Timing Matters: Evidence from Government Benefit Schedules*

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Abstract

We study how the calendar timing of income affects credit card borrowing and delinquency. In a model of present-biased consumers with fixed monthly expenses, liquidity declines over the paycycle, leading to greater reliance on short-term credit among households paid later in the month. Using administrative microdata linking Brazil's credit registry to the Bolsa Família program, which quasi-randomly assigns payment dates, we exploit rotation in the benefit calendar that preserves the order of pay across individuals, to separately identify paycycle and timing effects. Credit card borrowing and delinquency increase steadily as liquidity depletes, and later-paid households are 10% more likely to revolve debt and default more often. These findings reveal that even small differences in the timing of income, holding level and frequency constant, systematically shape household liquidity, debt accumulation, and financial fragility.

Keywords: income timing, paycycle, credit card usage, financial distress, conditional cash transfer

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1 Introduction

Most consumers receive income on a fixed schedule, such as monthly or biweekly, but the exact calendar date of payment varies between households. Standard frictionless models imply that these intra-month differences should not matter, but when credit access is limited, bills arrive on fixed dates, and present-biased consumers frontload spending, the position of income within the month becomes economically meaningful.

Changes in payroll calendars can determine how households manage liquidity and utilize credit to smooth consumption. If timing matters, it has far-reaching consequences for household well-being and for the design of benefit programs and payroll systems. In this paper, we investigate whether intra-month pay timing causally determines credit card borrowing and delinquency.

We begin by developing a theoretical framework that builds on Parsons and Van Wesep (2013) and Baugh and Correia (2022), who show that impatient households fare better when the timing of their pay aligns with the timing of their expenditures. We adapt their model to a setting where households face fixed-date expenses but receive benefits at different calendar dates. Our framework highlights that the liquidity path depends on pay timing: those paid earlier in the month encounter most fixed obligations later in their paycycle, while those paid later in the month face obligations earlier. This generates three testable hypotheses: (i) credit card usage and financial distress rise over the course of the paycycle; (ii) households paid later in the month rely more on credit cards; and (iii) later-paid households are more prone to financial distress.

We empirically test these predictions using administrative microdata from Brazil that link the consumer credit registry (SCR) with the Cadastro Único registry of Bolsa Família recipients. Bolsa Família is a conditional cash transfer directed at poverty alleviation. The setting is an ideal laboratory to identify intra-month timing effects. First, the benefit constitutes a significant share of disposable income for these low-income households. Second, the exact date of benefit receipt is determined solely by the last digit of the

NIS identification number, providing quasi-random assignment of households to early- or late-month payments. Third, the data track more than 1.2 million households in two states over 24 months (2018–2019), with detailed demographics and loan-level outcomes.

A key empirical challenge is that credit outcomes are observed only once a month, at the end-of-month snapshot. Because pay dates are randomly assigned across households, this snapshot captures some households just after receiving income and others a few days after, making income timing and paycycle position perfectly collinear within a single month. Our model shows that failing to separate these dimensions would conflate temporary liquidity depletion within the cycle with persistent timing effects. The Bolsa Família calendar resolves this issue: while the order of payments by NIS group is fixed, their exact calendar dates rotate across months. Pooling months therefore yields independent variation in both timing and paycycle position, allowing us to identify how each affects borrowing and financial distress.

We have two sets of results, consistent with the model, we find that credit card usage rises along the paycycle: the propensity to carry a credit card balance increases by around 10 percent, and balances rise by about 3.5 percent from the beginning to the middle of the cycle. Financial distress becomes more prevalent when we observe households further in their paycycle. From the start to the middle of their paycycle, the propensity to default increases fivefold, and the propensity to have an overdraft line more than doubles.

Second, timing matters for credit card utilization. Consumers paid latest in the month are 1.75 percentage points more likely to carry a credit card balance and hold balances about R$50 higher, conditional on borrowing. These households are also more financially fragile: delinquency rates rise by 1.5 percentage points (on a base of 8 percent), and default rates increase by 0.8 percentage points (on a base of 5 percent). Importantly, these effects are specific to short-term liquidity products: we find no timing effects on auto loans, which are long-term commitments less tied to liquidity shocks.

Our findings connect to a long literature on the timing of income and consumption

smoothing. Classic evidence shows that spending spikes around paydays and decays thereafter (Stephens 2003, 2006; Johnson, Parker and Souleles 2006; Mastrobuoni and Weinberg 2009; Gelman, Kariv, Shapiro, Silverman and Tadelis 2014; Baker and Yannelis 2017; Vellekoop 2018; Gelman, Kariv, Shapiro, Silverman and Tadelis 2020), consistent with liquidity constraints and present-biased preferences (Kaplan and Violante 2014). More recent work links the alignment between income and obligations to welfare and debt outcomes: Parsons and Van Wesep (2013) and Baugh and Correia (2022) show that households fare better when pay frequency or timing matches their spending needs. Our paper complements this literature by isolating variation in within-month income timing, holding income level and frequency constant, and estimating its causal effect on both borrowing and distress.

