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Payday Loan Choices and Consequences

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High-cost consumer credit has proliferated in the past two decades, raising regulatory scrutiny. We match administrative data from a payday lender with nationally representative credit bureau files to examine the choices of payday loan applicants and assess whether payday loans help or harm borrowers. We find consumers apply for payday loans when they have limited access to mainstream credit. In addition, the weakness of payday applicants' credit histories is severe and longstanding. Based on regression discontinuity estimates, we show that the effects of payday borrowing on credit scores and other measures of financial well-being are close to zero. We test the robustness of these null effects to many factors, including features of the local market structure.

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In the wake of the recent financial crisis, consumer financial protection has received substantial attention from policymakers. The 2010 Dodd–Frank Wall Street Reform and Consumer Protection Act established the Consumer Financial Protection Bureau (CFPB) to improve enforcement of federal consumer financial laws, while also expanding the scope for protective regulation. One notable

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new provision in Dodd–Frank is the prohibition on "abusive" acts and practices by financial firms, including taking "unreasonable advantage of—(A) a lack of understanding on the part of the consumer of the material risks, costs or conditions of the product or service; [or] (B) the inability of the consumer to protect the interests of the consumer in selecting or using a consumer financial product or service."[1] This new prohibition represents a shift away from the neoclassical view of consumer financial protection, which assumes people can costlessly protect their own interests when costs and terms are clearly disclosed, toward a view that acknowledges the potential for financial firms, despite making disclosures, to exploit consumer biases and cognitive limitations.

It is possible that high-interest consumer credit like payday loans will be found to be abusive and restricted by the CFPB.[2] Payday lenders typically charge 10–20% interest for a 1-to 2-week loan, implying an annualized percentage rate (APR) between 260% and 1,040%. Given such terms, and the fact that borrowers often owe more than half of their next paycheck to the lender, some question whether payday loans are used rationally. Payday loans might exploit overoptimistic consumers who wrongly predict they will be able to retire the debt quickly. If that is so, payday loans could exacerbate financial distress and reduce consumer welfare. In a recent public lecture, the new CFPB chief, Richard Cordray, stated, "The Bureau will be giving payday lenders much more attention ... [although the Bureau] recognize[s] the need for emergency credit ... it is important that these products actually help consumers, rather than harm them."[3]

In this paper, we draw on a novel data set to study the circumstances in which people turn to payday loans and the effect payday loans have on financial well-being. The data consist of payday loan application histories from a large payday lender merged at the individual level to a decade of quarterly credit record information. Payday borrowing is not generally reported to the major consumer credit bureaus, and thus it is not possible to study payday borrowing using mainstream credit record data alone. Merging these two data sets gives us an unprecedented, detailed, and dynamic look at the financial circumstances of payday loan applicants.

Our first finding is that initial payday loan applications occur precisely when consumers' access to liquidity from mainstream creditors is lowest. Although some individuals may make quite costly pecuniary mistakes by using payday loans instead of their credit cards (Agarwal, Skiba, and Tobacman 2009, Carter, Skiba, and Tobacman 2011), in our data this is rare. Instead, nearly 80% of payday applicants have no credit available on credit cards and 90% have less than $300 of credit available on credit

1. 12 USC §5531.

2. Prior to Dodd–Frank, with the 2007 Talent–Nelson Amendment, Congress imposed price caps and prohibitions on certain lending practices, effectively banning payday lending to military personnel and their families. A Department of Defense (2006) report had concluded that "predatory" lenders, including payday lenders, target young and financially inexperienced borrowers, who are less likely to compare such loans to lower-cost alternatives.

3. See http://www.consumerfinance.gov/pressreleases/consumer-financial-protection-bureau-examines-payday-lending/ (accessed February 22, 2014).

cards just before applying for a payday loan.[4,5] In addition, measures of shopping for—and failing to obtain—cheaper, mainstream credit surge around the time initial payday loan applications occur, especially for those with few existing credit accounts. These findings suggest that payday loans are generally sought as a last resort, with such loans near the bottom of the "pecking order" hypothesized by Lusardi, Schneider, and Tufano (2011).

Second, we investigate the long-term relationship between credit file characteristics and payday borrowing. With their short durations and high interest rates, payday loans are designed for managing temporary shocks. We find, however, extremely persistent weakness in credit record attributes among payday applicants. Payday applicants' average credit scores are 1.5 standard deviations below the general population average throughout the entire 10-year observation span. Payday applicants fall behind on payments and apply for new credit accounts much more frequently than the general population, long before and long after their initial payday loan application. This suggests payday loan users—12 million American adults in 2010 according to Pew (2012)—rarely accumulate precautionary savings and are persistently short on cash.[6]

To better understand the financial consequences of access to payday loans, we take advantage of a discontinuity in the payday loan approval process to estimate short- and long-run effects of getting a payday loan. Our regression discontinuity (RD) approach, following Skiba and Tobacman (2011), uses payday loan application scores (hereafter "Teletrack scores") to econometrically compare applicants who were barely approved to applicants who were barely rejected.[7] The main outcome of interest is a traditional consumer credit score (similar to a FICO score), which conveniently summarizes creditworthiness and reflects one's success in managing financial obligations. Traditional scores are distinct from the Teletrack score, computed from different information for a different purpose. Moreover, unlike consumers' use of more traditional credit such as credit cards, use of and performance on payday loans does not directly affect traditional credit scores. Rather, payday loans can only affect one's credit score *indirectly*, insofar as they help or hinder one's ability to meet financial obligations in general. For example, if payday loans help people manage cash flow and smooth financial shocks, they may in fact sustain or improve overall creditworthiness. Alternatively, if payday loans are misused due to cognitive limitations or behavioral biases, they could dig people into a deeper financial hole and

4. The median checking account balance payday applicants reported to the payday lender on their applications is just $58, although about 15% had balances of at least $500.

5. Recent survey research has indicated many payday borrowers confuse the fee quoted for payday loans (e.g., $15 per $100 borrowed on a 2-week loan) with an APR, and thus may believe that payday loan costs are comparable to the costs of credit cards (Bertrand and Morse 2011, Levy and Tasoff 2015, Pew 2012).

6. Lusardi, Schneider, and Tufano (2011) document that a large fraction of U.S. households are "financially fragile," in the sense of being unable to come up with $2,000 on short notice. One possible explanation for the absence of precautionary savings is provided by Skiba and Tobacman (2008), who find that payday loan borrowers' renewal and repayment behavior is consistent with naïve hyperbolic discounting.

7. Teletrack is an alternative consumer credit reporting agency. Agarwal, Skiba, and Tobacman (2009) provide more information on Teletrack scoring.

increase the chance of a downward financial spiral, damaging (or impeding recovery of) borrowers' creditworthiness.

This paper's most important result is that the path of traditional credit scores after initial payday loan applications differs very little between individuals who were barely approved and individuals who were barely rejected for payday loans. In most specifications across a range of time horizons, the point estimates indicate an effect of payday loans of no more than plus or minus 5 points, compared to an average credit score at the time of application of 513 points with a standard deviation of 77 points. Most confidence intervals rule out effects in excess of 25 points in either direction. Although there are a number of possible caveats that we discuss in detail later, we characterize these estimates as precise zeroes: effects of more than one-sixth of the gap between payday loan applicants and the average for all consumers are excluded from the 95% confidence interval. Payday applicants have very poor credit, and payday loan access appears to matter little for its repair or further deterioration.

One reason we find no effect of payday loans could simply be that these loans are sufficiently small and uncollateralized that their potential benefits and risks are limited.[8] This could be especially true when testing for effects on credit scores that are tuned to provide information relevant for underwriting much lower-cost credit. Alternatively, the availability of high-cost substitutes for payday loans (cf. Morgan, Strain, and Seblani 2012, Zinman 2010) could help explain the null findings: rejected applicants could turn elsewhere for credit that has similar effects on well-being. A third potential explanation arises because we only observe payday borrowing at one lender. This biases our baseline estimates toward zero because rejected applicants may succeed in getting payday loans at another lender. We discuss this issue in detail and take advantage of information on the presence of other nearby payday lenders to address it formally. In most of these specifications, we continue to find precise zero estimates of the impact of payday loans.

Overall, we believe we are able to credibly reject economically substantive effects of payday loans on creditworthiness, and thus we provide important new evidence on the effects of payday loans. A second, complementary contribution of this paper is that our rich data yield a number of important insights about the financial circumstances under which people use payday loans.

One advantage of our approach is that we are able to study individual payday applicants, as opposed to studying groups of people who have access to payday loans based on their geographic location.[9] Moreover, because we have panel data and know precisely when people first apply for payday loans, we can control for preapplication differences to improve precision and strengthen identification. Finally, this paper is one of the first to study the credit scores of payday applicants as an outcome variable. These scores reflect many of the outcomes studied previously, such as foreclosure and

8. Despite their small size, it should be noted that the extremely high interest rate of payday loans can generate a nontrivial increase in applicants' monthly debt interest burden, as we will see later.

9. In this we follow Skiba and Tobacman (2011), who use the same payday applicant data, but matched to public bankruptcy records. We carefully distinguish that paper's contributions and ours below.

bankruptcy, but allow detection of less extreme effects of payday loans and summarize the entire liability side of the household balance sheet. Thus, the null results we obtain are meaningful—especially in light of the conflicting findings of previous studies, in which payday loans help (Zinman 2010, Morse 2011, Morgan, Strain, and Seblani 2012) and harm (Melzer 2011, Carrell and Zinman 2014, Campbell, Martinez-Jerez, and Tufano 2011, Skiba and Tobacman 2011) consumers.[10]

The rest of the paper is organized as follows. Section 1 provides some additional background on payday lending. Section 2 describes the data and matching procedures. Section 3 explores static and dynamic credit record information, to understand the factors that may drive the decision to apply and the differences between payday loan applicants and the general population. Section 4 describes the RD strategy, presents results from this analysis, and discusses their interpretation and important caveats. Finally, Section 5 concludes.

1. PAYDAY LENDING

The payday loan industry has grown dramatically since its inception in the early 1990s. Stegman (2007) estimated that payday loan volume expanded fivefold to almost $50 billion from the late 1990s to the mid-2000s, and today 12 million American households borrow on payday loans each year (Pew 2012).[11]

A payday loan is typically a 1-to 2-week loan of no more than $1,000 that costs $10–$20 per $100 borrowed. Payday loans are usually provided by specialized finance companies that may also provide check cashing services and pawn loans. To borrow on a payday loan from a bricks-and-mortar lender, an applicant generally provides her most recent pay stub, which is used to verify employment and determine loan size caps. Most states cap the loan amount at half of take-home pay. An applicant must also show her most recent checking account statement, a valid government-issued ID, and a utility or phone bill to verify her address. Information from these documents can be sent electronically to a subprime credit bureau, Teletrack, which computes a score that determines whether the loan is approved. (We provide additional details on this credit scoring process in Section 4.) If approved, the borrower writes a postdated check for the principal plus interest and fees, which the lender may cash on or shortly after the loan's due date, which is typically the borrower's next payday. States generally regulate how long a borrower can have payday loan debt outstanding. Most states require the loan to be at least 7 or 14 days and no more than 30–45 days long.[12] However, borrowers can "roll over" or "renew" their loans by paying just the loan

10. Bhutta (2014) identifies the effect of borrowing on payday loans from ZIP code variation and also finds payday loan access has no effect on credit scores. Caskey (2012) provides a useful survey.

11. Using a Current Population Survey supplement, Avery and Samolyk (2011) find that about 5% of households in states that allow payday lending used payday loans at least once in 2008.

12. Carter, Skiba, and Sydnor (2011) provide additional details on the structure of loan lengths in this industry and study the impact of different loan lengths on payday borrower behavior.

fees on the due date; this grants the borrower an additional pay cycle to repay the loan and additional interest. The majority of states that allow payday loans have now limited the number of times a borrower can roll-over, but these restrictions can be difficult to enforce.[13]

The payday loan application process does not involve a traditional credit check, and payday borrowing activity is not reported to the national credit bureaus Equifax, Experian, or TransUnion. This means that payday borrowing is not a factor that directly affects one's traditional credit score. Instead, access to payday loans can only affect one's score indirectly, insofar as such loans affect consumers' ability to meet their financial obligations in general.

