Essays on Household Finance: Income, Consumption, Debt, and Financial Delinquency

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Essays on Household Finance:
Income, Consumption, Debt and Financial Delinquency

BY

Philippe d'Astous

A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree

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ACCEPTANCE

This dissertation was prepared under the direction of the Philippe d'Astous Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctoral of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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ABSTRACT

Essays on Household Finance:
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BY

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March 17th, 2016

Committee Chair: Stephen Shore
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This dissertation consists of three chapters. The first chapter uses credit card data to estimate the impact of increasing minimum payments on delinquency, payments, spending, and write-offs. The identification strategy exploits an unusual institutional feature: borrowers can use their account to make purchases with both revolving loans (on which minimum payments increased) and term loans (on which there was no change). Payment increases by delinquent borrowers are insufficient to match increasing minimums, resulting in lower cure rates and an increase in write-offs. Affected borrowers migrate away from these accounts by decreasing charges and increasing payments, consequently lowering the interest earned by the bank.

The second chapter analyzes the response of consumption, debt, and delinquency to an anticipated increase in cash-on-hand in the presence of liquidity constraints. It uses account-level data from a North American bank that allows clients to make purchases using credit card and term loans on the same account. Term loans are paid off in a predetermined number of equal monthly installments. The end of a term loan therefore generates a predictable

increase in cash-on-hand relative to months in which payments were required. Consistent with a model in which consumers are potentially liquidity constrained, consumers *ex-ante* identified as unconstrained do not increase their credit card expenditures, constrained consumers increase both their credit card expenditures and balance, and consumers for whom the credit card is the marginal source of funds decrease their balance. The propensity to take out a new term loan increases for all consumers, whether constrained or not. About 4% of unconstrained consumers delay taking out a new term loan until the original loan is repaid, contrary to theoretical predictions. Paying off the term loan reduces financial delinquency and the probability of default.

The third chapter analyzes the comovement of personal savings and income using administrative data provided by a North American bank that records the sum of monthly direct deposit income into its clients' checking accounts. It investigates how permanent and transitory income changes are smoothed by checking account balances. Transitory income changes, whether positive or negative, have only transitory effects on checking account balances, suggesting that consumption is excessively sensitive to them compared to theoretical predictions. Permanent income changes lead to permanent adjustments in consumption and modest permanent adjustments in checking account balances, consistent with theoretical predictions. There is evidence of anticipation of future income changes as much as three months in advance.

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Contents

List of Figures

List of Tables

Chapter 1

Liquidity Constraints and Credit Card Delinquency: Evidence from Raising Minimum Payments[1]

Abstract

We use credit card data to estimate the impact of increasing minimum payments on delinquency, payments, spending, and write-offs. Our identification strategy exploits an unusual institutional feature: borrowers can use their account to make purchases with both revolving loans (on which minimum payments increased) and term loans (on which there was no change). Payment increases by delinquent borrowers are insufficient to match increasing minimums, resulting in lower cure rates and an increase in write-offs. Affected borrowers migrate away from these accounts by decreasing charges and increasing payments, consequently lowering the interest earned by the bank.

JEL Classification: D12, D14, E21, G21.

[1]This essay is co-authored with Stephen Shore and is forthcoming in the *Journal of Financial and Quantitative Analysis*. We are grateful to Chris Carroll, Pierre-André Chiaporri, Keith Crocker, Glenn Harrison, Benjamin Keys, Maurizio Mazzocco, Kathleen McGarry, Corina Mommaerts, Noah Stoffman, and Tyson Van Alfen for helpful comments. We also thank seminar participants at the Cornell University IBHF Symposium on Household and Behavioral Finance, the Cleveland Federal Reserve Bank Household Economics and Decision Making Conference, the Georgia State University Income Risk Workshop, the 2015 FMA Annual Meetings, and the Huebner PhD Colloquium in Seattle for their valuable suggestions.

1.1 Introduction

Credit cards provide revolving lines of credit with low minimum monthly payments, typically 1% to 5% of the balance. Borrowers who choose to make only these minimum payments can take years to pay down their loan completely. Of the 68% of households holding at least one credit card, 55% revolve a balance (2010 U.S. Survey of Consumer Finances) and 18% make the minimum required payment on the account each month (TransUnion).

The Credit Card Accountability Responsibility and Disclosure (CARD) Act of 2009 increased transparency and restricted fees that could be charged on credit cards. To nudge borrowers into repaying their debt faster, the CARD Act forced issuers to disclose; a) the time needed to pay down the balance when making only the minimum payment, and b) the monthly payment required to pay down the balance in 36 months. These disclosure rules increased the payments made by borrowers who were previously paying only a small fraction of their balance (Agarwal et al., 2013; Jones et al., 2014; Keys and Wang, 2014).

We use proprietary data from a large North American bank for which the minimum payment required to remain current on credit card accounts was increased from 3% to 5% of the revolving balance.[2] Examining this change allows us to determine the impact of an actual increase in credit card minimum payments, as opposed to the impact of a disclosure rule intended to nudge borrowers into making higher debt repayment.

Our identification strategies exploit two different dimensions in which borrowers could be more or less affected by the policy. First, based on the nature of their credit card debt, minimum payments increased more for some borrowers than others. The bank allows borrowers to use their credit card to make purchases on both revolving loans (with no fixed term, on which the minimum payments increased) and term loans (with a fixed interest rate and repayment schedule, on which there was no policy change). Borrowers differ in the proportion of their revolving credit and, consequently, in the size of the minimum payment increase. Second, some borrowers are more affected than others, based on the revolving

[2]Minimum payment requirements bind for roughly 10% of borrowers in our sample. For these borrowers,the marginal cost of outside funds exceeds the interest rate on the credit card but is lower than the shadow cost of delinquency. The outside cost of funds could result from borrowing elsewhere or from reducing spending.

balance share they wish to pay down. Borrowers who wish to pay the balance in full are unaffected by the change. We use borrowers' payment histories to identify ex-ante those who are likely to make minimum payments and are therefore affected by the increase. Changes following the policy introduction are limited to borrowers for whom minimum payments actually increased and, within that group, to those likely to make minimum payments. We exploit both variations in an identification strategy akin to difference-in-differences: we compare the difference in outcomes across borrowers differently exposed to — or affected by — the minimum payment increase, before and after its implementation.

We examine the effect of minimum payment increases on payments, spending, delinquency, and write-offs. Current borrowers comply with the policy by consistently making the increased minimum payments. For delinquent borrowers, the payment increase is not sufficient to match the new minimum payment required; this results in a drop in cure rates (the rate at which accounts go from delinquent to current). The lower cure rate leads to a spike in write-offs six months after the policy change, as it takes six months for a current account to default when no additional payments are made on the account. In response to the policy change, the affected borrowers reduce spending on their credit card, increase their payments and, consequently, reduce their revolving balance. We investigate the transitory nature of the increase in write-offs and find it is driven by the group of borrowers identified ex-ante as those making small payments on their revolving debt, and were therefore most likely to be constrained by the new minimum payment requirement. The bank is affected by the increased write-offs and by the loss of interest revenues due to decreasing balances.

Our findings relate to a growing body of literature investigating credit card debt paydown in response to nudges (see discussion on the CARD Act above), institutional changes in minimum payments, and self-set goals. Traditional models have a difficult time explaining why borrowers would revolve a large amount of credit card debt while simultaneously holding low-yield liquid assets (Zinman, 2015). This has been called the "credit card debt puzzle". Such behavior can be rationalized with present-biased preferences (Meier and Sprenger, 2010; Skiba and Tobacman, 2008), although Telyukova (2013) shows the need for liquidity can almost fully explain why rational borrowers would hold both liquid assets and revolving debt simultaneously. Disentangling liquidity constraints (Carroll and Kimball, 1996; Carroll, 2001; Carroll and Kimball, 2005)[3] from hyperbolic discounting (Angeletos et al., 2001) can be challenging. Kuchler (2015) investigates credit card paydown for borrowers who sign up for a self-set planned payment schedule and finds planned debt paydown is the strongest predictor of actual paydown, although most borrowers fall short of their own goals. After eliminating potentially constrained borrowers, she suggests hyperbolic discounting could explain borrowers' failure to maintain a self-set repayment plan.

We find that borrowers most likely to make minimum payments also reduce spending on their card. This reduced spending — coupled with increased payments — leads to a drop in their revolving balance, and suggests migration away from a product providing an undesirable repayment schedule. These results are consistent with forward-looking behavior and inconsistent with naive hyperbolic discounting.

The paper closest to ours is a working paper by Keys and Wang (2014) which, in addition to their study of the CARD Act, exploits data from US banks that increased their floor minimum credit card payment. Our results complement theirs, but the policy change we study affects higher credit card balances and is likely to bind for more borrowers.[4]

1.2 Identification and Data

We use credit card data from a North American bank that recently changed its minimum payment policy. The new policy requires an increase in the fraction of the current revolving credit card balance that must be paid each month to keep the borrower out of delinquency. The previous minimum payment was either \$10 or 3% of the revolving balance, whichever

[3]Zeldes (1989) tests for the presence of liquidity constraints by estimating consumption Euler equations for groups of borrowers who have low assets. Jappelli et al. (1998) define constrained borrowers as those who were previously refused a loan, or who do not have access to a credit line. Closer to our interpretation of liquidity constraints, Gross and Souleles (2002a) and Agarwal et al. (2007) argue that households paying high interest rates on their revolving loans can also be thought of as liquidity constrained, due to the lack of a cheaper source of funding.

[4]Because *floor* minimum amounts were low both before and after their policy change, making these payments is a challenge only for the most constrained borrowers, and only affects low revolving balances. In contrast, the policy change we study results in a substantial dollar amount increase for the average borrower, due to a much higher initial balance. For the average revolving balance of \$2,300 in our sample, the minimum payment increases from \$69 to \$115.

is greater; the minimum increased to either \$10 or 5%, whichever is greater.[5] For revolving balances over \$333, the new policy represents a 66% increase in minimum payments. This change became mandatory for all account holders on a specific date, omitted here to protect data-provider confidentiality.

Borrowers can use their account to make purchases with both revolving loans (with no fixed term, on which the minimum payments increased) and term loans (with a fixed interest rate and repayment schedule, on which there was no policy change). Term loans can be contracted directly from the bank or at select merchants to finance durable goods, and are repaid in equal monthly installments over 12, 24, 36, 48 or 60 months. Both types of loans are linked to the same account and there is no penalty for prepaying either. These types of loans differ in the minimum payment schedule needed to keep the account current.[6]

Accounts can be current, or 1, 2, 3, 4, or 5 cycles delinquent; accounts that are six cycles delinquent are considered to be in default and must be written off. There is no distinction between delinquency on the revolving and term loans. The number of cycles delinquent depends on the payment history, not merely on the number of calendar months the account has been delinquent. The total minimum payment due is the sum of; a) the minimum payment on the revolving balance, b) the installment payment on the term balance, and c) any overdue amount from previously missed payments. For delinquent borrowers, paying this sum "cures" (makes current) the account; borrowers who pay less than this sum become or remain delinquent.[7] Appendix 1.6 shows a hypothetical account statement.

1.2.1 Identification Strategy

Our analysis highlights two different treatment effects: for *exposed* and *affected* borrowers. We identify the effect of increasing minimum payments; a) for borrowers *exposed* to the policy change (for whom minimum payments increased), and b) for the subset of borrowers

[5] All amounts are presented in local currency.

[6] For revolving loans, the minimum payment is 3% or 5% of the balance each month. For term loans, the minimum payment is a fixed dollar amount, and increases as a percentage of the balance from 5.6%, on average, at origination to 100% just before paydown.

[7] Accounts move forward in delinquency cycles (e.g., from 1 cycle delinquent to 2 cycles) when the total payment falls below the sum of (a) and (b) above; accounts can improve in delinquency cycles without curing if a portion of the overdue amount (c) is paid.

actually *affected* by the change (those likely to make minimum payments). First, because minimum payments increased on revolving balances but not on term loans, borrowers with a larger share of revolving debt are more *exposed* to the change. We define exposure to the policy change as the proportion of revolving balance to total balance:

$$\text{Prop Revol}_{i,t} = \frac{\text{Revolving Balance}_{i,t}}{\text{Revolving Balance}_{i,t} + \text{Term Loan Balance}_{i,t}}. \tag{1.1}$$

Second, the policy change only affects borrowers who were previously making payments at a level no longer sufficient under the new minimum payment requirement. We identify those borrowers by constructing a lagged measure of payments made on the revolving loan. We define *affected* borrowers using the average fraction of revolving balance repaid as:

$$\%\text{Revol Paid}_{i,t} = \frac{\text{Payments Made on the Revolving Account from } t \text{ to } t+1}{\text{Revolving Balance at } t}. \tag{1.2}$$

For each month t, we then calculate the rolling average of %Revol. $\text{Paid}_{i,t}$ over the months $t-12$ to $t-7$ and identify borrowers who were repaying less than 20%. Section 1.3 shows the effect of the policy is confined to this subset of borrowers. We present these results for the group of borrowers who do not have a term loan (i.e., their proportion of revolving balance is equal to 1), although the results could be extended to the entire sample with an appropriate set of control variables.

Our identification strategy compares the difference in outcomes across borrowers differently exposed to — or affected by — the minimum payment increase, before and after its implementation. In Section 1.3, we provide support for this research design by showing how these accounts followed parallel delinquency trends before the policy change, with the identifying assumption that they would have continued their parallel trends absent of the policy change (Angrist and Pischke, 2009).

Let $y_{i,t}$ be an outcome of interest — typically either payments, new purchases, indicators for delinquency transitions (e.g., when a current borrower goes delinquent), or write-offs.

Our main regression model in the analysis can be expressed as:

$$y_{i,t} = \delta_0 + \delta_1(\text{After?} \times \text{Treatment}_{i,t}) + \delta_2\text{Treatment}_{i,t} + \delta_3 \text{ After?} + \boldsymbol{\delta}_X\mathbf{X}_{i,t} + \epsilon_{i,t}. \quad (1.3)$$

"Treatment$_{i,t}$" measures whether the borrower is *exposed* to the policy change (as defined by equation (1.1)), or *affected* by the policy change (using a dummy variable to indicate whether the borrower was previously repaying less than 20% of the revolving balance in months $t-12$ to $t-7$, as defined by equation (1.2)). "After?" is an indicator variable that takes the value of one, if the observation is after the policy change, and zero otherwise. The key variable of interest is δ_1, which shows the response of borrowers affected by — or exposed to — the change relative to borrowers who are not.

$\mathbf{X}_{i,t}$ represents a vector of controls which vary in a sequence of four increasingly flexible specifications. The first specification excludes all controls. The second specification adds controls for; a) month fixed effects, b) a dummy variable indicating if the account only has a revolving balance, c) its interaction with a linear trend, and d) the interaction of the proportion of revolving balance with a linear trend. The third specification adds; a) delinquency cycle dummies, b) the interaction of linear delinquency cycles with a linear trend, and c) spell dummies (which indicate the number of months an account has spent in the current delinquency state). The last specification adds; a) six-months lagged measures of the total account balance, b) six-months lagged measures of the minimum payment that would have been required under the old policy, and c) the interaction of these variables. For these last variables, we construct bins that split the sample distribution into quartiles, and then we interact these dummy variables. In this specification, we also add a set of account characteristics.[8] Standard errors are corrected for within-account heteroscedasticity in all the specifications presented.

[8]This set of control variables includes: age and sex of the account holder; an external measure of credit score; an indicator variable equal to one if the borrower has other accounts at this institution; an indicator variable equal to one if the borrower pays for a reduced APR; APR charged on the revolving balance; average unemployment rate in the borrower's region; account age (in months); revolving credit limit; and utilization of the revolving balance (defined as revolving balance/revolving limit). All controls are taken at the beginning of the billing cycle to avoid spurious relationships with the independent variable.

1.2.2 Data Description

We use administrative data provided by a bank on the universe of its credit card accounts. Data include monthly information typically found on the front page of credit card statements, such as total spending, total payments, balance outstanding, interest rate, and delinquency. Data also include borrowers' demographic information — sex, age, credit score, and partial information about their zip code, for example. For accounts that default, we know the date of default and the amount written off. We do not have access to transaction-level data.

We monitor all accounts opened 12 months prior to the policy change, and follow them for 24 months or until they default, go bankrupt, or are closed in good standing, whichever comes first. We drop all accounts that were inactive during this subsample, as well as accounts with any missing months of observations. We focus on the subsequent borrower behavior of account-months observations with a revolving balance greater than \$333 because the floor minimum payment of \$10 did not bind for them, and their minimum payment therefore increased from 3% to 5%. The final sample covers $2,152,786$ accounts and $30,304,780$ account-months observations.[9]

Table 3.1 presents summary statistics for the sample. The average total balance is $\$3,410$, the average revolving balance is $\$2,300$ and the remaining $\$1,110$ is term loan balance. 28% of the sample has term loans, with an average balance of $\$3,947$. The total monthly payment is \$971. The average APR charged on the revolving balance is 17.05%. The external credit score is a bankruptcy prediction score and varies from 1 to $1,000$. Unlike FICO scores, which predict the probability of missing a payment on the loan, this type of measure predicts the probability of filing for bankruptcy in the next two years and is typically higher than average FICO scores.

Table 3.1 also shows the difference between all variables for accounts with high ($>$ 50%) and low ($\leq$ 50%) proportions of revolving balance. Although most variables differ, Section 1.3 shows these groups followed parallel delinquency trends before the policy change, consistent with the assumption outlined in our identification strategy. We control for these

[9] Many accounts never go delinquent, so we undersample them by randomly selecting 10% of them and assigning them a probability weight of 10. This yields $186,815$ overweighted accounts that never missed a payment in the period studied. All results presented are adjusted using an inverse probability weighting scheme.

Table 1.1: Descriptive Statistics

	Full Sample					Low Prop		High Prop		Diff
	Mean/(Std. Dev.)	p5	p50	p95	Obs.	Mean/(Std. Dev)	Obs.	Mean/(Std. Dev.)	Obs.	Mean/(Std. Error)
A. Account-Level										
Has Term Loan?	0.28	-	-	-	30,304,780	1.00	4,829,132	0.14	25,475,648	-0.86**
	-					-		-		(0.00)
Total Account Balance	$3,410	$416	$1,799	$11,955	30,304,780	$7,532	4,829,132	$2,628	25,475,648	-$4,904**
	($4,467)					($6,961)		($3,274)		(2.03)
Monthly Payment Made	$971	$0	$467	$3,500	30,304,780	$739	4,829,132	$1,014	25,475,648	$275**
	($1,799)					($1,147)		($1,895)		(0.89)
Payment/Balance (%)	0.44	0	0.20	1	30,304,780	0.14	4,829,132	0.50	25,475,648	0.36**
	(0.42)					(0.17)		(0.44)		(0.00)
Account Age (Months)	124.2	19.3	97.0	319.6	30,304,780	100.8	4,829,132	128.6	25,475,648	27.8**
	(95.9)					(82.1)		(97.7)		(0.05)
APR (%)	17.1	9.9	19.4	19.4	30,304,780	17.1	4,829,132	17.0	25,475,648	-0.1**
	(3.9)					3.8		3.9		(0.00)
External Credit Score	914	603	963	976	30,304,780	883	4,829,132	920	25,475,648	37**
	(141)					(169)		(134)		(0.07)
B. Credit Card										
Card Balance	$2,300	$397	$1,293	$7,661	30,304,780	$1,573	4,829,132	$2,438	25,475,648	$865**
	($2,810)					($1,698)		($2,954)		(1.39)
New Purchases	$816	$0	$328	$3,198	30,304,780	$474	4,829,132	$881	25,475,648	$406**
	($1,744)					($974)		($1,848)		(0.86)
Revolving Limit	$6,291	$500	$5,000	$18,700	30,304,780	$4,132	4,829,132	$6,700	25,475,648	$2,568**
	($136,802)					($341,501)		($12,418)		(67.90)
Balance/Limit (%)	0.53	0.06	0.49	1.03	30,304,646	0.62	4,829,118	0.51	25,475,528	-0.11**
	(0.50)					(0.89)		(0.38)		(0.00)
C. Term Loan | *Term Loan* > 0										
Term Loan Balance	$3,947	$162	$2,120	$14,206	8,518,692	$5,960	4,829,132	$1,311	3,689,560	-$4,648**
	($5,207)					($6,050)		($1,568)		(3.23)
Monthly Installment	$154	$0	$111	$441	8,518,692	$196	4,829,132	$99	3,689,560	-$97**
	($152)					($171)		($99)		(0.10)
Proportion of Revolving Loan (%)	0.46	0.07	0.43	0.93	8,518,692	0.25	4,829,132	0.74	3,689,560	0.49**
	(0.28)					(0.13)		(0.14)		(0.00)

Note: The descriptive statistics are calculated on account-month observations that have a revolving balance greater than $333 in a 24-month window around the policy change. Panel A presents account-level information, Panel B presents information concerning the revolving loan and Panel C presents information concerning the term loan attached to the account, if the borrower has one. “High Prop” and “Low Prop” indicate whether the account has more or less than 50% of its balance as revolving balance, respectively.

observable variables in the analysis and show our results are robust to their inclusion.

1.3 Main Results

In Section 1.3.1, we consider the impact of increased minimum payments on transitions into and out of delinquency, and from delinquency to write-off. We document a one-month, transitory spike in the share of current loans becoming delinquent and show how this spike passes through to write-offs six months later. We also show current borrowers comply with the new minimum payment requirements, so delinquency rates, on average are not affected. However, delinquent borrowers do not fully comply with the increased minimum payment requirements, resulting in a permanent drop in the cure rate. We further investigate the distribution of payments in Section 1.3.2. In Section 1.3.3, we decompose write-offs into exposure-at-default and the probability of being written-off. We investigate the forces driving the transitory increase in write-offs in Section 1.3.4, and show that borrowers affected by the increase in minimum payment reduce spending on the card, increase payments and, consequently, reduce their revolving balances as well as their future minimum payments. This provides evidence that borrowers who are most likely to be affected by the policy change migrate away from a product that no longer provides the desired repayment schedule.

1.3.1 Delinquency Transitions

Each month, an account can transition into one of three mutually exclusive delinquency states: current (C), delinquent (L), and written-off (W).[10] The write-off state is absorbing. Table 1.2 presents the proportion of accounts in each delinquency state, and the transition matrix between them. On average, 88.3% of the active accounts (those not written-off) are current, and the remaining 11.7% are delinquent. On average, 0.2% of active accounts are written off each month. A total of 93.7% of current accounts remain current in the next billing cycle, while 6.3% enter delinquency; virtually none are written off in the next billing cycle. Among delinquent accounts, 52.3% cure in the following billing cycle, while

[10] The delinquency state can also be further refined into the exact number of months past due.

Table 1.2: Aggregate Transition Probabilities

	C_t	L_t	W_t
C_{t+1}	0.937	0.523	0.000
L_{t+1}	0.063	0.460	0.000
W_{t+1}	0.000	0.017	1.000
% Accounts in each State	88.3%	11.7%	n/a

Note: This table shows the average transition probabilities between delinquency states calculated on account-month observations that have a revolving balance greater than $333 in a 24-month window around the policy change. The states are defined as (C) if the account is current, (L) if the account is at least one month late, (W) if the account is written off due to a default or due to bankruptcy.

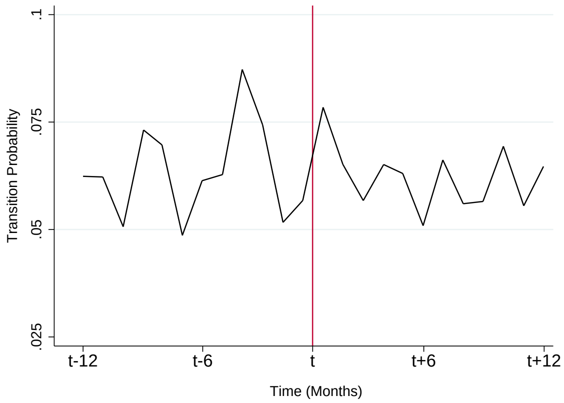
46.0% stay delinquent; 1.7% of delinquent accounts are written off each month into default or bankruptcy.

Figure 1.1 compares transitions before and after the minimum payment increase. The upper panels show the probability of entering delinquency; the middle panels show the cure rate for delinquent accounts; the bottom panels show write-off rates for delinquent accounts. The left panels show the average transition probabilities and the right panels show the breakdown of accounts with high ($\geq 95\%$) and low ($\leq 5\%$) proportions of revolving balance, as defined in equation (1.1).[11] Before the policy change, both high- and low-proportion-of-revolving-balance groups followed parallel trends with respect to delinquency transitions. This provides support for the parallel trend assumption required in this kind of difference-in-differences analysis (Angrist and Pischke, 2009).

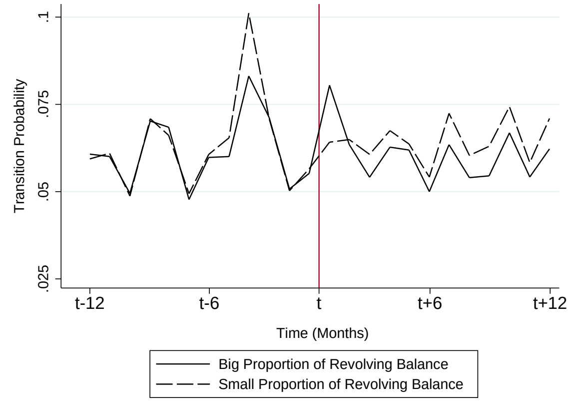
Panel (a) of Figure 1.1 shows no permanent change in transitions into delinquency, on average. However, when comparing high- and low-proportion groups, Panel (b) shows the high-proportion group experienced a spike in the rate of entering delinquency one month after the policy change. In Panels (e) and (f), this spike evolves into write-offs six months after the policy change, as it takes six month for an account to be written-off when no payments are made. The policy change had a permanent effect on the probability of curing delinquent accounts, as shown in Panels (c) and (d). Cure rates drop, on average, for borrowers with a high proportion of revolving balance, while they remain stable for accounts with a low

[11]Figure 1.1 shows month-to-month transitions for accounts with total (not revolving) balances greater than $333 to avoid dropping all but the highest-balance accounts among the group of accounts with a low proportion of revolving balance.

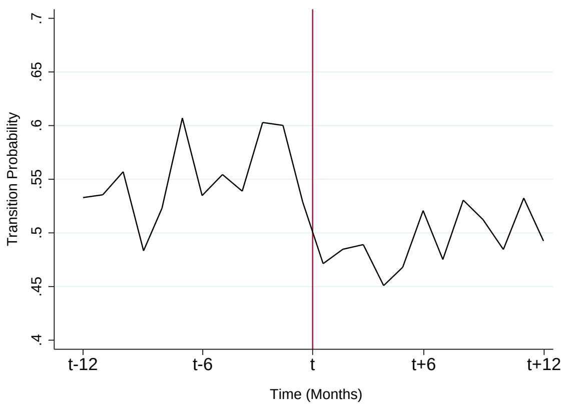
Figure 1.1: Transition Probabilities



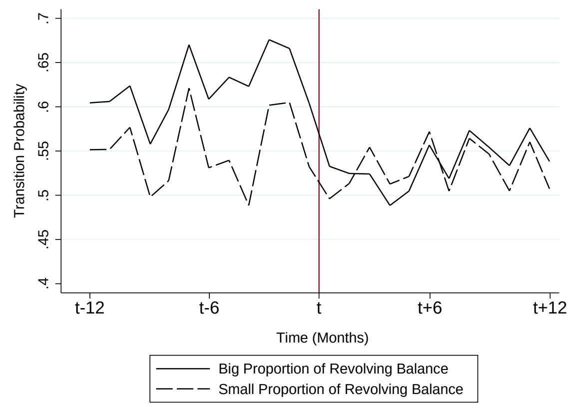
(a) $\mathbb{P}(L_{t+1}|C_t)$



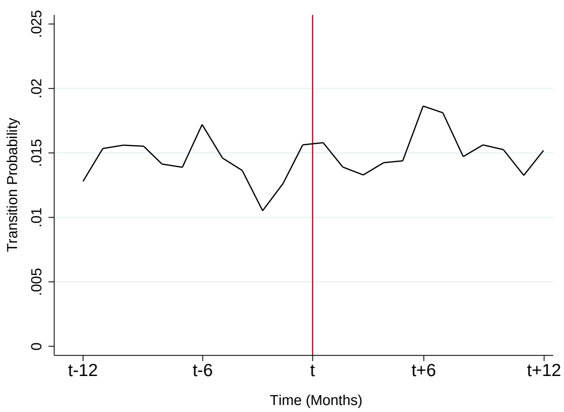
(b) $\mathbb{P}(L_{t+1}|C_t)$



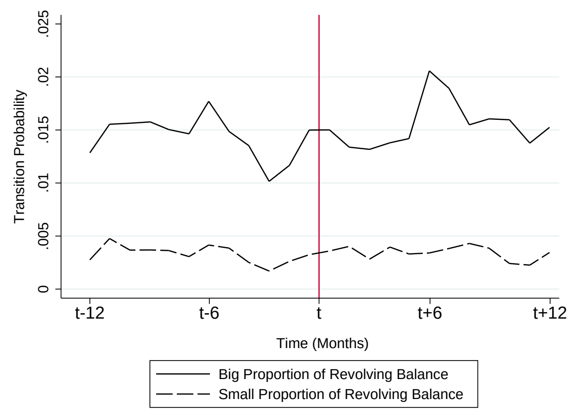
(c) $\mathbb{P}(C_{t+1}|L_t)$



(d) $\mathbb{P}(C_{t+1}|L_t)$



(e) $\mathbb{P}(W_{t+1}|L_t)$



(f) $\mathbb{P}(W_{t+1}|L_t)$

Note: This figure plots the aggregate transition probabilities between delinquency states for accounts that have a total balance greater than \$333 in a 24-month window around the policy change. Accounts are defined as having a big (greater than 95%) and a small (smaller than 5%) proportion of revolving balance to total balance to show the effect of the policy change for the groups most and least affected. We show month-to-month transitions for accounts with total (not revolving) balances greater than \$333 to avoid dropping all but the highest-balance accounts among the group of accounts with a low proportion of revolving balance.

Table 1.3: Effect of the Policy on Delinquency Transitions

	$\mathbb{P}(L_{t+1}\|C_t)$				$\mathbb{P}(C_{t+1}\|L_t)$				$\mathbb{P}(W_{t+1}\|L_t)$			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
After Change? × Prop. Revol.	0.0061**	0.0011	0.0021**	0.0013*	-0.0528**	-0.0845**	-0.0559**	-0.0502**	0.0015**	0.0028**	-0.0001	-0.0006
	(0.0005)	(0.0007)	(0.0007)	(0.0007)	(0.0021)	(0.0033)	(0.0029)	(0.0029)	(0.0004)	(0.0008)	(0.0006)	(0.0006)
After Change?												
$1 = yes$, $0 = no$	-0.0063**				-0.0333**				-0.0003			
	(0.0004)				(0.0018)				(0.0003)			
Prop. Revol.	-0.0143**	-0.0283**	-0.0133**	0.0337**	0.2530**	0.0814**	0.0812**	-0.0625**	-0.0068**	-0.0010	-0.0054**	0.0005
	(0.0005)	(0.0011)	(0.0009)	(0.0010)	(0.0016)	(0.0044)	(0.0031)	(0.0034)	(0.0003)	(0.0008)	(0.0007)	(0.0008)
Month F.E.	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES	YES
Only Revol.	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES	YES
Only Revol. × Trend	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES	YES
Prop. Revol. × Trend	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES	YES
Delinquency Dummies	-	-	-	-	NO	NO	YES	YES	NO	NO	YES	YES
Delinquency × Trend	-	-	-	-	NO	NO	YES	YES	NO	NO	YES	YES
Spell Dummies	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Total Bal. Dummies × Min. Pmt Dummies	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES
Account Characteristics	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES
R^2	0.000	0.004	0.099	0.136	0.020	0.024	0.154	0.186	0.002	0.003	0.516	0.528
Observations	26,668,849	26,668,849	26,668,849	23,979,721	3,534,717	3,534,717	3,534,717	3,310,085	3,534,717	3,534,717	3,534,717	3,310,085

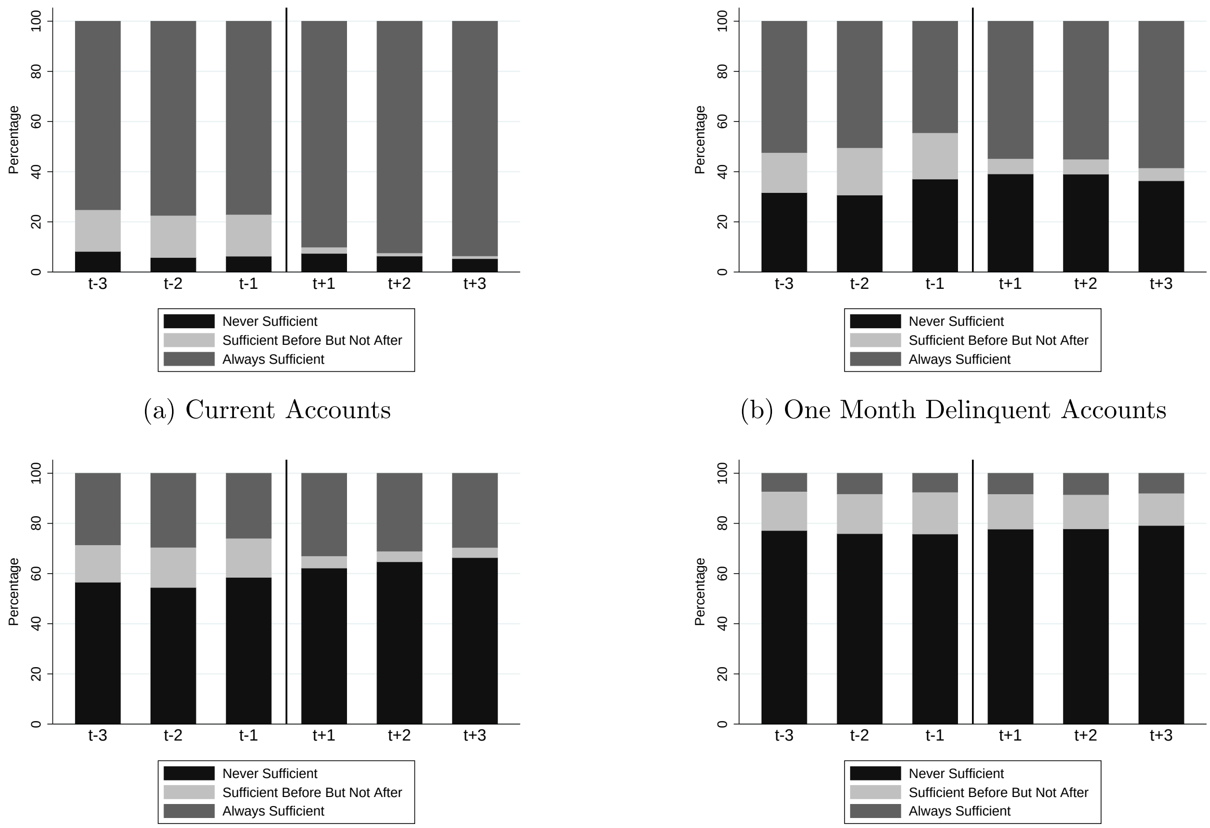
Note: This table shows the marginal effect of the policy on delinquency transitions estimated from a probit regression model using monthly credit card accounts with revolving balances greater than $333 in a 24-month window around the policy change. The set of control variables, which we group under "Account Characteristics" are age and sex of the account holder, an external measure of credit score, an indicator variable equal to one if the borrower has other accounts at this institution, an indicator variable equal to one if the borrower pays for a reduced APR, APR charged on the revolving balance, average unemployment rate in the borrowe's region, account age (in months), revolving credit limit and utilization of the revolving balance (defined as revolving balance/revolving limit). All controls are taken at the beginning of the billing cycle to avoid spurious relationships with the independent variable. Standard errors are corrected for within account heteroscedasticity in all the specifications presented. ** and * represent significance at the 1 and 5 percent levels, respectively.

proportion of revolving balance. Panel (f) shows the spike in write-offs six months after the policy change is confined to borrowers with a high proportion of revolving balance. Note that the transition rate from delinquency to write-off does not increase substantially, although a lower cure rate mechanically induces a larger number of accounts to be written-off each month.

Table 1.3 presents regression evidence on the effect of the policy change on transition rates. The table shows marginal effects calculated from probit regressions. The first set of results estimates the probability of entering delinquency for current accounts, and mirrors results from the top panels of Figure 1.1. Our main coefficient of interest — the interaction between the policy dummy and the proportion of revolving balance — is positive in all specifications: increasing minimum payments increases transitions into delinquency. However, this result is modest; in most specifications (and with varying statistical significance), increasing the minimum payment for current revolving-only accounts increases the probability of entering delinquency by 0.1 to 0.2 percentage points (a 1.6% to 3.3% increase on a base rate of 6.1% each month). The second set of results in Table 1.3 estimates the probability that a delinquent account cures, and mirrors results from the middle panels of Figure 1.1. Increasing minimum payments decreases the probability that an account cures by 5.1 to 8.5 percentage points (an 8.6% to 14.7% decrease on a base rate of 58.0%). These results are robust and highly significant. The third set of results estimates the probability that a delinquent account is written off, and mirrors results from the bottom panels of Figure 1.1. The results show no significant change in the probability that a delinquent account is written off in specifications with substantial controls (and a modest increase in specifications with fewer controls). We explore write-offs and the exposure at default further in Section 1.3.3.

Appendix Figure 1.10 compares borrowers who were either repaying less than or more than 20% of their revolving balance in a rolling window of months, $t - 12$ to $t - 7$. The figure indicates the results presented so far are confined to the group of borrowers who were previously repaying a small fraction of their balance each month. These borrowers are characterized by a transitory increase in the probability of entering delinquency, a permanent decrease in the cure rate, and a spike in write-off six months after the policy change. We

Figure 1.2: Proportion of Borrowers Making Payments Needed to Cure the Account



(a) Current Accounts

(b) One Month Delinquent Accounts

(c) Two Months Delinquent Accounts

(d) Three+ Months Delinquent Accounts

Note: This figure shows the proportion of account-month payments made relative to the minimum payment for observations that have a revolving balance greater than $333 in a six-month window around the policy change. The categories classify borrowers according to their payments being: never sufficient to cure the account; sufficient to cure the account before but not after the policy change; and always sufficient to cure the account. The counterfactual minimum payments used are based on the monthly revolving balance. The horizontal line represents the date of the policy change.

further investigate this group of borrowers to explain migration away from the credit card in Section 1.3.4.

1.3.2 Payments

Delinquency transitions are determined by the proportion of borrowers who make at least the minimum payments. To show the effect of the policy change on the segment of borrowers making the minimum payment, we construct counterfactual payments that would be required under the 3% and 5% rules. We classify monthly payments made into three categories: payments never sufficient to cure the account; payments sufficient to cure the account before but not after the change; and, payments always sufficient to cure the account.

Figure 1.2 shows that fewer current borrowers make payments sufficient to avoid delinquency before than after the policy change. The shift is almost perfect, with only a marginal increase in accounts paying less than the minimum payment after the policy change. This is consistent with the weak or absent evidence of increased transitions into delinquency by current borrowers in Figure 1.1 and Table 1.3. Among delinquent accounts, the fraction of borrowers who make payments in a range that would be sufficient to cure before but not after the policy change does not drop substantially; for highly delinquent accounts it barely drops at all. These results are consistent with the evidence from Figure 1.1 and Table 1.3. The policy change sharply reduced the cure rate for delinquent accounts, as borrowers continued to make payments in a range that is no longer sufficient to cure the account.

Figure 1.3 shows the change, induced by the increased minimum payment, in the distribution of payments made each month (as a fraction of the balance). We construct these estimates with a logistic quantile regression (Bottai et al., 2009) to predict the fraction of the balance paid using the covariates from our baseline specification.[12] The figure shows the predicted distributions of borrowers with only revolving balances before and after the policy change. Panel (a) of Figure 1.3 shows that, on average, current borrowers did not change the fraction of the payments made on the account after the policy change. This is what we would expect from a policy that affects only the minority of borrowers who were repaying around 3% of their balances before the policy change. Consistent with the finding that current accounts did not significantly increase their probability of entering delinquency, Panel

[12]Borrowers can pay more than 100% of their balance by making purchases and corresponding payments in the same billing cycle so we top-code the proportion of the balance paid at 100%. The regression includes observations in the six-month window around the policy change and is specificied as follows:

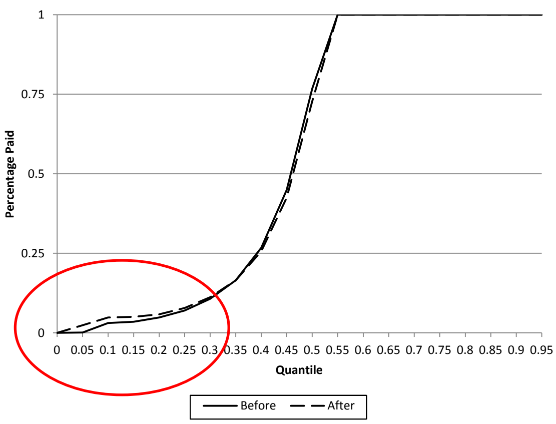
$$\begin{aligned} Q\tau(\text{logit}(pmt_{i,t})|\mathbf{X}_i) = \beta_0 + &\beta_1(\text{After?} \times \text{Prop Revol}_{i,t}) + \beta_2\text{Prop Revol}_{i,t} + \boldsymbol{\beta}_3\text{Only Revol}_{i,t} \\ &+ \boldsymbol{\beta}_4(\text{Only Revol}_{i,t} \times \text{Trend}_t) + \boldsymbol{\beta}_5\textbf{Month F.E.}_t + \epsilon_{i,t}, \end{aligned} \tag{1.4}$$

where $Q\tau(\text{logit}(pmt_{i,t}))$ represents the τth quantile of the $pmt_{i,t}$ distribution using the logistic transformation. The fraction of the balance that is repaid is defined as

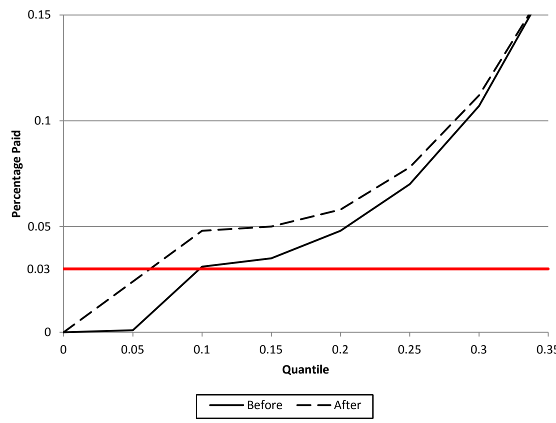
$$pmt_{i,t} = \frac{\text{Payments Posted on the Account for Statement of Date } t}{\text{Total Account Balance for Statement of Date } t}. \tag{1.5}$$

The logistic transformation is given by $logit(y) = \frac{y - y_{min}}{y_{max} - y}$ and ensures that predictions of the dependent variable will not exceed its lower and upper bound limits. We follow Bottai et al. (2009) and add $\epsilon = 0.001$ to allow values of y on the boundaries. We estimate all quantiles independently, starting at the fifth one and increasing in steps of 5%. Appendix Table 1.7 presents the regressions used to construct Figure 1.3, including the confidence intervals for the gap between the "before" and "after" distributions.

