What happens when payday borrowers are cut off from payday lending? A natural experiment *

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Abstract

This paper examines the impact of restricting credit to payday borrowers. Using administrative banking data from over fifteen thousand online payday loan users, I exploit a natural experiment surrounding a 2013 U.S. Department of Justice initiative known as Operation Choke Point (OCP), which unexpectedly shut down dozens of online payday lenders. Using a difference in differences framework, I find a persistent reduction in payday borrowing of treated households, those with a pre-existing relationship with a lender that is shut down. Relative to control households, treated households reduce expenditures on payday interest by $81 per month and reduce the frequency of financial distress by 5%. A cross-sectional analysis reveals that the benefits of reduced payday loan access vary dramatically across groups. Both heavy pre-treatment borrowers and those who borrowed in the month preceding Operation Choke Point experience the largest benefits in terms of reduced financial distress and increased consumption, and these benefits increase in magnitude over time. In contrast, light pre-treatment borrowers experience no change in financial distress or consumption. Using an instrumental variables approach, I estimate that a $1,000 decrease in borrowing will result in a$1,429 reduction in loan repayments, 0.2 fewer instances of financial distress, and a $316 increase in consumption.

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1 Introduction

I use administrative household-level data comprising of banking transactions of over fifteen thousand payday users to exploit a natural experiment surrounding the unexpected closure of dozens of online payday lenders during a 2013 Department of Justice initiative known as Operation Choke Point (OCP). Using a difference in differences framework, I compare household outcomes of treated households, those with pre-existing relationships with lenders who are shut down, to control households, those without pre-existing relationships with lenders who are not shut down.

I begin by showing a large and persistent treatment effect of Operation Choke Point. Treated households persistently reduce the amount of payday borrowing relative to control households. I proxy for household well-being with both consumption and the frequency of financial distress. Increases in consumption and reductions in the frequency of financial distress would be consistent with payday bans improving household welfare, while decreases in consumption and increases in the frequency of financial distress would be consistent with payday bans reducing household welfare. Consistent with payday bans improving household welfare, I find that treated households experience a persistent 5% reduction in the frequency of financial distress.

I proceed by analyzing how household behavior varies across households and find that the benefits of reduced payday loan access vary dramatically across groups. Both heavy pre-treatment borrowers and those who borrowed in the month preceding Operation Choke Point experience the largest benefits in terms of reduced financial distress and increased consumption, and these observed benefits increase in magnitude over time. In contrast, light pre-treatment borrowers experience no change in financial distress or consumption. These results are not driven by windfall gains of treated households.

I conclude with an instrumental variables analysis. I instrument payday borrowing with interactions of indicators for pre-OCP borrowing relationships and whether the given lender is alive. Whereas the difference in differences approach exploits variation in the extensive margin, the IV approach exploits variation in the intensive margin. Two-stage instrumental variables estimates indicate that a $1,000 decrease in borrowing will result in 0.2 fewer instances of financial distress and a $316 increase in consumption.

My paper adds to the literature in a several areas. First, I rely on a direct and immediate treatment effect caused by Operation Choke Point rather than a state-level change in payday lending laws. Whereas changes in state lending laws might slowly lead to lending closures or openings, the natural experiment I exploit is immediate and directly observable. Once OCP targets a particular lender, ACH transfers to and from this lender stop immediately, rendering the lender dead. Next, my data allows me to observe borrowing across dozens of payday lenders alongside high-frequency consumption and distress at the household level. Further, unlike prior papers which draw causal inferences on payday law changes using inferences from a broad population of payday users and non-users, I restrict my analysis to the subset of the population that uses online payday loans. By doing so, I have more power in making causal statements about the population of interest. Finally, I exploit variation in treatment along both the extensive and intensive margins to better understand the consequences of payday borrowing.

The paper proceeds as follows. Section 2 provides background information. Section 3 describes the data. Section 4 describes the identification strategy. Section 5 contains the pooled difference in differences analysis surrounding Operation Choke Point. Section 6 contains the cross-sectional difference in differences analysis surrounding Operation Choke Point. Section 7 contains the instrumental variables analysis. Section 8 concludes.

2 Background

Payday and installment loans are common types of high-interest credit utilized by households. Payday loans are typically small loans (around \$500) that are repaid in full at the time of the borrower's next paycheck, while installment loans offered by payday lenders are slightly larger loans (around \$1,500) that are repaid over several paychecks. Interest rates on both payday and installment loans are very high, ranging from 400% Effective Annual Rate (EAR) to over 1,000% EAR. Since the interest rates on both payday and installment loans offered by payday lenders are similar, I will hereafter refer to both types of loans simply as "payday loans." Despite the high interest rate of payday loans, 12 million U.S. households borrow from payday lenders every year, corresponding to five percent of the adult population (Pew (2014)).

Historically, payday loans have been obtained through brick-and-mortar locations in which the borrower enters a storefront and exchanges post-dated checks for cash. However, in recent years, payday loans are increasingly obtained through internet lenders in which the loans and repayments are distributed electronically via direct deposit. The percentage of high-interest loans originating from online lenders is growing at a rapid pace. Stephens (2013) estimates that online payday loan volume grew from 10% of payday loans in 2006 to 33% of payday loans in 2013.

While traditional payday loans are controversial, online payday loans are even more so as payday lenders often circumvent state laws by incorporating abroad or as tribal entities. During the application process, borrowers provide lenders proof of income along with their checking account and routing numbers. Once approved, the lender will distribute the loan through an electronic Automated Clearing House (ACH) transfer directly into the borrower's checking account. When the repayment date arrives, the lender will withdraw the agreed-upon amount irrespective of whether the borrower has the required amount in her checking account. If there are insufficient funds at the time of repayment, this will result in an overdraft, and multiple overdrafts may occur since as the lender will continue attempting withdrawals until repaid.

Given the triple- to quadruple-digit EAR of payday loans, the controversy on payday lending easy to understand. Opponents of payday lending argue that the availability of high-interest credit tempts financially unsophisticated or myopic households to borrow, potentially resulting in a debt trap (CFPB (2015)). Industry executives argue that payday lending provides necessary emergency financing to the financially constrained.[1] Empirically testing which of these arguments best explains borrowing behavior is not only important from a policy standpoint, but is also important in understanding how households make borrowing decisions.

A nascent literature has emerged which assesses the effects of access to payday loans on household well-being. To date, the empirical evidence has produced mixed results, with some papers concluding that payday borrowing does more harm than good (Melzer (2011), Carrell and Zinman (2014)) and others concluding the opposite (Morse (2011), Morgan, Strain, and Seblani (2012)). Though surprising, these mixed empirical results need not be contradictory (Zingales (2015)). Rather, the mixed empirical results could illustrate underlying heterogeneity in both household characteristics and how payday loans are used. Further, the mixed empirical results could be a result of differential responses over the short- and long-run. To date, only two papers explore how household heterogeneity matters in this setting. Carrell and Zinman (2014) find that negative outcomes associated with payday loan access are concentrated among inexperienced and unsophisticated airmen, while Dobrige (2014) finds that borrowers who borrow in "bad" states of the world, such as hurricanes and blizzards, exhibit positive outcomes of consumption smoothing. My paper addresses the gaps in the literature by exploiting a new identification strategy and dataset. This new dataset

[1]For example, "CFPB Sets Sights on Payday Loans," *Wall Street Journal*, written January 4, 2015.

provides household-level data on online payday borrowing, consumption, financial distress, and income.

Regulation on payday lending has fallen largely to the states. As of 2015, traditional payday lending is effectively illegal in 15 states[2] and online payday lending is illegal in 17 states.[3] Recently, however, the federal government has intervened on a few occasions. First, in 2007 the federal government passed the Military Lending Act, which effectively banned payday loans to military personnel. Second, the Consumer Financial Protection Bureau is in the midst of designing new federal payday lending laws (CFPB (2015)) despite the mixed empirical findings found to date.

3 Data

Aggregation of financial accounts is a popular service which allows households to easily monitor financial activities from across multiple financial institutions into a single web-page or smart-phone app. Account aggregation services often allow features such as budgeting, expense tracking, etc. There are dozens of companies which currently provide such services and my data comes from one of these services.

Once the user initially signs up for the free service, she is given the opportunity to provide the service with usernames and passwords to any of the financial institutions she has accounts with, such as banks, brokerages, or credit card companies. In practice, most households in my sample only link their primary checking account, meaning that the majority of my database consists of checking account data. After signing up, the service will automatically and regularly pull data from the user's financial institutions. The dataset contains

[2] www.paydayloaninfo.org/state-information. Note that several states technically allow payday lending, though they impose interest rate caps which are low enough to eliminate payday lending in the state. I classify payday lending activity in such states as "illegal" to capture the economic effect of such interest rate caps.

[3] www.online-payday-loans.org/

transaction-level data similar to those typically found on monthly bank or credit card statements, containing the amount, date, and description of each transaction. As a result, I have high-fidelity data on consumption and income for over a million households. There is very little attrition in my sample.

The nature of the data lends itself to a selection bias. First, payday borrowers in my data have checking accounts, while a common perception is that most payday borrowers are unbanked. Second, the households in the data have signed up for a free personal finance service, potentially biasing the sample towards more financially sophisticated households. These selection biases have important implications for the external validity of the paper. If I were to show that payday borrowing benefits households in my sample, the external validity of the results should be interpreted with caution. It's plausible that less sophisticated households that don't enter my sample would use payday loans less prudently than the more sophisticated households which entered my sample. If this were the case, the results would be difficult to generalize. However, if I were to show that payday borrowing harms households in my sample, the external validity of the results more straight forward. In this situation, the benefits to the more sophisticated sample might provide a lower-bound to the benefits to of a broader population.

I identify online payday loan transactions through a simple process. I first identify which transaction descriptions in my dataset are most frequently leading to overdrafts. I then manually identify which of these transactions are associated with online payday lenders. An alternate method of identifying payday transactions involves using internet searches and subsequent keyword searches to identify online payday lenders. The two methods produce a nearly identical list of payday lenders, though the mapping of payday lenders to transactions found on bank statements is much simpler with the former process.

I next visit each lender's website to determine if the lender also participates in other forms of lending such as auto title loans, debt consolidation, or mortgage refinancing. I exclude such lenders since these alternative loans have higher loan amounts and lower interest rates than payday loans as they are collateralized with physical assets. The exception to this rule is when I can clearly differentiate between a payday loan and other loans that the institution offers, such as Wells Fargo's Direct Deposit Advance product which is easily differentiated from its mortgage and car loans. This process leaves me with 704,357 payday loan transactions from 41 lenders and 36,303 households.

