

## RATIONALITY IN THE CONSUMER CREDIT MARKET<sup>†</sup>

# Payday Loans and Credit Cards: New Liquidity and Credit Scoring Puzzles?

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Among the many important questions highlighted by recent events in the financial sector, one concerns the features and determinants of the liability side of household balance sheets, and a second concerns the measurement of household creditworthiness. Had households taken on and accumulated debt with more wisdom and caution, and had lenders obtained and relied on more meaningful measures of creditworthiness, foreclosure rates might now be more moderate.

Using a unique dataset matched at the individual level from two administrative sources, we examine household choices between liabilities and assess the informational content of prime and subprime credit scores in the consumer credit market. (In abbreviated fashion, we aspire to follow the similar inquiries of Agarwal et al. (2007a) in the relationship banking context and William Adams, Liran Einav, and Jonathan Levin (2009) in the auto market context.) First, more specifically, we assess consumers' effectiveness at prioritizing use of their lowest-cost credit option. While Sumit Agarwal et al. (2007b) examine the choice between two different credit card contracts with different costs, here we study the choice between borrowing on

a credit card and borrowing on a payday loan. We find that most borrowers from one payday lender who also have a credit card from a major credit card issuer have substantial credit card liquidity on the days they take out their payday loans.<sup>1</sup> This is costly because payday loans have annualized interest rates of at least several hundred percent, though perhaps partly explained by the fact that borrowers have experienced substantial declines in credit card liquidity in the year leading up to the payday loan.

Second, we explore the relationship between prime and subprime credit scoring. Here we use our matched sample of credit cards and payday loans, from which we observe FICO scores and scores from the subprime credit bureau Teletrack. This payday lender approved or rejected first-time applicants exclusively on the basis of their Teletrack score, but conditional on the Teletrack score, higher FICO scores predict higher repayment rates by economically and statistically significant amounts. We show that the two scores have independent information and are specialized for the types of lending where they are used: Teletrack scores have eight times the predictive power for payday loan default as FICO scores. We also show that prime lenders should value information about their borrowers' subprime activity. Taking out a payday loan predicts nearly a doubling in the probability of serious credit card delinquency over the next year. The rest of the paper explains how we arrive at these facts and discusses the extent to which they present puzzles for standard models.

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<sup>1</sup> The term “payday loan” is used because these loans provide liquidity between paydays. The typical loan is due on the borrower's next payday, and hence has a duration of between one week and one month (John P. Caskey 1994; Michael Stegman 2007).

### I. Merged Administrative Datasets

Our analysis takes advantage of an unusual, individual-level match of two administrative data sources. Specifically, we have used individual identifiers to merge loan records from a large payday lender with transaction and credit histories from a financial institution that offers checking accounts, credit cards, mortgages, home-equity lines of credit, and auto financing. For detailed description of the two datasets, we refer readers to sources that have used them separately in the past (e.g., Agarwal et al. 2008; Skiba and Tobacman 2008a). Online Appendix Tables A1 and A2, available at <http://www.aeaweb.org/articles.php?doi=10.1257/aer.99.2.412>, respectively summarize characteristics of the individuals and accounts in what we refer to here as the payday lender and credit card issuer panels. In all that follows, we include the 102,779 persons who borrowed on a payday loan from this payday lender (i.e., we exclude unsuccessful payday loan applicants) and who had a full set of background variables, and the 143,228 persons with credit card accounts at the credit card issuer in the states where the payday lender operates.

Tables A1 and A2 also report information about the matched sample of 3,090 people, and this selected group is statistically different from both the full credit card issuer population and the full payday lender population on most measures.<sup>2</sup> Payday borrowers' average incomes are much lower, though the variation in their incomes is also much lower. Their accounts are older, and their credit lines smaller. Intriguingly, the income data from the credit card issuer for the matched sample are higher, by 50 percent, than the income data from the payday lender for the matched sample. The number of open credit card accounts with balances is almost identical, as is the amount of outstanding credit card debt.

<sup>2</sup> Out of the entire Texas population of roughly 20 million, the overall (nonrandom) payday loan coverage rate is about three-quarters of 1 percent. The credit card issuer panel includes 23,795 Texas-based accounts. Thus, if the payday loan and credit card samples were orthogonal, we would expect to obtain only 180 matches. We actually observe 1,707 Texas-based matches out of the 3,090 matches overall. Presumably much of the difference arises because only adults can borrow on credit cards and payday loans, and because both products attract people who seek credit.