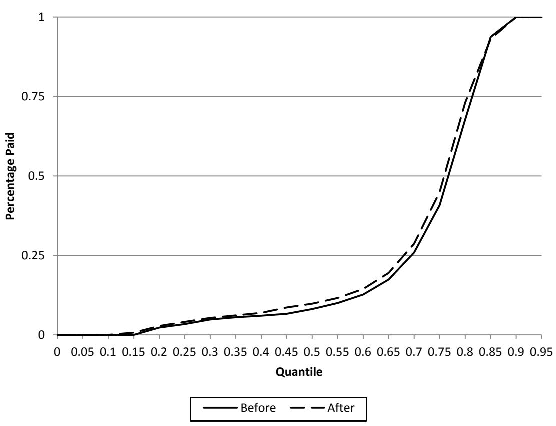
Figure 1.3: Payment Distributions



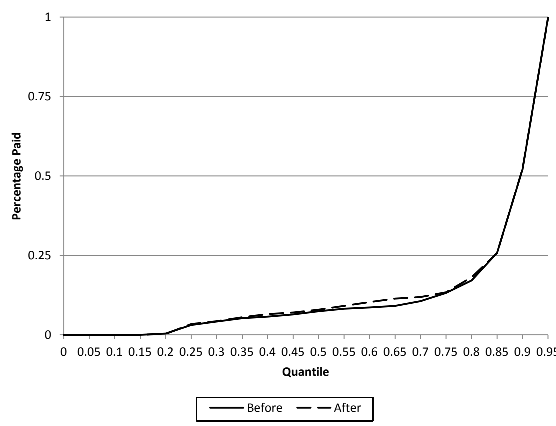
(a) Current Accounts



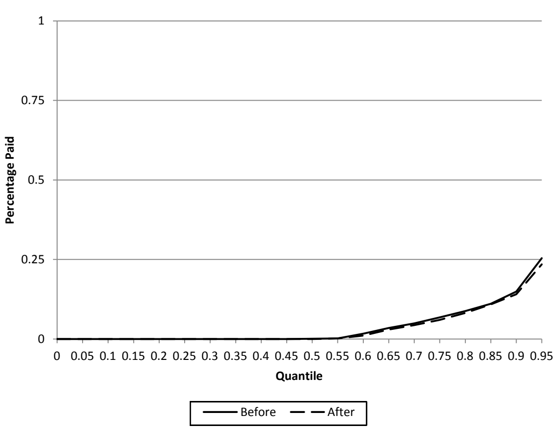
(b) Current Accounts (ZOOM)



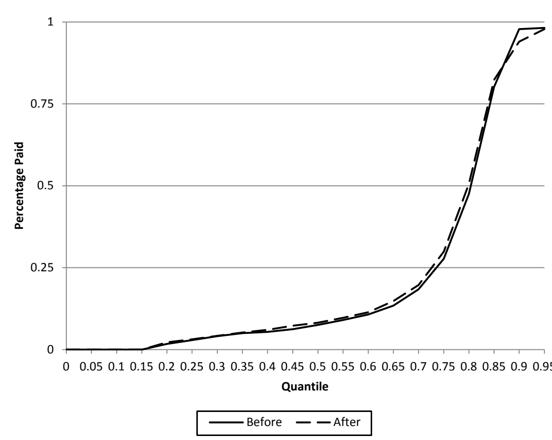
(c) One Month Delinquent Accounts



(d) Two Month Delinquent Accounts



(e) Three+ Months Delinquent Accounts



(f) All Delinquent Accounts Pooled

Note: This figure plots the conditional payment quantiles before and after the policy change as predicted by the results of Table 1.7, evaluated at a proportion of the revolving balance of 100%.

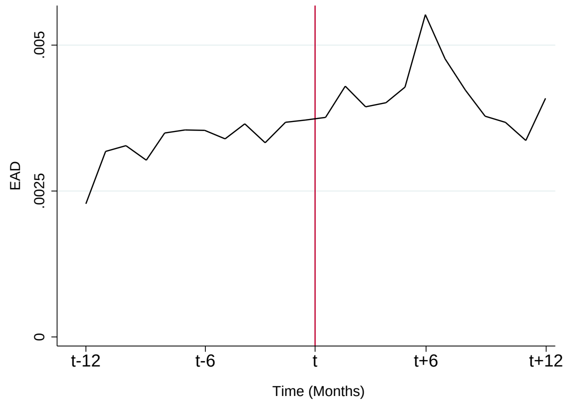
(b) of Figure 1.3 shows an increase in current account payments of about 2% around the tenth percentile of the payment distribution. This is the region in which current borrowers were previously paying about 3% of their balance, and increased their payments by 2% to the new minimum of 5%. Panels (c) through (f) of Figure 1.3 show the payment distributions of delinquent accounts. In general, the effect of the policy on payments is rather weak for delinquent accounts. Borrowers in their first delinquency cycle increase the percentage of their account balance paid each month, but the increase is not sufficient to comply with the minimum payment policy change. Given increased minimum payments, an unchanged payment distribution reduces the proportion of borrowers whose payments are sufficient to cure their account.

1.3.3 Write-Offs and Exposure at Default

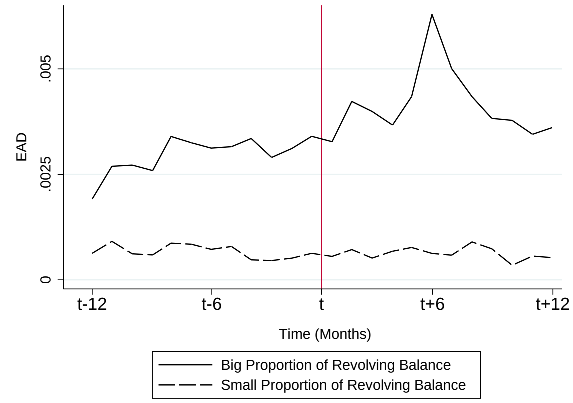
In this section, we decompose the effect of minimum payments on the rate at which accounts are written-off, and on the bank's exposure at default (EAD) for the written-off accounts. We measure the EAD as the proportion of the total account balance that is written-off at the time of default (net of any new term loans contracted during the last delinquency spell), normalized by the total account balance when the account was last current. We consider the proportion of all loans (current or delinquent) that are written off each month. Figure 1.4 shows the dynamics of the three measures of interest: i) the unconditional EAD in Panels (a) and (b) (the total exposure faced by the bank averaging over all accounts, including those not written-off); ii) the unconditional probability of being written-off in Panels (c) and (d); and, iii) the EAD given that an account has been written-off in Panels (e) and (f). Results are shown for all accounts (left panels); high and low proportions of revolving balance are separated (right panels). The average EADs presented are weighted by the last current balance on the account.

The number of write-offs spikes six months after the policy change (Figure 1.4 Panels (c) and (d)). This lag is expected; it takes six months for a loan to go from current to write-off in the absence of any additional payments. The spike appears to be transitory in the figure and is driven by the increase in the probability of entering delinquency, as shown in Panel

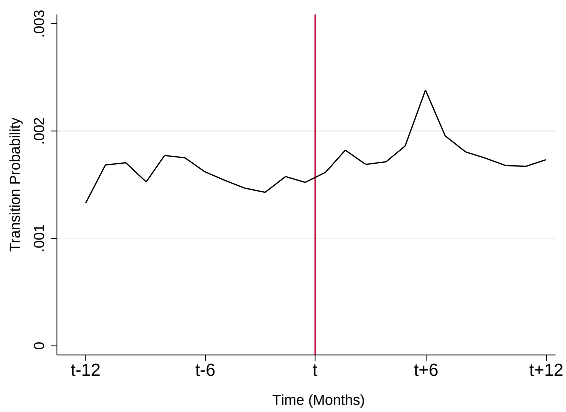
Figure 1.4: Write-Offs and Exposure at Default



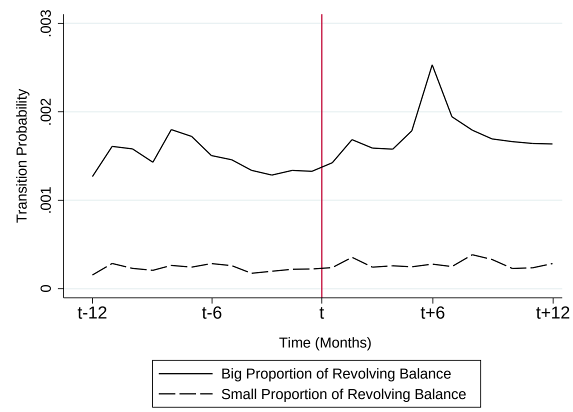
(a) $\overline{EAD}_{t+1}|L_t$ or C_t



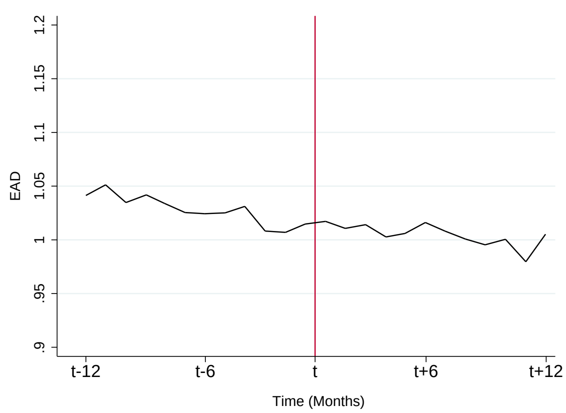
(b) $\overline{EAD}_{t+1}|L_t$ or C_t



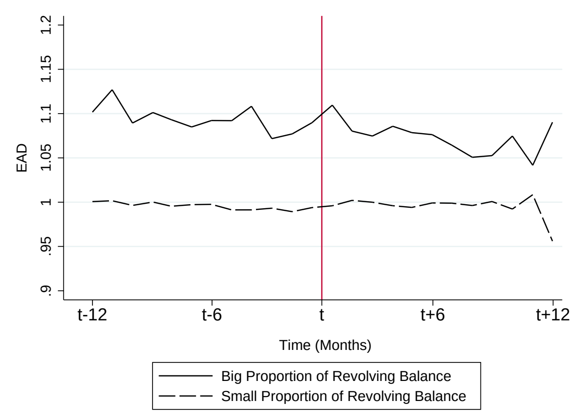
(c) $\mathbb{P}(W_{t+1}|C_t$ or $L_t)$



(d) $\mathbb{P}(W_{t+1}|C_t$ or $L_t)$



(e) $\overline{EAD}_{t+1}|L_t$ or C_t, and $W_{t+1} = 1$



(f) $\overline{EAD}_{t+1}|L_t$ or C_t, and $W_{t+1} = 1$

Note: This figure plots the EAD (unconditional and conditional on default) and the unconditional write-off probability for accounts that have a total balance greater than \$333 in a 24-month window around the policy change. To show the effect of the policy change for the groups most and least affected, accounts are defined as having a big ($\geq$ 95%) and a small ($\leq$ 5%) proportion of revolving balance to total balance. The EADs are weighted by the last current balance on the account. We present graphs for accounts with total (not revolving) balances greater than \$333. This enables us to avoid dropping all but the highest-balance accounts among the group of accounts with a low proportion of revolving balance.

Table 1.4: Exposure at Default

	$EAD_{t+6} \vert L_{t+5}$ or C_{t+5}				$\mathbb{P}(W_{t+6} \vert L_{t+5}$ or $C_{t+5})$				$EAD_{t+6} \vert L_{t+5}$ or $C_{t+5}, W_{t+6} = 1$			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
After Change? × Prop. Revol.	0.0576**	0.0883**	0.0986**	0.0879**	0.0002**	0.0007**	0.0008**	0.0008**	0.2283	-3.4567	-3.2132	-2.3988
	(0.0112)	(0.0162)	(0.0162)	(0.0140)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(2.3436)	(3.9816)	(4.0432)	(1.4484)
After Change?												
$1 = yes$, $0 = no$	-0.0285**				0.0000				-5.3540**			
	(0.0069)				(0.0001)				(0.9297)			
Prop. Revol.	-0.1378**	-0.1335**	-0.0632*	0.1072**	-0.0018**	-0.0015**	-0.0010**	0.0009**	26.5754**	18.9179**	20.6337**	12.2917**
	(0.0096)	(0.0313)	(0.0318)	(0.0330)	(0.0000)	(0.0002)	(0.0002)	(0.0002)	(2.0836)	(5.4824)	(5.3068)	(3.0391)
Month F.E.	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES	YES
Only Revol.	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES	YES
Only Revol. × Trend	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES	YES
Prop. Revol. × Trend	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES	YES
Delinquency Dummies	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Delinquency × Trend	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Spell Dummies	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Total Bal. Dummies × Min. Pmt Dummies	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES
Account Characteristics	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES
R^2	0.000	0.000	0.001	0.004	0.000	0.000	0.007	0.009	0.006	0.008	0.012	0.114
Observations	29,163,071	29,163,071	29,163,071	26,340,959	29,163,090	29,163,090	29,163,090	26,340,978	46,396	46,396	46,396	42,899

Note: This table shows OLS regressions of the exposure at default estimated using monthly credit card accounts with revolving balances greater than $333 in a 24-month window around the policy change. Exposure at default is calculated net of any new term loans contracted during the delinquency spell leading to a write-off and is normalized by the total account balance when the borrower was last current. It is then divided by 100 so the results presented should be interpreted in percentages. See text for the details on the different specifications estimated. Standard errors are corrected for within account heteroscedasticity in all specifications presented. ** and * represent significance at the 1 and 5 percent levels, respectively.

(b) of Figure 1.1. The spike in the number of write-offs drives a spike in the total amount written off (Figure 1.4 Panels (a) and (b)) and reflects larger losses for the bank. Panels (e) and (f) show the exposure for written-off accounts follows a slight downward trend, although there is no apparent effect from the policy change.

Table 1.4 presents regression evidence of the policy change effects on the EADs and the unconditional write-off probability, mirroring the evidence in Figure 1.4. We analyze these measures six months following the policy change, as it takes six months for a current account to be written off.[13] The first set of results shows an increase in the unconditional exposure at default. The coefficient is positive and stable across specifications and shows that the exposure at default increased between 0.06 and 0.1 percentage points (a 32% to 49% on a baseline of 0.17%). The second set of results shows that the unconditional monthly probability of write-off similarly increased between 0.02 and 0.08 percentage points (a 1.2% to 4.7% increase on a base rate of 1.7% each month). This implies 0.24% to 0.96% of the accounts were written-off due to the policy in the 12 months following its implementation. Finally, the last set of results shows that for written-off accounts, the EAD did not change significantly after the policy change. The increase in total exposure is driven by more write-offs, with no change in the exposure of written-off accounts. These results are consistent with the relatively constant rate of transition from delinquency to write-offs shown in Section 1.3.2; as the cure rate falls, delinquency rises and leads to more write-offs, even though the fraction of delinquent loans written-off stays relatively stable.

Appendix Figure 1.11 shows that increases in write-offs and the resulting increase in exposure at default is confined to the group of borrower identified *ex ante*, as repaying less than 20% of their revolving balance.

1.3.4 Spending and Balances

In this section, we show the impact of the policy change on borrowers most likely to be affected by the minimum payment increase; those who were previously making low payments on their revolving account. We focus on accounts that only have a revolving balance. In

[13]We also multiply the measure of exposure at default by 100, so coefficients can be interpreted as percentages.

each month t, we identify the affected borrowers with a dummy variable indicating whether they were paying an average fraction of their revolving balance smaller than 20% in a rolling window of months $t-12$ to $t-7$.

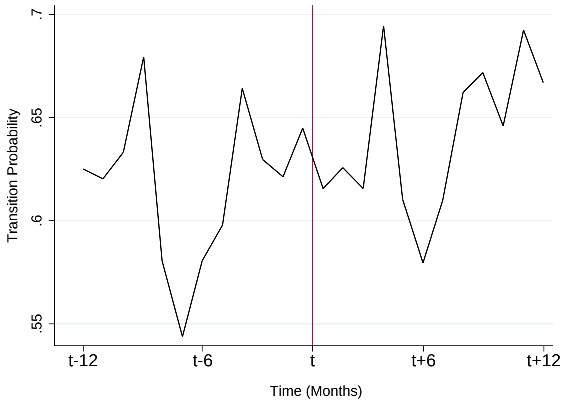
Figure 1.5 shows spending with the credit card in the upper panels, payments on the account in the middle panels, and credit card balances in the bottom panel. Left panels show the effect on the full sample, and right panels show the effect on the group of borrowers identified *ex-ante* as making low and high revolving payments. We normalize purchases, payments, and the change in credit card balance by the credit card balance in the previous billing cycle. The figure does not show an obvious difference in spending between affected and unaffected borrowers. However, payments by affected borrowers increase, leading to a reduction in their revolving balance; payments by unaffected borrowers do not change appreciably. This shows the policy nudged borrowers paying a small fraction toward reducing their revolving balances, and therefore reduced the interest-incurring debt for the bank.

Table 1.5 quantifies the effect shown in Figure 1.5 and focuses on the 12-month period around the policy change. The results show a decline in purchases made each month and suggest borrowers who valued low minimum payments the most are migrating away from this card.[14] Consistent with the graphical evidence presented in Figure 1.5, we find an increase in payments posted on the account. Affected borrowers decrease their revolving balances by 1.3% each month, leading to an average balance reduction of 4% during the six months following the policy implementation. At an average APR of 16% for this group, lost interest revenue totals 0.3% of their balances.

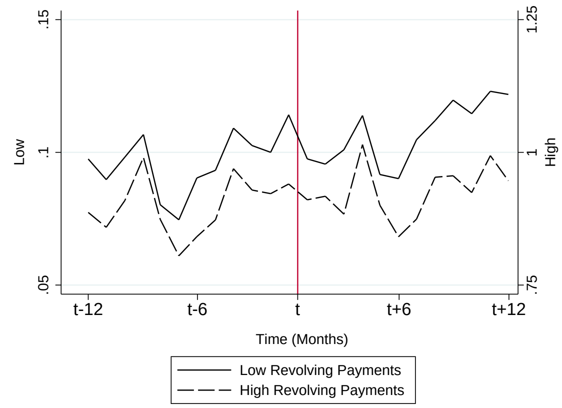
This suggests that by increasing the payments required each month on the account, the bank lowered its interest earning balances for the share of borrowers previously paying small portions of their balance each month, and therefore paying high interest fees. Because this is also the group of borrowers who experienced a transitory increase in write-offs (see Appendix Figure 1.11), the data suggest that borrowers who were constrained by the increase in minimum payment responded by migrating away from a product which no longer offered

[14] The reduction in spending is robust to different specifications. In a previous version of this paper, we found that borrowers in the lower quartile of the payment distribution reduce their spending by as much as 4% each month. These results are available on request.

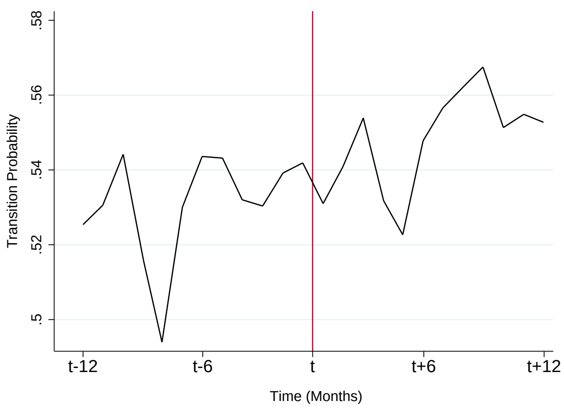
Figure 1.5: Spending



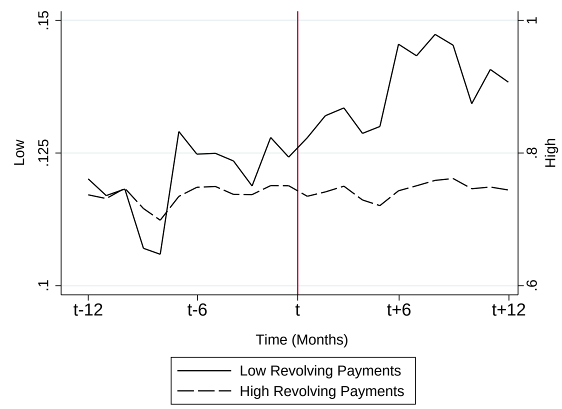
(a) Spending



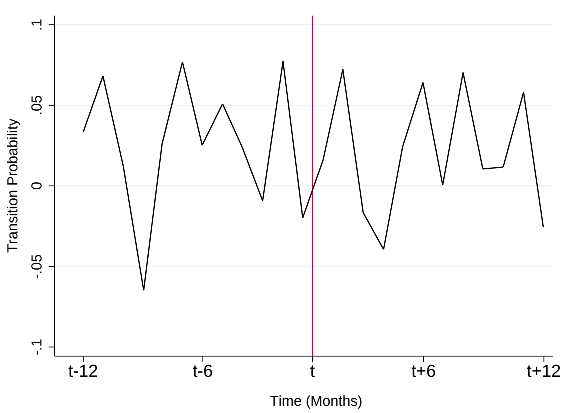
(b) Spending



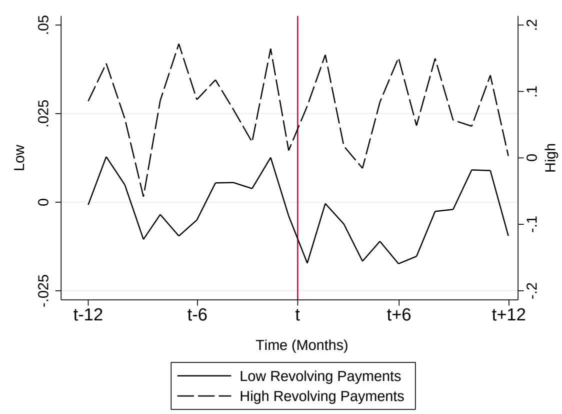
(c) Payments



(d) Payments



(e) Card Balance



(f) Card Balance

Note: This figure plots spending, payments and revolving balance for account that have no term loan and a revolving balance greater than \$333 in a 24-month window around the policy change. Accounts are defined as making low (smaller than 20%) and high (greater than 20%) monthly payments on their revolving account to show the effect of the policy change for the groups most and least affected.

Table 1.5: Spending, Payments and Balance

	Purchases		Payments		Δ Card Balance	
	(1)	(2)	(3)	(4)	(5)	(6)
After? × Low %Paid?	-0.0019	-0.0067**	0.0179**	0.0133**	-0.0133**	-0.0129**
	(0.0024)	(0.0025)	(0.0009)	(0.0009)	(0.0021)	(0.0022)
Low %Paid?	-0.8114**	-0.4769**	-0.6217**	-0.4083**	-0.0760**	0.0473**
	(0.0024)	(0.0034)	(0.0011)	(0.0017)	(0.0016)	(0.0020)
Month F.E.	YES	YES	YES	YES	YES	YES
Total Bal. Dummies × Min. Pmt Dummies	NO	YES	NO	YES	NO	YES
Account Characteristics	NO	YES	NO	YES	NO	YES
R^2	0.159	0.240	0.438	0.556	0.004	0.042
Observations	9,547,645	8,588,689	9,547,646	8,588,689	9,507,443	8,552,633

Note: This table shows the effect of the policy on purchases, payments and revolving balance (normalized by revolving balance in the previous billing cycle) using monthly credit card accounts with no term loan and revolving balances greater than $333 in a 12-month window around the policy change. The set of control variables, which we group under "Account Characteristics" are age and sex of the account holder, an external measure of credit score, an indicator variable equal to one if the borrower has other accounts at this institution, an indicator variable equal to one if the borrower pays for a reduced APR, APR charged on the revolving balance, average unemployment rate in the borrower's region, account age (in months), revolving credit limit and utilization of the revolving balance (defined as revolving balance/revolving limit). All controls are taken at the beginning of the billing cycle to avoid spurious relationships with the independent variable. Standard errors are corrected for within account heteroscedasticity in all the specifications presented. ** and * represent significance at the 1 and 5 percent levels, respectively.

a desirable repayment schedule.

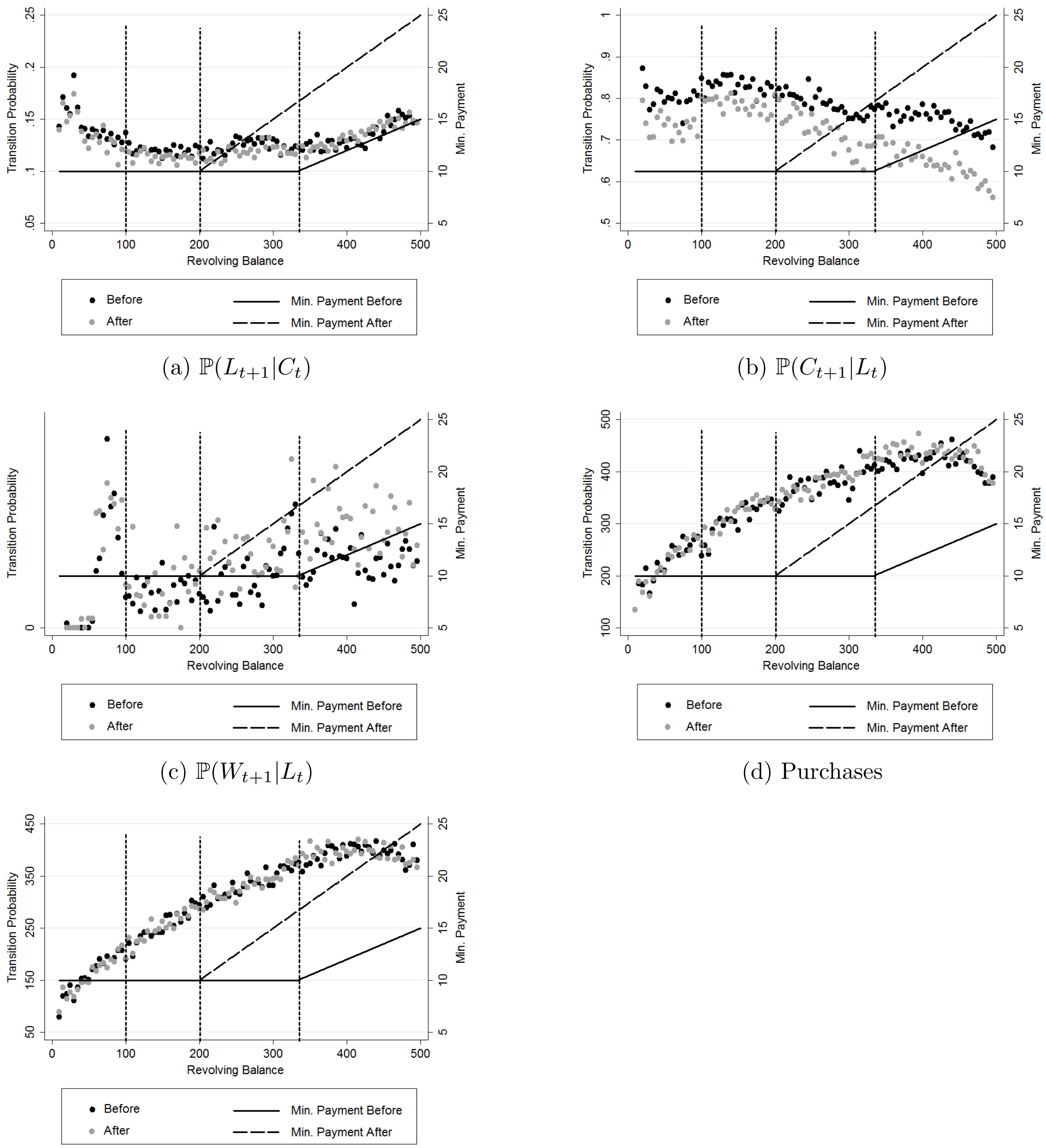
1.4 Extensions

1.4.1 Regression Kink Design

The minimum payment is either $10, or 3% / 5% of the revolving balance, whichever is greater. This maximum structure implies that the minimum payment is a kinked function of the revolving balance and suggests a regression kink design (RKD) to identify the effect of minimum payments while controlling non-parametrically for balance (Appendix Figure 1.9 plots the effect of the policy on the minimum monthly payment required on the revolving balance). This approach reveals the effect of very small increases in minimum payments, around the floor of $10, that must be repaid when the balance is under $334 (before the policy change), or under $200 (after the policy change). This is analogous to the changes in floor payment studied by Keys and Wang (2014), although our kinks are at lower balances than theirs.

We retain observations of accounts that have only a revolving balance, during a window of six months around the policy change, and we identify off the two kinks implied by the policy change. Figure 1.6 shows average transition probabilities, purchases, and payments

Figure 1.6: Average Outcomes Around the Minimum Payment Kinks



(a) $\mathbb{P}(L_{t+1}|C_t)$

(b) $\mathbb{P}(C_{t+1}|L_t)$

(c) $\mathbb{P}(W_{t+1}|L_t)$

(d) Purchases

(e) Payments

Note: This figure plots average outcomes before and after the minimum payment change for accounts with a revolving balance between \$0 and \$500 in a six-month window around the policy change.

Table 1.6: Kink Regression Design

	Min. Payment	$\mathbb{P}(L_{t+1}\|C_t)$	$\mathbb{P}(C_{t+1}\|L_t)$	$\mathbb{P}(W_{t+1}\|L_t)$	Purchases	Payments
A. First Kink (\$100 < *Revolving Balance* < \$334)						
$After \times (CardBalance - 200)/100$	3.1560***	0.0028**	-0.0113	-0.0020	-14.8554*	-6.4223
	(0.005)	(0.001)	(0.010)	(0.002)	(8.277)	(6.311)
$(CardBalance - 200)/100$	-1.2392***	0.0150**	0.0354	-0.0110	199.4779***	108.2610***
	(0.019)	(0.007)	(0.052)	(0.012)	(48.293)	(37.771)
Month F.E.	YES	YES	YES	YES	YES	YES
Revol. Bal. Dummies (\$5 bins)	YES	YES	YES	YES	YES	YES
Revol. Bal. Dummies × Trend	YES	YES	YES	YES	YES	YES
R^2	0.985	0.001	0.019	0.002	0.007	0.012
Observations	1,392,264	1,318,166	70,633	70,633	1,392,264	1,392,264
B. Second Kink (\$200 < *Revolving Balance* < \$500)						
$After \times (CardBalance - 334)/100$	3.2652***	0.0084***	-0.0385***	0.0004	11.5744	4.4177
	(0.003)	(0.001)	(0.008)	(0.002)	(7.938)	(5.829)
$(CardBalance - 334)/100$	-0.4367***	0.0157**	0.0344	0.0052	86.1159*	66.9560*
	(0.022)	(0.008)	(0.051)	(0.012)	(49.559)	(39.770)
Month F.E.	YES	YES	YES	YES	YES	YES
Revol. Bal. Dummies (\$5 bins)	YES	YES	YES	YES	YES	YES
Revol. Bal. Dummies × Trend	YES	YES	YES	YES	YES	YES
R^2	0.995	0.001	0.020	0.002	0.005	0.007
Observations	1,316,835	1,230,181	84,441	84,441	1,316,835	1,316,835

Note: This table presents the results of OLS regressions of equation (1.6) for values of k equal to 200 and 334, using monthly credit card accounts with revolving balances around each kinks in a six-month window around the policy change. Standard errors are corrected for within account heteroscedasticity. ** and * represent significance at the 1 and 5 percent levels, respectively.

before and after the policy change around the kinks. Only the probability of curing the account seems to be affected by the kinks.

Following the typical strategy in regression kink designs (Card et al., 2012), we quantify the effect implied around the kinks through the equation

$$y_{i,t} = \beta_0 + \beta_1 \text{After} \times \frac{(\text{Revolving Balance}_{i,t} - k_j)}{100} + \boldsymbol{\beta}_2 \boldsymbol{X}_{i,t} + \epsilon_{i,t}, \tag{1.6}$$

where k_j represents either the 200 or 334 kink marks, "After?" is an indicator variable that takes the value of one if the observation is after the policy change and zero otherwise, and $\boldsymbol{X}_{i,t,}$ includes month fixed effects and a set of dummy variables for revolving balance in \$5 bins. Everything is centered around the kinks and normalized by 100. The coefficient of interest is β_1, which measures the impact of increasing the revolving balance by \$100 in the regions around the kinks.

Table 1.6 presents the results. Panel A shows the effect around the first kink and Panel B shows the effect around the second kink. The first column shows the identification strategy works in identifying the increase in minimum payment. The next columns show the transition probabilities and present results similar to our main analysis. There is a negligible increase in the probability of entering delinquency and a decrease in the probability of exiting delinquency, although it is only statistically significant for the $334 kink. In this range of revolving balances, the probability of exiting delinquency is close to 75%, so a decrease of 3.85 percentage points in the probability of an account curing represents a drop of about 5%. This is smaller than the effect we find in the main analysis for accounts with higher balances. The last two columns indicate the average purchases and payments made on the card were not significantly affected by the policy change in this region of revolving balances.

1.4.2 Different Measures for the Proportion of Revolving Balance

The policy change could affect the proportion of revolving balances; a) if borrowers switch to term loans in response to the minimum payment increase, or b) if revolving balances increase for consumers who do not comply with the higher minimum payments. However, Panel (a) and (b) of Figure 1.8 respectively show the rate at which term loans are contracted and the average proportion of revolving balance are stable in the 24-month window around the policy change.[15] As a robustness check, we verify our results hold with alternative measures of the proportion of revolving balance.

We first run two-stage least squares regressions on the probability of delinquency transitions. The proportion of revolving balance is instrumented by its value, lagged by six months. Its interaction with the policy dummy is instrumented using the policy dummy in interaction with the six-month lagged proportion of revolving balance. We restrict the sample period to 12 months around the policy change so the policy change does not affect the instrument. Table 1.8 shows that the first stages have strong predictive power. The second stage regressions show our main results do not change once we instrument the proportion of revolving balance. We still find that the probability of entering delinquency only

[15] As a loss mitigation strategy, the bank offers the possibility for severely delinquent borrowers to consolidate their revolving balance into a term loan. If borrowers who cannot sustain the increase in minimum payment consolidate their revolving balance into a term loan, it limits our ability to find an effect from the policy. Panel (c) of Figure 1.8 shows there is evidence of an increase in the conversion of revolving loans to term loans as a result of the policy change, although the rate of conversion is still smaller than 0.025% at its peak.

marginally increased following the minimum payment increase, and the probability of exiting delinquency decreased by about 8.80 percentage points.

As a second robustness check, we use the average proportion of revolving balance in the six months before the start of our sample as the main identifying variable. For this exercise, accounts have a fixed value for the proportion of revolving balance which is not affected by the policy change. Table 1.9 shows our main results still hold; we estimate an increase in the probability of entering delinquency between 0.13 to 0.79 percentage points and a decrease in the probability of curing the account by 5.11 to 9.48 percentage points.

1.4.3 Falsification Test

Accounts with revolving balances under \$200 are not affected by the policy change at all because their minimum repayment is equal to the floor amount (\$10) both before and after the change. We thus perform a falsification test by retaining only accounts with balances under \$200, but above \$10, and perform the delinquency analysis again. The results are presented in Table 1.11 and show that the policy change did not affect the delinquency outcome with any economic significance.

1.4.4 Heterogeneous Effects

We investigate the effect of the minimum payment increase through the heterogeneous effects of several account characteristics: the revolving balance (measured both in dollars and as a proportion of the limit); the external credit score; and whether the account holder also holds other accounts with the institution. We re-estimate the probit models presented in Table 1.3 under specification (4) and interact the policy dummy with the proportion of revolving balance and these characteristics.

Panels A and B of Table 1.10 show the effect of the policy was more severe for accounts with a higher-dollar amount revolving balance, but not as a proportion of the credit limit. Accounts with higher balances are more likely to become delinquent and less likely to cure as a result of the policy change. There is evidence that a higher revolving balance also leads to a higher probability of write-off. Panel C shows borrowers with better external scores were less affected by the policy change as one would imagine. Finally, Panel D shows that account holders who conduct additional business with the institution have lower write-off rates as a result of the policy change.

1.5 Conclusion

We document the effect of increasing minimum credit card payments using data from a large North American bank that increased its minimum payment from 3% to 5% of the revolving balance. This change contrasts with the disclosure rules imposed by the 2009 CARD Act, which merely nudged borrowers into repaying their balance faster, but did not impose higher minimum payments.

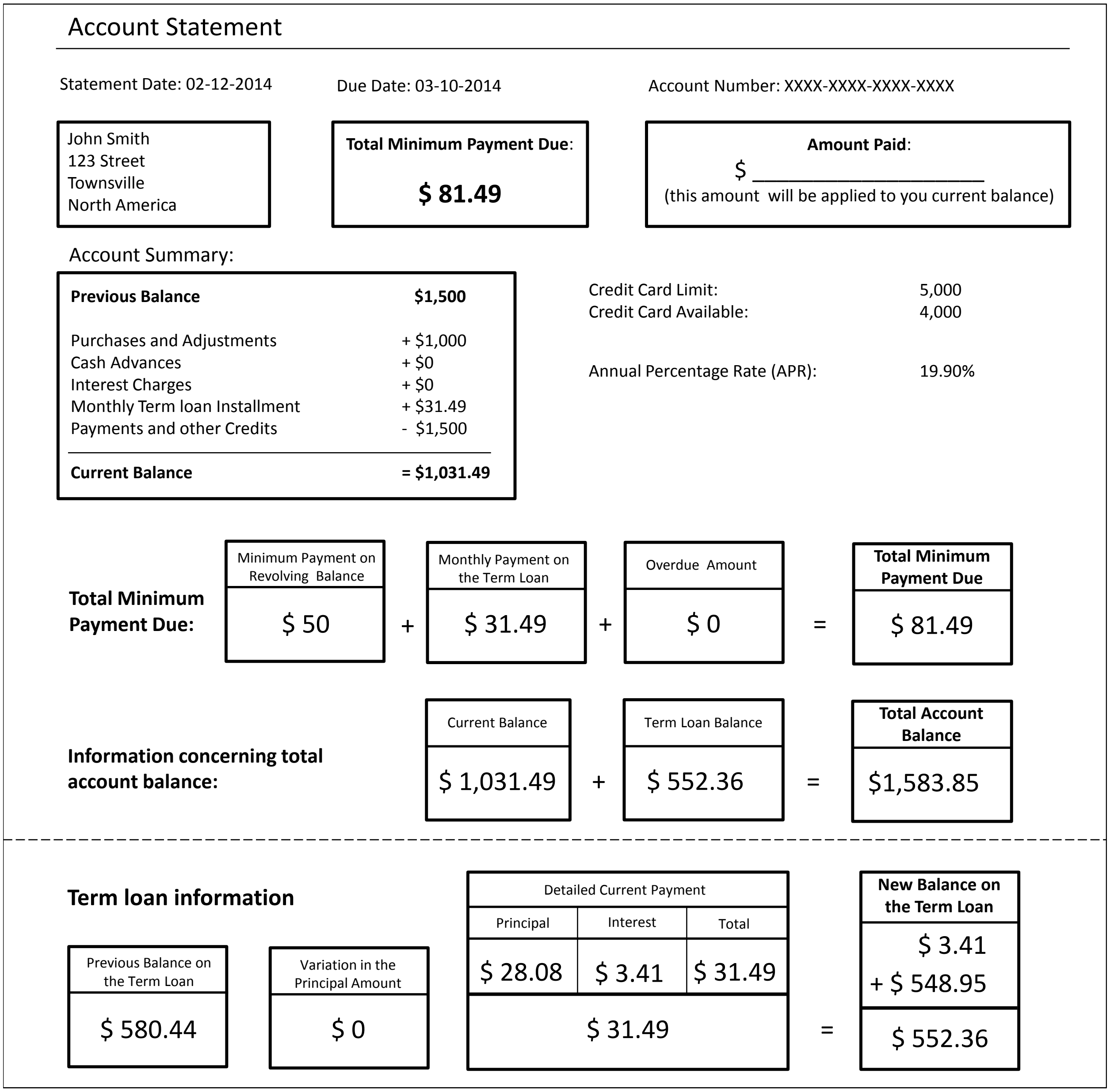
Liquidity constraints and inconsistent time preferences have been used to rationalize why some borrowers simultaneously hold both low-yield liquid assets and high-interest credit card debt (Meier and Sprenger, 2010; Skiba and Tobacman, 2008; Telyukova, 2013). Our analysis does not shed light on the role of behavioral biases in explaining the reason for credit card debt in the first place. However, our findings show that most affected borrowers respond to the policy change by increasing their payments. We also show evidence of forward-looking behavior; borrowers who are most likely to be affected by minimum payments in the future respond by reducing spending and lowering their revolving balance. This suggests a desire to reduce future minimum payments, or to migrate away from a product providing an undesirable repayment schedule. This forward-looking behavior is inconsistent with myopia and other naive present-biased preferences.

We show that a number of delinquent borrowers, who had previously made minimum payments, fail to comply fully with the new minimum. This implies that, for these borrowers, the cost of the next-cheapest source of funds exceeds the shadow cost of delinquency. This contrasts with current borrowers, whose ability to increase payments and comply with higher minimums suggests their next-cheapest cost of funds is lower than the shadow cost of delinquency.

For the bank, the change in policy has two important consequences. First, increasing the minimum payment leads to an increase in delinquency, which ultimately passes through to write-offs. The unconditional probability of write-off increases between 0.02 and 0.08 percentage points each month. This implies that, due to the policy, 0.24% to 0.96% of the accounts were written-off in the 12 months following its implementation. Part of this effect comes from a transitory spike in write-offs exactly six months after the policy was implemented; it takes six months for an account to transition from delinquency to write-off. Second, because borrowers reduce their revolving balances, the policy change results in lower interest fees collected by the bank. Affected borrowers decrease their revolving balances by 1.3% each month, leading to an average balance reduction of 4% during the six months following the policy implementation. At an average APR of 16% for this group, this balance reduction amounts to lost interest revenue of 0.3% of their balances.

1.6 Appendix

Figure 1.7: Account Statement Example


Account Statement

Statement Date: 02-12-2014
Due Date: 03-10-2014
Account Number: XXXX-XXXX-XXXX-XXXX

John Smith
123 Street
Townsville
North America

Total Minimum Payment Due:
$ 81.49

Amount Paid:
$ ______________________
(this amount will be applied to you current balance)

Account Summary:

Previous Balance	**$1,500**
Purchases and Adjustments	+ $1,000
Cash Advances	+ $0
Interest Charges	+ $0
Monthly Term loan Installment	+ $31.49
Payments and other Credits	- $1,500
Current Balance	**= $1,031.49**

Credit Card Limit:	5,000
Credit Card Available:	4,000
Annual Percentage Rate (APR):	19.90%

Total Minimum Payment Due:

Minimum Payment on Revolving Balance		Monthly Payment on the Term Loan		Overdue Amount		**Total Minimum Payment Due**
$ 50	+	$ 31.49	+	$ 0	=	$ 81.49

Information concerning total account balance:

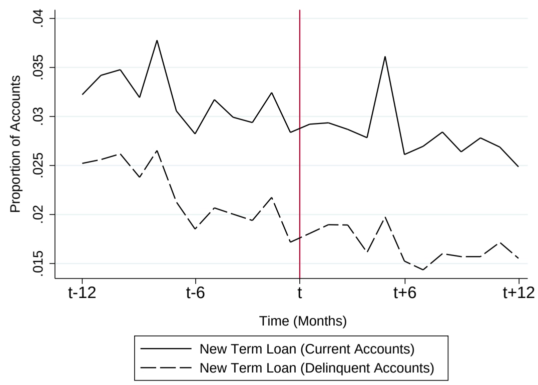
Current Balance		Term Loan Balance		**Total Account Balance**
$ 1,031.49	+	$ 552.36	=	$1,583.85

Term loan information

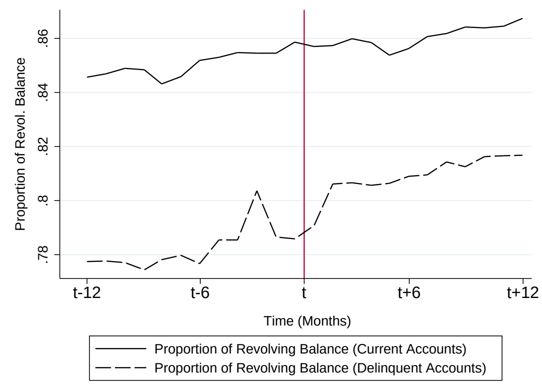
Previous Balance on the Term Loan	Variation in the Principal Amount	Detailed Current Payment: Principal	Interest	Total		**New Balance on the Term Loan**
$ 580.44	$ 0	$ 28.08	$ 3.41	$ 31.49		$ 3.41 + $ 548.95
		$ 31.49			=	$ 552.36

Note: This figure shows a typical account statement for a borrower at the bank. The monthly statement presents information about the revolving and term loans on the account. The total minimum payment due consists of the minimum payment on the credit card balance, the monthly term loan payment, and the overdue amount. The monthly payment on the term loan consists of the installment due on the term loan in the current month. The overdue amount consists of the cumulative amount that arises from paying less than the total minimum payment due on previous statements.

