ 4	$\geq$ 60 days	\$0	once per 12-month	NA	NA

Notes: If a feature is labeled as "NA", it means it is not specified for that state for that feature. The data is collected by the author based on each state's deferred deposit transaction law, not from Clarity.

B.4 Clarity Payday Loans

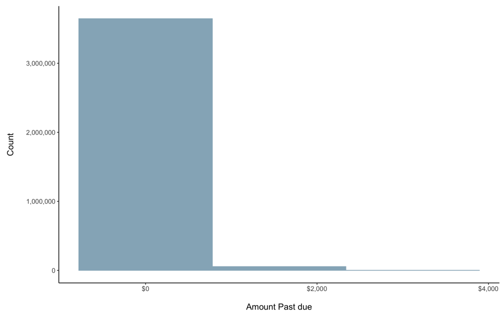
Figure B.4.1: Online vs Storefront Payday Loans Volumes



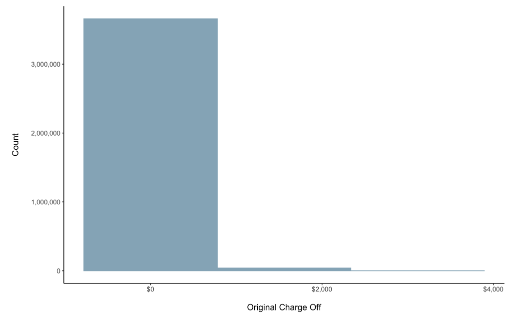
Notes: The data source is Clarity.

B.5 Histogram for Outcome Variables

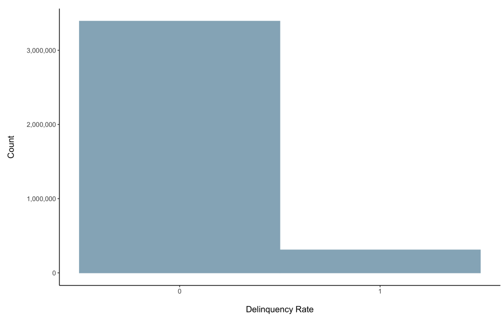
Figure B.5.1: Histogram for Each Outcome Variable



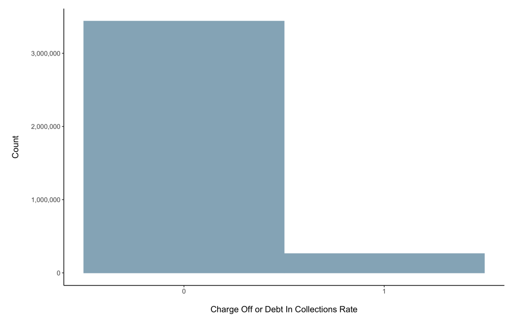
(a) Amount Past Due



(b) Original Charge-Off



(c) Delinquency Rate



(d) Charge-Off or Debt-in-Collections Rate

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

B.6 SDiD with Staggered Adoption: Estimation Algorithm for ATT

Data: Outcome variable $\boldsymbol{Y}$, treatment variable $\boldsymbol{D}$, covariates $\boldsymbol{X}$, and policy adoption $\boldsymbol{A}$[1].

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

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

For each $a \in A$:

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

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

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

6. Compute ATT across adoption-specific SDiD estimates:

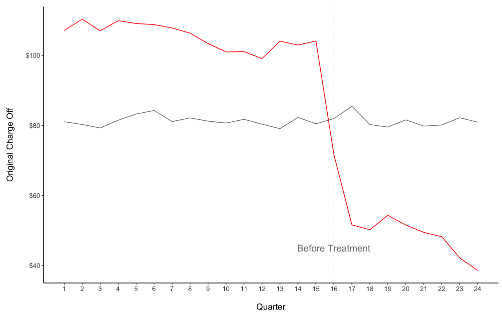
$$\widehat{ATT} = \sum_{for a \in A} \frac{T_{post}^{a}}{T_{post}} \times \hat{\tau}_a^{sdid} \tag{B.2}$$

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

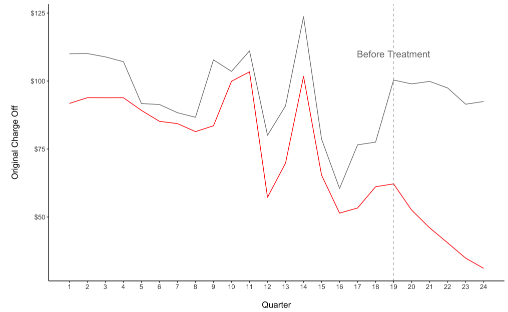
where T^a_{post} is the total treated periods for each adoption, and T_{post} is the total treated periods for all adoptions.

