Measuring the Individual-Level Effects of Access to Credit: Evidence from Payday Loans

JOB MARKET PAPER

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Abstract

An estimated ten million American households borrow on payday loans each year. Despite the prevalence of these loans, little is known about the effects of access to this form of short-term high-cost credit. We use a regression-discontinuity framework, which exploits the credit-scoring process used to approve or deny loan applications, to study the causal impact of access to payday loans on borrowing activity, bankruptcy, and crime. Using personal identifying information, public records on bankruptcy and crime are matched to a four-year panel dataset of 145,000 loan applicants from a large payday and pawn lender. We find that those approved for a payday loan apply for 8.8 more payday loans on average, amounting to $2400 of payday loan debt and $350 in finance charges. This high frequency of borrowing suggests that payday loan behavior is unlikely to be driven by temporary shocks to consumption needs. Payday loan approval decreases pawn loan borrowing in the short run, but this decrease dissipates after a few weeks. There is suggestive but inconclusive evidence that payday loans increase Chapter 13 bankruptcy filing rates. We find no compelling evidence that access to payday loan cash has an effect on the incidence of crime. JEL classification: D14 (Personal Finance), G11 (Portfolio Choice; Investment Decisions), D91 (Intertemporal Consumer Choice; Lifecycle Models and Saving

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1 Introduction

Each year ten million American households take out payday loans (Robinson and Wheeler 2003). This form of short-term, high-interest credit provides small amounts of liquidity until borrowers' next paydays.[1] Finance charges are typically 18 percent for the duration of the loan (usually two weeks), implying annualized interest rates above 400 percent. Though scarce prior to the 1990s, there are now more payday loan outlets in the United States than McDonald's.[2] Standard economic theory suggests that consumer credit—even high-interest credit—can facilitate consumption-smoothing, and the payday loan industry asserts that the loans help customers cope with short-term shocks which arise between paychecks. Yet the merits of payday lending have been hotly debated, and policymakers and consumer advocates have deemed the loans "predatory," "usurious," and a "scourge" to low-income workers. For example, State Senator Jim Ferlo of Pennsylvania argued, payday lenders"encourage you not to pay them back and they reel you in. They start the process of getting you hooked financially. You accumulate interest and it becomes a vicious cycle" (Mauriello 2005). The polarized debate on the consequences of this increasingly popular form of credit has led 11 states to pass legislation restricting payday lending, and, in November 2005, the FDIC limited the duration borrowers could be indebted to a payday lender (FDIC 2005).

Despite this debate about the merits of payday loans, little is known about their economic impact. In this study, we use a regression-discontinuity approach to analyze proprietary data from a large payday and pawn lender and to provide the first empirical estimates of the effects of access to payday loans. Specifically, first, we examine the effect on subsequent payday and pawn borrowing. Second, by matching individuals who applied for payday loans at a large payday lender to public records on bankruptcy and arrests, we estimate the effect of access to payday loans on personal bankruptcy petitions and arrests.

The institutional features of the payday loan application process make the regression-discontinuity approach possible.[3] Payday loan applications are approved if and only if the applicant's credit score

[1] Payday loans are one form of "fringe banking," such as check cashing, pawnshops, and other services which substitute for traditional banks. While some research exists—Caskey (1991, 1994, 2001, 2005) studies fringe banking in great depth; Flannery and Samolyk (2005) study the payday industry's profitability; Elliehausen and Lawrence (2001) survey payday borrowers; and Stegman and Faris (2003) study the payday industry's business practices—the literature lags far behind this ferociously growing industry. Washington (2006) and Adams, Einav and Levin (2006) have studied fringe banking and subprime lending more recently.

[2] Reliable aggregate data on the industry are scarce. The most recent reports suggest there are 30,000 payday loan outlets in the US and that the annual dollar volume of loans grew fourfold in four years to $40 billion dollars in 2003 (Robinson and Wheeler 2003, PricewaterhouseCoopers 2001).

[3] The regression-discontinuity approach is becoming commonplace. For foundations, see Thistlethwaite and Camp-

exceeds a fixed threshold, with few exceptions. We argue that unobservable characteristics of those in the immediate neighborhood around the threshold are similar, so that differences in outcomes for those who are barely approved to those barely denied can be attributed solely to payday loan access. Three main results emerge from this exercise. First, the effects of payday loan approval on subsequent payday loan applications and subsequent pawn borrowing speak to models of credit demand. In addition, our findings contribute to the vast literatures on the determinants of both bankruptcy and crime. We discuss each of these in turn.

Our first results document the striking frequency with which consumers borrow on payday loans. Applicants in our data who are approved for loans apply 8.8 more times on average within 12 months, borrowing $2400 in total with $350 in interest payments. In the short-run, loan approval reduces the probability of taking out a pawn loan from this company by a factor of two but this effect dissipates within a few weeks. Motivated by this high intensity of borrowing, a companion paper in progress, Skiba and Tobacman (2006a), develops a structural model of payday loan borrowing, repayment, and default to test the relative importance of self-control problems and consumption shocks (such unexpected expenses for car repair or health expenditures) in explaining the frequency of borrowing. At face value, however, the repeated and persistent borrowing we observe appears difficult to reconcile with temporary shocks to consumption needs.

As one test of whether payday loans might mitigate or exacerbate financial stress, we quantify the effect payday loans have on personal bankruptcy filings over several time horizons. Our benchmark estimates imply an increase of 27 percent in Chapter 13 bankruptcy petitions within two years of a successful payday loan application, an increase from a baseline petition rate of 1.219 percent among applicants.[4] In some specifications, however, the point estimates have large standard errors and the coefficients are not significant, making us cautious in interpreting the results. We discuss robustness of these results in Section 6.2.

Standard economic theory of consumption and savings over the life-cycle is ambiguous with regard to the mechanisms through which payday loans could increase financial stress. We weigh our evidence against the candidate hypotheses in Section 9. That discussion is supplemented with a

bell (1960), Hahn, Todd and der Klaauw (2001), Porter (2003) and Lee's recent work ((Lee forthcoming), (Lee and Card 2006), (Lee and McCrary 2005), (DiNardo and Lee 2004), (Lee, Moretti and Butler 2004)).

[4]We study bankruptcy petitions, regardless of whether the petition was dismissed. The majority of Ch13 petitions are dismissed in our data. We view petitions themselves as an outcome of interest, representing a form of financial distress. Because bankruptcy law precludes creditors from contacting debtors once a petition is filed, regardless of the outcome of the process, debtors may file to protect themselves from creditors even if their debts are unlikely to be discharged. Hereafter we use "petition" and "filling" interchangeably.

sample of detailed information from individual bankruptcy petitions where we can observe creditors, assets and debt levels. The absence of short-run effects of payday loan access on bankruptcy petitions casts doubt on the theory that payday borrowers are strategically accumulating debt in anticipation of bankruptcy. Our results are more consistent with a longer-term compromising of borrowers' overall financial stability due to repeated finance charges made to the payday lender.

A number of recent papers analyze the short-run effect of crime to a variety of factors, including sports (Card and Dahl 2006), movie violence (Dahl and DellaVigna 2006), the school calendar (Jacob and Lefgren 2003) and welfare payments (Dobkin and Puller 2006). In a similar vein, we study the short-run response of crime to the approval or rejection of a payday loan application. The effects of cash payments on crime has been documented most recently by Dobkin and Puller (2006), who show evidence that arrival of government transfer payments is associated with decreases in revenue-generating crime and increases in drug- and alcohol related hospitalizations and arrests. In light of these findings, we could similarly expect access to payday loan cash to increase drug, or alcohol-related crime. On the other hand, if payday loans provide a last resort to overcome shocks and consumption needs they might result in a decrease of revenue-generating crime in the short run. We find no conclusive evidence that payday loans have an effect on crime in the short or long run, but it is important to bear in mind that the very small baseline rates of crime, about 0.1% of applicants commit a crime within seven days of their first application, limit our precision.

Beyond these specific findings, the paper extends the literature on the effects of credit access both in terms of the range of institutions studied and in the nature of data employed. The payday loan industry, and the subprime-lending market more broadly, have grown dramatically in the last decade, yet have remained largely outside economists' purview. Data on high-interest lending are proprietary, confidential, and politically sensitive. Collaboration with a major payday lender has given us access to data on consumer-credit access, comprising detailed demographic and borrowing information for the full population of loan applications over a four-year period. Individual identifiers in the application records—such as name, date of birth, and Social Security number—allow us to match each applicant to public records on pertinent outcomes. This unique, large-scale, matched database allows us to shed light on the fastest growing source of credit for low-income workers. Our individual-level identification strategy also allows us explore the microeconomic channels through which credit affects consumers, complementing the rich literature which identifies macroeconomic impacts of credit.[5]

The analysis in this paper has several limitations. First, while our research design provides clean identification, it has limited ability to address welfare issues. To help address this and other questions, our companion paper in progress (Skiba and Tobacman 2006a), develops a structural dynamic-programming model of consumption, saving, payday-loan borrowing and default behavior. That paper's model includes standard features like liquidity constraints and stochastic income, and also incorporates shocks to consumption needs, institutionally-realistic payday loans, and generalizations of the discount function. Method of simulated moments estimates of the model's key parameters seek to test the relative importance of consumption shocks, partially naive quasi-hyperbolic discounting, overoptimism about future choices, and overoptimism about future states of the world. The results of this estimation will provide insight into whether consumption shocks alone can account for the frequency of payday loan borrowing. In addition, with the estimated structural model we will be able to evaluate the welfare implications of policy alternatives.

The second limitation is that our data derive from a single lender that operates hundreds of payday loan outlets but is not a monopolist. Thus, our estimates will likely represent an upper bound on any effects access to payday loans has on subsequent borrowing behavior and a lower bound on the effects on bankruptcy and crime. In Section 8 we address this issue and attempt to partially abate concerns by restricting the sample to regions where this lender has the highest market share and hence competition is lowest. We find results similar to the full sample specifications.

Finally, a limitation common to all research employing the regression-discontinuity approach[6] is that estimates are identified off of a small range around the threshold. Payday loan access may affect consumers with very high or very low credit scores differently than the marginal applicants that drive this paper's estimates. Moreover, because the payday loan market is unique, any results about its impact may not generalize to other forms of credit. Given that 10 million working households borrow on payday loans each year, we believe the payday industry is important to understand in its own right.

The annual dollar volume of loans written was up fourfold in four years to $40 billion dollars in 2003. Major banks have begun financing payday loan operations and there are currently six

[5] Among the vast literature in economics on borrowing and credit, there is very little empirical research on the causal impact of random individual variation in the ability to borrow money. Excellent exceptions are the work ofGross and Souleles (2002) and Ausubel (1999) on credit cards, and Karlan and Zinman's (2005, 2006b, 2006a) studies of South African consumer credit.

[6] More generally, discrete instrumental variables identify only local average treatment effects.

publicly traded payday lenders. The largest five payday lenders have approximately 30 percent of the nationwide market share. Skiba and Tobacman (2006b) provide estimates of the profitability of payday loans. We find lenders' returns differ little from typical financial returns and are consistent with an interpretation that payday lenders face high per-loan and per-store fixed costs in a competitive market. According to a 1999 report, 90 percent of payday loan activity in terms of locations, advances, fees, employees, payroll was accounted for by largest 25 percent of companies (PricewaterhouseCoopers 2001).

The remainder of the paper proceeds as follows. In Section 2, we provide additional background on payday loans. Section 3 outlines our estimation strategy, focusing on the credit-score discontinuity. We present our empirical results on payday loan applications, pawn borrowing, bankruptcy filing, and arrests in Sections 4, 5, 6 and 7, respectively. We discuss the results and conclude in Section 9.

2 Payday Loans: Data and Institutional Rules

To apply for payday loans individuals fill out loan applications and present their most recent pay stub, checking-account statement, and utility or phone bill, along with state-issued photo identification. Payday lenders use an applicant's pay stub to infer the date of the applicant's next payday and hence determine the due date of the loan. The duration of payday loans is hence extremely short, ranging from one week to one month depending on how frequently the borrower is paid. Payday loans are collateralized with personal checks dated on borrowers' upcoming paydays.[7]

The payday loan data we use come from a provider of financial services that offers payday loans.[8] Table 1 presents demographic and background characteristics of this population. Consistent with independent survey evidence on payday borrowers, women are slightly more common than men in our population, and a large share of the applicants are Black or Hispanic. Median annualized individual income is about \$20,000, and the median balance in applicants' checking accounts is \$66.[9]

[7] The longstanding practice of some employers who provide advances against upcoming paychecks is distinct from the topic studied here: payday lenders do not directly garnish paychecks to obtain loan repayment.

[8] The data are deflated with the CPI-U to January 2002 dollars, we censor the top $\frac{1}{10}$% of the distributions of bank balance and net pay, replacing those values with missing and also replace age with missing if age is less than 18.

[9] Having a checking account is a precondition for receiving a payday loan: applicants must have an account against which to write their postdated personal checks. As a result payday loans are not used by the unbanked

The data are deflated with the CPI-U to January 2002 dollars, we censor the top $\frac{1}{10}\%$ of the distributions of bank balance and net pay, replacing those values with missing and also replace age with missing if age is less than 18.

3 Identification

3.1 The Credit-Score Regression Discontinuity

Access to payday loans depends on a credit score calculated at the time of the loan application by a third party, Teletrack.[10] Scores above a fixed threshold result in loan approval, while applications with scores below that threshold are rejected. Among the 17.4 percent of first-time applicants with scores below the threshold, 99.6 percent are rejected, while 96.9 percent of first-time applicants scoring above the threshold are approved. The credit scoring formula and the threshold for approval were adjusted at all shops once during our period of observation, in August 2002. Throughout the paper we focus on a variable called $AmtAboveThr$, which is equal to the raw Teletrack score minus the approval threshold that was in force at the time of the application, divided by the corresponding pre- or post-August 2002 standard deviation of raw scores.[11] For convenience, in the rest of the paper we often refer to $AmtAboveThr$ as "the credit score." Figure 1 plots a histogram of $AmtAboveThr$ for first-time payday loan applicants.[12]

Consistent with the company's stated policy, the credit score has a discontinuous effect on the probability a payday loan application is approved. Figure 2 displays the probability of approval among first-time applicants, $App1Approved$, as a function of $AmtAboveThr$. Two quartic polynomials, fit independently to the data on either side of the credit score threshold, are superimposed on the figure.

We quantify the discontinuity by examining the coefficient on an indicator for being above the

(Washington 2006), though that population is targetted by services like check cashing that some payday lenders also offer.

[10] The credit scoring formula is proprietary, but we understand these scores to differ from FICO scores in depending on a shorter history of behavior and focusing on borrowing histories in the subprime market. Though Teletrack serves all major payday lenders, the lenders establish their own criteria for approving loan applications. Skiba and Tobacman (2006b) discuss more details of the credit scoring process in the context of profitibility of payday lenders.

[11] Though standard tests indicate the pre- and post-August 2002 distributions of $AmtAboveThr$ differ, we assume for simplicity in the rest of the paper that the functional form of the effects of $AmtAboveThr$ did not change. Quantitative conclusions change little, and qualitative conclusions not at all, if we interact functions of $AmtAboveThr$ with a Post-August-2002 dummy in all of the regressions.

[12] We focus on credit scores at the time of first payday loan applications for reasons discussed below.

threshold, $AboveThr$, in regressions of $App1Approved$ on $AboveThr$, functions of $AmtAboveThr$, and control variables presented in Table 2. Most generally, for first-time applicants we estimate:

$$App1Approved_i = \beta_0 + \beta_1 AboveThr_i + f\left(AmtAboveThr_i\right) + \gamma X_i' + \delta M_i'^{t} + \varepsilon_i, \quad (1)$$

where $f(\cdot)$ is a smooth function of the credit score; X_i is a vector of demographics and background characteristics including gender, race dummies, age, monthly income, job tenure, pay frequency dummies, checking account balance, the number of "not sufficient funds" events on the most recent bank statement, months in current residence, and dummies for homeownership, direct deposit, and garnishment of paycheck, and dummies for missing for each of these variables; and M^t is a full set of dummies for month of first payday-loan application, so $M_i^t = 1$ if i's first application was in month t and $M_i^{t'} = 0$ for $t' \neq t$.

Columns 1-5 report OLS (linear probability) regressions based on this specification. In every specification, the coefficient on $AboveThr$ is highly significant and equal to slightly less than 1. The R-squared in Column 1 equals 0.84 when only $AboveThr$ is included on the RHS. As the subsequent columns add in a quartic in $AmtAboveThr$ fully interacted with $AboveThr$, the demographics listed above, and the dummies for month of first payday-loan application, the coefficient on $AboveThr$ hardly changes and the R-squared increases by only 1 percent. Probits in Columns 6-8 (run with the dprobit command, so the coefficient on $AboveThr$ has the same interpretation as in the OLS regressions) reveal the same pattern.

Other institutional features permit us to exploit the exogeneity of $AboveThr$. During the application process, the payday loan company's employee submits information about the applicant electronically to the company's central servers, which in turn send a query to Teletrack. Within minutes, a yes-or-no notification of whether the application was approved or declined is returned. Neither applicants themselves nor the employees they interact with directly in the store are informed of the applicants' scores or the passing credit-score threshold. Thus no channel exists for $AboveThr$ to impact an individual's future choices except insofar as $AboveThr$ affects application approval. Hence the regressions reported above constitute the first stage of an IV strategy we use throughout the rest of the paper.

It should also be noted that throughout the paper we focus on identification from $first$ loan applications. In principle, more power would be available if our first stage included *all* applications. However, there is more slippage between $AboveThr$ and application approval after the first loan application: the lender is more likely to have a history on a repeat applicant that informs its approval choice. In addition, the regression results reported above indicate we already have considerable power in the first stage, and using all applications would require correcting for intra-applicant correlation structure in the effect of $AboveThr$ on application approval and the effect of approval on the outcome variables of interest. Last, we have replicated all of the analysis below using a new endogenous variable, an indicator for whether an individual *ever* has an application approved. Those results are qualitatively the same.