I determine whether each of the lenders closes during the 2013-2014 period spanned by my data by observing the date which each lender stops lending. Using this method, I let the data reliably indicate when the service was shut down. Figure 1 provides an illustration of how this is accomplished for a subset of three affected lenders. In this figure, the lending activities of three lenders are plotted as a function of time. The lending of each of the lenders is abruptly and permanently halted. Inferring the shut down dates from these follows easily. Obtaining shut-down dates through any other manner would be impossible due to the secrecy surrounding Operation Choke Point and the relative obscurity of most online payday lenders. Despite the lack of public information surrounding OCP closures, my dates align well with the few closure dates I found from affected households as reported on several internet forums.[4]

The resulting list of lenders is found in Table 1. The second column of Table 1 contains the number of payday loan transactions from each lender in the six month period before OCP, from January 2013 to June 2013. The third column contains the shut-down date identified. As shown in the table, the majority of payday lending is concentrated among a few lenders. For example, the top 5 lenders in my sample are CashnetUSA (41,472 pre-OCP transactions), Plain Green (27,176 pre-OCP transactions), Wells Fargo (19,768 pre-OCP transactions), Mobiloans (18,911 pre-OCP transactions), and Ameriloan (16,183 pre-OCP

[4] An example from Ameriloan. On Sept. 23, 2013 a user wrote: "I have used them before and not had a major problem.. But I am wondering now WHY their computers are down and have been for 3 weeks?????? HMMM." www.consumeraffairs.com/finance/ameriloan.html

transactions). The bottom 5 lenders in my sample are Regions Bank (278 pre-OCP transactions), LiquidCash (927 pre-OCP transactions), Netcredit (1,023 pre-OCP transactions), Dollar Premier (1,185 pre-OCP transactions), and Fedfinsvcs (1,206 pre-OCP transactions).

I require each household to have at least one payday loan transaction from January 2013 to June 2013, the approximate six month period before OCP begins. In the event that a household joins the service after 1/1/2013 the panel begins the month of the first observed transaction for the household. Likewise, if the household happens to cancel the service prior to 12/31/2014, I drop all household days after the household leaves the sample. Further, I require that each household have at least 365 days of activity between the first and last observed transaction. I collapse the data by household month.

Treated households are those who borrowed during the six month pre-OCP window from any lender that is subsequently shut down. Control households are those who, during the six month pre-OCP window, borrowed exclusively from lenders who are not subsequently shut down. Since my identification comes from the unexpected closure of online payday lenders through OCP, I remove any household who borrowed from an online payday lender who closed for reasons other than OCP. An example of this is the closure of Wells Fargo's Direct Deposit Advance product, which was not directly associated with OCP and was announced well ahead of time, which would have provided affected customers time to find alternative products and thus the inclusion of Wells Fargo would obscure causal inferences. After applying the above filters, I am left with 16,493 households, 8,659 of which are in the treatment group, and 7,834 in the control group.

The goal of the paper is to determine how household well-being changes following exogenous reductions in the availability of payday credit. One challenge is identifying relevant household well-being measures that are identifiable in my dataset. I identify two primary variables to assist in the evaluation of household outcomes. The first is the frequency with which a household is in financial distress, as proxied by the number of days a household has either bounced checks or overdrafts in a month. The second is household consumption. I identify consumption as the sum of all observable expenditures after removing transfers from one account to another. This measure of consumption is quite broad and includes expenditures on mortgages, car payments, retail, entertainment, rent, credit card payments, and restaurants. All variables are winsorized at the 99^{th} percentile.

Basic summary statistics are provided in Table 2. Panel A contains summary statistics for the whole sample, while Panels B and C contain summary statistics for the treated and control subsamples, respectively. The mean monthly pre-OCP income in my sample is $3,581, with treated households having a mean of $3,648 and control households having a mean of $3,506. The mean monthly pre-OCP amount borrowed in my sample is $160, with treated households having a mean of $186 and control households having a mean of $132. The mean monthly pre-OCP amount repaid in my sample is $276, with treated households having a mean of $338 and control households having a mean of $207. The difference between the monthly borrowing and monthly repayment can provide an estimate of the amount of interest paid by households in the sample. The average interest paid by households in the sample is $116 per month. The mean monthly pre-OCP days in financial distress in my sample is 1.00, with treated households having a mean of 1.06 and control households having a mean of 0.94. The mean monthly pre-OCP consumption in my sample is $4,444, with treated households having a mean of $4,447 and control households having a mean of $4,441. Finally, the mean number of unique pre-OCP relationships in my sample is 1.44, with treated households having a mean of 1.72 and control households having a mean of 1.12.

Table 2 illustrates that control and treatment households are generally similar in income, consumption, and financial distress. However, Table 2 also illustrates that treated households borrow $54 more per month than control households. Further, they have 0.6 more unique pre-OCP relationships.

It is interesting to note that observed consumption exceeds observed income by $863 in my sample. There are a few explanations for this. One explanation is that households in my sample are simply consuming more than they earn during this time period. Another explanation for this is that I fail to identify all relevant transactions as income. For example, I do not classify generic "deposit" items as income since these transactions could easily consist of transfers from one account to another.

4 Identification Strategy

In order to determine the causal impact of payday borrowing on household outcomes, a carefully constructed identification strategy is required. Absent a careful identification strategy, a naïve research design will be plagued by the selection bias surrounding payday loans. For example, it is inappropriate to regress household outcomes on payday loan usage since this would omit the unobserved emergencies which may have led to payday loan usage in the first place. A valid identification strategy, therefore, will need to exploit exogenous variation in payday loan demand or supply that is uncorrelated with unobserved emergencies.

To date, the majority of the literature has achieved identification by relying on state-level changes to payday lending laws (for example, Melzer (2010) and Morgan, Strain, and Seblani (2012)). Several papers have relied on state-level changes plus additional variation. Carrell and Zinman (2014) use the additional variation of random assignment of the location of servicemen, while Dobrige (2014) relies on the additional variation of weather as demand shocks. Morse (2011) stands alone in achieving identification without reliance on state-level changes in payday lending laws. She achieves identification through demand shocks, which occur exogenously in the form of earthquakes to different regions, and through the additional variation of the geographic location of lenders.

Online payday loans are illegal in 17 states, while in the remaining 33 states, online payday loans are generally only legal if the lender is registered with the state. Seldom is this the case. In a given state, there are generally no more than five licensed lenders,[5] meaning that much of online payday lending is operating in an unregulated and illegal manner. Despite operating illegally, these lenders are difficult for regulators to reign in since many are either incorporated abroad or as tribal entities. Further, the lack of physical locations has been another barrier inhibiting regulators from intervening.

Without warning, the Department of Justice introduced Operation Choke Point around August of 2013, an initiative that shut down many of these online payday lenders who were operating illegally. In this initiative, the Department of Justice pressured U.S. banks to stop processing ACH transfers involving online payday lenders. Without the ability to distribute loans or collect payment via ACH transfers, the lenders were effectively and immediately closed. This program was first uncovered in a *Wall Street Journal* article published on August 7, 2013.[6]

To illustrate simply the impact of OCP on household borrowing, I plot the average amount of payday borrowing with respect to time in Panel A of Figure 2. As shown clearly in Panel A, there is a large and persistent effect of OCP in curtailing payday borrowing. In the pre-treatment period, treated households borrowed approximately $60 more per month than control households. After OCP, treated households borrow approximately $40 less per month than control households. A plot of loan repayments in Panel B of Figure 2 reveals the same trend. Treated households have approximately $125 more per month in loan repayments than control households prior to OCP. After OCP, treated households have approximately $75 less per month in loan repayments than control households. These figures illustrate nicely the persistence of payday borrowing of control households. Entry into the sample requires one payday loan transaction in the first six months of the sample. Despite

[5] www.online-payday-loans.org/state-licensed-lenders/

[6] "Probe Turns Up Heat on Banks; Prosecutors Target Firms That Process Payments for Online Payday Lenders, Others," *Wall Street Journal*, written August 7, 2013.

this, control households continue to borrow at an elevated level over a year after entering the sample.

The plots succinctly demonstrate the effectiveness of OCP in altering household borrowing behavior. Treated households significantly reduced total payday borrowing and repayment following OCP. The remainder of this section investigates the implications of reduced high-interest borrowing caused by the exogenous shock.

It is important to point out that treated households do not reduce borrowing to zero. Rather, treated households reduce monthly payday borrowing from approximately \$175 per month to approximately \$40 per month. The fact that borrowing of treated households does not go to \$0 can be explained by a few reasons. First, treated households may have had pre-existing relationships with a number of lenders at the time of OCP. If one of the lenders remained in operation after OCP, this household would easily be able to continue borrowing from this lender. Second, treated households, after finding that their pre-OCP lender had shut down, may look for substitutes following OCP. In either case, it is important to understand that the change in payday borrowing activity was material, persistent, and exogenously driven by unforeseen policy changes. The fact that borrowing does not go to zero does not invalidate the identification.

It is also important to note that the observed treatment effect may be overstated. It could be the case that households perfectly substitute from online to brick and mortar borrowing since I don't observe brick and mortar borrowing. In Section 6.4, I restrict my sample to treated households living in states where payday lending is illegal and find that the results are unchanged from the unrestricted sample, indicating that unobserved substitution is not invalidating the identification.

5 Pooled Operation Choke Point Analysis

This section analyzes the pooled responses to OCP. Section 5.1 contains the simple difference in differences specification to capture the average response to the restriction of payday credit, whereas Section 5.2 analyzes the persistence of such responses.

5.1 Average response to the restriction of payday credit

In order to understand the average responses to OCP, I begin with the specification shown in Equation (1):

$$\begin{aligned} Y_{h,t} = \beta_1 \; Treated * After_{h,t} + \beta_2 \; Income_{h,t} + \beta_3 \; Income_{h,t-1} \\ + FE_t + FE_h + \epsilon_{h,t} \end{aligned} \tag{1}$$

The data is collapsed by household month. $Y_{h,t}$ is the dependent variable of interest, with subscripts h indicating household and t indicting time (in terms of month). The dependent variables I analyze are the dollar amount of online payday borrowing ($Payday\ Borrow_{h,t}$), the dollar amount of online payday repayment ($Payday\ Repay_{h,t}$), the number of days a household is in financial distress ($Financial\ Distress_{h,t}$), and total household consumption ($Consumption_{h,t}$). $Treated * After_{h,t}$ is an interaction term of $Treated_h$ and $After_t$. $Treated_h$ is an indicator that takes the value of 1 when household has a pre-existing relationship with a lender that is shut-down during OCP. $After_t$ is an indicator that takes the value of 1 after treatment. Both $Treated_h$ and $After_t$ are collinear with household and date fixed effects and are dropped from the regression. $Income_{h,t}$ is household income in dollars and $Income_{h,t-1}$ is lagged household income in dollars. I include income because many households are living paycheck-to-paycheck (Pew (2013)) and the dependent variables are likely to be influenced by recent income. FE_t and FE_h represent time and household fixed effects, respectively. Standard errors are clustered by household[7] and t-statistics are reported in parentheses.