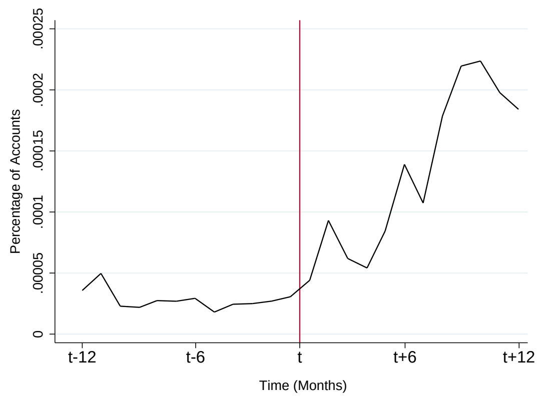
Figure 1.8: Term and Revolving Loans



(a) New Term Loans



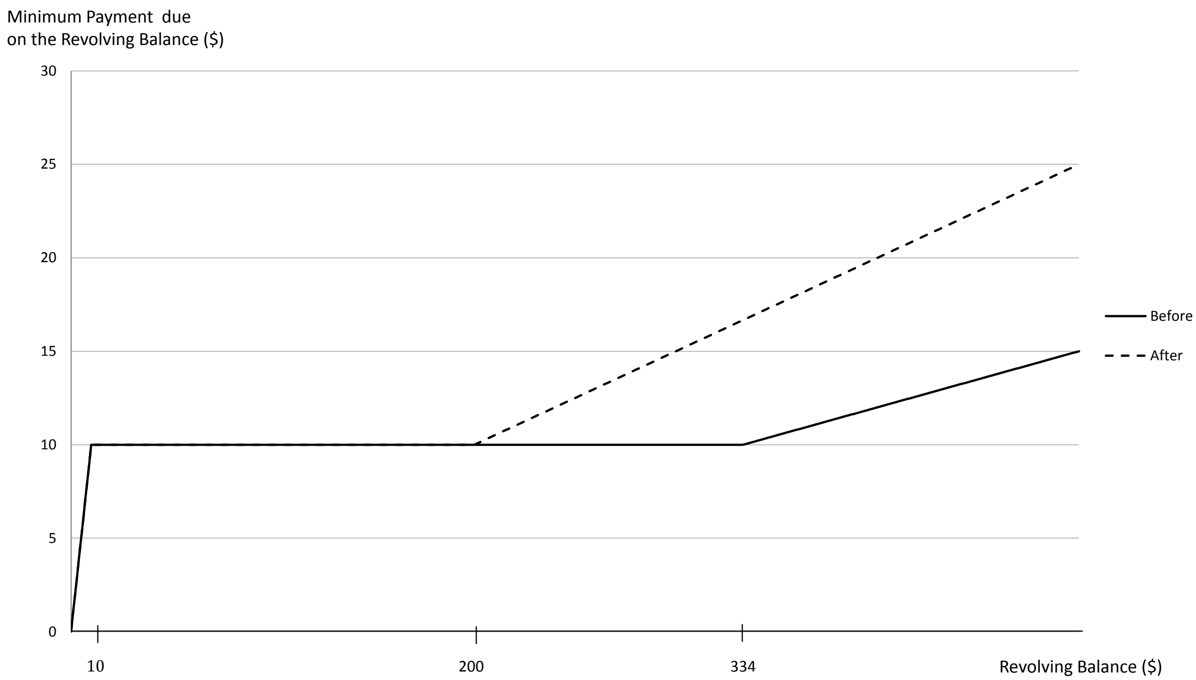
(b) Proportion of Revolving Balance



(c) New Conversions into Term Loans

Note: This figure shows term and revolving borrowing in the 24-month period around the policy change. Panel (a) shows the rate of new term loans being opened each month. Panel (b) shows the rate of conversions from revolving to term loans each month. Panel (c) shows the average proportion of revolving balance to total account balance for current and delinquent accounts.

Figure 1.9: Minimum Revolving Payment - Before and After the Policy Change



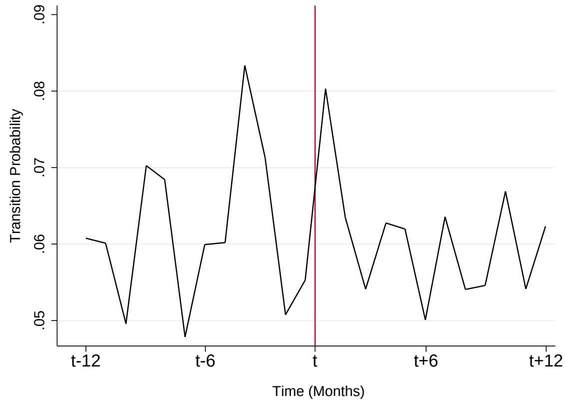
Note: This figure shows the effect of the policy change on the monthly minimum payment due on the revolving balance. The solid and dashed lines, respectively, represent the minimum payment schedules on the revolving balance before and after the policy change. The minimum payment on the revolving balance must be added to the monthly installment on the term loan (if the borrower has one) to yield the total monthly minimum payment.

Table 1.7: Payments - Quantile Regressions

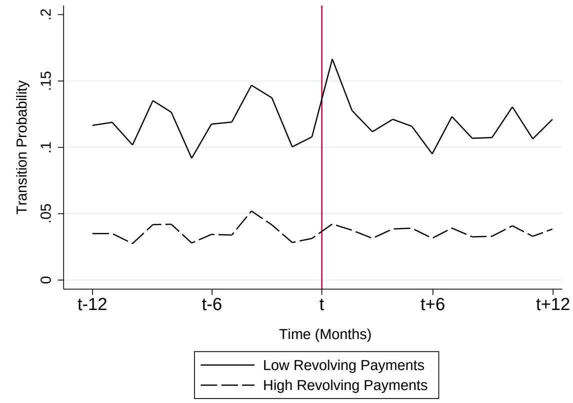
	Quantile Regressions					Least Squares
	0.10	0.25	0.50	0.75	0.90	OLS
A. Current Accounts						
After Change × Prop. Revolving Bal.	0.016***	0.006***	-0.030***	0.014***	0.004***	0.001
	(0.000)	(0.001)	(0.003)	(0.000)	(0.000)	(0.002)
Prop. of Revolving Bal	0.025***	0.040***	0.153***	0.210***	0.242***	0.293***
	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.001)
Constant	0.019***	0.029***	0.050***	0.084***	0.112***	0.061***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Observations	6,757,276	6,757,276	6,757,276	6,757,276	6,757,276	6,757,276
B. 1 Month Late						
After Change × Prop. Revolving Bal.	-	0.006***	0.015***	0.033***	-0.021***	0.011***
		(0.001)	(0.001)	(0.007)	(0.000)	(0.002)
Prop. of Revolving Bal	-	0.033***	0.066***	0.246***	0.272***	0.181***
		(0.001)	(0.001)	(0.006)	(0.000)	(0.002)
Constant	-	0.022***	0.051***	0.106***	0.107***	0.069***
		(0.000)	(0.000)	(0.002)	(0.000)	(0.001)
Observations		693,012	693,012	693,012	693,012	693,012
C. 2 Months Late						
After Change × Prop. Revolving Bal.	-	0.003	0.004**	0.001	0.002	0.002
		(0.002)	(0.002)	(0.004)	(0.023)	(0.004)
Prop. of Revolving Bal	-	0.030***	0.069***	0.145***	0.514***	0.148***
		(0.002)	(0.002)	(0.003)	(0.018)	(0.004)
Constant	-	0.009***	0.040***	0.084***	0.132***	0.047***
		(0.000)	(0.001)	(0.001)	(0.007)	(0.002)
Observations		155,738	155,738	155,738	155,738	155,738
D. 3+ Months Late						
After Change × Prop. Revolving Bal.	-	-	-0.003***	-0.008*	-0.008	-0.002
			(0.000)	(0.004)	(0.009)	(0.004)
Prop. of Revolving Bal	-	-	0.009***	0.076***	0.188***	0.080***
			(0.000)	(0.003)	(0.008)	(0.004)
Constant	-	-	0.003***	0.105***	0.116***	0.056***
			(0.000)	(0.005)	(0.006)	(0.003)
Observations			89,884	89,884	89,884	89,884
E. All Late Accounts						
After Change × Prop. Revolving Bal.	-	0.005***	0.008***	0.025***	-0.015***	0.011***
		(0.001)	(0.001)	(0.004)	(0.000)	(0.002)
Prop. of Revolving Bal	-	0.023***	0.063***	0.207***	0.245***	0.158***
		(0.001)	(0.001)	(0.003)	(0.000)	(0.002)
Constant	-	0.074***	0.090***	0.178***	0.314***	0.139***
		(0.001)	(0.001)	(0.002)	(0.000)	(0.001)
Observations		938,634	938,634	938,634	938,634	938,634

Note: This table shows the estimation of quantile regressions for which the independent variable is the ratio of payments to total account balance, as defined by equation (1.5). The sample used consists of observations that have a revolving balance greater than $333 in a six-month window around the policy change. Additional unreported controls are month fixed effects, a dummy variable indicating if the account has only a revolving balance and its interaction with a linear trend. For delinquent accounts, dummies for the delinquency cycle and their interaction with a linear trend are included. Some quantiles in the lower end of the payment distribution did not converge due to insufficient variation in the dependent variable and are therefore omitted. Because the dependent variable does not vary much in the tails of the distribution, some of the quantiles estimated do not converge. For this reason, in the graphics presented, we use the nearest converging quantile to replace ones that did not converge. This only affects some very small quantiles of the payment distribution in regions where the repayment is in any case 0%. ** and * represent significance at the 1 and 5 percent levels, respectively.

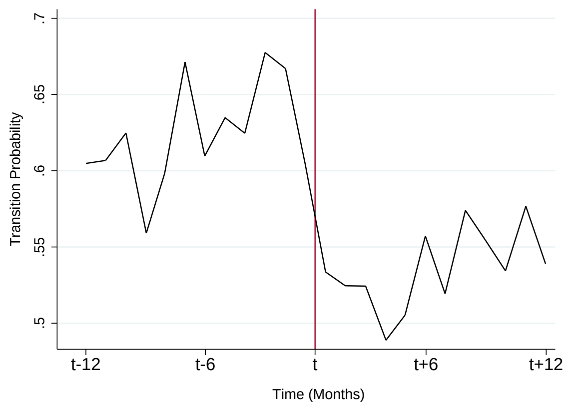
Figure 1.10: Transition Probabilities



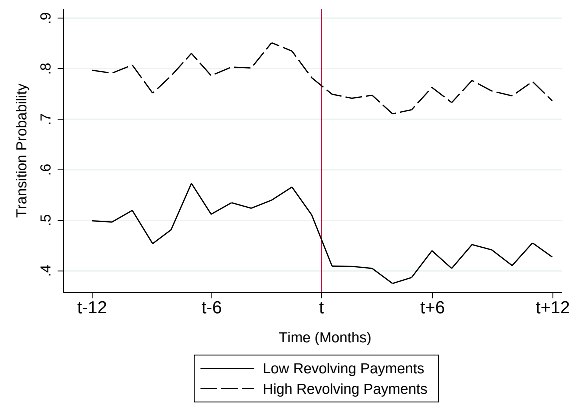
(a) $\mathbb{P}(L_{t+1}|C_t)$



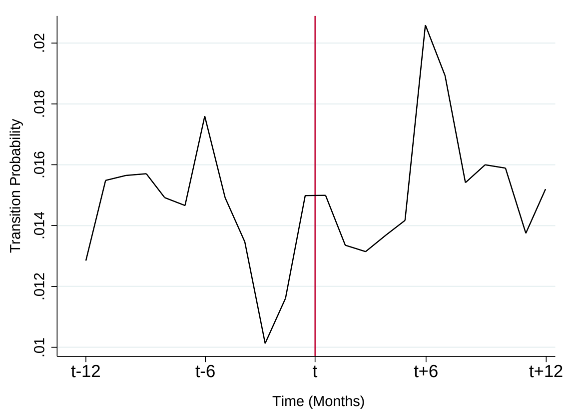
(b) $\mathbb{P}(L_{t+1}|C_t)$



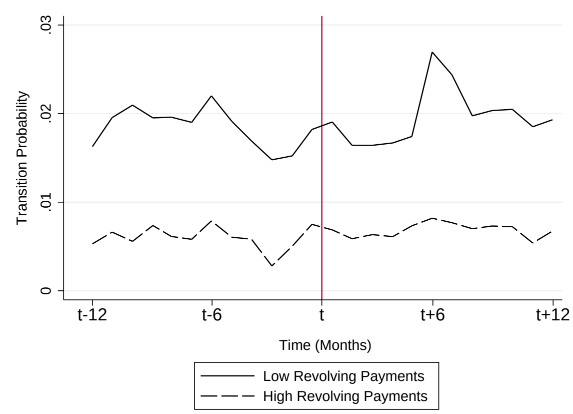
(c) $\mathbb{P}(C_{t+1}|L_t)$



(d) $\mathbb{P}(C_{t+1}|L_t)$



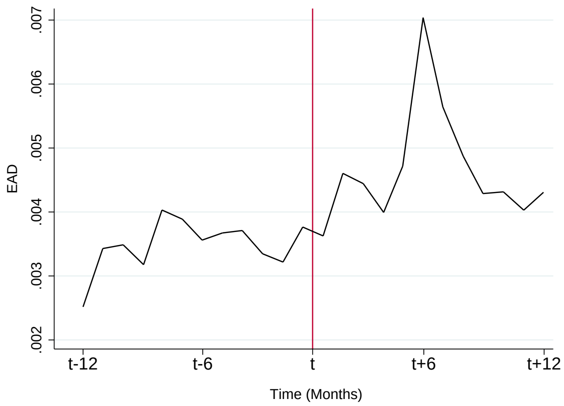
(e) $\mathbb{P}(W_{t+1}|L_t)$



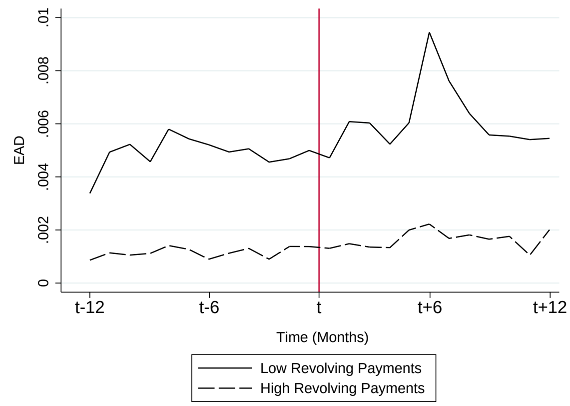
(f) $\mathbb{P}(W_{t+1}|L_t)$

Note: This figure plots the aggregate transition probabilities between delinquency states for accounts with no term loans that have a revolving balance greater than \$333 in a 24-month window around the policy change. Accounts are *ex ante* identified as repaying a big (greater than 20%) and a small (smaller than 20%) proportion of the revolving balance according to equation (1.2) which is first averaged over six months and then lagged by six months.

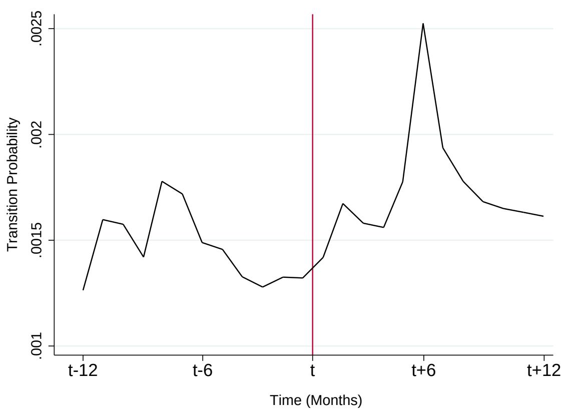
Figure 1.11: Write-Offs and Exposure at Default



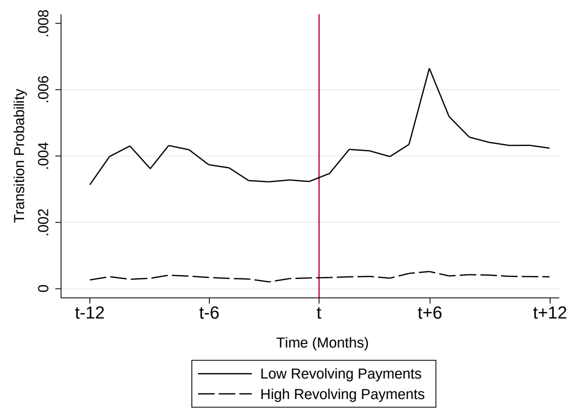
(a) $\overline{EAD}_{t+1}|L_t$ or C_t



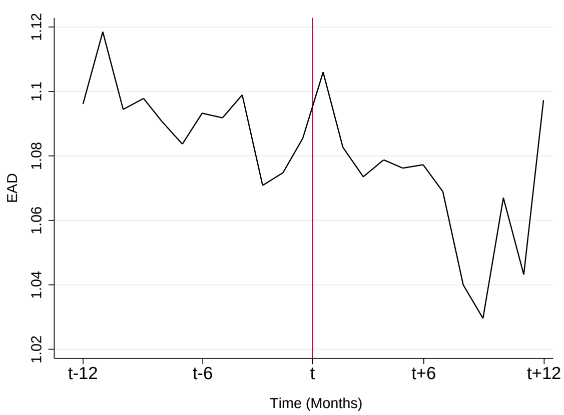
(b) $\overline{EAD}_{t+1}|L_t$ or C_t



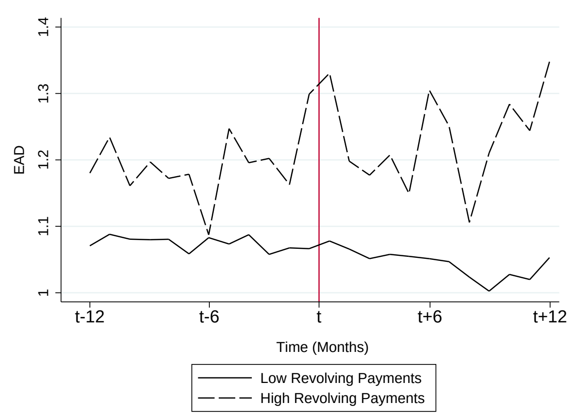
(c) $\mathbb{P}(W_{t+1}|C_t$ or $L_t)$



(d) $\mathbb{P}(W_{t+1}|C_t$ or $L_t)$



(e) $\overline{EAD}_{t+1}|L_t$ or $C_t,$ and $W_{t+1} = 1$



(f) $\overline{EAD}_{t+1}|L_t$ or $C_t,$ and $W_{t+1} = 1$

Note: This figure plots the EAD (unconditional and conditional on default) and the unconditional write-off probability for accounts with no term loans that have a revolving balance greater than \$333 in a 24-month window around the policy change. Accounts are *ex ante* identified as repaying a big (greater than 20%) and a small (smaller than 20%) proportion of the revolving balance according to equation (1.2) which is first averaged over six months and then lagged by six months. The EADs are weighted by the last current balance on the account.

Table 1.8: 2SLS Delinquency Transitions

	First Stages | C_t		Instrumented 2nd Stage	First Stages | L_t		Instrumented 2nd Stages	
	Prop. Revol	After Change ×Prop. Revol	$\mathbb{P}(L_{t+1}\|C_t)$	Prop. Revol	After Change × Prop. Revol	$\mathbb{P}(C_{t+1}\|L_t)$	$\mathbb{P}(W_{t+1}\|L_t)$
After Change × Prop. Revolv.			0.0139**			-0.0880**	-0.0018
			(0.0016)			(0.0047)	(0.0011)
Prop. Revolving Loan			0.0377**			-0.0127**	0.0085**
			(0.0089)			(0.0046)	(0.0011)
After Change × Prop. Revolv.$_{t-6}$	-0.0018	0.5329**		0.0040*	0.6814**		
	(0.0021)	(0.0022)		(0.0018)	(0.0016)		
Prop. Revolv.$_{t-6}$	0.3697**	-0.0789**		0.5429**	-0.0681**		
	(0.0032)	(0.0012)		(0.0021)	(0.0008)		
Month F.E.	YES	YES	YES	YES	YES	YES	YES
Only Revolv.	YES	YES	YES	YES	YES	YES	YES
Only Revolv. × Trend	YES	YES	YES	YES	YES	YES	YES
Prop. Revolv. × Trend	NO	NO	NO	NO	NO	NO	NO
Bal. Dummies × Min. Pay	YES	YES	YES	YES	YES	YES	YES
Delinquency Dummies	-	-	-	YES	YES	YES	YES
Delinquency × Trend	-	-	-	YES	YES	YES	YES
Spell Dummies	YES	YES	YES	YES	YES	YES	YES
Account Characteristics	YES	YES	YES	YES	YES	YES	YES
R^2	0.792	0.958	0.076	0.856	0.964	0.206	0.366
Observations	9,810,168	9,810,168	9,810,168	1,449,003	1,449,003	1,449,003	1,449,003

Note: This table shows the results of two-stage least squares estimates of the delinquency transitions. The proportion of revolving balance is instrumented by its value lagged of six months while its interaction with the policy dummy is instrumented using the policy dummy interacted with the six-month lagged proportion of revolving balance. The set of control variables grouped under "Account Risk" are age and sex of the account holder, internal and external measures of credit score, an indicator variable equal to one if the borrower has other accounts at the same institution, an indicator variable equal to one if the borrower pays for a reduced APR, APR charged on the revolving balance, average unemployment rate in the borrower's region, account age (in months), revolving credit limit, revolving balance, utilization of the revolving balance (defined as revolving balance/revolving limit), total account balance, and monthly installment on the term loan. All controls are taken at the beginning of the billing cycle to avoid spurious relationships with the independent variable. Standard errors are corrected for within account heteroscedasticity. ** and * represent significance at the 1 and 5 percent levels, respectively.

Table 1.9: Using Pre-Policy Average of Proportion Revolving

	$\mathbb{P}(L_{t+1}\|C_t)$		$\mathbb{P}(C_{t+1}\|L_t)$		$\mathbb{P}(W_{t+1}\|L_t)$	
	(1)	(2)	(3)	(4)	(5)	(6)
After Change × $\overline{\text{Prop. Revol.}}$	0.0013**	0.0079**	-0.0948**	-0.0511**	0.0010*	-0.0014*
	(0.0004)	(0.0006)	(0.0021)	(0.0022)	(0.0004)	(0.0006)
After?	-0.0028**		0.0003		-0.0007	
	(0.0004)		(0.0018)		(0.0004)	
$\overline{\text{Prop. Revol.}}$	-0.0167**	0.0018	0.2516**	-0.0274**	-0.0064**	0.0029**
	(0.0006)	(0.0013)	(0.0018)	(0.0022)	(0.0003)	(0.0005)
Month F.E.	NO	YES	NO	YES	NO	YES
Only Revolv.	NO	YES	NO	YES	NO	YES
Only Revolv. × Trend	NO	YES	NO	YES	NO	YES
Prop. Revolv. × Trend	NO	NO	NO	NO	NO	NO
Bal. Dummies × Min. Pay	NO	YES	NO	YES	NO	YES
Delinquency Dummies	-	-	NO	YES	NO	YES
Delinquency × Trend	-	-	NO	YES	NO	YES
Spell Dummies	NO	YES	NO	YES	NO	YES
Account Characteristics	NO	YES	NO	YES	NO	YES
R^2	0.000	0.086	0.025	0.226	0.000	0.347
Observations	24,406,551	21,993,773	3,159,000	2,964,165	3,159,000	2,964,165

Note: This table shows the main regressions when the proportion of revolving balance on the account is measured as the average over the 6 months period before the start of the orginal sample. Standard errors are corrected for within account heteroscedasticity. ** and * represent significance at the 1 and 5 percent levels, respectively.

Table 1.10: Heterogeneous Effects of the Policy Change

	$\mathbb{P}(L_{t+1}\|C_t)$	$\mathbb{P}(C_{t+1}\|L_t)$	$\mathbb{P}(W_{t+1}\|L_t)$
A. Revolving Balance/1000			
After Change × Prop. Revol. × Revol. Balance	0.0038**	-0.0064**	-0.0002
	(0.0005)	(0.0019)	(0.0005)
After Change × Prop. Revolv.	-0.0112**	-0.0516**	0.0032**
	(0.0012)	(0.0040)	(0.0010)
After Change × Revol. Balance	-0.0028**	0.0039*	0.0001
	(0.0005)	(0.0017)	(0.0005)
Prop. Revol. × Revol. Balance	0.0005	0.0063**	0.0009**
	(0.0005)	(0.0004)	(0.0001)
R^2	0.074	0.189	0.358
Observations	23,979,721	3,310,085	3,310,085
B. Revolving Balance/Revolving Credit Limit			
After Change × Prop. Revol. × Line Utilization	-0.0001	0.0133	0.0073
	(0.0035)	(0.0360)	(0.0058)
After Change × Prop. Revolv.	0.0089**	-0.1076**	-0.0069
	(0.0020)	(0.0320)	(0.0052)
After Change × Line Utilization	0.0228**	0.0019	-0.0074
	(0.0032)	(0.0327)	(0.0053)
Prop. Revol. × Line Utilization	0.0185**	-0.0910**	-0.0050**
	(0.0021)	(0.0092)	(0.0012)
R^2	0.081	0.195	0.359
Observations	23,979,721	3,310,085	3,310,085
C. External Score/1000			
After Change × Prop. Revol. × Ext. Credit Score	-0.0411**	0.0325**	-0.0241**
	(0.0086)	(0.0111)	(0.0049)
After Change × Prop. Revolv.	0.0217**	-0.0651**	0.0153**
	(0.0080)	(0.0092)	(0.0044)
After Change × Ext. Credit Score	0.0910**	-0.1177**	0.0268**
	(0.0074)	(0.0088)	(0.0041)
Prop. Revol. × Ext. Credit Score	-0.0345**	0.1332**	-0.0270**
	(0.0036)	(0.0031)	(0.0009)
R^2	0.075	0.191	0.359
Observations	23,979,721	3,310,085	3,310,085
F. Client at Institution? (1=yes, 0=no)			
After Change × Prop. Revol. × Client	0.0009	0.0015	-0.0047*
	(0.0038)	(0.0067)	(0.0019)
After Change × Prop. Revolv.	0.0001	-0.0707**	0.0053**
	(0.0038)	(0.0057)	(0.0018)
After Change × Client	-0.0093**	0.0085	0.0008
	(0.0034)	(0.0057)	(0.0018)
Prop. Revol. × Client	0.0271**	0.0237**	-0.0018*
	(0.0031)	(0.0036)	(0.0008)
R^2	0.075	0.189	0.358
Observations	23,979,721	3,310,085	3,310,085
Month F.E.	YES	YES	YES
Only Revolv.	YES	YES	YES
Only Revolv. × Trend	YES	YES	YES
Prop. Revolv. × Trend	YES	YES	YES
Delinquency Dummies	-	YES	YES
Delinquency × Trend	-	YES	YES
Spell Dummies	YES	YES	YES
Total Bal. Dummies × Min. Pay Dummies	YES	YES	YES
Account Characteristics	YES	YES	YES

Note: This table shows the heterogeneous effects of the policy on delinquency transitions estimated from separate probit regressions using monthly credit card accounts with revolving balances greater than $333 in a 24-month window around the policy change. The specification follows model (4) in Table 1.3 with added interaction terms. Standard errors are corrected for within account heteroscedasticity. ** and * represent significance at the 1 and 5 percent levels, respectively.

Table 1.11: Falsification Test

	$\mathbb{P}(L_{t+1}\|C_t)$				$\mathbb{P}(C_{t+1}\|L_t)$				$\mathbb{P}(W_{t+1}\|L_t)$			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
After Change? × Prop. Revol.	0.0048**	-0.0033**	-0.0032**	-0.0029**	-0.0079**	-0.0037	0.0107*	0.0190**	0.0008	0.0012	0.0001	-0.0000
	(0.0006)	(0.0010)	(0.0010)	(0.0011)	(0.0030)	(0.0052)	(0.0045)	(0.0046)	(0.0004)	(0.0009)	(0.0005)	(0.0005)
After Change?												
$1 = yes$, $0 = no$	-0.0081**				-0.0101**				0.0004			
	(0.0006)				(0.0015)				(0.0003)			
Prop. Revol.	-0.0161**	0.0107**	0.0029	0.0083**	0.1780**	-0.0926**	0.0658**	-0.0792**	0.0164**	0.0223**	-0.0067**	-0.0075**
	(0.0005)	(0.0029)	(0.0027)	(0.0029)	(0.0021)	(0.0090)	(0.0081)	(0.0089)	(0.0003)	(0.0012)	(0.0012)	(0.0014)
Month F.E.	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES	YES
Only Revol.	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES	YES
Only Revol. × Trend	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES	YES
Prop. Revol. × Trend	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES	YES
Delinquency Dummies	-	-	-	-	NO	NO	YES	YES	NO	NO	YES	YES
Delinquency × Trend	-	-	-	-	NO	NO	YES	YES	NO	NO	YES	YES
Spell Dummies	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Total Bal. Dummies × Min. Pmt Dummies	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES
Account Characteristics	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES
R^2	0.002	0.006	0.050	0.098	0.016	0.023	0.094	0.118	0.062	0.065	0.663	0.668
Observations	7,683,542	7,683,542	7,683,542	7,024,429	1,011,586	1,011,586	1,011,586	956,818	1,011,586	1,011,586	1,011,571	956,804

Note: This table mimics the regressions presented in Table 1.3 but for observations that have a monthly revolving balance between \$10 and \$200. The policy change did not affect these accounts so we would expect to find no significant effect. The set of control variables grouped under "Account Risk" are age and sex of the account holder, internal and external measures of credit score, an indicator variable equal to one if the borrower has other accounts at the same institution, an indicator variable equal to one if the borrower pays for a reduced APR, APR charged on the revolving balance, average unemployment rate in the borrower's region, account age (in months), revolving credit limit, revolving balance, utilization of the revolving balance (defined as revolving balance/revolving limit), total account balance, and monthly installment on the term loan. All controls are taken at the beginning of the billing cycle to avoid spurious relationships with the independent variable. Standard errors are corrected for within account heteroscedasticity. ** and * represent significance at the 1 and 5 percent levels, respectively.

Chapter 2

Consumption, Debt, and Delinquency Responses to an Anticipated Increase in Cash-on-Hand[1]

Abstract

I analyze the response of consumption, debt, and delinquency to an anticipated increase in cash-on-hand in the presence of liquidity constraints. I use account-level data from a North American bank that allows clients to make purchases using credit card and term loans on the same account. Term loans are paid off in a predetermined number of equal monthly installments. The end of a term loan therefore generates a predictable increase in cash-on-hand relative to months in which payments were required. Consistent with a model in which consumers are potentially liquidity constrained, consumers *ex-ante* identified as unconstrained do not increase their credit card expenditures, constrained consumers increase both their credit card expenditures and balance, and consumers for whom the credit card is the marginal source of funds decrease their balance. The propensity to take out a new term loan increases for all consumers, whether constrained or not. About 4% of unconstrained consumers delay taking out a new term loan until the original loan is repaid, contrary to theoretical predictions. Paying off the term loan reduces financial delinquency and the probability of default.

JEL Classification: D12, D14, E21, G21.

[1]I am grateful to my committee members Stephen Shore (chair), Conrad Ciccotello, Georges Dionne and Glenn Harrison for helpful comments. I also thank seminar participants at the Federal Reserve Bank of Richmond, Florida International University, Georgia State University, HEC Montréal, Laval University, Queen's University, and Utah State University for their valuable suggestions.

2.1 Introduction

Under the rational-expectation permanent income hypothesis (PIH), agents are averse to consumption fluctuations so they smooth consumption by borrowing and saving (Modigliani and Brumberg, 1954; Friedman, 1957). Agents are forward-looking: when cash-on-hand is expected to rise, they seek to increase consumption early by borrowing against their future wealth. As a result, the PIH predicts that unconstrained consumers adjust their consumption-savings decision when anticipating a change in cash-on-hand, not when it is realized. In the presence of liquidity constraints some consumers cannot borrow against future wealth. Liquidity constraints generate a correlation between consumption and cash-on-hand because constrained consumers—who are not able to adjust consumption when cash-on-hand is expected to increase—respond by increasing consumption once the cash increase is realized (Deaton, 1991; Carroll, 1997).

Researchers and policy makers have traditionally been interested in the marginal propensity to consume out of income changes because it provides a way to evaluate fiscal policy that affects income.[2] The typical empirical finding shows that consumption is excessively sensitive to predictable transitory changes in income relative to the theoretical predictions of the PIH.[3] This failure of the PIH has widely been attributed to the presence of liquidity constraints but, even when they are considered, mixed empirical results persist.[4] Liquidity constraints are hard to identify because they pertain to the consumer's shadow cost of borrowing. Early tests of liquidity constraints focused on splitting the sample according to net wealth (Zeldes, 1989) but net wealth might fail to accurately identify financial constraints (Jappelli, 1990). The use of high-frequency credit card data has gained popularity for the analysis of liquidity constraints (Gross and Souleles, 2002a; Agarwal et al., 2007) because

[2] See, for example, Agarwal et al. (2007); Agarwal and Qian (2014); Souleles (1999); Johnson et al. (2006); Hsieh (2003).

[3] Jappelli and Pistaferri (2010) survey theoretical results on the consumption response to income shocks, and Attanasion and Weber (2010) and Fuchs-Schuendeln and Hassan (2015) survey empirical results.

[4] Hsieh (2003) shows that some consumers smooth consumption for large recurring payments but not for smaller, infrequent ones. Scholnick (2013) provides evidence that consumers are more inclined to smooth large than small income changes. Browning and Collado (2001) cannot reject the PIH for income changes which occur frequently over the life cycle. Shea (1995) highlights that liquidity constraints can explain the sensitivity of consumption to income increases, but not to declines since consumers can save ahead of time.

maximum authorized limits on credit cards can proxy for credit quantity constraints. However, the shadow cost of borrowing might differ substantially among quantity unconstrained consumers, therefore affecting their response to an increase in cash-on-hand.

In this paper, I test predictions of a version of the PIH in which consumers differ in their shadow cost of funds. I use account-level data from a North American bank that allows clients to use both a credit card and term loans on the same account. The credit card is a revolving loan that is paid off on a flexible schedule. Term loans are paid off in a predetermined number of equal monthly installments. Because the amortization schedule of the term loan is provided on consumers' monthly account statement, the end of a term loan generates a predictable increase in cash-on-hand relative to months in which borrowers were required to make the monthly payment on the loan. I use this event to provide empirical evidence on the response of consumption, debt, and delinquency to an anticipated increase in cash-on-hand.[5]

I contribute to the literature on empirical tests of the PIH in three ways. First, the high-frequency nature of the data allows me to better measure who is constrained, in what way, and to what degree. I extend the typical tests of liquidity constraints by considering the shadow cost of funds faced by borrowers, as implied by their payment behavior on the credit card. Borrowers are categorized as full, partial, or minimum payers depending on their history of payment behavior. I show that the groups of partial and full payers are both unconstrained in the quantity of credit available, while minimum payers appear constrained. The important difference among unconstrained borrowers is that partial payers revolve a large fraction of their monthly balance (and therefore pay a median APR of 19,9%) whereas full payers are charged no interest.

Second, I measure the consumption response using two different channels: credit card and term loan expenditures. In addition, the data allow me to distinguish between two

[5]This is not the first paper using a reduction in loan payments to learn about the effect of anticipated increases in cash-on-hand: Coulibaly and Li (2006) and Scholnick (2013) use last mortgage payments and Stephens (2008) uses last auto loan payments. However, except for Scholnick (2013) — who strictly focuses on the "magnitude hypothesis" — these articles use low-frequency survey data such as the Consumption Expenditure Survey (CEX), without the detailed loan performance information provided by bank-level data such as those used in this paper and which allow me to study financial delinquency.

types of term loans. *Bank-originated* term loans are contracted with a bank representative and can be used for different (unobservable to the econometrician) purposes by borrowers (e.g. home renovations, car financing, investments). *Store-originated* term loans, which are contracted at select retail stores, are recorded separately and are solely used to finance "big-ticket" items over monthly installments. Store loans therefore provide a measure of durable consumption—a dimension usually ignored by research using only credit card data.

Third, the credit card and the term loans are linked to the same account, which allows me to quantify the impact of an increase in cash on financial delinquency. Because debt contracts feature limited commitment from the borrower, the possibility of being financially delinquent on one's obligation represents an important margin of adjustment for consumers.

The average results show that total payments made on the account decrease following the predetermined pay-off of the term loan. However, the decline in payments induced by the end of the term loan is attenuated by an increase in payments made on the credit card. Spending on the credit card increases almost one-for-one with increased payments, leaving credit card balances nearly unchanged. I estimate an average marginal propensity to consume (MPC) out of reduced debt payments of 9% each month on the credit card. In addition, the propensity to take out new term loans increases by about 35% after the original term loan is repaid (an increase of 0.84 percentage points on a baseline of 2.4%). This suggests that previous research using only credit card data might underestimate the MPC by omitting other channels for the consumption response.[6]

These average effects differ for borrowers *ex ante* identified as differently constrained. Consumers with a history of paying their credit card balance in full do not change their credit card expenditures. Constrained consumers, with a history of making minimum credit card payments, increase their credit card expenditures and revolving balance. Consumers for whom the credit card is the marginal source of funds, with a history of paying their balance partially, decrease their revolving balance.[7] Surprisingly, although the behavior of

[6] Gross and Souleles (2002a) estimate an MPC out of increased credit card limits of 10-14% which is close to what I find on the credit card without considering the term loan response.

[7] These results are in line with Mian et al. (2013), Di Maggio et al. (2015), and Keys et al. (2014), who find that the most indebted households choose to deleverage instead of increasing consumption in response to increased liquidity.

consumers on the credit card account is in accordance with a model in which consumers are potentially liquidity constrained, the propensity to take out a new term loan increases for all consumers, whether constrained or not. About 4% of unconstrained consumers delay taking out a new store-originated term loan until the original loan is repaid, contrary to theoretical predictions. Such behavior is consistent with borrowers having different mental accounts from which they finance consumption and, in particular, is consistent with some consumers self-imposing themselves limits on the amount of active term loans they can have at once. In the words of Thaler (1990): "there are two important sources of liquidity constraints: those imposed by capital markets, and those imposed by individuals on themselves."

The probability of missing a payment on the account is reduced after the term loan is repaid, with the greatest effect found among constrained borrowers. This leads to a decrease in the probability of consumer default (i.e. reaching six-months overdue on the account). These results highlight the trade-off for the bank between granting an additional dollar of term loan debt and increasing the probability of taking a loss on an unproductive loan.

Because the term loans can be prepaid without penalty, one methodological concern is that unobservable variables (e.g. windfall gains) might correlate with the prepayment decision and outcomes studied in the analysis. For this reason, I use the *anticipated* date of final payment — predicted 12 months before its realization — as the event generating an increase in cash-on-hand. In such intention-to-treat (ITT) approach (e.g. Imbens and Rudin, 2015), random assignment into the treatment is assumed for the predicted final payment date, not its actual realization. This mitigates concerns about unobservable variables correlating with the final term loan payment and subsequent consumption behavior, while still capturing a discontinuous decrease in monthly debt payments. The results are robust to modeling the term loan prepayment decision in a Heckman selection model (Heckman, 1979), where the identifying assumption is that the interest rate on the term loan affects the probability of prepayment but not subsequent consumption decisions. As additional robustness checks, I perform the analysis on the subsample of borrowers who comply exactly with the predicted final payment date (perfect-compliance analysis) and I use the actual final payment date as the event generating the increase in cash-on-hand (as-treated analysis).

2.2 Conceptual Framework

Theoretically, liquidity constraints refer to the inability to borrow against future wealth (Deaton, 1991; Carroll, 1997). This strict definition of liquidity constraints refers to a constraint on the quantity of funds that can be borrowed. Empirically, net wealth (Zeldes, 1989) and survey responses from borrowers that have been refused for loans (Jappelli, 1990) have been used as proxies for liquidity constraints. Recently, the "head-room" available on a credit card account or, conversely, the percentage of the maximum authorized credit limit drawn down, has gained popularity as a proxy for quantity constraints (Gross and Souleles, 2002a; Agarwal et al., 2007). However, as noted by Gross and Souleles (2002a), a weaker definition of liquidity constraints refers to the wedge between the lending and borrowing rate faced by consumers. A bigger wedge between the cost of funds and the interest rate on savings represents tighter liquidity constraints. Under this weaker definition of liquidity constraints, borrowers who are unconstrained in the quantity of credit available are allowed to differ in the marginal cost of funds they pay to finance consumption.

A borrower's cost of funds is difficult to measure. However, if borrowers are making optimal consumption and savings decisions, it can be bounded by observing their borrowing and payment behavior. Because credit cards are revolving loans, borrowers choose the fraction of their balance they repay each month. The payments made on a credit card therefore provide information about the interest rate which consumers are paying to fund consumption, and the amount borrowed at that rate. Using past payment behavior on the credit card, I classify borrowers into three levels of liquidity constraints described below and summarized in Table 2.1.

Full Payer. — Consumers who repay their revolving balance in full at the end of the month are not charged any interest fees. These borrowers are not willing to revolve debt at the interest rate offered on the card; they have an outside cost of fund that is smaller than the APR on the card. These consumers are not considered constrained. When anticipating an increase in cash-on-hand, their margin of adjustment is not to increase consumption (because they could already have done so), but rather to save the additional money at the interest

Table 2.1: Liquidity Constraints and Credit Card Payment Behavior

	Outside	Empirical Predictions		
	Cost of Funds	C.C. Purchases	Term Purchases	C.C. Debt
Full Payer	$R < APR$	No Changes	No Changes	No Changes
Partial Payer	$R = APR$	No Changes	No Changes	Decrease
Minimum Payer	$R > APR$	Increase	Increase	Increase

rate available on their savings account.

Minimum Payer. — Borrowers who bunch around minimum monthly payments are making the minimum dollar amount required in order to avoid delinquency. Such borrowers are revolving almost their entire end-of-the-month balance at the APR on the card. For these borrowers, the outside cost of fund is larger than the APR on the card and, if they could, they would potentially increase the amount of debt revolved on the card. Such borrowers are the most likely to be constrained, and in response to extra cash-on-hand we would expect them to increase consumption (through either credit card or new term loan expenditures). Because they are paying a small portion of their balance each month, the extra cash-on-hand could even be used to finance a higher amount of credit card debt.

Partial Payer. — Finally, some borrowers fall in between the full and minimum payers: they repay part of their balance, and revolve part of it. These borrowers use the credit card as their marginal source of borrowing. They could increase consumption by revolving an additional amount of debt on the credit card instead of paying it off. They are at an interior solution with respect to the amount borrowed on the card and have an outside cost of fund that is exactly equal to the APR on the card. Therefore, their margin of adjustment when receiving extra cash-on-and is not to increase consumption, but rather to reduce their revolving balance.

These empirical predictions are summarized in Table 2.1. Appendix Table 2.12 tabulates the interaction between the typical measure of quantity constraints (in terms of the utilization rate out of the credit card limit) and the measure of payment behavior proposed in this analysis. Interestingly, virtually every consumer that pays the balance partially or fully is also considered unconstrained in terms of the quantity of funds available to draw down. Consumers identified as paying the minimum amount fall in two groups: one group is both constrained in terms of quantity and cost of funds, while the other is only constrained in terms of cost of funds. The conceptual framework proposed in this paper can therefore be seen as augmenting the traditional binary view of liquidity constraints as binding or not, by separating the behavior of consumers for whom quantity constraints do not bind in terms of their outside cost of funds. The results highlight that, even for borrowers unconstrained in quantity, the consumption response to anticipated increase in cash-on-hand might differ depending on the outside cost of funds.