If a payday borrower's collateralizing postdated check bounces, the borrower is in default. A defaulting borrower may then face insufficient funds charges from her bank and bounced check fees from the payday lender, on top of the outstanding debt and interest, but otherwise payday loans are uncollateralized. Lenders often have internal collections departments that will attempt to collect the outstanding amount owed before selling the debt to collection agencies.

2. DATA

We use two sources of administrative panel data. The first is payday loan data from an anonymous provider of financial services. The second consists of anonymous credit records maintained by Equifax. We now discuss each of these data sources in greater detail, and then we describe our individual-level merging process.

2.1 Payday Loan Data

We obtained data on nearly 250,000 unique payday loan applicants from a provider of financial services that offers payday loans, with applications occurring between June 2000 and August 2004. Along with information on approved and denied applications themselves (principal amount, interest rate, outcome, start date, maturation date, etc.), many details about the individual applicants are available. These include an applicant's net take-home pay, her checking account balance, and some demographic data (age, gender, and race). Consistent with independent survey evidence on payday borrowers (e.g., Elliehausen and Lawrence 2001), women are slightly more prevalent than men in our sample, and minorities are substantially overrepresented. Median annualized individual income is about $20,000, and the median balance documented on applicants' most recent checking account statement is just $66 (in January 2002 dollars). The Teletrack score is also observed in the data for each applicant. Skiba and Tobacman (2011) provide additional details and summary statistics for these data.[14]

13. Carter (2012) provides detail regarding roll-over bans, interest rate caps, and other state-level regulations.

14. Skiba and Tobacman (2011) restrict their study to applicants from Texas in order to match with records from Texas bankruptcy courts.

2.2 *Federal Reserve Bank of New York Consumer Credit Panel*

The Federal Reserve Bank of New York's (FRBNY) Consumer Credit Panel (CCP) is a nationally representative, ongoing longitudinal data set with detailed information on consumer debt and loan performance taken at a quarterly frequency beginning in 1999. The CCP "primary sample" consists of a 5% subsample of all individual credit records maintained by Equifax and uses a methodology to ensure that the same individuals can be tracked over time. Each quarter, a random sample of people (typically younger people) is added to the sample so that it remains representative of the universe of credit records each quarter.[15,16]

The "full sample" CCP includes quarterly snapshots of the credit records of all individuals living at the same address as the primary sample members. In most cases, the same address implies the same housing unit, but in a nontrivial number of cases, the same address may be associated with hundreds of individuals because, for example, the address is for a large apartment complex and apartment numbers distinguishing housing units are not available. Thus, the full sample is far bigger than the primary sample, numbering almost 40 million people each quarter compared to around 12 million individuals per quarter in the primary sample.

In addition to detailed credit account information provided by banks and financial institutions, the CCP also contains information reported by collection agencies on actions associated with credit accounts and non-credit-related bills (e.g., phone or hospital bills). Records also contain information on inquiries made by consumers for new credit and a limited number of individual characteristics, including the consumer's year of birth and the geographic code (down to the Census block) of the consumer's mailing address.

Finally, an Equifax credit risk score (similar to the FICO score) is available for most individuals each quarter. In any given quarter, some individuals are not scorable due to their limited credit histories.[17] This score summarizes the information in one's credit report and is based on a model that predicts the likelihood of becoming delinquent by 90 days or more over the next 24 months on a new account.[18] The same model is applied to the data over time and thus scores are directly comparable during the

15. For more information on the CCP, see Lee and van der Klaauw (2010).

16. It is important to note that all individuals in the data are anonymous: names, street addresses, and social security numbers have been suppressed. Individuals are distinguished and can be linked over time through a unique, anonymous consumer identification number assigned by Equifax. As we discuss later, Equifax assisted with matching payday borrowers to the CCP so that the CCP data remain anonymous. The authors did not conduct the match themselves.

17. Multiple traditional credit scores exist; they differ because of variation in credit scoring models (e.g., VantageScore vs. FICO) and in the sets of credit record data used by the three different national credit bureaus. These various credit scores are typically very highly correlated. See https://help.equifax.com/app/answers/detail/a_id/244/related/1 (accessed February 22, 2014) for more on the Equifax score.

18. Credit scoring models take into account numerous factors such as the number of delinquent accounts, the degree of delinquency, the amount of credit being used on credit card lines, the age of accounts on file, and recent applications for credit (see https://help.equifax.com/app/answers/detail/a_id/136/noIntercept/1) (accessed February 22, 2014). Factors that are *not* included in the credit file or considered in credit score computations include income, assets, and employment history.

TABLE 1

Payday Loan: Consumer Credit Panel (CCP) Data Match Diagnostics

	N	Number of quarters in the panel (max is 48)
Payday applicants	248,523	–
Payday applicants who appear at least once in the full sample CCP	146,761	12.6
. . . and appear in the full sample CCP during the quarter prior to the quarter of their first payday loan application	41,948	26.1
. . . and have a credit score	38,220	18.5
Payday applicants who appear at least once in the 5% primary sample CCP	12,151	45.6
. . . and appear in the 5% primary sample during the quarter prior to the quarter of their first payday loan application	11,622	46.9
. . . and have a credit score	11,296	47.0

Notes: The administrative payday loan data were provided by a financial services firm and span 2000–04. The CCP is the Federal Reserve Bank of New York's Consumer Credit Panel, a nationally representative, ongoing panel data set with detailed quarterly information beginning in 1999. The primary sample consists of a 5% random subsample of all individual credit records maintained by Equifax. The full sample includes quarterly snapshots of the credit records of all individuals living at the same address as the primary sample members.

entire period of observation. The credit score ranges from 280 to 850, with a higher score corresponding to lower relative risk.

As noted before, payday lenders do not report on borrowers' activity to the traditional credit bureaus such as Equifax, which means that the use and repayment of payday loans does not directly affect one's traditional credit score in the way a closed-end consumer loan from a bank would. Rather, payday loans can have an indirect effect on one's credit score depending on how they affect consumers' ability to meet their other financial obligations.

2.3 Matching Payday Loan Applicants to Credit Record Data

The CCP has anonymous identification numbers (CCP-IDs) that allow individuals in the data to be linked over time. To merge the payday loan applicant data with the CCP data, Equifax transformed the personal identifying information available in the payday loan applicant data into CCP-IDs and then provided the payday loan applicant data, including these CCP-IDs and stripping all personal identifying information, to the Federal Reserve. These data could then be merged to the CCP using the CCP-IDs common to both data sets.[19]

Table 1 provides summary information about the quality of the matching process. As shown in the top row, the payday loan applicant data consists of 248,523 unique payday loan applicants. Because the primary CCP sample is a 5% random sample,

19. Only select Federal Reserve research staff had access to the merged data set. At the same time, the original payday loan applicant data with personal identifying information has not been made available to Federal Reserve staff; they are held solely by Professor Skiba. (Equifax did not retain a copy.) Thus, we have been able to credibly preserve the anonymity of the CCP data.

and because nearly the entire adult population has a credit record (although not all have a credit score), we expected to match roughly 12,400 applicants to the CCP.[20] We were able to match 12,151 individuals to the primary sample CCP data at some point in time and follow them for an average of 46 quarters (48 quarters maximum). A total of 11,622 appear in the primary sample in the quarter just before the quarter of their first payday loan application, and 11,296 of those have an Equifax score (last row). Overall, the matching appears to have been successful and these match results imply that nearly all of the payday loan applicants had a credit record at the time they applied for their first payday loan.

We also matched payday loan applicants to the full sample CCP. Almost 60% of applicants were found in the full sample CCP data at some point during the 48 quarters, but most cannot be tracked over the entire time frame. The large number of matches to the full sample seems to be related to the fact that payday borrowers predominantly rent rather than own their homes, with many applicants living at addresses such as apartment complexes that have large numbers of residents.[21] Nearly 42,000 applicants were matched to the CCP in the quarter just before their first payday application, and these applicants can be tracked for 26 quarters on average.

One sign that the match worked well is that borrower age at the time of first application, which is one of the only variables available in both data sets, is very highly correlated across the two data sets. The correlation coefficient between age in the two data sets among payday loan applicants matched to the full sample is 0.92, and the 10th, 50th, and 90th percentiles are nearly identical. The 10th and 50th percentiles of borrower age are 23 and 35, respectively, in both data sets, and the 90th percentile is 53 in the CPP compared to 52 in the payday loan application data.

3. WHEN DO PEOPLE APPLY FOR PAYDAY LOANS?

In this section, we study the credit records of payday loan applicants, just before their initial payday loan application and over longer-term dynamics, to gain insight into factors that may precipitate payday loan use.

3.1 Debt Burden, Credit Card Utilization, and Search Activity before Initial Payday Loan Applications

Table 2 reports various credit record statistics for the matched sample. Columns 1–4 describe the matched sample in the quarter before the initial payday

20. Payday borrowers should be captured in the general credit record data, as household survey research suggests that payday borrowers also apply for and use traditional forms of credit (credit cards, car loans, etc.; Elliehausen and Lawrence 2001). In fact, even those without active credit accounts, but who have some type of public record such as a tax lien or a collection account, or have simply applied for mainstream credit, will be in the database. Finally, the fact that payday borrowers must have a source of income and a checking account to qualify for a payday loan suggests that there is a good chance that they would have participated in the mainstream credit market at some point and therefore should have a credit record.

21. Skiba and Tobacman (2011) report that only about one-third of sample payday loan applicants own their home.

TABLE 2

CREDIT RECORD SUMMARY STATISTICS FROM THE CCP: MATCHED PAYDAY LOAN APPLICANTS AND THE GENERAL POPULATION

	Payday applicants matched to full CCP, variables measured as of the end of the quarter prior to to the first payday loan application				National random sample of people with a credit record, as as of end of 2002:Q4				National random sample of people with a credit record and score <600, as of end of 2002:Q4			
	(1) Mean	(2) Median	(3) SD	(4) *N*	(5) Mean	(6) Median	(7) SD	(8) *N*	(9) Mean	(10) Median	(11) SD	(12) *N*
Credit score[a]	513	517	77	38,220	680	703	108	103,609	523	538	61	24,930
Number of open accounts	3.8	3	3.8	38,220	5.0	4	4.3	103,609	4.0	3	4.1	24,930
Share of accounts not current[b]	0.53	0.5	0.39	33,084	0.13	0	0.29	93,983	0.50	0.5	0.40	21,364
Total debt ($)	19,656	5,977	63,578	38,220	49,204	9,160	97,038	103,609	26,803	5,749	55,866	24,930
Total payments ($, annualized)[c]	8,343	4,104	19,630	38,220	10,444	4,008	51,001	103,609	8,566	3,420	21,908	24,930
Nonmortgage debt ($)	10,481	4,688	54,225	38,220	11,369	3,225	22,677	103,609	10,845	4,176	18,412	24,930
Non-mtg payments ($, annualized)[c]	7,106	3,600	18,940	38,220	5,942	1,644	49,226	103,609	6,586	2,568	20,490	24,930
Has one or more credit cards[d]	0.59	1	0.49	38,220	0.75	1	0.43	103,609	0.64	1	0.48	24,930
Total limit for cardholders ($)	3,050	1,154	6,002	22,556	18,552	11,000	24,180	78,099	5,867	2,049	10,622	16,070
Total balance for cardholders ($)	2,921	1,340	5,086	22,556	5,049	1,563	10,955	78,099	5,263	2,089	9,157	16,070
Has delinquent card account[e]	0.69	1	0.46	22,556	0.16	0	0.37	78,099	0.66	1	0.47	16,070
Has car loan	0.39	0	0.49	38,220	0.28	0	0.45	103,609	0.29	0	0.45	24,930
Has delinquent car loan[e]	0.35	0	0.48	15,002	0.08	0	0.28	28,622	0.30	0	0.46	7,224
Has mortgage[f]	0.14	0	0.35	38,220	0.33	0	0.47	103,609	0.19	0	0.39	24,930
Has mortgage delinquency[e]	0.37	0	0.48	5,460	0.06	0	0.23	34,101	0.34	0	0.47	4,738
Number inquiries past 12 months	5.2	4	4.6	38,220	1.7	1	2.4	103,609	3.0	2	3.3	24,930
Number new accounts past 12 months	1.4	1	2.1	38,123	1.1	1	1.5	103,434	0.9	0	1.5	24,766
Age (years)[g]	37.4	36	11.7	37,573	46.9	45	16.9	93,030	38.7	37	13.1	23,023

[a]Equifax Risk Score 3.0, ranging from 280 to 850.
[b]"Not current" means at least 30 days behind.
[c]Reflects monthly scheduled minimum payments as reported by lenders.
[d]Does not include retail store cards.
[e]Delinquency rate calculated among those with at least one account of specified type.
[f]Includes both closed-end and home equity lines of credit.
[g]Age calculated as calendar year minus year of birth reported in CCP.

loan application (the median quarter is 2002:Q4). Columns 5–8 display national statistics for a random sample of the population with a credit record, and columns 9–12 show statistics for a random sample of the population conditional on having scores below 600.