The regression results are found in Table 3. Column (1) formally confirms what was illustrated simply in Panel A of Figure 2. Treated households reduce total payday borrowing by \$94 per month, as shown by the coefficient of $Treated * After_{h,t}$, corresponding to a 52% reduction in borrowing relative to the pre-treatment mean of treated households. Column (2) likewise confirms what was illustrated in Panel B of Figure 2. Treated households reduce total payday repayment by \$176 per month, corresponding to a 52% reduction in repayment relative to the pre-treatment mean of treated households. The difference between these two coefficients, or \$82 per month, represents the reduction in payday interest expenses incurred by treated households. The coefficients of these variables are highly statistically as well as economically significant. Clearly, OCP was effective in changing household borrowing behavior.

Next, Column (3) shows that the frequency of financial distress, as proxied by the number of days with overdrafts and bounced checks in a given month. Treated households experience a reduction in the frequency of financial distress. The coefficient -0.05 corresponds to a 5% reduction in the frequency of financial distress of treated households. Finally, Column (4) illustrates the effect of OCP on household consumption. The coefficient of \$27 is positive but statistically insignificant.

It is surprising that the consumption of treated households does not significantly increase following a \$82 per month reduction in the amount of payday interest and a 5% reduction in the frequency of financial distress. One potential explanation is that treated households increase savings to counteract the effect of reduced credit availability. Since I do not observe account balances, I am unable to test this formally.

It is also interesting to note the effect of income on the dependent variables of interest.

[7] Similar results are obtained if standard errors are clustered by time, or by household and time.

Payday repayment and consumption are positively correlated household income. Consumption will increase (decrease) by $47 for every $100 increase (decrease) in current income for households in my sample. Likewise, payday repayment will increase (decrease) by $1.50 for every $100 increase (decrease) in current income for households in my sample. Payday borrowing and financial distress are uncorrelated with household income.

5.2 Persistence of the response to the restriction of payday credit

A natural follow-on question is whether the observed treatment effects observed in Section 5.1 are persistent or only temporary. In order to answer this question, I introduce the following specification which allows for a comparison of short- versus long-term responses:

$$\begin{aligned} Y_{h,t} = \sum_{Z=1}^{6} \beta_Z \; Treated * QAZ_{h,t} + \beta_7 \; Income_{h,t} + \beta_8 \; Income_{h,t-1} \\ + FE_t + FE_h + \epsilon_{h,t} \end{aligned} \tag{2}$$

The only difference between this specification and the one described previously is the fact that the $Treated * After_{h,t}$ variable is divided into quarters after transition, with QAZ_t representing the $\mathrm{Z^{th}}$ quarter after the household is affected by OCP. I define quarters as 3-month periods after the treatment effect. To illustrate, consider a household who had a pre-existing relationship with a lender who was closed during OCP on August 1, 2013. This household would be assigned the value of 1 for $Treated * QA1_{h,t}$ for the months of August 2013, October 2013, and November 2013 and 0 otherwise.

The regression results are shown in Table 4. Columns (1) and (2) show the borrowing and repayment responses to OCP, respectively. The borrowing and repayment responses are persistent across the observation window. Column (1) indicates that households initially borrow $80 less per month than control households in the first quarter after being affected by OCP (corresponding to a 43% reduction from the pre-treatment mean), and this number remains persistently high through the observation window, peaking at $96 per month in the fourth quarter after OCP (corresponding to a 52% reduction from the pre-treatment mean). Similar observations are shown in Column (2) for the repayment of payday loans.

Column (3) analyzes the number of days a household encounters financial distress in a given month. Treated households initially reduce the number of days in the frequency of financial distress by a statistically significant 0.06 instances per month beginning the second quarter after treatment (corresponding to a 6% reduction from the pre-treatment mean) and persists through the end of the sample, reaching a peak reduction of 0.08 instances per month (corresponding to a 8% reduction from the pre-treatment mean) in the sixth quarter after OCP.

Column (4) analyzes how household consumption changes in response to OCP. The $Treated * QA1_{h,t}$ is negative yet insignificant. All other $Treated * QAZ_{h,t}$ coefficients are positive yet insignificant.

It's clear from Table 4 that the treatment effect from Operation Choke Point was large and persistent. Further, analysis of Table 4 reveals interesting variations in responses across time. As a result, subsequent tables will utilize this more granular specification outlined in Equation (2).

6 Cross-Sectional Operation Choke Point Analysis

Given the richness of my data, I am able to explore how heterogeneity in household characteristics influences the response to restrictions in payday credit. I explore heterogeneity in pre-treatment borrowing behavior in Section 6.1, heterogeneity in income in Section 6.2, heterogeneity in recency of payday borrowing in Section 6.3, heterogeneity in payday lending payday lending laws in Section 6.4, and heterogeneity in windfall receipts in Section 6.5.

6.1 Do chronic borrowers respond differently than occasional borrowers to the restriction of payday credit?

Households with heavier pre-OCP payday activity are likely to be different types of households from those with lighter pre-OCP activity. Heavier pre-OCP borrowers are more likely to be chronic payday users, while lighter pre-OCP borrowers are more likely to be responsible payday users. To understand how each of these groups responds to the restriction of payday credit, I divide the sample into two groups based on the number of payday loan transactions observed in the six month period from January 2013 to June 2013. I refer to households above the median number of transactions as "heavy borrowers" and those below the median number of transactions as "light borrowers." I use the specification outlined in Equation (2) to understand how each group responds. Results for the subsample of heavy borrowers is found in Panel A of Table 5 while the results for the subsample of light borrowers is found in Panel B of Table 5.

Consider first the response of heavy borrowers in Panel A of Table 5. Column (1) shows that treated households, relative to control households, dramatically reduce payday borrowing. The reduction in borrowing begins at $119 per month (corresponding to a 41% reduction from the pre-treatment mean) in the first quarter after treatment and ends at $133 per month in the sixth quarter after treatment (corresponding to a 46% reduction from the pre-treatment mean). The results are highly statistically significant throughout the observation window. Similar results are found for payday repayment in Column (2).

Column (3) evaluates how the frequency of financial distress of heavy borrowers responds to the restriction of payday credit. Treated households reduce the number of days per month that they are in financial distress by 0.09 days per month beginning the second quarter after treatment (corresponding to a 8% reduction from the pre-treatment mean). This reduction is persistent and reaches a peak reduction of 0.12 days per month in the fifth quarter after treatment (corresponding to an 11% reduction from the pre-treatment mean).

Column (4) evaluates how the consumption of heavy borrowers responds to the restriction of payday credit. The coefficients on every quarter are positive, and statistically significant for three of the six quarters. Treated households increase consumption by $83 per month in the third quarter after treatment (corresponding to a 2% increase from the pre-treatment mean), by $105 per month in the fifth quarter after treatment (corresponding to a 2% increase from the pre-treatment mean), and by $131 per month in the sixth quarter after treatment (corresponding to a 3% increase from the pre-treatment mean).

I next evaluate the response of light borrowers in Panel B of Table 5. Column (1) shows that treated households, relative to control households, also reduce payday borrowing. The reduction in borrowing begins at $29 per month (corresponding to a 42% reduction from the pre-treatment mean) in the first quarter after treatment and ends at $24 per month in the sixth quarter after treatment (corresponding to a 35% reduction from the pre-treatment mean). Similar results are found for payday repayment in Column (2).

Columns (3) and (4) evaluate how the frequency of financial distress and consumption of light borrowers responds to the restriction of payday credit. Column (3) shows that treated households experience no change in the frequency of financial distress. Similarly, Column (4) shows that treated households experience no change in consumption.

Overall, the findings in Table 5 indicate that households that were the heaviest of pre-OCP borrowers were most affected by Operation Choke Point. Heavy borrowers reduced borrowing the most, reducing payday interest by an average of $98 per month. Further, heavy borrowers experienced a large and persistent reduction in the frequency of financial distress, peaking at an 11% reduction. Heavy borrowers also experienced transitory increases in consumption.

Despite the benefits of OCP to heavy borrowers, light users are not obviously better off after OCP in terms of reduced financial distress or increased consumption. This would be consistent with this set of households using payday loans more prudently, such as in times of short-term emergencies. Despite this, it is also not immediately clear that such prudent households are any worse off after OCP in terms of increased financial distress or reduced consumption. Unfortunately, for this subset of households, I lack the power to take a stance on one side or the other.

6.2 Do high income households respond differently than low income households to the restriction of payday credit?

Next, I proceed by asking how income affects household responses to the restriction of payday credit. It is plausible that payday loans are more useful to lower income households since lower income households are more likely to be financially constrained. It is also plausible that payday loans are more harmful to lower income households since lower income households are less able to afford the interest incurred through payday borrowing if they are borrowing excessively. I investigate empirically how different groups respond to the ban.

I divide the sample into two groups based on the income observed in the six month period from January 2013 to June 2013. I refer to households above the median income as high income and those below the median income as low income. I use the specification outlined in Equation (2) to understand how each group responds. Results for the subsample of high income borrowers is found in Panel A of Table 6 while the results for the subsample of low income borrowers is found in Panel B of Table 6.

Consider first the response of high income borrowers in Panel A of Table 6. Column (1) shows that treated households, relative to control households, greatly reduce payday borrowing. The reduction in borrowing begins at \$98 per month (corresponding to a 42% reduction from the pre-treatment mean) in the first quarter after treatment and ends at \$122 per month in the sixth quarter after treatment (corresponding to a 53% reduction from the pre-treatment mean). The results are highly statistically significant throughout the observation window. Similar results are found for payday repayment in Column (2).

Column (3) evaluates how the frequency of financial distress of high income borrowers responds to the restriction of payday credit. Treated households reduce the number of days per month that they are in financial distress by 0.06 days per month beginning the second quarter after treatment (corresponding to a 5% reduction from the pre-treatment mean). This reduction is relatively persistent and reaches a peak reduction of 0.09 days per month in the fifth quarter after treatment (corresponding to an 8% reduction from the pre-treatment mean), though the coefficient on the third quarter is negative but insignificant.

Column (4) evaluates how the consumption of high income borrowers responds to the restriction of payday credit. Treated households increase consumption by $129 per month in the sixth quarter after treatment (corresponding to a 2% increase from the pre-treatment mean).