2.3 Data and Research Design

I use account-level data provided by a large North American bank. Borrowers can use their account to make purchases with both a credit card and term loans. All accounts are originally linked to a credit card and borrowers can then choose to use the account to contract term loans. There is no penalty for prepaying either loan. The credit card is a typical revolving loan: borrowers use it to make purchases and pay interest only on the portion of the balance that is unpaid after a billing cycle. It has no fixed repayment schedule other than a minimum monthly payment equal to a small portion of the monthly balance.[8] Term loans are repaid in equal monthly installments over 12, 24, 36, 48 or 60 months. Two types of term loans are offered by the bank: the *bank-originated* term loans are contracted at the bank, whereas the *store-originated* terms loans are contracted at selected retail stores as a way of financing consumer goods over monthly installments. Accounts have separate borrowing limits for term and revolving loans. The bank advertises that taking out a term loan does not affect the credit card limit and vice versa.

The data made available by the bank include monthly information typically found on

[8]The bank increased the minimum revolving payment from 3% to 5% of the monthly credit card balance during the time frame analyzed in this study, see d'Astous and Shore (2015). However, because the date of the final term loan payment varies across borrowers and because I control for time fixed effects, this does not affect the results.

the front page of credit card statements such as total spending, total payments, balance outstanding, interest rate, and delinquency. Data also include demographics such as sex, age, credit score and partial information about zip code.[9]

Figure 2.1 presents a typical monthly statement. The total account balance is the sum of the term and revolving balances and, equivalently, purchases and payments can be analyzed on each type of loan or aggregated at the account level. The total minimum payment due is the sum of; a) the minimum payment on the revolving balance, b) the installment payment on the term balance, and c) any overdue amount from previously missed payments. For delinquent borrowers, paying this sum "cures" (makes current) the account. Borrowers who pay less than this sum miss a payment and increase their delinquency cycle by one. Accounts can be current, or 1, 2, 3, 4, or 5 cycles delinquent. Accounts that are six cycles delinquent are considered to be in default and must be written off.[10] There is no distinction between delinquency on the revolving and term loans; delinquency is recorded at the account level. Each month, an account can transition into one of three mutually exclusive delinquency states: current, delinquent, and written-off. The write-off state is absorbing and arises from either default or bankruptcy.

[9]The data do not explicitly distinguish between payments made on term and revolving loans. I back out this information using the evolution of the balances and spending. Term loan prepayment occurs when the term balance goes down by an amount greater than the monthly installment. The monthly term loan installment plus the prepayment amount is the monthly term loan payment. Total payments net of term loan payments is the payment made towards the revolving balance.

The interest rate and amortization schedule are missing for the term loans. I calculate this information using the monthly installment — which is given — and the evolution of the term balances. Specifically, I first use the variation in balance on the term loan to back out the interest charged on the account as

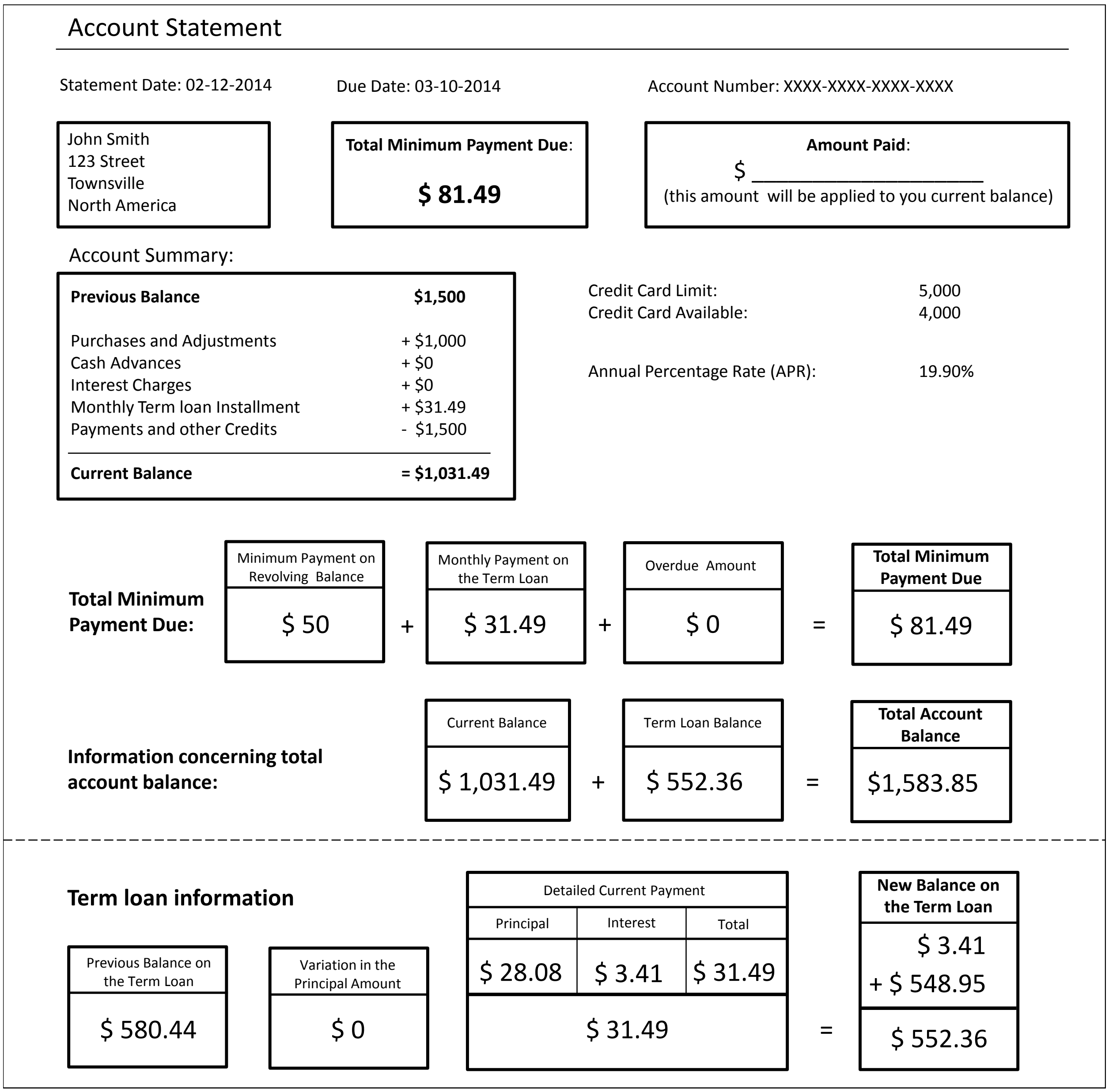
$$i = \frac{Installment_t - \Delta Balance_t}{Balance_{t-1}}.$$

Using this rate, I calculate the number of months left before the term loan is repaid as

$$n = \frac{\log\left(\frac{Installment}{(Installment - \Delta Blance_t)} \times i\right)}{\log(1+i)}.$$

[10]The number of cycles delinquent depends on the payment history, not merely on the number of calendar months the account has been delinquent. Accounts move forward in delinquency cycles (e.g., from 1 cycle delinquent to 2 cycles) when the total payment falls below the sum of (a) and (b) above; accounts can improve in delinquency cycles without curing if a portion of the overdue amount (c) is paid.

Figure 2.1: Account Statement Example



Note: This figure shows a typical account statement for a borrower at the bank. The monthly statement presents information about the revolving and term loans on the account. The total minimum payment due consists of the minimum payment on the credit card balance, the monthly term loan payment, and the overdue amount. The monthly payment on the term loan consists of the installment due on the term loan in the current month. The overdue amount consists of the cumulative amount that arises from paying less than the total minimum payment due on previous statements.

2.3.1 Sample Construction

The original data consist of monthly observations on the universe of the bank's credit card accounts — close to 5 million unique accounts — over the period ranging from December 2009 to May 2013. A total of $2,649,863$ accounts have an active term loan at some point in the sample.

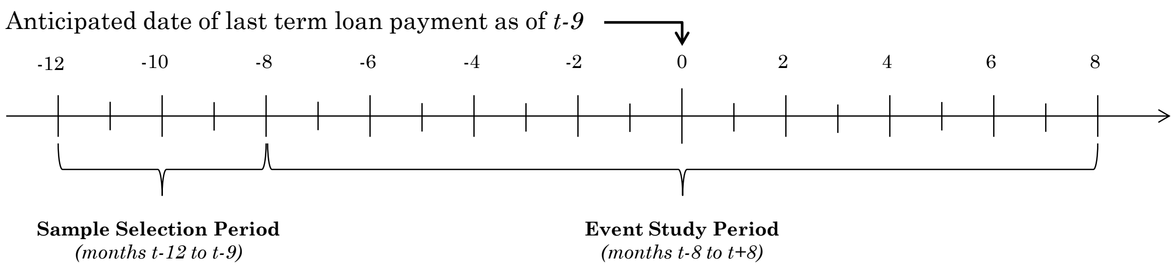
I use an event-study methodology with an intention-to-treat (ITT) approach. The month of final term loan payment is predicted one year before its realization and the behavior of borrowers is then analyzed in the months prior to and following the *predicted* final term loan payment. This has the advantage of preventing unobservable variables to correlate directly with the outcomes of interest in the month of *actual* term loan paydown, particularly in the case of prepayment. For example, using the actual last payment month could bias the results if unobservable variables affect both the decision to prepay and the subsequent consumption-savings decision. In this ITT framework, the random assignment assumption is on the predicted date of final payment, rather than on its actual date. This methodology has the advantage of capturing the anticipation of a change in cash-on-hand, which is consistent with the theoretical implications tested. It also allows me to analyze term loan prepayment and new term loan expenditures in the period before the final term loan payment.[11]

Figure 2.2 shows the timeline of the event-study. I require borrowers to conform to the term loan payment schedule during the period 12 months to 9 months before the anticipated final payment. I also require that borrowers have only one active term loan during this selection period, to rule out the possibility that a consumer is identified as paying off a term loan although a second one is still active in the account.[12] Time 0 corresponds to the first month in which the borrower is anticipated to have paid down the term loan. Control variables and measures of financial constraints are calculated during the sample-selection period — before the event study starts — in order to avoid confounding the impact of term loan repayment with any of the outcomes studied.

[11] Focusing solely on borrowers who follow the term loan's exact repayment schedule would also be problematic as it might introduce a selection bias towards more financially constrained borrowers — who are not able to take advantage of the option to prepay. I present the results for such an extension in Section 2.5.

[12] However, during the event study borrowers can have two types of term loans (*merchant* and *bank* loans) simultaneously, in which case I aggregate them to a single term loan.

Figure 2.2: Event Study Timeline

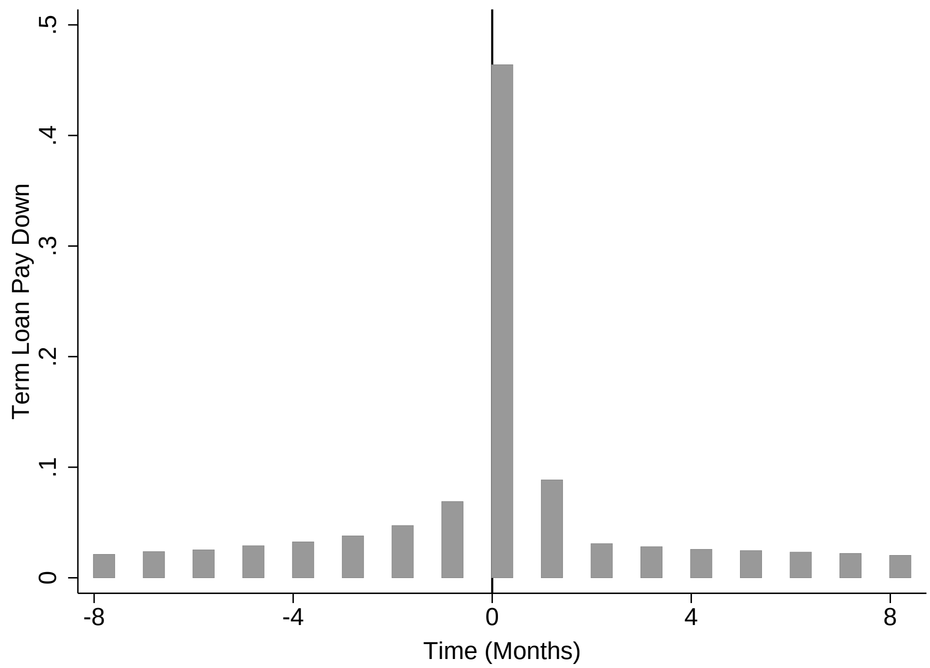


To be included in the sample, accounts must have an anticipated term loan repayment event and have observations over the full event-study period. Accounts that default prior to the end of the sample period are nevertheless allowed in the sample. As a result, $1,225,965$ events of term loan repayment are observed in the data. Following the sample selection described above yields $291,777$ unique accounts and $4,803,365$ account-month observations.

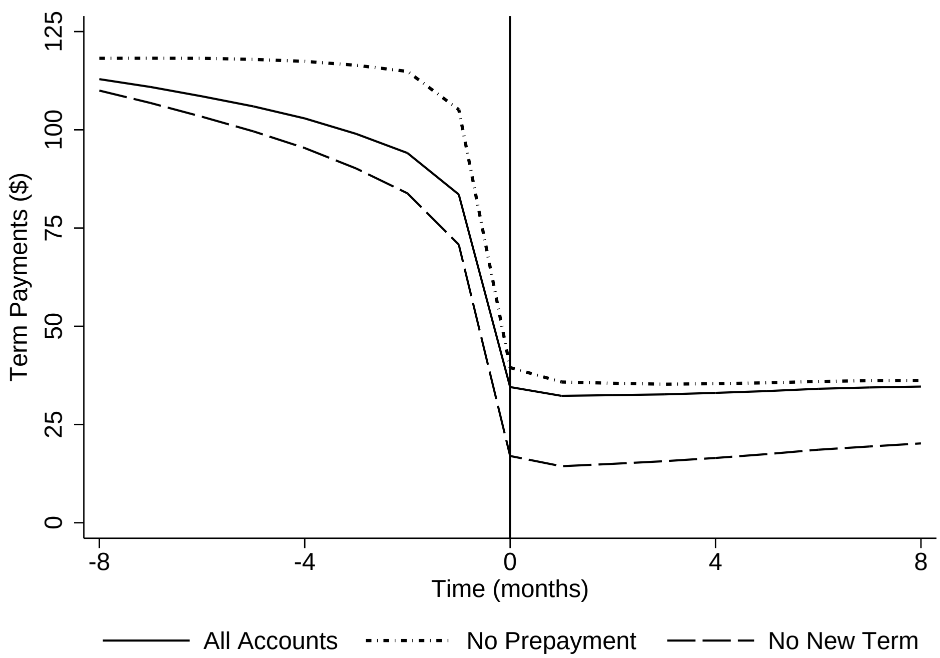
Compliance with Anticipated Last Payment Date

Because of the nature of the research design, I provide evidence of compliance with the predicted date of last term payment. Panel (a) of Figure 2.3 shows the fraction of borrowers paying down their term loan each month (that is, bringing the term loan balance to zero). Time 0 corresponds to the first month in which the borrower is predicted to have paid down the term loan. 46% of accounts-holders finish paying their term loan in month 0 of the event study, exactly as predicted one year before the event. The rest of the account-holders finish paying their term loans in the months surrounding $t = 0$. Panel (b) shows the monthly term loan installment for the full sample, and for groups of borrowers who do not prepay and who do not take out new term loans before the original one is repaid. There is a discontinuous decrease in term loan installment in the month of the predicted final payment. Installments do not go down to zero because some borrowers take out new term loans before the original term is repaid, which dampens the reduction in monthly required payments. This nevertheless provides the source of variation in cash-on-hand used in the analysis.

Figure 2.3: Compliance with Predicted Last Payment



(a) Actual Term Loan Paydown



(b) Monthly Term Installment

Note: Panel (a) shows the fraction of borrowers paying off their term loan (i.e. bringing the term balance to zero) each month. Panel (b) shows the monthly term loan installment for the full sample and for groups of borrowers who do not prepay and who do not take out new term loans before the original one is repaid. Time 0 corresponds to the first month in which the borrower is predicted to have paid down the term loan.

2.3.2 Identification Strategy

To analyze the response of consumers to an increase in cash-on-hand, one needs to determine appropriate treated and control groups. A natural way to proceed is to compare borrowers who experience a final term loan payment with those who do not. To compare groups of borrowers who are as homogeneous as possible, I compare borrowers who have active term loans, but who face an anticipated term loan paydown at different point in time. Because borrowers finish repaying their term loans in different months, there is variation in the timing of the increased cash-on-hand which allows me to average out seasonal effects.

The baseline analysis exploits the time variation of the anticipated final payment across borrowers in an equation of the form

$$Y_{i,t} = \beta \text{After?}_{i,t} + \text{Controls}_{i,t} + \lambda_t + \varepsilon_{i,t}, \tag{2.1}$$

where $Y_{i,t}$ represents outcomes such as spending (using the credit card or term loans), debt payments, debt levels and delinquency events.[13] After?$_{i,t}$ is a dummy variable equal to one if the observation is after the anticipated final term payment date, and 0 otherwise. The control variables are taken in the four months period prior to the start of the event study and consist of monthly term loan installment, external credit score, revolving limit on the account, APR on the revolving loan, age of the account, age of the account-holder, average credit card and term loan balances and average monthly purchases. Month fixed effects and a quadratic trend in event-study time are included in all specifications.

To measure the consumer response as a fraction of the dollar amount of debt payment reduction, I augment the baseline specification by interacting the dummy variable indicating the predicted final payment date with the dollar amount of monthly term loan installment.

[13]The equations presented in this section represent the versions that are estimated by OLS. However, because expenditures feature an excess realization of zeros, I also estimate two-part models where the zero realizations and the conditional distribution of positive expenditures are modeled separately. In such cases, each equation is then estimated with a Probit model and a truncated-normal model. Probit models are also estimated when modeling the probability of financial delinquency.

I estimate a regression equation of the form

$$Y_{i,t} = \beta_1 \text{After?}_{i,t} \times D_i + \beta_2 \text{After?}_{i,t} + \beta_3 D_i + \lambda_t + \text{Controls}_{i,t} + \varepsilon_{i,t}, \tag{2.2}$$

where D_i is the monthly installment on the term loan calculated in the period before the event study starts. β_1 gives the average monthly response in dollars to a reduction of the term loan installment of \$1. This coefficient therefore measures the marginal propensity to consume out of a reduction in committed debt payments when the outcome of interest is consumption.

Because financial constraints may explain the failure of the permanent income hypothesis, I estimate their effects by interacting the payment behavior outlined in Section 2.2 with the dummy variable indicating the predicted final payment date. In such case, I estimate a model of the form

$$\begin{aligned} Y_{i,t} = {} & \beta_1 \text{After?}_{i,t} \times \text{Min Payer}_i + \beta_2 \text{After?}_{i,t} \times \text{Med Payer}_i + \beta_3 \times \text{After?}_{i,t} \\ & + \beta_4 \times \text{Min Payer}_i + \beta_5 \text{Med Payer}_i + \lambda_t + \text{Controls}_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{2.3}$$

where "Min Payer" and "Med Payer" are dummy variables identifying borrowers by their payment behavior in the four months prior to the start of the event-study, and with the "Full Payer" category being omitted and therefore absorbed in the "After?" coefficient. This equation is also augmented by interacting the dollar amount of monthly installment D, as is the case in equation (2.2)

The identification strategy assumes that consumers rationally anticipate the ending of the term loan. As this information is provided on their monthly statement, there is no reason to believe that they do not systematically do so. The main threat to identification is that unobservable variables correlate with prepayment and subsequent consumption, debt or, delinquency patterns. To address this concern, in Section 2.5 I extend the analysis to take into account the decision to prepay the term loan. I exploit the fact that some term loans are offered at 0% APR to provide the exclusion restriction required to model prepayment in a Heckman selection model. The identifying assumption is that having a 0% APR on the term loan affects the probability of prepaying the loan without otherwise affecting the consumption and debt repayment decisions.

2.4 Main Results

2.4.1 Descriptive Statistics

Table 3.1 presents summary statistics for the variables used in the analysis. All statistics are presented for the full sample, and broken down by periods before and after the predicted final term loan payment. Panel A shows borrower demographics. Panel B shows purchases, payments and balances aggregated at the total account level. The total account variables are the sum of the activity on the credit card and term loans, which are presented separately in Panels C and D.

Panel D shows that the monthly installment due on the term loan goes down by \$64 after the anticipated final payment date, from an initial amount of \$102. It does not go exactly to zero because some borrowers take out new loans or prepay during the event study. The reduction in term loan installment drives the total account payments down by \$32 and the revolving payments increase by the difference: $\$64 - \$32 = \$32$. This provides preliminary evidence that borrowers are shifting payments towards the revolving account after paying down the term loan. Total purchases on the account go up by \$44, out of which \$32 come from an increase in revolving purchases and \$12 from an increase in term loans. The size of new term loans is similar before and after the event date, which suggests that the increase in term loan purchases is driven by an increase in the extensive margin (i.e., the propensity to take out a new term loan).

The average APR on the credit card is 18% while it is 4% for term loans. This very small interest rate on term loans is driven by some of the loans taken out at retail store being offered at 0% APR financing. The external credit score is a bankruptcy prediction score and varies from 1 to $1,000$. Unlike FICO scores, which predict the probability of missing a payment on a loan, this type of measure predicts the probability of filing for bankruptcy over

Table 2.2: Descriptive Statistics

	Full Sample					Before		After		Diff
	Mean/(Std. Dev.)	p5	p50	p95	Obs.	Mean/(Std. Dev.)	Obs.	Mean/(Std. Dev.)	Obs.	Mean/(Std. Error)
A. Borrower Characteristics										
Age	46	24	46	71	4,803,365	-	-	-	-	-
	(15)									
Male?	0.51	-	-	-	4,803,365	-	-	-	-	-
	-									
Account age (in years)	9	1	7	24	4,803,365	-	-	-	-	-
	(7)									
External Credit Score	915	601	963	976	4,803,365	911	2,296,214	920	2,507,151	9.26***
	(140)					(147)		(133)		(0.13)
B. Total Account										
Monthly Purchases	376	0	0	1,967	4,803,365	353	2,296,214	397	2,507,151	44.01***
	(1,164)					(1,125)		(1,199)		(1.06)
Payments	426	0	110	1,946	4,803,365	443	2,296,214	411	2,507,151	-32.00***
	(1,102)					(1,077)		(1,124)		(1.01)
Balance	1,701	0	689	6,994	4,803,365	1,776	2,296,214	1,632	2,507,151	-143.42***
	(2,942)					(2,720)		(3,131)		(2.69)
C. Credit Card										
Monthly Purchases	327	0	0	1,754	4,803,365	311	2,296,214	342	2,507,151	31.82***
	(995)					(970)		(1,018)		(0.91)
Payments	358	0	20	1,820	4,803,365	341	2,296,214	374	2,507,151	32.47***
	(1,079)					(1,050)		(1,105)		(0.99)
Balance	1043	0	129	5,033	4,803,365	1042	2,296,214	1044	2,507,151	1.98
	(2,189)					(2,172)		(2,205)		(2.00)
Limit	3,598	400	1,500	15,000	4,803,365	3,488	2,296,214	3,698	2,507,151	209.95***
	(4,636)					(4,531)		(4,727)		(4.23)
% Limit Used	0.27	0	0	1	4,803,365	0.29	2,296,214	0.26	2,507,151	-0.03***
	(0.36)					(0.37)		(0.35)		(0.00)
% Balance Paid	0.40	0	0.09	1	4,803,365	0.44	2,296,214	0.36	2,507,151	-0.08***
	(0.45)					(0.46)		(0.44)		(0.00)
APR	18.05	10	19	19.40	4,803,365	18.07	2,296,214	18.03	2,507,151	-0.04***
	(3.16)					(3.14)		(3.17)		(0.00)
Has Reduced APR?	0.07	0	0	1	4,803,365	0.07	2,296,214	0.07	2,507,151	0.00***
	(0.26)					(0.26)		(0.26)		(0.00)
D. Term Loan										
Monthly Purchases	49	0	0	0	4,803,365	42	2,296,214	54	2,507,151	12.19***
	(578)					(546)		(607)		(0.53)
Monthly Purchases | Purchases > 0	2,198	345	1,200	7,291	106,158	2,097	46,217	2,275	59,941	178.10***
	(3,228)					(3,241)		(3,216)		(19.97)
Payments	68	0	23	265	4,803,365	102	2,296,214	37	2,507,151	-64.46***
	(147)					(150)		(137)		(0.13)
Balance	658	0	145	2,738	4,803,365	734	2,296,214	588	2,507,151	-145.40***
	(1,774)					(1,469)		(2,011)		(1.62)
Limit	3,042	0	2,500	8,000	4,803,365	3,033	2,296,214	3,050	2,507,151	17.36***
	(2,934)					(2,853)		(3,005)		(2.68)
Monthly Installment	66	0	32	255	4,803,365	102	2,296,214	34	2,507,151	-68.79***
	(107)					(115)		(87)		(0.09)
Rate	4.07	0	0	13.58	4,803,365	-	-	-	-	-
	(5.62)									

Note: All statistics are presented for the full sample, and broken down by periods before and after the predicted final term loan payment. See Section 2.3.1 for the sample selection details.

the next two years and is typically higher than average FICO scores. There is evidence that credit quality, as measured by an external agency, increases after the term loan is repaid, although this could be spurious evidence that credit rating agencies update their credit scores to consumers' debt levels.

Sample Selection

Two types of sample selection are worth investigating: selection into getting a term loan, and selection into the type of term loan contracted. Table 2.13 first shows descriptive statistics for accounts included in the event-study, and a 10% random sample of accounts that never have a term loan in the original dataset.[14] The credit card balance is similar for both group, with a difference of only $35. However, borrowers with a term loan have a smaller credit card limit, which is compensated by a higher term loan limit. The external credit scores are similar and do not provide evidence that any group is of significantly better or worse credit quality.

Table 2.14 shows descriptive statistics for groups of borrowers that originally had a store-originated or a bank-originated term loan. Borrowers with a store-originated term loan have smaller credit card and term loan balances. They are also making smaller monthly payments. They have higher credit card and term loan limits and a better external score. In Section 2.4.3, the main results presented below are also segmented by the type of loan borrowers originally held.

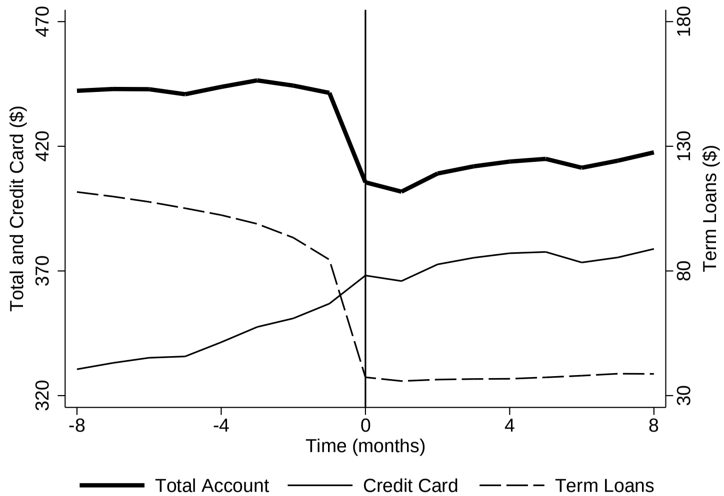
2.4.2 Average Effects

Expenditures, Payments, and Debt Levels

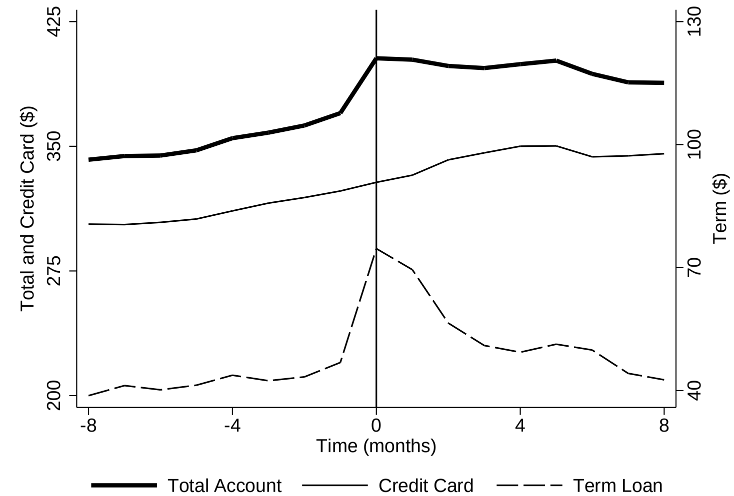
Figure 2.4 presents preliminary evidence of the average response to the anticipated final term loan payment over the period of the event study. Panel (a) shows total payments made on the account, and payments made on the credit card and term loans separately. There is evidence of substitution of payments from the term loan to the credit card: as the term loans

[14]The descriptive statistics are calculated as the average over the four months pre-event study for borrowers with a term loan and as the first four months available in the sample for borrowers with no term loans.

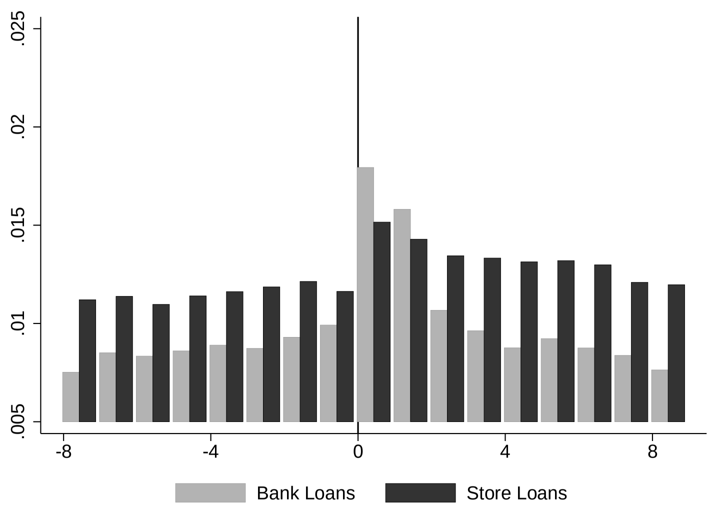
Figure 2.4: Average Payments, Expenditures, and Balances



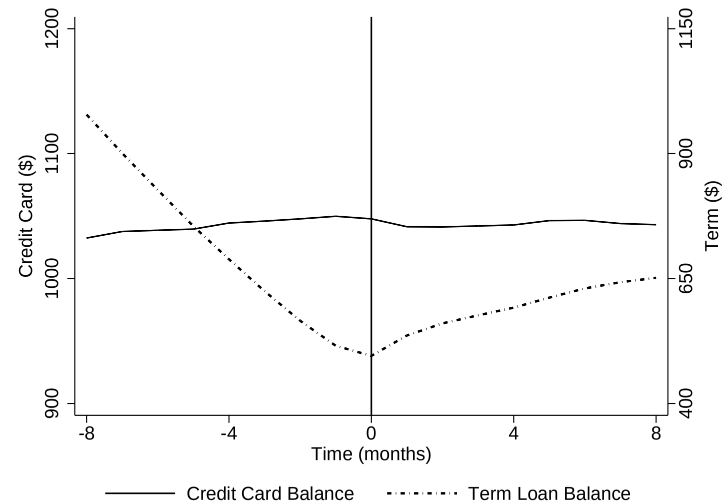
(a) Payments



(b) Expenditures



(c) Propensity to Contract New Term Loans



(d) Balances

Note: Panel (a) presents average payments made towards the credit card and the term loan over the event-study. Panel (b) shows average purchases made with the credit card or new term loans. Panel (c) shows the propensity to take out a new term loan each month, segmented by the type of term loan taken out. Panel (d) shows the evolution of credit card and term loan balances.

are paid off, borrowers use part of the previous monthly installment towards the credit card. Panel (b) shows total expenditures on the account, and expenditures on the credit card and on new term loans separately. There is no obvious discontinuity in credit card purchases around the final payment month. However, new term loan expenditures exhibit a transitory increase around the month of the final payment, followed by a small permanent increase. Panel (c) shows the fraction of borrowers taking out new term loans in each months of the event study, broken down by bank-originated and store-originated loans. The transitory increase in new term loan expenditures is confined to new bank loans and the permanent level increase to new store loans. These patterns are further explored in Section 2.4.4. Finally, Panel (d) shows the evolution of credit card and term loan balances. The credit card balance is relatively stable over the event study. Note that term loan balance represents the sum of all active term loans on the account. It decreases in the months before the final payment and increases after, as some consumers take out new term loans.

Table 2.3 quantifies these effects by estimating equation (2.1). The outcomes analyzed are new expenditures, payments, and changes in balances. They are presented aggregated at the account level as well as segmented by credit card and term loans. The effect on the total account is the sum of the effect on each type of loans, and the changes in balances result from differences in expenditures and payments — up to differences due to interests and fees charged on the account. The specification presented includes months fixed effects, a quadratic trend in event-study time, as well as a set of account characteristics.

The results show that payments made towards the term loan account decline by \$51 after the final term loan payment, in line with the reduced installment payments. At the same time, payments made on the revolving account increase by \$8, which drives the total payments made on the account down by \$43. Part of the reduction in term loan monthly payments is therefore passed through to an increase in credit card payments.

Total purchases on the account increase by \$30 and can be traced back to an increase in revolving expenditure of \$6 and an increase in term loan expenditures of \$24.[15] The

[15] The results of estimating an OLS model on expenditures is presented in column (1) of Table 2.3. Because there is an excess realization of months with no new expenditures (specially for term loans), I also decompose total expenditures by estimating a two-part model in columns (2) and (3): I present the marginal effects for the

Table 2.3: Average Effects

	Purchases			Payments	Δ Balance
	(1)	(2)	(3)	(4)	(5)
	In Dollars	$\mathbb{P}$(New Purchases)	Purchases $\mid > 0$	In Dollars	In Dollars
A. Total Account					
After?	30.4407***	0.0149***	52.7924***	-43.1718***	62.7994***
	(1.6441)	(0.0006)	(3.7965)	(1.4307)	(2.0528)
R^2	0.397	0.308	0.338	0.449	0.003
Observations	4,803,365	4,803,365	2,053,541	4,803,365	4,787,607
B. Revolving Loan					
After?	6.0724***	0.0109***	4.3564	7.7700***	-3.4339***
	(1.1637)	(0.0006)	(2.7614)	(1.4126)	(1.2742)
R^2	0.518	0.319	0.473	0.438	0.001
Observations	4,803,365	4,803,365	2,008,154	4,803,365	4,787,607
C. Term Loan					
After?	24.3683***	0.0084***	44.0295	-50.9419***	66.2333***
	(1.1427)	(0.0003)	(38.0151)	(0.2736)	(1.6771)
R^2	0.004	0.013	0.082	0.204	0.006
Observations	4,803,365	4,803,365	106,158	4,803,365	4,787,607
Month F.E.	YES	YES	YES	YES	YES
Quadratic Trend	YES	YES	YES	YES	YES
Account Controls	YES	YES	YES	YES	YES

Note: This table shows the results of estimating equation (2.1) by OLS for all columns except for column (2) which is estimated using a Probit model and for which I report the marginal effects. The control variables grouped under "Account Characteristics" are taken in the four months period prior to the start of the event study and consist of monthly term loan installment, external credit score, revolving limit on the account, age of the account, age of the account-holder, average credit card and term loan balances, average monthly purchases and a dummy variable indicating if the borrower pays for a reduced APR on the credit card. Standard errors corrected for within-account heteroscedasticity are presented in parentheses. ***, ***, and * represent significance at the 1, 5 and 10 percent level, respectively.

increase in credit card purchases comes from an increase in the probability of using the card of 1 percentage points (2.8% increase on a baseline of 39.3%). The size of the average term loan taken out does not change: the increase in term loan expenditures is driven solely by an increase of 0.84 percentage point in the probability of taking out a new term loan (35% increase on a baseline of 2.4%). For this reason, the right measure of consumption response through term loan expenditures is the propensity of consumers to take out new term loans. The simultaneous increase of spending and payments made with the credit card leaves the revolving balance nearly unchanged. Term and total account balances increase as borrowers take out new term loans.

probability of making a purchase estimated by a Probit equation and the results of estimating a truncated-normal model on expenditures conditional on them being positive.

Marginal Propensity to Consume

Table 2.4 measures the credit card response as a fraction of the reduction in monthly installment by estimating equation (2.2). In this specification, the effect measured is the marginal propensity to consume out of reduced term loan payments. Panel A interacts the dummy variable "After?" with the dollar amount of term loan installment D. The consumption response through the credit card is on average 9%. This is in-line with previous research using credit card expenditures to measure the MPC.[16] An increase in payments almost perfectly offsets the increase in new expenditures, leading to a decrease in average credit card balance of 2% of the monthly installment each month. Panel B investigates the effect of the size of monthly payment reduction. To this end, the dollar amount of term loan installment is segmented in bins of [$0-$75], [$75-$150], [$150-$250], [$250+]. Dummy variables are constructed for each categories (D_1 to D_4), with the lowest category being omitted. The results show that the consumption response increases in the amount of reduced debt installments.[17]

2.4.3 Liquidity Constraints

In this section, I test the empirical predictions derived in Section 2.2. Consumers repaying their balance fully are not constrained and should not react to the final payment on the term loan. On the other hand, consumers repaying minimum monthly amounts on their credit card account are most likely to be constrained, and are expected to increase consumption once the original term loan is repaid as this frees up cash-on-hand. Borrowers for whom the credit card provides the marginal source of funds (i.e., those who are paying part of their balance, and revolving part of it) are expected to use the amount of monthly installment freed up to reduce the revolving balance.

[16] For example, Gross and Souleles (2002a) estimate an MPC out of increased credit card limits of 10-14%.

[17] This also provides a test of the magnitude hypothesis (e.g. Scholnick, 2013). Proponents of this hypothesis argue that, due to bounded rationality, individuals do not smooth out small variations in anticipated income changes, but might smooth out larger changes (Browning and Collado, 2001). The prediction is that larger changes in cash-on-hand should therefore not affect consumption. The results do not provide evidence of such behavior in this context.

Table 2.4: Credit Card Response: MPC, Payments, and Balance

	Expenditures	Payments	Δ Balance
	(1)	(2)	(3)
A. Monthly Installment Linear			
After? $\times$ D	0.0904***	0.0933***	-0.0216***
	(0.0134)	(0.0138)	(0.0075)
After?	-5.0606***	-3.6928*	-0.8274
	(1.8739)	(2.0417)	(1.4575)
D	-2.0714***	-1.9024***	0.0225*
	(0.1783)	(0.1724)	(0.0130)
R^2	0.521	0.440	0.001
Observations	4,803,365	4,803,365	4,787,607
B. Monthly Installment in Bins			
After?	-0.4492	1.0061	-0.8237
	(1.3381)	(1.5716)	(1.3263)
After? $\times$ D_2?	5.6435***	5.3612***	-2.7694***
	(1.4716)	(1.5994)	(1.0533)
After? $\times$ D_3?	13.1407***	13.2637***	-4.6520***
	(2.0722)	(2.2774)	(1.4683)
After? $\times$ D_4?	28.1578***	31.6555***	-10.4687***
	(3.5532)	(3.8905)	(2.4224)
R^2	0.518	0.438	0.001
Observations	4,803,365	4,803,365	4,787,607
Month F.E.	YES	YES	YES
Quadratic Trend	YES	YES	YES
Baselines	YES	YES	YES
Account Controls	YES	YES	YES

Note: This table shows the results of estimating equation (2.2). Panel A uses the linear monthly installment on the term loan (D) and Panel B uses dummy variables for bins of the monthly installment. The control variables grouped under "Account Characteristics" are taken in the four months period prior to the start of the event study and consist of monthly term loan installment, external credit score, revolving limit on the account, age of the account, age of the account-holder, average credit card and term loan balances, average monthly purchases and a dummy variable indicating if the borrower pays for a reduced APR on the credit card. Standard errors corrected for within-account heteroscedasticity are presented in parentheses. ***, ***, and * represent significance at the 1, 5 and 10 percent level, respectively.

Table 2.5: Effect of Liquidity Constraints

	Purchases			Payments	Δ Balance
	(1)	(2)	(3)	(4)	(5)
	In Dollars	$\mathbb{P}$(New Purchases)	Purchases | > 0	In Dollars	In Dollars
A. Total Account					
After? × Min. Payer	39.3492***	0.0549***	29.3714***	26.1168***	14.3565***
	(2.2346)	(0.0010)	(4.8501)	(2.0135)	(2.2792)
After? × Med. Payer	-5.9463**	0.0021**	-30.5004***	28.5261***	-32.8437***
	(2.6083)	(0.0010)	(5.0162)	(2.2607)	(2.3869)
After?	22.0399***	-0.0032***	49.7534***	-55.9532***	64.7616***
	(2.0743)	(0.0008)	(4.7041)	(1.8245)	(2.3375)
R^2	0.395	0.296	0.344	0.442	0.003
Observations	4,248,783	4,248,783	2,030,437	4,248,783	4,233,301
B. Revolving Loan					
After? × Min. Payer	33.8394***	0.0554***	36.7917***	15.5579***	14.5100***
	(1.6797)	(0.0010)	(3.8777)	(1.9634)	(1.4598)
After? × Med. Payer	-1.1563	0.0035***	-14.5635***	12.4856***	-16.5821***
	(2.0976)	(0.0010)	(4.1945)	(2.2057)	(1.2992)
After?	-2.7823*	-0.0076***	-2.3772	1.2043	-3.6640**
	(1.5978)	(0.0007)	(3.7889)	(1.7941)	(1.4310)
R^2	0.514	0.305	0.475	0.432	0.002
Observations	4,248,783	4,248,783	1,993,042	4,248,783	4,233,301
C. Term Loan					
After? × Min. Payer	5.5098***	0.0008**	40.2010	10.5589***	-0.1535
	(1.4239)	(0.0003)	(50.1103)	(0.5127)	(1.8915)
After? × Med. Payer	-4.7900***	-0.0023***	-126.2760***	16.0405***	-16.2617***
	(1.4681)	(0.0004)	(48.0345)	(0.5657)	(2.0251)
After?	24.8222***	0.0089***	55.1804	-57.1575***	68.4256***
	(1.3012)	(0.0003)	(44.1570)	(0.3830)	(1.9120)
R^2	0.004	0.013	0.080	0.194	0.005
Observations	4,248,783	4,248,783	97,441	4,248,783	4,233,301
Month F.E.	YES	YES	YES	YES	YES
Quadratic Trend	YES	YES	YES	YES	YES
Account Controls	YES	YES	YES	YES	YES
Interactions	YES	YES	YES	YES	YES

Note: This table shows the results of estimating equation (2.2) by OLS for all columns except for column (2) which is estimated using a Probit model and for which I report the marginal effects. All baselines are included in the estimation but are omitted from the result table. The control variables grouped under "Account Characteristics" are taken in the four months period prior to the start of the event study and consist of monthly term loan installment, external credit score, revolving limit on the account, age of the account, age of the account-holder, average credit card and term loan balances, average monthly purchases and a dummy variable indicating if the borrower pays for a reduced APR on the credit card. Standard errors corrected for within-account heteroscedasticity are presented in parentheses. ***, ***, and * represent significance at the 1, 5 and 10 percent level, respectively.

Expenditures, Payments, Debt, and Liquidity Constraints

Figures 2.7, 2.8, and 2.9 show the response of payments, expenditures and debt levels segmented by groups of constrained borrowers. Table 2.5 quantifies these results by estimating equation (2.3) on these outcomes. The results show that unconstrained borrowers do not change their spending behavior on the card, nor their payments. On the other hand, minimum payers increase their credit card expenditures by $33 with an increase in payments of only $16. This leads to a monthly increase in credit card balances of $15. Consumers who were repaying their balance partially do not change their credit card expenditures, but they use part of the reduction in monthly installment to increase the payments made toward the credit card balance by $12, reducing their credit card balance by about $17 each month.

