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 households' 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 Adams, Einav and Levin (forthcoming) in the auto market context.) First, more specifically, we assess consumers' effectiveness at prioritizing use of their lowest-cost credit option. 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.[1] This is costly because payday loans have annualized interest rates of at least several hundred percent, but borrowers have

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[1] 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 (Caskey 1994, Stegman 2007).

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. For the matched sample we observe regularly-updated FICO scores and scores from the subprime credit bureau Teletrack. This payday lender only used Teletrack scores to make loan approval decisions for first-time applicants, though 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.

1 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 (Agarwal, Liu and Souleles 2007a, Skiba and Tobacman 2008a, e.g.). Online Appendix Tables A1 and A2 respectively summarize characteristics of the individuals and accounts in what we'll refer to here as the payday lender and credit card issuer panels. In all that follows, we include the 102,779 people who borrowed on a payday loan from this payday lender (i.e., we exclude unsuccessful payday loan applicants) and had a full set of background variables, and the 143,228 people 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 3090 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.[2] Payday borrowers' average incomes are much lower,

[2] Out of the entire Texas population of roughly 20 million, the overall (non-random)

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. 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.

2 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 has at least \$1000 of credit card liquidity on the day they take their first payday loans, much more than the typical \$300 payday loan. For a two-week payday loan with a finance charge of 18 percent, using credit card liquidity first would save these households $\$300 * \left(0.18 - \left(1.18^{1/26} - 1\right)\right) = \$52$, if the credit card APR is 18 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

payday loan coverage rate is about three-quarters of one 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, while we actually have 1707 Texas-based matches out of the 3090 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.

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 her first loan, on dates $\{d_{i1}, d_{i2}, ..., d_{in_i}\}$, 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 $\acute{\imath}$'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.[3] Then $LOSS_i = \sum_{k=1}^{n_i} \max\left[\min\left[b_i(d_{ik}), l_i(d_{ik})\right], 0\right] * \left[r^{pdl} - \left(R_i^{cc}(d_{ik})^{t_i(d_{ik})/365} - 1\right)\right]$.

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.[4]

A number of other authors including Gross and Souleles (2002), Bertaut and Haliassos (forthcoming), and Agarwal, Chomsisengphet, Liu and Souleles (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. Telyukova and Wright (2008) argue that the puzzle is an illusion, which can be explained by a model of variable transaction needs. 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're 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 (Caskey 1994, Skiba and Tobacman 2008b, e.g.) and survey evidence about the alternatives available to payday borrowers. Regarding the latter, a nationally representative sample of one thousand payday loan

[3] To emphasize again, this is a per-loan proportional charge, not an APR.

[4] It would be to interesting to investigate how $LOSS$ varies through the population, e.g. by regressing $LOSS$ on the controls in the credit card dataset (including a high-order polynomial in the FICO score), and looking at predicted values for typical customers.

customers, surveyed by Elliehausen and 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 IoData (2002) and covering 2600 payday borrowers found 55 percent in possession of credit cards. Again, access to liquidity for 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 in Table 1. First, credit card liquidity falls by $545 over the previous year on average, an amount that is much larger than the average $300 size 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. However, fourth, 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.

3 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, 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 Appendix Tables A4-A5 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 1sd increase predicting a default probability that is lower by 7.6 percentage points. This makes it somewhat puzzling 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 A5 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 had 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 or not 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 more 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 Teletrack scores and not FICO scores when making lending decisions, and why do credit card issuers not aggressively seek information about payday borrowing by their customers?

4 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, Zinman (2009) and Borzekowski and Kiser (2008) discuss models of account-specific characteristics that can incorporate the realistic variety of pecuniary, non-pecuniary, and cognitive costs, pointing us in a promising direction.