At the time of their first applications, prospective payday borrowers appear to be having major financial difficulties. Their average and median credit scores are below 520, whereas the average and median scores in the general population are 680 and 703, respectively. Payday loan applicants tend to have nearly four open credit accounts compared to five for the general population, but on average, applicants with at least one account are reported delinquent by at least 30 days on half of their accounts.

Applicants have an average of less than $20,000 in outstanding debt compared to nearly $50,000 for the general population. This difference is largely attributable to the low likelihood of payday applicants having a mortgage. Indeed, the average level of nonmortgage debt among payday applicants is similar to the national average, and the median level is significantly higher.

Annualized, the total monthly debt payment burden (scheduled minimum payments, including principal and interest) of the median payday loan applicant is just over $4,000, similar to the median in the general population. The implied payments of $333 per month suggest payday loans could have a nontrivial impact on debt service burdens. For example, if the median applicant takes out a $300 payday loan with a 2-week interest rate of 15%, the interest payments would add $90 to their monthly debt payments, an increase of over 25%.

Median income reported on payday loan applications is about $18,000, while Census estimates indicate that median personal income in 2002 for adults was about $23,000.[22] Although it is difficult to draw definitive conclusions based on these numbers alone, debt service burdens for the payday applicants at this one lender are somewhat higher than the general population.

Only 59% of the payday loan applicants have a general-purpose credit card. Among those who have at least one card, the average (cumulative) credit limit is only about $3,000, while the average balance is about $2,900, implying little available credit remains. In total, over 78% of payday applicants (including those without a card) have zero credit available on credit cards and another 4% have less than $50 available. Ninety percent have no more than $300—the typical size of a payday loan—available on credit cards. Thus, while some payday applicants could be making a costly pecuniary mistake by using payday loans as found in Agarwal, Skiba, and Tobacman (2009), in our data relatively few could simply borrow on credit cards instead.

Given this lack of liquidity, it is reasonable to wonder whether payday applicants are trying to get additional credit on credit cards or other traditional sources that generally are much cheaper than payday loans. Evidence on this can help us further

22. Income data are not reported in Table 2. For the Census data, see http://www.census.gov/hhes/www/income/data/historical/people/2010/P15AR_2010.xls (accessed February 22, 2014).

understand whether consumers are cognizant of alternatives and successfully search for the cheapest option. The CCP yields some insight on this question because it provides information on the number of credit inquiries over the past 12 months. Credit inquiries are instances where a lender requests an individual's credit report because that individual is applying for a new credit account.[23] As Table 2 shows (third row from the bottom), payday applicants had an average of over five credit inquiries during the 12 months leading up to their initial payday loan application—a level three times higher than that of the general population and even considerably higher than that of the general "subprime" population. Moreover, payday applicants were generally unsuccessful in getting credit, obtaining only 1.4 new accounts on average (penultimate row of Table 2). In other words, first-time payday applicants appear to be searching intensively, but unsuccessfully, for traditional (and presumably cheaper) credit.

3.2 Dynamic Credit Record Information

The previous subsection indicates heightened credit demand immediately preceding initial payday loan applications. We now use the panel aspect of the CCP to see whether credit demand surged in the quarters leading up to this point, perhaps due to a financial shock, precipitating payday loan applications.

Figure 1 shows several CCP variables for payday loan applicants plotted over a 40-quarter window centered around the quarter of initial payday loan applications.[24] Overall, the figures indeed suggest increased credit demand and financial distress at the time people apply for payday loans relative to previous quarters, but at the same time they indicate persistent, long-term financial problems among payday loan applicants.

The top left panel of Figure 1 shows that median total debt begins to climb steeply about 2 years before the initial application from about $4,000 to $7,000 two quarters after application. Although not shown in Figure 1, this debt growth largely reflects increased use of auto loans. The top right graph indicates that credit card liquidity becomes exhausted, on average, just around the time of first payday loan applications. However, even 5 years earlier the average amount available was just $300.

The middle left panel shows the path of credit inquiries. The darker line shows the average number of inquiries for all payday loan applicants, while the lighter line shows the average number of inquiries for the subset of applicants who have only one

23. The specific type of credit sought is not available in the CCP. Multiple applications for the same type of credit within a 30-day period count as only one inquiry. Inquiries do not include instances when lenders pull credit reports without an individual's consent for marketing campaigns or portfolio risk management. Inquiries also do not include instances when a consumer requests his or her own credit report for monitoring purposes.

24. Since the payday data span from June 2000 to August 2004, with a median initial application date in December 2002, and the CCP data begin in January 1999, the typical person in the data set has 4 years of leads. Figure S1 in the online appendix reports the numbers of observations versus event time. All the patterns we report in the paper are nearly identical if we eliminate compositional effects by restricting to people with minimum observed history lengths. (See the discussion of Figure S2.)

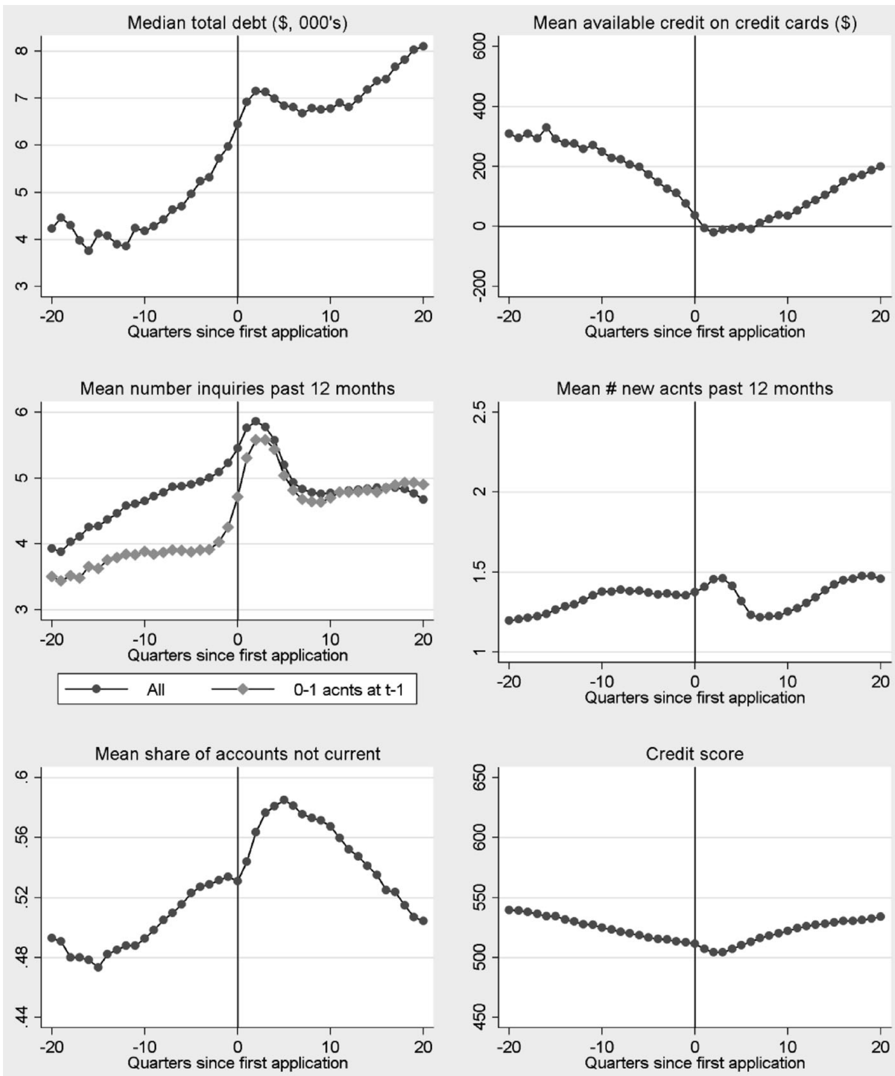

Fig. 1. Credit Record Attributes Before and After First Payday Loan Application.

Notes: Figures are based on data from the payday applicant data matched to full sample CCP. For the matched applicants, six quarterly CCP data series are plotted: mean total debt, mean credit card liquidity, mean number of credit inquiries in the previous year, mean number of new accounts in the previous year, mean share of delinquent accounts, and the credit score.

or zero traditional credit accounts in the quarter just before applying. The darker line indicates an upward trend in inquiries and then an acceleration right around the time of application. About one-third of payday applicants have no more than one account at $t-1$ and this group (the lighter line) shows a sharp increase in inquires at the time of applying for payday loans, consistent with a sudden surge in credit demand (note that because the inquiry variable is backward looking, the actual peak in inquiries likely occurred in the same quarter as the payday loan applications). At the same time, inquiries were high even 5 years earlier, indicating a persistently intense search for credit.[25]

The bottom left figure shows a rising likelihood of account delinquency leading up to payday loan applications, and then a jump in the quarters immediately following payday loan applications. Financial distress, as measured by this variable, peaks about five quarters after initial payday loan applications. A reasonable interpretation of this figure (combined with the others) is that payday loans were sought to help alleviate an intensification of adverse shocks. The delinquency jump just after application could be a consequence of, or may have been mitigated by, getting a payday loan; these possibilities will be assessed in the next section.

Finally, the bottom right panel of Figure 1 shows the average credit score of payday applicants over time. Credit scores conveniently summarize consumers' credit records and allow us to compare payday applicants to the rest of the population over time. Although the average score exhibits something of a V-shape around the time of application, overall the figure indicates that the average score is consistently below 550, which is well within the bottom quartile of the national score distribution.[26] In other words, payday applicants have persistently very low credit scores.[27] Notwithstanding noticeable changes around the time of payday loan application, persistently low scores reflect factors such as persistently high inquiry levels and delinquency rates.

To get a better sense of the persistence of low scores, Figure 2 plots the path of scores for payday loan applicants who first applied in 2002:Q2 alongside the path of scores for a nationally representative sample from the CCP, where each individual is weighted such that the weighted score distribution in 2002:Q2 matches the score distribution for payday loan applicants. This graph suggests that the average person with a score of about 500 in 2002:Q2—the same as the average score among payday applicants that quarter—dropped more sharply in prior quarters and recovered more robustly in subsequent quarters. After about 4 years, the average person's score approaches 580, about 50 points above payday applicants' scores. Although 580 still constitutes a subprime score, it would at least meet current eligibility

25. The median calendar date 20 quarters prior to first application is 1999:Q2; the average number of inquiries for the general population in 1999:Q2 was 1.6 and for the population with scores under 600 was nearly 3, numbers that are nearly identical to the averages shown in Table 2 for 2002:Q4.

26. The credit score distribution has been extremely stable, and an Equifax risk score of just over 600 has marked the 25th percentile since 1999 (see FRBNY 2011).

27. Figure S3 in the online appendix shows the distribution of Equifax risk scores before and after the initial payday loan application. The 10th, 25th, 50th, 75th, and 90th percentiles of the distribution follow astonishingly parallel paths, and 20 quarters before their initial payday application, more than 80% of applicants have Equifax risk scores below 600. Figure S4 shows the distribution of long-term average scores for payday loan applicants relative to the general population.