3.2 Empirical Specifications

Using the credit-score discontinuity described in the previous section, we estimate the effect of payday-loan approval on each outcome of interest at horizons from $\tau = 1d$ to $\tau = 3y$ after the first payday-loan application. We denote the outcome by individual i between the date of first payday-loan application and horizon τ by $Outcome_i^\tau$. Our basic specification is

$$Outcome_i^\tau = \beta_0 + \beta_1 App1Approved_i + f\left(AmtAboveThr_i\right) + \gamma X_i' + \delta M_i'^t + \varepsilon_i. \tag{2}$$

Our most parsimonious specification is the reduced form, where we replace $App1Approved$ in Equation 2 with $AboveThr$. We also run IV regressions, instrumenting for $App1Approved$ with $AboveThr$.[13]

We perform two robustness checks in all cases. First, we run regressions for time τ *before* each outcome (checking for the absence of effects on "placebo outcomes"). Second, we randomly generate thresholds and test for discontinuities around those thresholds. Results are as expected and are available from the authors upon request.

4 Payday Loan Applications

First we use the credit score regression discontinuity to estimate the effect of first application approval–i.e., access to payday loan credit–on subsequent payday loan applications at the same lender.[14]

[13] A natural next step will be to employ nonparametric tools for analyzing regression discontinuities as in (Hahn et al. 2001, Porter 2003).

[14] Because $AboveThr$ is correlated with subsequent loan approval probabilities, the effect of $App1Approved$ on the total dollar value of subsequent payday loans is not identified. Thus we focus on the number of subsequent

Our main regression specification in this section is:

$$(nbr\ pdl\ applications)_i^\tau = \beta_0 + \beta_1 App1Approved_i + f\left(AmtAboveThr_i\right) + \gamma X_i' + \delta M_i'^t + \varepsilon_i.$$

4.1 Estimation Results

In the OLS specification using the full range of credit scores for $\tau = 1y$, β_1 is 4.606, interpreted as applicants whose first payday-loan application was approved applied on average 4.606 more times within 1 year of their first application compared to applicants whose first application was denied. Our reduced-form estimate is 5.016. When we instrument for the indicator of whether first application was approved with an indicator for whether the credit score was above the threshold, we find similar but slightly higher estimates (5.126). In the OLS specification using the full range of credit scores for $\tau = 24months$, β_1 is 4.527 and for the reduced form, 4.486. In our IV specification, the coefficient is 4.559. All are coefficients are highly significant. Results for the payday-loan regressions are shown in Table 3 $\tau = 1y$. For brevity, we show just $\tau = 1y$ in table form. Columns 2-3 of these tables restrict the sample to 0.5, and 0.1 standard deviations in the credit score using the OLS specification. Columns 6-7 similarly restrict the sample for the IV estimates. In each case, standard errors rise as sample sizes fall significantly, though all coefficient remain positive, and significant.

Figures 3a and 3b plot these results for the number of loans and dollar amount of loans as well. Each point represents a centile in the credit score. The points shown are the medians of their quantiles on the x-axis and at the means of their quantiles on the y-axis. Overlaid are the predicted application-rate functions of the best-fitting quartic polynomials on either side of the credit score threshold.[15]

To summarize the coefficients over the full range of time horizons, Figures 4a, 4b and 4c plot the estimated discontinuity for a series of time horizons, i.e., the difference in payday-loan applications for payday applicants whose first loan was approved versus those whose first loan was denied. We rely on the IV-full range specification in this graph. The line is above zero, implying payday-loan applicants who were approved for their first loan applied more subsequently than those whose first application was denied. The number of observations at only a three-year time horizon is small since

applications rather than the subquent dollar amounts borrowed.

[15] Results are not sensitive to the order of the polynomial. Results are available upon request.

we only include observations on applicants for whom we observe over the full τ period after their applications, little data remains at the longer horizons. Two-standard-error bands are also shown on the graph.

5 Pawn Loans

5.1 Data

We measure the extent to which applicants who are denied access to payday loans substitute between forms of credit. We should observe no effect of being approved or denied payday loans on subsequent outcomes if applicants who are denied access to payday credit can perfectly substitute to other forms of credit. A natural starting point is credit to which consumers would have easy access. Pawnshops are accessible to anyone who has a personal item to hock; no credit score is required.

Pawn loans are collateralized with a personal item, most often jewelry, electronics, tools and guns, for which the pawnor typically receives 50 percent of the item's retail value in principal. To receive a pawn loan, a customer must show a valid government-issued id, typically a driver's license. Items are stored at the pawnshop until (and if) the customer returns to repay or service the loan. Pawn loans are less expensive than payday loans, having a ninety-day duration with a monthly interest rate of 20 percent on loans from \$1-\$150 and 15 percent on loans above \$150. At the maturation date, the customer can renew her loan by paying the interest or she can repay the full principal plus interest to redeem her item. Loans can be renewed indefinitely. If the customer does not return by the maturation date, the loan will continue to accrue interest for 30 days after which the item will be removed from storage and put on sale at the pawnshop. Loans can be for as little as \$1 to as much as several thousand dollars. Selling items outright to the pawnshop is also an option, for which one typically receiving 50 percent of the resale value, as in the loan case.

We use pawn data from the same company that our payday data derive. The data span January 1997 though November 2004, which contain 7,860,491 pawns loans for 1,310,018 applicants. Each pawn slip includes start- and maturation date of the loan, location, a loan number which allows us to follow the complete cycle of the loan, principal amount, description of the pawned item. The same company whose data we use also operates pawn shops and we use their data. In fact most of the payday outlets are located within a pawnshop itself. Because of this fact, we would not be surprised if approved payday applicants were more likely to pawn since pawn loans are easily accessible to those patronizing this company.[16] The internal customer number allows us to match the data to the company's payday business.

Table 4 provides pawn-loan summary statistics. Panel A shows data for the pawn records. The average loan size is \$76. Thirty-seven percent of first-time pawns are redeemed, 58 percent are defaulted on, after which their personal item then become property of the shop which puts it up for resale. Seventy-eight percent of pawnors borrowed five or fewer times. The average number of loans per customer during the entire sample is 5.8. Panel B shows summary statistics from the perspective of payday-loan applicants. 33,817 or 23 percent of payday-loan applicants ever pawned. 20,739 or 14 percent of payday-loan applicants ever pawned *subsequent* to their first payday loan. The average loan size for payday-loan applicants who pawned is \$88. Payday-loan applicants averaged 4.5 pawns.[17]

5.2 Estimation Results

Exploiting the credit-score discontinuity as described in Section 3, we estimate the effect of payday-loan approval on the number- and dollar-amount of pawnshop use subsequently at horizons from 1 day to 3 years after the first payday-loan application. We denote the cumulative number of filings by individual i between the date of first payday-loan application and horizon τ by $Pawn_i^\tau$, $PawnAmt_i^\tau$, for number of pawn loans and dollar amount of pawn loans, respectively.[18] Analogous to our subsequent payday-loan analysis, our basic specifications are

$$PawnNbr_i^\tau = \beta_0 + \beta_1 App1Approved_i + f\left(AmtAboveThr_i\right) + \gamma X_i' + \delta M_i'^t + \varepsilon_i, \tag{3}$$

and

$$PawnAmt_i^\tau = \beta_0 + \beta_1 App1Approved_i + f\left(AmtAboveThr_i\right) + \gamma X_i' + \delta M_i'^t + \varepsilon_i, \tag{4}$$

[16] We could limit estimation to those shops which offer both pawnshops and payday loans within one location. Because we include all pawnshops and payday loan outlets in our regressions, we believe we may be estimating a lower bound for this substitutibility between these forms of credit.

[17] Applicants whose first payday application was approved and ever pawned subsequently, pawned on average \$84.30 after that first PDL application, \$56.90 for declined applicants. Approved applicants repaid 42.7 percent of their loans and declined applicants 45.8 percent. Approved applicants paid \$9.70 in pawn interest and declined applicants paid \$5.91 in interest.

[18] As τ rises our number of observations falls: we construct $Pawn_i^\tau$ and $PawnAmt_i^\tau$ for individual i only if i's first PDL application is at least τ before the end of the pawn-sample period. This induces cohort effects which we attempt to control by including dummies for month of first PDL application in our regressions below.

where $f(\cdot)$ contains independent quartic polynomials in the credit score on both sides of the approval threshold, and X_i and M_i^t are, respectively, a vector of demographics and background characteristics and a full set of month dummies, as in the payday-loan regressions. Table 5 reports estimates of equations 3 and 4 for $PawnNbr^{2weeks}$ and $PawnAmt^{2days}$. Column 1 in each table presents OLS results. The coefficients reveal small but significant negative association between loan approval and number of pawn loans within 2 weeks of an applicant's first payday-loan application. Approval causes a decrease of -0.020 percentage points in pawn loan use. Some rejected payday-loan applicants substitute toward pawn loans at this company in the short term. The estimate discontinuity if very small. The coefficient on $App1Approved$ for $PawnAmt^{2weeks}$ is -3.072 which can be interpreted as payday-loan applicants who were approved for their first payday-loan borrowed \$2 less on pawn loans within two weeks than those whose first payday application was approved. These coefficients are significant at the 1-percent level. This \$3 coefficient implies having one's first application rejected causes a threefold spread over the people who are approved in dollar amounts pawned.

The OLS results could well be biased. Any number of omitted characteristics that affect pawnshop use could be correlated with $App1Approved$ even beyond their correlation with $f(AmtAboveThr_i)$ and X. For example, approval could be positively correlated with the omitted variable "resourcefulness," and resourcefulness could help people avoid needing to pawn. As a result, we focus more closely on individuals with credit scores close to the threshold for loan approval. For them, there is more reason to believe that approval may be randomly assigned conditional on the other independent variables. Specifically, Columns 2 through 3 restrict the subsample to credit scores of no more than 0.5, 0.1 standard deviations from the credit score threshold for loan approval. For both $PawnNbr_i^{\tau}$ and $PawnAmt_i^{\tau}$ the standard errors on $App1Approved$ rise in these columns as the number of observations falls.

Section 3 demonstrated that a large share of the variation in $App1Approved$ can be explained by $AboveThr$, an indicator for whether the credit score is above a lender-defined threshold. To the extent individual characteristics cause slippage between $AboveThr$ and loan approval, correlation between those characteristics and the outcome of interest (e.g., if loan approval is correlated with resourcefulness) which could bias even the restricted-range OLS estimates. However, controlling for $f(AmtAboveThr_i)$ and X, which *do* change discontinuously at the credit-score threshold, we can estimate the causal impact of $AboveThr$ on pawnshop use. In Column 4 of Table 5 we show that this "reduced-form" effect of $AboveThr$ on $PawnNbr^{2days}$ is also negative, smaller than the full-sample OLS coefficient on $App1Approved$ and significant at the 1 percent level.

Finally, to obtain another measure of the impact of $App1Approved$, we instrument with $AboveThr$. The IV results using the full sample, in column 5 of each table, are our preferred specifications.[19] They use all of the available data but identify the parameter of interest solely off of the variation in $App1Approved$ induced at the credit-score threshold by $AboveThr$. As we would predict given the first-stage regressions reported in Section 3, these regressions yield results almost identical to the reduced-form in magnitude and significance. Columns 6-7 again narrow the range of observations to 0.5 and 0.1 standard deviations around the credit-score threshold and find sign changes of the IV estimates and increases in the standard errors.

These regression findings are also reflected in Figures 5a and 5b. Figure 5a plots the number of pawn loans against the credit score for each centile in the credit score. Points shown are at the medians of their quantiles on the x-axis and at the means of their quantiles on the y-axis. In addition, the figure plots a predicted pawn rate generated from the reduced-form regression. We view the figure as reinforcing the conclusions of the regression analysis and identifying their limitations: a large effect of payday-loan approval on pawn loans appears to be present, but the effect may be sensitive to the range around the threshold chosen and to the functional form of the credit-score controls (i.e., to the form of $f\left(AmtAboveThr_i\right)$).

We run the same empirical specifications for additional time horizons, ($\tau = 1d$ to $\tau = 3y$) presented in Figure 5b which plot the estimated coefficients on $App1Approved$ in IV full-range regressions for each horizon. The results show the substitution to pawn loans when payday loans are not available, but the dollar amounts are very small and the effect dissipates; within one year there are not significant differences between the two groups.

6 Bankruptcy

Using procedures similar to those described above for measuring impacts of access to payday loan credit on subsequent payday-loan applications and pawn loan borrowing, we investigate the effect of payday loan approval on Chapter 7 and Chapter 13 personal bankruptcy filings.

We examine petitions for both Chapter 7 and Chapter 13 bankruptcies.

[19] Both stages use OLS, even though the instrument and the endogenous variable are binary and the outcome variable is composed of counts. Alternatively we could use logits in both the first and second stages.

Payday loan approval could affect the probability of bankruptcy in various ways.[20] First, people with little outstanding credit are unlikely to file for court protection from creditors, implying that loan approval, by providing a creditor, could increase the probability of bankruptcy. Loan approval could alternatively temporarily alleviate financial pressure– for instance until employment is found. In this case we might expect *rejection* of a payday loan to increase bankruptcy petitions. Payday loans could also take a longer-term effect on the personal finances of borrowers due to the steep interest paid. Because payday loans mature each pay period, typically two weeks, whereas other loans, like credit cards are due each month, payday interest payments may take priority and borrowers may fall further behind in mortgage or credit card debt. To explore these possibilities, we use publicly available data on personal bankruptcy filings in Texas.

6.1 Data

Approved and denied personal bankruptcy petitions are available online through Public Access to Court Electronic Records (PACER). We use data from three of the four United States Bankruptcy Courts in Texas (the Northern, Eastern and Western Districts). The data consist of the universe of 278,482 Chapter 7 and Chapter 13 personal bankruptcy filings in those courts from January 2001 through June 2005[21] and include the date of filing, the Chapter of filing (7 or 13), the disposition of the bankruptcy case (generally, dismissal or discharge of debts), and individual identifiers that permit linkage to the payday loan data. We supplement these data with a small sample of the detailed bankruptcy petitions debtors submit during the filing process. The sample consists of the 100 applicants closest to the credit-score threshold, with 50 on each side. These data include the names of the creditors (loan-collection agencies in some cases), and the amount and description of the type of debt for each creditor.

[20] The literature on personal bankruptcy filings has largely focused on two questions. First, do filers act strategically when they file, i.e., do they accumulate debt which will be discharged in the event of bankruptcy, hold assets up to and not above the state's exemption limit, and choose the optimal Chapter for their case? Second, to what extent does bankruptcy serve as a form of social insurance? Papers in the former literature are divided. White (1998), for example, concludes that at least 10 percent of households would gain financially from bankruptcy filing. Other studies using state variation are divided on whether consumers are strategic in their filings. Lehnert and Maki (2002) find that filers optimally "negative estate plan," by converting liquid assets into dischargeable debts before filing. Literature examining the social insurance aspect of bankruptcy is limited. Himmelstein, Warren, Thorne and Woolhandler (2005) survey bankruptcy filers and find that half cite medical debt as a factor in their filings. Domowitz and Sartain (1999) find that employment and medical shocks account for some bankruptcies, supporting the "bankruptcy as insurance" point of view.

[21] Implementation of the Bankruptcy Reform Act of 2006 began in October, after the end of our sample period, and any anticipatory effects of the Act would have been orthogonal to *abovethr*.

Our approach complements existing empirical work on the determinants of bankruptcy by distinguishing between Chapter 7 and 13 bankruptcy petitions. Chapters 7 and 13 result in different private and social benefits and costs. Chapter 7 bankruptcy relieves a debtor of all dischargeable debts. Some debts, including most students loans, tax debts, child-support and alimony payments, are non-dischargeable, meaning the debtor must repay those loans. Non-exempt assets must be turned over to the filers' trustees at the time of filing. A trustee sells these assets and repays creditors. Texas has homestead and car exemptions, allowing debtors to protect these assets. Chapter 13 bankruptcy does not relieve debtors of all dischargeable debt: each filer proposes a repayment plan to the court, typically three years in duration, and the judge determines whether the repayment plan is reasonable based on income, assets, etc. After successful completion of the repayment plan, the remainder of debts are discharged. The judge determines whether a filer can afford Chapter 13 bankruptcy, and, if so, does not permit filing under Chapter 7. (The Bankruptcy Abuse Prevention and Consumer Protection Act of 2005 made it harder to file for bankruptcy. For example, an earnings means test is now used to determine whether a debtor qualifies for Chapter 7. This occurred after the end of our sample period.) Debtors can file Chapter 7 bankruptcy every 6 years and Chapter 13 bankruptcy as often as they wish, i.e., they can revise their repayment plan and submit changes to the judge repeatedly. Debtors can file Chapter 7 bankruptcy following a Chapter 13 filing and often do so if they find they cannot afford their original repayment plan. Bankruptcy filings appear on debtors' credit reports for 10 years. The costs to file Chapter 7 and 13 bankruptcy are \$200 and \$185, respectively. Thirty-five percent complete Chapter 13 repayment plans.

Table 6 provides an overview of these data. Panel A shows a bankruptcy rate (as a fraction of population) for Texas as a whole of slightly less than 0.4 percent per year (about $\frac{3}{4}$ of the national bankruptcy rate), and documents that about 70 percent of all Texas bankruptcies are filed in the Northern, Eastern and Western Districts. Panel B reports that personal bankruptcy filings are roughly equally divided between Chapters 7 and 13. In addition, following almost all Chapter 7 filings debts are discharged, while almost all Chapter 13 filings result in dismissal of cases. (According to informal communications with the PACER Service Center, debtors file under Chapter 13 in order to protect their homes from foreclosure, but rarely complete court-supported development and implementation of repayment plans.) On average there are 3.8 parties to each case.[22]

[22] The raw PACER dataset and online documentation do not explicitly distinguish between debtors and creditors.