I next evaluate the response of low income borrowers in Panel B of Table 6. Column (1) shows that treated households, relative to control households, also reduce payday borrowing. The reduction in borrowing begins at $61 per month (corresponding to a 40% reduction from the pre-treatment mean) in the first quarter after treatment and ends at $59 per month in the sixth quarter after treatment (corresponding to a 39% reduction from the pre-treatment mean). Similar results are found for payday repayment in Column (2).

Column (3) evaluates how the frequency of financial distress of low income borrowers responds to the restriction of payday credit. Treated households reduce the number of days per month that they are in financial distress by 0.06 days per month during the second quarter after treatment (corresponding to a 6% reduction from the pre-treatment mean) and 0.08 days per month during the sixth quarter after treatment (corresponding to a 8% reduction from the pre-treatment mean).

Column (4) evaluates how the consumption of low income borrowers responds to the restriction of payday credit. Treated households do not change consumption, though the coefficient in the third quarter after treatment is positive and marginally significant.

Overall, the findings in Table 6 indicate that both high- and low-income households benefited from a reduction in the supply of payday credit. However, high income households appear to have benefited more due to the more persistent decline in financial distress relative to low income households. Further, high income households experienced transitory consumption gains and low income households did not.

6.3 Does the recency of borrowing affect household outcomes following the restriction of payday credit?

It is plausible that the recency of borrowing influences household responses to the restriction of payday credit. On the one hand, households who borrow before recently before OCP are more likely to have recently experienced an emergency. Given the recency to the underlying emergency, these households are likely to benefit from uninterrupted access to payday credit. On the other hand, if payday lending is dangerous in that it leads people into debt traps, recent borrowers are likely to benefit the most due to the interrupted access to the supply of payday credit.

I proceed by dividing the sample into two groups based on the recency of borrowing. The recent group consists of any household who borrowed in June of 2013, approximately one month before OCP. The non-recent group consists of any household who borrowed from January 2013 to May 2013 and did not borrow in June of 2013.

I use the specification outlined in Equation (2) to understand how each group responds. Results for the subsample of recent borrowers is found in Panel A of Table 7 while the results for the subsample of non-recent borrowers is found in Panel B of Table 7.

Consider first the response of recent payday borrowers in Panel A of Table 7. Column

(1) shows that treated households, relative to control households, greatly and persistently reduced payday borrowing. The reduction in borrowing begins at $186 per month (corresponding to a 49% reduction from the pre-treatment mean) in the first quarter after treatment and ends at $199 per month in the sixth quarter after treatment (corresponding to a 53% reduction from the pre-treatment mean). The results are highly statistically significant throughout the observation window. Similar results are found for payday repayment in Column (2).

Column (3) evaluates how the frequency of financial distress of recent borrowers responds to the restriction of payday credit. Treated households reduce the frequency of financial distress in the third and fourth quarters after treatment by 0.11 and 0.12 days per month (corresponding to a 12% and 13% reduction from the pre-treatment mean).

Column (4) evaluates how the consumption of recent borrowers responds to the restriction of payday credit. Treated households increase consumption by $146 per month in the second quarter after treatment (corresponding to a 3% increase from the pre-treatment mean), and this increase in consumption remains persistently high until reaching a peak of $234 per month in the sixth quarter after treatment (corresponding to a 5% increase from the pre-treatment mean).

I next evaluate the response of non-recent borrowers in Panel B of Table 7. Column (1) shows that treated households, relative to control households, also reduce payday borrowing. The reduction in borrowing begins at $38 per month (corresponding to a 34% reduction from the pre-treatment mean) in the first quarter after treatment and ends at $52 per month in the sixth quarter after treatment (corresponding to a 46% reduction from the pre-treatment mean). Similar results are found for payday repayment in Column (2).

Column (3) evaluates how the frequency of financial distress of non-recent borrowers responds to the restriction of payday credit. Treated households reduce the number of days per month that they are in financial distress by 0.05 days per month during the first quarter after treatment (corresponding to a 5% reduction from the pre-treatment mean). The reduction is statistically significant for four of the six quarters in the observation window.

Column (4) evaluates how the consumption of non-recent borrowers responds to the restriction of payday credit. Treated households do not change consumption.

Overall, the results of Table 7 paint an interesting picture of how recent borrowers respond differently from non-recent borrowers following OCP. In contrast to non-recent borrowers who experience no consumption gains following OCP, recent borrowers experience large and persistent consumption gains following treatment. It seems that OCP served as a circuit breaker which prevented treated households from spiraling into a debt trap, resulting in large consumption gains for treated households.

6.4 Are the results driven by windfall gains of treated households?

As discussed previously, the unexpected nature of Operation Choke Point led to the immediate collapse of the operations of dozens of payday lenders. A natural question to ask is whether the results from the previous sections are driven primarily by windfall gains. A household would experience a windfall gain if it borrowed from a lender a week before the lender was shut down before the household had the opportunity to repay the loan. Since the lender would be unable to process the ACH repayment withdrawal, the household will end up with a windfall gain if she does not repay by other means, such as by credit card over the telephone. If results from the previous sections are driven solely by windfall gains, the policy and behavioral implications are much less relevant, since households who receive windfall gains will be unambiguously better off than otherwise identical households not receiving windfall gains.

To do so, I use the following empirical specification:

$$
\begin{aligned}
Y_{h,t} = &\sum_{Z=1}^{6} \beta_Z \; Treated * QAZ * Candidate * Windfall_{h,t} \\
&+ \sum_{Z=1}^{6} \beta_{Z+6} Treated * QAZ * Candidateh, t + \sum_{Z=1}^{6} \beta_{Z+12} \; Treated * QAZh, t \\
&+ \beta_{19} \; Income_{h,t} + \beta_{20} \; Income_{h,t-1} + FE_t + FE_h + \epsilon_{h,t} \qquad (3)
\end{aligned}
$$

The difference between this specification and the baseline specification used in Equation (2) is the introduction of two sets of interaction terms, $Treated * QAZ * Candidate * Windfall_{h,t}$ and $Treated * QAZ * Candidate_{h,t}$. $Candidate_h$ is an indicator variable representing which takes the value of 1 if the household had borrowed from a lender in the fourteen day period prior to the lender closing and 0 otherwise. It is meant to capture whether a household is a candidate for potentially receiving a windfall, having very recently borrowed from a lender that is shut down within fourteen days. $Windfall_h$ is an indicator variable which takes the value of 1 in the event that the candidate windfall actually received the windfall and did not repay the loan. To put the size of these groups into perspective, 9% of treated households are windfall candidates, while only 4% of treated households received a windfall.

Similar to the analysis of recent borrowers in Section 6.3, $Candidate_h$ captures a group of recent borrowers. It could be the case either that such borrowers had an emergency right before OCP or that they are chronic borrowers. In either case, neither is likely to fare very well after treatment relative to households that had not borrowed recently.

Regression results are found in Table 8. Column (1) analyzes the effect of windfall receipt on future borrowing. The coefficients of $Treated * QAZ * Candidate * Windfall_{h,t}$ are negative for all six quarters after treatment and statistically significant for quarters three through six.

Column (2) analyzes the effect of windfall receipt on future loan repayments. The coefficient of $Treated * QA1 * Candidate * Windfall_{h,t}$ is negative and statistically significant, indicating a \$178 per month reduction in payday repayment the first quarter after treatment relative to the candidate group who had borrowed fourteen days prior to lender shut-down. The remaining $Treated * QAZ * Candidate * Windfall_{h,t}$ coefficients are negative yet significant.

Column (3) analyzes the effect of windfall receipt on financial distress. The coefficients of $Treated * QAZ * Candidate * Windfall_{h,t}$ are all statistically positive yet insignificant, indicating that the receipt of the windfall did not change the frequency of financial distress relative to the candidate group who had borrowed fourteen days prior to lender shut-down, though the coefficients on the first two quarters are positive and marginally significant.

Finally, Column (4) analyzes the effect of windfall receipt on consumption. The coefficients of $Treated * QAZ * Candidate * Windfall_{h,t}$ are all insignificant, indicating no change in consumption relative to the candidate group who had borrowed fourteen days prior to lender shut-down.

Overall, the Table 8 provides strong evidence that households receiving windfall gains are not driving the results of previous sections.

6.5 What about unobserved substitution to brick and mortar lenders?

I proceed by investigating how unobserved substitution to other payday lenders could influence my results. If it were costless for households to perfectly substitute to other online or brick and mortar lenders that I don't observe in my data, the observed reduction in payday borrowing would be mismeasured. With perfect substitution, the reduction in observed borrowing would be zero. Observed changes to financial distress or consumption would be due to the difference in borrowing terms between the old lender and the new lender, not due to the elimination of high interest credit.

I address this concern by restricting my sample into two groups. First, I restrict the treated group to those households that reside in a state where payday lending is illegal. This mitigates the concern that the household can substitute to unobserved online or brick and mortar payday lenders. Next, I restrict the control group to those households that reside in a state where payday lending is legal. This guarantees that the control group has unrestricted access to payday borrowing over the sample period.

Regression results are found in Table 9. Similar to Table 4, treated households in this specification significantly reduce the frequency of financial distress relative to control households. The economic magnitude is similar to that of Table 4. Similar to Table 4, there is no change in the consumption of treated households. In untabulated results, I rerun the analyses of Sections 6.1 though 6.4 for this more restrictive subsample and find that the results are qualitatively similar.

7 Instrumental Variable Analysis

The previous sections containing the difference in differences analyses do not fully exploit the heterogeneity in treatment. In order to exploit variation in treatment on the intensive margin, I implement an instrumental variable (IV) analysis in this section.

Recall that the identification challenge with identifying a causal impact of payday borrowing on household outcomes is centered around the unobserved underlying emergency leading households to borrow in the first place. A valid instrument, therefore, will have to be correlated with payday borrowing and uncorrelated with the underlying emergency.

I propose a simple instrument which exploits exogenous variation in borrowing driven by Operation Choke Point. In the first stage, household borrowing is a function of the pre-OCP relationships the borrower has and whether these lenders are alive at any point in time. The second stage then predicts household outcomes as a function of the instrumented payday borrowing. The first and second stages of the regression are shown below in Equations (4) and (5), respectively:

$$PaydayBorrow_{h,t} = \sum_{Z=1}^{39} \beta_Z \; AliveZ * RelationshipZ_{h,t} + \beta_{40} \; Income_{h,t} + \beta_{41} \; Income_{h,t-1} + FE_t + FE_h + \epsilon_{h,t} \tag{4}$$

$$Y_{h,t} = \beta_1 \; Payday\widehat{B}orrow_{h,t} + \beta_2 \; Income_{h,t} + \beta_3 \; Income_{h,t-1} + FE_t + FE_h + \epsilon_{h,t} \tag{5}$$

The data is collapsed by household month. $Y_{h,t}$ is the dependent variable of interest, with subscripts h indicating household and t indicting time (in terms of month). The dependent variables I analyze are the number of days a household is in financial distress ($Financial\ Distress_{h,t}$) and total household consumption ($Consumption_{h,t}$). $AliveZ * RelationshipZ_{h,t}$ is an interaction term of $RelationshipZ_h$ and $AliveZ_t$. $RelationshipZ_h$ is an indicator that takes the value of 1 when household has a pre-existing relationship with a lender Z and 0 otherwise. $AliveZ_t$ is an indicator that takes the value of 1 if lender Z is alive and 0 otherwise. Since $RelationshipZ_h$ and $AliveZ_t$ are collinear with household and time fixed effects, they are dropped from the regression. $Income_{h,t}$ is household income in dollars and $Income_{h,t-1}$ is lagged household income in dollars. FE_t and FE_h represent time and household fixed effects, respectively. Standard errors are bootstrapped.