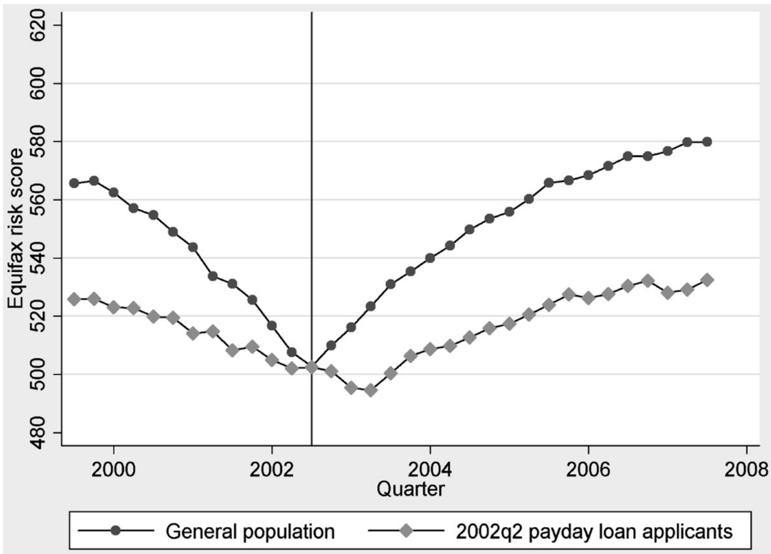

FIG. 2. Credit Score Path of 2002:Q2 Payday Loan Applicants versus General Population with Identical Scores in 2002:Q2.

NOTES: "General population" refers to a 1% random sample of consumers drawn from the primary sample CCP, with each individual weighted such that the credit score distribution in 2002:Q2 is identical to that of payday applicants in 2002:Q2 (who were merged to the full sample CCP). Each data point represents the average Equifax 3.0 credit score in each quarter.

requirements for a mortgage insured by the Federal Housing Administration (FHA).[28]

On average, credit scores of payday applicants appear to be unusually stable at a low level. However, this average masks underlying heterogeneity in score movement. Figure 3 shows the distribution of 1- and 2-year score changes for our sample of payday loan applicants. These distributions indicate that large score changes are not uncommon. For example, Panel B indicates that over the 2 years after their first payday loan application, about 20% of the sample experiences a score change of at least 75 points in absolute value. In addition, Table S1 [29] in the online appendix reports that even for people with Equifax scores initially below 600, each marginal delinquent account predicts a score decline of about 20 points. If payday loans are helpful or harmful, they could be contributing to some of these nontrivial score changes. We turn to the impacts of payday loan access next.

28. FHA mortgage loans, especially in recent years, are very common among those seeking to purchase homes (Avery et al. 2011).

29. All appendix tables and figures, along with further text description of them, may be obtained at https://jmcb.osu.edu/sites/jmcb.osu.edu/files/13-027.pdf, from the authors, or in the online version of this article.

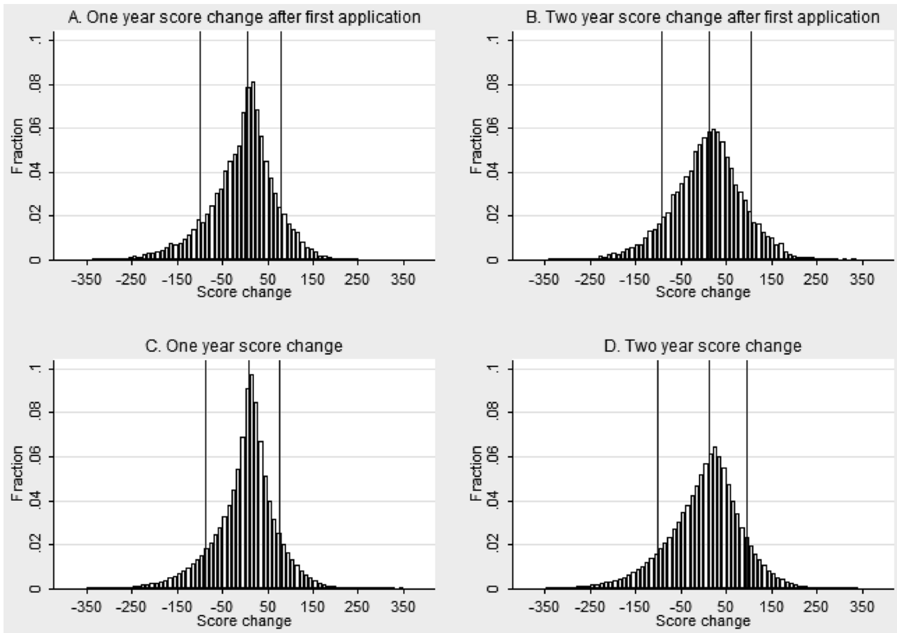

FIG. 3. Distributions of Credit Score Changes.

NOTES: Panels A and B show the distribution of changes in credit scores in the 1- and 2-year periods after the first payday loan application. Panels C and D show analogous distributions of changes in credit scores, over any observed 1- and 2-year periods for the full (matched) sample. Vertical lines indicate 10th, 50th, and 90th percentiles of distribution of score changes.

4. THE EFFECT OF ACCESS TO PAYDAY LOANS ON FINANCIAL WELL-BEING

Previous research has found that access to payday loans can impact financial well-being and welfare. However, in some cases the findings have been positive and in others negative. We add evidence on this unsettled, policy-relevant question using our matched data set and an RD design that allows us to exploit individual variation in payday loan access.

4.1 Empirical Strategy

This section briefly describes the RD design employed in this paper to identify the effect of getting a payday loan on subsequent creditworthiness.[30] At outlets of the payday loan data provider, a credit score is calculated by a third-party firm, Teletrack,

30. We follow Skiba and Tobacman (2011) closely. They discuss this econometric approach in more detail.

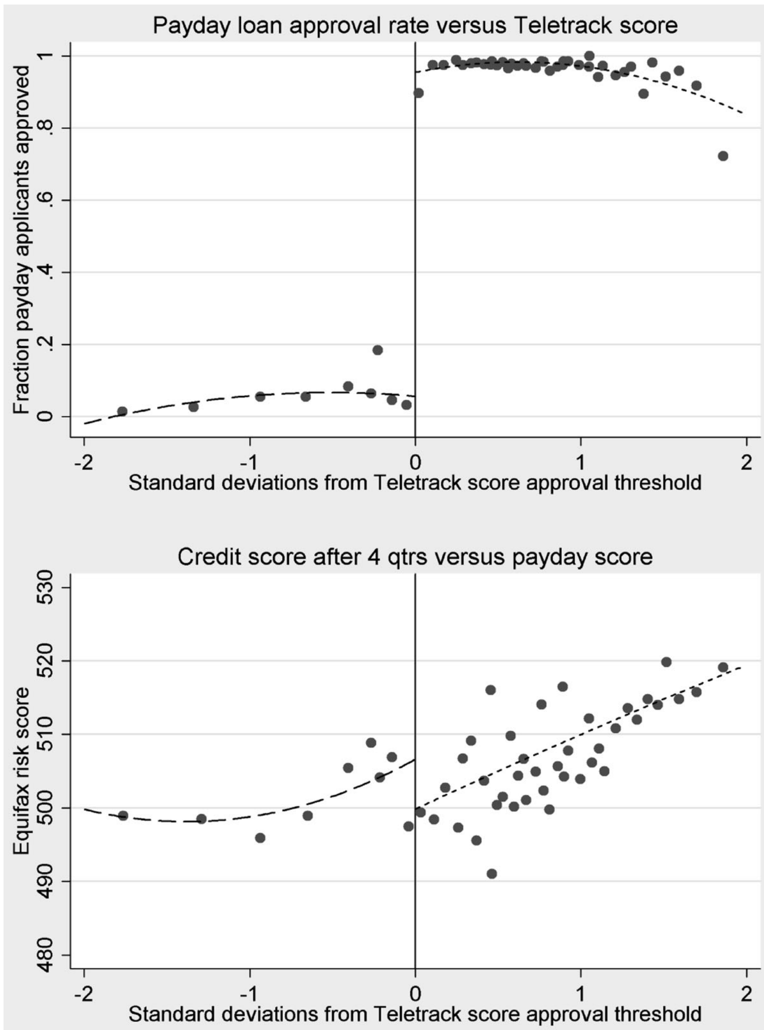

FIG. 4. Regression Discontinuity Design First Stage and Reduced Form.

NOTES: Each point represents one of 50 quantiles. Points shown are at the median of their quantiles on the *x*-axis and at the means of their quantiles on the *y*-axis. Both graphs include independent quadratic fits of the underlying data on either side of the threshold.

and scores above a fixed threshold almost always result in loan approval. The top panel of Figure 4 plots the approval rates against the normalized Teletrack score, with the score threshold rescaled to zero. The top panel (our first stage) shows a strong discontinuity, with the approval rate jumping from under 10% for those with scores just below the threshold to an approval rate of over 90% for those with Teletrack scores just above the threshold.[31]

In this paper, we exploit the discontinuity in approval rates to test whether payday loans might be financially helpful or harmful. Informally, because applicants just above and just below the approval threshold should be very similar otherwise, approval can be thought of as being randomly assigned in the neighborhood of the threshold, conditional on observed characteristics.[32] Like any instrumental variable identification strategy, RD designs identify local average treatment effects based on the particular available source of exogenous variation. Due to a pair of underwriting changes by the payday lender, the approval threshold ranged during the observation period between the 13th and 21st percentiles of the matched applicant Teletrack score distribution. Formally, our estimates here represent a weighted average that pertains only over this range, and extrapolation elsewhere in the credit score distribution would depend on the usual variety of (strong) assumptions. We will test for discontinuities in various credit record outcomes at the threshold where payday loan approval jumps. One key outcome is a traditional credit score (analogous to the FICO score), which summarizes a person's traditional credit record information, such as payment performance on credit cards, mortgages, and auto loans. The bottom panel of Figure 4 illustrates the basic idea, plotting credit scores along the same x-axis as in the top panel of that figure. This figure indicates that roughly 1 year after applying, applicants just above the threshold (those likely to have been barely approved) have slightly lower scores than those just below the threshold (those likely to have been barely rejected).

One potential shortcoming of RD designs is that the selection variable (in our case the Teletrack score) may be subject to manipulation. In this setting, a few details of the process for evaluating loans increase our confidence in the validity of the RD design. Specifically, during the application process, the lender's employee electronically submits information about the applicant to Teletrack, and within minutes a yes/no notification indicating whether the application was approved or declined is returned to the employee. Neither applicants nor the employees are informed of applicants' scores or what the passing credit score threshold is, and thus gaming is unlikely.[33] In addition, Table 3 tests for covariate balance around the passing Teletrack threshold. The first column shows raw differences in each covariate across the threshold. Subsequent columns report the coefficient and standard error on an *AboveThreshold* indicator in regressions (analogous to the RD estimates to be discussed below) for bandwidths of 0.5 and 0.25 standard deviations around the threshold, for various functional forms. Some covariates show modest or statistically significant differences, especially months living at current residence and the preperiod Equifax score,

31. Skiba and Tobacman (2011) show detailed regression results for the first stage and plot the first stage for numerous subpopulations as well. See their appendix.

32. Appendix Table S2 in the online appendix tests for differences in observable characteristics across the approval threshold prior to an applicant's first payday loan application.

33. Indeed, a histogram of applicant density (not shown) fails to provide evidence of a jump in density just above the Teletrack score approval threshold.