We identify debtors in the three Texas Districts bankruptcy data with payday-loan applicants if the following variables in the two datasets match exactly: first name, last name, zip code of home residence, and last four digits of Social Security number. By these criteria, as reported in Panel C of Table 6, 6,656 of the 145,519 payday-loan applicants from the payday lender filed for personal bankruptcy during the bankruptcy sample period, and three-quarters of them filed under Chapter 13.[23],[24] Given that the average amount of time from first payday-loan application to the end of the bankruptcy data period is 2.48 years, if we assume that payday applicants are distributed in proportion to bankruptcies across the four Texas districts, this corresponds to a rate of $\frac{6656}{145519*2.48*0.71} = 0.0261$ bankruptcy petitions per payday applicant per year. Comparing to Panel A of Table 6, we see that payday loan applicants have a bankruptcy base rate that is $0.0261/0.004 \approx 7$ *times* the average rate in the population.

6.2 Estimation Results

Using the credit-score regression discontinuity, we estimate the effect of payday loan approval on Chapter 7, Chapter 13, and total personal bankruptcy filings at horizons from $\tau = 1d$ to $\tau = 3y$ after the first payday-loan application. We denote the cumulative number of filings by individual i between the date of first payday-loan application and horizon τ by $Bkcy7_i^\tau$, $Bkcy13_i^\tau$, and $BkcyAll_i^\tau$ for Chapter 7, Chapter 13, and all personal bankruptcies, respectively.[25] Analogously to the analyses of subsequent payday-loan applications and pawn loan borrowing above, our basic specification is

$$Bkcy\,(Ch)_i^\tau = \beta_0 + \beta_1 App1Approved_i + f\,(AmtAboveThr_i) + \gamma X_i' + \delta M_i'^t + \varepsilon_i, \tag{5}$$

where (Ch) could be 7, 13, or All, and the dependent variables are as above.

Staff at the PACER Service Center helpfully explained that the first party to be added to a case, who has the lowest value of an internal PACER identifier called the "party sequence number," is a debtor; and if a co-debtor is present, he or she has the second-lowest value of the party sequence number. We assume that a second party is a co-debtor (ie, a joint filer) if his or her street address is nonempty and matches that of the first party. By this definition, 50,886 of the bankruptcies were filed jointly in the Northern District, for example.

[23] Alternatively, we could obtain slightly different numbers of matches using different combinations to match on. In all cases the qualitative pattern of results we report below is unchanged.

[24] Of the 3,768 people who match in the Northern District for example, included are 244 couples in which both spouses applied for payday loans. Our analysis below ignores the intra-household correlation structure of bankruptcy filing.

[25] As τ rises our number of observations falls: we construct $Bkcy\,(Ch)_i^\tau$ for individual i only if i's first PDL application is at least τ before the end of the bankruptcy sample period. This induces cohort effects which we attempt to control by including dummies for month of first PDL application in our regressions below.

Tables 9 and 10 report estimates of Equation 5 for $Bkcy7^{2y}$ and $Bkcy13^{2y}$, respectively. We multiply $Bkcy7^{2y}$ and $Bkcy13^{2y}$ by 100, so coefficients in the table can be interpreted as the increase in bankruptcies in percentage points associated with unit increases in the independent variables. Column 1 presents the OLS results for the full sample, which shows little association between loan approval and Chapter 7 bankruptcy, and a strong and significant association between loan approval and Chapter 13 bankruptcy. Specifically, approval is associated with an increase of 0.397 percentage points in Chapter 13 bankruptcies. Relative to the baseline bankruptcy rate of 1.137 percent, this is an increase of $\frac{.397}{1.219} = 32.5$ percent.

However, the OLS results could well be biased. For example omitted characteristics that affect bankruptcy declarations, like household assets, could be correlated with $App1Approved$ even beyond their correlation with $f\,(AmtAboveThr)$ and X. As a result, we focus more closely on individuals with credit scores close to the threshold for loan approval. For them, there is more reason to believe that approval may be randomly assigned conditional on the other independent variables. Specifically, Columns 2 and 3 restrict to the subsample with credit scores no more than 0.5 and 0.1 standard deviations, respectively, from the credit-score threshold for loan approval. For both Chapter 7 and Chapter 13 bankruptcy, the standard errors on $App1Approved$ rise in these columns as the number of observations falls.

Section 3 demonstrated that a large share of the variation in $App1Approved$ can be explained by $AboveThr$, an indicator for whether the credit score is above a lender-defined threshold. To the extent individual characteristics cause slippage between $AboveThr$ and loan approval, correlation between those characteristics and propensity or ability to declare bankruptcy (e.g., if loan approval is correlated with resourcefulness at paperwork, which is also necessary for completing a bankruptcy filing) could bias even the restricted-range OLS estimates. However, controlling for $f\,(AmtAboveThr)$ and X, which do change discontinuously at the credit-score threshold, we can estimate the causal impact of $AboveThr$ on bankruptcy propensities. In Column 4 of Tables 9 and 10 we show that this "reduced-form" effect of $AboveThr$ on $Bkcy7^{2y}$ is smaller than the full-sample OLS coefficient on $App1Approved$ and statistically insignificant. Column 4 in Table 10 again shows the reduced form effect for Chapter 13 which is the same as the OLS coefficient; $AboveThr$ increases Chapter 13 bankruptcies by 0.341 percentage points, or $\frac{.341}{1.219} = 27.1$ percent above their baseline rate. The standard errors of these reduced-form OLS regressions fall by an order of magnitude if we use Poisson or negative binomial regression instead.

Finally, to obtain another measure of the impact of $App1Approved$, we instrument with $AboveThr$. The IV results using the full sample, in Column 5 in these tables are our preferred specifications.[26] They use all of the available data but identify the parameter of interest only off of the variation in $App1Approved$ induced at the credit-score threshold by $AboveThr$. As we would predict given the first stage regressions (reported in Section 3), these regressions yield results almost identical to the reduced-form in magnitude and significance. Columns 6 and 7 again narrow the range of observations to 0.5 and 0.1 standard deviations around the credit-score threshold. The coefficients rise, and become significant in one case, but we find large increases in the standard errors of the estimates.

These regression findings are also reflected in Figures 6a and 6b, which plot 1-year and 2-year effects for Ch7 filings and Figures 7a and 7b, which plot the same effects for Ch13 petitions. These figures plot bankruptcy rates against the credit score for each of 100 credit-score quantiles. Points shown are at the medians of their quantiles on the x-axis and at the means of their quantiles on the y-axis. In addition, the figure plots a predicted bankruptcy rate generated from the reduced form regression. We view the figure as reinforcing the conclusions of the regression analysis and identifying their limitations: a large effect of payday loan approval on bankruptcy appears to be present, but the effect may be sensitive to the range around the threshold that's examined and to the functional form of the credit-score controls (i.e., to the form of $f\left(AmtAboveThr\right)$).

Tables 8 and 7 report the same specifications for a 1 year time horizon. The OLS coefficient for Ch13 bankruptcy during this 1 year horizon is significant at the 5 percent level and equal to 0.3. The coefficients at this 1 year horizon are in general sensitive to the specification however. The sign of coefficients for the Ch7 bankruptcy fillings at the one-year horizon are sensitive to the specification but suggest if anything a negative effect of payday loan access on bankruptcy.

We have examined this dependence on functional form further. In the context of the IV regressions with dependent variable $Bkcy13^{2y}$, we experiment with constraining $f\left(AmtAboveThr\right)$ to be identical on either side of the threshold; removing $f\left(AmtAboveThr\right)$ entirely; removing the dummies for month of first payday-loan application; and removing the financial and demographic control variables. We use also use probits and linear probability models. Most of the coefficients in these specifications go in the same direction, but most also are not significant.[27]

[26] Both stages of the IV use OLS, even though the instrument and the endogenous variable are binary and the outcome variable is composed of counts which rarely exceed 1.

[27] Results are available from the authors upon request.

All of the analysis so far has focussed on the cumulative effect until $\tau = 2y$ after the first payday application. Effects on Chapter 7, Chapter 13 and all bankruptcies at horizons from $\tau = 1d$ to $\tau = 3y$ are presented in Figures 8a-8c, which plot the estimated coefficients on $App1Approved$ in IV full-range regressions. Non-parametric estimates, using locally weighted regressions for each outcome, do show a clear treatment effect.[28]

7 Arrests

7.1 Data

We use the universe of arrests in the Texas Department of Public Safety's Criminal Conviction History (CCH) database from 2000 to 2004. The data include date of arrest; type of crime committed; sentence and conviction information; and demographic information. We use the restricted version of the CCH, which also includes personal identifiers, such as first and last name, date of birth and Social Security number. We match the CCH arrests records to the payday loan records using last name and date of birth. We have also used the more rigorous match of name, date of birth and SSN, which of course kresults in many fewer matches. We use the more liberal match because we view the SSNs in the CCH database as unreliable. Those taken into custody self-report their SSNs, as opposed to the payday loan data where SSNs are verified at the time of the loan application. There is a trade off between type 1 and type 2 errors in this matching‘ process, and we view the more liberal match as the most parsimonious. Table 11 provides statistics on the criminal database, including the frequency of types of crime committed. Information on type of crime, date of offense and gender is missing in some cases. DUIs are the most frequent type of crime. We use date of arrest rather than date of crime in the few cases when the former is missing. Table 11 provides summary statistics for the CCH database and for the payday-loan applicants who appear in the database. Traffic crimes, which consist largely of DUIs, are the most frequent type of arrest in the CCH database. Property crimes, such as larceny. are the most frequent type of crime that payday-loan applicants were arrested for after applying for a payday loan. A major drawback with the CCH database is that more than half of the types of crime in the database are missing for reasons unknown to use.

[28] We use the Stata command *lowess*. Available upon request from authors.

7.2 Estimation Results

We estimate the following regression equation of arrest records for each major type of crime in the CCH records. As with the other outcomes of interest, we estimate OLS, reduced form and IV specifications for various ranges around the threshold.

$$Crime\,(type)_i^{\tau} = \beta_0 + \beta_1 App1Approved_i + f\,(AmtAboveThr_i) + \gamma X_i' + \delta M_i'^{t} + \varepsilon_i \qquad (6)$$

We estimate equation 6 for the following types of crime: felonies; misdemeanors; drug crimes including possession of drugs and selling drugs; alcohol crimes, largely DUI; traffic crimes, i.e., DUIs; the following property crimes, burglary, larceny, stolen property, and stolen vehicle; assault; gambling; sex crimes such as prostitution; fraud or forgery such as writing bad checks; mischief; prostitution; harassment; and revenue-generating crimes including property crimes and prostitution. We also estimate the equation for all property crimes together, "other" types of crime; possession of drugs and sale of drugs separately; all types of crime jointly; and for when type of crime is missing.

Table 12 shows the results for all types of crime two days after applying for a payday loan. Because there are very few crimes committed in the short run, the standard errors are large. The coefficients in the table can be interpreted as the increase in arrests in percentage points associated with unit increases in the independent variables. The point estimates for the IV is -0.08, interpreted as a decrease of 0.08 percentage points in arrests within 2 days associated with access to payday loans, with base rate of crimes within 2 days is .083 percent. The coefficients in the short run are negative, implying access to payday loans decreases arrests. But the standard errors are large and none of the coefficients are significant. For brevity, the remainder of results are reported in Figures 9a-9f.[29] These figures plot estimated coefficient for all arrests, drug crimes, DUIs, revenue-generating crimes, assaults, and fraud and forgery arrests, such as writing bad checks. The figures include two-standard-error bands, which show no significant effect on crime.

[29] Results for all types of crime and time horizons are available upon request.

8 Robustness Checks

We first report further tests of the exogeneity of $AboveThr$ and demographic characteristics of payday loan applicants. A potential source of bias in this research design is selection close to either side of the threshold. If payday-loan applicants knew both their credit score and the passing threshold used to approve loans, we could expect applicants who knew they would be declined not to apply, and lots of mass in the distribution in credit scores just above the threshold. Figure 1, a histogram of the credit score, shows that, while there are some credit scores that are common because of the discrete nature of the scoring process, there is not bunching near the threshold which would indicate selection issues.

The discontinuity is not sensitive to the inclusion of control variables. We also performed two sets of first stage placebo regressions. In both types, we regressed $App1Approved$ on the usual pair of quartics in $AmtAboveThr$, the usual X's, and the usual month dummies. In the first set of placebo regressions, we included modified versions of $AboveThr$ for every value of the credit score. The coefficient on these pseudo-$AboveThr$'s, and its statistical significance, were maximized when it was equivalent to the true $AboveThr$. The true version of $AboveThr$ was included in every element of the the second set of placebo regressions, but in that set we again included, one by one, pseudo-$AboveThr$'s defined for every possible value of the credit score. In this case, the coefficient on the true $AboveThr$ was always larger and more highly significant than the coefficient on the pseudo-$AboveThr$.

We attempt to partially address the concern that our data come from a single lender. In talking to executives in both the payday industry and subprime credit scoring industry, we know that all major payday lenders use the same credit-scoring procedure; but because each lender chooses their own threshold for which to evaluate applications, we cannot know whether other lenders chose the same threshold. If all lenders do choose exactly the same threshold, our estimated coefficients will not reflect bias due to substitution opportunities. Endogeneity of the specific threshold should not matter if the distribution of credit scores is smooth. In the extreme case, people rejected at this company could borrow as much as people approved to borrow elsewhere. People approved to borrow here are also likely to be approved at other companies thus they may be borrowing more on payday loans than we can observe. To partially address this issue, we restrict our sample to those shops at this company that have the highest reapplication rate. Presumably these shops have fewer competitors. While the sample sizes shrink dramatically, we find similar results to those using the whole sample. While this presence of competition does not affect the importance of the result regarding subsequent payday lending, it does matter for our interpretation of the effects on personal bankruptcy and crime. Unfortunately, these regions are the same where we are lacking data on bankruptcy so we cannot test whether the effects are the same for bankruptcy in regions where there is less competition.

We also run placebo regressions for each outcome, estimating the regression discontinuity for each time horizon *before* applicants' first application. Results are available upon request.

9 Discussion and Conclusion

We find that payday loan applicants approved for their first loan borrow with striking frequency at this company. Approved applicants borrow 8.8 subsequently on average and denied applicants just 1.4 over their entire borrowing tenure.[30] Two models of behavior are consistent with these results. Approval at a shop provides information that future access is likely.[31] These results are consistent with a search model.[32] Search costs may be significant for this population; once people find access to credit at one location, they are likely to stay. While forty-eight percent of applicants who were first declined ever re-apply, just nine percent of declined applicants ever borrow, borrowing on average \$212, paying \$36 in interest, as compared to approved applicants who accumulated on average \$2793 in payday debt over their borrowing tenure, paying \$477 in interest. It is useful to note that payday borrowers cannot be indebted more than about \$300 at a time.

Applicants denied access to payday loans turn to pawn loans to meet their short-term credit needs. The results that payday-loan applicants who were rejected on their first payday loan application at this company borrow more on pawn loans is not surprising, given even moderate search costs. What is surprising is the small dollar amounts. Denied applicants borrowed on average \$75

[30] Because the credit score depends on prior borrowing history, ninety-two percent of loan applications subsequent to a first approval were approved. Thirty-four percent of approved applicants ever defaulted. Because default rates are high–more than a third of all borrowers end up defaulting at some point, this will adversely affect their subsequent credit score resulting in likely denial of loan applications.

[31] An important question is whether denied applicants try to shop around for a loan after being denied. Because we have data from just one lender, we cannot answer that directly. We can look at how many shops within this company applicants apply to. Just 1 percent of approved payday applicants went to a different store for their second application, compared to six percent for denied applicants. The approval rate for second loans was 97 percent for those whose first application was approved and just 5.8 percent for those denied. Beyond attempting to borrow on payday loans, applicants may try to substitute to additional forms of credit to meet their short-run cash needs.

[32] See for example, Hortacsu and Syverson (2004) and references therein.

in pawn loans total after being rejected on their first payday-loan application. Within the first couple of weeks after being denied payday loans, they borrowed $27 on average at this company's pawnshops. Comparing this to the average $261 first two-week loan for approved applicants, denied applicants borrowed a small fraction of what their counterparts who got approved did. So while denied applicants turn to pawn loans to meet their short-term credit needs, they borrow less.

We can explain these results in a number of ways. Importantly, pawnshop terms are different than payday loans'. Pawn loans by nature are smaller. Pawnors can only get 50 percent of the resale value of their item, and pawnors may not want to part with their television for 90 days or they may not have enough collateral to obtain anything but a small loan. A survey by researchers at the Georgetown Credit Research Center shows 34 percent of payday borrowers reported borrowing for "discretionary uses" or other non-emergency uses (Elliehausen and Lawrence 2001). Discretionary use of payday and pawn loans, at such high interest rates is at first blush difficult to reconcile with a rational model of borrowing on payday loans. While these numbers confirm that the affect of access to payday loans indeed leads to increased indebtedness, we remain puzzled *how* approval for a single payday loan could have such an impact on a cumulative financial outcome like bankruptcy. The interaction of payday interest payments and other forms of credit like mortgages and credit cards at the margin could lead people into bankruptcy. We now turn to this discussion.

The bankruptcy rate in the population of payday loan borrowers that we study is an order of magnitude larger than the rate in the general population. The mechanism through which payday and pawn loans affect bankruptcy remain unclear: these are small amounts of debt. We explore candidate hypotheses for why payday loan access would affect bankruptcy. Strategic gaming of the bankruptcy system implies filers would accumulate as much debt as possible before filing. This does not seems consistent with our results. Payday borrowers who filed for bankruptcy repaid 85 percent of their loans. Moreover, payday borrowers can only be in debt by about $300 at anyone time. Among this population, the probability of filing for bankruptcy puzzlingly *increases* in the first application credit score. We conjecture this could be because people with very low credit scores receive too little credit to accumulate substantial liabilities. Recall though that these credit scores are distinct from FICO scores. In addition, people with high scores who apply for payday loans may have recently experienced significant negative financial shocks. They may have substantial assets they wish to protect, and they may have additional experience with financial institutions that helps them to undertake a bankruptcy filing.