Home equity line and mortgage balances are also similar.

One important measure on which the matched sample differs less than we expected is the FICO score. Among all credit card account holders, the average FICO score is 730, with a standard deviation of 69, compared to 673 for the matched sample. The standard deviation for the matched sample is slightly smaller than for the full credit card population. Conventionally, the subprime population is viewed as having scores below 620, implying that a large share of payday borrowers likely have continuing access to prime credit. In the data, FICO scores are current as of the previous month.

Below we focus on questions that are of interest within the selected matched sample, and we analyze the causes and aftermath of the selection itself.

### II. Liquidity's Decline

Using this matched dataset, we first examine how effectively consumers choose between payday loans and credit cards. One summary measure suggests a common pecuniary mistake: two-thirds of the matched sample have at least \$1,000 of credit card liquidity on the day they take their first payday loans, much more than the typical \$300 payday loan. For a typical payday loan with a two-week finance charge of 18 percent, using credit card liquidity first would save these households  $\$300 \times (0.18 - (1.15^{1/26} - 1)) = \$52$ , if the credit card APR is 15 percent. Appendix Table A3 elaborates on how credit card liquidity and APRs vary across the population on the days people take their payday loans. Most notably, liquidity is strongly increasing in credit scores; married credit card account holders had almost twice the liquidity of singles; and credit card liquidity was much higher for the elderly. Across these distributions, most people in the matched sample appear to have credit card liquidity exceeding the size of the typical payday loan.

Since many payday borrowers take loans repeatedly, we also construct a measure called *LOSS* that cumulates interest losses over the one year beginning with each borrower's first payday loan. Specifically, for the  $i$ 'th person in the matched dataset, we compute  $LOSS_i$  as follows. Suppose individual  $i$  takes  $n_i$  payday loans within a year of her first loan, including

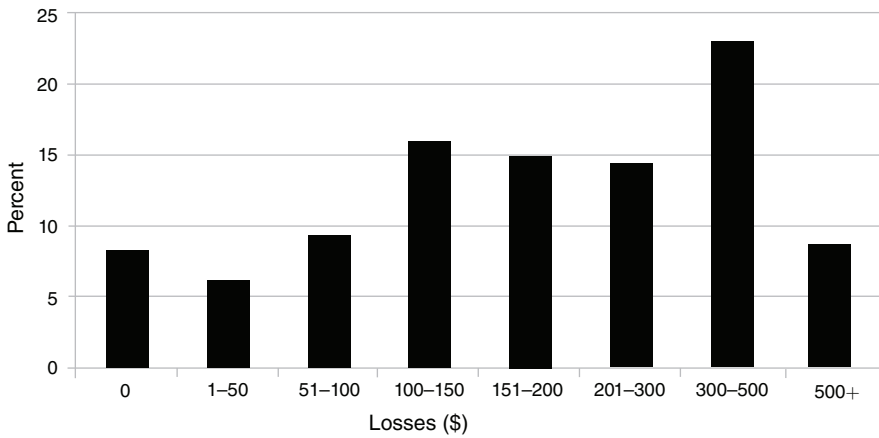


FIGURE 1. HISTOGRAM OF INTEREST LOSSES

Note: Losses represent how much account holders could have saved if they had borrowed as much as they could on credit cards before borrowing on payday loans.

her first loan, on dates  $\{d_{i1}, d_{i2}, \dots, d_{in_i}\}$ , where  $d_{i1} = 0$  and  $d_{in_i} \leq 365 \forall i$ . Denote the size of  $i$ 's  $k$ 'th payday loan by  $b_i(d_{ik})$ ; the length or term of that loan in days by  $t_i(d_{ik})$ ; available credit card liquidity on the date of  $i$ 's  $k$ 'th loan by  $l_i(d_{ik})$ ; and  $i$ 's prevailing credit card gross APR on the same date by  $R_i^{cc}(d_{ik})$ . Finance charges are fixed for payday loans at  $r^{pdl} = 18$  percent.<sup>3</sup> Then,  $LOSS_i = \sum_{k=1}^{n_i} \max [\min [b_i(d_{ik}), l_i(d_{ik})], 0] \times [r^{pdl} - (R_i^{cc}(d_{ik})^{t_i(d_{ik})/365} - 1)]$ .