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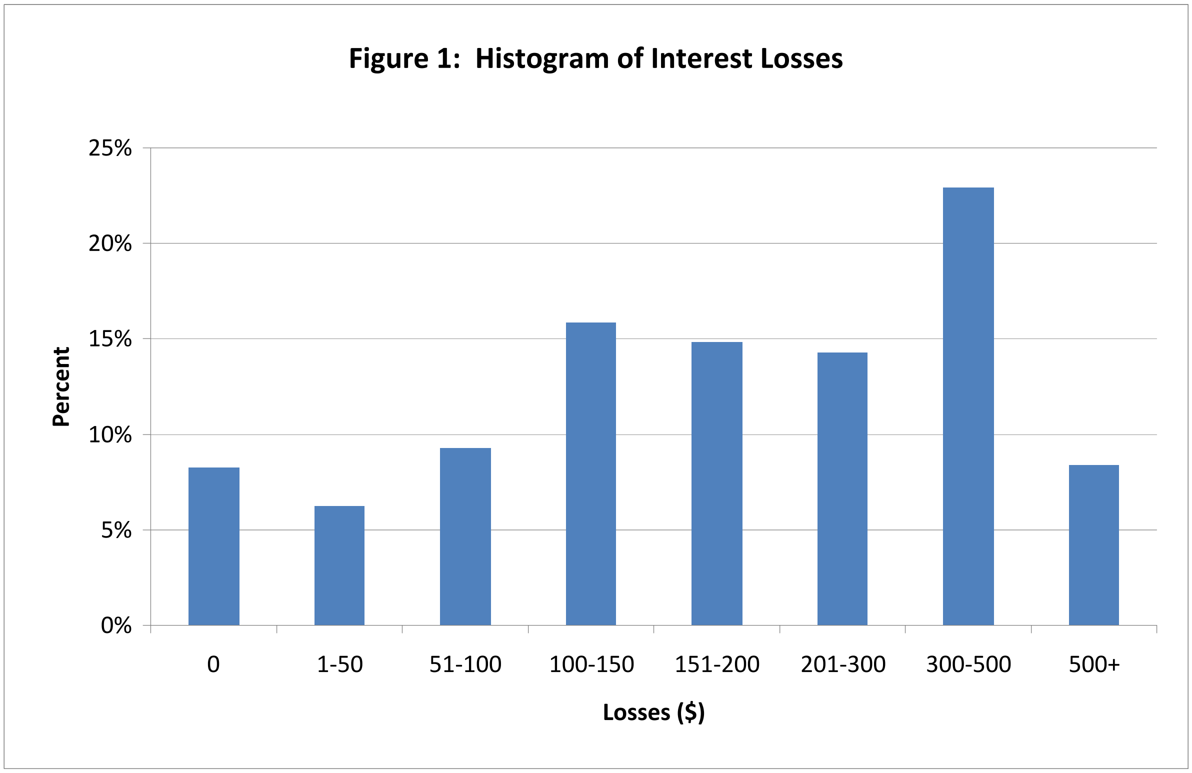
Figure 1: Histogram of Interest Losses
Percent
25%
20%
15%
10%
5%
0%
0
1-50
51-100
100-150
151-200
201-300
300-500
500+
Losses ($)

Table 1
Liquidity Declines as the Payday Borrowing Event Approaches

Lag Time Before the PDL (Months)	Liquidity Percentiles ($)				Liquidity ($)	
	90th	75th	25th	10th	Mean	Std
t-12	2557	2018	1069	478	1556	1036
t-11	2581	2086	1070	440	1572	1171
t-10	2531	2091	1118	395	1587	991
t-9	2587	1841	1023	382	1413	1205
t-8	2451	1739	867	357	1595	1104
t-7	2460	1643	867	346	1421	1148
t-6	2509	1585	804	334	1380	1118
t-5	2319	1585	793	311	1396	899
t-4	2348	1375	711	282	1284	842
t-3	2280	1395	663	287	1249	818
t-2	2171	1390	664	265	1122	722
t-1	2177	1359	623	262	990	677
t	2102	1244	583	263	1011	653

Appendix Table A1
Summary Statistics: Credit Card Data

	Unmatched Sample		Matched Sample	
	Mean	Std Dev	Mean	Std Dev
Overall Characteristics				
Fico Score	729.57	69.20	673.44	67.61
Income	62258.29	244547.48	34115.48	100286.85
Number of CC Accounts	25.76	11.60	22.51	11.86
Open CC Accounts	3.67	3.41	3.19	3.01
Open CC with balance	2.14	2.37	2.63	2.50
Total Balance of CC	6625.79	11640.12	10917.41	15355.09
% Delinquent	5.45%	77.26%	13.85%	56.05%
Issuer's Credit Card				
Account Age (months)	93.33	81.44	62.27	54.26
Behavior Score	593.55	262.08	545.62	288.66
Credit Line	7521.94	3665.30	3240.29	3652.78
Current Balance	2968.02	2992.54	2479.44	2796.09
Chargeoff Amount	4867.48	3817.89	3773.32	3588.47
Purchases	256.42	744.62	240.49	75181.91
Number of Monthly Purchases	2.01	3.30	1.85	3.54
APR	17.57	5.71	18.23	6.37
Cycle Payments	319.94	864.28	209.79	644.13
Monthly Payments	340.08	908.27	343.59	96191.91
Debt	1933.10	2840.80	2120.30	3218.55
Cycle Cash Withdrawl	10.13	144.38	3.91	64.60
Cycle Purchases	259.01	749.69	146.78	510.37
Other Accounts with this Issuer				
Home Equity Blanace	2531.58	12620.68	1669.09	7586.31
Mortgage Balance	43849.55	87776.67	31585.94	71495.08
Auto Balance	3944.08	7335.66	2632.25	8369.89
Demographics				
Female Applicant	30%	31%	18%	38%
Co-Applicant	11%	32%	22%	41%
Singles	32%	47%	33%	47%
Age	51.06	16.97	50.78	14.34
Number of Accounts	143,228		3090	