TABLE 3

COVARIATE BALANCE: TESTS FOR DIFFERENCES ACROSS THE APPROVAL THRESHOLD PRIOR TO PAYDAY LOAN APPLICATION

	All observations		Observations within 0.5 standard deviations of threshold						Observations within 0.25 standard deviations of threshold					
	Unconditional difference		Difference controlling for all other variables						Difference controlling for all other variables					
	No control function		Linear control function		Quadratic control function		Quartic control function		Linear control function		Quadratic control function		Quartic control function	
Credit score	13.79**	(0.95)	−7.52*	(3.18)	−5.47	(4.59)	−2.55	(7.45)	−9.588*	(4.513)	−1.767	(6.315)	15.853	(13.576)
ln(1+monthly pay)	0.59**	(0.04)	−0.02	(0.02)	−0.03	(0.02)	−0.02	(0.04)	−0.009	(0.023)	0.003	(0.033)	−0.082	(0.076)
Checking balance	181.69**	(4.93)	23.86	(16.48)	−74.66**	(24.54)	−119.58*	(48.60)	−34.5	(24.319)	−130.5**	(36.597)	−378.7**	(113.984)
Job tenure	1.51**	(0.06)	0.03	(0.19)	−0.21	(0.26)	−0.79	(0.47)	−0.541	(0.308)	−1.05**	(0.368)	−4.333**	(1.148)
Age	2.54**	(0.13)	−0.07	(0.46)	−0.56	(0.66)	1.66	(1.10)	0.457	(0.654)	1.069	(0.933)	3.110	(1.892)
Months at residence	14.78**	(0.89)	12.35**	(3.04)	23.98**	(4.51)	57.61**	(8.23)	35.27**	(4.319)	39.92**	(6.708)	118.52**	(17.757)
NSF count	−1.08**	(0.05)	0.22	(0.19)	−0.02	(0.27)	−0.41	(0.44)	0.463	(0.270)	−0.338	(0.366)	−2.385*	(1.045)
Direct deposit	0.05**	(0.01)	−0.00	(0.02)	−0.03	(0.02)	−0.10**	(0.04)	−0.021	(0.023)	−0.080*	(0.032)	−0.205**	(0.074)
Wages garnished	−0.00**	(0.00)	0.01	(0.01)	−0.00	(0.01)	0.00	(0.01)	0.004	(0.009)	0.005	(0.012)	0.013	(0.034)
Owns home	0.07**	(0.00)	−0.02	(0.01)	−0.00	(0.02)	−0.02	(0.03)	−0.018	(0.017)	−0.028	(0.024)	−0.132*	(0.062)
Female	0.02**	(0.01)	−0.01	(0.01)	−0.02	(0.02)	0.01	(0.03)	−0.007	(0.020)	0.003	(0.029)	0.011	(0.066)

NOTES: Robust standard errors are in parentheses. Each cell represents the coefficient on *AboveThreshold* from a regression of the variable listed in the left-most column on *AboveThreshold* and other controls as specified in each column. Regressions based on payday applicant data matched to full sample CCP ($N = 10{,}795$ for each regression within 0.5 standard deviations of threshold, $N = 4{,}093$ for each regression within 0.25 standard deviations). Slopes of control functions are allowed to vary on either side of the approval threshold. Credit score is measured in the quarter just before the first payday loan application; all other variables are measured at the time of the first payday loan application. Missing values are set to zero and then separate dummy indicators for missing values are also included in all regressions.

though these differences largely disappear once we control for Teletrack score, and the discontinuity in preapplication Equifax score is smaller using higher order control functions. Given the possible discontinuity in preperiod Equifax scores, we consistently report estimates in the main text that control for this variable, and Table S2 in the online appendix reports discontinuity-based estimates of the effect on *changes* in the Equifax score.

Using the Teletrack score discontinuity, we estimate the effect of payday loan approval on traditional credit scores and other credit record outcomes over various time horizons (τ) after the first payday loan application. In addition to graphical evidence, we also present results from two-stage least squares (2SLS) regressions. The second stage equation is

$$y_{\mathrm{i}}^{\tau} = \beta_0 + \beta_1 \, Approved_i + f(TeletrackScore_i) + \boldsymbol{x}_i^{'}\beta + \varepsilon_{\mathrm{i}}, \tag{1}$$

and we instrument for *Approved*—a dummy variable indicating whether first-time payday loan applicants were approved—with a dummy variable (*AboveThreshold*) indicating whether a borrower's Teletrack score (*TeletrackScore*) was above the underwriting threshold. Thus, the first-stage equation is

$$Approved_i = \delta_0 + \delta_1 \, AboveThreshold_i + f(TeletrackScore_i) + \boldsymbol{x}_i^{'}\beta + \eta_i. \tag{2}$$

The function f (*TeletrackScore*) is a function of the payday underwriting score, and **x** is a vector of demographic and background characteristics. In RD parlance, the Teletrack score is the "running" or selection variable, and our identification assumption is that the dummy variable *AboveThreshold* is exogenous conditional on our controls for the running variable and other covariates. Equivalently, unobservable factors must not change discontinuously at the threshold.

Analyses identified off discontinuities generally introduce a trade-off as more data are included around the discontinuity (i.e., as the "bandwidth" increases). The additional data reduce sampling noise, but they potentially add bias as weight is placed on observations where unobservables may be correlated with the outcome. To mitigate these potential problems, we show that our results are robust to the choice of bandwidth. We are also able to control for preapplication values of credit scores.

The principal outcome of interest is a traditional credit score from Equifax, which is based on information reported to mainstream credit bureaus. Payment history on traditional loans like mortgages and credit cards is incorporated into the score. A different credit score, the Teletrack score, appears on the right-hand side of equation (1), and it relies on alternative information generally not available to credit bureaus such as monthly income and funds available in deposit accounts. As the bottom panel of Figure 3 indicates, the two scores are positively correlated, but the correlation is relatively weak at about 0.10.[34]

34. Figure S5 in the online appendix shows a scatterplot of Equifax and Teletrack scores, indicating only a weak correlation of 0.1. As found in Agarwal, Skiba, and Tobacman (2009), traditional scores could

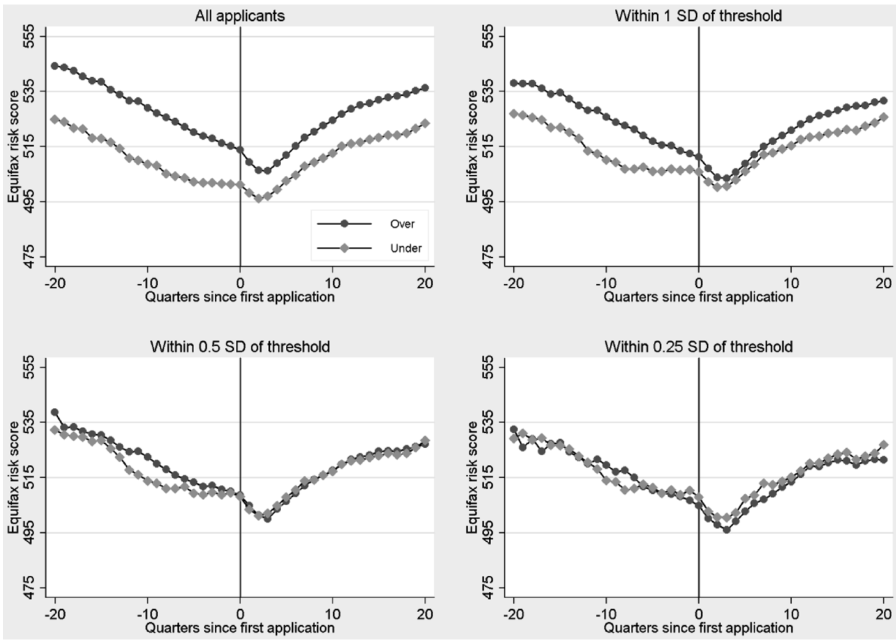

Fig. 5. Credit Score Dynamics Before and After First Payday Loan Application: Applicants with Teletrack Scores Over and Under Approval Threshold.

Notes: Figure is based on data from the payday loan applications matched to full sample CCP. Each data point represents the average Equifax 3.0 credit risk score at the end of a quarter relative to the quarter of first payday loan application.

4.2 *Main Results*

Figure 5 shows long-term trends in the average credit score for payday loan applicants whose first application was likely to have been accepted (dark circles), versus those whose first application was likely to have been rejected (light diamonds). Using all applicants, regardless of the distance from their Teletrack score to the threshold (top left), the two trends move in a mostly parallel manner. Comparing applicants within narrower bandwidths around the threshold in the other panels of Figure 5, especially the bottom two panels, the two lines lie virtually on top of each other, indicating little difference prior to applying (supporting our identification assumption), and no effect in short or long-term credit scores as a result of getting a payday loan.

Table 4 provides 2SLS RD estimates of the effect of getting a payday loan on credit scores at various times after application, following the methodology presented

potentially help payday lenders differentiate riskier applicants. However, payday lenders do not use such information, perhaps because it is costly to obtain and adds little information beyond the Teletrack score (also see Einav, Jenkins, and Levin 2013, who study credit scoring practices for subprime auto loans). In addition, the lack of reporting of payday loans to the traditional credit bureaus might be an important attribute of payday loans that consumers value.

TABLE 4

RD ESTIMATES: THE EFFECT OF PAYDAY LOAN ACCESS ON CREDIT SCORES

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1 quarter out		4 quarters out		8 quarters out		12 quarters out		Pooled, first 12 quarters	
Bandwidth[a]	0.5 SD	0.25 SD	0.5 SD	0.25 SD	0.5 SD	0.25 SD	0.5 SD	0.25 SD	0.5 SD	0.25 SD
Panel A. Applicants observed in full sample CCP, within specified bandwidth										
First payday loan application approved										
Linear *f(TeletrackScore)*	−9.48**	−13.19**	−2.76	1.77	−4.59	−3.48	−4.10	−3.88	−4.60	−2.97
	(3.55)	(5.11)	(3.58)	(5.27)	(3.32)	(4.74)	(3.33)	(4.81)	(2.52)	(3.70)
Quartic *f(TeletrackScore)*	−10.39	5.40	−1.44	−2.49	5.51	13.26	−1.21	1.97	1.64	7.10
	(9.35)	(12.32)	(9.83)	(13.35)	(8.57)	(11.77)	(8.78)	(12.46)	(6.79)	(9.23)
N	10,714	4,029	10,573	4,002	10,419	3,937	10,079	3,780	125,466	47,216
Panel B. Applicants observed in full sample CCP; controls for preapplication score										
First payday loan application approved										
Linear *f(TeletrackScore)*	−2.29	−2.07	−0.36	4.01	0.63	0.47	0.77	1.90	−1.17	0.80
	(2.81)	(4.13)	(3.83)	(5.72)	(4.01)	(5.87)	(4.36)	(6.36)	(2.77)	(4.14)
Quartic *f(TeletrackScore)*	−4.25	7.70	4.63	3.17	7.09	15.36	4.44	10.81	2.98	8.09
	(7.35)	(10.03)	(10.35)	(14.43)	(10.66)	(15.28)	(11.72)	(17.17)	(7.46)	(10.42)
N	8,547	3,223	7,065	2,702	5,918	2,298	5,216	2,001	77,988	29,888
Panel C. Applicants observed in primary sample CCP; controls for preapplication score										
First payday loan application approved										
Linear *f(TeletrackScore)*	−2.06	0.31	−3.66	5.35	−0.12	8.16	2.01	5.53	−2.32	3.79
	(4.73)	(7.03)	(5.85)	(8.75)	(5.60)	(8.36)	(5.49)	(8.06)	(4.10)	(6.21)
Quartic *f(TeletrackScore)*	9.10	27.73	13.94	8.80	28.24	38.41	15.92	24.03	14.52	21.67
	(11.86)	(17.26)	(14.83)	(20.93)	(14.60)	(21.27)	(14.34)	(20.81)	(10.36)	(14.69)
N	2,994	1,156	2,979	1,151	2,969	1,147	2,956	1,139	35,687	13,776

NOTES: Every parameter estimate is from a separate instrumental variables regression (see estimating equations (1) and (2) in text). Robust standard errors in columns 1–8, and standard errors clustered at the individual level in columns 9 and 10, are in parentheses. Outcome variable in all regressions is the Equifax credit risk score. Controls include distance from threshold interacted with above threshold, "Linear *f(TeletrackScore),*" or a quartic in distance from threshold interacted with above threshold, "Quartic *f(TeletrackScore)*"; log monthly pay; checking balance; job tenure; age; months in current home; NSF count; pay frequency; garnished wages; direct deposit; a homeownership indicator; sex; and year and quarter of payday loan application dummy variables. Pooled regressions in columns 9 and 10 include a dummy variable for the number of quarters since application. *$p < 0.05$; **$p < 0.01$.