Figure 1 plots the histogram of  $LOSS$ , including the share of credit card customers who have  $LOSS = 0$  because they have no credit card liquidity when they borrow from the payday lender. Typical credit card account holders would have saved almost \$200 by borrowing up to their credit card limits before turning to payday loans.<sup>4</sup>

A number of other authors, including David Gross and Nicholas Souleles (2002), Carol Bertaut and Michael Haliassos (forthcoming), and Agarwal et al. (2007b), have measured similar liquid debt “puzzles” using other data.

Consensus is elusive, but the size of the interest losses found elsewhere (with more representative samples) tends to be smaller on average than what we measure. Irina Telyukova and Randall Wright (2008) further explore liquidity needs as an explanation for the credit card debt puzzle. The current paper's results are notable because (i) the interest losses are shown to be very large; (ii) since the individuals in our matched dataset might borrow on payday loans elsewhere and might have access to other sources of liquidity, we believe we are measuring a lower bound on the actual interest losses; and (iii) over ten million US households borrow on payday loans each year.

Our findings complement existing research on the causes of payday borrowing patterns (e.g., Caskey 1994; Skiba and Tobacman 2008b) and survey evidence about the alternatives available to payday borrowers. Regarding the latter, a nationally representative sample of one thousand payday loan customers, surveyed by Gregory Elliehausen and Edward C. Lawrence (2001), found 56.5 percent of respondents in possession of bank-issued credit cards. However, of the individuals with cards, 61 percent hadn't used them in the past year in order to avoid exceeding the cards' credit limits. A collection of other representative surveys across six states conducted by Io Data Corporation (2002) and covering 2,600 payday borrowers found 55 percent in possession of credit cards. Again, access to liquidity for

<sup>3</sup> To emphasize again, this is a per-loan proportional charge, not an APR.

<sup>4</sup> Appendix Table A4 shows the impact of demographic variables on  $LOSS$ . Our results suggest that losses decline with income and credit risk characteristics. Additionally they are higher for married borrowers. One potential explanation is that couples are more likely to seek payday loans to hide expenditures from their spouses.

TABLE 1—LIQUIDITY DECLINES AS THE PAYDAY BORROWING EVENT APPROACHES

Lag time before the payday loan (months)	Liquidity percentile (\$)				Liquidity (\$)	
	90th	75th	25th	10th	Mean	Std.
$t - 12$	2,557	2,018	1,069	478	1,556	1,036
$t - 11$	2,581	2,086	1,070	440	1,572	1,171
$t - 10$	2,531	2,091	1,118	395	1,587	991
$t - 9$	2,587	1,841	1,023	382	1,413	1,205
$t - 8$	2,451	1,739	867	357	1,595	1,104
$t - 7$	2,460	1,643	867	346	1,421	1,148
$t - 6$	2,509	1,585	804	334	1,380	1,118
$t - 5$	2,319	1,585	793	311	1,396	899
$t - 4$	2,348	1,375	711	282	1,284	842
$t - 3$	2,280	1,395	663	287	1,249	818
$t - 2$	2,171	1,390	664	265	1,122	722
$t - 1$	2,177	1,359	623	262	990	677
$t$	2,102	1,244	583	263	1,011	653

Note: This table reports changes in credit card liquidity defined as the credit limit minus outstanding balances, as account holders approach the dates of their first payday loans.

these respondents might nonetheless have been limited, as only 34 percent “almost always” or “sometimes” paid monthly credit card balances in full. Across these surveys, the anticipation of rejection caused two-thirds of respondents not to apply for credit on at least one occasion in the past five years.

Table 1 presents information about the path that credit card liquidity takes during the year leading up to a customer’s first payday loan. Several features of the data are apparent. First, credit card liquidity falls by \$545 over the previous year on average, an amount that is much larger than the average \$300 of a first-time payday borrower’s loan. Second, most of the deterioration in liquidity happens in the five months before the payday loan is taken. This is interesting because it speaks to the question of why people borrow on payday loans. If liquidity were flat until a large drop one month before the payday loan application, we would suspect that a single large bad shock had unexpectedly arrived. Since we find average liquidity falling steadily, impatience, general financial mismanagement, or persistent shocks seem more likely explanations. Third, deterioration happens across the distribution of credit card liquidity, and the standard deviation falls substantially. Fourth, however, combined with the declines in liquidity across the board, there is substantial heterogeneity. The people at the top (with the most liquidity) don’t decline very fast; the people at the bottom have little further to descend; and the upper-middle group collapses. These numbers offer

some insight into how households’ cash flow can evolve, as well as illustrating the process of selection from the full credit card population into the matched sample.