Appendix Table A2

Summary Statistics: Payday Loan Data

	Unmatched Sample		Matched Sample	
	Mean	Std Dev	Mean	Std Dev
Teletrack Score	626.09	166.36	424.65	282.88
<u>Income Variables</u>				
Paid Monthly	0.17	0.37	0.14	0.35
Paid Biweekly	0.52	0.50	0.34	0.47
Paid Weekly	0.15	0.36	0.09	0.29
Monthly Pay ($)	1685.98	1074.02	1731.22	1048.40
Job Tenure (Years)	4.66	7.57	5.75	8.60
Garnishment from Paycheck	1.03	0.16	1.03	0.16
<u>Banking Variables and Demographics</u>				
Months at Residence	68.89	94.40	81.83	100.52
Bank Balance on Last Statement ($)	257.39	546.21	222.09	510.21
NSF Count on Last Statement	1.00	2.62	1.04	2.61
Age	37.15	11.46	50.78	14.34
Female	0.63	0.48	0.60	0.49
Number of Accounts	102779		3090	

Appendix Table A3
Credit Card Liquidity and APRs in the Matched Sample

A: FICO Ranges	Variables	Mean	Std	N
<500	liquidity	-554.45	701.95	41
	apr	24.48	3.22	41
500-550	liquidity	-356.49	927.11	93
	apr	23.66	5.43	93
550-600	liquidity	496.27	1698.95	216
	apr	21.32	7.37	216
600-650	liquidity	711.81	2967.09	834
	apr	20.39	6.95	834
650-700	liquidity	1099.00	3281.15	1153
	apr	17.53	6.23	1153
>700	liquidity	2050.20	3797.71	753
	apr	15.02	5.85	753
B: Revolvers/Transactors				
Debt Revolvers	liquidity	613.93	3082.05	2264
	apr	19.05	6.71	2264
Transactors	liquidity	2498.54	3604.64	826
	apr	16.01	5.33	826
C: Single/Married				
Married	liquidity	1315.66	2277.76	2069
	apr	18.24	6.32	2069
Single	liquidity	720.11	3006.74	1021
	apr	18.20	6.49	1021
D: Age Range				
<30	liquidity	1091.01	4034.30	272
	apr	18.79	6.30	272
30-40	liquidity	976.99	4189.46	535
	apr	18.45	6.47	535
40-50	liquidity	896.28	4154.83	856
	apr	17.95	6.61	856
50-60	liquidity	963.12	4466.89	802
	apr	17.99	6.16	802
60-70	liquidity	1497.23	3908.58	334
	apr	18.42	6.45	334
>70	liquidity	2048.72	3585.83	291
	apr	18.53	5.85	291

Notes: Calculated by the authors from matched administrative data. "Liquidity" refers to credit card liquidity on the days individuals take out their first payday loans. Liquidity is calculated as the difference between the credit limit on the credit card and the amount of outstanding debt. The APR is the average over accounts within the group and is not debt weighted. "Transactors" are defined as credit card account holders who paid their credit card bills in full in the one month before taking out their first payday loans. Note that each partition contains the total of 3090 people in the matched sample.