We also extend evidence from experimental studies (Aydin 2022) and transaction-level data (Baker and Yannelis 2017; Baugh and Wang 2024; Baugh and Correia 2022; Gelman, Kariv, Shapiro, Silverman and Tadelis 2014) by using administrative data that track credit card balances and defaults for more than a million low-income households. Our empirical strategy paired with our conceptual framework allows us to use lower-frequency (monthly) high-fidelity data to study high-frequency (paycycle day) intra-month financial outcomes.

The closest to our work is Baugh and Wang (2024), who exploit differences in time between paychecks and show that households are likely to experience financial shortfalls during longer paycycles. We complement their findings by showing that even within a fixed monthly frequency, the relative timing of income within the month matters for short-term borrowing. Our findings on delinquency support their description of the mechanism: variation in liquidity constraints caused by unadjusted expense timing, relative to income timing, determines incidence of financial distress.

Finally, our study relates to work on the consequences of government benefit schedules, which has focused primarily on consumption responses (Stephens Jr and Unayama

2011; Sahm, Shapiro and Slemrod 2012; Aguila, Kapteyn and Perez-Arce 2017; Goldin, Homonoff and Meckel 2022; Zhang 2023; LaPoint and Sakabe 2024). We add to the literature by showing that exogenous shifts in pay dates alter the use of high-cost credit and the incidence of delinquency. This is a new and policy-relevant margin of liquidity management. Seemingly minor design features of payroll and transfer calendars can meaningfully influence household debt dynamics and financial stability, even when total income and frequency remain unchanged.

2 Theoretical Framework

We build directly on Parsons and Van Wesep (2013) and the model developed in Baugh and Correia (2022). Consumers are infinitely lived and receive a fixed paycheck of size Y once a month, on the first day of their paycycle, $\tau = 1$. Each day $\tau \in \{1, \ldots, D\}$ within the paycycle, the consumer chooses consumption C_τ to maximize time-separable log utility with present bias. We normalize daily discounting to zero and let the only source of impatience be the present-bias parameter $\beta < 1$. At each day τ, the consumer solves a dynamic program:

$$\max_{C_\tau} \left[\log(C_\tau) + \beta \sum_{k=\tau+1}^{\infty} \log(C_k^*) \right]$$

where the consumer foresees choosing optimally in all future periods, subject to the intertemporal budget constraint.

Following Harris and Laibson (2001), present bias implies that, once income is received, the optimal consumption path is decreasing over the paycycle. Consequently, marginal utility rises over the cycle, $u'(C_D^*) > u'(C_1^*)$, and it is optimal to exhaust remaining resources by the last day of the paycycle. The consumer effectively lives paycheck-to-paycheck and the relevant optimization happens within paycycle. We describe the steady-state infinitely repeatable paycycle. The consumer's intra-month problem be-

comes a repeatable paycycle problem subject to the within-paycycle budget constraint $Y = \sum_{s=1}^{D} \log(C_s^*)$:

$$\max_{C_\tau} \left[\log(C_\tau) + \beta \sum_{k=\tau+1}^{D} \log(C_k^*) \right] \tag{1}$$

Costless Revolving Credit. As in Baugh and Correia (2022), we introduce a costless revolving debt instrument, conceptually a credit card, allowing the consumer to borrow up to a limit αY and repay in full at payday. This means that at payday, the consumer effectively receives only $(1-\alpha)Y$. The revolving credit merely shifts liquidity within the cycle and does not alter lifetime resources, since the consumer still has Y to allocate per month. This extension does not generate any equilibrium distinction across days of income receipt within a month: in paycycle time, there is no timing of income.

From Paycycle to Calendar Time. Consumers live and make decisions in calendar time, where both income and expenses are tied to specific dates. Liquidity-constrained households care about aligning cash inflows and outflows, using liquidity instruments such as credit cards to bridge any mismatch. Each household receives income once a month, on a calendar date t_Y (e.g., the 1st, 10th, or 25th).

Calendar-linked Expenses. All households share a fixed calendar expense of size E due at a common date t_E (for example, rent due on the 5th) for all households. This is consistent with limited evidence of households adjusting commited expenditures (Vellekoop 2018; Baugh and Wang 2024). Although total income and pay frequency are identical, the relative position of t_Y and t_E varies between households. In steady-state, households commit to having enough resources to fund the expenditure. This implies that they only allocate $Y - E$ across days in their consumption choice. In the limit case of no-adjustment, where all households have an expense at the same date, later paid households face that expense earlier in paycycle time. For the cycle to repeat, households are forward-looking and cannot roll over debt indefinitely between paycycles. Hence, the expenses of each month are financed from the preceding paycheck.