### III. Information from Prime and Subprime Credit Scores

By examining the separate and combined predictive power of the FICO and Teletrack scores for the matched sample, which is *publicly* available to firms, higher-quality information may emerge for lenders. The correlation coefficient between the FICO and Teletrack scores within the matched sample is 0.2555, implying substantial differences between the two scores, presumably because Teletrack scores emphasize information from subprime lenders (including car title lenders and rent-to-own establishments, in addition to payday lenders). In a prior study, Agarwal et al. (2007a) study the impact of relationships a credit card holder has with her bank (deposits, loans, and investments) on credit card defaults. They find that *privately* available information about deposit, loan, and investment accounts is highly predictive of credit card defaults.

In Appendix Tables A5–A6 (available at <http://www.aeaweb.org/articles.php?doi=10.1257/aer.99.2.412>), we report estimates from a series of regressions. The first series examines what the credit card variables predict about payday loan sizes and payday loan default. The payday loan default (logit) regression illustrates new and

valuable information about the relative value of prime and subprime credit scores. The FICO score's coefficient is very large in absolute value, with a  $t$ -stat of 15 and a one-standard-deviation increase predicting a default probability that is lower by 7.6 percentage points. This makes it somewhat puzzling that FICO is not used to evaluate payday loan applications. However, the coefficient we find on the Teletrack score is  $(-0.0601/-0.0270) = 2.23$  times the magnitude of the coefficient on the FICO score, and (as reported in Table A1) the standard deviation of Teletrack scores is 4.18 times as large as the standard deviation of the FICO score in the matched sample. Thus, the Teletrack score has more than eight times as much power for predicting payday loan default as FICO does, suggesting why payday lenders might prioritize Teletrack scores over FICO scores in making lending decisions.

Table A6 focuses on the question of what the payday loan variables predict about credit card usage and default. Usage is defined here as outstanding debt divided by the limit. The most important result speaks to the value credit card companies might place on knowledge that an account holder has taken out a payday loan. Define "serious" credit card delinquency as an indicator for whether an account becomes 90 days past due (90dpd) at any point during the following year. Then a logit of 90dpd on credit card control variables and an indicator for whether a payday loan is taken implies that taking a payday loan predicts a 92 percent higher serious delinquency rate. Overall in the credit card issuer data, the annual serious delinquency rate is 6 percent, so we are finding an increase of about 5.5 percentage points in this rate. Selection issues have been discussed above, but a credit card lender might well be interested in the joint implication of the treatment (the payday loan) and the selection (that the account holder is looking for very expensive credit).

Because we don't observe borrowing at other payday lenders, our estimate is a lower bound on the true predicted increase in credit card default risk following a borrower's initial payday loan. These findings suggest credit card issuers might find information about account holders' payday borrowing very valuable, insofar as it provides sufficient advance warning to limit or rein in credit. We are left with two possible puzzles: why do payday lenders generally use only Teletrack

scores and not also FICO scores when making lending decisions, and why do credit card issuers not aggressively seek information about payday borrowing by their customers?

#### IV. Conclusion

This paper identifies and discusses possible liquidity and credit scoring puzzles. Regarding liquidity, we find that most account holders with a major credit card issuer have substantial unused liquidity on their credit cards at the time they borrow on payday loans. Their annual pecuniary losses from payday borrowing, compared to using their credit cards, are large compared to previously identified liquid debt puzzles. Regarding credit scores, payday lenders could obtain useful information about default probabilities by examining the FICO scores of applicants in addition to Teletrack scores, and credit card issuers would benefit from having frequently updated information about whether their account holders are payday borrowers.

We conjecture that small costs could at least begin to explain these phenomena. Credit bureaus charge lenders small fees for each score query, and those fees might exceed the value of the marginal creditworthiness information obtained. On the consumer side, Jonathan Zinman (2009) and Ron Borzekowski and Elizabeth Kiser (2008) discuss models of account-specific characteristics that can incorporate the realistic variety of pecuniary, nonpecuniary, and cognitive costs. Their work points in promising directions for explaining this paper's new facts.

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