It is important to understand where the variation in predicted payday borrowing is coming from. Since household fixed effects are included in the first stage regression in Equation (4), the only source of variation in predicted payday borrowing comes from the variation in the status of the lenders each household has a pre-established relationship with. If a household borrows exclusively from lenders who remain open through Operation Choke Point, this household will serve as the control group in Equation (4). It is only households which have a relationship with at least one lender who experience any treatment effect in Equation (4). Further, households that have relationships with multiple lenders that are shut down during Operation Choke Point will have the largest treatment effect in Equation (4). As a result, the instrumental variables analysis provides a more insightful analysis of treatment along the intensive margin.

Regression results are found in Table 10. Column (1) investigates how instrumented payday borrowing affects the amount of payday repayment. The coefficient of 1.429 indicates that for every \$1,000 reduction in payday borrowing, the dollar amount spent on repaying loans will decrease by \$1,429.

Column (2) investigates how instrumented payday borrowing effects the frequency of financial distress. The coefficient of 0.0002 indicates that for every \$1,000 reduction in payday borrowing, that number of days a household will be in financial distress will decrease by 0.2.

Column (3) investigates how instrumented payday borrowing effects consumption. The coefficient of -0.315 indicates that, for every \$1,000 reduction in payday borrowing, consumption increases by \$315.

Overall, the results are consistent with restrictions in payday credit improving household incomes in terms of reduced distress and increased consumption. The results are consistent with Sections 5 and 6.

8 Conclusion

This paper examines the impact of restricting credit to payday borrowers. Using administrative banking data from over fifteen thousand online payday loan users, I exploit a natural experiment surrounding a 2013 U.S. Department of Justice initiative known as Operation

Choke Point (OCP). I find a persistent reduction in payday borrowing of treated households, those with a pre-existing relationship with a lender that is shut down. Relative to control households, treated households reduce expenditures on payday interest by $81 per month and reduce the frequency of financial distress by 5%. A cross-sectional analysis reveals that the benefits of reduced payday loan access vary dramatically across groups. Both heavy pre-treatment borrowers and those who borrowed in the month preceding Operation Choke Point experience the largest benefits in terms of reduced financial distress and increased consumption, and these benefits increase in magnitude over time. In contrast, light pre-treatment borrowers experience no change in financial distress or consumption. Using an instrumental variables approach, I estimate that a $1,000 decrease in borrowing will result in 0.2 fewer instances of financial distress and a $316 increase in consumption.

The results are difficult to reconcile with standard neoclassical models of human behavior. Rather, the results are consistent with more behavioral models of human behavior such as those captured by hyperbolic discounting (Laibson (1997)). Though consistent with hyperbolic discounting, the results are also consistent with both financial unsophistication and myopia. Determining which, among the many potential explanations, is causing households to "misbehave" (Thaler (2015)) will be a fruitful area of future research.

Figure 1: This figure presents total payday lending from a subset of payday lenders that shut down due to Operation Choke Point. The x-axis is weeks after January 1, 2013. The y-axis is the count of loans from the given lender. Three lenders are represented in this figure: Ameriloan, United Cash Loans, and Great Plains Lend.

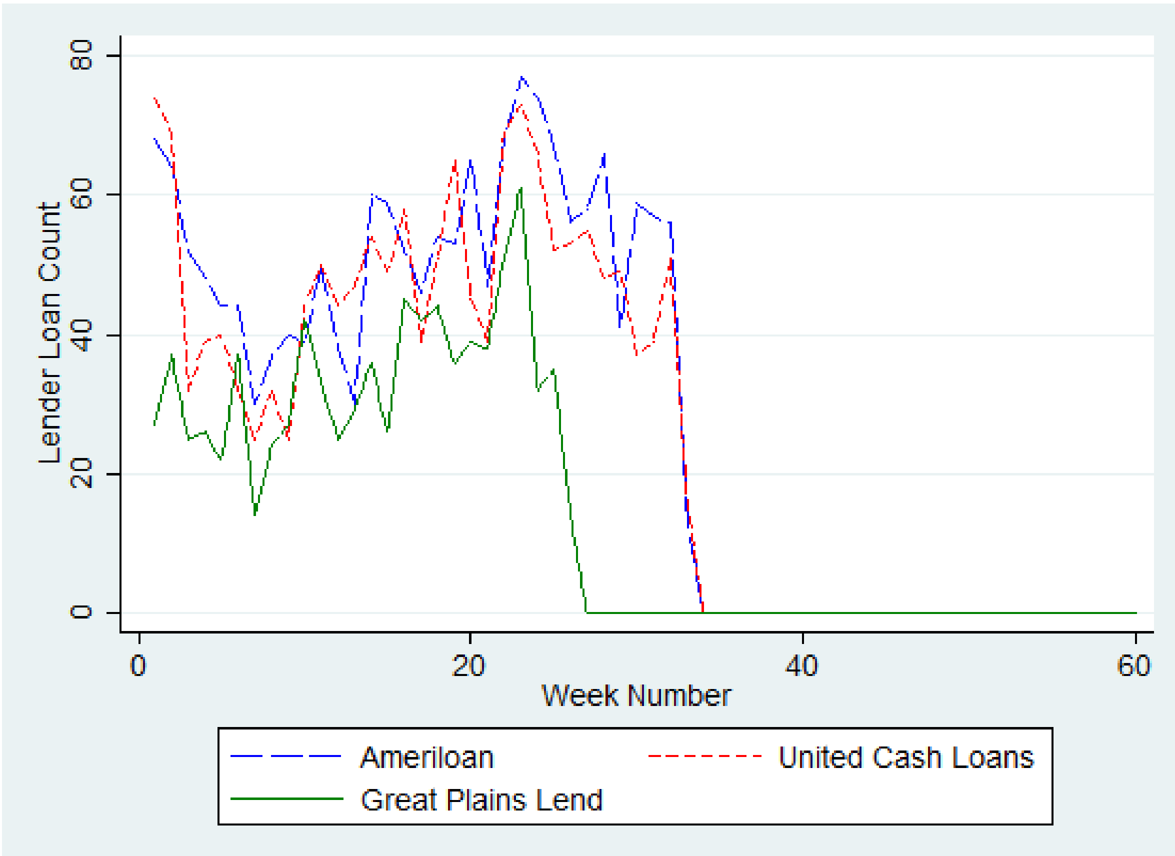

Figure 2: This figure presents average daily amounts in a given category for any household that borrowed in the roughly six month period before Operation Choke Point from January 2013 to June 2013. Treated households are those who borrowed from at least one lender who was subsequently shut down. Control households are those who borrowed exclusively from lenders who were not shut down. Month 1 is January 2013. Month 24 is December 2014. Operation Choke Point is implemented primarily over the 3-month period from August 2013 (Month 8) to October 2013 (Month 10), and this period is highlighted in gray. Panel A illustrates average payday borrowing activity, while Panel B illustrates average payday repayment activity.

Figure 2: Panel A

Figure 2: Panel B

Table 1: Summary of payday lenders in sample. The second column contains the number of observed pre-OCP transactions over the six month period prior to OCP, from January 2013 to June 2013. The third column lists the date of lender shut-down as identified in the data as when the lender stopped lending. The table is sorted in descending order by transaction count in Column (2).

Lender Name	Pre-OCP Transaction Count	Date of Shutdown
CashnetUSA	41,472	
Plain Green	27,176	
Wellsfargo	19,768	21-May-14
Mobiloans	18,911	
Ameriloan	16,183	15-Aug-13
Unitedcashloans	15,088	14-Aug-13
Mycashnow	13,214	12-Aug-13
Oneclickcash	11,884	12-Aug-13
Fastcash	10,633	16-Aug-13
Zip Com	10,150	6-Jan-14
Ace Cash Express	9,653	
Greatplainslend	9,560	25-Jun-13
Paydaymax	8,519	9-Aug-13
Castlepayday	7,521	
Cash Central	6,947	
Cash Jar	6,062	2-Aug-13
Viploanshp	6,040	15-Oct-13
Hydra Fund	5,743	2-Aug-13
Bdpdlservices	4,656	15-Oct-13
Americanwebloan	4,086	15-Oct-13
Usbank	3,791	27-May-14
Pdo	3,240	13-Jun-13
Golden Valley	2,795	
Silvercloud Fin	2,710	27-Jul-13
Spot On Loans	2,657	7-Jun-13
Starcashprcssng	2,092	26-Jun-13
Spotloan	1,939	
Actionpdl	1,923	15-Oct-13
Magnum Cash	1,816	3-Aug-13
Vip Cash	1,757	
Cash In A Wink	1,601	30-Aug-13
Fifththird	1,597	
Integrity	1,448	15-Oct-13
Lendingbooth	1,437	29-Aug-13
Nxtdaycash	1,369	16-Oct-13
Fast Efunds	1,228	8-Jul-14
Fedfinsvcs	1,206	30-Oct-13
Dollar Premier	1,185	
Netcredit	1,023	
Liquidcash	927	8-Oct-13
Regions	278	

Table 2: This table illustrates basic summary statistics for households in my sample for the six month period prior to OCP, from January 2013 to June 2013. The data is collapsed by household month. The variables analyzed are monthly income, payday borrowing, payday repayment, the number of days a household is in financial distress, and total household consumption, and the number of unique pre-OCP relationships. Panel A contains summary statistics for the whole sample. Panel B contains summary statistics for the treated subsample. Panel C contains summary statistics for the control subsample.