Optimal Consumption. The consumer solves this problem recursively by backward

induction, anticipating future re-optimization. Solving recursively for the full paycycle of length D, we obtain the closed-form optimal path:

$$
\begin{aligned}
C_i^* &= A_i \times (Y - E) \\
A_1 &= \frac{1}{1 + (D-1)\beta} \\
A_i &= \frac{1}{1 + (D-i)\beta} \prod_{j=1}^{i-1} \frac{(D-j)\beta}{1 + (D-j)\beta}, \qquad i \in \{2, 3, \ldots, D\}
\end{aligned} \tag{2}
$$

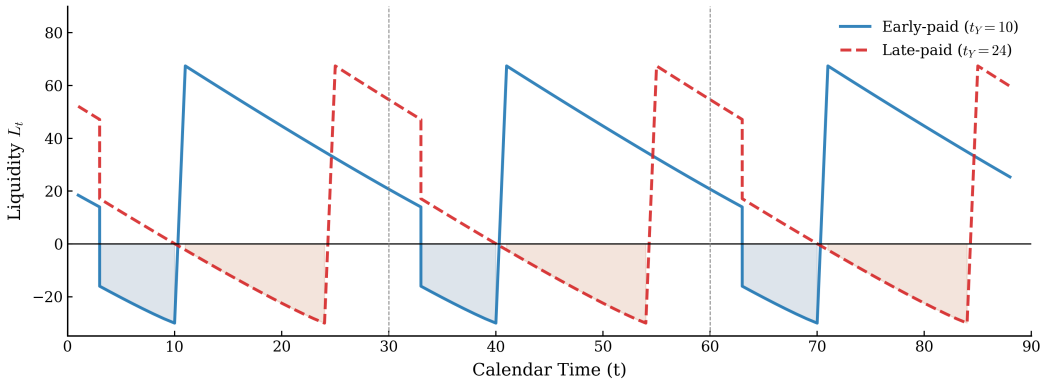
This expression mirrors the result in Baugh and Correia (2022), where present bias generates a declining consumption profile within the paycycle: $C_1^* > C_2^* > \cdots > C_D^*$. Because the agent cannot carry over debt indefinitely, the consumer exhausts all resources by the final day of the cycle. In the limit as $\beta \to 1$, consumption is smoothed evenly across the cycle, $C_i^* = (Y - E)/D$ for all i.

Liquid Balances. Let $m \equiv (t_E - t_Y) \bmod D$ denote the position of the fixed expense within the paycycle. Because each household finances the same expense E from the preceding paycheck, the optimal policy functions A_i are identical across households. However, the observed liquidity paths differ. For a household with expense location m, liquidity at the start of day τ is:

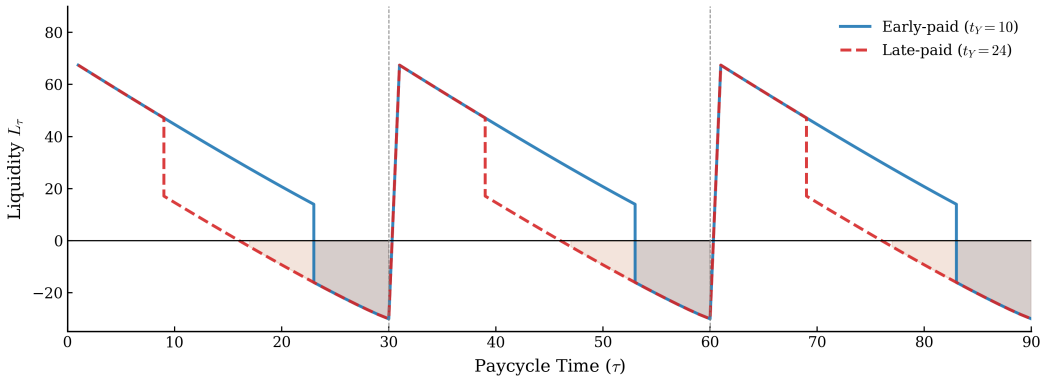
$$
L_{\tau+1} = (1 - \alpha)Y - \sum_{s=1}^{\tau} C_s^* - E \cdot \mathbf{1}\{\tau \geq m\}.
$$

Later-paid households (smaller m) encounter their fixed expense earlier in paycycle time, depleting liquidity sooner and increasing their reliance on revolving credit to smooth consumption. Earlier-paid households (larger m) face the expense later in the paycycle and maintain higher liquidity throughout the month.

Implications. This structure delivers three main predictions illustrated in Figure 1. First, within the paycycle, revolving credit balances increase monotonically in τ as liquid-



(a) Liquid Balance and Borrowing in Calendar Time



(b) Liquid Balance and Borrowing in Paycycle Time

Figure 1: Liquid Balances and Credit Card Borrowing. This figure illustrates how liquid balances vary in steady-state with income timing. For both consumers (blue and red), $\beta = 0.9$, $Y = 100$, $\alpha = 0.3$, $E = 30$, and $t_E = 3$. The only difference is that early-paid individuals (in solid blue) have income day $t_Y = 10$ and late-paid individuals have income day $t_Y = 24$. Shaded areas illustrate credit card usage.

ity declines, and so does the likelihood of financial distress. Second, across households, those paid later in calendar time experience the liquidity trough earlier in paycycle time, implying higher credit card utilization. With diminished steady-state liquidity, less flexibility to accommodate shocks leads to greater likelihood financial distress. These predictions form the basis for the empirical analysis that follows.