[a]Bandwidth specified in terms of standard deviations of the Teletrack score from the approval threshold.

in the previous section. We implement the RD using a linear or quartic function of the selection variable (*TeletrackScore*) that can differ on either side of the threshold, and we restrict the sample to applicants with Teletrack scores no more than 0.5 or 0.25 standard deviations from the threshold.[35]

The first cells of columns 1 and 2 in Table 4 show estimates of the effect on credit scores one quarter after application. There is some indication that credit scores decline slightly in the short run as a result of obtaining a payday loan. When we control for quartic functions of the distance to the *TeletrackScore* approval threshold, statistical significance disappears and standard errors rise by a factor of 2–3. When we control for individuals' credit score in the quarter just prior to application in Panel B, the point estimates are much closer to zero and the standard errors also shrink somewhat.[36]

The remainder of Table 4 shows there is little evidence of an effect on credit scores from obtaining a payday loan at various horizons after application and regardless of the sample or specification. The point estimates and 95% confidence intervals rule out substantive effects of payday loans on credit scores. Our most precise estimate in Panel B, in column 9, pools observations across the first 12 quarters and indicates a 1-point drop in scores with a standard error of less than 3 points. The largest estimate in Panel B, in column 6, implies just a 15-point increase on average after eight quarters and rules out effects larger than about 45 points.

To help put these numbers in perspective, recall that Figure 2 indicates that after four quarters payday applicants' scores are already about 30 points lower than those of the average person with a score of 500 in 2002:Q2. Also recall Table 2, which shows that the score gap between payday loan applicants and the general population around the time of application was nearly 170 points and that the standard deviation of scores among payday applicants is 77 points. These comparisons give rise to our characterization of the main results as a precise zero. Of course, for some consumers a few credit score points could be meaningful. CFPB (2012) reports that default probabilities are convex in FICO scores, and in the mid-500s each FICO point corresponds to a 0.4 percentage point change in default probability for new accounts from a baseline default probability of about 40%. Additionally, many lenders use credit score threshold rules for loan pricing and eligibility, and thus a few points could in some instances be associated with large changes in credit access. However, we can ordinarily rule out a score change that is larger than one-sixth of the baseline average gap between payday applicants and the general population.

35. The relationship in the bottom panel of Figure 4 appears approximately linear.

36. The fact that controlling for the preapplication credit score alters some results indicates that treatment status may be correlated with pretreatment credit score. Table 3 reports a modest, statistically significant discontinuity in preapplication credit score of about −7 points conditional on a linear function of the running variable and other covariates using observations within 0.5 standard deviations of the threshold. This discontinuity raises a concern that unobservable factors may also change discontinuously at the threshold. However, Table 3 fails to show differences across the threshold in most other covariates once we control for Teletrack score, and the discontinuity in preapplication Equifax score is smaller using higher order control functions.

The sample sizes in Panel B of Table 4 are smaller than those in Panel A because not all applicants observed in the CCP in a given quarter after application, $t + q$, are also observed at $t - 1$, particularly those applicants not found in the primary sample CCP. Sample sizes in Panel B shrink relative to Panel A as q gets large. Panel C presents identical regressions to those in Panel B, but using only applicants that match to the primary sample CCP, who are much more likely to be observed in both $t + q$ and $t - 1$ because these are the individuals actively followed in the CCP. Indeed, sample sizes at $t + 12$ are nearly the same as the sample sizes at $t + 1$ for the primary sample. Although less precise due to smaller sample sizes relative to the full sample CCP, the point estimates continue to be quite small in the specifications with a linear f*(TeletrackScore)* in Panel C.[37]

These quantitative results are compatible with the Skiba and Tobacman (2011) finding that payday loan access doubles Chapter 13 personal bankruptcy filings. That paper's large relative effect is a small absolute effect, in the sense that the bankruptcy rate is increased from about 2 percentage points to about 4 percentage points. Adverse effects of bankruptcy filings on credit scores are heterogeneous and difficult to quantify. In practice, when individuals file for bankruptcy, their credit scores will already have deteriorated substantially due to multiple severely delinquent accounts, and the bankruptcy filing itself may not push scores down much more.[38] Even if filings were to lower credit scores by 200 points on average, the Skiba and Tobacman bankruptcy effects could account for a reduction in average Equifax scores of $(0.04 - 0.02) \times 200 = 4$ points, which is close to this paper's main point estimates and well within all our confidence intervals.

Nonetheless, in our view the current paper's finding of a null effect on credit scores is surprising. Bankruptcy is a rare and extreme outcome, while credit scores are highly sensitive summary measures of the entire liability side of the household balance sheet. Even if the population of payday applicants had little space to fall further in creditworthiness, payday loans might have differentially affected recovery of their credit scores.

Credit scores can be influenced by a variety of factors, with the most important factor being one's payment history. In Table 5, we examine whether payday loans affect delinquency on traditional accounts, which is a narrower but perhaps more easily interpretable measure of financial health than the credit score. The first four columns show results for the share of all accounts 30 or more days late (Panels

37. Table S2 in the online appendix presents estimates using the change in credit score as an outcome rather than controlling for preapplication credit score, and Tables S3a and S3b present estimate where the outcome is an indicator for a substantial score change of at least 25 or at least 50 points. Some of the point estimates in Table S2 are larger than the linear *f(TeletrackScore)* point estimates in Table 4, especially when we limit to the smaller primary sample. However, these estimates also are less precise, and none of the estimates in Tables S2 and S3 are statistically significant.

38. Figure S6 in the online appendix indicates that, on average, credit scores fall less than 100 points for bankruptcy filers among the payday applicant sample. Moreover, scores experience this decline over a period of 3 years *prior* to the bankruptcy filing. Then the scores bottom out, and they begin to recover during the quarter of the bankruptcy filing. Similarly, Brevoort and Cooper (2013) study credit score dynamics around another type of public filing, that of foreclosure. They show that scores decline over the 2 years prior to the foreclosure period.

TABLE 5

RD Estimates: The Effect of Payday Loans on Traditional Credit Delinquency

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Outcome: Share of all accounts 30+ days late				Outcome: Share of consumer credit accounts 30+ days late				Outcome: Share of mortgage and auto accounts 30+ days late			
	4 quarters out		Pooled, first 12 quarters		4 quarters out		Pooled, first 12 quarters		4 quarters out		Pooled, first 12 quarters	
Bandwidth[a]	0.5 SD	0.25 SD	0.5 SD	0.25 SD	0.5 SD	0.25 SD	0.5 SD	0.25 SD	0.5 SD	0.25 SD	0.5 SD	0.25 SD
Panel A. Applicants observed in full sample CCP, within specified bandwidth												
First application approved	0.024	0.020	0.023	0.021	0.020	0.013	0.010	−0.011	–0.001	0.007	0.009	0.025
	(0.019)	(0.028)	(0.013)	(0.019)	(0.021)	(0.030)	(0.014)	(0.020)	(0.035)	(0.049)	(0.021)	(0.030)
N	8,968	3,429	105,291	39,999	7,866	3,015	91,305	34,844	4,464	1,761	53,668	20,875
Panel B. Applicants observed in full sample CCP; controls for preapplication outcome and credit score												
First application approved	0.007	−0.024	0.004	−0.010	−0.000	0.001	−0.009	−0.028**	0.022	0.010	0.015	0.025
	(0.021)	(0.030)	(0.007)	(0.010)	(0.023)	(0.032)	(0.007)	(0.011)	(0.045)	(0.062)	(0.014)	(0.020)
N	5,438	2,120	59,451	23,113	4,628	1,791	50,037	19,380	2,108	867	22,360	9,100
Panel C. Applicants observed in primary sample CCP; controls for preapplication outcome and credit score												
First application approved	0.021	0.006	0.009	−0.006	−0.013	−0.017	−0.031**	−0.063**	0.112	0.065	0.042*	0.063*
	(0.031)	(0.044)	(0.010)	(0.014)	(0.034)	(0.048)	(0.011)	(0.016)	(0.063)	(0.092)	(0.019)	(0.029)
N	2,415	948	28,413	11,087	2,073	803	24,045	9,353	983	413	10,959	4,577

(*Continued*)

TABLE 5

CONTINUED

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Outcome: Share of all accounts 30+ days late				Outcome: Share of consumer credit accounts 30+ days late				Outcome: Share of mortgage and auto accounts 30+ days late			
	4 quarters out		Pooled, first 12 quarters		4 quarters out		Pooled, first 12 quarters		4 quarters out		Pooled, first 12 quarters	
Bandwidth[a]	0.5 SD	0.25 SD	0.5 SD	0.25 SD	0.5 SD	0.25 SD	0.5 SD	0.25 SD	0.5 SD	0.25 SD	0.5 SD	0.25 SD
Panel D. Applicants observed in full sample CCP, within specified bandwidth												
First application approved	0.032	0.035	0.023	0.022	0.033	0.038	0.010	−0.014	0.004	0.040	0.014	0.043
	(0.020)	(0.029)	(0.014)	(0.020)	(0.022)	(0.031)	(0.015)	(0.021)	(0.033)	(0.046)	(0.022)	(0.031)
N	8,968	3,429	105,291	39,999	7,866	3,015	91,305	34,844	4,464	1,761	53,668	20,875
Panel E. Applicants observed in full sample CCP; controls for preapplication outcome and credit score												
First application approved	−0.006	−0.013	0.003	−0.008	0.019	0.038	−0.004	−0.019	−0.023	−0.017	−0.004	0.014
	(0.022)	(0.031)	(0.007)	(0.010)	(0.024)	(0.034)	(0.008)	(0.011)	(0.040)	(0.055)	(0.013)	(0.018)
N	5,438	2,120	59,451	23,113	4,628	1,791	50,037	19,380	2,108	867	22,360	9,100
Panel F. Applicants observed in primary sample CCP; controls for preapplication outcome and credit score												
First application approved	0.021	0.012	0.008	−0.004	0.009	0.018	−0.025*	−0.049**	0.059	0.059	0.026	0.043
	(0.032)	(0.046)	(0.010)	(0.015)	(0.036)	(0.050)	(0.012)	(0.017)	(0.057)	(0.081)	(0.018)	(0.026)
N	2,415	948	28,413	11,087	2,073	803	24,045	9,353	983	413	10,959	4,577

NOTES: Instrumental variables regression results shown (see estimating equations (1) and (2) in text). Robust standard errors in 4-quarters-out regressions, and standard errors clustered at the individual level in pooled regressions, are shown in parentheses. Controls include distance from threshold interacted with above threshold, log monthly pay, checking balance, job tenure, age, months in current home, NSF count, pay frequency, garnished wages, direct deposit, home owner, sex, year, and quarter of payday loan application dummy variables; pooled regressions include a dummy variable for the number of quarters since application. $^*p < 0.05$; $^{**}p < 0.01$.

[a]Bandwidth specified in terms of standard deviations of the Teletrack score from the approval threshold.

A–C) and 90 or more days late (Panels D–F) at 4 quarters out and pooled over the first 12 quarters. The point estimates are generally very small given average delinquency shares in the range of 50–60% (cf. Table 2 and Figure 1). Columns 5–12 provide analogous estimates separately for uncollateralized consumer credit accounts (columns 5–8) and mortgage and auto credit (columns 9–12). Some of these estimates indicate that payday loans have a beneficial effect on uncollateralized delinquencies but exacerbate delinquency on secured credit. Also, the estimates are not robust across full and primary samples and different bandwidths. Overall, there is little evidence of a systematic impact of payday loans on delinquency.[39]

When we examine subpopulations, the sample shrinks and the precision of the null effect weakens. Nonetheless, the results support the message that payday loans have little impact on credit scores. We analyze potential heterogeneous effects of payday loans in Section 4.4. First we discuss a potential limitation of our work, namely, that we have data from just one payday lender.