Panel A: Pooled Sample

Variable	Mean	P25	Median	P75	Max
Monthly Income	$3,581	$1,814	$2,982	$4,664	$14,097
Monthly Payday Borrow	$160	$0	$0	$0	$3,400
Monthly Payday Repay	$276	$0	$120	$357	$2,847
Monthly Days in Financial Distress	1.00	0.00	0.00	1.00	9.00
Monthly Consumption	$4,444	$2,049	$3,535	$5,875	$17,870
Number of Unique Pre-OCP Relationships	1.44	1.00	1.00	2.00	13.00

Panel B: Treated Subsample

Variable	Mean	P25	Median	P75	Max
Monthly Income	$3,648	$1,856	$3,015	$4,742	$14,097
Monthly Payday Borrow	$186	$0	$0	$150	$3,400
Monthly Payday Repay	$338	$0	$150	$450	$2,847
Monthly Days in Financial Distress	1.06	0.00	0.00	2.00	9.00
Monthly Consumption	$4,447	$2,020	$3,521	$5,898	$17,870
Number of Unique Pre-OCP Relationships	1.72	1.00	1.00	2.00	13.00

Panel C: Control Subsample

Variable	Mean	P25	Median	P75	Max
Monthly Income	$3,506	$1,768	$2,944	$4,592	$14,097
Monthly Payday Borrow	$132	$0	$0	$0	$3,400
Monthly Payday Repay	$207	$0	$73	$295	$2,847
Monthly Days in Financial Distress	0.94	0.00	0.00	1.00	9.00
Monthly Consumption	$4,441	$2,076	$3,548	$5,842	$17,870
Number of Unique Pre-OCP Relationships	1.12	1.00	1.00	1.00	5.00

Table 3: This table explores household outcomes following Operation Choke Point. The regression specification is: $Y_{h,t} = \beta_1 \; Treated * After_{h,t} + \beta_2 \; Income_{h,t} + \beta_3 \; Income_{h,t-1} + FE_t + FE_h + \epsilon_{h,t}$, where $Y_{h,t}$ is the dependent variable of interest, with subscripts h indicating household and t indicting time. The unit of observation is household month. Dependent variables analyzed in this table include $Payday\ Borrow_{h,t}$ (the dollar amount of online payday borrowing), $Payday\ Repay_{h,t}$ (the dollar amount of online payday repayment), $Financial\ Distress_{h,t}$ (the number of days a household is in financial distress), and $Consumption_{h,t}$ (the total dollar amount of household consumption). $Treated * After_{h,t}$ is an interaction term of $Treated_h$ and $After_t$. $Treated_h$ is an indicator that takes the value of 1 when household has a pre-existing relationship with a lender that is shut-down during OCP. $After_t$ is an indicator that takes the value of 1 after treatment and 0 otherwise. Both $Treated_h$ and $After_t$ are collinear with household and date fixed effects and are dropped from the regression. $Income_{h,t}$ is current household income and $Income_{h,t-1}$ is lagged household income. FE_t represent household time fixed effects and FE_h represent date fixed effects. Standard errors are clustered by household. t-statistics are reported in parentheses.

	Payday Borrow (1)	*Payday Repay* (2)	*Financial Distress* (3)	*Consumption* (4)
*Treated * After*	-94.493***	-175.557***	-0.050***	27.018
	(-24.56)	(-36.51)	(-3.06)	(1.20)
Income	0.001	0.015***	-0.000*	0.468***
	(1.58)	(23.53)	(-1.82)	(79.96)
Lagged Income	-0.000	-0.000	-0.000	0.005
	(-1.36)	(-1.06)	(-0.12)	(1.17)
N	271426	271426	271426	271426
R-sq	0.23	0.39	0.42	0.71
Time FE?	Yes	Yes	Yes	Yes
Household FE?	Yes	Yes	Yes	Yes
Pre-OCP Category Mean of Treated	$186	$338	1.06	$4,447

Table 4: This table explores how household outcomes change over time following Operation Choke Point. The regression specification is: $Y_{h,t} = \sum_{Z=1}^{6} \beta_Z \ Treated * QAZ_{h,t} + \beta_7 \ Income_{h,t} + \beta_8 \ Income_{h,t-1} + FE_t + FE_h + \epsilon_{h,t}$, where $Y_{h,t}$ is the dependent variable of interest, with subscripts h indicating household and t indicting time. The unit of observation is household month. Dependent variables analyzed in this table include $Payday\ Borrow_{h,t}$ (the dollar amount of online payday borrowing), $Payday\ Repay_{h,t}$ (the dollar amount of online payday repayment), $Financial\ Distress_{h,t}$ (the number of days a household is in financial distress), and $Consumption_{h,t}$ (the total dollar amount of household consumption). $Treated * QAZ_{h,t}$ is an interaction term of $Treated_h$ and QAZ_t. $Treated_h$ is an indicator that takes the value of 1 when household has a pre-existing relationship with a lender that is shut-down during OCP. QAZ_t is an indicator that takes the value of 1 the Z^{th} quarter after treatment and 0 otherwise. Both $Treated_h$ and QAZ_t are collinear with household and date fixed effects and are dropped from the regression. $Income_{h,t}$ is current household income and $Income_{h,t-1}$ is lagged household income. FE_t represent household time fixed effects and FE_h represent date fixed effects. Standard errors are clustered by household. t-statistics are reported in parentheses.

	Payday Borrow (1)	*Payday Repay* (2)	*Financial Distress* (3)	*Consumption* (4)
*Treated * QA1*	-80.172***	-132.085***	-0.023	-0.847
	(-20.18)	(-28.02)	(-1.38)	(-0.04)
*Treated * QA2*	-84.032***	-161.802***	-0.059***	28.368
	(-20.29)	(-31.83)	(-3.22)	(1.12)
*Treated * QA3*	-86.714***	-171.579***	-0.044**	37.944
	(-21.11)	(-32.85)	(-2.25)	(1.32)
*Treated * QA4*	-96.146***	-187.631***	-0.054**	5.531
	(-21.80)	(-33.39)	(-2.50)	(0.17)
*Treated * QA5*	-87.159***	-183.385***	-0.068***	8.116
	(-19.96)	(-32.64)	(-2.90)	(0.24)
*Treated * QA6*	-91.893***	-178.482***	-0.081***	52.328
	(-17.99)	(-28.07)	(-3.04)	(1.32)
Income	0.001	0.015***	-0.000*	0.468***
	(1.56)	(23.48)	(-1.82)	(79.97)
Lagged Income	-0.000	-0.000	-0.000	0.005
	(-1.35)	(-1.10)	(-0.12)	(1.17)
N	271426	271426	271426	271426
R-sq	0.23	0.39	0.42	0.71
Time FE?	Yes	Yes	Yes	Yes
Household FE?	Yes	Yes	Yes	Yes
Pre-OCP Category Mean of Treated	$186	$338	1.06	$4,447

Table 5: This table explores how household outcomes differ between heavy and light payday users following Operation Choke Point. Heavy borrowers are those with above the median number of payday transactions in the six month period before OCP from January 2013 to June 2013, while light borrowers are those below the median. Panel A presents the results of the subsample of heavy borrowers, while Panel B presents the results of the subsample of light borrowers. The regression specification is: $Y_{h,t} = \sum_{Z=1}^{6} \beta_Z \; Treated{*}QAZ_{h,t} + \beta_7 \; Income_{h,t} + \beta_8 \; Income_{h,t-1} + FE_t + FE_h + \epsilon_{h,t}$, where $Y_{h,t}$ is the dependent variable of interest, with subscripts h indicating household and t indicting time. The unit of observation is household month. Dependent variables analyzed in this table include $Payday\ Borrow_{h,t}$ (the dollar amount of online payday borrowing), $Payday\ Repay_{h,t}$ (the dollar amount of online payday repayment), $Financial\ Distress_{h,t}$ (the number of days a household is in financial distress), and $Consumption_{h,t}$ (the total dollar amount of household consumption). $Treated * QAZ_{h,t}$ is an interaction term of $Treated_h$ and QAZ_t. $Treated_h$ is an indicator that takes the value of 1 when household has a pre-existing relationship with a lender that is shut-down during OCP. QAZ_t is an indicator that takes the value of 1 the Z$^{\text{th}}$ quarter after treatment and 0 otherwise. Both $Treated_h$ and QAZ_t are collinear with household and date fixed effects and are dropped from the regression. $Income_{h,t}$ is current household income and $Income_{h,t-1}$ is lagged household income. FE_t represent household time fixed effects and FE_h represent date fixed effects. Standard errors are clustered by household. t-statistics are reported in parentheses.

Table 5: Panel A - Heavy Borrowers.

	Payday Borrow (1)	*Payday Repay* (2)	*Financial Distress* (3)	*Consumption* (4)
*Treated * QA1*	-118.519***	-173.769***	-0.037	4.515
	(-16.84)	(-21.58)	(-1.52)	(0.15)
*Treated * QA2*	-126.458***	-220.402***	-0.094***	48.863
	(-16.96)	(-25.32)	(-3.52)	(1.38)
*Treated * QA3*	-133.590***	-236.189***	-0.084***	83.222**
	(-18.43)	(-26.86)	(-2.93)	(2.04)
*Treated * QA4*	-142.646***	-258.180***	-0.104***	60.240
	(-18.33)	(-27.47)	(-3.30)	(1.36)
*Treated * QA5*	-127.736***	-251.733***	-0.121***	104.843**
	(-16.32)	(-26.46)	(-3.45)	(2.14)
*Treated * QA6*	-132.904***	-245.806***	-0.114***	131.006**
	(-14.91)	(-23.06)	(-2.89)	(2.31)
Income	0.001	0.022***	-0.000	0.433***
	(1.07)	(19.28)	(-0.87)	(53.61)
Lagged Income	-0.000	-0.001	-0.000***	0.126***
	(-0.84)	(-0.89)	(-7.33)	(10.97)
N	129305	129305	129305	129305
R-sq	0.25	0.43	0.43	0.72
Time FE?	Yes	Yes	Yes	Yes
Household FE?	Yes	Yes	Yes	Yes
Pre-OCP Category Mean of Treated	$286	$532	1.13	$4,536

Table 5: Panel B - Light Borrowers.