Final do NIS	DIA E MÊS DO PAGAMENTO											
1	18/jan	15/fev	18/mar	16/abr	20/mai	14/jun	18/jul	19/ago	17/set	18/out	18/nov	10/dez
2	21/jan	18/fev	19/mar	17/abr	21/mai	17/jun	19/jul	20/ago	18/set	21/out	19/nov	11/dez
3	22/jan	19/fev	20/mar	18/abr	22/mai	18/jun	22/jul	21/ago	19/set	22/out	20/nov	12/dez
4	23/jan	20/fev	21/mar	22/abr	23/mai	19/jun	23/jul	22/ago	20/set	23/out	21/nov	13/dez
5	24/jan	21/fev	22/mar	23/abr	24/mai	21/jun	24/jul	23/ago	23/set	24/out	22/nov	16/dez
6	25/jan	22/fev	25/mar	24/abr	27/mai	24/jun	25/jul	26/ago	24/set	25/out	25/nov	17/dez
7	28/jan	25/fev	26/mar	25/abr	28/mai	25/jun	26/jul	27/ago	25/set	28/out	26/nov	18/dez
8	29/jan	26/fev	27/mar	26/abr	29/mai	26/jun	29/jul	28/ago	26/set	29/out	27/nov	19/dez
9	30/jan	27/fev	28/mar	29/abr	30/mai	27/jun	30/jul	29/ago	27/set	30/out	28/nov	20/dez
0	31/jan	28/fev	29/mar	30/abr	31/mai	28/jun	31/jul	30/ago	30/set	31/out	29/nov	23/dez

Figure 2: Bolsa Família Disbursement Schedule. This figure presents the official 2019 payment calendar, released in December 2018. Beneficiaries locate their withdrawal day each month based on the last digit of their Social Identification Number (NIS).

3 Setting and Data

3.1 Bolsa Família: the Laboratory

Bolsa Família (BF) is Brazil's flagship means-tested conditional cash transfer program, designed to alleviate poverty and promote human capital accumulation. The program provides monthly cash benefits to low-income families conditional on school attendance and vaccination compliance, and is widely recognized for its targeting precision and conditionality enforcement (Lindert et al. 2007).

Beneficiaries fall into two categories: (i) *extremely poor* families, who receive a basic

benefit of 89 BRL per month plus variable benefits conditional on household composition and compliance; and (ii) *poor* families, who may receive variable benefits conditional on household composition and compliance. Variable benefits are 41 BRL per child aged 0–15 (as well as 41 BRL for pregnancy and nursing), up to five benefits per family (maximum 205 BRL), and 48 BRL per adolescent aged 16–17, up to two benefits per family (maximum 96 BRL).

A large literature documents BF's contributions to poverty and inequality reduction (e.g., Barros, Carvalho, Franco and Mendonça 2007a; Barros, Cury and Ulyssea 2007b; Soares, Osório, Soares, Medeiros and Zepeda 2009; Cury, Mori Coelho, Callegari and Pedrozo 2010), as well as to improved school attendance and health outcomes (Cardoso, Souza et al. 2004; Glewwe and Kassouf 2012). Recent work documents the impact of BF in the local economy, by stimulating demand and increasing formal labor market participation (Gerard, Naritomi and Silva 2025)

BF benefits are disbursed monthly through the public bank *Caixa Econômica Federal*, accessible via bank branches, ATMs, lottery outlets, and accredited retailers. Payments follow a nationally standardized schedule that assigns each household a withdrawal date based on the final digit of its *Número de Identificação Social* (NIS), a randomly assigned identifier in the federal registry for low-income households (*Cadastro Único*). The disbursement schedule is announced each December for the upcoming year and typically spans the final fifteen working days of each month (except December). Figure 2 reproduces the official 2019 calendar. The uniform distribution of last NIS digits implies that the timing of benefit availability is effectively random, generating exogenous variation in income timing across otherwise identical households.

3.2 Data

We combine three administrative data sources: (i) the *Cadastro Único para Programas Sociais do Governo Federal* (CadÚnico); (ii) the *Sistema de Informações de Crédito* (SCR),

Brazil's comprehensive credit registry; and (iii) the *Relação Anual de Informações Sociais* (RAIS), an annual census of formal employment contracts.

CadÚnico, managed by the Ministry of Citizenship, contains detailed demographic and socioeconomic information for all registered low-income households, including household composition, income, and geographic identifiers. SCR, maintained by the Central Bank of Brazil, is a loan-level registry covering all individual and household credit operations above 200 BRL, with granular information on loan types, balances, payment schedules, and delinquency status. RAIS, collected by the Ministry of Labor, provides employer–employee matched data on annual earnings and employment status for the universe of formally employed workers in Brazil. Linking these sources enables us to jointly observe households' demographic characteristics, credit behavior, and formal labor outcomes at a monthly frequency.

Starting from the universe of CadÚnico households, we merge credit operations and employment data for those participating in credit and labor markets, respectively. From SCR, we construct measures of credit use, such as credit card utilization and delinquency, and identify the timing of scheduled debt payments. From RAIS, we extract indicators of formal labor participation, total wage income, and entrepreneurship status, complementing the demographic and income information in CadÚnico.

Our analysis focuses on households in the states of Ceará and Minas Gerais between January 2018 and December 2019. Ceará, located in Brazil's Northeast, is among the country's poorest regions, while Minas Gerais is the third largest state economy, after São Paulo and Rio de Janeiro. This cross-state sample provides both social and geographic heterogeneity, strengthening the external validity of our results. The sample period ends immediately before the onset of the COVID-19 pandemic. The resulting balanced panel contains 24 monthly observations per household, with matched information on income transfers, credit outcomes, and labor market participation.