These results are in line with the predictions of a model in which borrowers behave according to the permanent income hypothesis and in which some of them have liquidity constraints as measured by their outside cost of funds. Importantly, in terms of quantity constraints, the groups of borrowers paying their balance in full and partially are not considered constrained (see Table 2.12). However, the results highlight that even within groups of consumers who are not quantity constrained, the outside cost of funds affects their consumption-savings behavior: borrowers with a higher cost of funds choose to pay down their debt.

The term loan response is homogeneous across groups of constrained borrowers — a surprising fact. All groups of borrowers see an increase in term loan expenditures ranging from $20 to $30, with the most constrained borrowers increasing them the most. This average increase in term loan expenditures is driven by an increase in the propensity to take out new term loans, not in the amount of the loan taken out. It is surprising that even non-constrained borrowers increase their term loan expenditures after paying off the first term loan. This is investigated in details in Section 2.4.4.

Marginal Propensity to Consume and Liquidity Constraints

Table 2.6 measures the credit card response as a fraction of the reduction in monthly installment, and segmented across categories of liquidity constraints. In this specification, the

Table 2.6: Credit Card Response: Liquidity Constraints

	Expenditures	Payments	Δ Balance
	(1)	(2)	(3)
After? × D × Min. Payer	0.0849***	0.0713*	-0.0105
	(0.0318)	(0.0378)	(0.0240)
After? × D × Med. Payer	0.0252	0.0593*	-0.0368**
	(0.0347)	(0.0335)	(0.0179)
After? × D	0.0627***	0.0583***	-0.0084
	(0.0217)	(0.0214)	(0.0090)
R^2	0.517	0.434	0.002
Observations	4,248,783	4,248,783	4,233,301
Month F.E.	YES	YES	YES
Quadratic Trend	YES	YES	YES
Account Controls	YES	YES	YES
Interactions	YES	YES	YES

Note: This table shows the results of estimating equation (2.2) augmented with the interaction of the monthly installment D. All interactions and baselines are included in the estimation but are omitted from the result table. The control variables grouped under "Account Characteristics" are taken in the four months period prior to the start of the event study and consist of monthly term loan installment, external credit score, revolving limit on the account, age of the account, age of the account-holder, average credit card and term loan balances, average monthly purchases and a dummy variable indicating if the borrower pays for a reduced APR on the credit card. Standard errors corrected for within-account heteroscedasticity are presented in parentheses. ***, ***, and * represent significance at the 1, 5 and 10 percent level, respectively.

results measure the marginal propensity to consume out of reduced term loan payments and are in line with the response in dollar amounts presented in Table 2.5. Borrowers who pay in full are the least responsive to the final term loan payment: their MPC is 6% and is offset by an equivalent increase in payments, leaving their revolving balance unchanged. Minimum payers have an MPC of about 15%, with a similar increase in payments, such that their balance does not change as a fraction of the monthly installment. Finally, consumer for who the credit card provides the marginal source of funds do not increase expenditures more than full payers, although they do increase payments, which leads to a reduction in credit card balance each month.

2.4.4 Term Loans

Figure 2.5 presents the propensity to take out a new term loan, segmented across new bank loans and new store loans, for each categories of liquidity constraints.[18] Two surprising

[18]Table 2.16 shows that the results previously presented on the credit card response are robust to the type of term loan generating the increase in cash-on-hand. In both cases, minimum payers increase their expenditures, full payers dot not respond to the increase in cash-on-hand and partial payers reduce their revolving balance.

facts should be noted. First, the patterns of new term loan take outs are similar across all groups. Second, the take out patterns differ across new store and new bank loans. There is a transitory increase in the propensity of taking out a new bank loan around the month in which the original term loan ends, while there is a permanent increase in the propensity of taking out a new store loan that seems persistent over the period studied.

Just as new term loan expenditures can be segmented across store and bank loans, it is possible to segment the sample according to the type of loan which was originally contracted — and which is being used as instrument for the increase in cash-on-hand. Figures 2.10 and 2.11 shows the propensity to take out new term loans for the sub sample of loans that were originated at the bank and at a merchant store, respectively. These figures show interesting patterns: both the subsample of bank-originated and store-originated loans have a permanent increase in the propensity to take out new store loans but only the subsample of bank-originated term loans have the transitory increase in the probability of new bank loans taken out.

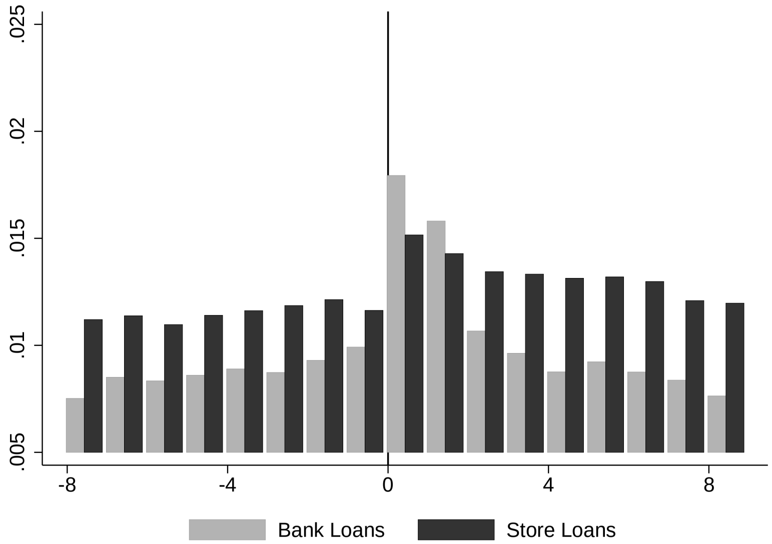
Table 2.7 quantifies the average term loan response by segregating the response depending on the original term loan being store-originated or bank-originated. The variable "During?" is a dummy variable indicating whether the event study months is equal to 0 or 1, and the "After?" variable is redefined as the event study month being strictly greater than 1. This allows me to separate the transitory and permanent effects noted in new term loan expenditures. Panel (A) shows that both store-originated and bank-originated sample increase expenditures in new store loans, although the effect is bigger for store-originated loans because the baseline take-out rate is larger for this subsample. Panel (B) shows that the increase in new bank loan expenditures is limited to the subsample of borrower who originally had a bank-originated term loan. Appendix Table 2.18 further decomposes these results in terms of liquidity constraints, and in terms of propensity to take out the new terms. The results are in line with graphical evidence, and the average effects presented in Table 2.7.

Table 2.7: New Term Loans Response

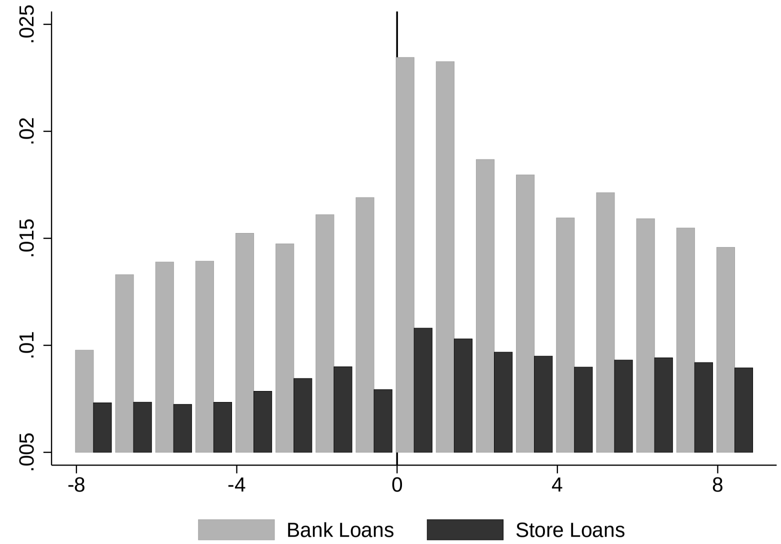
	Store-Originated Term Loans	Bank-Originated Term Loans
	(1)	(2)
A. New Store Loans		
During?	8.3658***	0.6463***
	(0.5946)	(0.1796)
After?	7.1094***	0.9438***
	(0.7435)	(0.2902)
R^2	0.001	0.000
Observations	3,369,400	1,433,954
B. New Bank Loans		
During?	-0.8377	72.8071***
	(0.9157)	(3.1641)
After?	-0.5513	26.3171***
	(1.1298)	(3.5246)
R^2	0.002	0.007
Observations	3,369,402	1,433,963
Month F.E.	YES	YES
Quadratic Trend	YES	YES
Account Controls	YES	YES

Note: This table shows the average new term and bank loan expenditures, as segmented by the type of term loan originally held by the borrower. The control variables grouped under "Account Characteristics" are taken in the four months period prior to the start of the event study and consist of monthly term loan installment, external credit score, revolving limit on the account, age of the account, age of the account-holder, average credit card and term loan balances, average monthly purchases and a dummy variable indicating if the borrower pays for a reduced APR on the credit card. Standard errors corrected for within-account heteroscedasticity are presented in parentheses. ***, ***, and * represent significance at the 1, 5 and 10 percent level, respectively.

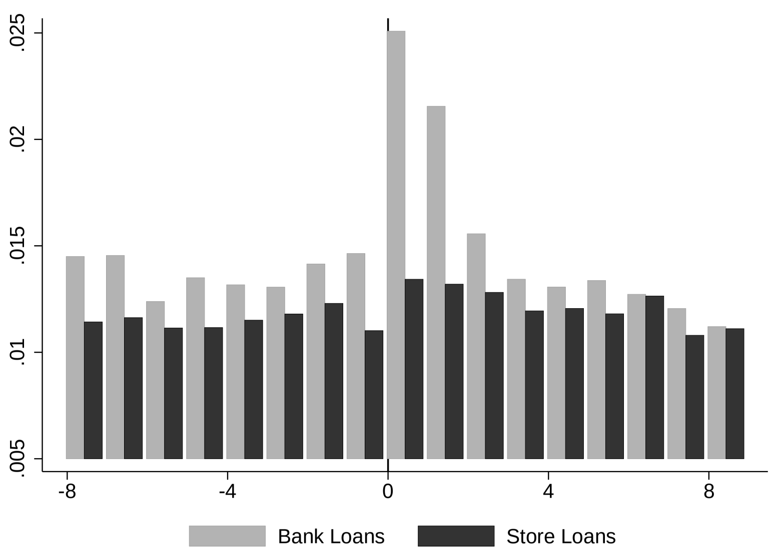
Figure 2.5: New Term Loan Propensity



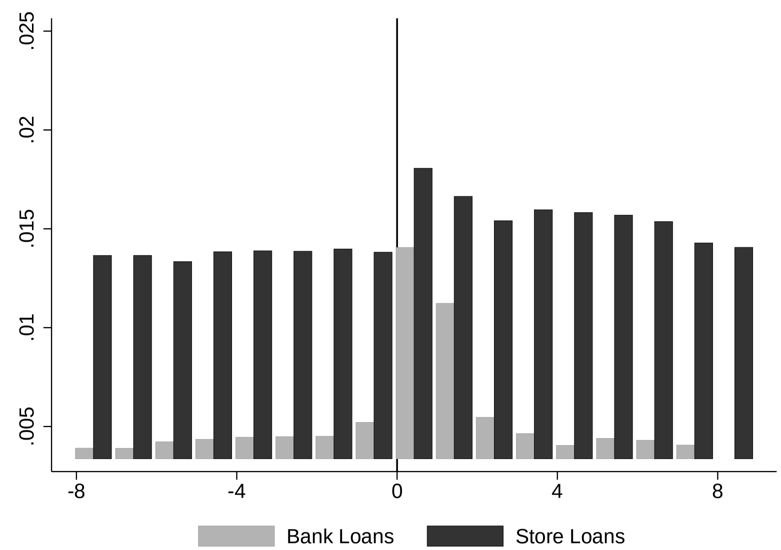
(a) All Accounts



(b) Min Payers



(c) Med Payers



(d) Full Payers

Note: This figure shows the propensity to take out new store and bank loans each month, segmented by type.

Explaining the Increase in Term Loan Expenditures

Bank-Originated Term Loans.- There is a rational explanation for the transitory increase in new bank loans being confined to the subsample of borrowers who originally held a bank loan. At the end of each year, consumers who qualify can contribute to their retirement saving and reduce their gross income by the amount of the contribution. This has the advantage of reducing the amount of income tax that must be paid to the tax authority. Consumers may want to contribute but they might not want to use their personal savings to make the contribution. As a marketing strategy, the bank offers to take out term loans (of a 1 year maturity) to cover for the contribution. It is optimal for consumers to use term loans to make their contributions if the reduction in income tax is larger than the interest paid on the loan. Many consumer make this contribution financed by a term in the *same month* each year. The response in new bank loan expenditures for the subsample of consumers who had a bank-originated term loan — and who are rolling into a new bank loan in the same month of the following year — will exhibit a transitory seasonal effect.[19] This explains why only the subsample of borrowers who originally had a bank term loan roll over into a new bank loan once the loan is repaid. Such behavior appears to be rational and therefore, should not be interpreted as a failure of the PIH.

Store-Originated Term Loans.- Note that store-originated loans do not have seasonal patterns because they are taken out uniformly throughout the year (see Figure 2.12). Accordingly, for the subsample of store-originated term loans, Figure 2.11 shows no change in the propensity to take out new bank loans. However, there is still a permanent increase in the propensity to take out a new store-originated term loan that is present in both subsamples of borrowers with store-originated and bank-originated term loans. This behavior holds for all groups of liquidity constraints. In particular, full payers have an abnormal increase of 0.3 percentage point in the monthly propensity to take out a new term loan after the first one is repaid (23% on a monthly baseline of 1.3%), while for partial payers the increase is of 0.2 percentage points (16.7% on a monthly baseline of 1.2%). This adds up to a monthly

[19]This is verified in the data by noting that the increase in bank loan coincides with the last month in which consumers are allowed to make a contribution to their retirement account (see Figure 2.12). It is also verified by talking with bank representatives.

Table 2.8: Average Delinquency Transitions

	C_t	L_t	W_t
C_{t+1}	0.945	0.463	0.000
L_{t+1}	0.055	0.513	0.000
W_{t+1}	0.000	0.024	1.000
% of Accounts	0.895	0.105	N/A

Note: This table shows the average transition probabilities between delinquency states. The states are defined as (C) if the account is current, (L) if the account is at least one month late, (W) if the account is written off due to a default or due to bankruptcy.

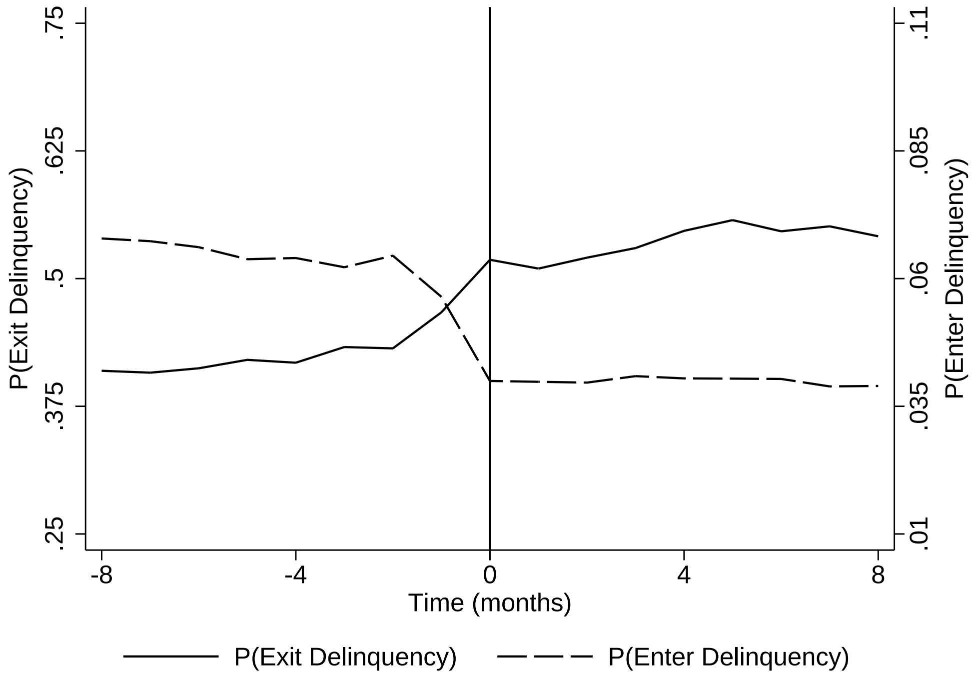
abnormal increase in the propensity to take out store-loans of 0.5 percentage points, which translates to 4% of the sample of unconstrained consumers behaving contrary to theoretical predictions over the 8 months after the first term loan is repaid.

It is hard to rationalize such results with the PIH because unconstrained consumers should not delay consumption until the reception of an increase in cash-on-hand. One explanation, put forth by Thaler (1990), is that such consumers could be doing mental accounting. In particular, these results would be consistent with a scenario in which some consumers force themselves to finish repaying their original term loan before allowing themselves to purchase a new "big-ticket" item via installment financing. For the econometrician, distinguishing between liquidity constraints and such self-control mechanisms is usually hard to do. However, because the same groups of borrowers have a credit card behavior which is consistent with a model in which they are potentially liquidity constrained, it is hard to rule out such behavioral explanation.

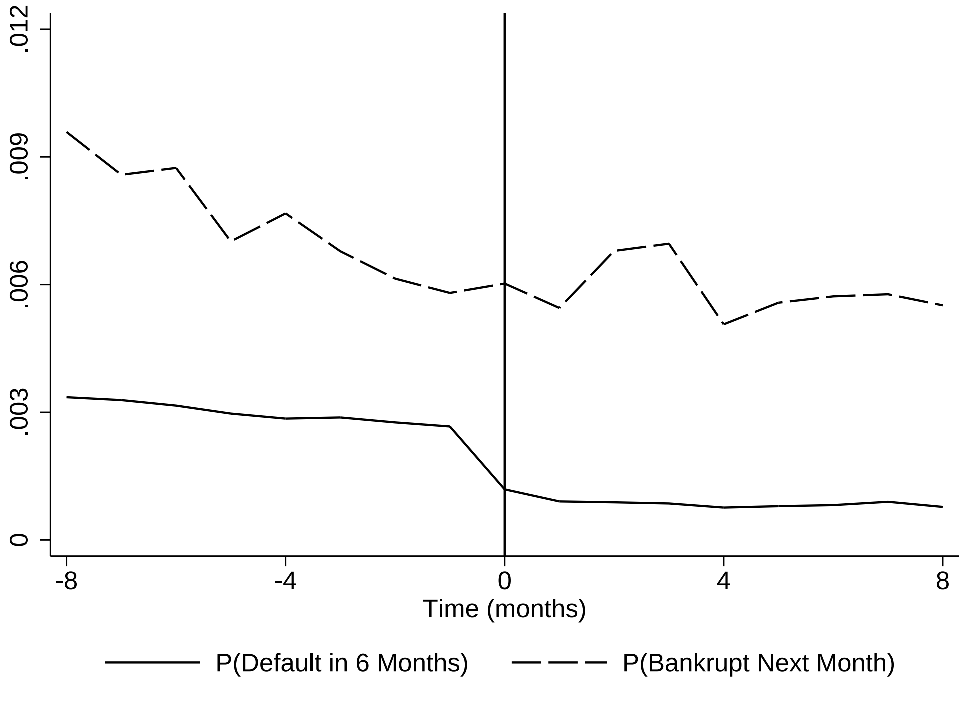
2.4.5 Delinquency Response

Table 2.8 presents the proportion of accounts in each delinquency state, and the transition matrix between them. On average, 89.5% of the active accounts (i.e. those not written-off) are current, and the remaining 10.5% are delinquent. On average, 0.4% of active accounts are written off each month. A total of 94.5% of current accounts remain current in the next billing cycle, while 5.5% enter delinquency and virtually none are written off. Among delinquent accounts, 46.3% cure in the following billing cycle, while 51.3% stay delinquent

Figure 2.6: Delinquency



(a) Delinquency



(b) Default at $t + 6$

Note: This figure provides average probabilities of curing the account, of missing a payment, and of defaulting at $t + 6$. Time 0 corresponds to the first month in which the borrower is anticipated to have paid down the term loan. See text for the details about the sample selection.

Table 2.9: Delinquency, Write-offs and Liquidity Constraints

	$\mathbb{P}(L_{t+1}\|C_t)$	$\mathbb{P}(C_{t+1}\|L_t)$	$\mathbb{P}(D_{t+6})$	$\mathbb{P}(B_{t+1}\|L_t)$
A. Before vs After				
After?	-0.0430***	0.0604***	-0.0022***	0.0001
	(0.0005)	(0.0026)	(0.0001)	(0.0005)
R^2	0.134	0.196	0.267	0.150
Observations	4,315,865	487,500	4,531,889	487,500
B. Liquidity Constraints				
After? × Min. Payer	0.0085***	0.0652***	-0.0002	0.0010
	(0.0005)	(0.0038)	(0.0002)	(0.0007)
After? × Med. Payer	0.0013**	0.0432***	-0.0005***	0.0001
	(0.0006)	(0.0041)	(0.0002)	(0.0008)
After?	-0.0456***	0.0230***	-0.0022***	-0.0004
	(0.0007)	(0.0040)	(0.0002)	(0.0007)
R^2	0.145	0.202	0.270	0.153
Observations	3,776,131	472,652	4,000,005	472,652
Month F.E.	YES	YES	YES	YES
Quadratic Trend	YES	YES	YES	YES
Account Controls	YES	YES	YES	YES
Delinquency Controls	YES	YES	YES	YES
Interactions	YES	YES	YES	YES

Note: This table shows the results of estimating equations (2.1) and (2.3) on the delinquency transitions. The results presented are the marginal effects estimated from a probit regression. The control variables grouped under "Account Characteristics" are taken in the four months period prior to the start of the event study and consist of monthly term loan installment, external credit score, revolving limit on the account, age of the account, age of the account-holder, average credit card and term loan balances, average monthly purchases and a dummy variable indicating if the borrower pays for a reduced APR on the credit card. Standard errors corrected for within-account heteroscedasticity are presented in parentheses. ***, ***, and * represent significance at the 1, 5 and 10 percent level, respectively.

and 2.4% are written off into default or bankruptcy.

Each month, an account can transition into one of three mutually exclusive delinquency states: current (C), delinquent (L), and written-off (W).[20] Accounts transition from current to delinquent when a monthly payment is missed (i.e., the sum of the minimum credit card payment and the term loan installment). Accounts transition from delinquent to current when the overdue amount is repaid. The write-off state is absorbing and results from either bankruptcy or default (i.e., when an account spends six cycles delinquent).

Figure 2.6 presents preliminary evidence of the delinquency response to the anticipated final term loan payment over the event-study. Panel (a) shows the average transitions into and out of delinquency. After the final term loan payment, there is a discontinuous drop

[20]The delinquency state can also be further refined into the exact number of months past due.

in the probability of entering delinquency, and a discontinuous increase in the probability of curing the account. Panel (b) shows write-offs decomposed into bankruptcy filings and defaults. Bankruptcy is presented conditional on the account being late, whereas default is measured lagged by six months — because it takes six months for a loan to go from current to written off when no additional payments are made on the account. There is a discontinuous drop in the probability that the account will be written off due to default but there is no discontinuous change in the probability of filing for bankruptcy. Because it takes six months for an unproductive loan to be deemed defaulted (and be written-off), this shows that the bank has the possibility of taking preemptive actions in mitigating the loss associated to such events.

I model financial delinquency, defaut and bankruptcy using dynamic probit models, which are equivalent to discrete hazard models (Shumway, 2001; Gross and Souleles, 2002b), and report average partial effects. Table 2.9 shows the results of estimating equations (2.1) and (2.2) on the probability of entering delinquency, of exiting delinquency, of defaulting in 6 months, and of filing for bankruptcy in the next month. Panel (A) shows that the final payment on the term loan leads to a decline of 4.3 percentage points in the probability entering delinquency (67% decrease on a baseline of 6.4%). This provides strong evidence that reducing debt payments leads to a decline in delinquency. The probability of curing the account after the final term loan payment goes up by 6 percentage points (14.2% increase on a baseline of 42.4%). This supports the evidence that lower debt repayment facilitate the transition out of delinquency. The probability that a borrower will default in six months also goes substantially down. At an average rate of six-month-ahead default of 0.3% before the final term loan payment, the results represent a 73% decrease in the probability of the account being written off by the bank. Finally, there is no evidence of a change in the probability of filing for bankruptcy induced by the final payment on the term loan.

Figures 2.13 and 2.13 show the delinquency results as segmented by type of liquidity constraints. Panel (B) of Table 2.9 quantifies the effects. The probability of entering delinquency is relatively stable across categories of liquidity constraints, but the probability of exiting delinquency is significantly larger for more constrained borrowers. The probability of defaulting is similar and there is still no effect on the probability of filing for bankruptcy.

These results have implications for the credit granting decision of financial institutions. They show that there is a trade-off between granting additional credit to consumers and potentially risking write-offs for those who do not have the ability-to-pay for their debt. In particular, the results provide evidence that can be used by banks to calculate the trade-off between additional interest revenue earned by granting a new term loan to a consumer and the risk of write-off due to consumer default.

2.5 Extensions

The intention-to-treat research design used in the event-study implies that some accounts do not comply with the anticipated month of final payment. Non-compliance happens when a borrower takes out a new term loan prior to paying off the original one, or when a borrower prepays the original term loan. Borrowers taking out a new term loan before the predicted date of final payment still have a discontinuous decrease in their monthly debt payments, although the required payments do not fully decrease to zero. However, borrowers who prepay the term loan do not have such decrease at the anticipated payoff date. More importantly, prepayment of the term loan could bias the results if unobservable variables correlate both with the term loan prepayment and the outcomes studied. In this section I consider these issues and show that the main results hold under different extensions.

2.5.1 Selection into Prepayment

The most important threat to identification comes from unobservable variables that could potentially correlate with prepayment and subsequent consumption, debt repayment or delinquency patterns. This would violate the identifying assumption of orthogonality between the final term loan payment and other outcomes of interest. Luckily, prepayment events can be identified in the sample. A Heckman selection model (Heckman, 1979) is used to correct for the potential sample selection induced by term loan prepayment. In such a model, the decision to prepay the term loan is first modeled in a probit equation for which the dependent

Table 2.10: Heckman Selection: Decision to Prepay

	Expenditures	Payments	ΔBalance
	(1)	(2)	(3)
A. Outcome Equations			
After? × D	0.0828***	0.0847***	-0.0413***
	(0.0064)	(0.0073)	(0.0071)
D	-1.6795***	-1.6275***	-0.0145
	(0.0163)	(0.0187)	(0.0181)
After?	-0.5996	3.1666	-2.8179
	(1.6920)	(1.9371)	(1.8891)
IMR	-190.0604***	-82.3137***	60.0101***
	(7.1221)	(8.1559)	(7.8616)
B. Selection Equation			
Zero i Term	0.2397***		
	(0.0014)		
After? × D	0.0000**		
	(0.0000)		
D	-0.0016***		
	(0.0000)		
After?	0.0015		
	(0.0029)		
All Observations	4,803,365		
Censored Observations	1,167,300		
Month F.E.	YES		
Quadratic Trend	YES		
Account Controls	YES		

Note: This table shows the result of estimating equation (2.2) using a Heckman selection model. The decision to prepay is first modeled using a binary variable equal to 1 if the term loan is financed at 0% APR as the exclusion restriction.

variable is a dummy variable indicating whether the term loan is prepaid or not. A sample correction variable is then created — the Inverse-Mills Ratio (IMR). This variable is used in the second stage estimation to correct for sample selection in the outcome equations.

The Heckman selection model requires an exclusion restriction — in this case, a variable that influences the decision to prepay the term loan but that does not influence the other outcomes studied. Such an exclusion restriction is analog to an instrumental variable for the case of an endogenous regressor. The institutional setting of the bank providing the data leads to an ideal candidate for such exclusion restriction. Because some of the term loans contracted at retail stores are provided with 0% APR, there is essentially no incentive for the borrower to prepay them. Having a cost of capital equal to zero on the term loan should negatively affect the probability of prepaying the term loan, although there is no obvious reasons as to why it would affect their subsequent consumption decisions. This variable is therefore an ideal candidate for an exclusion restriction in modeling the prepayment decision.

The results of estimating the selection equation are presented in Panel B of Table 2.10. The dummy variable indicating if the original term loan is financed under a 0% APR contract is strongly significant and has the effect of increasing the probability that the term loan is *not* prepaid by 24 percentage points. Given that about 75% of the term loans are not prepaid this variable has a strong predictive power.

The IMR is then constructed and added to the outcome equations. This corrects the conditional expectation function for potential bias induced by borrowers self-selecting into term loan prepayment. Panels A of Table 2.10 presents the results. The marginal propensity to consume out of reduced debt payments is still around 9% on the credit card, in line with the results presented in the main analysis. Table 2.17 shows the results augmented with the interactions of liquidity constraints. Again, the results are both qualitatively and quantitatively in line with the baseline analysis: full payers do not respond, minimum payers increase credit card expenditures the most and partial payers decrease the credit card balance. This provides evidence that the inclusion of some borrowers that prepay the term loan in the intention-to-treat framework does not introduce a sample selection bias. The results go through even after considering the potential sample selection induced by borrowers repaying their term loans before the final payment date.

2.5.2 Analysis of Compliers

The second extension looks at the effect of reduced debt installments on the subsample of "compliers" and is presented in the first set of results in Table 2.11. The analysis consists in estimating the baseline model only for the subsample of borrowers who finishing repaying their term loan exactly in the month predicted one ahead. This is also called a "perfect-compliance" analysis (Imbens and Rudin, 2015) and is similar to what previous studies have done.[21] In the context of this bank, it has the disadvantage of introduc-

[21] Most research using variation in debt payments has restricted the analyzed sample to observations for which the loans were not prepaid and for which borrowers followed exactly the payment schedule (Stephens, 2008; Scholnick, 2013).

Table 2.11: Perfect Compliance and As-Treated Analyses: MPC and Liquidity Constraints

	Compliers Only			As-Treated		
	(1) Expenditures	(2) Payments	(3) ΔBalance	(4) Expenditures	(5) Payments	(6) ΔBalance
A. Marginal Propensity to Consume						
After? $\times$ D	0.1277***	0.1278***	-0.0379***	0.0638**	0.0651**	-0.0017
	(0.0230)	(0.0231)	(0.0104)	(0.0275)	(0.0254)	(0.0047)
D	-3.4637***	-3.1701***	0.0564*	-2.0936***	-1.9160***	0.0044
	(0.3698)	(0.3677)	(0.0297)	(0.1755)	(0.1699)	(0.0127)
After?	-1.2531	-1.4036	-2.6227	17.9687***	9.7567***	8.1056***
	(2.8941)	(3.0676)	(2.0697)	(3.9554)	(3.6835)	(0.7512)
R^2	0.571	0.511	0.001	0.521	0.440	0.002
Observations	1,955,633	1,955,633	1,952,956	4,803,365	4,803,365	4,787,607
B. Liquidity Constraints						
After? $\times$ Min. Payer	28.9406***	30.6309***	-7.6017***	25.1916***	4.7287**	17.7741***
	(2.4947)	(2.8014)	(2.0526)	(2.2484)	(2.3038)	(0.9766)
After? $\times$ Med. Payer	6.1080*	19.5891***	-20.8176***	17.4765***	17.2047***	-1.0889
	(3.3951)	(3.5651)	(2.2053)	(2.7695)	(2.8640)	(0.8874)
After?	5.4362**	2.4354	-1.1099	8.9369***	8.5353***	1.6166***
	(2.4773)	(2.7126)	(2.2040)	(2.1211)	(2.1541)	(0.6043)
R^2	0.562	0.501	0.002	0.514	0.432	0.002
Observations	1,673,554	1,673,554	1,670,950	4,248,783	4,248,783	4,233,301
Month F.E.	YES	YES	YES	YES	YES	YES
Quadratic Trend	YES	YES	YES	YES	YES	YES
Account Controls	YES	YES	YES	YES	YES	YES
Baselines	YES	YES	YES	YES	YES	YES

Note: This table shows the results of estimating equation (2.2) on the subsample of accounts that exactly comply with the anticipated date of last term loan payment and on the full sample analyzed as-treated, that is, for which the observed date of final term loan installment is used instead of the anticipated date.

ing a bias towards more constrained borrowers — who might be unable to increase their payments on the term loan and prepay — and therefore potentially overestimates the effects found. Panel A of Table 2.11 shows that the consumption response on the credit card is higher than the results presented in the main analysis: the MPC is estimated to be 12%. However, Panel B shows that the different group of constrained consumers behave qualitatively as in the baseline analysis.

2.5.3 Analysis of As-Treated Observations

The third extension consists in analyzing each account exactly in the way they have been treated, that is, to measure the term loan payoff date as the *observed* month in which the term loan balance first decreases to zero, rather than using the *predicted* final payment date. This is called an "as-treated" analysis (Imbens and Rudin, 2015). Although this provides the exact timeline event of debt repayment, it has the disadvantage of allowing unobservable windfall gains to correlate with both the term loan repayment and the outcomes studied. The results are presented in the second set of results of Table 2.11 and show that the marginal propensity to consume is underestimated by this type of analysis. The MPC on the credit card is estimated to be 6%. Qualitatively, the different groups of borrowers respond similarly to the baseline analysis.

2.6 Conclusion

This paper contributes to our understanding of the response of consumption, debt, and delinquency to an anticipated increase in cash-on-hand in the presence of liquidity constraints. I use the end of a term loan as an event generating a predictable increase in cash-on-hand, and to which unconstrained consumers should not respond. The data used allow me to measure the consumption response arising from credit card and term loan expenditures on the account. Term loans can be contracted at the bank or at selected retail stores. Store-originated term loans are used to finance "big-ticket" items and therefore provide a measure of the response of durable consumption to an increase in cash-on-hand — a dimension usually ignored by research using only credit card data. Relative to previous work, I introduce a new framework to think about liquidity constraints in terms of the outside cost of funds faced by borrowers. Payments posted on a revolving account make it possible to infer bounds on the marginal cost of funds that borrowers are willing to pay to finance consumption. This allows me to segment borrowers who we typically think of as unconstrained (in the quantity sense) into borrowers who are paying high interest fees on their revolving balance and borrowers who are paying their balance in full and therefore charged no interest.

Unconstrained consumers, who pay their credit card balance in full each month, do not change their credit card expenditures. Consumers who make minimum credit card payments, and who are more likely to be constrained, increase credit card expenditures and their revolving balance. Consumers for whom the credit card is the marginal source of funds decrease their revolving balance. Surprisingly, the propensity to take out a new term loan increases for all consumers, whether constrained or not. About 4% of unconstrained consumers delay taking out a new term loan until the original loan is repaid, contrary to theoretical predictions. Because consumers behave according to a version of the PIH in which they are potentially liquidity constrained with respect to their credit card, I interpret this abnormal term loan response as evidence that some borrowers could be financing consumption according to mental accounts (Thaler, 1990). In this particular case, such unconstrained borrowers seem to refrain from borrowing on more than one term loan at a time. Although this hypothesis can not be directly tested with these observational data, it is consistent with the dichotomous consumption response on credit card and term loans.

Because the credit card and term loans are linked to the same account, the data also allows me to quantify the causal effect of decreasing monthly debt payments on financial delinquency. Delinquency is reduced after the final payment, with the greatest effect found for constrained borrowers, leading to a substantial decrease in default probability. Such results show that the presence of liquidity constraints has implications for the credit-granting decision of financial institutions.

2.7 Appendix

Table 2.12: Liquidity Constraints and Quantity Constraints

	Low Util (0%-80%)	High Util (80%-100%)	Total
Min. Payer	38,657	40,519	79,176
Med. Payer	57,892	6,522	64,414
Full Payer	115,225	208	115,433
Total	216,774	47,249	259,023

Note: This table shows the number of accounts in each category of payment behavior and liquidity constraints (in the quantity sense), as well as their interactions.

Table 2.13: Descriptive Statistics
Term vs Non-Term Accounts

	Has Term Mean/(Std. Dev)	Obs.	No Term Mean/(Std. Dev.)	Obs.	Diffrence Mean/(Std. Error)
Credit Card Balance	1,015	291,777	977	203,287	37.43***
	(2,042)		(1,832)		(5.66)
Term Loan Balance	1,190	291,777	0	203,287	1,190.20***
	(1,121)		-		(2.49)
Payments	436	291,777	514	203,287	-78.44***
	(843)		(1,171)		(2.86)
External Score	898	291,777	908	203,276	-10.23***
	(162)		(180)		(0.49)
APR	18.08	291,777	18.02	203,287	0.06***
	(3.12)		(3.21)		(0.01)
Credit Card Limit	3,344	291,777	5,153	203,276	-1,809.23***
	(4,365)		(5,130)		(13.56)
Term Loan Limit	3,158	291,777	1,283	203,287	1,874.70***
	(2,712)		(2,123)		(7.18)
Reduced APR?	0.07	291,777	0.06	203,287	0.01***
	-		-		(0.00)

Note: This table compares the samples of accounts included in the event study to a 10% random sample of accounts that never have an active term loan. Averages are measured during the four months prior to the start of the event-study for the sample of borrowers that have a term loan, and during the first four months observed in the dataset for accounts with no term loans.

Table 2.14: Descriptive Statistics
Bank vs Store Loans

	Store-Originated Mean/(Std. Dev)	Obs.	Bank-Originated Mean/(Std. Dev.)	Obs.	Diffrence Mean/(Std. Error)
Credit Card Balance	841	202,358	1,407	89,419	-565.83***
	(1,904)		(2,275)		(8.13)
Term Loan Balance	979	202,358	1,669	89,419	-690.31***
	(825)		(1,494)		(4.32)
Payments	420	202,358	472	89,419	-52.38***
	(849)		(828)		(3.38)
External Score	910	202,358	872	89,419	38.01***
	(152)		(181)		(0.65)
APR	18.28	202,358	17.63	89,419	0.65***
	(2.92)		(3.49)		(0.01)
Credit Card Limit	3,411	202,358	3,192	89,419	218.93***
	(4,506)		(4,021)		(17.52)
Term Loan Limit	3,405	202,358	2,599	89,419	805.95***
	(2,522)		(3,026)		(10.79)
Reduced APR?	0.06	202,358	0.10	89,419	-0.05***
	-		-		(0.00)

Note: This table compares the subsamples of accounts for which the increase in cash-on-hand is generated by a store-originated and a bank-originated term loan. Averages are measured during the four months prior to the start of the event-study for both samples.

Table 2.15: Credit Card Response: Store- and Bank-Originated Loans

	Expenditures	Payments	Δ Balance
	(1)	(2)	(3)
A. Store-Originated Loan			
After? $\times$ D	0.0400***	0.0007	-0.0133
	(0.0150)	(0.0162)	(0.0114)
After?	-0.2539	3.1154	-0.6302
	(1.8961)	(2.1399)	(1.7620)
D	-0.3987**	-0.3177**	0.0282
	(0.1625)	(0.1598)	(0.0195)
R^2	0.540	0.465	0.001
Observations	3,369,402	3,369,402	3,362,162
B. Bank-Originated Loan			
After? $\times$ D	0.0946***	0.1079***	-0.0178*
	(0.0212)	(0.0216)	(0.0107)
After?	-6.0987	-1.9569	-3.2148
	(4.0024)	(4.3001)	(2.7556)
D	-2.4716***	-2.3235***	-0.0166
	(0.3844)	(0.3808)	(0.0206)
R^2	0.478	0.384	0.002
Observations	1,433,963	1,433,963	1,425,445
Month F.E.	YES	YES	YES
Quadratic Trend	YES	YES	YES
Account Controls	YES	YES	YES

Note: This table shows the response of credit card expenditures. Panel A and B respectively show the results for the subsamples of accounts that have an increase in cash-on-hand generated by a store-originated and a bank-originated term loan.

Table 2.16: Credit Card and Liquidity Constraints: Store- and Bank-Originated Loans

	Expenditures	Payments	Δ Balance
	(1)	(2)	(3)
	In Dollars	In Dollars	In Dollars
A. Store-Originated Loans			
After? × Min. Payer	32.8965***	9.6030***	20.9535***
	(2.1666)	(2.7162)	(2.2308)
After? × Med. Payer	-0.0996	9.4177***	-13.3117***
	(2.5467)	(2.6916)	(1.6575)
After?	-2.6781	-0.1994	-3.2620*
	(1.8355)	(2.0643)	(1.7129)
R^2	0.533	0.457	0.002
Observations	2,869,010	2,869,010	2,862,001
B. Bank-Originated Loans			
After? × Min. Payer	22.9760***	4.3168	9.6999***
	(3.4601)	(3.7573)	(2.2004)
After? × Med. Payer	-13.4103***	2.2807	-20.4356***
	(4.1925)	(4.4256)	(2.2988)
After?	5.1537	15.6302***	-4.6193*
	(3.6654)	(4.0671)	(2.7208)
R^2	0.468	0.376	0.002
Observations	1,379,773	1,379,773	1,371,300
Month F.E.	YES	YES	YES
Quadratic Trend	YES	YES	YES
Account Controls	YES	YES	YES
Baselines	YES	YES	YES

Note: This table shows the response of credit card expenditures by liquidity constraints. Panel A and B respectively show the results for the subsamples of accounts that have an increase in cash-on-hand generated by a store-originated and a bank-originated term loan.

Table 2.17: Heckman Selection and Liquidity Constraints

	Expenditures	Payments	ΔBalance
	(1)	(2)	(3)
A. Outcome Equations			
After? × Min. Payer	33.3132***	30.6609***	-5.5690**
	(1.9278)	(2.2226)	(2.1706)
After? × Med. Payer	-0.0998	15.5610***	-23.5227***
	(2.0924)	(2.4130)	(2.3532)
After?	1.0975	2.9766	-1.6070
	(1.9075)	(2.1993)	(2.1453)
IMR	-88.6028***	-2.1873	47.9550***
	(7.1631)	(8.2601)	(8.0220)
B. Selection Equation			
Zero i Term	0.2760***		
	(0.0015)		
After? × Min. Payer	-0.0420***		
	(0.0032)		
After? × Med. Payer	-0.0179***		
	(0.0032)		
After?	0.0207***		
	(0.0031)		
All Observations	4,248,783		
Censored Observations	1,055,875		
Month F.E.	YES		
Quadratic Trend	YES		
Account Controls	YES		
Baselines	YES		

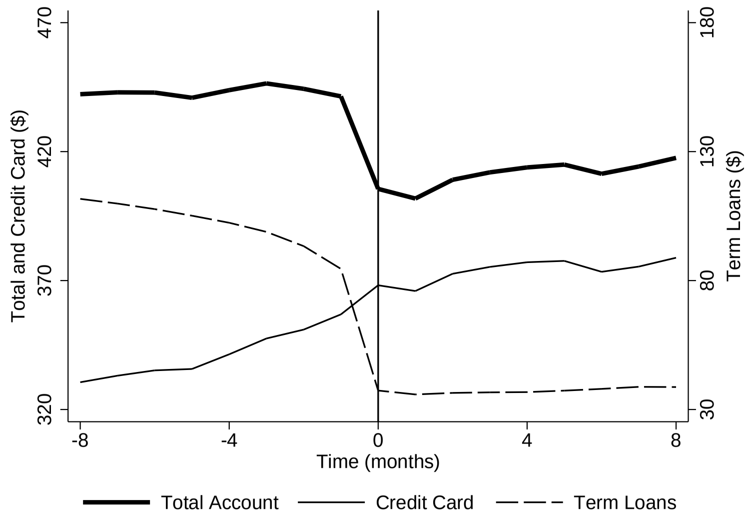
Note: This table shows the result of estimating equation (2.2) using a Heckman selection model. The decision to prepay is first modeled using a binary variable equal to 1 if the term loan is financed at 0% APR as the exclusion restriction.