4.3 Adjusting for Proximity to Competing Payday Lenders

One drawback of our data is that we observe payday loan applicants at just one lender. Thus, we do not observe whether these applicants got payday loans elsewhere prior to their first application with our payday lender, or if rejected applicants can easily obtain a payday loan from another lender. If rejected applicants can easily get loans by applying elsewhere or again at this lender, our identification strategy would produce estimates of the impact of payday loan access that are biased toward zero. We try to address this issue in a few ways.

First, Skiba, and Tobacman (2011) show that just-rejected applicants are far less likely than just-accepted applicants to apply for another loan at the observed payday lender. This fact suggests that applying for a payday loan is at least somewhat costly, and that rejection may discourage applicants from trying to use payday loans in the future. Moreover, rejection may provide information: rejected applicants may feel that they will not be accepted at other lenders because the same or similar underwriting criteria may be used again. Furthermore, rejection may be more likely to deter someone from trying to get another payday loan if this was his or her first experience with payday lenders. Although we cannot provide direct evidence on this, recall that Figure 1 indicates that prime credit scores tend to bottom out and that credit demand (as measured by credit inquiries and credit card utilization) peaks right around the time of the first application we observe. These facts suggest that this observed payday loan application is not occurring at a random time, but rather at a time of peaking financial stress and could hence be the first payday loan application at any company.

39. We also examine effects on other factors that affect credit scores. Figure S7 and Table S4 in the online appendix elaborate, for each of the score components shown in Figure 1, generally demonstrating null effects of payday loans.

Second, the ease of reapplying elsewhere should be directly related to the number of payday lenders in close proximity. Thus, attenuation bias should be mitigated for those applicants who live in areas with relatively few competing payday lenders. We test this proposition using Census data on the number of payday lenders near an applicant's home ZIP code and data assembled from *ReferenceUSA* on the market share of the observed lender by ZIP code.[40]

Table 6 presents reduced-form regressions of the Equifax credit score on the above-threshold indicator variable and its interaction with three different market structure variables: the number of payday loan establishments within a 5-mile radius of an applicant's ZIP code, the number of establishments per 10,000 people within a 5-mile radius, and one minus the market share of our observed lender in a given ZIP code. In these regressions, the coefficient on the main above-threshold dummy variable can be interpreted as the estimated effect of a payday loan for borrowers living in areas with no payday loan establishments or in ZIP codes where our observed payday lender is a monopolist. In general, these coefficients are close to zero and precisely estimated. The estimated coefficients on the interaction terms are also small and insignificant.

Ideally, we would also have information on the ZIP where applicants went to get a loan and the concentration of payday lenders in that ZIP. Unfortunately, we do not observe the ZIP codes of the payday loan stores that applicants visited.

4.4 Testing for Heterogeneous Effects

The results above suggest that, on average, payday loans have little effect on creditworthiness. In this section, we stratify the sample in various ways to test whether there is an effect for various subgroups of interest.

We first examine whether the effect of access to payday loans varies across the distribution of preapplication Equifax credit scores. Figure 6 shows the path of credit scores for those just above and just below the acceptance threshold conditional on being in the bottom quartile (first graph) or top quartile (second graph) of the distribution at $t-1$.[41] Bottom-quartile applicants exhibit a large decline in their credit scores of nearly 100 points in the 2 years before application, and then their credit scores recover to about 500 after roughly 12 quarters, regardless of whether the applicants are approved for the payday loan.

The second graph shows almost exactly the opposite pattern. Top-quartile applicants exhibit a rise in scores of about 60 points in the 3 years prior to application, and

40. The number of payday lender establishments is proxied using the 2002 ZIP Code Business Patterns data published annually by the Census Bureau, which reports the number of establishments by ZIP code and six-digit NAICS code. NAICS codes 522291 (nondepositories providing unsecured consumer cash loans) and 522390 (check cashing services) capture payday lenders. See Bhutta (2014) for more details. The distance between two ZIP codes is calculated using the Haversine formula and ZIP code centroid locations from the Census. Market share calculations are based on data from *ReferenceUSA* (http://www.referenceusa.com) for Texas ZIP codes. See Skiba and Tobacman (2011) for more details.

41. Because we are stratifying on a $t-1$ variable and looking at patterns up to 20 quarters beyond the application date, we use only payday applicants matched to the primary sample. Applicants outside of the primary sample who are observed both at $t-1$ and well after the application quarter are relatively few.

TABLE 6

RD Estimates: Testing for Heterogeneous Effects by Market Structure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Market structure variable	No. of payday loan stores in 5-mile radius (mean: 24.5, SD: 19.1)				Stores per 10,000 people in 5-mile radius (mean: 1.3, SD: 0.87)				1 – ZIP code market share (mean: 0.84, SD: 0.20)			
	4 quarters out		Pooled, first 12 quarters		4 quarters out		Pooled, first 12 quarters		4 quarters out		Pooled, first 12 quarters	
Bandwidth[a]	0.5 SD	0.25 SD	0.5 SD	0.25 SD	0.5 SD	0.25 SD	0.5 SD	0.25 SD	0.5 SD	0.25 SD	0.5 SD	0.25 SD
Panel A. Applicants observed in full sample CCP, within specified bandwidth												
1 (score > threshold)	−3.05	3.24	−6.29*	−2.56	−0.69	3.89	−3.97	−0.63	−2.13	−2.69	−5.68	−8.29
	(3.82)	(5.61)	(2.65)	(3.85)	(4.03)	(6.10)	(2.80)	(4.18)	(4.64)	(7.02)	(3.28)	(4.87)
1 (score > threshold) × (no. of stores)	0.03	−0.05	0.09	0.01								
	(0.08)	(0.12)	(0.06)	(0.08)								
No. of stores in 5-mile radius	0.08	0.18	0.02	0.15*								
	(0.07)	(0.09)	(0.05)	(0.07)								
1 (score > threshold) × (stores per 10,000)					−1.54	−2.12	−0.29	−1.86				
					(1.75)	(2.84)	(1.24)	(2.03)				
Stores per 10,000 people					−1.58	−3.34	−1.84	−0.39				
					(1.46)	(2.25)	(1.03)	(1.56)				
1 (score > threshold) × (1 − market share)									-3.05	19.31	-0.88	19.98
									(10.73)	(18.62)	(7.13)	(11.99)
1 − market share									-4.66	6.61	-3.38	9.24
									(9.20)	(15.43)	(6.03)	(9.86)
N	10,573	4,002	125,466	47,216	10,412	3,940	123,483	46,485	5,756	2,106	67,856	24,540
Panel B. Applicants observed in full sample CCP; controls for preapplication score												
1 (score > threshold)	1.85	8.56	−1.79	1.59	−1.11	4.70	−1.98	3.14	1.26	−1.29	−1.86	−2.99
	(4.10)	(6.01)	(2.94)	(4.16)	(4.36)	(6.59)	(3.09)	(4.64)	(4.85)	(7.22)	(3.58)	(5.32)
1 (score > threshold) × (no. of stores)	−0.09	−0.21	0.03	−0.03								
	(0.09)	(0.14)	(0.06)	(0.09)								
No. of stores in 5-mile radius	0.11	0.18	0.02	0.11								
	(0.07)	(0.10)	(0.05)	(0.07)								

(*Continued*)

TABLE 6
CONTINUED

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Market structure variable	No. of payday loan stores in 5-mile radius (mean: 24.5, SD: 19.1)				Stores per 10,000 people in 5-mile radius (mean: 1.3, SD: 0.87)				1 – ZIP code market share (mean: 0.84, SD: 0.20)			
	4 quarters out		Pooled, first 12 quarters		4 quarters out		Pooled, first 12 quarters		4 quarters out		Pooled, first 12 quarters	
Bandwidth[a]	0.5 SD	0.25 SD	0.5 SD	0.25 SD	0.5 SD	0.25 SD	0.5 SD	0.25 SD	0.5 SD	0.25 SD	0.5 SD	0.25 SD
Panel B. Applicants observed in full sample CCP; controls for preapplication score												
1 (score > threshold) × (stores per 10,000)					0.48	−1.06	0.49	−2.17				
					(1.92)	(3.06)	(1.38)	(2.24)				
Stores per 10,000 people					−1.73	−0.48	−1.94	0.20				
					(1.63)	(2.51)	(1.18)	(1.84)				
1 (score > threshold) × (1 − market share)									10.03	19.99	4.32	12.68
									(11.15)	(18.88)	(7.96)	(13.53)
1 − market share									6.30	9.33	3.83	13.25
									(9.62)	(15.56)	(6.82)	(11.37)
N	7,065	2,702	77,988	29,888	6,964	2,665	76,866	29,478	3,832	1,433	42,126	15,664

(*Continued*)

TABLE 6

CONTINUED

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Market structure variable	No. of payday loan stores in 5-mile radius (mean: 24.5, SD: 19.1)				Stores per 10,000 people in 5-mile radius (mean: 1.3, SD: 0.87)				1 – ZIP code market share (mean: 0.84, SD: 0.20)			
	4 quarters out		Pooled, first 12 quarters		4 quarters out		Pooled, first 12 quarters		4 quarters out		Pooled, first 12 quarters	
Bandwidth[a]	0.5 SD	0.25 SD	0.5 SD	0.25 SD	0.5 SD	0.25 SD	0.5 SD	0.25 SD	0.5 SD	0.25 SD	0.5 SD	0.25 SD
Panel C. Applicants observed in primary sample CCP; controls for preapplication score												
1 (score > threshold)	−3.40	4.85	−5.57	−1.03	−5.20	3.35	−2.42	5.73	−4.06	−3.32	−4.99	−0.18
	(6.28)	(9.33)	(4.43)	(6.22)	(6.71)	(10.44)	(4.65)	(7.05)	(7.94)	(11.99)	(5.64)	(8.57)
1 (score > threshold) × (no. of stores)	0.03	0.04	0.16	0.22								
	(0.14)	(0.23)	(0.09)	(0.13)								
No. of stores in 5-mile radius	0.04	0.01	−0.10	−0.07								
	(0.11)	(0.15)	(0.08)	(0.10)								
1 (score > threshold) × (stores per 10,000)					1.46	1.07	0.23	−1.40				
					(2.86)	(4.78)	(2.07)	(3.38)				
Stores per 10,000 people					−2.82	−2.20	−2.37	−1.46				
					(2.42)	(3.67)	(1.72)	(2.66)				
1 (score > threshold) × (1 − market share)									28.20	38.05	11.03	10.44
									(19.68)	(33.09)	(12.25)	(21.04)
1 − market share									19.83	22.98	9.32	10.65
									(17.14)	(28.17)	(9.89)	(17.32)
N	2,971	1,146	35,589	13,713	2,925	1,128	35,038	13,500	1,529	561	18,321	6,698

NOTES: Reduced-form regressions shown. Robust standard errors in 4-quarters-out regressions, and standard errors clustered at the individual level in pooled regressions, are in parentheses. Census Zip Code Business Patterns 2002 data and Census 2000 population data were used to estimate the number of payday lender stores and number of stores per capita in a 5-mile radius around the applicant's residential zip. ZIP code market share estimates in Panel B are based on data from *ReferenceUSA*. Controls include distance from threshold interacted with above threshold, log monthly pay, checking balance, job tenure, age, months in current home, NSF count, pay frequency, garnished wages, direct deposit, homeowner, sex, year, and quarter of payday loan application dummy variables; pooled regressions include a dummy variable for the number of quarters since application. The reported means and standard deviations of the market structure variables were computed at the individual level for the full sample without bandwidth restrictions. $*p < 0.05$; $**p < 0.01$.

[a]Bandwidth is specified in terms of standard deviations of the Teletrack score from the approval threshold.