Our final sample consists of 29,668,296 household-month observations, a balanced

		Conditional on borrowing:		
Credit Type	**% with Credit**	**Mean (R$)**	**p50 (R$)**	**N**
Credit Card	14%	1,297	782	4,274,315
Installment	3%	652	325	953,344
Payroll Loan	0%	6,916	6,663	89,681
Personal Loan	2%	1,800	1,131	648,094
Auto Loan	1%	9,108	8,261	296,190
Rural Credit	2%	14,741	9,280	445,253
Total Credit (any product)	25%	3,926	1,350	7,517,772
Credit Risk		**%**		**N**
Weighted Avg. Interest Rate (%)		85%		7,517,772
Is 30 Days Late?		10%		29,668,296
Is 60 Days Late?		10%		29,668,296
Is up to 89 Days Late?		8%		29,668,296
Default?		5%		29,668,296
Has Overdraft?		2%		29,668,296

Table 1: Credit Outcomes: Bolsa Família Recipients. This table reports summary statistics for credit outcomes in our sample of Bolsa Família recipients. "% with Credit" is the share of observations with a balance larger than zero for each credit type. Mean and p50 are conditional on having the product. "Total Credit" aggregates balances across products for households with any credit. N is the count of product holders (or relevant observations for performance rows). Amounts are in Brazilian reais (R$).

panel of 1,236,179 households who are enrolled in the program for 24 months. The last digit of the NIS with least households is 8 (122,937 households or 9.95%), and the most common last digit is 1 (124,533 households or 10.07%), revealing a near-perfect uniform distribution across the ten possible digits.

Table 1 reports household-month level patterns of formal credit participation and balances among Bolsa Família recipients in Ceará and Minas Gerais between 2018 and 2019. Roughly one in four households held at least one form of credit in a given month, most commonly credit cards (14%) and, to a lesser extent, installment credit (3%) or personal loans (2%). Payroll, auto, and rural loans were rare, each below 2% of households. Conditional on holding the product, average balances were around R$1,300 for credit cards and R$1,800 for personal loans, but much larger for secured or specialized credit, such as R$9,100 for auto loans and R$14,700 for rural credit. Median balances were consistently lower, indicating skewed distributions driven by a small number of higher exposures.

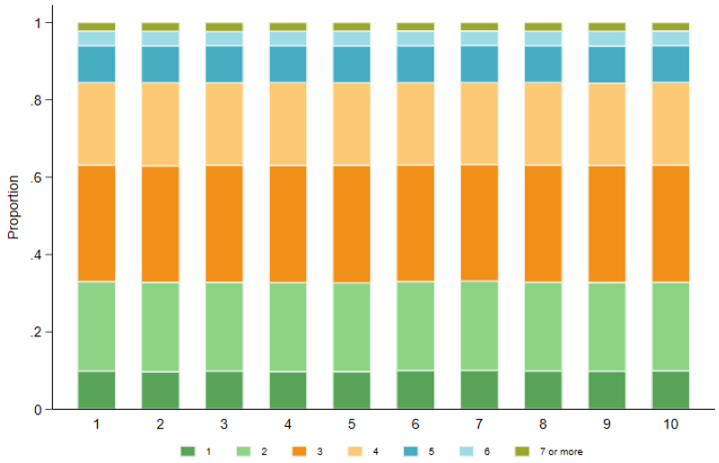
	Last NIS Digit									
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Avg. Age in Household										
Mean	35.4	35.4	35.5	35.4	35.4	35.5	35.4	35.4	35.4	35.4
St. Dev.	9.3	9.3	9.3	9.3	9.3	9.4	9.4	9.3	9.3	9.3
Formal Income per Capita										
Mean	39.8	39.8	40.1	39.7	39.8	39.7	40.1	38.9	39.0	38.9
St. Dev.	160.6	158.5	175.3	153.8	166.5	155.4	175.1	153.2	154.6	155.1
Total Income per Capita										
Mean	47.1	47.3	47.2	47.2	47.3	47.4	47.1	47.2	47.3	47.2
St. Dev.	47.7	47.9	47.6	47.7	47.8	47.6	47.6	47.3	47.8	47.7
Bank Accounts per Capita										
Mean	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
St. Dev.	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
Has Formal Employment (%)	10.4	10.4	10.3	10.4	10.4	10.2	10.4	10.2	10.2	10.1
Woman Head Household (%)	91.6	91.6	91.5	91.7	91.6	91.6	91.5	91.5	91.7	91.7
Head HH Reads & Writes (%)	85.5	85.4	85.5	85.4	85.5	85.2	85.6	85.5	85.4	85.4

Table 2: Statistics by NIS Last Digit. This table assesses covariate balance across each group. Groups are based on the last digit of their NIS, which is randomly assigned across individuals.