Table 2.18: New Term Loans by Original Type of Loan and Liquidity Constraints

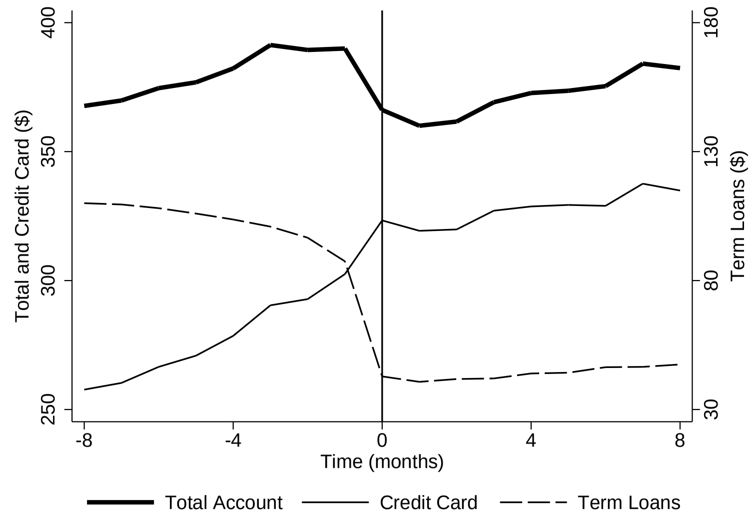
	Store-Originated Term Loans			Bank-Originated Term Loans		
	(1) In Dollars	(2) $\mathbb{P}$(New Purchases)	(3) Purchases | > 0	(1) In Dollars	(2) $\mathbb{P}$(New Purchases)	(3) Purchases | > 0
A. New Store Loans						
During? × Min. Payer	-0.8043	0.0004	-30.2286	0.3476	0.0003	153.0222
	(1.2981)	(0.0006)	(43.7327)	(0.3083)	(0.0002)	(290.6209)
After? × Min. Payer	-0.3493	0.0001	-3.2137	-1.0223***	-0.0001	-443.9424*
	(0.7964)	(0.0004)	(31.3026)	(0.3087)	(0.0002)	(253.6442)
During? × Med. Payer	-4.2141***	-0.0020***	-75.4532*	0.8049**	0.0001	349.3426
	(1.3027)	(0.0006)	(41.5993)	(0.4033)	(0.0002)	(263.6136)
After? × Med. Payer	-3.2453***	-0.0017***	-57.6212*	-0.6228*	-0.0004***	-58.2937
	(0.8264)	(0.0004)	(30.3300)	(0.3449)	(0.0002)	(229.7262)
During?	9.0367***	0.0047***	121.4096***	0.2584	0.0003	-276.6111
	(0.8129)	(0.0004)	(28.0218)	(0.2587)	(0.0002)	(235.5931)
After?	7.3601***	0.0031***	154.0184***	1.5833***	0.0006***	347.0205
	(0.8748)	(0.0004)	(33.1121)	(0.4350)	(0.0002)	(290.1286)
R^2	0.001	0.006	0.035	0.000	0.040	0.081
Observations	2,869,008	2,869,008	51,018	1,379,764	1,379,764	1,205
B. New Bank Loans						
During? × Min. Payer	-0.6811	-0.0003	-152.3745	-87.6950***	-0.0165***	497.7525***
	(2.7426)	(0.0003)	(420.5174)	(7.3513)	(0.0010)	(133.4954)
After? × Min. Payer	-0.0203	0.0004**	-524.6502*	17.3751***	0.0040***	346.5470***
	(1.7322)	(0.0002)	(314.7093)	(3.4010)	(0.0008)	(128.9355)
During? × Med. Payer	-2.0912	-0.0004	-291.8942	-70.5115***	-0.0158***	212.4310
	(2.0665)	(0.0003)	(429.2871)	(8.2566)	(0.0010)	(132.8256)
After? × Med. Payer	-2.4403*	0.0002	-610.1816*	-3.2800	-0.0020**	-6.3902
	(1.3378)	(0.0002)	(320.3726)	(3.8428)	(0.0008)	(135.8833)
During?	-0.3953	0.0002	-76.0705	133.5533***	0.0295***	-388.3003***
	(0.9425)	(0.0002)	(340.4323)	(6.6313)	(0.0008)	(120.7397)
After?	0.0135	-0.0003*	559.8276	17.9181***	0.0041***	68.0984
	(1.2714)	(0.0002)	(375.2054)	(4.2998)	(0.0009)	(142.6295)
R^2	0.002	0.049	0.099	0.007	0.034	0.111
Observations	2,869,010	2,869,010	9,107	1,379,773	1,379,773	36,760
Month F.E.	YES	YES	YES	YES	YES	YES
Quadratic Trend	YES	YES	YES	YES	YES	YES
Account Controls	YES	YES	YES	YES	YES	YES
Interactions	YES	YES	YES	YES	YES	YES

Note: This table shows the response of term loan expenditures by liquidity constraints. Each column is estimated by OLS, except for columns labeled (2) which are estimated using a Probit model and for which I report the marginal effects. Panel A and B respectively show the results for the subsamples of accounts that have an increase in cash-on-hand generated by a store-originated and a bank-originated term loan.

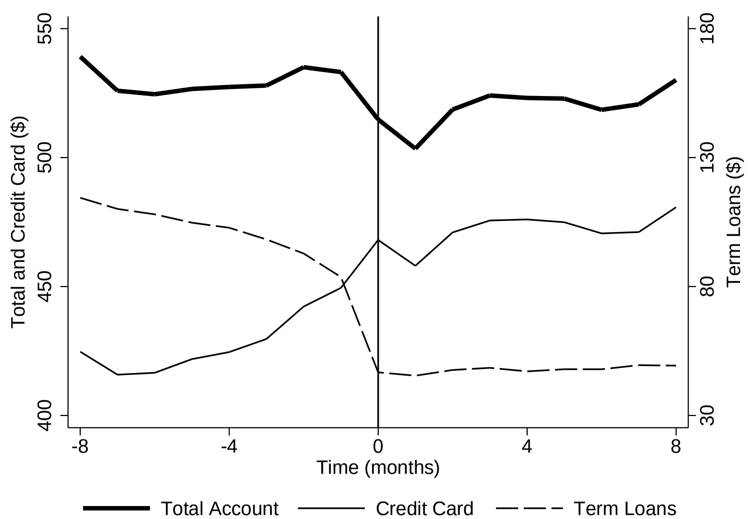
Figure 2.7: Payments by Liquidity Constraints



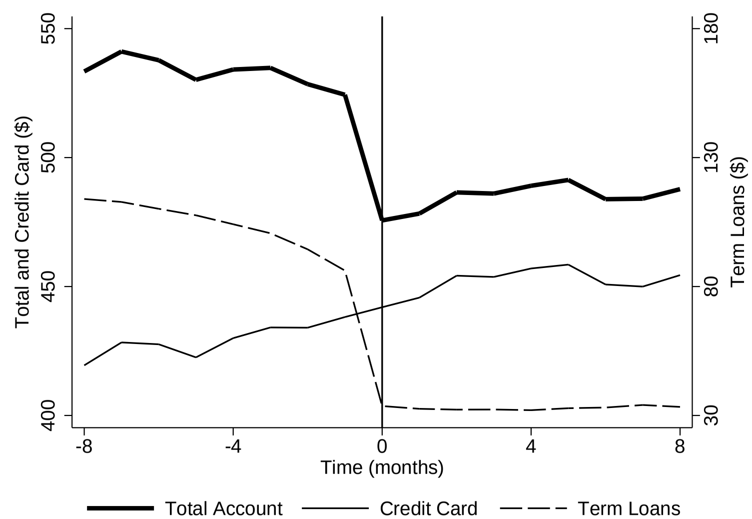
(a) All Accounts



(b) Min Payers



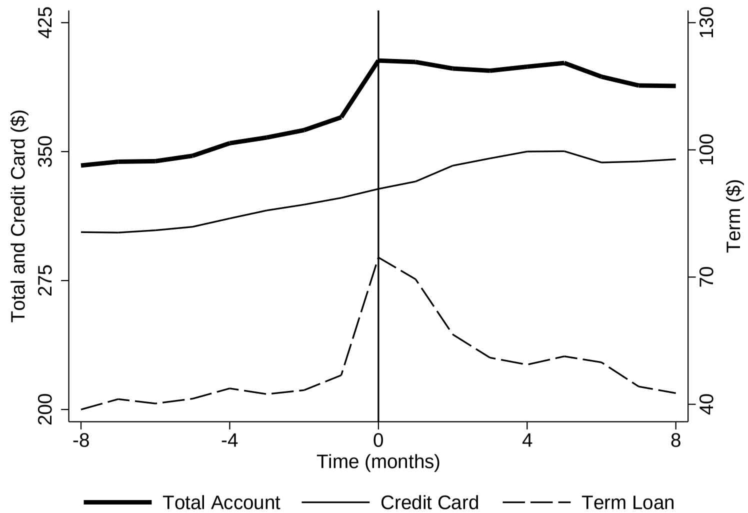
(c) Med Payers



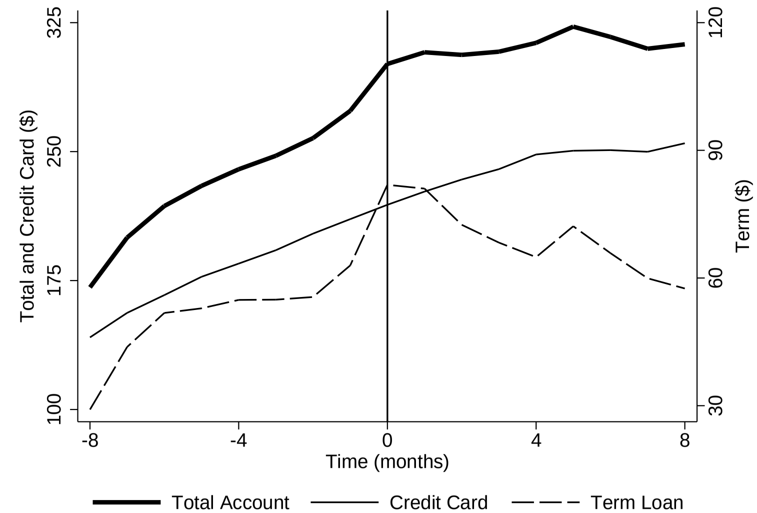
(d) Full Payers

Note: This figure shows average payments segmented by groups of liquidity constraints.

Figure 2.8: Expenditures by Liquidity Constraints



(a) All Accounts



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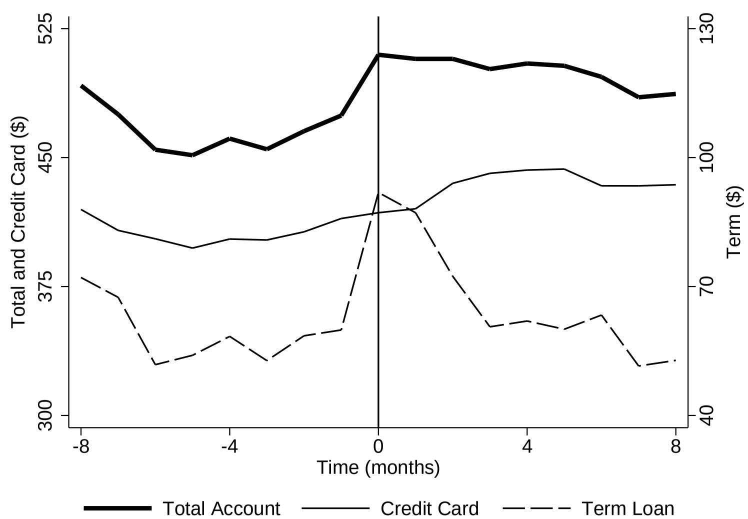
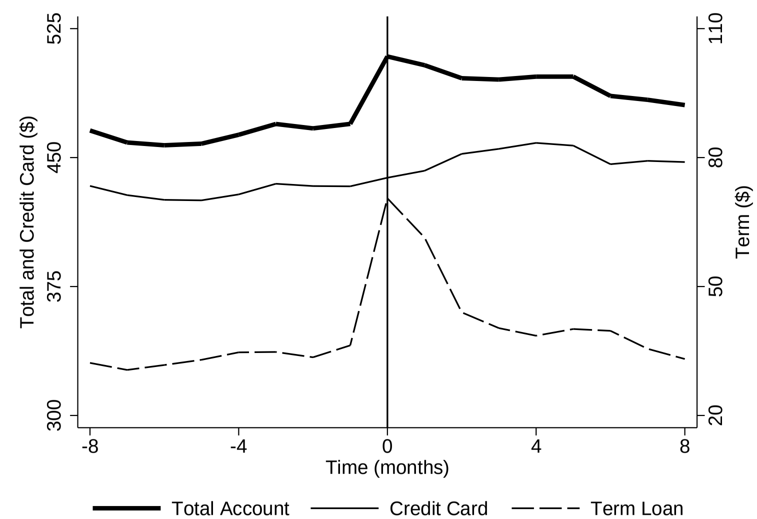


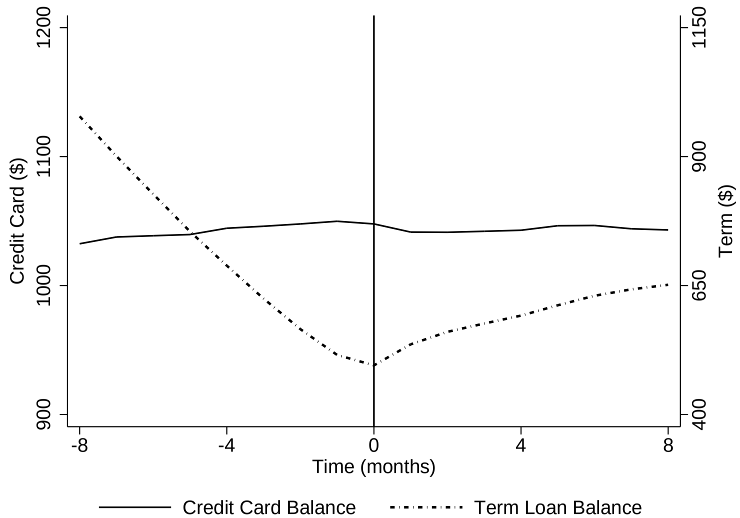
(c) Med Payers



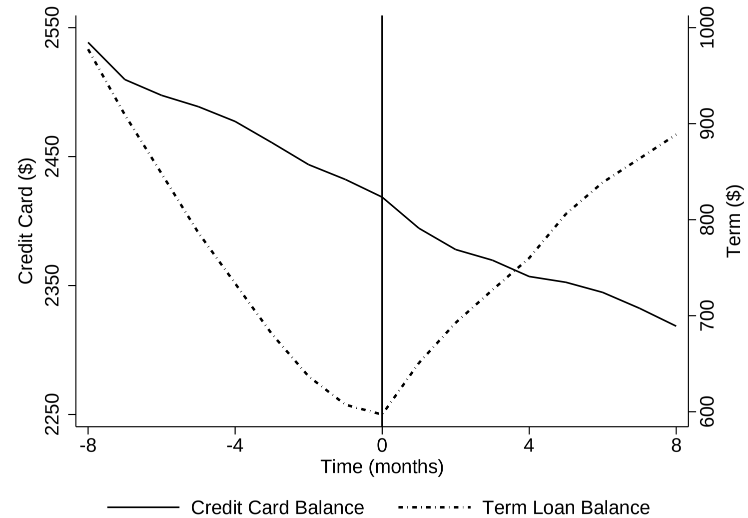
(d) Full Payers

Note: This figure shows average expenditures segmented by groups of liquidity constraints.

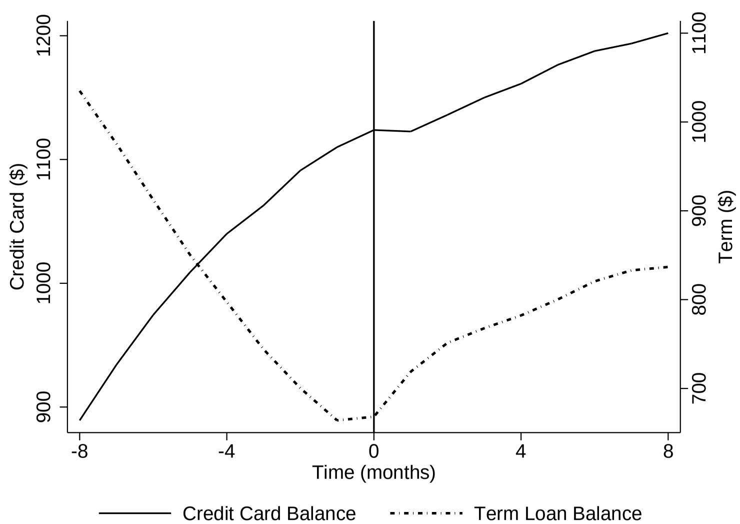
Figure 2.9: Balances by Liquidity Constraints



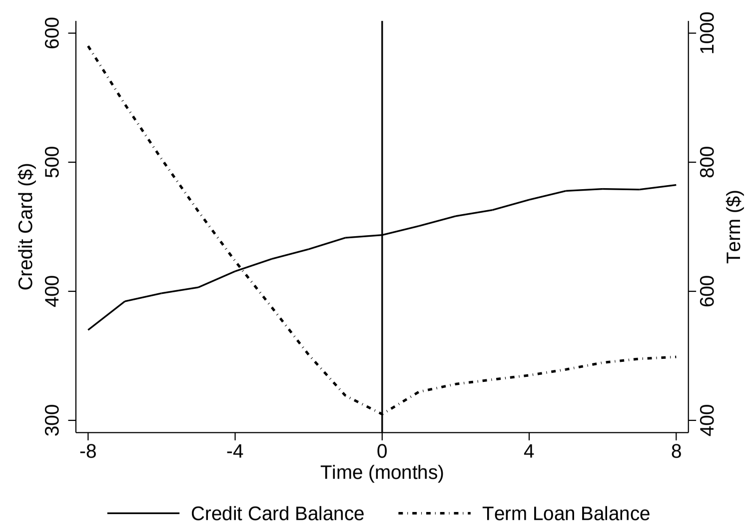
(a) All Accounts



(b) Min Payers



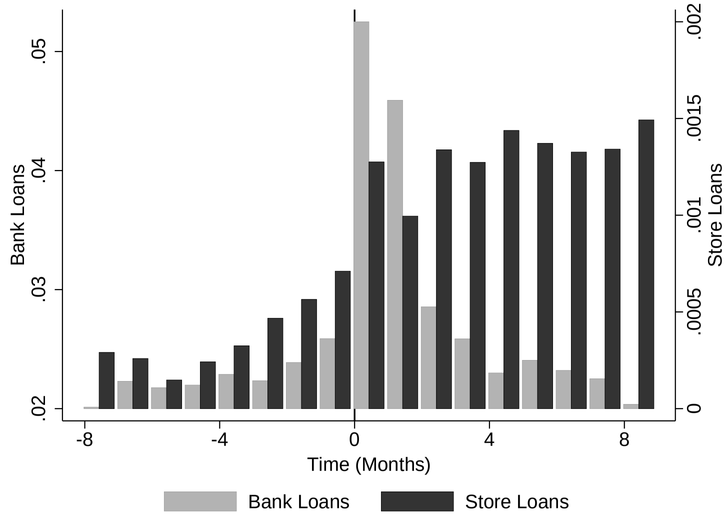
(c) Med Payers



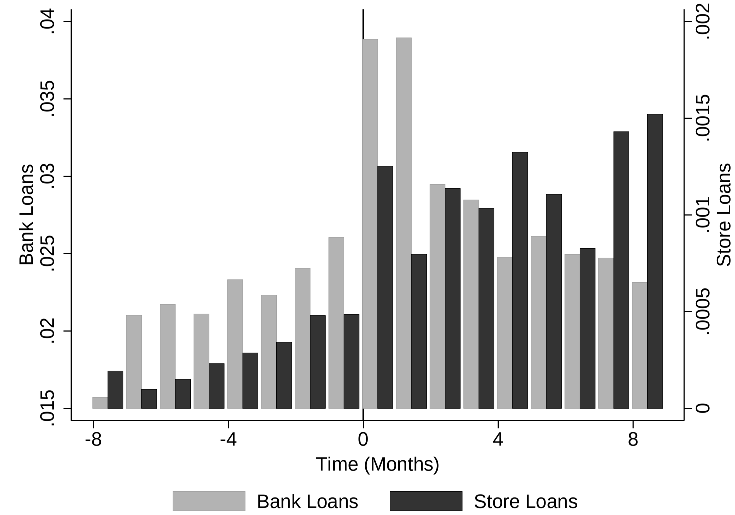
(d) Full Payers

Note: This figure shows average balances segmented by groups of liquidity constraints.

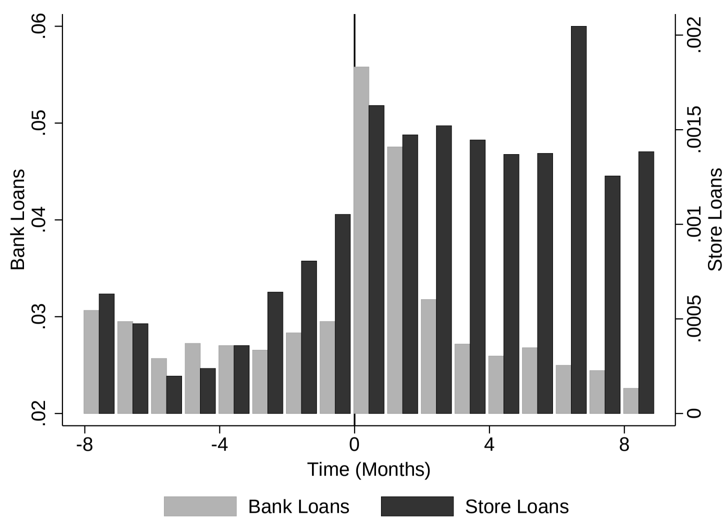
Figure 2.10: New Term Loan Propensity
(Subsample of Bank-Originated Loans)



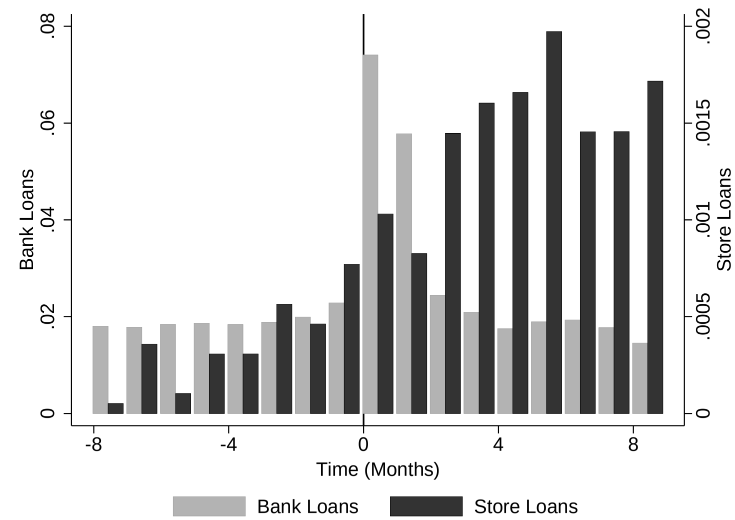
(a) All Accounts



(b) Min Payers



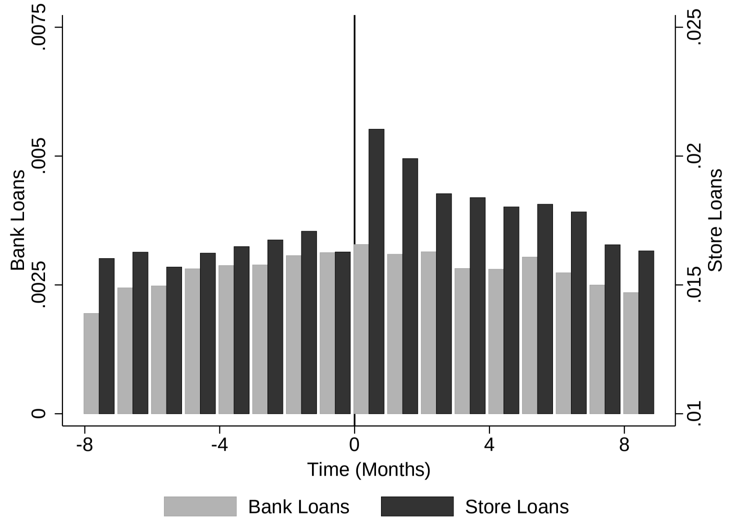
(c) Med Payers



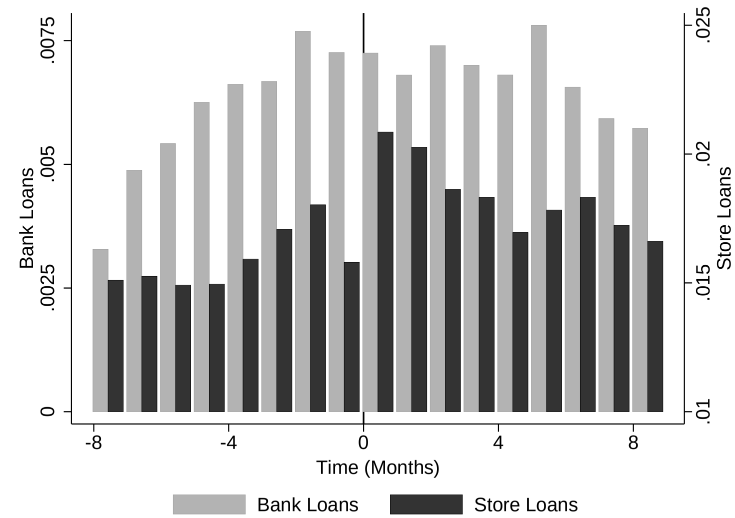
(d) Full Payers

Note: This figure shows the propensity to take out new bank and store term loans segmented by groups of liquidity constraints, for the subsample of bank-originated term loans.

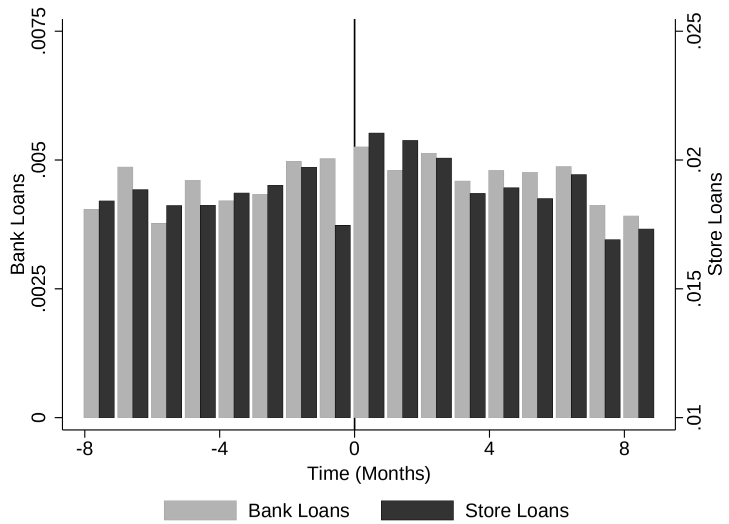
Figure 2.11: New Term Loan Propensity
(Subsample of Store-Originated Loans)



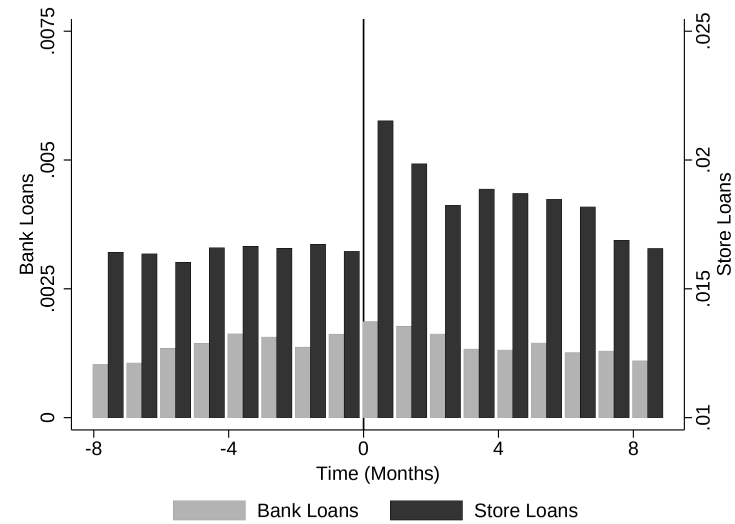
(a) All Accounts



(b) Min Payers



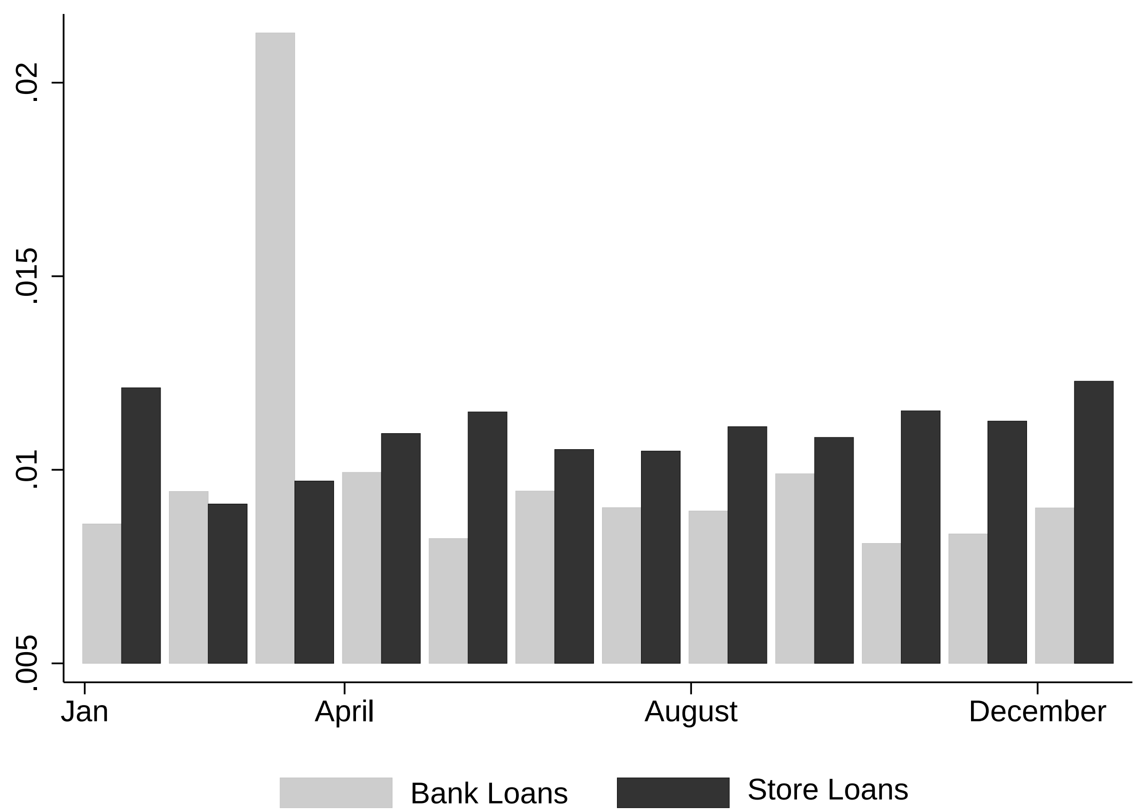
(c) Med Payers



(d) Full Payers

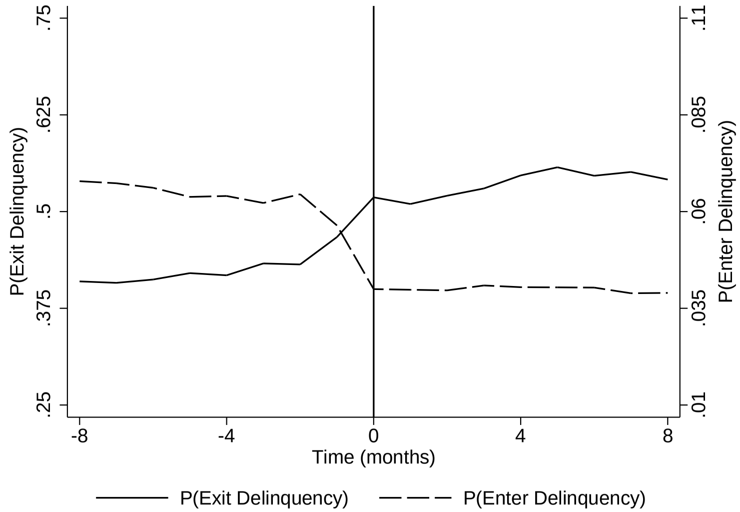
Note: This figure shows the propensity to take out new bank and store term loans segmented by groups of liquidity constraints, for the subsample of store-originated term loans.

Figure 2.12: New Term Loan Propensity
(Seasonal Patterns)

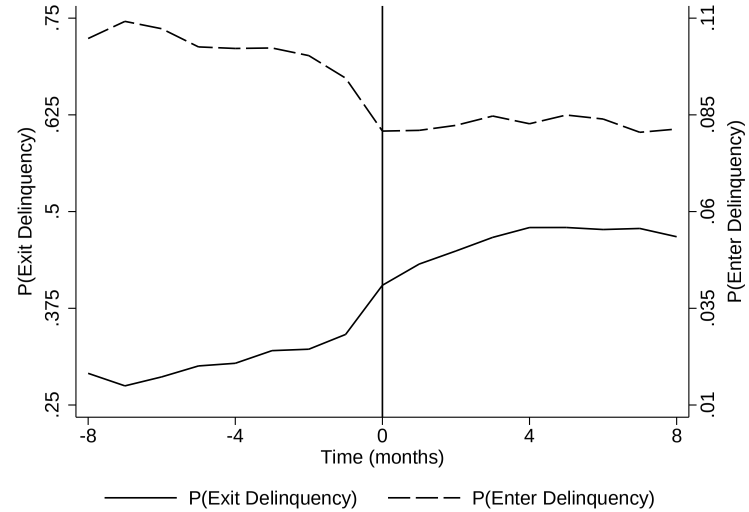


Note: This figure shows the propensity to take out new bank and store term loans across calendar months.

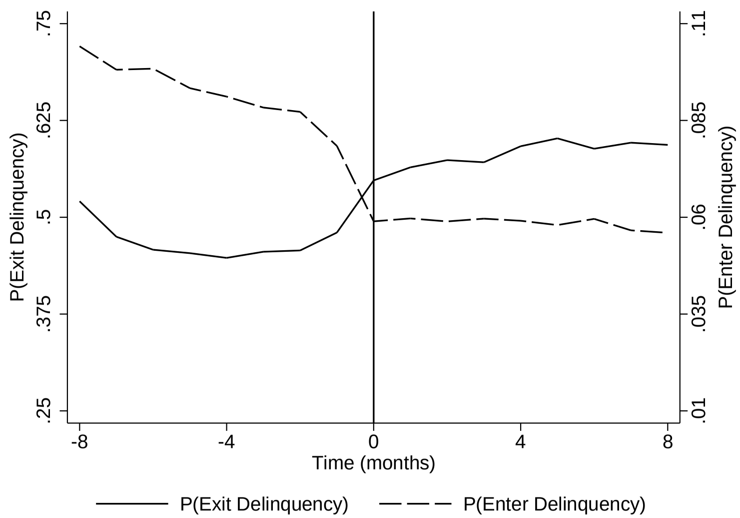
Figure 2.13: Delinquency by Liquidity Constraints



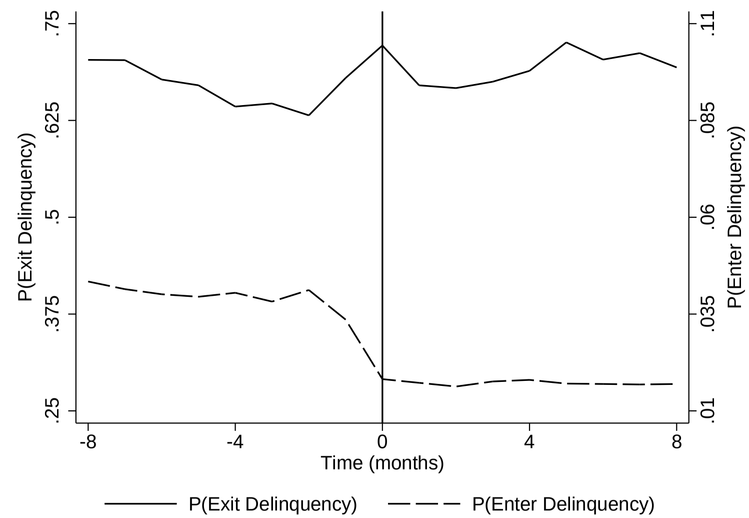
(a) All Accounts



(b) Low Pmnts



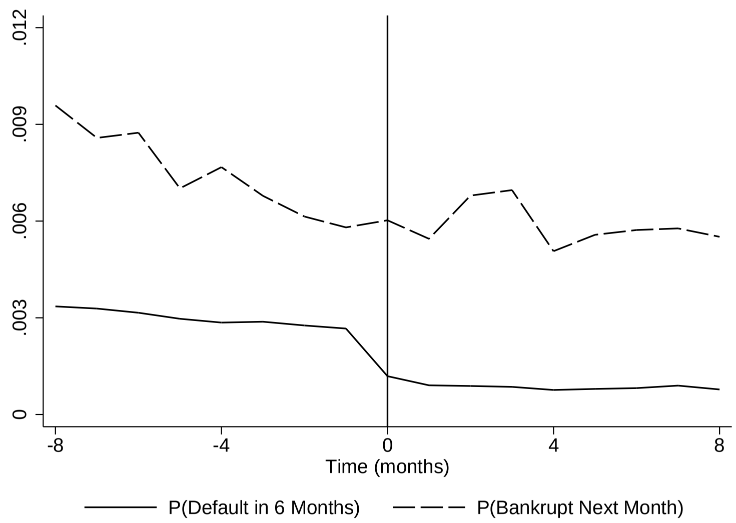
(c) Med Pmnts



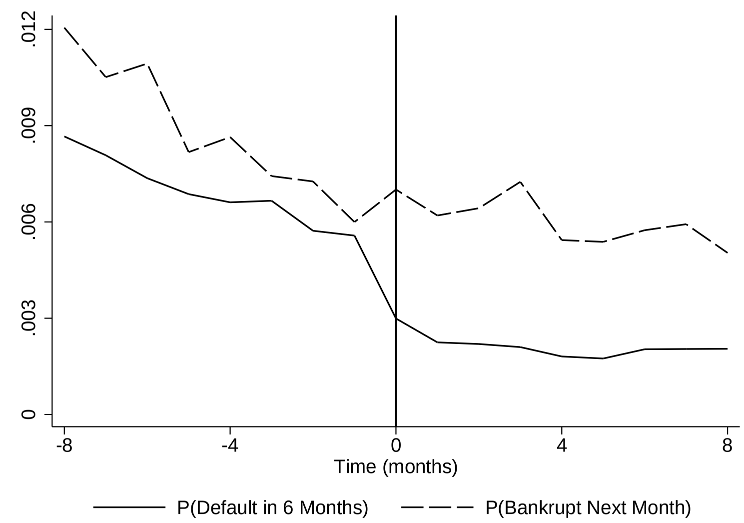
(d) High Pmnts

Note: This figure shows the probability of entering and exiting delinquency segmented by groups of liquidity constraints.

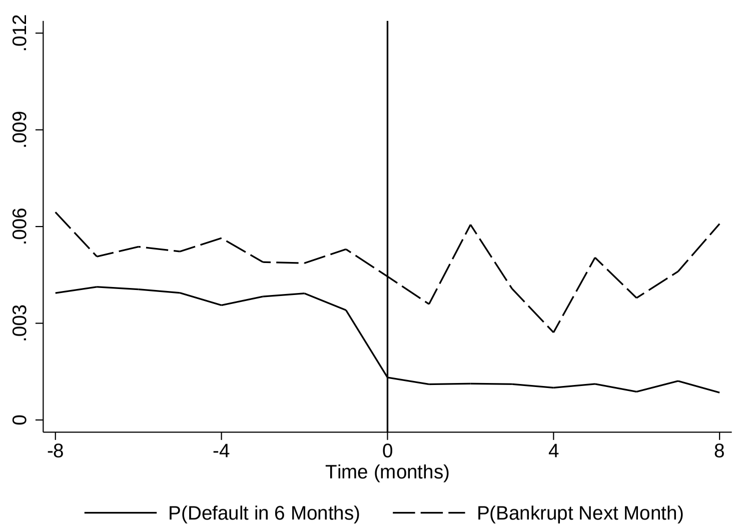
Figure 2.14: Write-offs by Liquidity Constraints



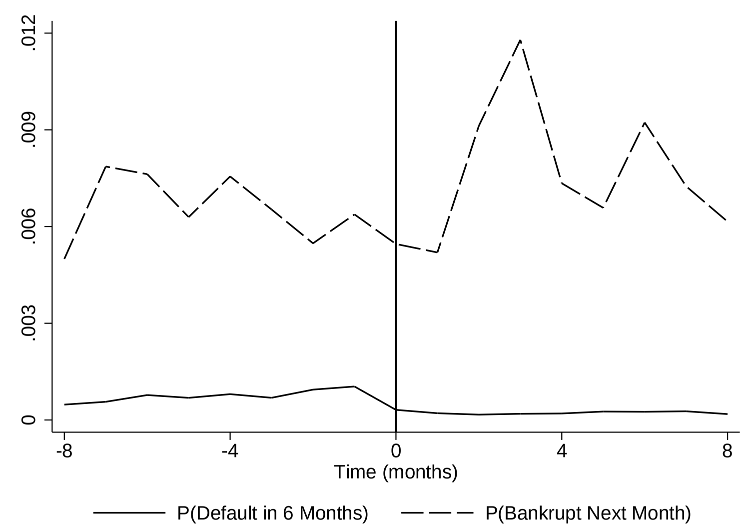
(a) All Accounts



(b) Min Payers



(c) Med Payers



(d) Full Payers

Note: This figure shows the probability of defaulting and filing for bankruptcy segmented by groups of liquidity constraints.

Chapter 3

Are Income Shocks Predictable?

Income Shocks Transmission to Savings[1]

Abstract

We analyze the comovement of personal savings and income using administrative data provided by a North American bank that records the sum of monthly direct deposit income into its clients' checking accounts. We investigate how permanent and transitory income changes are smoothed by checking account balances. Transitory income changes, whether positive or negative, have only transitory effects on checking account balances, suggesting that consumption is excessively sensitive to them compared to theoretical predictions. Permanent income changes lead to permanent adjustments in consumption and modest permanent adjustments in checking account balances, consistent with theoretical predictions. We find evidence of anticipation of future income changes as much as three months in advance.

JEL Classification: D12, D31, D91, E21.

[1] I am grateful to my committee members Stephen Shore (chair), Conrad Ciccotello, Georges Dionne and Glenn Harrison for helpful comments.

3.1 Introduction

There is an extensive literature studying the sensitivity of consumption to income changes.[2] In a model with complete markets, consumption can be fully insured against income changes. In reality, although there exists a host of mechanisms available to insure labor income, the hypothesis of full insurance is usually rejected.[3] Alternatively, the rational-expectation permanent income hypothesis (RE-PIH) assumes that savings are the only way to smooth consumption against income changes (Friedman, 1957; Modigliani and Brumberg, 1954). Personal savings can be used to smooth consumption from transitory income changes, but they cannot permanently hedge consumption against permanent income drops. Under the RE-PIH, permanent income changes therefore lead to permanent changes in consumption, while transitory income changes do not substantially affect consumption. In this paper, we test such predictions by studying the comovement of personal savings and income using administrative data from a North American bank.

The response of consumption to changes in income depends on the predictability of the income change. Under the RE-PIH, individuals adjust their consumption-saving decision when a change in income is anticipated, not when it is realized. One line of research therefore analyzes events in which changes in cash-on-hand are known to be predictable by individuals to investigate the sensitivity of consumption to their realization.[4] The typical empirical findings show that, relative to the benchmark RE-PIH model, consumption overreacts to predictable transitory changes in income and underreacts to permanent changes. Excess sensitivity of consumption to income relative to the predictions of the RE-PIH has largely been attributed to the presence of liquidity constraints because constrained consumers—who are not able to adjust consumption when income is expected to increase—respond by increasing consumption once the increase is realized (Deaton, 1991; Zeldes, 1989). The

[2]See literature reviews by Jappelli and Pistaferri (2010); Attanasion and Weber (2010); Fuchs-Schuendeln and Hassan (2015)

[3]Examples include family networks, progressive income taxation, limited financial commitment (i.e. bankruptcy), and unemployment insurance. See Blundell et al. (2008) for a discussion and relevant references.