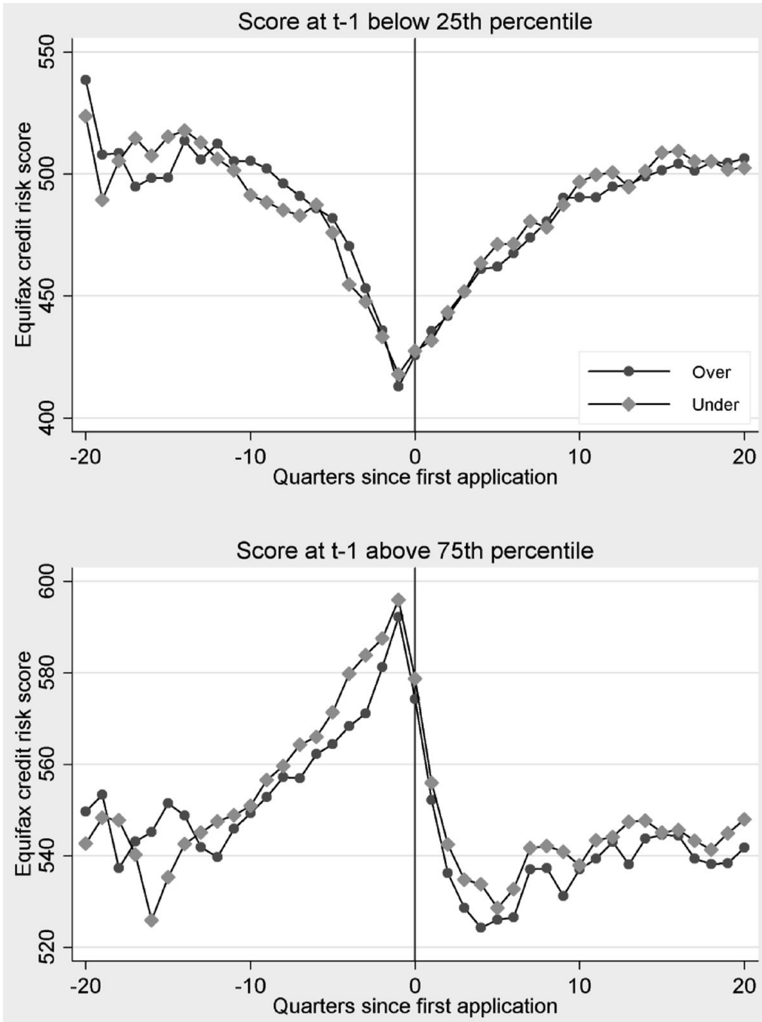

FIG. 6. The Effect of Access to Payday Loans on Credit Score Dynamics.

NOTES: Figures are based on data from the payday loan applicants matched to the primary sample CCP. Each data point represents the average Equifax 3.0 credit risk score at the end of a quarter. The top (bottom) panel shows credit score dynamics for applicants with a credit score in the quarter just before payday loan application in the bottom (top) quartile of the $t-1$ score distribution. The sample for both graphs is restricted to those with a Teletrack score within 0.25 standard deviations of the approval threshold.

then scores drop by a similar amount after the payday loan application. Approved applicants in the top quartile have slightly larger drops than rejected applicants, but the difference is statistically insignificant (regressions not reported).

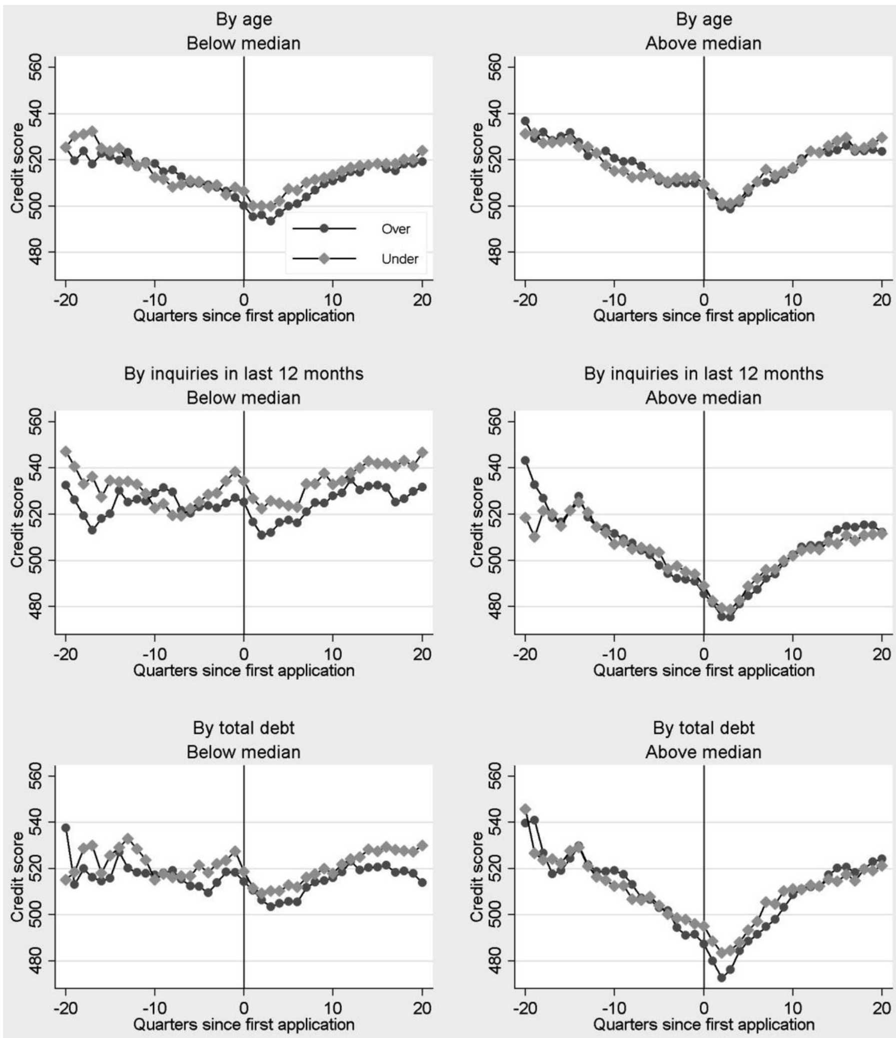

FIG. 7. The Effect of Access to Payday Loans on Credit Scores by Applicant Age, Number of Inquiries, and Total Debt.

NOTES: Top two figures based on full sample CCP data matched to payday loan applicant records, with age of payday applicants coming from payday applicant records measured at the time of first application. Remaining figures based on primary sample CCP data matched to payday applicant records; median number of inquiries and median total debt are measured in the quarter prior to first payday loan application. Each data point represents the average Equifax 3.0 credit risk score at the end of a quarter. Sample for all graphs restricted to those with Teletrack score within 0.25 standard deviations of the approval threshold.

Overall, the two panels of Figure 6 reinforce the view that payday applicants have long-standing, persistent weakness in their credit files. Whatever the (unobserved) shocks that lead to substantial improvement into the top quartile or worsening into the bottom quartile of Equifax scores in the few years before a payday loan application, these one-standard-deviation changes are undone in the subsequent few years.[42] The medium-term mean reversion in Equifax scores, consistent with Figures 5 and S3, is remarkably strong across the score distribution.

Figure 7 shows the effect of payday loan access stratified separately by three different variables measured at the time of application: applicant age, number of credit inquiries, and total debt. Applicant age may proxy for credit market experience, and those with less experience may be more prone to mistakes; the number of inquiries may reflect a willingness to search for or awareness about alternatives; and total debt may also serve as a proxy for credit market experience or awareness of alternatives. We split the sample at the median value of each of these variables and then compare the path of credit scores for barely approved versus barely rejected applicants within each subgroup.[43]

Overall, once again there is little evidence that payday loans make a difference for the path of scores after application. There is perhaps a minor divergence in scores among those individuals with less than the median number of inquiries, but this divergence first appears prior to the payday loan application.

5. CONCLUSION

Since the financial crisis there has been a renewed focus on consumer financial protection. One controversial product is the payday loan, and the Dodd–Frank Act of 2010, which created the CFPB, gives federal regulators new supervisory powers over payday lenders and new authority to regulate such products to the extent they are deemed "unfair, deceptive, or abusive."

In this paper, we use a novel data set of payday loan applicants matched with 10 years of prime credit history to study the circumstances under which people seek payday loans and the financial consequences of using these loans. One finding is that payday loans appear to be used as a last resort: payday loan applications occur when credit card lines are generally exhausted and when the search for credit becomes much more intense but is largely unsuccessful.

While liquidity needs immediately preceding application for payday loans appear extreme, our long-term panel data indicate that applicants actually face persistent shortfalls, with delinquency rates and credit application volumes far exceeding national averages over the entire 10-year observation period. Compared to the average person with the same credit score as our average payday applicant at the time of application, payday loan applicants' credit scores stagnate at very low levels.

42. Curiously, top-quartile applicants have an asymmetric experience between their rate of improvement in scores before the payday application and the much faster rate of post-application decline.

43. In Figure S8, in the online appendix we show that the distribution of credit scores seems unaffected by payday loans. Specifically, the path of the 25th and 75th percentiles of the applicant score distribution is the same for barely rejected and barely accepted applicants.

Finally, and most importantly, we use an RD design to study the consequences of getting a payday loan. We find that the path of traditional credit scores following first-time payday loan applications does not differ between those barely approved and those barely rejected. The 95% confidence intervals for our point estimates exclude effects on credit scores larger than one-sixth of the average gap between payday loan applicants and the rest of the population.

We evaluate the robustness of our findings in a number of ways. First, we assess the extent to which observing payday borrowing at only one lender biases the baseline estimates toward zero. This could occur if rejected applicants at this lender succeed in getting payday loans at another lender. Point estimates change little and remain tightly bounded when we focus on loan applicants with limited access to other payday lenders, but future work with data from multiple lenders could improve on our analysis. Second, we consider various credit file samples and various structures for the credit score dynamics. Third, we try many RD specifications, varying the function of *AboveThreshold* we control for and the bandwidth around the threshold.

Our findings complement and extend the existing literature on credit score dynamics and payday loan impacts. Given the mix of prior findings on impacts (e.g., in Carrell and Zinman 2014, Zinman 2010, Campbell, Martinez-Jerez, and Tufano 2011, Melzer 2011, Morse 2011, Skiba and Tobacman 2011, Morgan, Strain, and Seblani 2012), the work of Bhutta (2014) provides particular reassurance. He uses the descriptive results on the credit profile of payday loan applicants provided in this paper, along with variation in state payday lending laws, and also finds no effect of access to payday loans on credit scores.

There are a variety of possible reasons for the null effects we find. High-cost alternatives to payday loans may be sought by rejected payday applicants and have similar net effects (e.g., Morgan, Strain, and Seblani 2012, Zinman 2010).[44] To the extent that is true, regulators would be advised to treat the alternative financial services sector as a whole.[45] Another possible explanation is simply that payday loans are small and uncollateralized, limiting their potential benefits and risks. However, most payday borrowers take out sequences of loans, incurring nontrivial cumulative finance charges relative to their other debt service obligations. Third, effects might appear on other indicators of well-being (Dunn and Mirzaie 2014), or the null effects on average might reflect offsetting effects for different subpopulations. We do not find differentially impacted groups, however, and under either of these hypotheses one would expect to find average effects on at least some measures in the credit file.

44. If payday loan applicants tend to have time-inconsistent preferences, consistent with Skiba and Tobacman (2008) and the longstanding pre-payday-application financial distress that we document here, denial of payday loan applications could be welfare improving. Time-inconsistent preferences, however, would not have an unambiguous effect on credit scores, since those scores reflect behavior on other credit lines.

45. As Laibson (1977) shows, limiting credit access for those with commitment problems can be welfare improving. To be sure, as Campbell, Jackson, Madrian, and Tufano (2011) note, such bans do not address the underlying behavioral factors that give rise to demand for the product.

Finally, it might be the case—supported by the longstanding woes evident in their credit histories—that payday applicants are so financially constrained at the time they apply that creative or very large interventions would be necessary to appreciably affect their credit scores. Other outcome measures (cf. Melzer 2011) like financial fragility and subjective well-being might be more diagnostic for this population and should be pursued in future work.

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