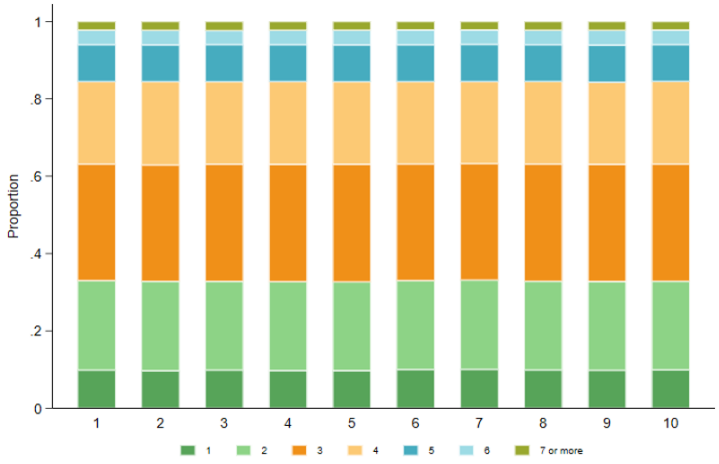
Across all credit holders, the mean total balance was approximately R$3,900 per household-month. The weighted average interest rate on outstanding credit was extremely high (85%), consistent with the high-cost structure of consumer credit in Brazil. Delinquency rates were also nontrivial: about 10% of household-months were 30 or 60 days late, 8% were up to 89 days late, and 5% were in default. Finally, 2% of households needed and had access to overdraft liquidity facilities.

4 Empirical Strategy

The Bolsa Família (BF) payment calendar assigns households to disbursement days based on the last digit of their NIS number. Because NIS digits are uniformly distributed, this assignment is orthogonal to household characteristics and can be interpreted as random. We verify this property by showing balance in pre-determined covariates and baseline credit outcomes across NIS groups. Table 2 reports statistics by NIS groups, namely average age in the household, formal and total income per capita, number of bank accounts, employment status, head of household gender, and literacy.



(a) Household Composition by NIS Last Digit

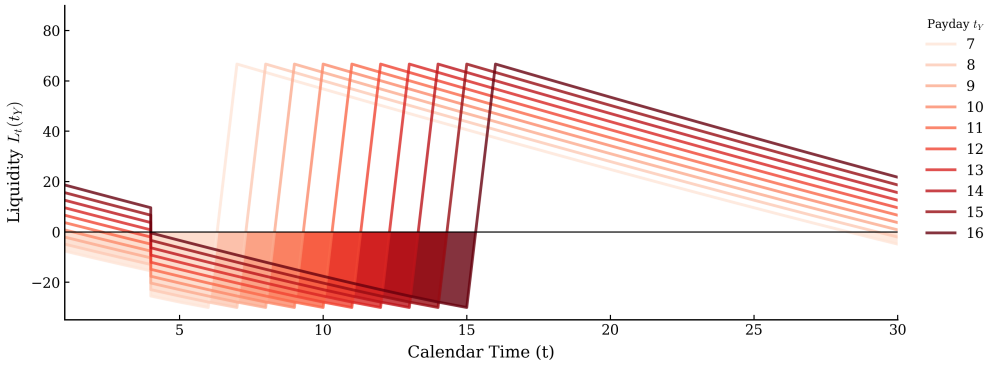


(b) Head of Household Educational Attainment by NIS Last Digit

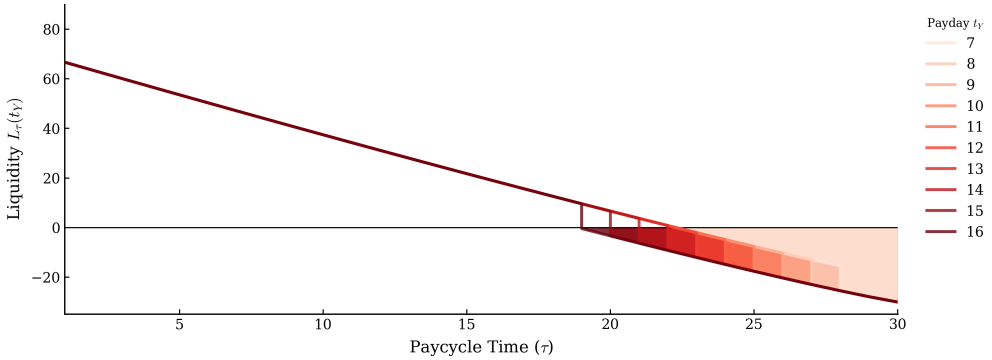
Figure 3: Household Composition and Literacy by NIS Last Digit. This figure presents distributions of number of people in the household (in panel (a)), and the educational attainment of the head of household (in panel (b)) by NIS last digit.

Household characteristics are very similar across NIS groups, both for averages and standard deviations of continuous variables. Proportions also display high degree of similarity, confirming random assignment. In Figure 3, we show that the distributions of number of people in a household, and the educational attainment of the head of household are also similar across groups.