B.7 SDiD Plots for More Outcome Variables

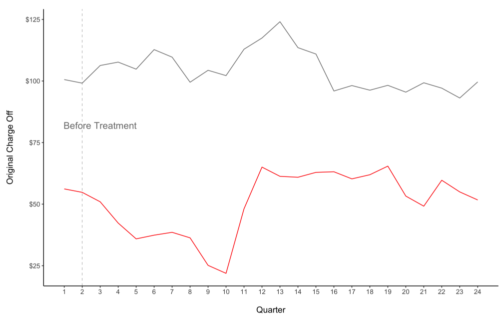
Figure B.7.1: SDiD Plot for Original Charge-Off: ATT for Each Treated State



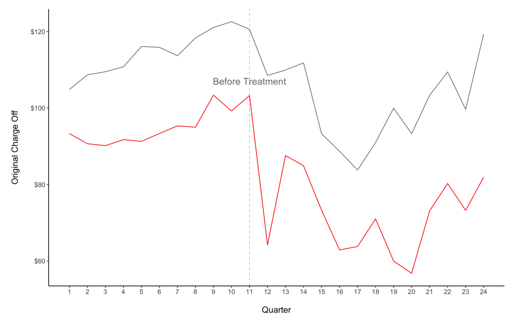
(a) Delaware



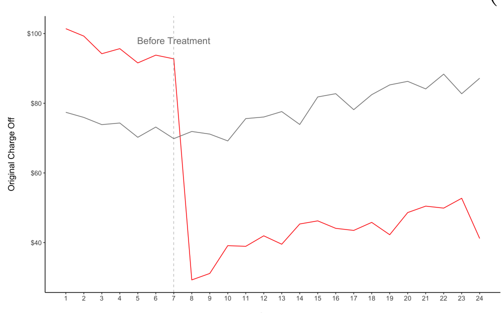
(b) Florida



(c) Louisiana



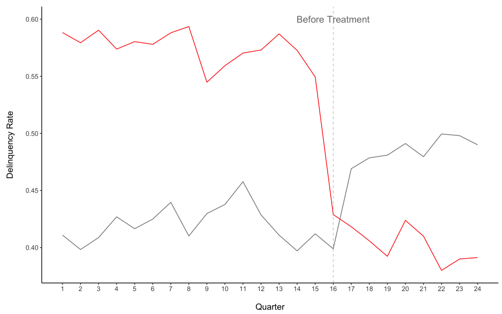
(d) Nevada



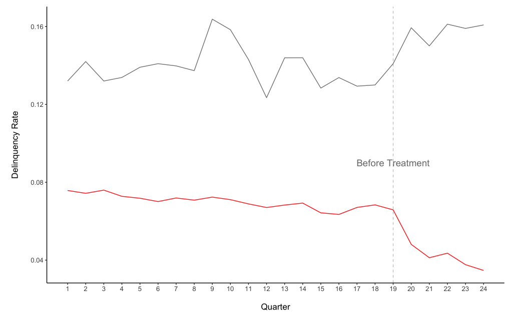
(e) Utah

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

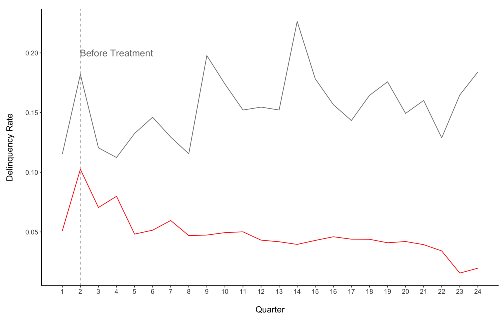
Figure B.7.2: SDiD Plot for Delinquency Rate: ATT for Each Treated State