Second, if payday loan applicants had no other debt, those approved would mechanically be more likely to file bankruptcy since they have now obtained a creditor. The small sample of detailed data on creditors, debts and assets is informative here. Thirty-two percent of payday applicants who filed for bankruptcy had payday loan debt, and 15 percent had payday loan debt at this company. This debt accounts for a small fraction of all debt, however. In this small sample, applicants had on average $33,000 of unsecured debt and $78,000 of secured debt (mostly mortgages and auto loans), just $478 of that debt was from this payday lender. This sample also had $1011 outstanding debt to other payday lenders. The majority of this total unsecured debt include credit card debts ($7900 on average), student loans ($20,500), medial bills ($22,000) and car leases ($14,700). This sample of data give us a unique look at the financial landscape of bankruptcy filers and payday loan applicants. Collecting more detailed data on these bankruptcy filers is in the process and will help us understand the financial situation of payday borrowers, and the determinants of bankruptcy. The latter is especially pressing, given the major overhaul of personal bankruptcy laws with the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005.

The mechanisms through which access to credit affects crime are more straightforward than a bankruptcy. A number of recent papers analyze the short-run effect of crime to a variety of factors.[33] The effects of cash payments on crime has been documented most recently by Dobkin and Puller (2006). In light of these findings, we could similarly expect access to payday loan cash to increase drug, or alcohol-related crime. Further, if payday loans allow consumers to overcome shocks to consumption needs, and because payday loans are often a last resort, access to payday loans could decrease revenue-generating crime in the short run. Surveys provide specific evidence that 61 percent of payday borrowers could not use their credit card because they were, or would become, maxed out (Elliehausen and Lawrence 2001). People with tarnished credit apply for payday loans with few other options. We would expect revenue-generating crime to increase following a rejection from payday loans in this case.

The underlying question is why people use payday loans. Rational consumers who borrow on payday loans do so because their marginal utility is high enough to warrant 450 percent interest

[33] Studies documenting the cyclical nature of drug-related hospitalizations, deaths and crime include (Phillips, Christenfeld and Ryan 1999) and (Halpern and Mechem 2001). In a more recent study, Dobkin and Puller (2006) provide evidence that drug and alcohol abuse and arrests increase—and revenue generating crime decrease—following receipt of government transfer payments. Our work also adds to the literature documenting immediate consumption responses to: paychecks (Stephens forthcoming) and (Huffman and Barenstein 2005), Social Security check receipt (Stephens 2003), expected tax refunds (Johnson, Parker and Souleles 2004), Social Security taxes (Parker 1999), semi-annual bonuses (Browning and Collado 2001), and payments from the Alaska Permanent Fund (Hsieh 2003).

rate. This could be due to extreme discount rates or more plausibly consumption shocks such as an illness or car repair. Alternatively, consumers with self-control problems may borrow even in the absence of a consumption shock warranting 450 APR. With sufficient repeated borrowing behavior, the interest payments would slowly take a toll on the agents ability to stay solvent during a future shock and thus in the longer run may lead to increased bankruptcy fillings. Because in this dataset we cannot disentangle consumption shocks from self-control problems, we take a structural approach in our companion paper (Skiba and Tobacman 2006a).

Overall, these results shed light on patterns of borrowing behavior and its consequences, but they are preliminary and inconclusive. Several extensions are underway. We are in the process of completing our analysis of bankruptcy by obtaining data from the Southern Texas Bankruptcy Court. Exploring other outcomes could help address the welfare questions regarding payday loans. By examining credit scores after a customer's first application we can understand whether payday borrowing leads to increased or decreased credit-worthiness. Second, survey evidence suggests borrowers use payday loans to pay bills, and often rent or mortgage payments. With propriety data on home foreclosure postings, we can explore whether getting a payday loan decreases the probability of eviction or home foreclosure. This work is underway.

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Table 1: Payday-Loan Demographics

Variable	Mean	Median	SD	N
Loan Size ($)	301.41	289	139.60	1,097,330
$ Loans Per Person	2278.52	978	3493.67	145,159
Default (%)	0.04		0.20	1,229,353
Default (%) per person	0.34		0.59	145,159
Age	36.46	35	11.25	145,154
Black	0.43	0	0.49	65,528
Hispanic	0.34	0	0.48	65,528
Female	0.62	1	0.49	65,780
Monthly Pay ($)	1699	1545	1047	93,997
Months at Current Job	4.28	2	7.23	94,384
Paid Weekly	0.13	0	0.34	94,384
Paid Biweekly	0.51	1	0.50	94,384
Paid Semimonthly	0.19	0	0.39	94,384
Paid Monthly	0.17	0	0.37	94,384
Wages Garnished	0.03	0	0.17	67,908
Direct Deposit	0.69	1	0.46	94,384
Checking Account Balance ($)	235	66	552	142,407
NSF's on Bank Statement	1.09	0	3.00	145,159
Owns Home	0.34	0	0.47	67,908
Months at Current Residence	66.85	36	91.41	145,157
Month of Application	12/2002	1/2003	One year	145,159

Notes: Data provided by a company that makes payday loans. Included are all available demographics for the universe of payday-loan applicants in Texas between 9/2000 and 8/2004. Quantities are calculated from each individual's first application. These variables, with the exception of Month of First Application, represent the full set of "demographic controls" included in most regression specifications reported in this paper. Whenever we include these controls, we also include dummies for missing for each of them. Dummies for each value of Month of First Application are often included as well, and indicated separately. "NSF's" are "Not Sufficient Funds" events like bounced checks.

Table 2: The Credit Score Regression Discontinuity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All Columns: Dependent Variable = First Application Approved							
	OLS					Probit		
Above Threshold Indicator	0.966	0.968	0.953	0.954	0.944	0.966	0.972	0.979
	(0.001)**	(0.002)**	(0.003)**	(0.003)**	(0.003)**	(0.001)**	(0.002)**	(0.001)**
Quartic in AmtAboveThr		x	x	x	x		x	x
(Quartic in AmtAboveThr) x AboveThr			x	x	x		x	x
Demographic Controls				x	x			x
Month Dummies					x			x
Constant	0.004	0.005	0.001	-0.056	-0.054			
	(0.001)**	(0.001)**	(0.002)	(0.009)**	(438.692)			
Observations	145,159	145,159	145,159	145,159	145,159	145,159	145,159	145,157
R-squared	0.84	0.85	0.85	0.85	0.85			

Source: Authors' calculations based on data from a payday lending company. This table documents the discontinuous effect of the credit score on approval of candidate payday borrowers' first applications. The key independent variable is the Above Threshold Indicator, a dummy for whether AmtAboveThr>=0. Columns 1-5 perform OLS regressions; Columns 6-8 report marginal effects from probit regressions. Demographic controls include: gender, race dummies, age, sex, monthly income, job tenure, log pay frequency dummies, log checking account balance, the number of "not sufficient funds" events on the most recent bank statement, months in current residence, and dummies for homeownership, direct deposit, and garnishment of paycheck, and dummies for missing for each of these variables. "Month Dummies" refer to dummies for the month of first payday loan application. Standard errors are in parentheses. * implies significant at 5%; ** implies significant at 1%.

Table 3: The Effect of First-Application Approval on Subsequent Payday Loan Applications within 1 Year

	(1) OLS full range	(2) OLS range = 0.5sd	(3) OLS range = 0.1sd	(4) Reduced Form	(5) IV full range	(6) IV range = 0.5sd	(7) IV range = 0.1sd
First-application approved dummy	4.606	4.902	5.318		5.126	5.173	7.103
	(0.123)**	(0.223)**	(0.582)**		(0.183)**	(0.426)**	(1.471)**
Abovethr dummy				5.016	Instrument	Instrument	Instrument
				(0.180)**			
Quartic in AmtAbovethr	Yes	Yes	Yes	Yes	Yes	Yes	Yes
(Quartic in AmtAbovethr) X Abovethr	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Biweekly dummy	1.886	1.353	1.056	1.881	1.889	1.353	1.057
	(0.079)**	(0.114)**	(0.267)**	(0.079)**	(0.079)**	(0.114)**	(0.267)**
Semimonthly dummy	1.487	1.141	0.666	1.485	1.490	1.141	0.672
	(0.093)**	(0.132)**	(0.313)*	(0.093)**	(0.093)**	(0.132)**	(0.313)*
Weekly dummy	1.148	0.569	0.444	1.121	1.153	0.571	0.439
	(0.102)**	(0.143)**	(0.342)	(0.103)**	(0.102)**	(0.143)**	(0.342)
Months in same residence	0.002	0.003	0.004	0.002	0.002	0.003	0.004
	(0.000)**	(0.000)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**
Direct-deposit dummy	0.215	0.172	0.220	0.213	0.216	0.173	0.216
	(0.058)**	(0.078)*	(0.186)	(0.058)**	(0.058)**	(0.078)*	(0.187)
Monthly Pay ($)	0.855	0.845	0.442	0.902	0.852	0.843	0.442
	(0.055)**	(0.076)**	(0.180)*	(0.056)**	(0.055)**	(0.076)**	(0.180)*
Homeowner dummy	0.344	0.731	0.075	0.467	0.338	0.727	0.059
	(0.077)**	(0.137)**	(0.332)	(0.078)**	(0.078)**	(0.137)**	(0.333)
Job tenure (years)	0.003	-0.013	-0.017	0.009	0.003	-0.013	-0.018
	(0.004)	(0.008)	(0.018)	(0.004)*	(0.004)	(0.008)	(0.018)
Male	-0.594	-0.392	0.079	-0.601	-0.595	-0.393	0.091
	(0.077)**	(0.108)**	(0.261)	(0.077)**	(0.077)**	(0.108)**	(0.261)
Age	0.071	0.072	0.065	0.072	0.071	0.072	0.064
	(0.003)**	(0.004)**	(0.008)**	(0.003)**	(0.003)**	(0.004)**	(0.008)**
Black	0.063	-0.293	-1.203	0.021	0.069	-0.290	-1.189
	(0.096)	(0.134)*	(0.341)**	(0.097)	(0.096)	(0.135)*	(0.342)**
Hispanic	0.715	0.344	-0.522	0.700	0.717	0.345	-0.507
	(0.100)**	(0.142)*	(0.360)	(0.100)**	(0.100)**	(0.142)*	(0.361)
Paycheck-garnishment dummy	-0.551	-0.240	-0.778	-0.595	-0.541	-0.234	-0.781
	(0.206)**	(0.298)	(0.672)	(0.207)**	(0.206)**	(0.298)	(0.673)
Checking balance ($)	-0.059	0.097	0.106	-0.050	-0.060	0.096	0.105
	(0.015)**	(0.021)**	(0.050)*	(0.015)**	(0.015)**	(0.021)**	(0.050)*
# Not-Sufficient-Funds Events	-0.072	-0.099	-0.116	-0.088	-0.070	-0.099	-0.115
	(0.009)**	(0.010)**	(0.021)**	(0.009)**	(0.009)**	(0.010)**	(0.021)**
Observations	62192	30007	3711	62192	62192	30007	3711
R-squared	0.20	0.19	0.30	0.19	0.20	0.19	0.30

Standard errors in parentheses

* significant at 5%; **significant at 1%

Notes: Demographic controls include dummies for pay frequency, direct deposit, homeownership, race, paycheck garnishment, and dummies for missing values of these; log monthly pay, log checking-account balance, job tenure, age, sex, months at current residence, and number of non-sufficient funds on checking statement. "Range" refers to the standard deviation around the credit-score threshold to which the sample is restricted. Columns (2) and (6) restrict the sample to payday-loan applicants who first loan was scored within 0.5 standard deviations above or below the threshold, for OLS and IV, respectively. Columns (3) and (7) restrict the sample to payday-loan applicants who first loan was scored within 0.1 standard deviations above or below the threshold, for OLS and IV, respectively.

Table 4: Pawn-Loan Summary Statistics

A: Pawn Loans

Year of Loan	Number of Loans	Avg loan size ($)
2000	1,021,468	73.46
2001	1,037,867	75.16
2002	1,054,460	76.25
2003	1,044,263	77.13
2004 (through November)	698,770	77.70
Total	8,118,327	

B: Pawn Loans and Payday Loans

Year of Loan	Pawnors who ever apply or applied for PDL (number pawnors)	Avg loan size ($) pawnors who ever apply or applied for PDL	Total Payday Applicants	Percent Payday Applicants who Subsequently Pawned
2000	13,884	86.27	28,388	0.13
2001	15,942	86.88	52,451	0.15
2002	16,349	88.14	71,939	0.17
2003	12,027	87.05	61,687	0.18
2004 (through August)	14,551	87.08	53,616	0.16

Sources and Notes: In Panel A data are from a provider of financial services loan records. Panel B reports the dollar amount and number of pawn loans for individuals who applied for payday loans from the same national lender. The data are linked by the company's internal customer number. All data are in January 2002 dollars.

Table 5: The Effect of First-Application Approval on Subsequent Pawn Loans within 2 Days

	(1) OLS full range	(2) OLS range = 0.5sd	(3) OLS range = 0.1sd	(4) Reduced Form	(5) IV full range	(6) IV range = 0.5sd	(7) IV range = 0.1sd
First-application approved dummy	-0.020	-0.008	-0.017		-0.017	-0.008	-0.084
	(0.002)**	(0.005)	(0.014)		(0.003)**	(0.008)	(0.059)
Abovethr dummy				-0.017	Instrument	Instrument	Instrument
				(0.003)**			
Quartic in AmtAbovethr	Yes	Yes	Yes	Yes	Yes	Yes	Yes
(Quartic in AmtAbovethr) X Abovethr	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Biweekly dummy	-0.002	-0.007	-0.011	-0.002	-0.002	-0.007	-0.011
	(0.002)	(0.003)*	(0.008)	(0.002)	(0.002)	(0.003)*	(0.008)
Semimonthly dummy	0.002	-0.004	-0.008	0.002	0.002	-0.004	-0.008
	(0.002)	(0.004)	(0.010)	(0.002)	(0.002)	(0.004)	(0.010)
Weekly dummy	0.007	0.005	0.009	0.007	0.007	0.005	0.008
	(0.002)**	(0.004)	(0.011)	(0.002)**	(0.002)**	(0.004)	(0.011)
Months in same residence	-0.000	0.000	-0.000	-0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Direct-deposit dummy	-0.000	-0.005	-0.019	-0.000	-0.000	-0.005	-0.019
	(0.001)	(0.002)*	(0.006)**	(0.001)	(0.001)	(0.002)*	(0.006)**
Monthly Pay ($)	-0.002	0.003	-0.001	-0.002	-0.002	0.003	-0.000
	(0.001)	(0.002)	(0.006)	(0.001)	(0.001)	(0.002)	(0.006)
Homeowner dummy	0.003	-0.004	-0.002	0.003	0.003	-0.004	-0.001
	(0.002)	(0.004)	(0.009)	(0.002)	(0.002)	(0.004)	(0.009)
Job tenure (years)	-0.000	-0.000	-0.001	-0.000	-0.000	-0.000	-0.001
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Male	-0.001	0.004	0.023	-0.001	-0.001	0.004	0.023
	(0.002)	(0.003)	(0.009)**	(0.002)	(0.002)	(0.003)	(0.009)**
Age	0.000	-0.000	0.000	0.000	0.000	-0.000	0.000
	(0.000)*	(0.000)	(0.000)	(0.000)*	(0.000)*	(0.000)	(0.000)
Black	-0.011	-0.015	-0.054	-0.011	-0.011	-0.015	-0.055
	(0.003)**	(0.004)**	(0.011)**	(0.003)**	(0.003)**	(0.004)**	(0.011)**
Hispanic	-0.008	-0.004	-0.035	-0.008	-0.008	-0.004	-0.034
	(0.003)**	(0.005)	(0.012)**	(0.003)**	(0.003)**	(0.005)	(0.012)**
Paycheck-garnishment dummy	0.002	0.002	-0.020	0.002	0.002	0.002	-0.019
	(0.004)	(0.007)	(0.017)	(0.004)	(0.004)	(0.007)	(0.017)
Checking balance ($)	0.001	-0.000	-0.000	0.001	0.001	-0.000	-0.000
	(0.000)**	(0.000)	(0.001)	(0.000)*	(0.000)*	(0.000)	(0.001)
# Not-Sufficient-Funds Events	0.000	0.000	0.001	0.000	0.000	0.000	0.001
	(0.000)	(0.000)	(0.001)*	(0.000)	(0.000)	(0.000)	(0.001)*
Observations	145159	41273	5993	145159	145159	41273	5993
R-squared	0.03	0.04	0.08	0.03	0.03	0.04	0.07

Standard errors in parentheses

* significant at 5%; **significant at 1%

Notes: Demographic controls include dummies for pay frequency, direct deposit, homeownership, race, paycheck garnishment, and dummies for missing values of these; log monthly pay, log checking-account balance, job tenure, age, sex, months at current residence, and number of non-sufficient funds on checking statement. "Range" refers to the standard deviation around the credit-score threshold to which the sample is restricted. Columns (2) and (6) restrict the sample to payday-loan applicants who first loan was scored within 0.5 standard deviations above or below the threshold, for OLS and IV, respectively. Columns (3) and (7) restrict the sample to payday-loan applicants who first loan was scored within 0.1 standard deviations above or below the threshold, for OLS and IV, respectively.

Table 6: Bankruptcy Summary Statistics

A: Aggregates

	Personal Bankruptcies, All TX	TX Population (millions)	Personal Bankruptcy Rate, All TX	Personal Bankruptcies, Northern, Eastern, and Western TX	Northern, Eastern, and Western TX Districts Share
2001	73,845	21.33	0.00346	52,582	0.71
2002	77,058	21.72	0.00355	56,608	0.73
2003	88,675	22.10	0.00401	63,473	0.72
2004	90,649	22.47	0.00403	64,240	0.71
2005 (Jan-June)	48,974	22.86	0.00214	34,291	0.70

B: Personal Bankruptcies, Northern, Eastern and Western TX Districts

	Number	Share	% Discharge Granted	% Case Dismissed	Number of Parties
All Personal Bankruptcies	278,482	1.00	0.70	0.29	3.80
Chapter 7 Bankruptcies	160,925	0.58	0.96	0.02	3.21
Chapter 13 Bankruptcies	117,557	0.42	0.10	0.90	4.61

C: Personal Bankruptcies and Payday Loans

Year of bankruptcy filing	Bankruptcy filers who ever apply or applied for PDL	Ch 7 filers who ever apply or applied for PDL	Ch 13 filers who ever apply or applied for PDL
2001	1,217	442	775
2002	1,421	544	877
2003	1,673	526	1,147
2004	1,535	429	1,106
2005 (Jan-June)	810	275	535
Total	6,656	2,216	4,440

Sources and Notes: In Panel A, bankruptcy data are from the American Bankruptcy Institute (http://www.abiworld.org/Template.cfm?Section=Filings_by_District1), and Texas population data are from the US Census Bureau, http://www.census.gov/popest/states/tables/NST-EST2005-01.xls. Panel B data are from Public Access to Court Electronic Records (PACER), Northern District of Texas Bankruptcy Court. These PACER data include 1.6% more cases than the aggregate statistics. Panel C reports the number of bankruptcy filers that have the same first name, last name, zip code and final four SSN digits as individuals who applied for loans from a national payday lender. There are a significant number of missing values for observations of "Discharge Granted" and "Case Dismissed," so these percentages cannot be compared to the share of Ch7 bankruptcies and Ch13 bankruptcies.