[4]For example, changes in committed debt payments (Coulibaly and Li, 2006; Stephens, 2008; Scholnick, 2013; d'Astous, 2016), income tax rebates (Agarwal et al., 2007; Souleles, 1999; Johnson et al., 2006), cost of attending college (Souleles, 2000), etc.

identification of unambiguously predictable income changes however comes at the cost of context-specific results.

Alternatively, another set of papers models income realizations without identifying off of predictable income changes, a literature pioneered by Hall (1978) and Flavin (1981) using aggregate data, and Hall and Mishkin (1982) using household-level data. After conditioning on observable variables, income changes are decomposed into transitory and permanent shocks. Under the RE-PIH, the consumption response to unanticipated transitory shocks should be small, while the response to unanticipated permanent shocks should result in a permanent consumption change. In this context, an important assumption is that the information sets of consumers and of the econometrician are the same or, in the words of Deaton (1992): "the implausible but near-universal assumption that consumers' expectations and econometricans' expectations are the same".[5]

Recently, the comovement of consumption and income has been used to test for partial consumption insurance (e.g. in a reduced form model, Blundell et al. (2008), and in a structural model, Heathcote et al. (2014)). If full insurance were available, consumption should not vary with income shocks. However, the mechanisms by which individuals are insured against labor income are not modeled in such papers and disentangling partial insurance from advance information using only income and consumption data is notoriously difficult (Kaufmann and Pistaferri, 2009).

The response of savings to income changes is also of interest. The buffer-stock version of the RE-PIH (Carroll, 1997) shows that if consumers have a precautionary saving motive, are impatient enough, and face income uncertainty, they build buffer-stocks of liquidity which can be used to smooth out income shocks. The model gives rise to a target wealth-to-income ratio under which savings grow in expectation, and above which savings decrease in expectation. Using aggregate data Campbell (1987) argues that, because savings represent the residual of total income (including capital income) on consumption, analyzing the comovement of

[5]Such assumption fails, for example, if what look likes a positive income shock to the econometrician is perceived as a negative shock by a consumer expecting a bigger increase. In an effort to adress this issue, some studies exploit survey responses on consumers' subjective expectations of future income (Pistaferri, 2001; Alessie and Lusardi, 1997), while others model how the information consumers have about their own income profile is gradually resolved in a Bayesian learning model (Guvenen, 2007; Guvenen and Smith, 2014).

income and savings can also serve to infer superior information consumers might have about their future income. Under the RE-PIH, if consumers have advance information about their future income, savings should counter income changes prior to their realization. Using aggregate data however comes at the cost of aggregation assumptions.

In this paper, we study the comovement of personal savings and income using administrative data from a North American bank that records the monthly sum of direct deposits into its clients' checking accounts. We study how personal savings are used by individuals to smooth income changes. We allow for asymmetric effects of positive and negative income changes, and we decompose income changes into transitory and permanent shocks. The dynamic response of savings to past and future income changes allows us to test whether savings hold information about future income. If individuals have no advance information, future changes in income should not predict current changes in savings. The use of high frequency, administrative data are a new and ideal way to investigate these questions with minimal measurement error on income and savings.[6]

We find that future income changes are anticipated up to three months in advance as evidenced by increases (decreases) in checking account balances prior to an income decrease (increase). Such anticipation is found both for permanent and transitory income changes. Permanent changes lead to modest permanent adjustments of checking account balances: a 10% increase (decrease) in income translates into a 0.5% increase (decrease) in checking account balance. Surprisingly, transitory changes—whether positive of negative—are fully absorbed by checking account balances within two to three months of their realization. We calculate the implied consumption response from the changes in checking account balances net of direct deposit changes. The results show that consumption moves almost in lock step with permanent incomes changes, as predicted by the RE-PIH. However, compared to the predictions of the RE-PIH, consumption is excessively sensitive to transitory changes in

[6]Alternatively, the standard in the literature is typically to use surveys such as the Panel Study of Income Dynamics (PSID), which collects income data for a panel of households since 1967 but only measures food consumption, or the Consumer Expenditure Survey (CEX), which has good measures of consumption but is a repeated cross-section and has poor income measures. Some further alternatives include imputing consumption in the PSID using estimates from the CEX, see Blundell et al. (2006). However, household surveys have issues with non-response and measurement errors (Meyer et al., 2015).

income.

3.2 Data

The data were provided by a regional subsidiary of a large North American bank. The original dataset consists of monthly observations on every accounts the subsidiary's clients have at this institution for the period ranging from February 2010 to January 2015. There is a total of 71,632 clients. The products are roughly defined as checking accounts, savings (investment) accounts, revolving lines of credit, mortgages, and term loans. The bank records the sum of monthly direct deposits into its clients' checking accounts and such information is available to us for the period ranging from November 2013 to January 2015 inclusively (15 month of observations).[7] Because the focus of our analysis is on the response of personal savings to changes in income, we limit our sample to this time period. We retain the 38,270 clients who are over 18 years old at the beginning of our study and who have a positive direct deposit at least once during this period.

3.2.1 Descriptive Statistics

Table 3.1 presents descriptive statistics for the sample, including demographic variables such as the age and gender of the account-holder, an internal credit score, and occupation. The credit score is constructed by the bank and varies from 0 to 8, with lower values representing better credit quality. Occupation is originally segmented across 14 categories which we group under white collar, blue collar, student, and retired or unemployed. Occupation is undefined for about 4% of the sample.

Panel A of Table 3.1 shows that the average monthly direct deposit is $1,879. The average month-to-month change is close to zero both in dollars and relative to the previous month. Figure 3.1 shows empirical density functions for different measures of direct deposits. Panel (a) shows the distribution of direct deposits in levels, truncated at the 99th percentile.

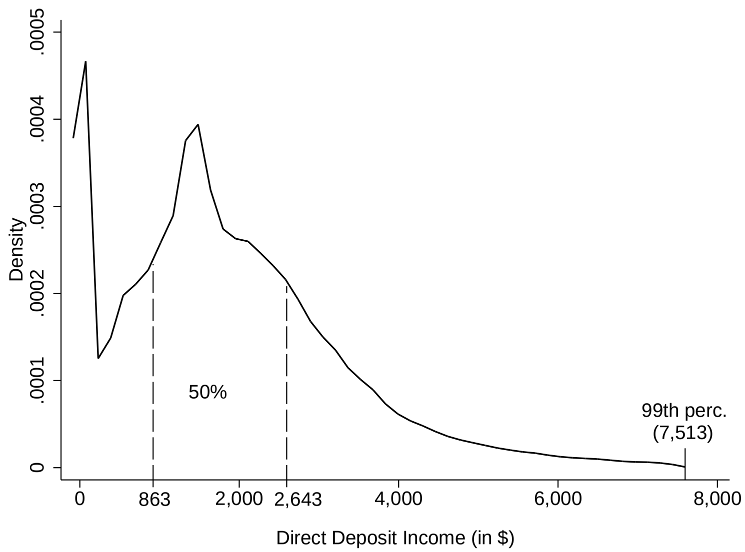
[7] The direct deposits recorded by the bank include income directly deposited by employers in the consumers' checking accounts, but could also be retirement pension payments, employer or government benefits, employment insurance payments, or salary bonuses.

Table 3.1: Descriptive Statistics

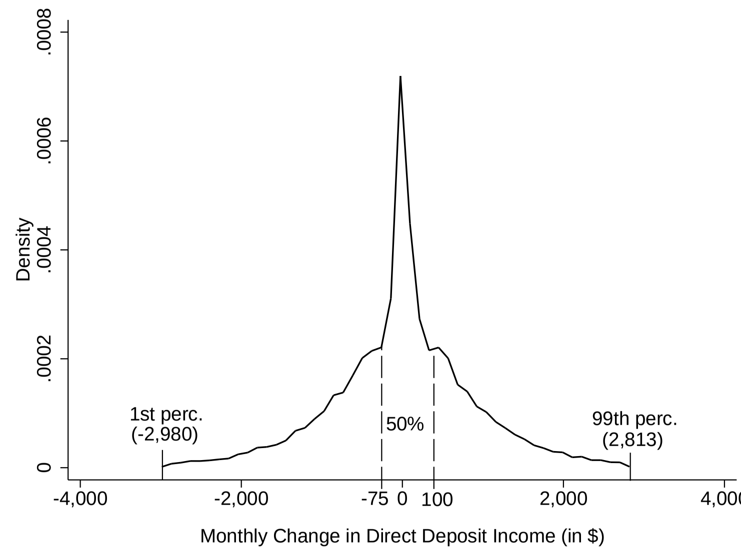
	Mean	Std. Dev.	p5	p50	p95	Obs
A. Direct Deposit Income						
Level (in $)	1,935	1,871	0	1,642	4,713	565,053
Monthly Change (in $)	1.96	1,559	-1,332	0	1,328	526,774
Monthly Change (in %)	0.03	0.54	-0.50	0	0.61	435,621
B. Checking Account						
Level (in $)	4,027	10,254	-8	742	18,336	565,053
Monthly Change (in $)	3	4,851	-1,558	0	1,538	526,774
Monthly Change (in %)	0.04	1.51	-0.79	0	0.79	293,546
C. Savings Account						
Level (in $)	17,534	66,579	0	0	98,148	565,053
Monthly Change (in $)	132	6,852	-5	0	409	526,774
Monthly Change (in %)	0.02	0.86	-0.05	0	0.08	158,725
D. Credit Line						
Level (in $)	6,353	24,780	0	0	28,321	211,856
Monthly Change (in $)	-44	15,743	-1,396	0	1,775	196,971
Monthly Change (in %)	0.19	4.60	-1	0	0.71	73,413
E. Demographics						
Age	50	19	21	50	82	565,053
Male?	0.49	-	-	-	-	565,053
Internal Credit Score	1	1.73	0	1	5	565,053
E. Occupation						
	Count	Percentage	Cumul			
Undefined	1,247	3.26	3.26			
White Collar	10,052	26.27	29.52			
Blue Collar	15,497	40.49	70.02			
Student	2,370	6.19	76.21			
Retired/Unemployed	9,104	23.79	100.00			
Total	38,270	100.00				

Note: Panel A presents mean direct deposits as well as their monthly changes in dollars, and in percentage when the previous month's direct deposit was greater than $500. Panel B presents checking accounts in levels, as well as their monthly changes in dollars, and in percentage when the previous month's balance was greater than $500. Panel C presents savings accounts in levels, as well as their monthly changes in dollars, and in percentage when the previous month's balance was greater than $500. Panels D and E present demographics.

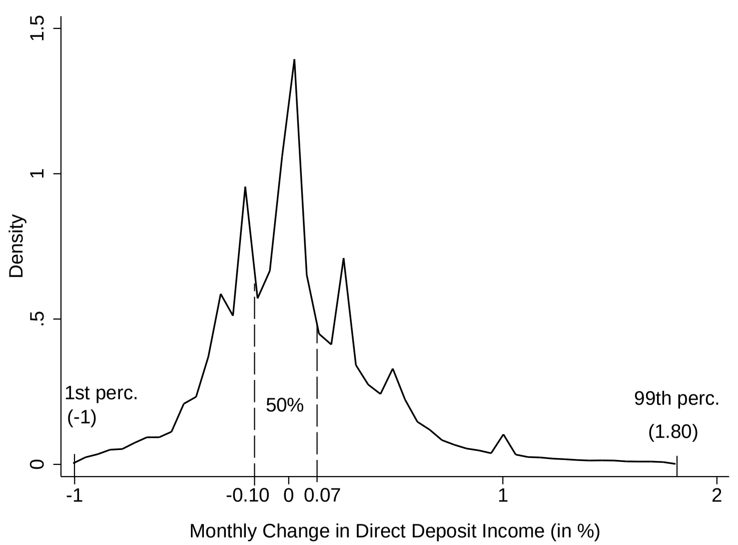
Figure 3.1: Direct Deposit Distributions



(a) Monthly Direct Deposits (in $)



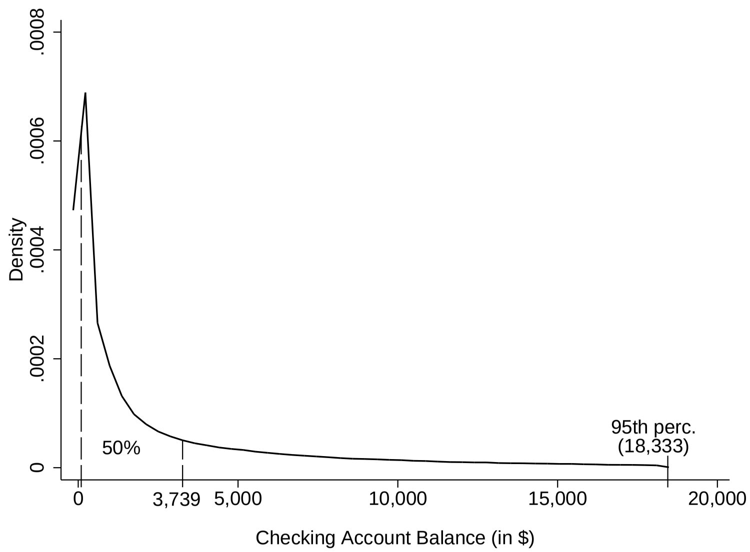
(b) Monthly Changes in Direct Deposits (in $)



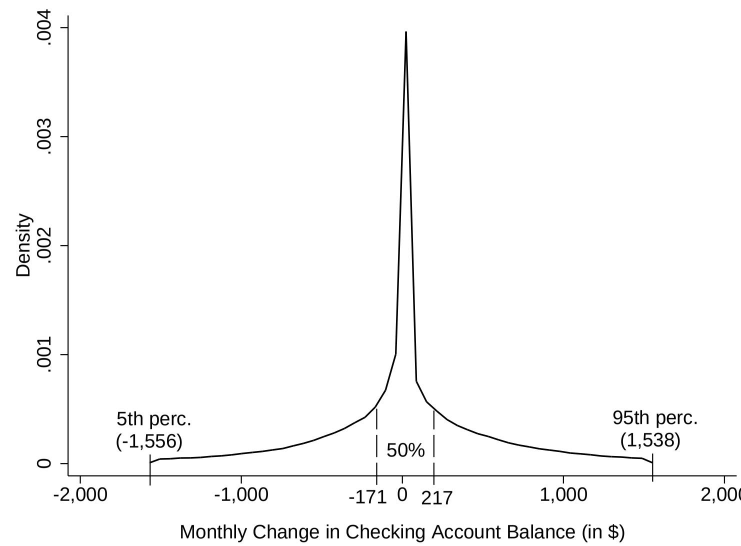
(c) Monthly Changes in Direct Deposits (in %)

Note: Panel (a) presents the empirical pdf of monthly direct deposits in levels. Panel (b) presents the empirical pdf of monthly direct deposit changes in dollars. Panel (c) presents the empirical pdf of monthly direct deposit changes in percentage, when the previous month's direct deposit was larger than $500.

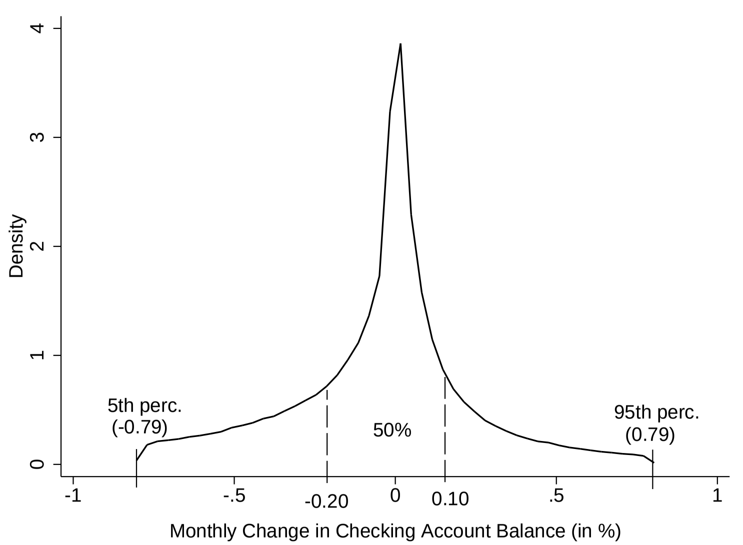
Figure 3.2: Checking Account Balance Distributions



(a) Monthly Checking Account Balance (in $)



(b) Monthly Changes in Checking Account Balance (in $)



(c) Monthly Changes in Checking Account Balance (in %)

Note: Panel (a) presents the empirical pdf of checking account balances in levels. Panel (b) presents the empirical pdf of checking account balance changes in dollars. Panel (c) presents the empirical pdf of monthly checking account balance changes in percentage, when the previous month's balance was larger than $500.

50% of the monthly deposits are between \$766 and \$2,598. Note that there is an excess realization of zeros in income-month observations which motivates our use of hurdle models in the analysis. Panel (b) shows the monthly direct deposit changes in dollars. On average, the change is close to zero, although the distribution has long tails. About 50% of the monthly changes in direct deposits are between -\$77 and \$100. Panel (c) shows monthly direct deposit changes in percentage of the previous month's deposit for cases when it was larger than \$500. 50% of the changes are between -10% and 7%.

Panel (a) of Appendix Figure 3.5 shows average monthly direct deposits over the sample period, segmented by occupation. White collar workers are the highest earners, retired or unemployed worker face the least amount of income variation, and students have the lowest average income. Panel (b) shows the average monthly direct deposit segmented by age and illustrates the typical life-cycle pattern of earnings: it is hump-shaped in early years and there is a notable decrease around the typical retirement age of 60 years old.

Panel B of Table 3.1 shows that the average checking account balance is \$3,927. The month-to-month change in balance is close to zero both in dollars and in percentage change. Figure 3.2 shows empirical density functions for different measures of checking account balances. Panel (a) shows the distribution of balances in levels, truncated at the 95th percentile. 50% of the monthly balances are between \$36 and \$3,739. Panel (b) shows the monthly balance changes in dollars. On average, the change is close to zero and about 50% of the monthly changes in direct deposits are between -\$171 and \$217. Panel (c) shows monthly balance changes in percentage of the previous month's balance for cases when it was larger than \$500. 50% of the changes are between -20% and 10%.

Panel (a) of Appendix Figure 3.6 shows average monthly checking account balances over the sample period, segmented by occupation. Retired or unemployed worker keep the highest balances. Panel (b) shows the average checking account balance segmented by age and shows that the level of savings increases with age.

Panel C of Table 3.1 shows that the average savings account balance is \$16,907. A large portion of consumers do not have any money in a savings account, motivating again the use of zero-inflated hurdle models in the analysis. The month-to-month changes in savings account balance are close to zero on average and feature less variation then changes in checking account balance. Panel D shows the average amount drawn down on revolving lines of credit.

3.3 Results

3.3.1 Dynamic Model

In this section, we provide reduced form evidence of the comovement of income and personal savings. We estimate a model in which log savings are explained by changes in log direct deposits at different time horizons. We model savings as a two-part process in which the first equation represents the probability of having positive savings in a given month (estimated with a conditional logit model to allow for account fixed effects), and the second equation represents the truncated-at-zero distribution of savings (estimated with a truncated OLS on a log scale).

Changes in log direct deposits are modeled as a four-part process in which direct deposits can be (1) positive both at time $t-1$ and t, (2) positive at $t-1$ and zero at t, (3) zero at $t-1$ and positive at t, and (4) zero at both $t-1$ and t. We further decompose the direct deposit changes into their positive and negative components to allow for asymmetric effects of positive and negative income shocks on savings. Specifically, we estimate the model

$$
\begin{aligned}
\ln(BAL_{i,t}|BAL_{i,t} > 0) = &\sum_{j=-3}^{3} \beta_j^{+} \Delta \ln DIR^{+}_{i,t+j} \times \mathbb{I}(DIR_{i,t+j} > 0, DIR_{i,t+j-1} > 0) \\
&+ \sum_{j=-3}^{3} \beta_j^{-} \Delta \ln DIR^{-}_{i,t+j} \times \mathbb{I}(DIR_{i,t+j} > 0, DIR_{i,t+j-1} > 0) \\
&+ \delta_1 \mathbb{I}(DIR_{i,t} = 0, DIR_{i,t-1} > 0) + \delta_2 \mathbb{I}(DIR_{i,t} > 0, DIR_{i,t-1} = 0) \\
&+ \delta_3 \mathbb{I}(DIR_{i,t} = 0, DIR_{i,t-1} = 0) + \alpha_i + \lambda_t + \epsilon_{i,t},
\end{aligned}
$$

where

$$\Delta \ln DIR^{+}_{i,t+j} = \begin{cases} \Delta \ln DIR_{i,t+j} & \text{if } \Delta \ln DIR_{i,t+j} > 0 \\ 0 & \text{otherwise} \end{cases}$$

and

$$\Delta \ln DIR^{-}_{i,t+j} = \begin{cases} \Delta \ln DIR_{i,t+j} & \text{if } \Delta \ln DIR_{i,t+j} < 0 \\ 0 & \text{otherwise.} \end{cases}$$

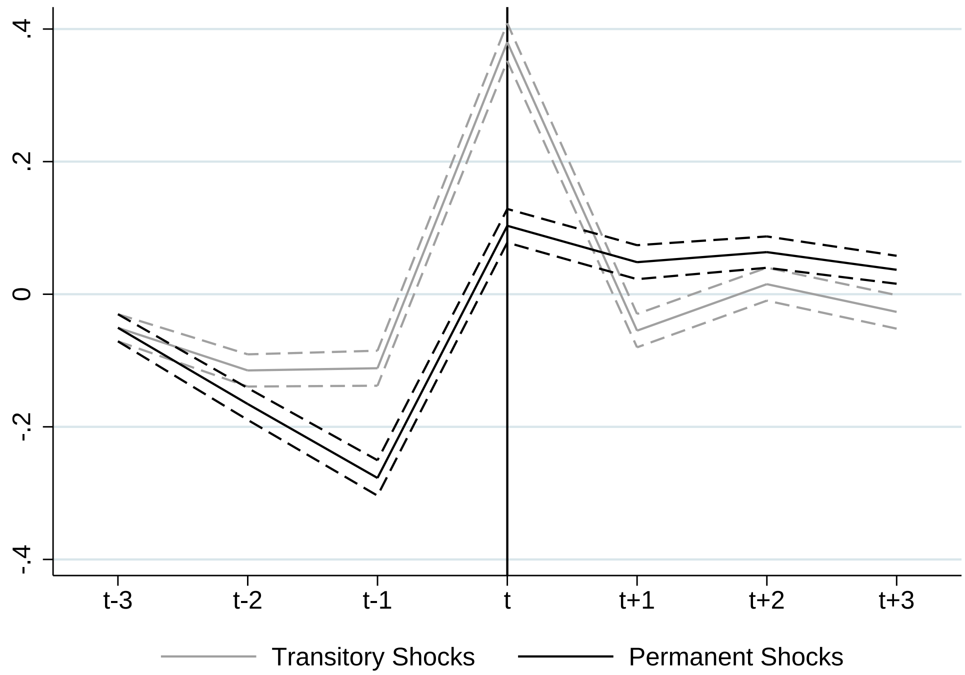
We use the same explanatory variables in estimating the conditional logit model for the probability of having positive savings in a given month. The specification includes account and time fixed effects. $BAL_{i,t}$ represents either the level of money in the consumer's checking or savings accounts, or the amount drawn down on the credit line account. β^{+}_{j} captures the impact of positive income growth at different lags j, β^{-}_{j} captures the impact of negative income growth at different lags j, and the three δ parameters capture the impact of the different extensive margins of earnings. For example, δ_1 measure the effect on savings of going from positive earnings in the previous month to zero earnings in the current month.

Savings Reponse

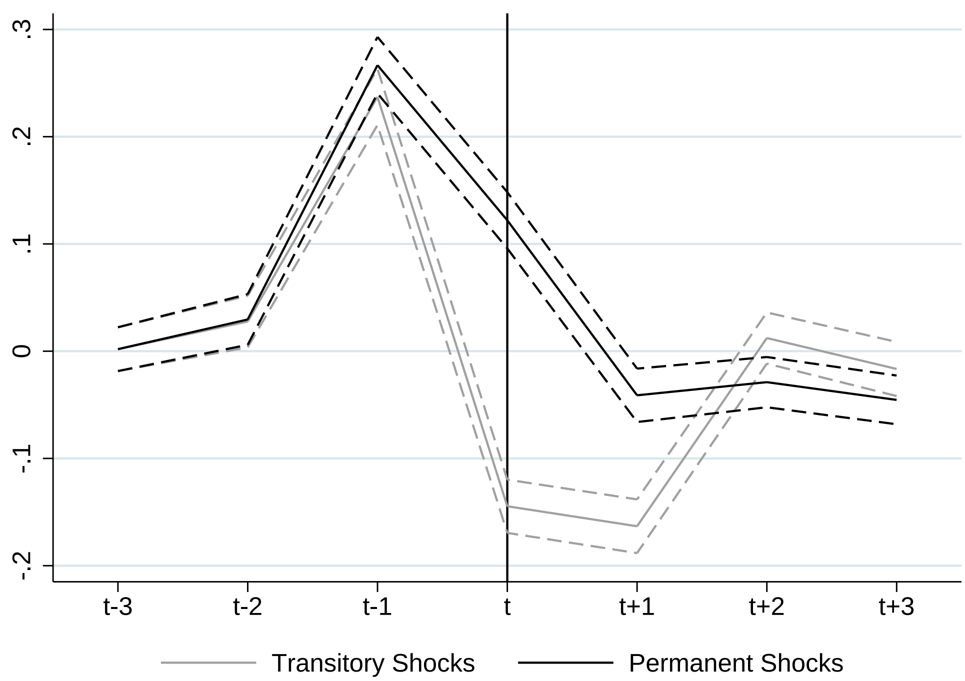
The results from estimating this two-part model are presented in Tables 3.7 to 3.9, respectively using checking account balances, savings account balances, and credit line usage as independent variables. From these results, we construct different impulse response functions of savings to transitory and permanent income shocks. Although the extensive margin of savings is of some interest, we focus on the results of the distribution of savings conditional on them being positive. The results presented in Tables 3.7 to 3.9 show that the effect of the independent variables are almost invariably of the same sign for the probability of positive savings and its level truncated at zero. In what follows, a transitory shock is a one-time change in direct deposit happening at time 0, and a permanent shock is a series of changes in direct deposits happening from time 0 and on.

Panel (a) of Figure 3.3 shows the comovement of checking account balances to positive income shocks. A 10% transitory increase in direct deposit income at time t translates into a

Figure 3.3: Impulse Response Functions - Checking Account



(a) Checking Account Response to Positive Income Shocks



(b) Checking Account Response to Negative Income Shocks

Note: This figure presents the impulse response functions of credit line usage for transitory income shocks (i.e. a one-time dollar at time t), and permanent income shocks (i.e. one dollar from time t and on) calculated from Column (1) of Table 3.7. Panel (a) presents the effect of positive shocks, and panel (b) presents the effect of negative shocks. The dashed line represent the 95% confidence intervals.

reduction in balance of 0.5% to 1% in the three months prior to its realization. The balance increases by about 4% in the month the income increase is realized, and decreases back to its original level in the next month. A permanent increase in direct deposits results in a larger reduction in balance in the months prior to the income change: a 10% permanent increase leads to a decrease checking account balance of -2.8% in the month prior to its realization. After the permanent shock is realized, the balance increases by 0.5% and stabilizes at that new level.

Panel (b) of Figure 3.3 shows that both permanent and transitory decreases in direct deposit income translate into an increase in checking account balance in the month prior to their realization. A transitory decline is absorbed by the checking account balance in about 2 months, whereas a 10% permanent decline translates into a permanent decrease in checking account balance of about 0.5%. Together, these results are consistent with consumers having a target level of checking account savings which adjusts with permanent but not transitory income changes but not transitory, in the spirit of the buffer-stock version of the PIH (Carroll, 1997). There is evidence of anticipation of income shocks, as evidenced by checking account balance movements prior to their realizations.

Figure 3.7 repeats the exercise using the consumer's savings account. The results are qualitatively similar to the checking account response, although they are noisier. Figure 3.8 repeats the exercise using the consumer's credit line account (when the individual has one active). The results show that consumers tend to draw down on the credit line one month prior to a positive direct deposit shock, and seem to repay part of their credit line once the income increase is realized. The opposite is true in the case of negative shocks.

Implied Consumption Response

To get a sense of the implications of these results on consumption, we back out the implied consumption from the changes in checking account balances net of direct deposit changes. The results are presented in Figure 3.4. The black bars represent the income shocks studied and the grey bars represent the implied consumption response. Panel (a) shows that in response to a permanent positive income shock, consumption increases in advance by up to

10% per month. In the first month of the income increase, consumption increases by about 60% of the income increase and then stabilizes at 100% of the income increase. This is consistent with the RE-PIH if we allow some consumers to gradually learn about the income change in the months prior to its realization. Panel (b) shows the consumption response to a permanent negative income shock. The anticipated reduction in consumption is concentrated in the month prior to the income change and, once the income change is realized, it takes two months for consumption to fully adjust downwards.

Panel (c) shows the response to a transitory positive income shock. There is evidence of some anticipation in the month prior to its realization but the most surprising result is that the increase is fully consumed within two months of it realization. This is not consistent with the RE-PIH. A positive transitory shock does not have a big impact on lifetime resources, and the resulting increase in consumption should be spread out over the consumer's lifetime. Similarly, in the case of a transitory negative shock, Panel (d) shows that the reduction in consumption is concentrated in the three months around the transitory decline, also in contradiction with predictions of the RE-PIH.

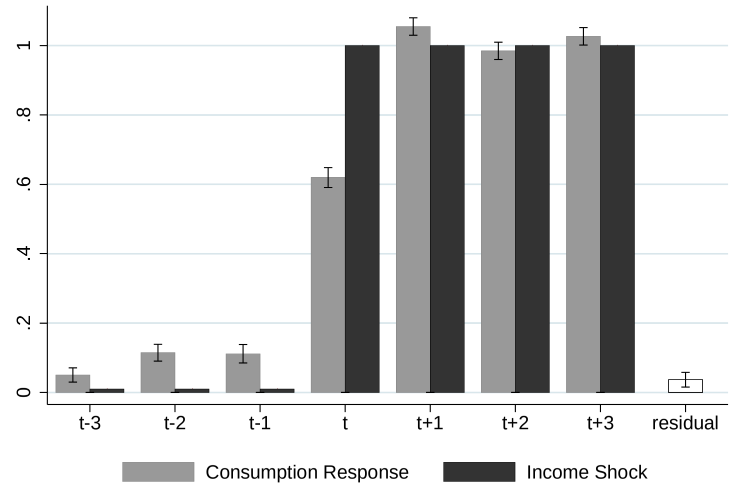
3.3.2 The Income Process

We now match our findings to the income process typically studied in the literature (e.g. following Hall (1978), Meghir and Pistaferri (2004), Blundell et al. (2008) and many others). However, in an attempt to correct for the excess realization of zeros in monthly direct deposits ($DIR_{i,t}$), we augment the income process by including it in a hurdle model.[8] We separate the income process in two parts, first the probability that the income realization is positive, and second the level of income on a log scale, conditional on a positive income realization. The first equation for the dichotomous event of having zero or positive income in a given month is modeled using a probit, such that

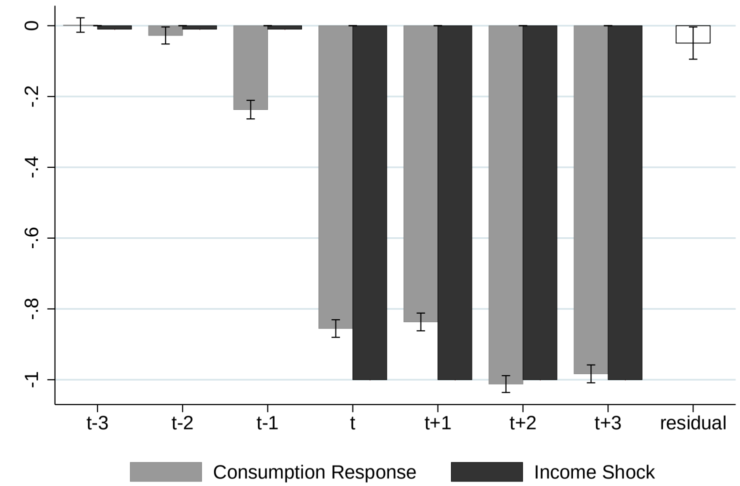
$$\mathbb{P}(DIR_{i,t} > 0 | Z_{i,t}) = \Phi(\beta_1' Z_{i,t}). \tag{3.1}$$

[8] An alternative to considering zero-inflated hurdle models is to winsorize the data such that zero realizations are replaced with a low value (for example, the 5th percentile of the distribution of the variable) and then to control for observations which have been winsorized by including a dummy variable in the regression. We have also used this methodology and the results are qualitatively similar to using hurdle models.

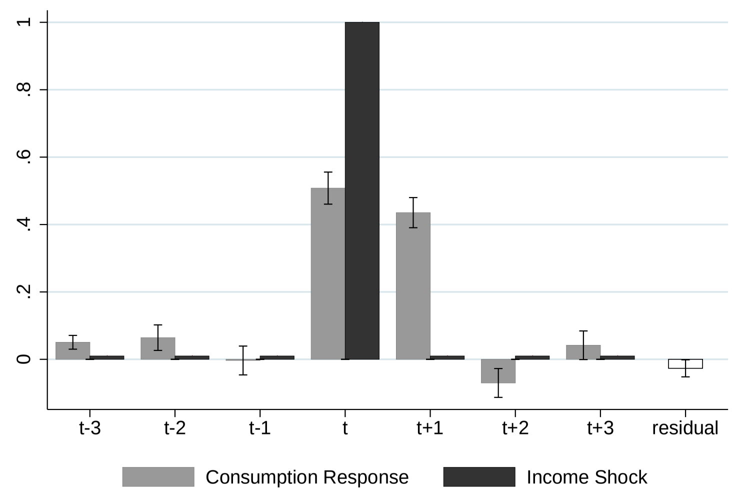
Figure 3.4: Implied Consumption Response



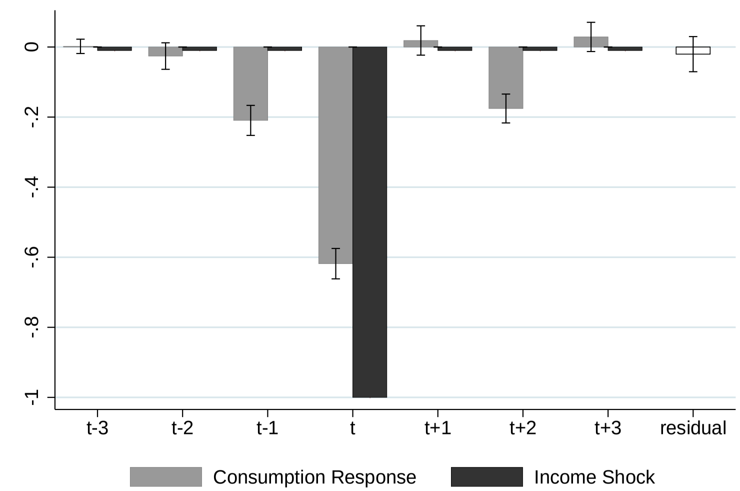
(a) Permanent Positive Shock



(b) Permanent Negative Shock



(c) Transitory Positive Shock



(d) Transitory Negative Shock

Note: This figure plots the implied consumption changes from the response of checking account balances to positive and negative income shocks.

The second equation for positive monthly income realizations is modeled as

$$\ln(DIR_{i,t}|DIR_{i,t} > 0) = \beta_2' Z_{i,t} + P_{i,t} + \nu_{i,t}, \tag{3.2}$$

where the vector of observable variables $Z_{i,t}$ consists of time dummies, a quadratic polynomial in age and dummies for occupation. The permanent component of income is assumed to follow a martingale process of the form

$$P_{i,t} = P_{i,t-1} + \zeta_{i,t}, \tag{3.3}$$

with $\zeta_{i,t}$ serially uncorrelated. The transitory component of income is assumed to follow an MA(1) process of the form[9]

$$\nu_{i,t} = \varepsilon_{i,t} + \theta_1 \varepsilon_{i,t-1}. \tag{3.4}$$

Calling $dir_{i,t} = \ln(DIR_{i,t}|DIR_{i,t} > 0) - \beta_2' Z_{i,t}$, the unexplained log earnings growth is then given by

$$\Delta dir_{i,t} = \zeta_{i,t} + \Delta \nu_{i,t}. \tag{3.5}$$

The likelihood contribution for an observation can be written as

$$\mathcal{L}_{i,t} = \{1 - \Phi(\beta_1' Z_{i,t})\}^{\mathbb{I}(DIR_{i,t}=0)} \times \{\Phi(\beta_1' Z_{i,t}) \ln(DIR_{i,t}|DIR_{i,t} > 0)\}^{\mathbb{I}(DIR_{i,t}>0)}, \tag{3.6}$$

where $\mathbb{I}(.)$ represents the indicator function. Such model is considered by Duan et al. (1983) for the case of medical expenditures. Estimating the parameters of this model is straightforward and can be done independently for the probit and the truncated-at-zero parts. Predictions of $DIR_{i,t}$ can be constructed by multiplying the predictions of each part of the model,[10]

$$\mathbb{E}[DIR_{i,t}|Z_{i,t}] = \mathbb{P}(DIR_{i,t} > 0|Z_{i,t}) \times \mathbb{E}[DIR_{i,t}|DIR_{i,t} > 0, Z_{i,t}]. \tag{3.7}$$

[9] This can be generalized to an MA(q) process, where the order of lag q is estimated empirically. Evidence suggests that an MA(1) process is sufficient in our data.

[10] In this particular case, if the error is i.i.d and normally distributed with variance σ^2, we get that $\mathbb{E}[DIR_{i,t}|DIR_{i,t} > 0, Z_{i,t}] = e^{\beta_2' Z_{i,t}} e^{0.5\sigma^2}$. However, Duan (1983) shows that if the error is not normally distributed, a better "smearing" estimate can be derived where $\mathbb{E}[DIR_{i,t}|DIR_{i,t} > 0, Z_{i,t}] = e^{\beta_2' Z_{i,t}} \mathbb{E}[e^{\mu_{i,t}}]$. We use this smearing estimate in making our predictions.

Transmission of Income Shocks to Savings

In an analogy to the model of transmission of income shocks to consumption derived in Blundell et al. (2008), we model the transmission of permanent and transitory income shocks to (residual) savings. We model checking account balances ($BAL_{i,t}$) in a hurdle model. The first equation for the dichotomous event of having zero or positive savings in a given month is modeled using a probit, such that

$$\mathbb{P}(BAL_{i,t} > 0 | Z_{i,t}) = \Phi(\gamma_1' Z_{i,t}). \tag{3.8}$$

The second equation for positive monthly income realizations is modeled as

$$\ln(BAL_{i,t} | BAL_{i,t} > 0) = \gamma_2' Z_{i,t} + \mu_{i,t}. \tag{3.9}$$

Calling $bal_{i,t} = \ln(BAL_{i,t} | BAL_{i,t} > 0) - \gamma_2' Z_{i,t}$, we then posit that the transmission of income shocks to unexplained (to the econometrician) log savings can be written as

$$\Delta bal_{i,t} = \phi_{i,t}\zeta_{i,t} + \psi_{i,t}\varepsilon_{i,t} + \xi_{i,t}. \tag{3.10}$$

In this case, $\phi_{i,t}$ and $\psi_{i,t}$ respectively measure the impact of permanent ($\zeta_{i,t}$) and transitory ($\varepsilon_{i,t}$) income shocks on savings, and $\xi_{i,t}$ represents innovations in savings that are independent of income shocks. The parameters $\phi_{i,t}$ and $\psi_{i,t}$ can be viewed as self-insurance parameters and measure how income shocks are transmitted to personal savings. In the case of full self-insurance, income shocks are fully passed through to savings such that $\phi_{i,t} = \psi_{i,t} = 1$. In the case of no self-insurance, savings do not absorb incomes shocks and $\phi_{i,t} = \psi_{i,t} = 0$. The model allows for partial self-insurance, in which case the value of these parameters quantify the extent to which savings are used to buffer income shocks.

This simple setting makes the strong assumption that consumers do not posses advance information about their income changes. It also assumes that consumers distinguish between permanent and transitory shocks in the same way we do, and that they hold rational expectations about their income realizations. If consumers have superior information relative to the econometrician and take preemptive action to mitigate the effects of income shocks, the estimated reaction of savings to income shocks will be a combination of both self-insurance and advance information.

Identification

To identify the parameters of interest of the model, we start by imposing structure on the earnings and savings processes presented previously. Assume that $\zeta_{i,t}, \nu_{i,t}$ and $\xi_{i,t}$ are uncorrelated processes. Then

$$\text{cov}(\Delta dir_t, \Delta dir_{t+s}) = \begin{cases} \text{var}(\zeta_t) + \text{var}(\Delta\nu_t) & \text{if } s = 0, \\ \text{cov}(\Delta\nu_t, \Delta\nu_{t+s}) & \text{if } s \neq 0. \end{cases}$$

$$\text{cov}(\Delta bal_t, \Delta bal_{t+s}) = \begin{cases} \phi_t^2 \text{var}(\zeta_t) + \psi_t^2 \text{var}(\Delta\varepsilon_t) + \text{var}(\xi_t) & \text{if } s = 0, \\ 0 & \text{if } s \neq 0. \end{cases}$$

$$\text{cov}(\Delta bal_t, \Delta dir_{t+s}) = \begin{cases} \phi_t \text{var}(\zeta_t) + \psi_t \text{var}(\varepsilon_t) & \text{if } s = 0, \\ \psi_t \text{cov}(\varepsilon_t \Delta\nu_{t+s}) & \text{if } s > 0. \end{cases}$$

These three sets of equations identify the cross-sectional covariances of the processes considered. They can be estimated over the whole sample, over subgroups of the population, or over specific times. As in Meghir and Pistaferri (2004), we can identify

$$\text{var}(\zeta_t) = \text{cov}(\Delta dir_t, \Delta dir_{t-1} + \Delta dir_t + \Delta dir_{t+1}), \text{ and,}$$
$$\text{var}(\varepsilon_t) = -\text{cov}(\Delta dir_t, \Delta dir_{t+1}).$$

We then follow Blundell et al. (2008) in deriving the partial insurance parameters with respect to permanent and transitory shocks. In their context, these insurance parameters reflect the comovement of consumption and income, whereas in our case they reflect the comovement of savings and income. They are respectively identified by

$$\text{Permanent Shock Insurance: } \phi = \frac{\mathbb{E}[\Delta bal_t(\Delta dir_{t-1} + \Delta dir_t + \Delta dir_{t+1})]}{\mathbb{E}[\Delta dir_t(\Delta dir_{t-1} + \Delta dir_t + \Delta dir_{t+1})]}, \text{ and}$$
$$\text{Transitory Shock Insurance: } \psi = \frac{\mathbb{E}[\Delta bal_t \Delta dir_{t+1}]}{\mathbb{E}[\Delta dir_t \Delta dir_{t+1}]}.$$

We present the estimated covariance functions of the different processes pooled over the whole sample in Table 3.2. Asymptotic standard errors clustered at the individual level are reported. The unexplained earnings growth rates are negatively correlated, with the first lag being the most economically significant. Unexplained savings growth rates, as measured by the checking account, are also negatively correlated. The covariance between earnings growth and savings growth shows a negative correlation one period ahead of a change in earnings.