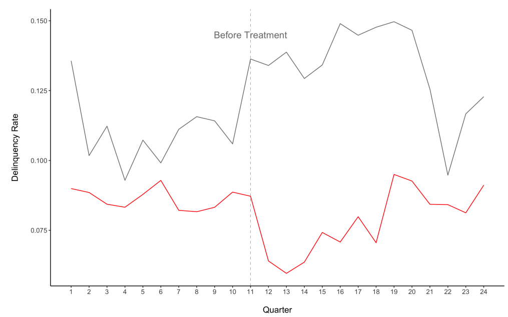
(a) Delaware



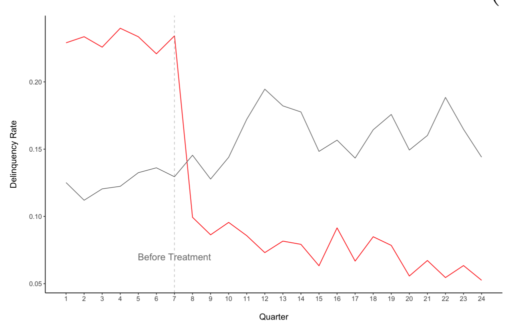
(b) Florida



(c) Louisiana



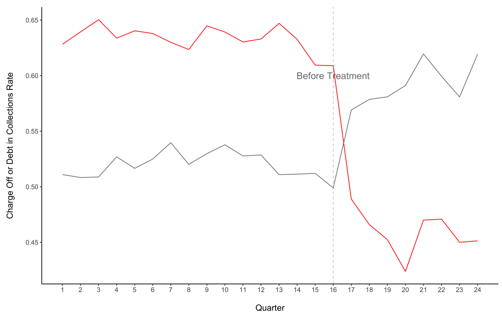
(d) Nevada



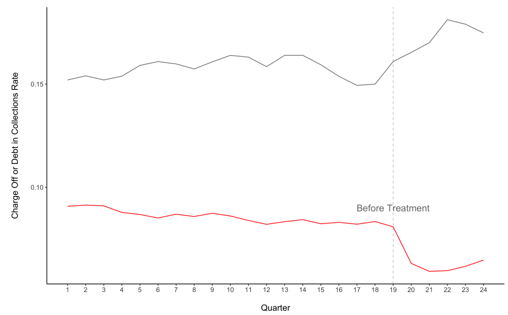
(e) Utah

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

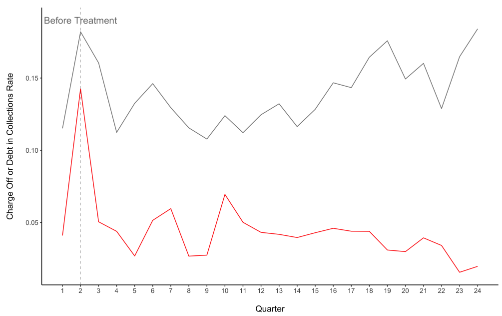
Figure B.7.3: SDiD Plot for Charge-Off or Debt-in-Collections Rate: ATT for Each Treated State



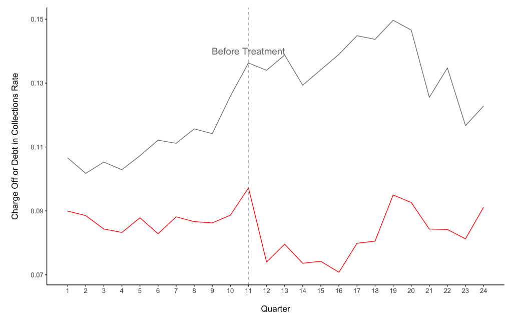
(a) Delaware



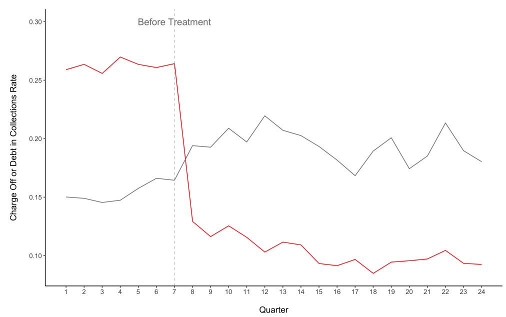
(b) Florida



(c) Louisiana



(d) Nevada



(e) Utah

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

B.8 SDiD with Staggered Adoption: Estimation Algorithm for Variance Using Bootstrap

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

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

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

For $b \leftarrow 1$:

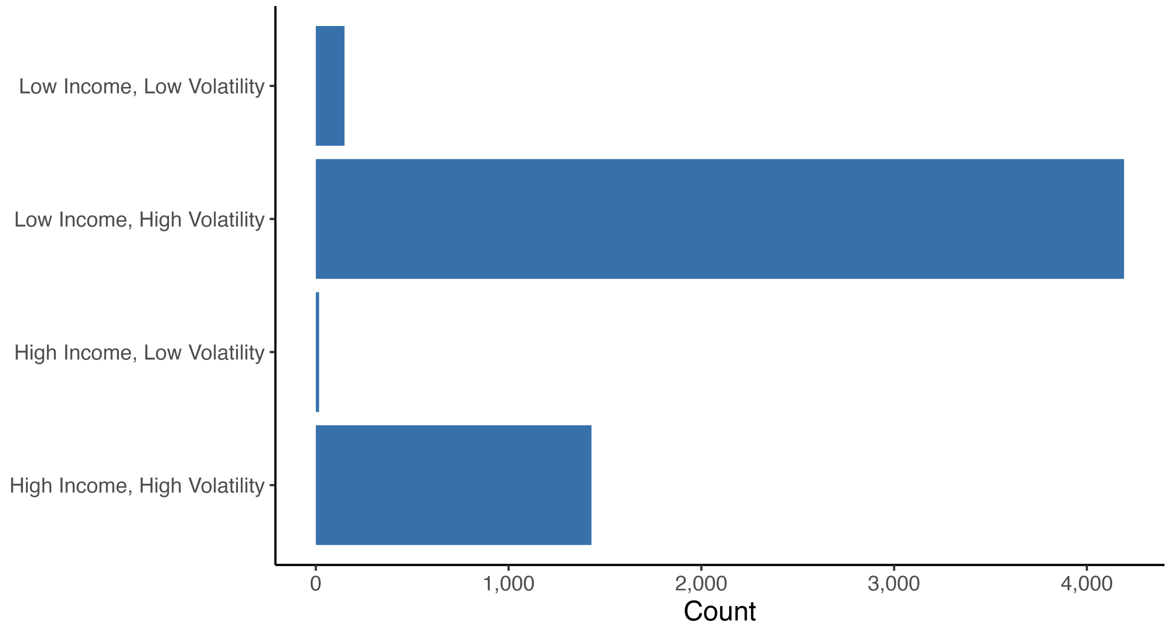
1. Sample N rows of $(\boldsymbol{Y}, \boldsymbol{D})$ with replacement and construct bootstrap dataset $(\boldsymbol{Y}^{(b)}, \boldsymbol{D}^{(b)}, \boldsymbol{A}^{(b)})$.
2. If no treated or control units are in the bootstrap sample, then redo step 1.
3. Compute SDiD estimate $ATT^{(b)}$ following algorithm in Appendix B.6 based on bootstrap data. Generate a vector of adoption-date specific resampled SDiD estimates $\tau_a^{(b)}$ for all $a \in \boldsymbol{A}^{(b)}$.
4. Define estimated variance $\hat{V}^{cb}_{ATT} = \frac{1}{B}\sum_{b=1}^{B}(\widehat{ATT^{(b)}} - \frac{1}{B}\sum_{b=1}^{B}\widehat{ATT^{(b)}})^2$. Estimate adoption-date specific variances for each τ_a^{sdid} estimate as the variance over each $\tau_a^{(b)}$.

Appendix C

Chapter 3

C.1 Bar Plot for Income Volatility

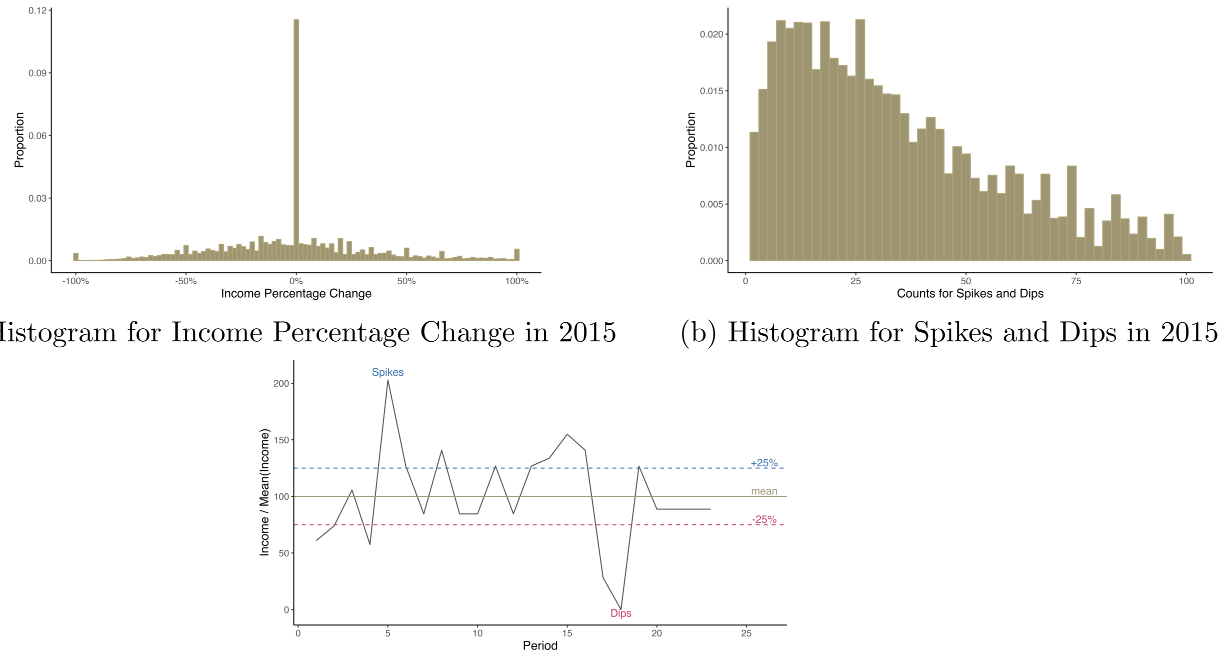
Figure C.1.1: Income Volatility in Four Groups - 2015 Data