Table 7 : The Effect of First-Application Approval on Chapter 7 Bankruptcy Filings within 1 Year

	(1) OLS full range	(2) OLS range = 0.5sd	(3) OLS range = 0.1sd	(4) Reduced Form	(5) IV full range	(6) IV range = 0.5sd	(7) IV range = 0.1sd
First-application approved dummy	-0.039	0.004	0.092		-0.050	0.181	0.467
	(0.085)	(0.171)	(0.519)		(0.124)	(0.304)	(1.909)
Abovethr dummy				-0.048	Instrument	Instrument	Instrument
				(0.120)			
Quartic in AmtAbovethr	Yes	Yes	Yes	Yes	Yes	Yes	Yes
(Quartic in AmtAbovethr) X Abovethr	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Biweekly dummy	-0.224	-0.162	-0.102	-0.224	-0.224	-0.163	-0.103
	(0.065)**	(0.113)	(0.308)	(0.065)**	(0.065)**	(0.113)	(0.308)
Semimonthly dummy	-0.208	-0.262	-0.292	-0.208	-0.208	-0.263	-0.293
	(0.077)**	(0.132)*	(0.360)	(0.077)**	(0.077)**	(0.132)*	(0.360)
Weekly dummy	-0.322	-0.176	-0.327	-0.322	-0.322	-0.176	-0.325
	(0.085)**	(0.142)	(0.392)	(0.085)**	(0.085)**	(0.142)	(0.392)
Months in same residence	-0.000	0.000	0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Direct-deposit dummy	0.001	-0.000	-0.514	0.001	0.001	0.000	-0.516
	(0.049)	(0.079)	(0.219)*	(0.049)	(0.049)	(0.079)	(0.219)*
Monthly Pay ($)	0.315	0.305	0.533	0.314	0.315	0.303	0.530
	(0.046)**	(0.076)**	(0.210)*	(0.046)**	(0.046)**	(0.076)**	(0.211)*
Homeowner dummy	0.304	0.244	-0.434	0.303	0.304	0.241	-0.440
	(0.058)**	(0.125)	(0.310)	(0.058)**	(0.058)**	(0.125)	(0.311)
Job tenure (years)	-0.004	0.002	-0.034	-0.004	-0.004	0.002	-0.034
	(0.003)	(0.008)	(0.018)	(0.003)	(0.003)	(0.008)	(0.018)
Male	-0.101	-0.020	-0.071	-0.101	-0.101	-0.020	-0.070
	(0.055)	(0.088)	(0.238)	(0.055)	(0.055)	(0.088)	(0.238)
Age	0.014	0.015	0.019	0.014	0.014	0.015	0.019
	(0.002)**	(0.003)**	(0.007)**	(0.002)**	(0.002)**	(0.003)**	(0.007)**
Black	-0.360	-0.143	-0.133	-0.360	-0.360	-0.143	-0.131
	(0.069)**	(0.112)	(0.313)	(0.069)**	(0.069)**	(0.112)	(0.313)
Hispanic	-0.305	-0.191	0.026	-0.305	-0.305	-0.192	0.025
	(0.072)**	(0.118)	(0.330)	(0.072)**	(0.072)**	(0.118)	(0.330)
Paycheck-garnishment dummy	-0.002	-0.204	-0.310	-0.002	-0.002	-0.203	-0.312
	(0.155)	(0.248)	(0.641)	(0.155)	(0.155)	(0.249)	(0.641)
Checking balance ($)	0.019	0.021	0.105	0.019	0.019	0.020	0.104
	(0.010)	(0.016)	(0.045)*	(0.010)	(0.010)	(0.016)	(0.045)*
# Not-Sufficient-Funds Events	0.005	0.006	-0.024	0.005	0.005	0.007	-0.023
	(0.006)	(0.008)	(0.019)	(0.006)	(0.006)	(0.008)	(0.019)
Observations	145159	47434	6387	145159	145159	47434	6387
R-squared	0.00	0.00	0.01	0.00	0.00	0.00	0.01

Standard errors in parentheses

* significant at 5%; **significant at 1%

Notes: Demographic controls include dummies for pay frequency, direct deposit, homeownership, race, paycheck garnishment, and dummies for missing values of these; log monthly pay, log checking-account balance, job tenure, age, sex, months at current residence, and number of non-sufficient funds on checking statement. "Range" refers to the standard deviation around the credit-score threshold to which the sample is restricted. Columns (2) and (6) restrict the sample to payday-loan applicants who first loan was scored within 0.5 standard deviations above or below the threshold, for OLS and IV, respectively. Columns (3) and (7) restrict the sample to payday-loan applicants who first loan was scored within 0.1 standard deviations above or below the threshold, for OLS and IV, respectively.

Table 8: The Effect of First-Application Approval on Chapter 13 Bankruptcy Filings within 1 Year

	(1) OLS full range	(2) OLS range = 0.5sd	(3) OLS range = 0.1sd	(4) Reduced Form	(5) IV full range	(6) IV range = 0.5sd	(7) IV range = 0.1sd
First-application approved dummy	0.318	0.805	0.713		0.165	1.990	2.460
	(0.139)*	(0.282)**	(1.155)		(0.204)	(0.503)**	(4.249)
Abovethr dummy				0.159	Instrument	Instrument	Instrument
				(0.197)			
Quartic in AmtAbovethr	Yes	Yes	Yes	Yes	Yes	Yes	Yes
(Quartic in AmtAbovethr) X Abovethr	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Biweekly dummy	0.037	0.081	0.849	0.036	0.036	0.074	0.845
	(0.107)	(0.188)	(0.686)	(0.107)	(0.107)	(0.188)	(0.686)
Semimonthly dummy	-0.047	-0.057	1.340	-0.047	-0.047	-0.063	1.338
	(0.127)	(0.218)	(0.802)	(0.127)	(0.127)	(0.218)	(0.802)
Weekly dummy	0.298	0.106	0.955	0.295	0.296	0.109	0.964
	(0.140)*	(0.235)	(0.873)	(0.140)*	(0.140)*	(0.235)	(0.874)
Months in same residence	-0.002	-0.001	-0.006	-0.002	-0.002	-0.001	-0.006
	(0.000)**	(0.001)	(0.002)**	(0.000)**	(0.000)**	(0.001)	(0.002)**
Direct-deposit dummy	0.091	0.180	0.407	0.090	0.090	0.185	0.399
	(0.081)	(0.131)	(0.488)	(0.081)	(0.081)	(0.131)	(0.489)
Monthly Pay ($)	0.406	0.631	0.848	0.408	0.407	0.622	0.833
	(0.076)**	(0.126)**	(0.469)	(0.076)**	(0.076)**	(0.126)**	(0.470)
Homeowner dummy	1.892	2.290	4.177	1.898	1.894	2.271	4.149
	(0.095)**	(0.207)**	(0.689)**	(0.095)**	(0.095)**	(0.208)**	(0.692)**
Job tenure (years)	0.008	0.019	0.140	0.008	0.008	0.019	0.140
	(0.005)	(0.014)	(0.041)**	(0.005)	(0.005)	(0.014)	(0.041)**
Male	0.367	0.449	0.517	0.367	0.368	0.449	0.517
	(0.090)**	(0.145)**	(0.529)	(0.090)**	(0.090)**	(0.145)**	(0.530)
Age	0.036	0.039	0.059	0.036	0.036	0.039	0.059
	(0.003)**	(0.005)**	(0.016)**	(0.003)**	(0.003)**	(0.005)**	(0.016)**
Black	0.139	0.211	1.408	0.137	0.138	0.213	1.419
	(0.113)	(0.185)	(0.696)*	(0.113)	(0.113)	(0.185)	(0.696)*
Hispanic	-0.427	-0.358	0.163	-0.428	-0.427	-0.362	0.157
	(0.118)**	(0.196)	(0.734)	(0.118)**	(0.118)**	(0.196)	(0.734)
Paycheck-garnishment dummy	0.623	0.779	-0.407	0.620	0.623	0.787	-0.414
	(0.255)*	(0.411)	(1.426)	(0.255)*	(0.255)*	(0.411)	(1.426)
Checking balance ($)	0.031	0.053	0.125	0.031	0.031	0.049	0.122
	(0.017)	(0.027)*	(0.100)	(0.017)	(0.017)	(0.027)	(0.101)
# Not-Sufficient-Funds Events	0.027	0.029	0.014	0.026	0.026	0.032	0.017
	(0.010)**	(0.013)*	(0.042)	(0.010)*	(0.010)**	(0.013)*	(0.043)
Observations	145159	47434	6387	145159	145159	47434	6387
R-squared	0.01	0.01	0.03	0.01	0.01	0.01	0.03

Standard errors in parentheses

* significant at 5%; **significant at 1%

Notes: Demographic controls include dummies for pay frequency, direct deposit, homeownership, race, paycheck garnishment, and dummies for missing values of these; log monthly pay, log checking-account balance, job tenure, age, sex, months at current residence, and number of non-sufficient funds on checking statement. "Range" refers to the standard deviation around the credit-score threshold to which the sample is restricted. Columns (2) and (6) restrict the sample to payday-loan applicants who first loan was scored within 0.5 standard deviations above or below the threshold, for OLS and IV, respectively. Columns (3) and (7) restrict the sample to payday-loan applicants who first loan was scored within 0.1 standard deviations above or below the threshold, for OLS and IV, respectively.

Table 9: The Effect of First-Application Approval on Chapter 7 Bankruptcy Filings within 2 Years

	(1) OLS full range	(2) OLS range = 0.5sd	(3) OLS range = 0.1sd	(4) Reduced Form	(5) IV full range	(6) IV range = 0.5sd	(7) IV range = 0.1sd
First-application approved dummy	0.008	0.215	0.597		-0.065	0.472	2.055
	(0.121)	(0.234)	(0.700)		(0.181)	(0.433)	(2.575)
Abovethr dummy				-0.064	Instrument	Instrument	Instrument
				(0.177)			
Quartic in AmtAbovethr	Yes	Yes	Yes	Yes	Yes	Yes	Yes
(Quartic in AmtAbovethr) X Abovethr	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Biweekly dummy	-0.301	-0.385	0.151	-0.301	-0.301	-0.386	0.150
	(0.083)**	(0.135)**	(0.371)	(0.083)**	(0.083)**	(0.135)**	(0.372)
Semimonthly dummy	-0.302	-0.532	-0.158	-0.302	-0.302	-0.533	-0.159
	(0.098)**	(0.157)**	(0.434)	(0.098)**	(0.098)**	(0.157)**	(0.434)
Weekly dummy	-0.438	-0.518	-0.228	-0.438	-0.438	-0.517	-0.220
	(0.109)**	(0.169)**	(0.471)	(0.109)**	(0.109)**	(0.169)**	(0.472)
Months in same residence	-0.000	-0.000	-0.002	-0.000	-0.000	-0.000	-0.002
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Direct-deposit dummy	0.004	-0.011	-0.442	0.004	0.004	-0.010	-0.448
	(0.062)	(0.094)	(0.262)	(0.062)	(0.062)	(0.094)	(0.262)
Monthly Pay ($)	0.385	0.434	0.673	0.384	0.385	0.432	0.659
	(0.059)**	(0.091)**	(0.253)**	(0.059)**	(0.059)**	(0.091)**	(0.254)**
Homeowner dummy	0.509	0.398	-0.498	0.508	0.509	0.393	-0.524
	(0.074)**	(0.149)**	(0.372)	(0.074)**	(0.074)**	(0.149)**	(0.375)
Job tenure (years)	-0.004	0.002	-0.015	-0.004	-0.004	0.002	-0.015
	(0.004)	(0.010)	(0.022)	(0.004)	(0.004)	(0.010)	(0.022)
Male	-0.025	0.104	-0.640	-0.025	-0.025	0.104	-0.633
	(0.076)	(0.117)	(0.325)*	(0.076)	(0.076)	(0.117)	(0.326)
Age	0.020	0.017	0.025	0.020	0.020	0.017	0.024
	(0.003)**	(0.004)**	(0.010)*	(0.003)**	(0.003)**	(0.004)**	(0.010)*
Black	-0.558	-0.182	-0.204	-0.558	-0.559	-0.182	-0.205
	(0.095)**	(0.148)	(0.426)	(0.095)**	(0.095)**	(0.148)	(0.426)
Hispanic	-0.429	-0.090	-0.023	-0.429	-0.429	-0.091	-0.034
	(0.099)**	(0.157)	(0.455)	(0.099)**	(0.099)**	(0.157)	(0.455)
Paycheck-garnishment dummy	0.002	-0.347	-0.516	0.002	0.002	-0.345	-0.522
	(0.197)	(0.294)	(0.766)	(0.197)	(0.197)	(0.294)	(0.766)
Checking balance ($)	0.031	0.022	0.075	0.031	0.031	0.022	0.074
	(0.015)*	(0.022)	(0.062)	(0.015)*	(0.015)*	(0.022)	(0.062)
# Not-Sufficient-Funds Events	0.004	0.009	-0.005	0.004	0.004	0.010	-0.002
	(0.008)	(0.010)	(0.024)	(0.008)	(0.008)	(0.010)	(0.025)
Observations	117511	36048	4689	117511	117511	36048	4689
R-squared	0.00	0.00	0.02	0.00	0.00	0.00	0.01

Standard errors in parentheses

* significant at 5%; **significant at 1%

Notes: Demographic controls include dummies for pay frequency, direct deposit, homeownership, race, paycheck garnishment, and dummies for missing values of these; log monthly pay, log checking-account balance, job tenure, age, sex, months at current residence, and number of non-sufficient funds on checking statement. "Range" refers to the standard deviation around the credit-score threshold to which the sample is restricted. Columns (2) and (6) restrict the sample to payday-loan applicants who first loan was scored within 0.5 standard deviations above or below the threshold, for OLS and IV, respectively. Columns (3) and (7) restrict the sample to payday-loan applicants who first loan was scored within 0.1 standard deviations above or below the threshold, for OLS and IV, respectively.

Table 10: The Effect of First-Application Approval on Chapter 13 Bankruptcy Filings within 2 Years

	(1) OLS full range	(2) OLS range = 0.5sd	(3) OLS range = 0.1sd	(4) Reduced Form	(5) IV full range	(6) IV range = 0.5sd	(7) IV range = 0.1sd
First-application approved dummy		1.150	-0.074		0.349	2.845	2.282
		(0.413)**	(1.710)		(0.302)	(0.764)**	(6.286)
Abovethr dummy				0.341	Instrument	Instrument	Instrument
				(0.296)			
Quartic in AmtAbovethr	Yes	Yes	Yes	Yes	Yes	Yes	Yes
(Quartic in AmtAbovethr) X Abovethr	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Biweekly dummy	0.342	0.451	1.682	0.342	0.342	0.443	1.679
	(0.139)*	(0.238)	(0.907)	(0.139)*	(0.139)*	(0.239)	(0.907)
Semimonthly dummy	0.084	0.093	2.102	0.084	0.084	0.084	2.101
	(0.164)	(0.277)	(1.059)*	(0.164)	(0.164)	(0.277)	(1.059)*
Weekly dummy	0.501	0.337	1.738	0.499	0.501	0.342	1.750
	(0.181)**	(0.299)	(1.151)	(0.181)**	(0.181)**	(0.299)	(1.152)
Months in same residence	-0.003	0.000	-0.005	-0.003	-0.003	0.000	-0.006
	(0.001)**	(0.001)	(0.003)	(0.001)**	(0.001)**	(0.001)	(0.003)
Direct-deposit dummy	0.054	0.288	0.532	0.054	0.054	0.294	0.522
	(0.104)	(0.165)	(0.640)	(0.104)	(0.104)	(0.165)	(0.641)
Monthly Pay ($)	0.738	0.806	0.871	0.742	0.739	0.795	0.849
	(0.099)**	(0.160)**	(0.617)	(0.099)**	(0.099)**	(0.160)**	(0.620)
Homeowner dummy	3.130	3.383	5.852	3.139	3.131	3.354	5.809
	(0.124)**	(0.263)**	(0.908)**	(0.124)**	(0.124)**	(0.264)**	(0.914)**
Job tenure (years)	0.022	0.039	0.205	0.023	0.022	0.038	0.205
	(0.007)**	(0.017)*	(0.054)**	(0.007)**	(0.007)**	(0.017)*	(0.054)**
Male	0.484	0.715	1.470	0.484	0.484	0.716	1.482
	*(0.127)***	*(0.206)***	*(0.795)*	*(0.127)***	*(0.127)***	*(0.206)***	*(0.795)*
Age	0.054	0.058	0.094	0.054	0.054	0.058	0.094
	(0.004)**	(0.007)**	(0.025)**	(0.004)**	(0.004)**	(0.007)**	(0.025)**
Black	0.414	0.314	2.105	0.410	0.413	0.316	2.102
	(0.159)**	(0.261)	(1.040)*	(0.159)**	(0.159)**	(0.261)	(1.040)*
Hispanic	-0.307	-0.349	0.107	-0.308	-0.307	-0.357	0.090
	(0.165)	(0.278)	(1.110)	(0.165)	(0.165)	(0.278)	(1.111)
Paycheck-garnishment dummy	0.829	0.974	-1.588	0.826	0.829	0.986	-1.597
	(0.329)*	(0.519)	(1.870)	(0.329)*	(0.329)*	(0.519)	(1.871)
Checking balance ($)	0.044	0.064	0.307	0.045	0.044	0.059	0.305
	(0.025)	(0.039)	(0.152)*	(0.024)	(0.025)	(0.039)	(0.152)*
# Not-Sufficient-Funds Events	0.029	0.010	-0.016	0.028	0.029	0.014	-0.011
	(0.014)*	(0.017)	(0.059)	(0.014)*	(0.014)*	(0.017)	(0.061)
Observations	117511	36048	4689	117511	117511	36048	4689
R-squared	0.01	0.01	0.03	0.01	0.01	0.01	0.03

Standard errors in parentheses

* significant at 5%; **significant at 1%

Notes: Demographic controls include dummies for pay frequency, direct deposit, homeownership, race, paycheck garnishment, and dummies for missing values of these; log monthly pay, log checking-account balance, job tenure, age, sex, months at current residence, and number of non-sufficient funds on checking statement. "Range" refers to the standard deviation around the credit-score threshold to which the sample is restricted. Columns (2) and (6) restrict the sample to payday-loan applicants who first loan was scored within 0.5 standard deviations above or below the threshold, for OLS and IV, respectively. Columns (3) and (7) restrict the sample to payday-loan applicants who first loan was scored within 0.1 standard deviations above or below the threshold, for OLS and IV, respectively.