Appendix Table A4

Predictors of Payday Borrowing and Default

Variables	Payday Loan Amount ($)			Probability of Payday Loan Default			
	Coeff Val	Std Err	T-Stat	Coeff Val	Std Err	T-stat	Marg Eff.
Credit Scores							
FICO Score	-0.06331	0.01380	-4.58	-0.02697	0.00176	-15.32	-0.11%
Teletrack Score	0.07740	0.02597	2.98	-0.06006	0.00200	-30.03	-0.04%
Credit Card Account Variables							
Credit Line	-0.00530	0.00180	-2.94	-0.00056	0.00012	-4.66	-0.05%
APR	0.05200	0.00476	10.92	0.13210	0.02070	6.38	0.05%
Account Age	-0.08822	0.02700	-3.26	-0.03337	0.00332	-10.05	-0.17%
Payment Amount	0.03589	0.00700	5.12	-0.00793	0.00082	-9.67	0.05%
Purchase Amount	0.00600	0.00132	4.54	0.01340	0.00135	9.92	0.10%
Balance of Credit Card	0.00053	0.00025	2.13	0.00069	0.00001	69.01	0.01%
Overdue Minimum Payment (Dummy)	19.19370	1.09650	17.50	0.40539	0.03342	12.13	3.90%
Number of Days Overdue	4.34420	0.17660	24.59	0.14592	0.07100	2.05	0.66%
Number of Days Before the Due date	-3.31410	0.61221	-5.41	0.06320	0.06469	0.97	0.28%
Other CC Issuer Variables							
Auto Balance	0.00019	0.00004	4.97	0.00703	0.00230	3.05	0.02%
Mortgage Balance	0.00003	0.00007	0.49	0.00083	0.00022	3.77	0.02%
Income Variables							
Paid Monthly	-5.26310	17.35700	-0.30	-0.09816	0.48640	-0.20	-0.01%
Paid Biweekly	0.43350	10.99200	0.03	-0.00317	0.28677	-0.01	-0.02%
Paid Weekly	-14.93060	6.33300	-2.35	-0.09075	0.24304	-0.37	-0.10%
Monthly Pay	0.02014	0.00310	6.49	-0.00003	0.00012	-0.26	-0.01%
Job Tenure	0.90007	0.28670	3.13	-0.04652	0.00732	-6.35	-0.02%
Garnishment from Paycheck	-14.43000	8.99580	-1.60	0.01516	0.02388	0.63	0.02%
Banking Variables and Demographics							
Months at Residence	-0.00200	0.04199	-0.04	-0.00430	0.00166	-2.59	-0.10%
Balance	1.31000	0.11800	11.10	0.00205	0.00027	7.59	0.02%
NSF Count	1.11130	0.36010	3.08	0.01110	0.00400	2.77	0.10%
Age	0.04168	0.02613	1.59	0.01854	0.00788	2.35	0.08%
Male	-0.32060	0.13000	-2.46	0.07559	0.07219	1.04	0.08%
Intercept	208.49400	37.18800	5.60	-0.04898	0.00491	-9.98	
Number of Obs	3090			3090			
R-Sq	0.3402			0.0627			

Appendix Table A5

Credit Card Borrowing and Default

	Credit Card Usage			Credit Card Default			
Variables	Coeff Val	Std Err	T-Stat	Coeff Val	Std Err	T-Stat	Marg Eff.
Credit Scores							
FICO Score	-0.0075	0.0127	-0.59	-0.0085	0.0015	-5.78	-0.02%
Behavior Score	-0.0058	0.0032	-1.81	-0.0099	0.0011	-9.21	-0.04%
Teletrack Score	-0.0054	0.0028	-1.93				
Payday Loan Account Variables							
PDL Application Dummy				0.9238	0.1387	6.66	0.063425
Number of Days since PDL	0.0694	0.0186	3.73				
Payday Loan Size ($)	0.0208	0.0079	2.63				
Credit Card Account Variables							
Credit Line				-0.0011	0.0002	-4.79	0.00%
APR	-0.0133	0.0015	-8.87	0.0230	0.0047	4.80	0.04%
Account Age	0.0080	0.0242	0.33	-0.0098	0.0055	-1.79	-0.01%
Payment Amount				-0.0019	0.0009	-2.03	-0.01%
Purchase Amount				-0.0009	0.0002	-4.41	-0.01%
Balance of Credit Card				0.0028	0.0005	5.79	0.02%
Other CC Issuer Variables							
Auto Balance	-0.0049	0.0020	-2.45	0.0002	0.0001	3.52	0.00%
Mortgage Balance	-0.0006	0.0001	-6.00	0.0000	0.0000	5.16	0.00%
Income Variables							
Paid Monthly	-0.0372	0.0187	-1.99				
Paid Biweekly	-0.0376	0.0152	-2.47				
Paid Weekly	-0.0304	0.0066	-4.61				
Monthly Pay	0.0122	0.0018	6.78				
Job Tenure	0.0046	0.0036	1.28				
Garnishment from Paycheck	0.6533	0.6286	1.04				
Banking Variables and Demographics							
Months at Residence	0.0008	0.0019	0.42				
Balance	-0.0013	0.0016	-0.81				
NSF Count	0.0575	0.0707	0.81				
Age	0.0349	0.0090	3.88				
Male	0.1243	0.3448	0.36				
Intercept	0.4181	0.0606	6.90	-1.9797	0.2463	-8.04	
Number of Obs	3090			215,927			
R-Sq	0.4808			0.1022			