Notes: This bar plot separates borrowers from 2015 into four groups. It is defined as "low income" if an individual's mean income in 2015 is below the third quartile \$3,524, and "high income" is above \$3,524. It is defined as "Low volatility" if an individual's income CV is below 75%, and "high volatility" if it is above 75%. The data source is Clarity.

C.2 Measuring Income Volatility

Figure C.2.1: Alternative Ways to Measure Income Volatility



(a) Histogram for Income Percentage Change in 2015

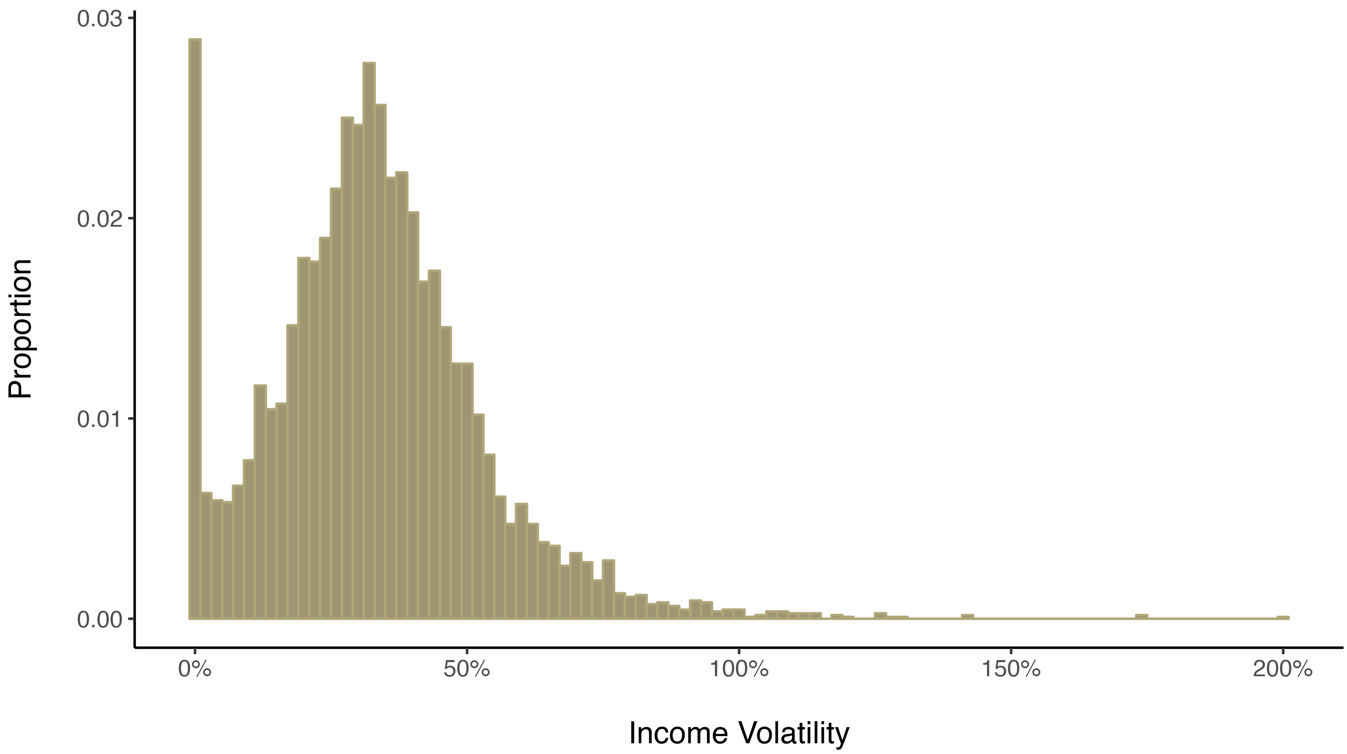
(b) Histogram for Spikes and Dips in 2015