Table 11: Criminal Conviction History Database Summary

	(1)	(2)
	Aggregate Arrests 1/2000-8/2004	PDL Sample 1/2000-8/2004
	%	%
Revenue generating	8.3	13.9
Felony	11.3	12.2
Misdemeanor	30.8	35.8
Assault	4.0	5.1
Burglary	1.7	1.3
Fraud or Forgery	1.3	1.9
Harassment	0.3	0.4
Larceny	5.8	9.2
Obstruction of Justice	2.8	3.3
Possession of Drugs	4.9	5.3
Prostitution	0.4	0.7
Robbery	0.4	0.4
Traffic Crimes (DUIs)	13.1	13.9
		0.0
Other	8.9	6.3
Missing	56.3	50.6
Male	77.6	67.6
Black	22.7	35.6
N	3,071,598	22,372

Source: Data in column (1) is from the Texas Department of Public Safety Criminal Convinction Database. Data in column (2) is from the CCH Database merged by personal identifiers with data on payday loan applicants from a large lender. Sample periods are Jan. 2000 - Aug. 2004.

Table 12: The Effect of First-Application Approval on All Arrests within 2 days

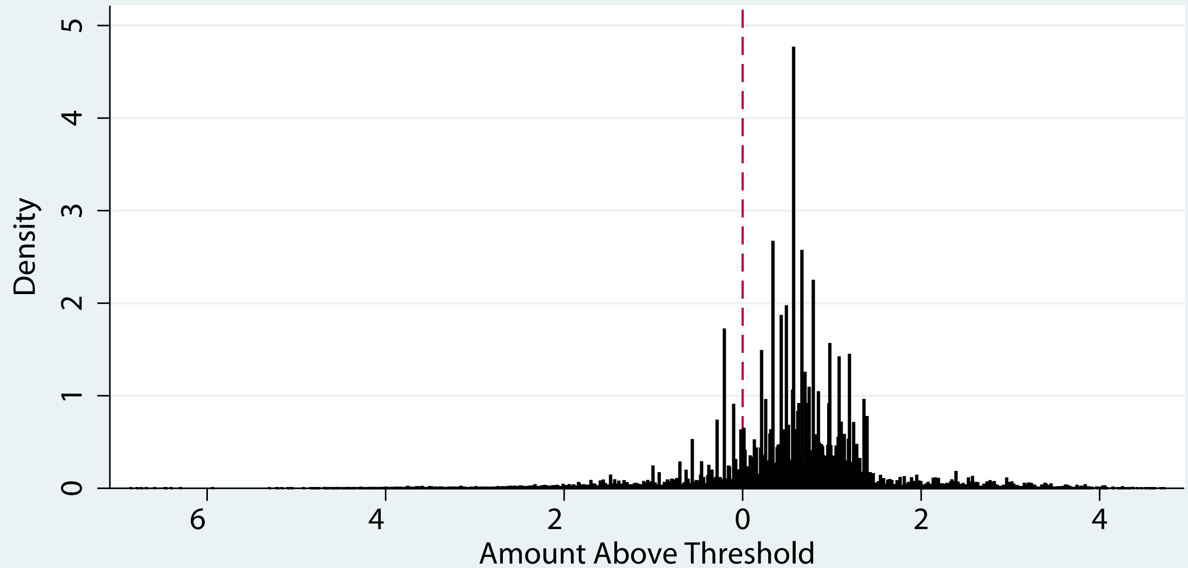
	(1) OLS full range	(2) OLS range = 0.5sd	(3) OLS range = 0.1sd	(4) Reduced Form	(5) IV full range	(6) IV range = 0.5sd	(7) IV range = 0.1sd
First-application approved dummy	-0.018289	0.075425	0.254260		-0.088233	0.070942	0.611375
	(0.044060)	(0.108242)	(0.287308)		(0.068776)	(0.200861)	(1.163967)
Abovethr dummy				-0.083338	Instrument	Instrument	Instrument
				(0.064981)			
Quartic in AmtAbovethr	Yes	Yes	Yes	Yes	Yes	Yes	Yes
(Quartic in AmtAbovethr) X Abovethr	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Biweekly dummy	0.042	0.098	-0.124	0.042	0.042	0.099	-0.126
	(0.032)	(0.071)	(0.171)	(0.032)	(0.032)	(0.071)	(0.171)
Semimonthly dummy	0.001	-0.022	-0.210	0.001	0.001	-0.021	-0.210
	(0.038)	(0.083)	(0.201)	(0.038)	(0.038)	(0.083)	(0.201)
Weekly dummy	-0.017	-0.020	-0.160	-0.017	-0.017	-0.019	-0.159
	(0.042)	(0.089)	(0.218)	(0.042)	(0.042)	(0.089)	(0.218)
Months in same residence	-0.000	-0.000	0.001	-0.000	-0.000	-0.000	0.001
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Direct-deposit dummy	-0.022	0.030	-0.014	-0.023	-0.023	0.031	-0.015
	(0.024)	(0.050)	(0.123)	(0.024)	(0.024)	(0.050)	(0.123)
Monthly Pay ($)	-0.004	-0.100	-0.243	-0.005	-0.004	-0.098	-0.245
	(0.023)	(0.048)*	(0.117)*	(0.023)	(0.023)	(0.047)*	(0.117)*
Homeowner dummy	-0.005	0.033	0.331	-0.006	-0.004	0.033	0.326
	(0.029)	(0.079)	(0.178)	(0.029)	(0.029)	(0.079)	(0.178)
Job tenure (years)	-0.000	0.007	0.044	-0.000	0.000	0.007	0.043
	(0.002)	(0.005)	(0.011)**	(0.002)	(0.002)	(0.005)	(0.011)**
Male	0.067	0.042	0.178	0.067	0.066	0.042	0.177
	(0.023)**	(0.046)	(0.108)	(0.023)**	(0.023)**	(0.046)	(0.108)
Age	-0.002	-0.003	0.002	-0.002	-0.002	-0.003	0.002
	(0.001)*	(0.002)	(0.004)	(0.001)*	(0.001)*	(0.002)	(0.004)
Black	-0.046	-0.103	-0.214	-0.046	-0.046	-0.103	-0.213
	(0.025)	(0.048)*	(0.113)	(0.025)	(0.025)	(0.048)*	(0.114)
Hispanic	-0.122	-0.174	-0.230	-0.122	-0.122	-0.173	-0.231
	(0.035)**	(0.073)*	(0.174)	(0.035)**	(0.035)**	(0.073)*	(0.174)
Paycheck-garnishment dummy	0.014	0.086	-0.137	0.014	0.014	0.087	-0.140
	(0.077)	(0.156)	(0.350)	(0.077)	(0.077)	(0.156)	(0.350)
Checking balance ($)	-0.012	0.001	0.023	-0.012	-0.012	0.001	0.022
	(0.005)*	(0.010)	(0.025)	(0.005)*	(0.005)*	(0.010)	(0.025)
# Not-Sufficient-Funds Events	0.001	0.003	0.025	0.001	0.001	0.003	0.025
	(0.003)	(0.005)	(0.011)*	(0.003)	(0.003)	(0.005)	(0.011)*
Observations	145159	41490	6037	145159	145159	41490	6037
R-squared	0.00	0.00	0.03	0.00	0.00	0.00	0.03

Standard errors in parentheses

* significant at 5%; **significant at 1%

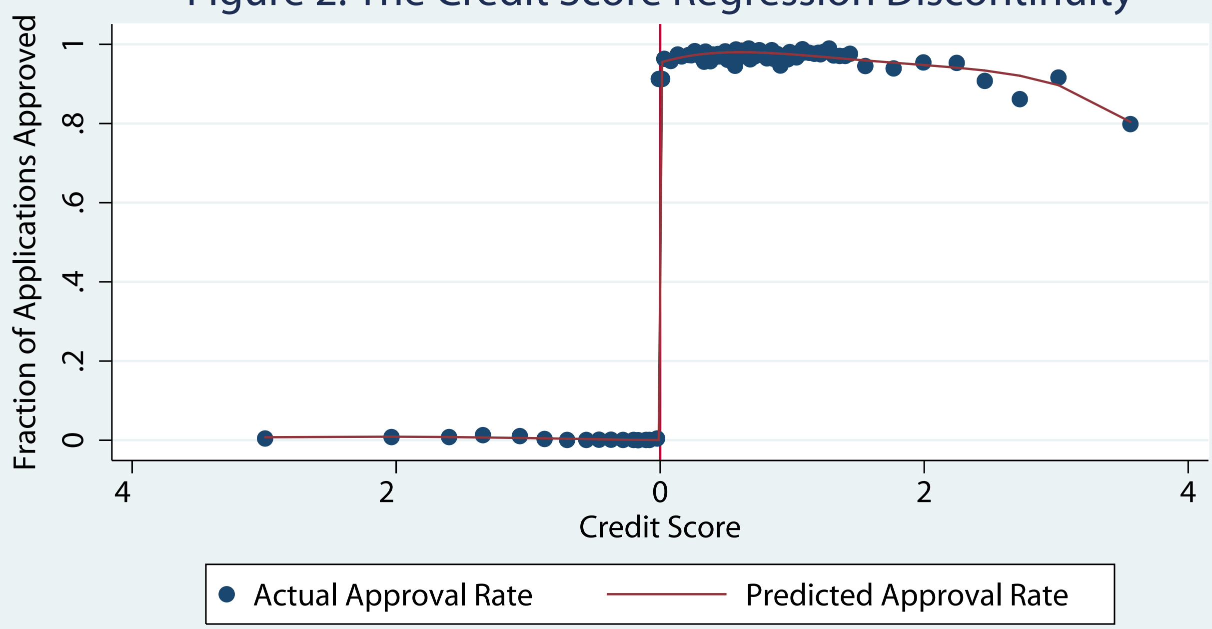
Notes: Demographic controls include dummies for pay frequency, direct deposit, homeownership, race, paycheck garnishment, and dummies for missing values of these; log monthly pay, log checking-account balance, job tenure, age, sex, months at current residence, and number of non-sufficient funds on checking statement. "Range" refers to the standard deviation around the credit-score threshold to which the sample is restricted. Columns (2) and (6) restrict the sample to payday-loan applicants who first loan was scored within 0.5 standard deviations above or below the threshold, for OLS and IV, respectively. Columns (3) and (7) restrict the sample to payday-loan applicants who first loan was scored within 0.1 standard deviations above or below the threshold, for OLS and IV, respectively.

Figure 1: The Distribution of Credit Scores

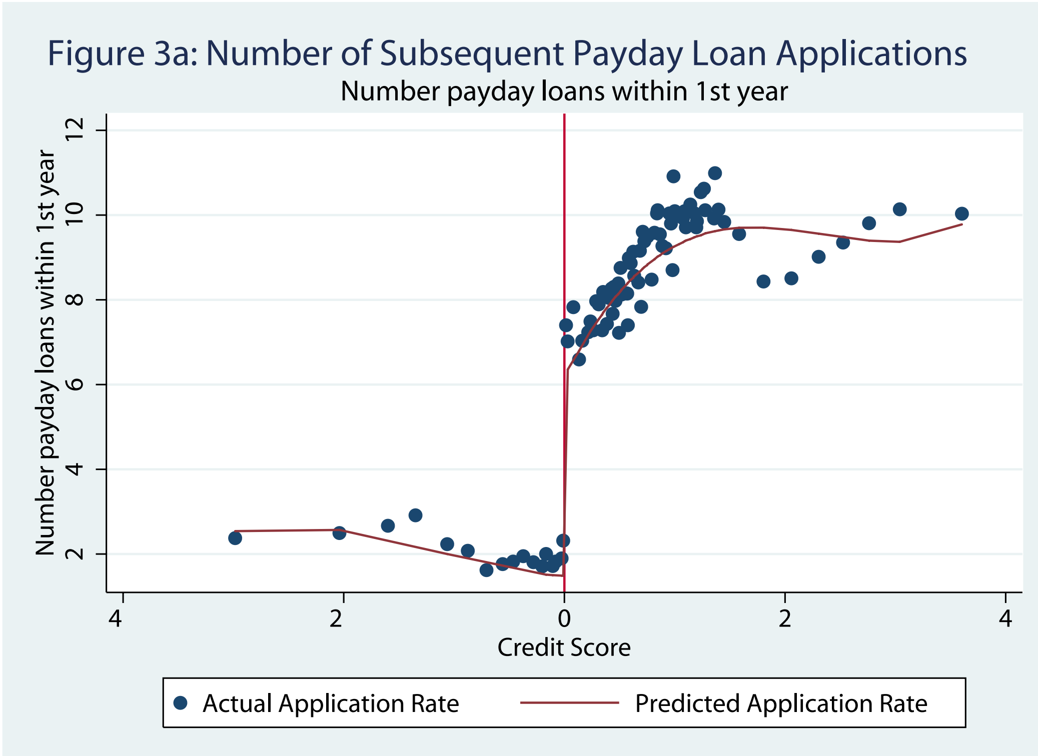


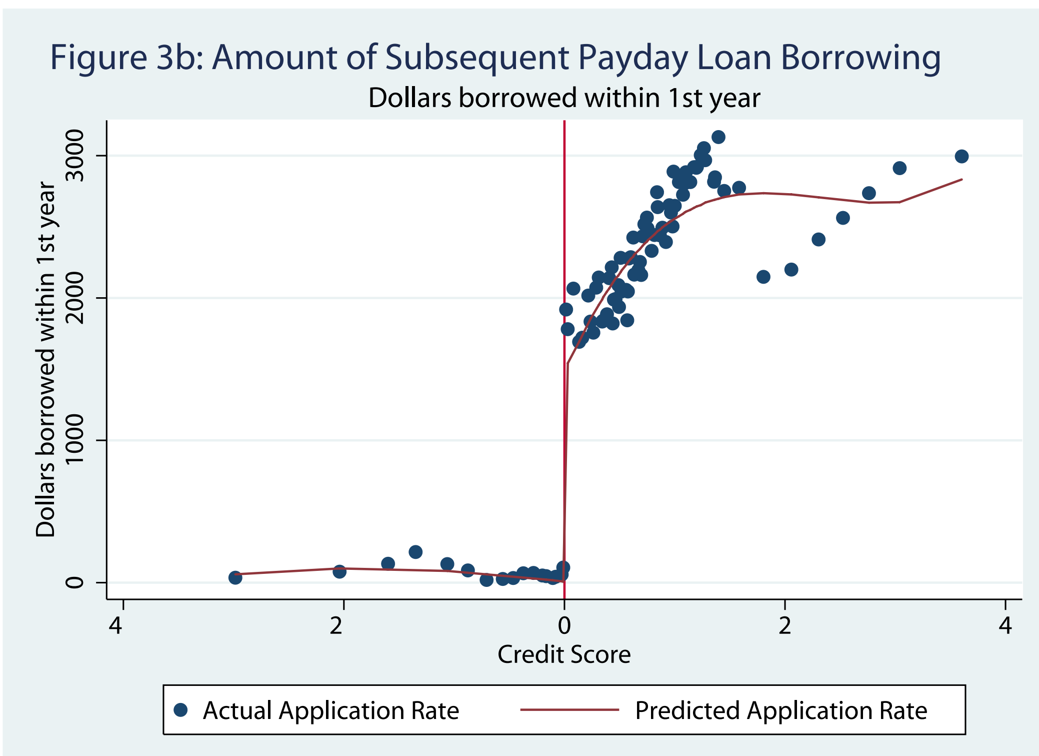
Source: Authors' calculations based on data from a national payday lending company. This figure plots the distribution of AmtAboveThr for firsttime payday loan applicants. AmtAboveThr is equal to the raw credit score provided by Teletrack minus the threshold for loan approval chosen by the lender, divided by the standard deviation of Teletrack scores among this lender's firsttime applicants. We normalize by different standard deviations for applications before and after an August, 2002, change in the Teletrack scoring formula. The vertical red line marks the threshold for loan approval; about 80% of firsttime applications are approved.