In principle, with daily data for credit and distress outcomes, one could separately identify two distinct objects: (i) the paycycle effect: how credit use and financial distress



(a) Liquidity Profile in Calendar Time

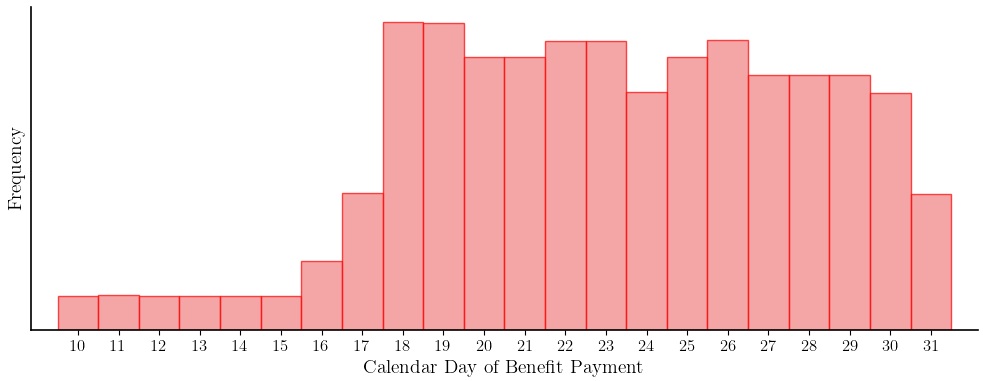


(b) Liquidity Profile in Paycycle Time

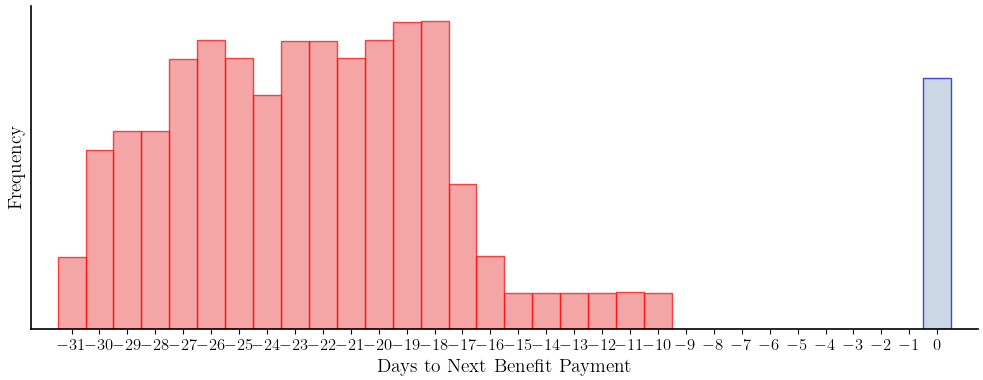
Figure 4: Liquidity Profile by Timing of Pay This figure shows the steady-state liquidity profile of individuals with different income dates (7th to 16th of a 30-day month). For all consumers $\beta = 0.9$, $Y = 100$, $\alpha = 0.3$, $E = 10$, and $t_E = 3$. Shaded areas illustrate credit card usage.

evolve as liquidity decays between paydays, and (ii) the timing effect: how the location of income within the month (early vs. late) shifts overall liquidity, inducing credit usage and financial distress.

In our setting, however, we observe each household's credit position only once a month: Brazilian banks report to the Central Bank the status of each loan as of the last day of each calendar month. Within a given month, this implies a perfect mapping between payment timing and paycycle position at the time of observation. For instance, in a 30-day month where NIS 1 is paid on the 12th and NIS 9 on the 27th, the month-end snapshot observes NIS 1 households nineteen days after payday and NIS 9 households four days after payday. Thus, within a single month, timing and paycycle position are collinear.



(a) Distribution of Income Days (t_E)



(b) Distribution of Paycycle Time ($\tau - D$) at Time of Observation

Figure 5: Variation in Timing of Income This figure shows distributions for calendar days of paycheck receipt in panel (a), and paycycle time at the time of observation in panel (b).

Figure 4 summarizes this challenge. We model similar consumers in a 30-day month, where the only difference among them is the payday, which we vary from the 7th (very light red) to the 16th (very dark red). Their consumption choices along the paycycle are identical. In Panel (a), we illustrate their liquidity profile and credit card usage in calendar time. At the beginning of the month ($t_E = 3$), all consumers are hit with an expense of 15, and all of them accumulate debt up to 30% of their income, which they repay in full when they are paid. Panel (b) illustrates the dynamics of liquidity in the paycycle.

Importantly, if we were to compare these modeled consumers at the last day of the calendar month, a problem would arise. We would erroneously observe that early paid consumers are more likely to use credit or to experience financial distress, even though

the model predicts otherwise. This is explained by the fact that at the last day of the calendar month, each NIS group is observed at a different paycycle time.

The key identifying feature of the BF calendar is that, while the order of NIS payment days is fixed, their exact calendar dates rotate across months. Consequently, the same NIS group is observed at different paycycle positions across months, and each paycycle position is observed for different NIS groups. This month-to-month rotation generates a rich two-dimensional cross-section of observations that can be used to separately identify paycycle and timing effects even though we observe only one snapshot per month.

In Figure 5, we show that we have substantial variability of income receipt days, and that for the first half of the paycycle (-30 to -16), we have more than one last NIS digit identifying the paycycle period. We compute paycycle time as days until next paycheck so as to normalize months with different lengths.