(c) Income Spikes and Dips for a Random Borrower

Notes: For income percentage change, the range is limited between ±100 since the remaining observations are very large and thus excluded as outliers. The counts for income spikes and dips are limited to 100 since the observations beyond that are rare and thus excluded as outliers. For the random borrower, his average income is $3,549.22 (which is about $500 higher than the sample average). The data source is Clarity.

C.3 Histogram for Income Coefficient of Variation

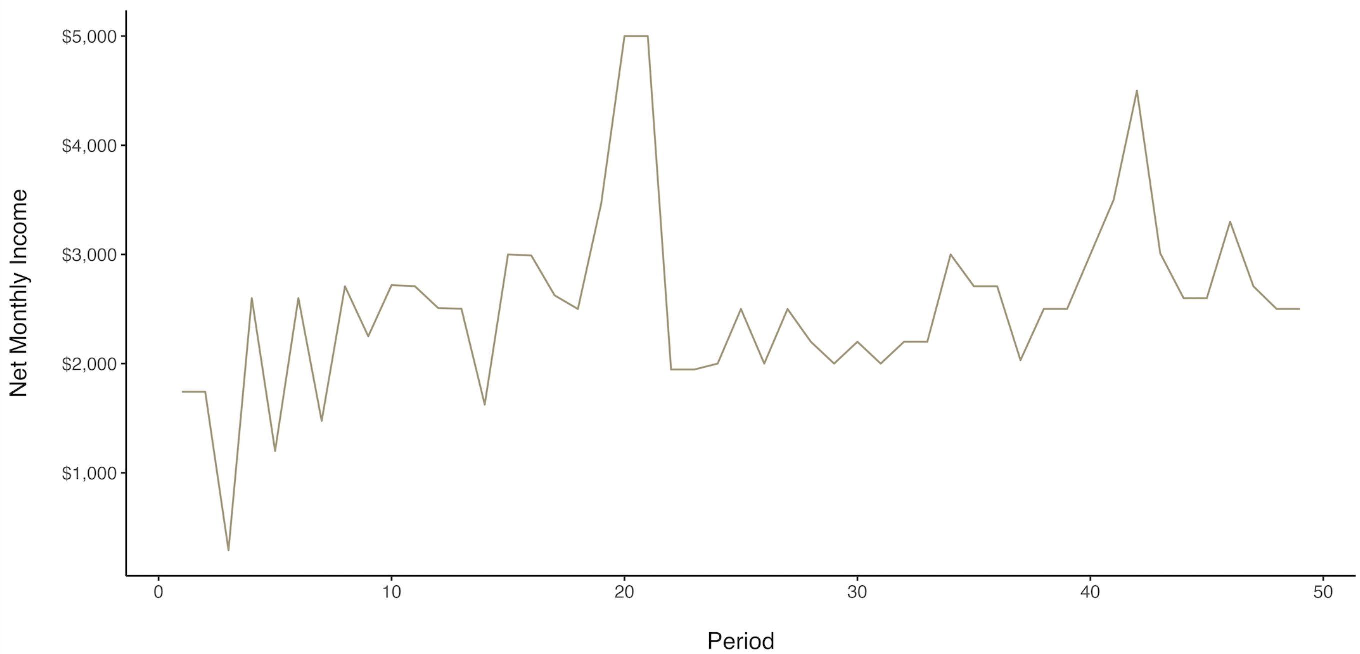
Figure C.3.1: Histogram for Income Coefficient of Variation in 2015



Notes: The histogram of income coefficient CV for the rest of the years is very similar. Thus, they are omitted in this appendix. The data source is Clarity.