Appendix Table 3.4 shows the same covariance functions broken down by age and work category. In this case, the regression model only includes time dummy. Panel A shows that income shocks are more important for younger individuals, both in terms of the size of the contemporaneous variance and its persistence. Individuals aged 66 or older face very little income risk, as their income mostly comes from retirement payments or social security. For all age groups, the covariance with a lag of order 2 or more seems mostly negligible. Panel B shows the autocovariance function of the buffer stock, as measured by the checking account. Younger individuals have more persistent changes in savings. Finally, Panel C shows the covariance between income shocks and changes in the buffer stock of liquidity. This shows that younger individual's buffer stocks are most sensitive to changes in income. At the other extreme, individuals age 66 and older are almost non-sensitive to changes in income, which could be due to lower income risk (see Panel A).

Because these processes are only defined for the cases in which earnings and savings are positive at both lags studied, we also present in Appendix Table 3.5 the changes in savings (in levels) conditional on the possible extensive margins of income across two consecutive months. The results show that going from a positive direct deposit in the previous month

Table 3.2: Covariance of Processes

	Direct Deposit Income	Buffer Stock: Checking Accounts	Income / Buffer Stock
	$\text{cov}(\Delta dir_t \Delta dir_{t+s})$	$\text{cov}(\Delta bal_t \Delta bal_{t+s})$	$\text{cov}(\Delta dir_t \Delta bal_{t+s})$
4	-0.0010	-0.0193***	-0.0082***
	(0.0009)	(0.0045)	(0.0011)
3	-0.0105***	-0.0379***	-0.0015
	(0.0009)	(0.0044)	(0.0011)
2	0.0026**	-0.0439***	0.0011
	(0.0009)	(0.0046)	(0.0010)
1	-0.0664***	-0.4292***	-0.0031**
	(0.0014)	(0.0074)	(0.0010)
0	0.1857***	1.2923***	0.0523***
	(0.0025)	(0.0143)	(0.0011)
-1			-0.0395***
			(0.0011)
-2			0.0012
			(0.0010)
-3			-0.0020
			(0.0011)
-4			-0.0012
			(0.0011)

Note: Estimation is pooled over all individuals and months in the sample. Asymptotic standard errors clustered at the individual level are reported under the coefficient values.

to a negative direct deposit in the current month leads to a decrease in the level of savings in the checking account of $282. Conversely, going from zero to positive direct deposits increases the checking account balance by $169, and staying a zero direct deposits in two consecutive months leads to a decrease in the balance of $52.

Table 3.3 presents the components of the variance of monthly direct deposit and the partial insurance parameters pooled over the whole sample. The partial insurance parameters with respect to income shocks show what fraction of the shocks are passed through to the checking account. Consistent with the dynamic model presented in Section 3.3, checking account balances do not react a lot to permanent income shocks: a 10% permanent change in income leads to an adjustment of 1.2% in balances. However, checking account balances move a lot more with transitory income shocks: a 10% transitory change in income leads to a transitory adjustment of 6.4% in balances.

Table 3.3: Variance Decomposition and Partial Insurance

Income Variance Decomposition			Partial Insurance Parameters	
Variance of Innovations	Permanent Component	Transitory Component	Permanent Shocks	Transitory Shocks
0.1857***	0.0218***	0.0664***	0.1166*	0.6387***
(0.0025)	(0.0012)	(0.0014)	(0.0499)	(0.0162)

Note: Estimation is pooled over all individuals and months in the sample. Asymptotic standard errors clustered at the individual level are reported under the coefficient values.

Appendix Table 3.6 segments these numbers across ages and work categories. Young individuals face the highest variance of permanent income shocks, which is also reflect in the category of consumers which are students. The transitory variance of income seems to hit all categories of occupation in the same way, except for consumers aged 66 and older, who are for the most part retired. The measure of partial insurance to permanent shock is also noisy across age and occupation categories, although for younger individuals, a 10% permanent change in income leads to a significant adjustment of 2.3% in savings. The partial insurance parameter to transitory income shocks is highest for the younger individuals in the sample.

3.4 Discussion, Limitations and Potential Extensions

In this paper, we study how personal savings are used by individuals to smooth permanent and transitory income shocks. Permanent shocks lead to modest permanent adjustments of checking account balances while transitory shocks are fully absorbed by checking account balances within two to three months of their realization. The results show that consumption moves in lock step with permanent incomes changes, as predicted by the RE-PIH, but that consumption is also excessively sensitive to transitory changes in income. We find evidence of advance information about future income contained in savings, as evidenced by movements in checking account balances prior to income changes.

There are limitations in using observational data to infer consumers' reaction to income changes. First, using data from a single bank does not allow us to see substitution across accounts at different banks. This can be problematic if consumers systematically respond to income changes by moving money in and out of their checking accounts at this bank, and into accounts at other financial institutions. Second, we analyze the response of consumers to *realized* income changes, but the way consumers form expectations about income shocks matters for the way they respond to them. In particular, consumers' subjective expectation about income changes could differ from the way they are modeled in this paper. Investigating the dynamics of income and savings potentially elicits advance information about income changes included in saving behavior but it cannot fully capture the timing and nature of subjective beliefs. What we might classify as a positive shock could well be perceived negatively by a consumer who was expecting a higher increase, and what we identify as transitory could have been expected to be permanent by the consumer.

One potential extension to our analysis would be to elicit the consumer's subjective expectations about their future income changes in a controlled laboratory experimental setting. One could then test whether the income process typically used in the literature effectively captures the subjective beliefs of consumers about the sign and durability of income shocks. The response to income shocks could then be analyzed conditional on consumers' subjective expectations, thereby augmenting the results found when survey responses about future income growth are used (Pistaferri, 2001; Alessie and Lusardi, 1997).

3.5 Appendix

Table 3.4: Autocovariance of the Processes
(Segmented by Age and Occupation)

	Pooled	Age						Occupation			
	All Sample	18-25	26-35	36-45	46-55	56-65	66+	White Collar	Blue Collar	Student	Retired/Unemp.
A. $\text{cov}(\Delta dir_t \Delta dir_{t+n})$											
0	0.1852***	0.3683***	0.2459***	0.2215***	0.1866***	0.1839***	0.0609***	0.1917***	0.1988***	0.3922***	0.1097***
	(0.0025)	(0.0078)	(0.0077)	(0.0087)	(0.0068)	(0.0051)	(0.0031)	(0.0060)	(0.0035)	(0.0130)	(0.0040)
1	-0.0664***	-0.0858***	-0.0793***	-0.0821***	-0.0711***	-0.0800***	-0.0329***	-0.0716***	-0.0697***	-0.0857***	-0.0520***
	(0.0014)	(0.0034)	(0.0044)	(0.0049)	(0.0038)	(0.0030)	(0.0022)	(0.0034)	(0.0019)	(0.0054)	(0.0027)
2	0.0026**	-0.0184***	-0.0063*	-0.0014	-0.0009	0.0156***	0.0107***	-0.0028	0.0010	-0.0208***	0.0155***
	(0.0009)	(0.0023)	(0.0025)	(0.0025)	(0.0028)	(0.0016)	(0.0015)	(0.0020)	(0.0012)	(0.0037)	(0.0018)
3	-0.0105***	-0.0344***	-0.0038	-0.0044	-0.0065*	-0.0149***	-0.0074***	-0.0042*	-0.0093***	-0.0362***	-0.0133***
	(0.0009)	(0.0027)	(0.0022)	(0.0026)	(0.0027)	(0.0015)	(0.0017)	(0.0021)	(0.0010)	(0.0042)	(0.0019)
4	-0.0009	-0.0160***	-0.0075***	-0.0077**	-0.0019	0.0085***	0.0054**	-0.0048*	-0.0027**	-0.0211***	0.0103***
	(0.0009)	(0.0027)	(0.0020)	(0.0027)	(0.0024)	(0.0015)	(0.0019)	(0.0019)	(0.0010)	(0.0039)	(0.0021)
B. $\text{cov}(\Delta bal_t \Delta bal_{t+n})$											
0	1.2925***	2.1687***	1.7729***	1.7551***	1.3369***	1.0216***	0.5365***	1.3670***	1.4716***	1.9258***	0.7990***
	(0.0143)	(0.0523)	(0.0382)	(0.0449)	(0.0326)	(0.0274)	(0.0219)	(0.0281)	(0.0233)	(0.0766)	(0.0233)
1	-0.4295***	-0.7463***	-0.6142***	-0.5972***	-0.4542***	-0.3452***	-0.1489***	-0.4345***	-0.5121***	-0.6689***	-0.2493***
	(0.0074)	(0.0279)	(0.0196)	(0.0273)	(0.0164)	(0.0135)	(0.0108)	(0.0134)	(0.0132)	(0.0413)	(0.0106)
2	-0.0440***	-0.0978***	-0.0649***	-0.0537**	-0.0492***	-0.0281**	-0.0110*	-0.0667***	-0.0426***	-0.0506*	-0.0210***
	(0.0046)	(0.0194)	(0.0118)	(0.0170)	(0.0108)	(0.0090)	(0.0056)	(0.0091)	(0.0084)	(0.0242)	(0.0063)
3	-0.0377***	-0.0601**	-0.0608***	-0.0607***	-0.0311**	-0.0353***	-0.0113*	-0.0403***	-0.0478***	-0.0705**	-0.0185**
	(0.0044)	(0.0186)	(0.0122)	(0.0148)	(0.0108)	(0.0085)	(0.0055)	(0.0086)	(0.0078)	(0.0241)	(0.0064)
4	-0.0195***	-0.0351	-0.0175	-0.0498**	-0.0444***	0.0121	-0.0083	-0.0245**	-0.0276***	-0.0250	-0.0037
	(0.0045)	(0.0189)	(0.0127)	(0.0158)	(0.0103)	(0.0092)	(0.0053)	(0.0090)	(0.0075)	(0.0267)	(0.0067)
C. $\text{cov}(\Delta dir_t \Delta bal_{t+s})$											
-4	-0.0012	-0.0105*	0.0008	0.0062	-0.0003	-0.0008	-0.0021**	0.0002	-0.0001	-0.0107	-0.0026*
	(0.0011)	(0.0053)	(0.0037)	(0.0041)	(0.0028)	(0.0021)	(0.0007)	(0.0022)	(0.0019)	(0.0079)	(0.0013)
-3	-0.0021	-0.0038	-0.0063	-0.0104**	-0.0018	0.0019	0.0012	0.0009	-0.0061**	-0.0065	0.0029*
	(0.0010)	(0.0050)	(0.0035)	(0.0039)	(0.0028)	(0.0020)	(0.0007)	(0.0021)	(0.0019)	(0.0073)	(0.0012)
-2	0.0012	-0.0156***	0.0074*	0.0106**	0.0024	0.0009	0.0007	-0.0001	0.0079***	-0.0204**	-0.0015
	(0.0010)	(0.0047)	(0.0032)	(0.0035)	(0.0025)	(0.0021)	(0.0007)	(0.0020)	(0.0017)	(0.0066)	(0.0012)
-1	-0.0393***	-0.0800***	-0.0668***	-0.0598***	-0.0475***	-0.0289***	-0.0060***	-0.0442***	-0.0512***	-0.0747***	-0.0124***
	(0.0011)	(0.0047)	(0.0036)	(0.0038)	(0.0027)	(0.0023)	(0.0009)	(0.0021)	(0.0019)	(0.0073)	(0.0014)
0	0.0525***	0.1267***	0.0810***	0.0750***	0.0566***	0.0374***	0.0099***	0.0532***	0.0646***	0.1237***	0.0198***
	(0.0011)	(0.0050)	(0.0037)	(0.0040)	(0.0027)	(0.0023)	(0.0008)	(0.0021)	(0.0019)	(0.0078)	(0.0014)
1	-0.0033***	0.0033	-0.0103**	-0.0137***	-0.0008	-0.0007	-0.0013	-0.0050**	-0.0057***	0.0093	-0.0018
	(0.0010)	(0.0046)	(0.0032)	(0.0032)	(0.0025)	(0.0018)	(0.0009)	(0.0018)	(0.0017)	(0.0067)	(0.0013)
2	0.0010	0.0009	0.0008	0.0072	-0.0049	0.0010	0.0018*	0.0027	-0.0004	0.0006	0.0020
	(0.0010)	(0.0048)	(0.0032)	(0.0037)	(0.0027)	(0.0019)	(0.0008)	(0.0020)	(0.0017)	(0.0072)	(0.0013)
3	-0.0016	-0.0070	-0.0024	-0.0059	-0.0007	-0.0006	0.0015	-0.0041	-0.0018	-0.0098	0.0017
	(0.0011)	(0.0050)	(0.0034)	(0.0038)	(0.0031)	(0.0022)	(0.0012)	(0.0023)	(0.0018)	(0.0077)	(0.0017)
4	-0.0082***	-0.0117*	-0.0105**	-0.0098*	-0.0127***	-0.0053**	-0.0047***	-0.0100***	-0.0093***	-0.0027	-0.0061***
	(0.0011)	(0.0053)	(0.0036)	(0.0039)	(0.0032)	(0.0019)	(0.0009)	(0.0024)	(0.0019)	(0.0077)	(0.0013)

Note: Estimation is pooled over all individuals and months in the sample. Asymptotic standard errors clustered at the individual level are reported under the coefficient values.

Table 3.5: Changes in Balances and Extensive Margins of Earnings

	Pooled	Age						Occupation			
	All Sample	18-25	26-35	36-45	46-55	56-65	66+	White Collar	Blue Collar	Student	Retired/Unemp.
A. $\mathbb{E}[BAL_{i,t} \mid DIR_t = 0, DIR_{t-1} > 0]$											
	-282	-290	-301	-221	-327	-132	-545	-384	-260	-338	-57
	(5,222)	(1,727)	(2,289)	(2,656)	(3,606)	(13,721)	(4,423)	(3,778)	(2,591)	(1,231)	(12,616)
B. $\mathbb{E}[BAL_{i,t} \mid DIR_t > 0, DIR_{t-1} = 0]$											
	169	120	53	188	270	113	1,302	50	217	192	62
	(8,105)	(1,579)	(4,510)	(2,107)	(4,668)	(19,402)	(10,868)	(8,951)	(6,982)	(1,682)	(12,999)
C. $\mathbb{E}[BAL_{i,t} \mid DIR_t = 0, DIR_{t-1} = 0]$											
	-52	-101	-47	-30	-5	25	-216	-42	-25	-132	-70
	(4,631)	(5,913)	(2,183)	(1,522)	(5,388)	(6,571)	(3,873)	(5,275)	(1,975)	(2,244)	(9,969)

Note: Estimation is pooled over all individuals and months in the sample. Asymptotic standard errors clustered at the individual level are reported under the coefficient values.

Table 3.6: Variance Decomposition and Partial Insurance

	Pooled	Age						Occupation			
	All Sample	18-25	26-35	36-45	46-55	56-65	66+	White Collar	Blue Collar	Student	Retired/Unemp.
I. Income Variance Decomposition											
A. Variance of Monthly Income Innovations											
	0.1852***	0.3683***	0.2459***	0.2215***	0.1866***	0.1839***	0.0609***	0.1917***	0.1988***	0.3922***	0.1097***
	(0.0025)	(0.0078)	(0.0077)	(0.0087)	(0.0068)	(0.0051)	(0.0031)	(0.0060)	(0.0035)	(0.0130)	(0.0040)
B. Estimatimated Variance of the Permanent Component											
	0.0213***	0.1051***	0.0370***	0.0260***	0.0172***	0.0068**	-0.0080***	0.0235***	0.0238***	0.1246***	-0.0069**
	(0.0012)	(0.0043)	(0.0035)	(0.0036)	(0.0031)	(0.0026)	(0.0016)	(0.0024)	(0.0017)	(0.0071)	(0.0021)
C. Estimatimated Variance of the Transitory Component											
	0.0664***	0.0858***	0.0793***	0.0821***	0.0711***	0.0800***	0.0329***	0.0716***	0.0697***	0.0857***	0.0520***
	(0.0014)	(0.0034)	(0.0044)	(0.0049)	(0.0038)	(0.0030)	(0.0022)	(0.0034)	(0.0019)	(0.0054)	(0.0027)
II. Partial Insurance											
D. Permanent Shocks											
	0.1309*	0.2305***	-0.1517	-0.0832	0.2804	0.2357	0.0358	-0.0101	0.0553	0.3185***	0.0636
	(0.0508)	(0.0484)	(0.1068)	(0.1577)	(0.1621)	(0.2505)	(0.0922)	(0.0937)	(0.0845)	(0.0609)	(0.1891)
E. Transitory Shocks											
	0.6367***	1.0274***	0.9221***	0.7338***	0.7168***	0.3579***	0.1884***	0.6620***	0.7844***	0.9456***	0.2435***
	(0.0161)	(0.0605)	(0.0519)	(0.0519)	(0.0388)	(0.0237)	(0.0222)	(0.0340)	(0.0267)	(0.0928)	(0.0223)

Note: Estimation is pooled over all individuals and months in the sample. Asymptotic standard errors clustered at the individual level are reported under the coefficient values.

Table 3.7: Checking Account

	(1) $\log(BAL_{i,t})$	(2) $\mathbb{P}(BAL_{i,t} > 0)$
F3.$\Delta \log(DIR_{i,t})^+$	-0.0506***	-0.0397
	(0.0104)	(0.0349)
F2.$\Delta \log(DIR_{i,t})^+$	-0.1655***	-0.2754***
	(0.0123)	(0.0363)
F.$\Delta \log(DIR_{i,t})^+$	-0.2771***	-0.4043***
	(0.0136)	(0.0390)
$\Delta \log(DIR_{i,t})^+$	0.1033***	0.2215***
	(0.0129)	(0.0418)
L.$\Delta \log(DIR_{i,t})^+$	0.0484***	0.2068***
	(0.0131)	(0.0400)
L2.$\Delta \log(DIR_{i,t})^+$	0.0635***	0.0981***
	(0.0121)	(0.0377)
L3.$\Delta \log(DIR_{i,t})^+$	0.0369***	-0.0007
	(0.0108)	(0.0366)
F3.$\Delta \log(DIR_{i,t})^-$	-0.0019	0.0844***
	(0.0104)	(0.0323)
F2.$\Delta \log(DIR_{i,t})^-$	-0.0296**	0.1071***
	(0.0120)	(0.0349)
F.$\Delta \log(DIR_{i,t})^-$	-0.2667***	-0.3831***
	(0.0134)	(0.0403)
$\Delta \log(DIR_{i,t})^-$	-0.1221***	-0.1113***
	(0.0134)	(0.0388)
L.$\Delta \log(DIR_{i,t})^-$	0.0411***	0.0559
	(0.0127)	(0.0376)
L2.$\Delta \log(DIR_{i,t})^-$	0.0289**	0.1279***
	(0.0120)	(0.0353)
L3.$\Delta \log(DIR_{i,t})^-$	0.0454***	0.0790**
	(0.0116)	(0.0363)
$\mathbb{I}(DIR_t = 0, DIR_{t-1} > 0)$	-0.1695***	-0.4723***
	(0.0243)	(0.0604)
$\mathbb{I}(DIR_t > 0, DIR_{t-1} = 0)$	0.0771***	0.3120***
	(0.0221)	(0.0631)
$\mathbb{I}(DIR_t = 0, DIR_{t-1} = 0)$	-0.4087***	-0.4591***
	(0.0250)	(0.0483)
Month F.E.	YES	YES
Account F.E.	YES	YES
R^2	0.025	
Observations	285,738	76,804

Note: This table presents the estimation of a hurdle model on savings, as measured by checking accounts. Column (1) presents the OLS estimation of log changes in balance for cases where the balance was positive in periods $t-1$ and t. Columns (2) to (3) are estimated by conditional logit models. Column (2) presents the results for the probability that the balance was positive at $t-1$ and zero at t. Column (3) presents the results for the probability that the balance was zero at $t-1$ and positive at t. Column (4) presents the results for the probability that the balance was zero at $t-1$ and at t. Account fixed effects and time dummies are included in all specifications.

Table 3.8: Savings Account

	(1)	(2)
	$\log(BAL_{i,t})$	$\mathbb{P}(BAL_{i,t} > 0)$
F3.$\Delta \log(DIR_{i,t})^{+}$	-0.0212	-0.2685***
	(0.0157)	(0.0720)
F2.$\Delta \log(DIR_{i,t})^{+}$	-0.0690***	-0.2102***
	(0.0182)	(0.0750)
F.$\Delta \log(DIR_{i,t})^{+}$	-0.0916***	-0.2838***
	(0.0191)	(0.0798)
$\Delta \log(DIR_{i,t})^{+}$	-0.0448**	-0.2764***
	(0.0186)	(0.0780)
L.$\Delta \log(DIR_{i,t})^{+}$	-0.0021	-0.2463***
	(0.0204)	(0.0776)
L2.$\Delta \log(DIR_{i,t})^{+}$	0.0035	-0.1300*
	(0.0196)	(0.0737)
L3.$\Delta \log(DIR_{i,t})^{+}$	0.0177	0.0486
	(0.0165)	(0.0752)
F3.$\Delta \log(DIR_{i,t})^{-}$	-0.0076	-0.0357
	(0.0155)	(0.0721)
F2.$\Delta \log(DIR_{i,t})^{-}$	-0.0215	-0.1076
	(0.0163)	(0.0762)
F.$\Delta \log(DIR_{i,t})^{-}$	-0.0467**	-0.1192
	(0.0184)	(0.0796)
$\Delta \log(DIR_{i,t})^{-}$	-0.0139	-0.0564
	(0.0206)	(0.0802)
L.$\Delta \log(DIR_{i,t})^{-}$	-0.0009	0.0215
	(0.0192)	(0.0785)
L2.$\Delta \log(DIR_{i,t})^{-}$	0.0091	-0.0164
	(0.0191)	(0.0780)
L3.$\Delta \log(DIR_{i,t})^{-}$	0.0073	-0.0563
	(0.0191)	(0.0791)
$\mathbb{I}(DIR_t = 0, DIR_{t-1} > 0)$	-0.0770**	-0.2491*
	(0.0377)	(0.1443)
$\mathbb{I}(DIR_t > 0, DIR_{t-1} = 0)$	-0.0291	-0.4060***
	(0.0364)	(0.1439)
$\mathbb{I}(DIR_t = 0, DIR_{t-1} = 0)$	-0.1327***	-0.5179***
	(0.0452)	(0.1179)
Month F.E.	YES	YES
Account F.E.	YES	YES
R^2	0.002	
Observations	118,867	17,217

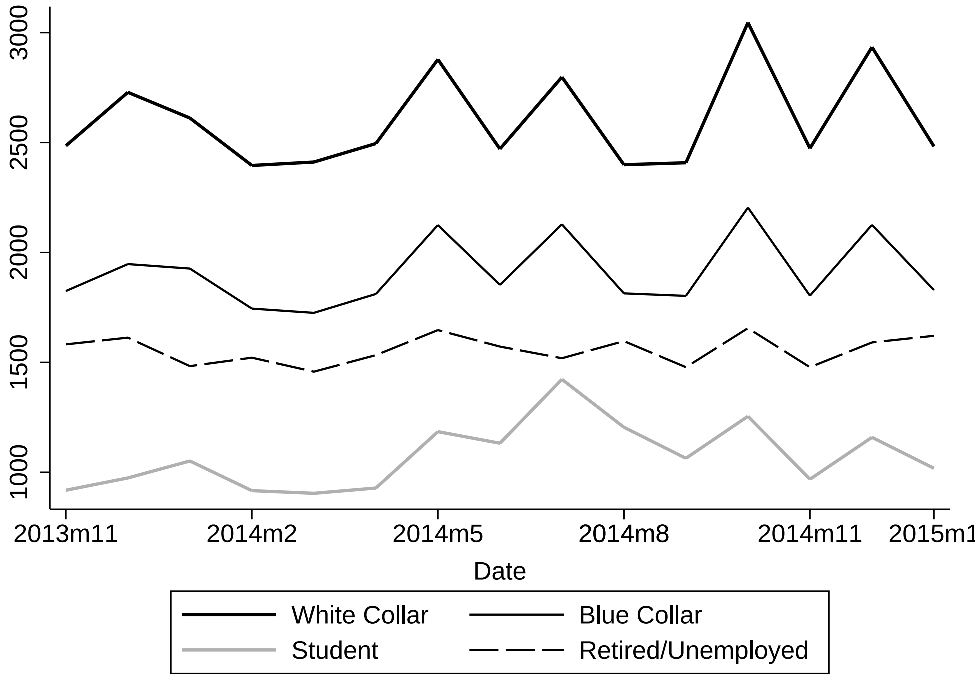
Note: This table presents the estimation of a hurdle model on savings, as measured by savings accounts. Column (1) presents the OLS estimation of log changes in balance for cases where the balance was positive in periods $t-1$ and t. Columns (2) to (3) are estimated by conditional logit models. Column (2) presents the results for the probability that the balance was positive at $t-1$ and zero at t. Column (3) presents the results for the probability that the balance was zero at $t-1$ and positive at t. Column (4) presents the results for the probability that the balance was zero at $t-1$ and at t. Account fixed effects and time dummies are included in all specifications.

Table 3.9: Credit Line Usage

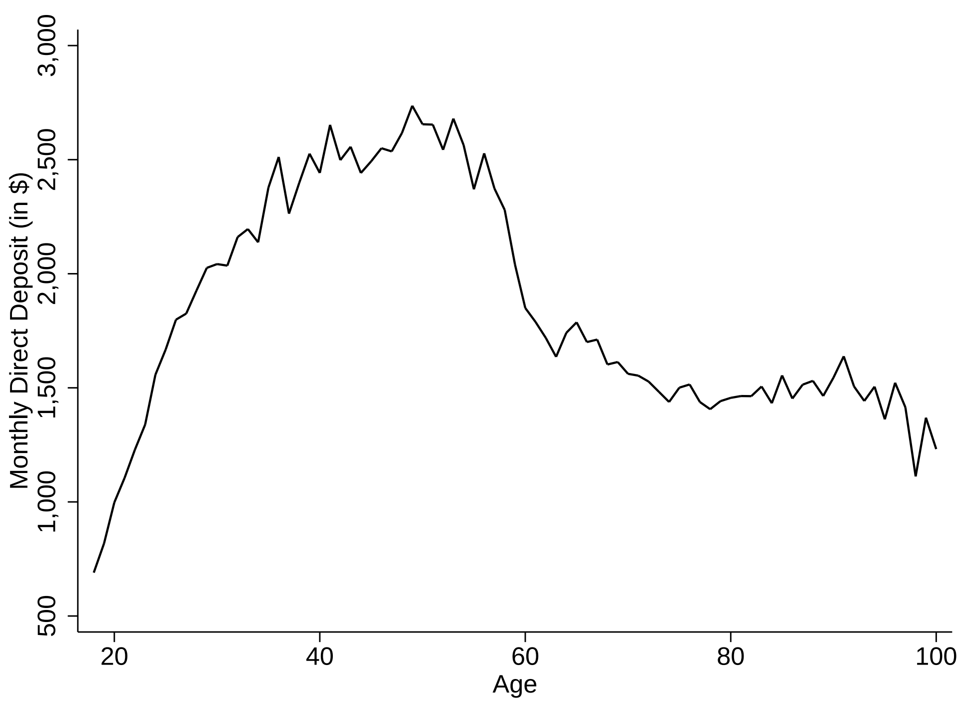
	(1)	(2)
	$\log(BAL_{i,t})$	$\mathbb{P}(BAL_{i,t} > 0)$
F3.$\Delta \log(DIR_{i,t})^+$	0.0188	0.0823
	(0.0146)	(0.0527)
F2.$\Delta \log(DIR_{i,t})^+$	0.0502***	0.4072***
	(0.0164)	(0.0572)
F.$\Delta \log(DIR_{i,t})^+$	0.1082***	0.5636***
	(0.0188)	(0.0612)
$\Delta \log(DIR_{i,t})^+$	0.0025	-0.0572
	(0.0184)	(0.0588)
L.$\Delta \log(DIR_{i,t})^+$	0.0170	-0.0469
	(0.0178)	(0.0577)
L2.$\Delta \log(DIR_{i,t})^+$	0.0069	-0.0989*
	(0.0169)	(0.0538)
L3.$\Delta \log(DIR_{i,t})^+$	-0.0099	-0.0956*
	(0.0147)	(0.0520)
F3.$\Delta \log(DIR_{i,t})^-$	0.0147	0.0714
	(0.0138)	(0.0485)
F2.$\Delta \log(DIR_{i,t})^-$	0.0181	0.0417
	(0.0161)	(0.0540)
F.$\Delta \log(DIR_{i,t})^-$	0.0916***	0.5463***
	(0.0181)	(0.0573)
$\Delta \log(DIR_{i,t})^-$	0.0860***	0.3318***
	(0.0194)	(0.0564)
L.$\Delta \log(DIR_{i,t})^-$	0.0316*	0.0046
	(0.0175)	(0.0550)
L2.$\Delta \log(DIR_{i,t})^-$	0.0407***	0.0268
	(0.0158)	(0.0527)
L3.$\Delta \log(DIR_{i,t})^-$	0.0169	0.0207
	(0.0166)	(0.0519)
$\mathbb{I}(DIR_t = 0, DIR_{t-1} > 0)$	-0.0529	0.0464
	(0.0326)	(0.1086)
$\mathbb{I}(DIR_t > 0, DIR_{t-1} = 0)$	0.0005	-0.2387**
	(0.0302)	(0.1068)
$\mathbb{I}(DIR_t = 0, DIR_{t-1} = 0)$	0.0279	0.2625***
	(0.0284)	(0.0923)
Month F.E.	YES	YES
Account F.E.	YES	YES
R^2	0.006	
Observations	54,952	41,641

Note: This table presents the estimation of a hurdle model on credit line utilization. Column (1) presents the OLS estimation of log changes in balance for cases where the balance was positive in periods $t-1$ and t. Columns (2) to (3) are estimated by conditional logit models. Column (2) presents the results for the probability that the balance was positive at $t-1$ and zero at t. Column (3) presents the results for the probability that the balance was zero at $t-1$ and positive at t. Column (4) presents the results for the probability that the balance was zero at $t-1$ and at t. Account fixed effects and time dummies are included in all specifications.

Figure 3.5: Direct Deposits by Age and Occupation



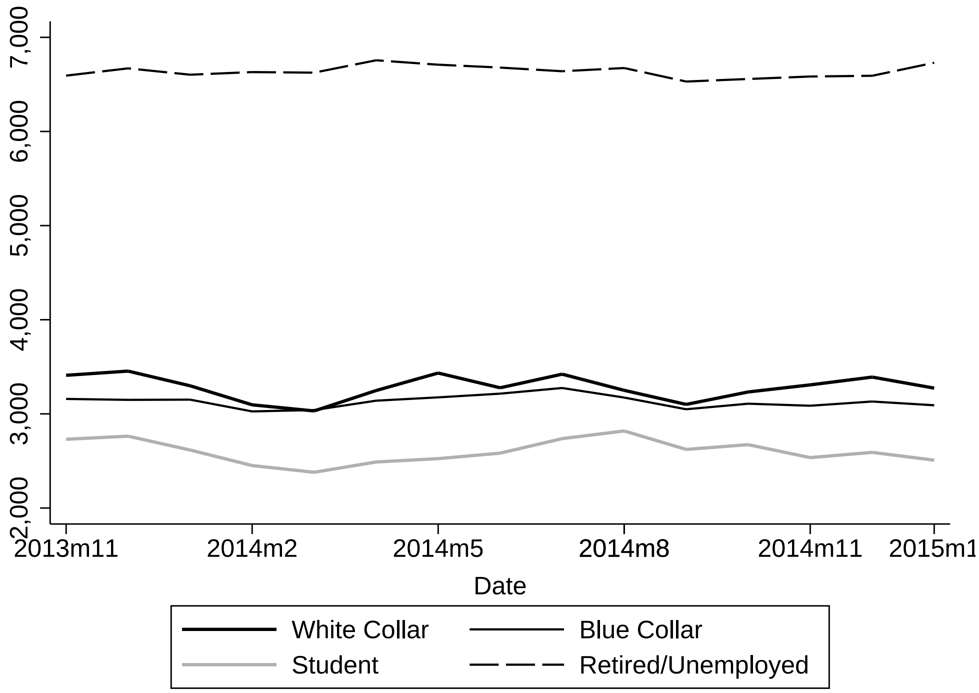
(a) Direct Deposits by Occupation



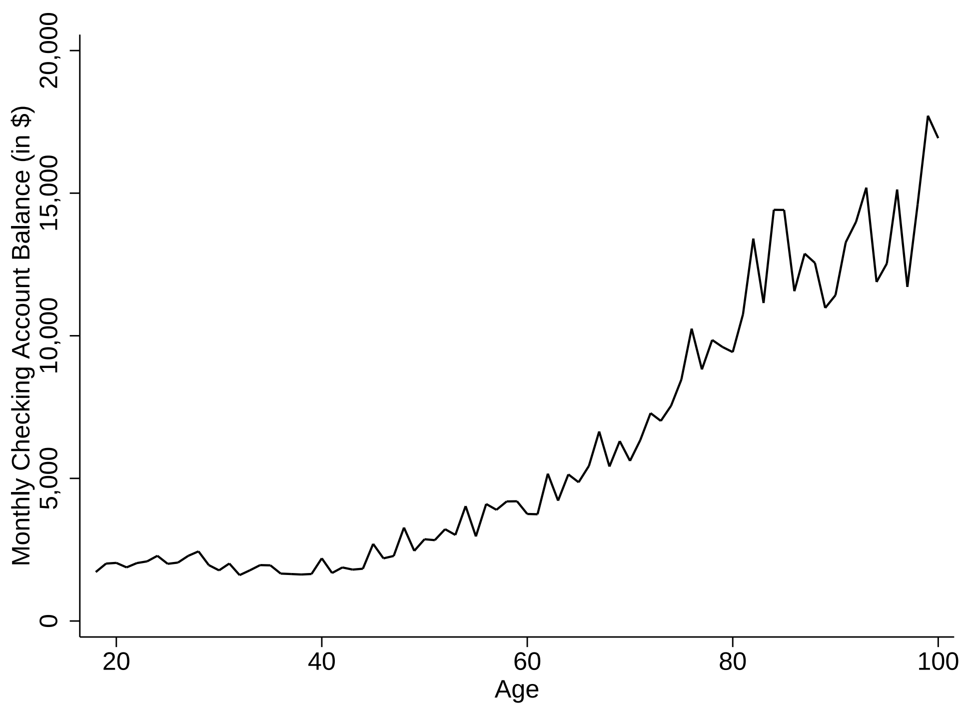
(b) Average Monthly Direct Deposit by Age

Note: Panel (a) shows the average monthly direct deposits segmented by occupation over the period covered by the data. Panel (b) shows the average monthly income direct deposits segmented by age.

Figure 3.6: Checking Account Balances by Age and Occupation



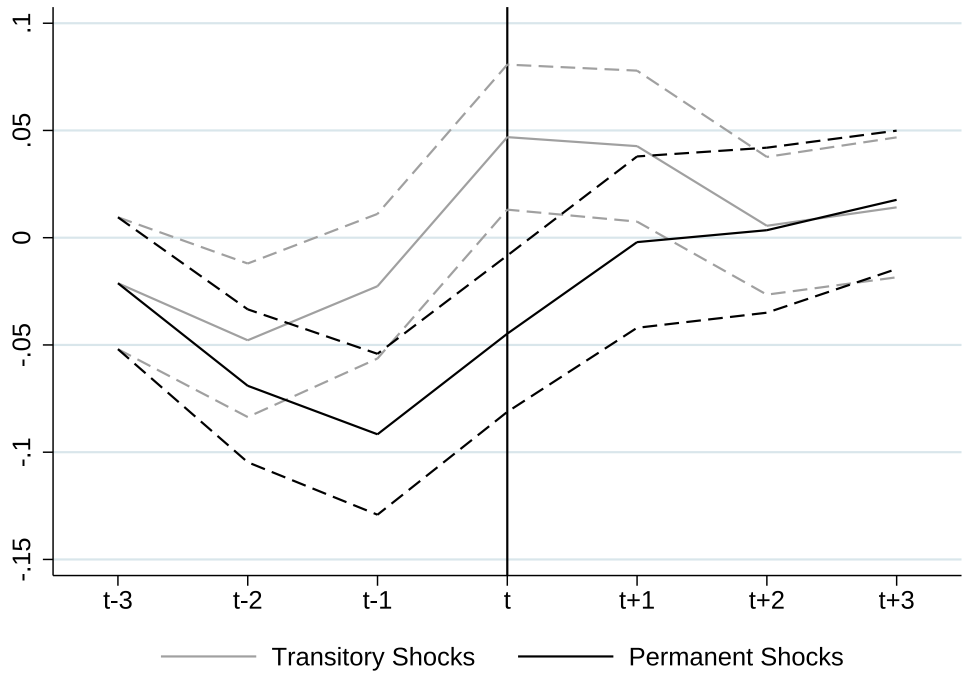
(a) Checking Account Balances by Occupation



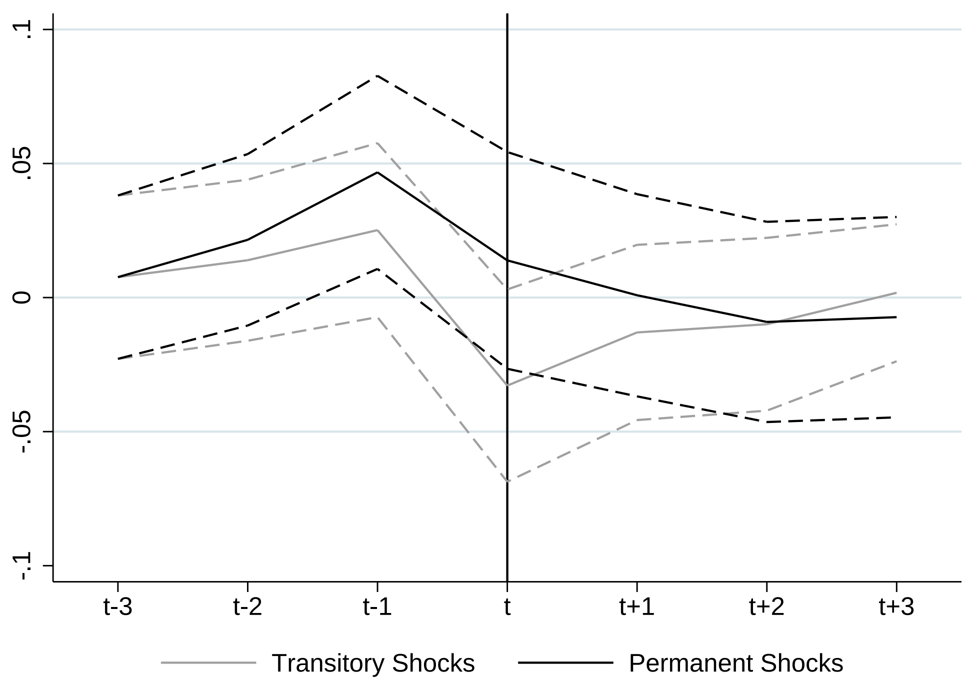
(b) Average Checking Account Balances by Age

Note: Panel (a) shows the average monthly direct deposits segmented by occupation over the period covered by the data. Panel (b) shows the average monthly income direct deposits segmented by age.

Figure 3.7: Impulse Response Functions - Savings Account



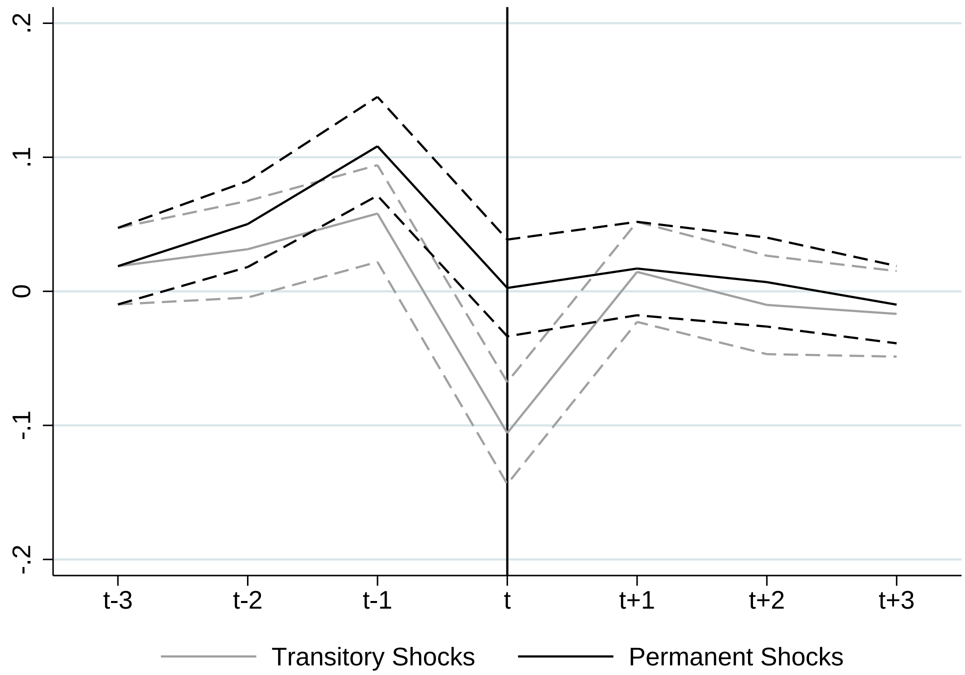
(a) Savings Account Response to Positive Income Shocks



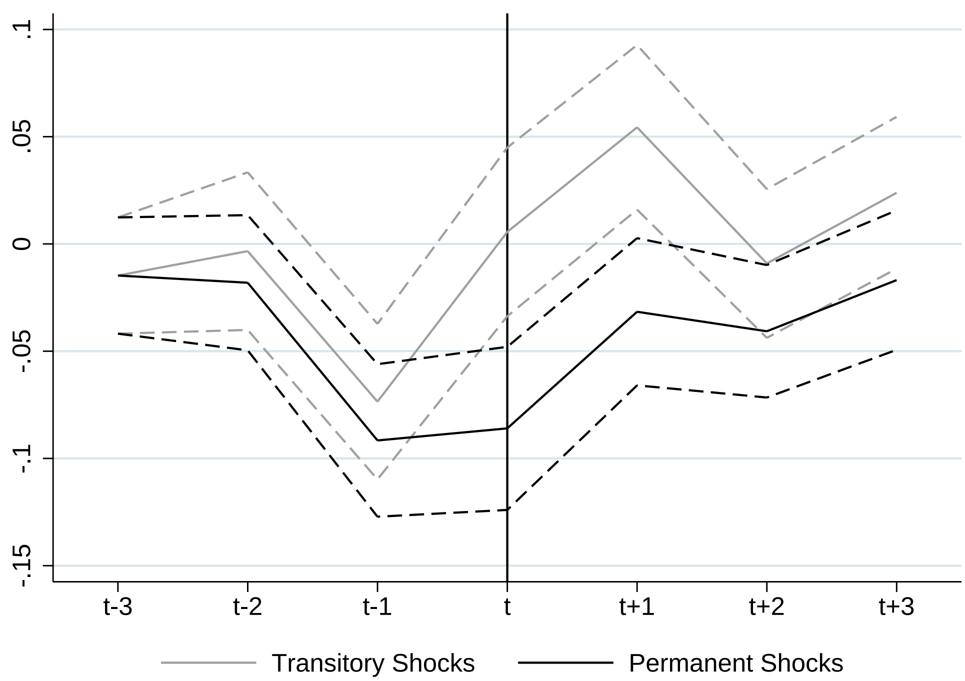
(b) Negative Income Shocks

Note: This figure presents the impulse response functions of credit line usage for transitory income shocks (i.e. a one-time dollar at time t), and permanent income shocks (i.e. one dollar from time t and on) calculated from Column (1) of Table 3.8. Panel (a) presents the effect of positive shocks, and panel (b) presents the effect of negative shocks. The dashed line represent the 95% confidence intervals.

Figure 3.8: Impulse Response Functions - Credit Line Usage



(a) Positive Income Shocks



(b) Negative Income Shocks

Note: This figure presents the impulse response functions of credit line usage for transitory income shocks (i.e. a one-time dollar at time t), and permanent income shocks (i.e. one dollar from time t and on) calculated from Column (1) of Table 3.9. Panel (a) presents the effect of positive shocks, and panel (b) presents the effect of negative shocks. The dashed line represent the 95% confidence intervals.

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