	Payday Borrow (1)	*Payday Repay* (2)	*Financial Distress* (3)	*Consumption* (4)
*Treated * QA1*	-29.321***	-64.594***	-0.016	-6.974
	(-9.88)	(-17.64)	(-0.66)	(-0.21)
*Treated * QA2*	-25.309***	-63.776***	-0.025	4.341
	(-8.14)	(-16.49)	(-0.99)	(0.12)
*Treated * QA3*	-17.890***	-59.842***	-0.004	8.137
	(-5.63)	(-14.94)	(-0.15)	(0.20)
*Treated * QA4*	-26.512***	-65.986***	0.001	-46.122
	(-7.50)	(-14.72)	(0.04)	(-1.04)
*Treated * QA5*	-24.440***	-66.255***	-0.013	-85.092*
	(-6.56)	(-14.28)	(-0.39)	(-1.75)
*Treated * QA6*	-24.125***	-53.867***	-0.049	-25.790
	(-5.21)	(-10.25)	(-1.34)	(-0.46)
Income	0.000	0.009***	-0.000	0.471***
	(0.73)	(15.07)	(-0.70)	(56.87)
Lagged Income	-0.000	-0.000*	0.000	0.003
	(-1.59)	(-1.66)	(0.86)	(1.27)
N	141944	141944	141944	141944
R-sq	0.16	0.27	0.41	0.70
Time FE?	Yes	Yes	Yes	Yes
Household FE?	Yes	Yes	Yes	Yes
Pre-OCP Category Mean of Treated	$70	$114	0.97	$4,349

Table 6: This table explores how household outcomes differ between high and low income payday users following Operation Choke Point. High income households are those with above the median income in the six month period before OCP from January 2013 to June 2013, while low income households are those below the median. Panel A presents the results of the subsample of high income borrowers, while Panel B presents the results of the subsample of low income borrowers. The regression specification is: $Y_{h,t} = \sum_{Z=1}^{6} \beta_Z \; Treated * QAZ_{h,t} + \beta_7 \; Income_{h,t} + \beta_8 \; Income_{h,t-1} + FE_t + FE_h + \epsilon_{h,t}$, where $Y_{h,t}$ is the dependent variable of interest, with subscripts h indicating household and t indicting time. The unit of observation is household month. Dependent variables analyzed in this table include $Payday\ Borrow_{h,t}$ (the dollar amount of online payday borrowing), $Payday\ Repay_{h,t}$ (the dollar amount of online payday repayment), $Financial\ Distress_{h,t}$ (the number of days a household is in financial distress), and $Consumption_{h,t}$ (the total dollar amount of household consumption). $Treated * QAZ_{h,t}$ is an interaction term of $Treated_h$ and QAZ_t. $Treated_h$ is an indicator that takes the value of 1 when household has a pre-existing relationship with a lender that is shut-down during OCP. QAZ_t is an indicator that takes the value of 1 the Z^{th} quarter after treatment and 0 otherwise. Both $Treated_h$ and QAZ_t are collinear with household and date fixed effects and are dropped from the regression. $Income_{h,t}$ is current household income and $Income_{h,t-1}$ is lagged household income. FE_t represent household time fixed effects and FE_h represent date fixed effects. Standard errors are clustered by household. t-statistics are reported in parentheses.

Table 6: Panel A - High Income Borrowers.

	Payday Borrow (1)	*Payday Repay* (2)	*Financial Distress* (3)	*Consumption* (4)
*Treated * QA1*	-98.132***	-154.620***	-0.004	1.598
	(-15.31)	(-20.89)	(-0.17)	(0.04)
*Treated * QA2*	-103.348***	-189.114***	-0.060**	60.323
	(-15.64)	(-23.48)	(-2.24)	(1.51)
*Treated * QA3*	-112.143***	-204.286***	-0.046	18.979
	(-16.92)	(-24.67)	(-1.59)	(0.41)
*Treated * QA4*	-123.432***	-223.350***	-0.083***	14.310
	(-17.32)	(-24.85)	(-2.61)	(0.28)
*Treated * QA5*	-115.910***	-219.942***	-0.093***	5.692
	(-16.43)	(-24.56)	(-2.70)	(0.10)
*Treated * QA6*	-122.498***	-218.676***	-0.086**	129.465**
	(-14.61)	(-21.48)	(-2.18)	(2.01)
Income	0.000	0.016***	-0.000	0.458***
	(0.47)	(18.69)	(-1.21)	(65.24)
Lagged Income	-0.000	-0.000	0.000	0.004
	(-1.29)	(-1.14)	(0.16)	(1.21)
N	135284	135284	135284	135284
R-sq	0.24	0.39	0.43	0.65
Time FE?	Yes	Yes	Yes	Yes
Household FE?	Yes	Yes	Yes	Yes
Pre-OCP Category Mean of Treated	$232	$417	1.15	$6,444

Table 6: Panel B - Low Income Borrowers.

	Payday Borrow (1)	*Payday Repay* (2)	*Financial Distress* (3)	*Consumption* (4)
*Treated * QA1*	-60.952***	-107.621***	-0.046*	2.433
	(-13.18)	(-18.69)	(-1.92)	(0.09)
*Treated * QA2*	-62.974***	-131.912***	-0.061**	4.052
	(-12.83)	(-21.64)	(-2.42)	(0.13)
*Treated * QA3*	-59.727***	-136.433***	-0.046*	70.978**
	(-12.61)	(-21.93)	(-1.72)	(2.08)
*Treated * QA4*	-67.065***	-149.178***	-0.027	3.304
	(-13.16)	(-22.63)	(-0.95)	(0.09)
*Treated * QA5*	-56.645***	-143.952***	-0.044	21.893
	(-11.25)	(-21.68)	(-1.37)	(0.54)
*Treated * QA6*	-59.488***	-135.989***	-0.079**	-19.726
	(-10.38)	(-18.17)	(-2.22)	(-0.43)
Income	0.001	0.013***	-0.000	0.442***
	(0.83)	(14.11)	(-0.87)	(46.12)
Lagged Income	-0.000	-0.001*	-0.000***	0.164***
	(-0.22)	(-1.68)	(-7.11)	(17.10)
N	135332	135332	135332	135332
R-sq	0.22	0.38	0.40	0.61
Time FE?	Yes	Yes	Yes	Yes
Household FE?	Yes	Yes	Yes	Yes
Pre-OCP Category Mean of Treated	$151	$279	1.01	$3,062

Table 7: This table explores how household outcomes differ between recent and non-recent payday borrowers following Operation Choke Point. Recent borrowers are those who borrowed in June 2013, approximately 1 month before OCP, while non-recent borrowers are those who did not.Panel A presents the results of the recent borrowers, while Panel B presents the results of the non-recent borrowers. The regression specification is: $Y_{h,t} = \sum_{Z=1}^{6} \beta_Z \ Treated * QAZ_{h,t} + \beta_7 \ Income_{h,t} + \beta_8 \ Income_{h,t-1} + FE_t + FE_h + \epsilon_{h,t}$, where $Y_{h,t}$ is the dependent variable of interest, with subscripts h indicating household and t indicting time. The unit of observation is household month. Dependent variables analyzed in this table include $Payday\ Borrow_{h,t}$ (the dollar amount of online payday borrowing), $Payday\ Repay_{h,t}$ (the dollar amount of online payday repayment), $Financial\ Distress_{h,t}$ (the number of days a household is in financial distress), and $Consumption_{h,t}$ (the total dollar amount of household consumption). $Treated * QAZ_{h,t}$ is an interaction term of $Treated_h$ and QAZ_t. $Treated_h$ is an indicator that takes the value of 1 when household has a pre-existing relationship with a lender that is shut-down during OCP. QAZ_t is an indicator that takes the value of 1 the Z$^{\text{th}}$ quarter after treatment and 0 otherwise. Both $Treated_h$ and QAZ_t are collinear with household and date fixed effects and are dropped from the regression. $Income_{h,t}$ is current household income and $Income_{h,t-1}$ is lagged household income. FE_t represent household time fixed effects and FE_h represent date fixed effects. Standard errors are clustered by household. t-statistics are reported in parentheses.

Table 7: Panel A - Recent Borrowers.

	Payday Borrow (1)	*Payday Repay* (2)	*Financial Distress* (3)	*Consumption* (4)
*Treated * QA1*	-186.133***	-249.227***	0.044	34.612
	(-17.13)	(-20.15)	(1.38)	(0.82)
*Treated * QA2*	-206.148***	-323.516***	-0.053	146.205***
	(-17.91)	(-23.97)	(-1.53)	(3.09)
*Treated * QA3*	-211.948***	-332.792***	-0.029	105.513**
	(-19.11)	(-24.77)	(-0.78)	(2.00)
*Treated * QA4*	-212.885***	-350.106***	-0.112***	189.243***
	(-18.14)	(-24.43)	(-2.85)	(3.23)
*Treated * QA5*	-197.822***	-335.541***	-0.122***	183.944***
	(-16.90)	(-23.48)	(-2.76)	(2.79)
*Treated * QA6*	-198.579***	-330.615***	-0.080	234.161***
	(-15.24)	(-20.96)	(-1.55)	(3.13)
Income	0.002	0.023***	-0.000	0.475***
	(1.53)	(14.25)	(-1.59)	(44.63)
Lagged Income	-0.000	-0.000	0.000**	0.002
	(-1.20)	(-0.60)	(2.33)	(1.50)
N	76077	76077	76077	76077
R-sq	0.32	0.43	0.41	0.72
Time FE?	Yes	Yes	Yes	Yes
Household FE?	Yes	Yes	Yes	Yes
Pre-OCP Category Mean of Treated	$377	$505	0.96	$4,605

Table 7: Panel B - Non-Recent Borrowers.

	Payday Borrow (1)	*Payday Repay* (2)	*Financial Distress* (3)	*Consumption* (4)
*Treated * QA1*	-38.534***	-86.624***	-0.049**	-5.046
	(-13.03)	(-21.68)	(-2.46)	(-0.19)
*Treated * QA2*	-38.580***	-101.241***	-0.061***	-6.988
	(-12.24)	(-22.92)	(-2.85)	(-0.24)
*Treated * QA3*	-39.474***	-110.221***	-0.050**	24.427
	(-12.13)	(-23.27)	(-2.14)	(0.72)
*Treated * QA4*	-51.549***	-125.150***	-0.030	-61.567*
	(-14.14)	(-24.27)	(-1.17)	(-1.67)
*Treated * QA5*	-47.585***	-127.920***	-0.049*	-45.738
	(-12.50)	(-23.76)	(-1.75)	(-1.15)
*Treated * QA6*	-52.407***	-121.548***	-0.083***	0.695
	(-11.16)	(-19.58)	(-2.66)	(0.02)
Income	0.001	0.013***	0.000	0.429***
	(1.45)	(19.52)	(0.18)	(64.37)
Lagged Income	-0.001**	-0.000	-0.000***	0.139***
	(-2.14)	(-0.95)	(-10.16)	(27.77)
N	195333	195333	195333	195333
R-sq	0.16	0.33	0.42	0.70
Time FE?	Yes	Yes	Yes	Yes
Household FE?	Yes	Yes	Yes	Yes
Pre-OCP Category Mean of Treated	$113	$275	1.09	$4,387