Figure 2: The Credit Score Regression Discontinuity

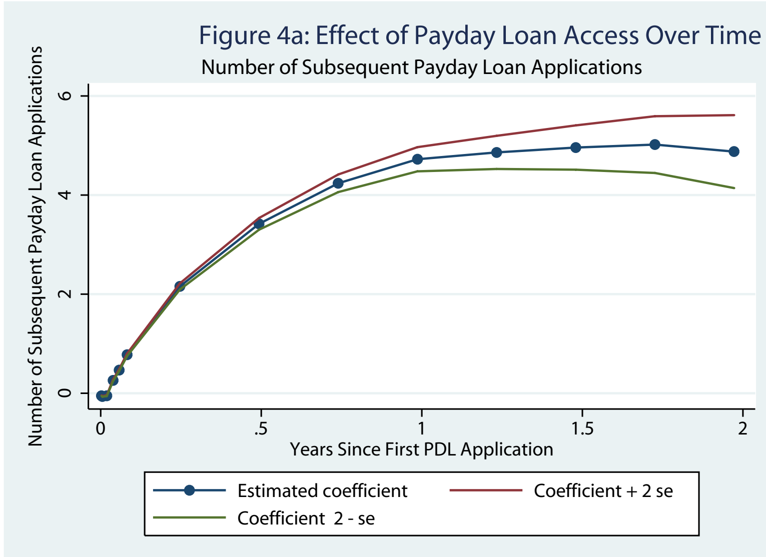


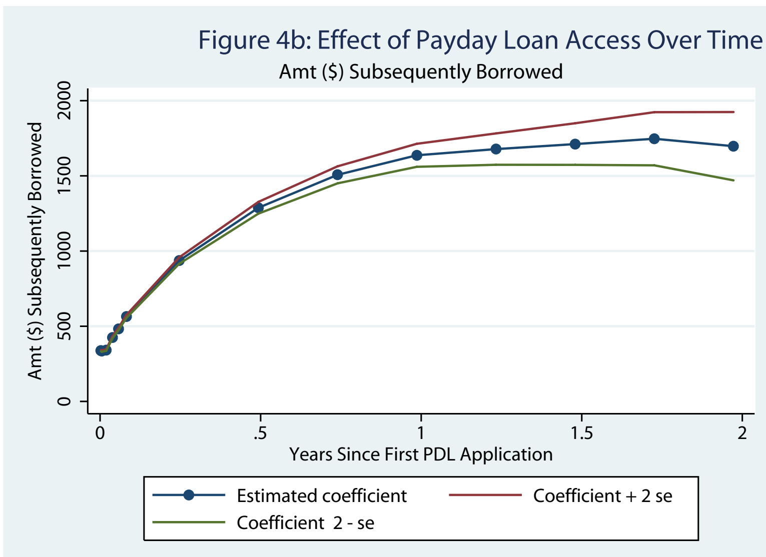
Source: Authors' calculations based on data from a national payday lending company. This figure plots the probability of approval for firsttime payday loan applicants as a function of their credit score. Each point represents one of 100 quantiles in the credit score. Points shown are at the medians of their quantiles on the xaxis and at the means of their quantiles on the yaxis. The predicted approvalrate function plots the bestfitting quartic polynomials on both sides of the credit score threshold.

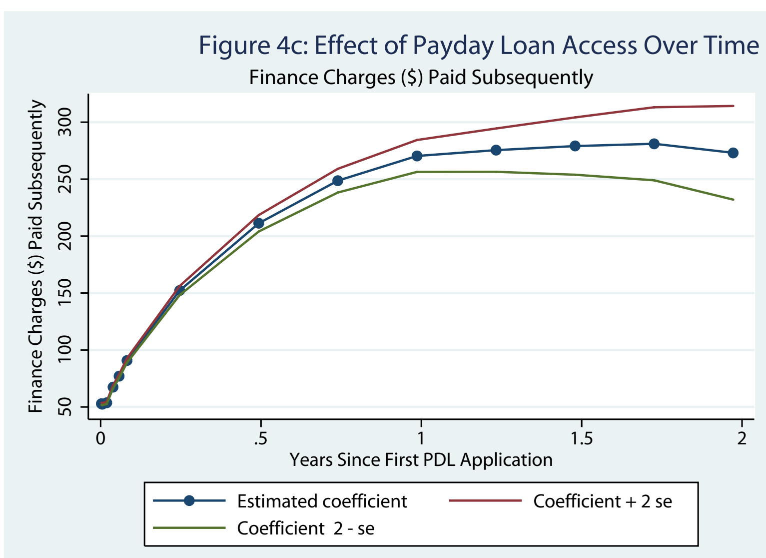




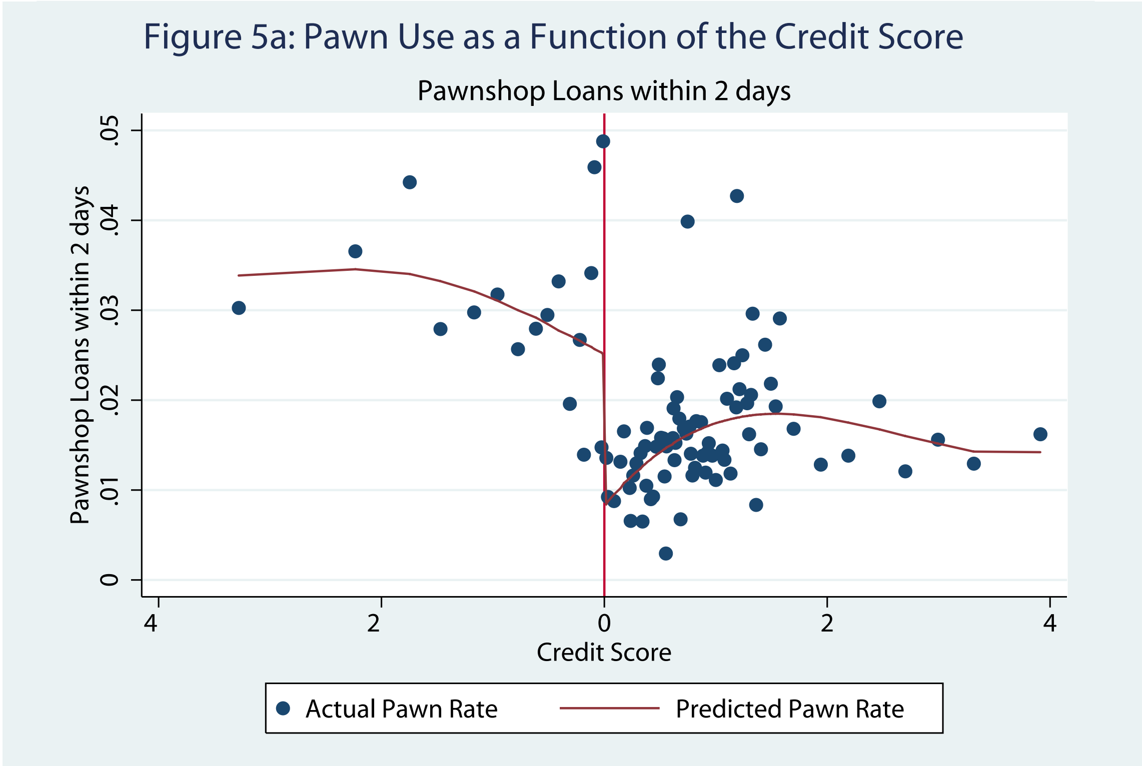
Figures 3a and 3b. Source: Authors' calculations based on data from a national payday lending company. Each point represents one of 100 quantiles. Points shown are the medians of their quantiles on the x axis and at the mean of their quantiles on the yaxis. The predicted line plots the best-fitting quartic polynovials on both sides of the credit-score threshold. All data are from Texas, 9/2000-8/2004. Figure 3a plots the effect of payday loan access on the number of subsequent payday loan applications made. Figure 3b plots the dollar amount subsequently borrowed.

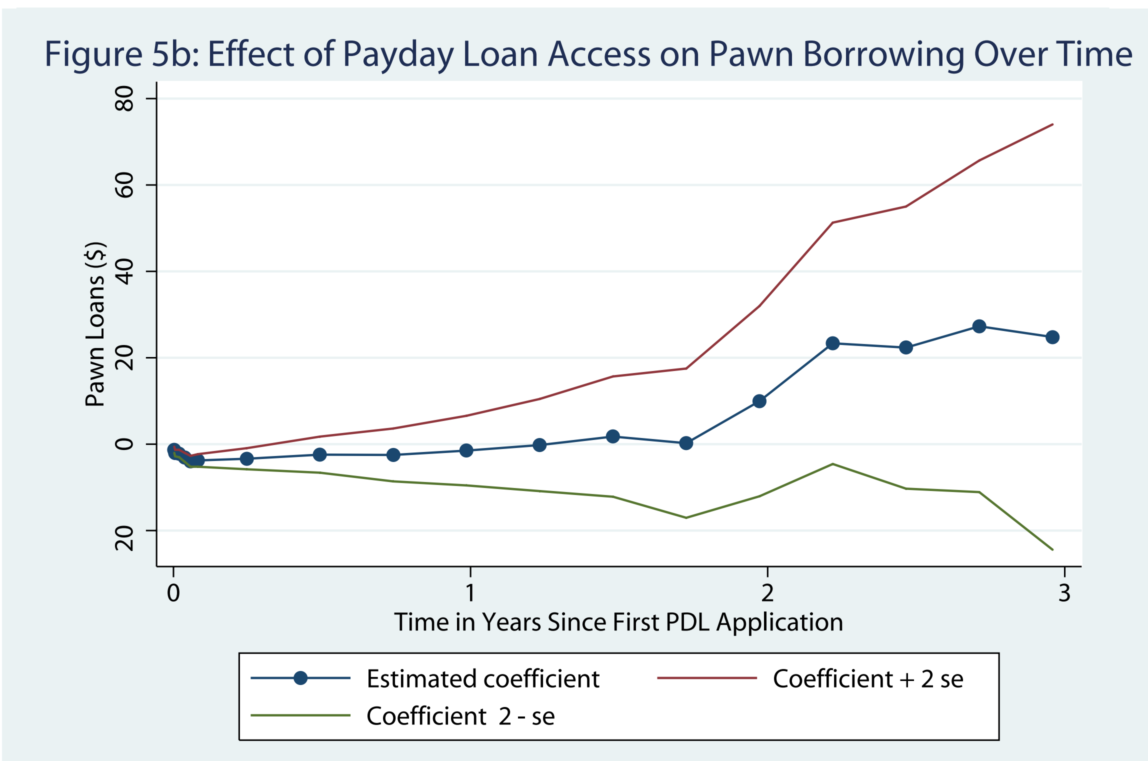




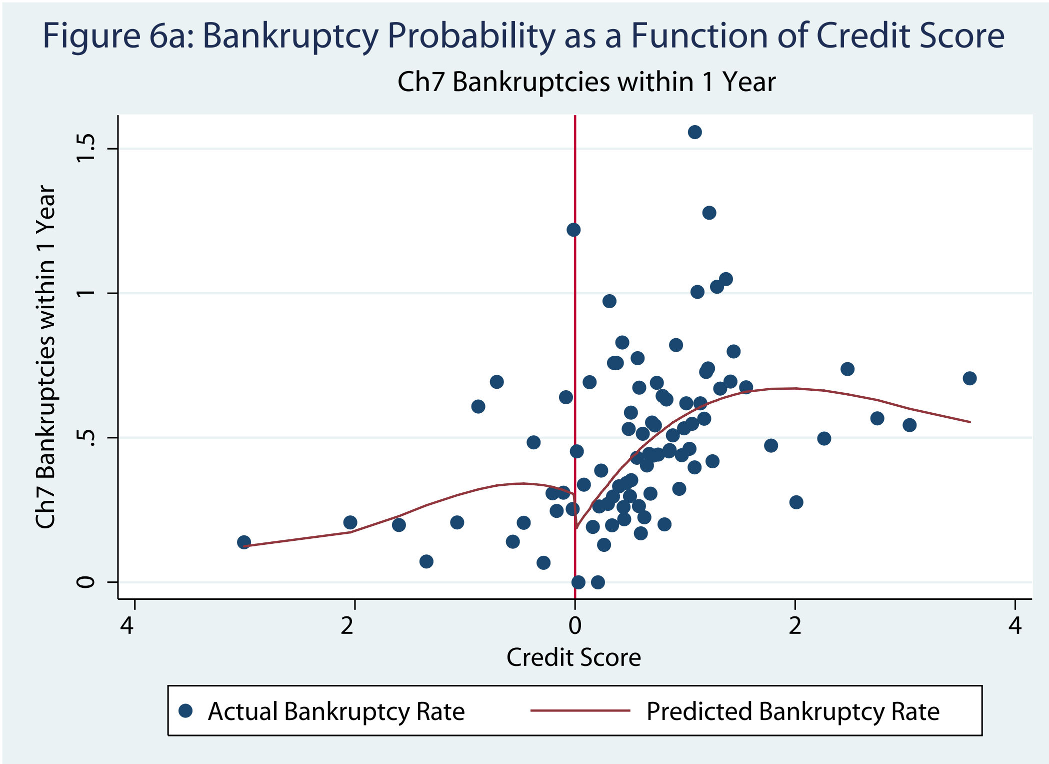


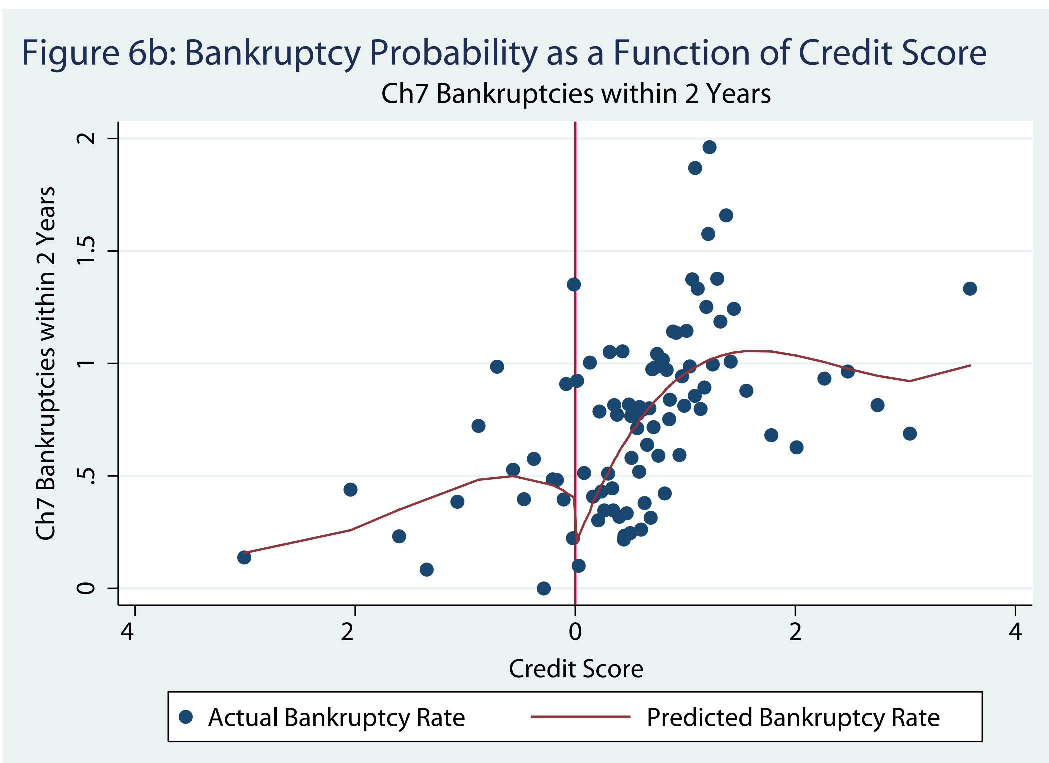
Figures 4a, 4b , 4c. Source: Authors' calculations based on data from a national payday lending company . The middle line represents the IV estimated effect of First Application Approved on subsequent behavior in the payday loan market. The other lines are two-standard-error bands. Regressions producing these estimates include quartic polynomials on both sides of the credit-score threshold, demographic controls , and dummies for month of first application. Figures 4a, 4b and 4c plot the number of subsequent application made at this company, the dollar amount borrowed, and the finance charges paid to this company, respectively.