C.4 Income for a random borrower

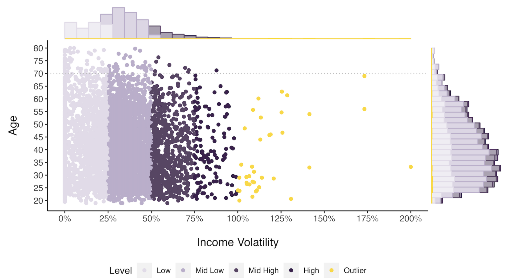
Figure C.4.1: Income for a random borrower across time



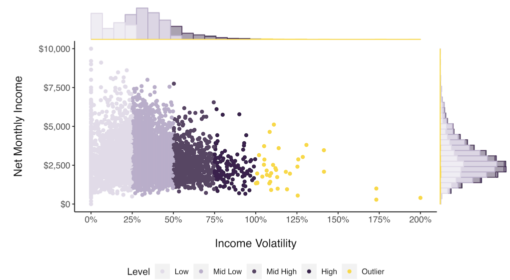
Notes: This borrower's income coefficient of variation is 32% (same as the sample average), and his average income is $2,543 (which is about $500 lower than the sample average). The data source is Clarity.

C.5 Income CV vs Features

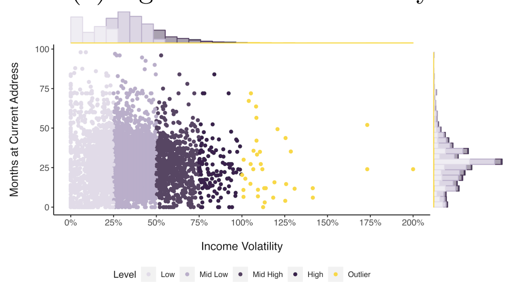
Figure C.5.1: Income CV vs Features in 2015



(a) Age vs Income Volatility



(b) Income vs Income Volatility



(c) Months at Current Address vs Income Volatility

(d) Pay Frequency vs Income Volatility

(e) Housing Status vs Income Volatility

Notes: The plots are very similar for the rest of the years. Hence, they are omitted in this appendix. The data source is Clarity.

C.6 Double Machine Learning Procedure

The algorithm procedure follows Chernozhukov et al. (2018).

Interactive regression model procedure

Let K be a fixed integer, N be the sample size. Construct a K-fold random partition of the entire sample $1, ..., N$ into equal parts $(I_k)_{k=1}^{K}$ each size $n = \frac{N}{K}$, and construct the K estimators

$$\theta_0(I_k, I_k^c),\ k = 1, ..., K, \tag{C.1}$$

that employ the machine learning estimators

$$\hat{\eta}_0(I_k^c) = \left(\hat{g}_0(0, X; I_k^c),\ \hat{g}_0(1, X; I_k^c),\ \hat{m}_0(X; I_k^c),\ \frac{1}{N-n}\sum_{i \in I_k^c} D_i\right)', \tag{C.2}$$

of the nuisance parameters $(g_0(0, X),\ g_0(1, X), m_0(X),\ E[D])$, and where each estimator $\theta_0(I_k, I_k^c)$ is defined as the root θ of the corresponding equation:

$$\frac{1}{|I|}\sum_{i \in I_k} \psi(W, \theta, \hat{\eta}_0(I_k^c)) = 0 \tag{C.3}$$

The score function $\psi(\cdot)$ is defined as:

$$\psi(W, \theta, \eta) = \theta - \frac{D(Y - \eta_2(X))}{\eta_3(X)} - \frac{(1-D)(Y - \eta_1(X))}{1 - \eta_3(X)} - (\eta_1(X) - \eta_2(X)), \tag{C.4}$$

$$\eta_0(X) = (g_0(0,X), g_0(1,X), m_0(X))', \tag{C.5}$$

Where $\eta(X) = (\eta_j(X))_{j=1}^3$ is the nuisance parameter consisting of measurable functions mapping the support of X to $\mathbb{R} \times \mathbb{R} \times (0,1)$. The true value of this parameter is given above by $\eta_0(X)$, and $\hat{\eta}_0(X)$ are machine learning estimators of $\eta_0(X)$.