Table 8: This table explores how windfall gains affect household responses to Operation Choke Point. The regression specification is: $Y_{h,t} = \sum_{Z=1}^{6} \beta_Z \; Treated * QAZ * Candidate * Windfall_{h,t} + \sum_{Z=1}^{6} \beta_{Z+6} \; Treated * QAZ * Candidateh, t + \sum_{Z=1}^{6} \beta_{Z+12} \; Treated * QAZh, t + \beta_{19} \; Income_{h,t} + FE_t + FE_h + \epsilon_{h,t}$, where $Y_{h,t}$ is the dependent variable of interest, with subscripts h indicating household and t indicting time. The unit of observation is household month. Dependent variables analyzed in this table include $Payday\ Borrow_{h,t}$ (the dollar amount of online payday borrowing), $Payday\ Repay_{h,t}$ (the dollar amount of online payday repayment), $Financial\ Distress_{h,t}$ (the number of days a household is in financial distress), and $Consumption_{h,t}$ (the total dollar amount of household consumption). $Treated_h$ is an indicator that takes the value of 1 when household has a pre-existing relationship with a lender that is shut-down during OCP. QAZ_t is an indicator that takes the value of 1 the Z^{th} quarter after treatment and 0 otherwise. $Candidate_h$ is an indicator that takes the value of 1 if the household borrowed from a lender in the fourteen day period prior to the lenders closure and 0 otherwise. $Windfall_h$ is an indicator that takes the value of 1 if the household received a windfall gain through the closure of a lender and 0 otherwise. $Treated * QAZ_{h,t}$ is the interaction of $Treated_h$ and QAZ_t. $Treated * QAZ * Candidate_{h,t}$ is the triple interaction of $Treated_h$, QAZ_t, and $Candidate_h$. $Treated * QAZ * Candidate * Windfall_{h,t}$ is the quadruple interaction of $Treated_h$, QAZ_t, $Candidate_h$, and $Windfall_h$. Both $Treated_h$ and QAZ_t are collinear with household and date fixed effects and are dropped from the regression. $Income_{h,t}$ is current household income. FE_t represent household time fixed effects and FE_h represent date fixed effects. Standard errors are clustered by household. t-statistics are reported in parentheses.

	Payday Borrow (1)	*Payday Repay* (2)	*Financial Distress* (3)	*Consumption* (4)
*Treated * QA1 * Candidate * Windfall*	-50.900	-178.725***	0.167*	-5.388
	(-1.36)	(-4.22)	(1.87)	(-0.04)
*Treated * QA2 * Candidate * Windfall*	-57.379	-45.579	0.186*	30.299
	(-1.43)	(-0.98)	(1.94)	(0.22)
*Treated * QA3 * Candidate * Windfall*	-97.191**	-78.320*	0.058	101.791
	(-2.44)	(-1.66)	(0.63)	(0.70)
*Treated * QA4 * Candidate * Windfall*	-114.658***	-86.856*	0.078	5.903
	(-2.82)	(-1.79)	(0.77)	(0.04)
*Treated * QA5 * Candidate * Windfall*	-78.406**	-59.409	0.069	-42.548
	(-2.01)	(-1.31)	(0.71)	(-0.26)
*Treated * QA6 * Candidate * Windfall*	-103.461**	-39.201	0.111	198.894
	(-2.44)	(-0.83)	(1.00)	(1.13)
*Treated * QA1 * Candidate*	-50.895**	2.018	0.151***	188.233**
	(-2.20)	(0.09)	(2.70)	(2.29)
*Treated * QA2 * Candidate*	-202.765***	-202.889***	0.105*	311.380***
	(-8.33)	(-7.23)	(1.75)	(3.44)
*Treated * QA3 * Candidate*	-237.677***	-225.255***	0.218***	126.747
	(-9.65)	(-7.79)	(3.65)	(1.43)
*Treated * QA4 * Candidate*	-226.007***	-228.785***	0.189***	282.666***
	(-9.20)	(-7.75)	(2.83)	(2.87)
*Treated * QA5 * Candidate*	-216.121***	-232.397***	0.167**	253.922**
	(-8.94)	(-8.09)	(2.51)	(2.27)
*Treated * QA6 * Candidate*	-207.836***	-237.598***	0.185**	187.981
	(-7.84)	(-7.61)	(2.51)	(1.61)
*Treated * QA1*	-74.248***	-125.791***	-0.045**	-17.995
	(-20.90)	(-29.02)	(-2.54)	(-0.77)
*Treated * QA2*	-63.549***	-141.816***	-0.076***	-2.303
	(-18.01)	(-30.67)	(-4.02)	(-0.09)
*Treated * QA3*	-60.285***	-147.293***	-0.067***	22.785
	(-16.22)	(-29.77)	(-3.28)	(0.77)
*Treated * QA4*	-70.024***	-162.514***	-0.075***	-20.902
	(-17.08)	(-30.08)	(-3.36)	(-0.64)
*Treated * QA5*	-65.680***	-161.067***	-0.086***	-12.725
	(-15.53)	(-29.07)	(-3.51)	(-0.36)
*Treated * QA6*	-68.810***	-154.903***	-0.103***	27.018
	(-14.00)	(-24.72)	(-3.72)	(0.66)
Income	0.001*	0.015***	-0.000*	0.468***
	(1.67)	(23.75)	(-1.85)	(79.94)
Lagged Income	-0.000	-0.000	-0.000	0.005
	(-1.37)	(-1.10)	(-0.13)	(1.17)
N	271426	271426	271426	271426
R-sq	0.24	0.39	0.42	0.71
Time FE?	Yes	Yes	Yes	Yes
Household FE?	Yes	Yes	Yes	Yes
Pre-OCP Category Mean of Treated	$186	$338	1.06	$4,447

Table 9: This table explores whether substitution to unobserved lenders is contaminating the results in previous sections. In this table, I restrict the treated sample to households living in states where payday lending illegal. Further, control households are limited to households living in states where payday lending is legal. The regression specification is: $Y_{h,t} = \sum_{Z=1}^{6} \beta_Z \; Treated * QAZ_{h,t} + \beta_7 \; Income_{h,t} + \beta_8 \; Income_{h,t-1} + FE_t + FE_h + \epsilon_{h,t}$, where $Y_{h,t}$ is the dependent variable of interest, with subscripts h indicating household and t indicting time. The unit of observation is household month. Dependent variables analyzed in this table include $Payday\ Borrow_{h,t}$ (the dollar amount of online payday borrowing), $Payday\ Repay_{h,t}$ (the dollar amount of online payday repayment), $Financial\ Distress_{h,t}$ (the number of days a household is in financial distress), and $Consumption_{h,t}$ (the total dollar amount of household consumption). $Treated{*}QAZ_{h,t}$ is an interaction term of $Treated_h$ and QAZ_t. $Treated_h$ is an indicator that takes the value of 1 when household has a pre-existing relationship with a lender that is shut-down during OCP. QAZ_t is an indicator that takes the value of 1 the Z$^{\text{th}}$ quarter after treatment and 0 otherwise. Both $Treated_h$ and QAZ_t are collinear with household and date fixed effects and are dropped from the regression. $Income_{h,t}$ is current household income and $Income_{h,t-1}$ is lagged household income. FE_t represent household time fixed effects and FE_h represent date fixed effects. Standard errors are clustered by household. t-statistics are reported in parentheses.

	Payday Borrow (1)	*Payday Repay* (2)	*Financial Distress* (3)	*Consumption* (4)
*Treated * QA1*	-102.533***	-182.614***	0.028	-52.676
	(-18.04)	(-24.79)	(1.06)	(-1.48)
*Treated * QA2*	-104.980***	-223.874***	-0.012	-14.996
	(-17.53)	(-27.66)	(-0.45)	(-0.39)
*Treated * QA3*	-100.956***	-233.649***	-0.048*	14.565
	(-16.47)	(-27.77)	(-1.75)	(0.34)
*Treated * QA4*	-122.885***	-251.617***	-0.065**	8.886
	(-18.82)	(-28.41)	(-2.11)	(0.19)
*Treated * QA5*	-116.036***	-253.708***	-0.089***	-40.953
	(-17.68)	(-28.27)	(-2.68)	(-0.80)
*Treated * QA6*	-121.795***	-252.685***	-0.115***	28.433
	(-17.38)	(-25.95)	(-3.12)	(0.49)
Income	0.001*	0.016***	-0.000	0.468***
	(1.94)	(18.01)	(-1.64)	(60.29)
Lagged Income	-0.000*	-0.000	0.000	0.003
	(-1.69)	(-1.18)	(0.56)	(1.27)
N	149929	149929	149929	149929
R-sq	0.21	0.37	0.42	0.70
Time FE?	Yes	Yes	Yes	Yes
Household FE?	Yes	Yes	Yes	Yes
Pre-OCP Category Mean of Treated	$183	$346	0.95	$4,177

Table 10: This table contains the two-stage least squares estimates of payday borrowing on household outcomes. The first-stage specification is: $PaydayBorrow_{h,t} = \sum_{Z=1}^{39} \beta_Z \ AliveZ * RelationshipZ_{h,t} + \beta_{40} \ Income_{h,t} + \beta_{41} \ Income_{h,t-1} + FE_t + FE_h + \epsilon_{h,t}$, and the second stage specification is: $Y_{h,t} = \beta_1 \ \widehat{PaydayBorrow}_{h,t} + \beta_2 \ Income_{h,t} + \beta_3 \ Income_{h,t-1} + FE_t + FE_h + \epsilon_{h,t}$, where $Y_{h,t}$ is the dependent variable of interest, with subscripts h indicating household and t indicting time. The unit of observation is household month. Dependent variables analyzed in this table include $Payday \ Repay_{h,t}$ (the dollar amount of online payday repayment), $Financial \ Distress_{h,t}$ (the number of days a household is in financial distress), and $Consumption_{h,t}$ (the total dollar amount of household consumption). $AliveZ * RelationshipZ_{h,t}$ is an interaction term of $RelationshipZ_h$ and $AliveZ_t$. $RelationshipZ_h$ is an indicator that takes the value of 1 when household has a pre-existing relationship with a lender Z and 0 otherwise. $AliveZ_t$ is an indicator that takes the value of 1 if lender Z is alive and 0 otherwise. Since $RelationshipZ_h$ and $AliveZ_t$ are collinear with household and time fixed effects, they are dropped from the regression. $Income_{h,t}$ is household income in dollars and $Income_{h,t-1}$ is lagged household income in dollars. FE_t and FE_h represent time and household fixed effects, respectively. Standard errors are bootstrapped. t-statistics are reported in parentheses.

	Payday Repay (1)	*Financial Distress* (2)	*Consumption* (3)
$\widehat{PaydayBorrow}$	1.4293***	0.0002***	-0.3146***
	(41.51)	(2.77)	(-2.70)
Income	0.0144***	-0.0000	0.4678***
	(21.24)	(-1.57)	(27.04)
Lagged Income	0.0000	-0.0000	0.0048
	(0.07)	(-0.01)	(0.08)
N	271426	271426	271426

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