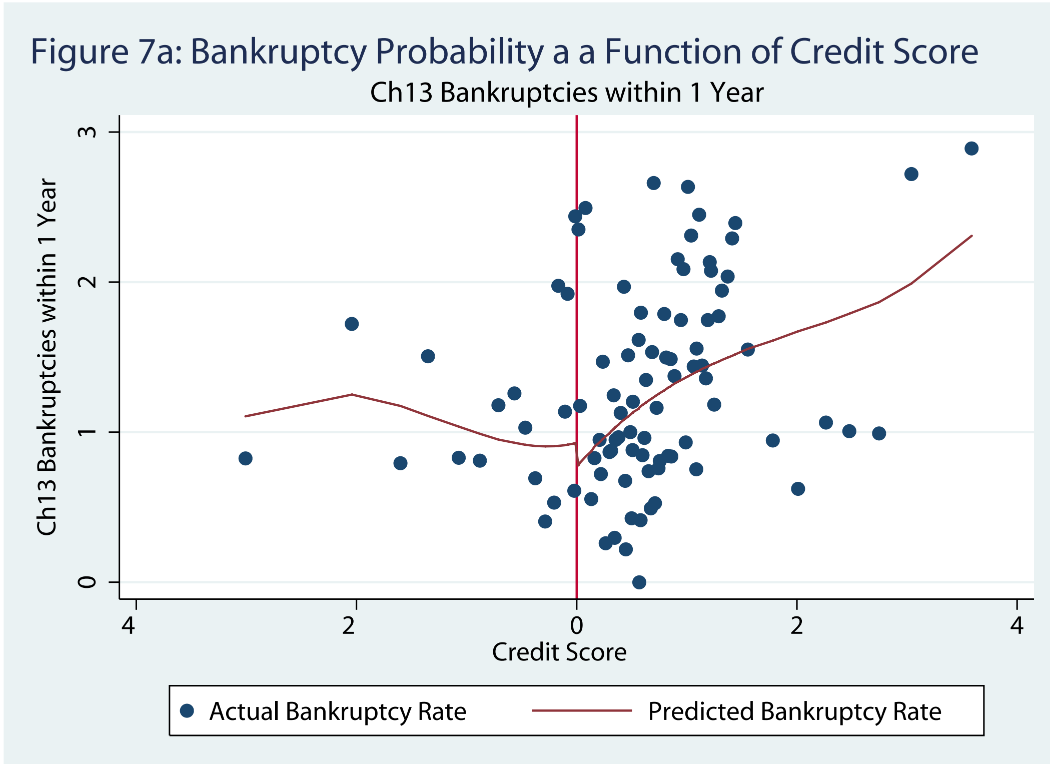


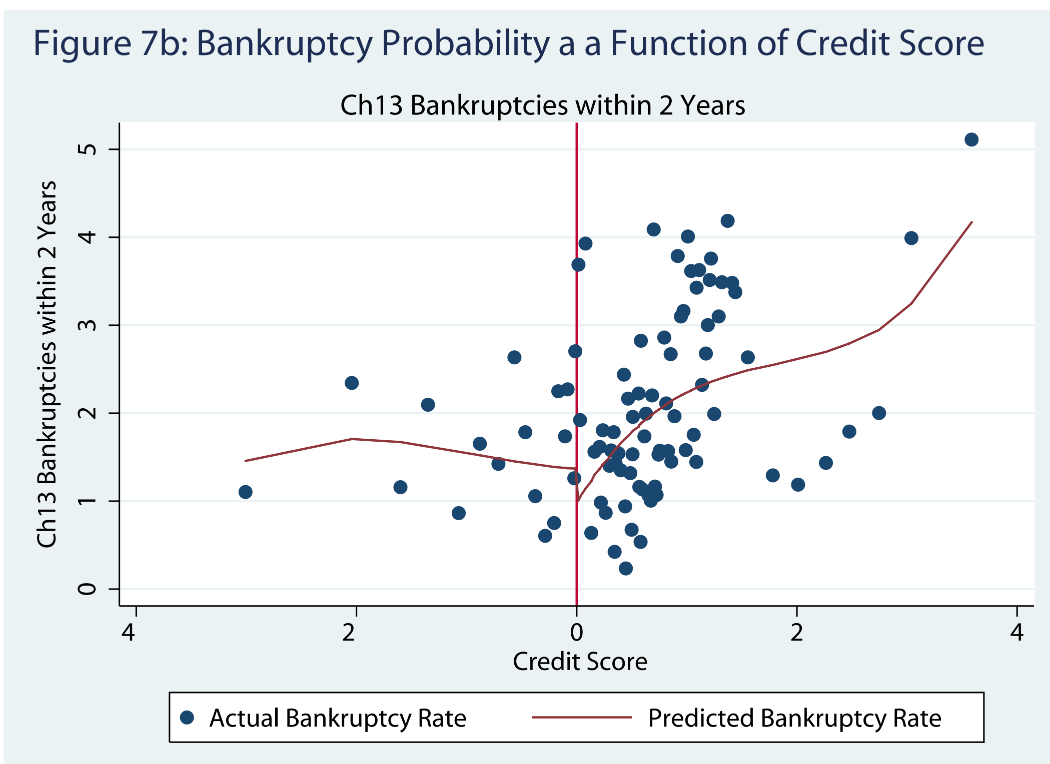
Figures 5a and 5b: The effect of payday loan access on pawnshop borrowing. Figure 5a shows the effect of payday loan access on the number of pawn loans within 2 days of payday loan application. Figure 5b plots the effect of payday loan access on the dollar amount of pawnshop loans borrowed over time. The middle line represents the IV estimated effect of First Application Approved. The other lines are two-standard error bands. Regressions producing these estimates include quartic polynomials on both sides of the credit-score threshold, demographic controls, and dummies for first month of application. Source: Authors' calculations based on data from a national payday lender. All data are from Texas, 9/2000-8/2004.





Figures 6a and 6b: The effect of payday loan access on Chapter 7 bankruptcy petitions. Figure 6a plots the effect of payday loan access on Ch. 7 bankruptcy petitions within 1 year after first payday loan application. Figure 6b plots this effect for 2 years. Each point represents one of 100 quantiles. Points shown are at the medians of their quantils on the x-axis and at the means of their quantiles on the y-axis. The predicted bankruptcy-rate function plots the best-fitting quartic polynomials on both sides of the credit-score threshold. Source; Authors' calculations based on data from a national payday lending company and the North, East and West Texas Bankruptcy Court PACER database.





Figures 7a and 7b: The effect of payday loan access on Chapter 13 bankruptcy petitions. Figure 6a plots the effect of payday loan access on Ch. 13 bankruptcy petitions within 1 year after first payday loan application. Figure 6b plots this effect for 2 years. Each point represents one of 100 quantiles. Points shown are at the medians of their quantils on the x-axis and at the means of their quantiles on the y-axis. The predicted bankruptcy-rate function plots the best-fitting quartic polynomials on both sides of the credit-score threshold. Source; Authors' calculations based on data from a national payday lending company and the North, East and West Texas Bankruptcy Court PACER database.

Fig 8a: Effect of Payday Loan Access Over Time: All Bankruptcies

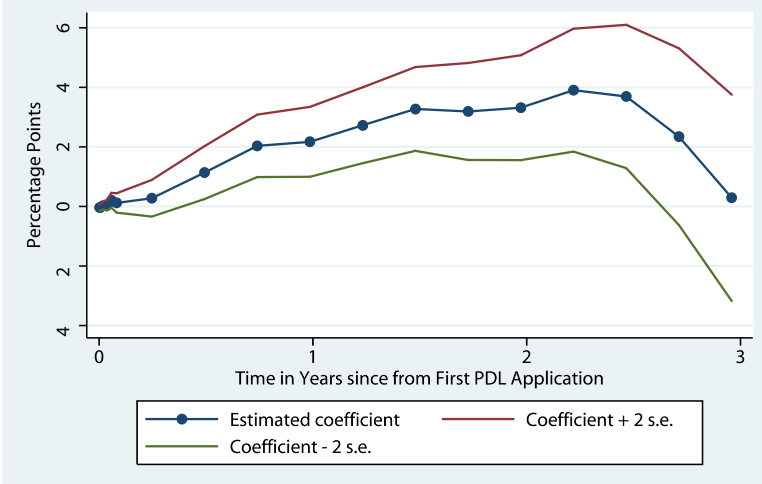


Fig 8b: Effect of Payday Loan Access Over Time: Ch7 Bankruptcies

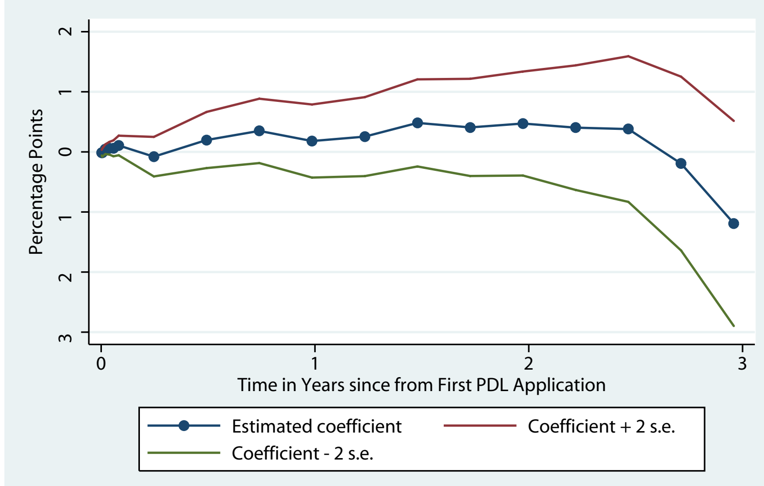
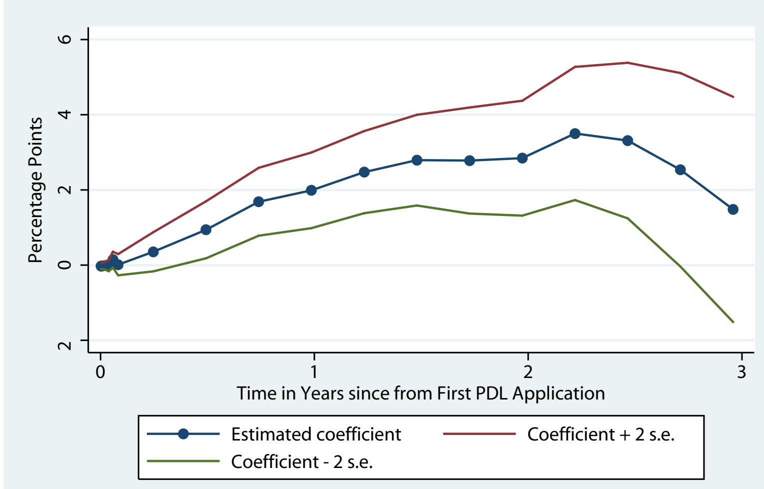


Fig 8c: Effect of Payday Loan Access Over Time: Ch13 Bankruptcies



Figures 8a, 8b, 8c. Source: Authors' calculations based on data from a national payday lending company and the electronic records from the Northern, Eastern and Western Texas Bankruptcy Courts via PACER. The middle line represents the IV estimated effect of First Application Approved. The other lines are two-standard-error bands. Regressions producing these estimates include quartic polynomials on both sides of the credit-score threshold, demographic controls , and dummies for month of first application. Figures 8a, 8b and 8c plot bankruptcy petitions for all Chapters, Chapter 7 and Chapter 13, respectively.

Figure 9a: Effect of Payday Loan Credit Access on Arrests over Time

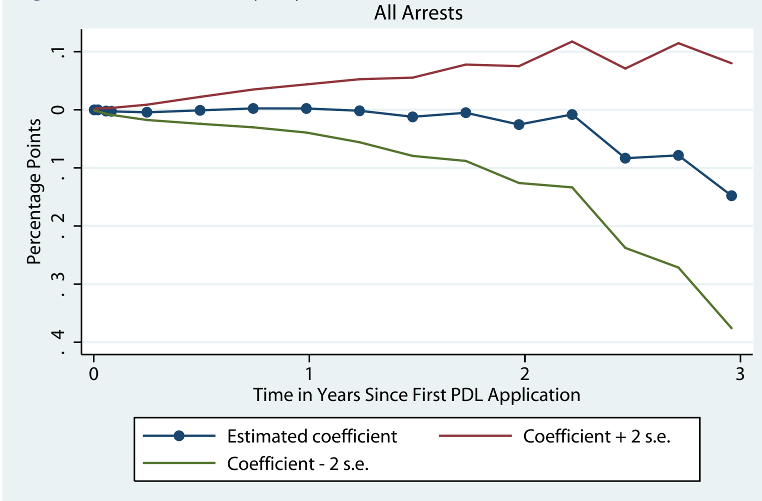


Figure 9b: Effect of Payday Loan Credit Access on Arrests over Time

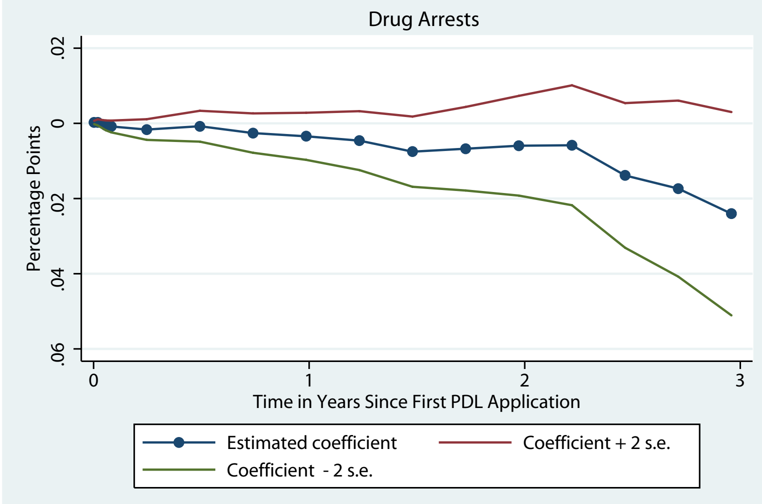
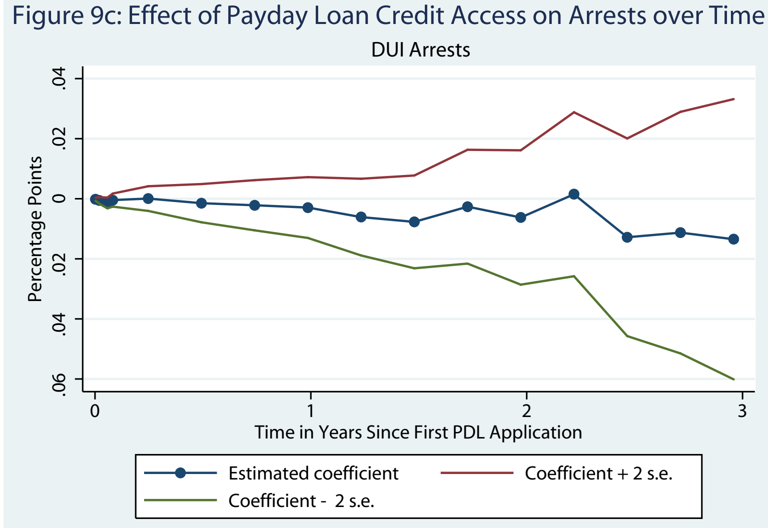


Figure 9c: Effect of Payday Loan Credit Access on Arrests over Time



Figures 9a, 9b, 9c. Source: Authors' calculations based on data from a national payday lending company and the Texas Department of Public Safety Criminal Convinction Database. The middle line represents the IV estimated effect of First Application Approved. The other lines are two-standard-error bands. Regressions producing these estimates include quartic polynomials on both sides of the credit-score threshold, demographic controls, and dummies for month of application. Figures 9a, b and c plot these estimates for all arrests, drug-related arrests, and DUIs, respectively.

Figure 9d: Effect of Payday Loan Credit Access on Arrests over Time

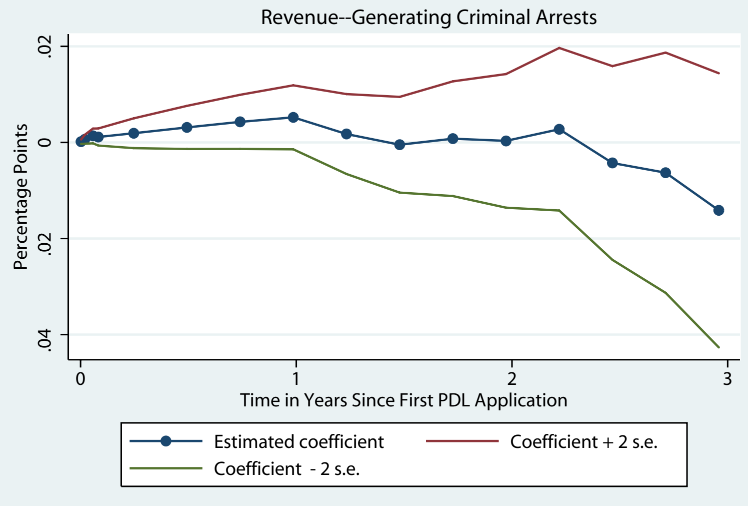


Figure 9e: Effect of Payday Loan Credit Access on Arrests over Time

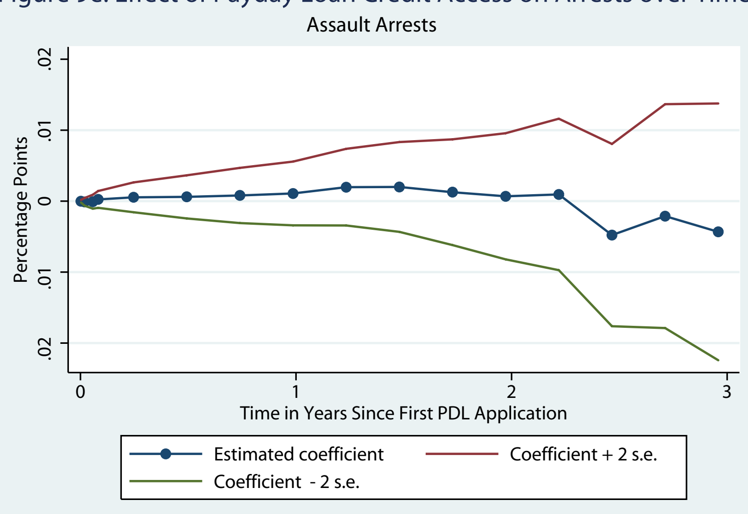
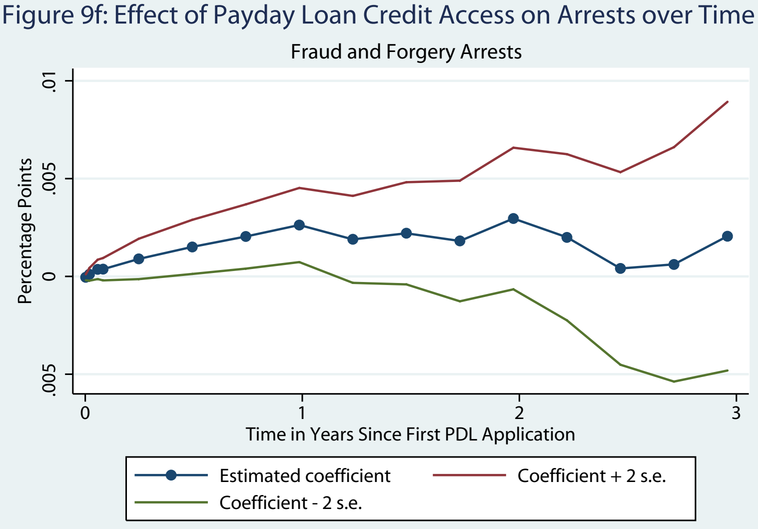


Figure 9f: Effect of Payday Loan Credit Access on Arrests over Time



Figures 9d, 9e, 9f. Source: Authors' calculations based on data from a national payday lending company and the Texas Department of Public Safety Criminal Convinction Database. The middle line represents the IV estimated effect of First Application Approved. The other lines are two-standard-error bands. Regressions producing these estimates include quartic polynomials on both sides of the credit-score threshold, demographic controls, and dummies for month of application. Figures 9d, e and f plot these estimates for revenue-general criminal arrests, including prostitution and all property crimes; assult arrests, and fraud or forgery arrests, respectively.