The solution can be given explicitly, since the equations are affine in θ. We then average the K estimators to obtain the final estimator:

$$\tilde{\theta}_0 = \frac{1}{K}\sum_{k=1}^{K} \theta_0(I_k, I_k^c) \tag{C.6}$$

The approximate standard error for this estimator is given by $\frac{\hat{\sigma}}{\sqrt{N}}$, where

$$\hat{\sigma}^2 = \frac{1}{N}\sum_{i=1}^{N} \hat{\psi}_i^2 \tag{C.7}$$

Where $\hat{\psi}_i = \psi(W_i, \tilde{\theta}_0, \hat{\eta}_0(I_{k(i)}^c))$, and $k_{(i)} = \{k \in \{1, ..., K\} : i \in I_k\}$. The approximate $(1-\alpha) \times 100\%$ confidence interval is given by:

$$[\tilde{\theta}_0 \pm \Phi^{-1}(1-\alpha/2)\hat{\sigma}/\sqrt{N}] \tag{C.8}$$

K-fold cross-fitting

We proceed with a K-fold random split $I_k, k = 1, ..., K$ of the entire sample $\{1, ..., N\}$, so that $\pi = K - 1$. In this case, the size of split I_k is $n = \frac{N}{K}$, the size of split $I_k^c = \mathbb{U}_m I_m$ is $N \cdot [(K-1)/K]$, and the total sample size is N. We may then construct K estimators

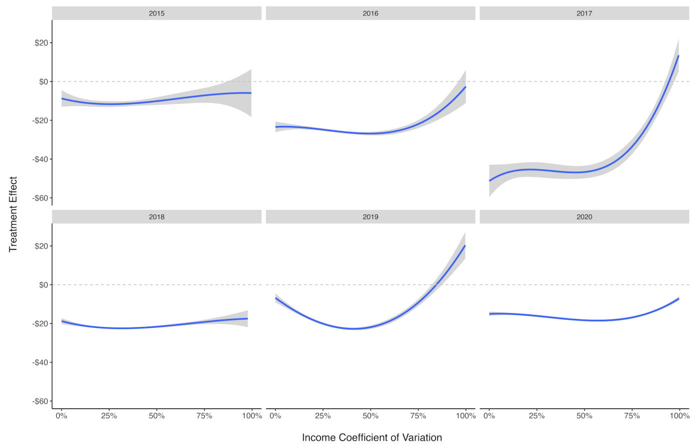
$$\theta_0(I_k, I_k^c),\ \ k = 1, ..., K \tag{C.9}$$

that employ the nuisance parameter estimators $\hat{\eta}_0(I_k^c)$. The K estimators may then be aggregated into

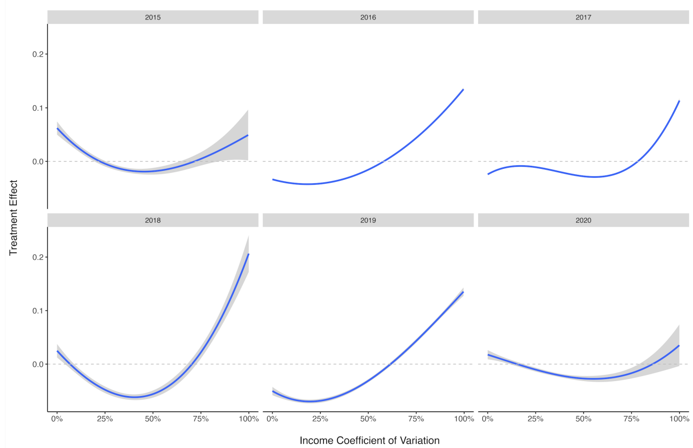
$$\tilde{\theta}_0 = \frac{1}{K}\sum_{k=1}^{K}\theta_0(I_k, I_k^c). \tag{C.10}$$

C.7 CATE for the Rest of Outcome Variables

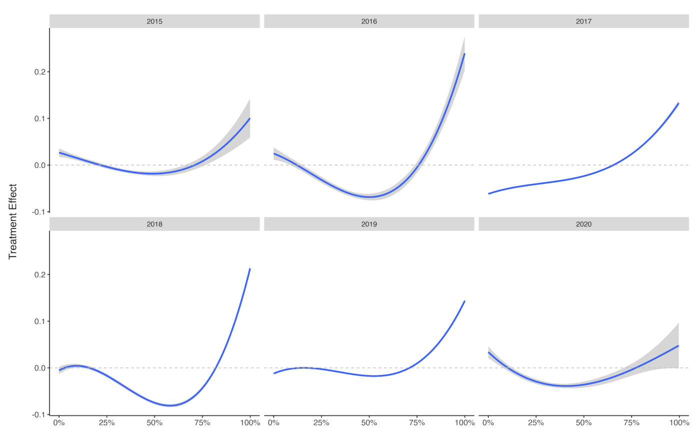
Figure C.7.1: CATE Plots for the Rest of Outcome Variables



(a) CATE - Original Charge-Off



(b) CATE - Delinquency Rate



(c) CATE - Charge-Off or Debt-in-Collections Rate

Notes: The data source is Clarity.