4.1 Baseline Specification

Let Y_{im} denote a credit outcome for household i observed in month m (e.g., an indicator for carrying a revolving balance or being in default). Let $NIS_i \in 1, \ldots, 10$ denote the household's payment group, and define the observed paycycle time as:

$$PCT \equiv \text{days until next payment at the month-end snapshot}$$

We discretize PCT into single-day bins $k \in \mathcal{K}$, allowing for a nonparametric cycle profile. The estimating equation is:

$$Y_{im} = \sum_{d=1}^{10} \gamma_d \mathbf{1}(\text{NIS}_i = d) + \sum_{k \in \mathcal{K}} \delta_k \mathbf{1}(\text{PCT}_{im} = k) + \mathbf{X}'_{im}\theta + \mu_c + \varepsilon_{im} \tag{3}$$

where μ_c are municipality fixed effects, and $\mathbf{X}_{im}$ includes controls for household composition, formal labor indicators, and income. Standard errors are clustered at the house-

hold level.

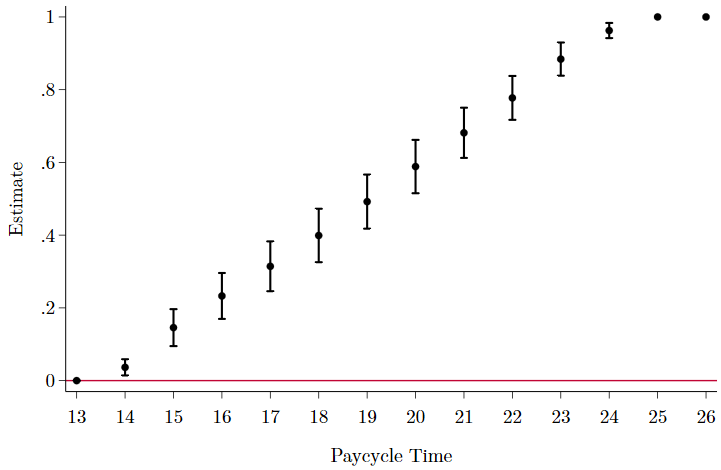
The coefficients δ_k capture the paycycle effect: the within-cycle pattern of credit use as liquidity declines. The coefficients γ_d capture timing effects or systematic differences between households paid early and those paid late, holding paycycle position fixed.

Estimating these jointly is necessary and sufficient. It is necessary because omitting δ_k would ascribe cycle-driven variation to γ_d, while omitting γ_d would force timing differences to load onto δ_k. Within a month, the mapping between NIS and paycycle time is one-to-one. Thus, any model that uses only NIS indicators or only paycycle indicators is unidentified for separating timing and cycle effects. Because we have a single snapshot per month, identification must come from comparing the same NIS group across different paycycle positions in other months.

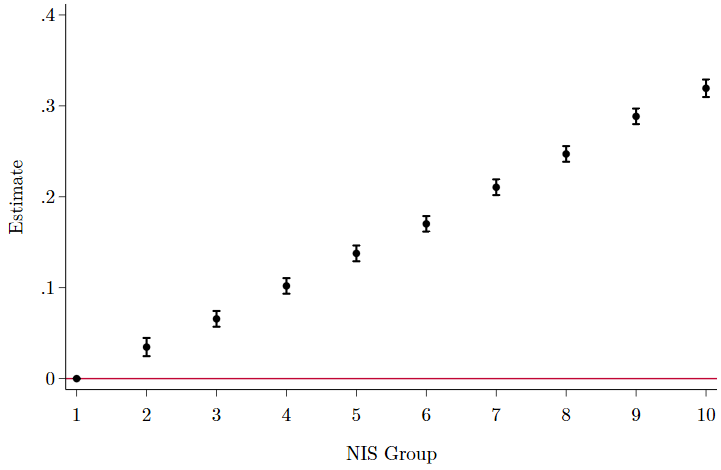
It is sufficient because across months, the BF calendar rotates payment dates while maintaining the NIS ordering. Stacking months yields a dataset where each NIS group appears at multiple paycycle positions, and each paycycle position is observed for multiple NIS groups.[1] Because each month is treated as an independent realization of the same random assignment, the analysis does not rely on time-series dynamics or serial dependence.

We simulate a daily dataset, where 150 individuals are randomly assigned to 10 paydates (15 for each group) preserve the relative income timing order between groups, in each month. Each individual draws income Y from $\{95, 100, 105\}$, credit limit α from $\{.35, .4, .45\}$, and present bias β from $\{.88, .9, 92\}$. These individuals live for 28 months of 30 days each month. Their group determines the day they receive income in each month. Each individual draws an expense date t_E from $\{2, 3\}$ every month, of value $E = 30$. At each day, given their parameters, and their paycycle time and length of

[1]Under random assignment of NIS, after conditioning on μ_c and $\mathbf{X}_{im}$, and multiple month rotations, the design matrix $[\mathbf{G}\ \mathbf{C}\ \mathbf{Z}]$ (NIS, paycycle, and controls) is of full column rank. This ensures that γ and δ are separately identified. Formally, within any given month, the columns of $\mathbf{G}$ lie in the span of $\mathbf{C}$. Across months, that span rotates, expanding the column space and allowing separate estimation of the two sets of effects.



(a) Paycycle Effects (δ_k)



(b) Timing Effects (γ_d)

Figure 6: Simulated Data. This figure shows simultaneously estimated coefficients on simulated data for a dummy variable equaling one if the consumer is using credit card debt at that day on paycycle time dummies (in panel (a)) and on income timing group dummies (in panel (b))

paycycle dictated by the calendar, individuals decide how much to consume, and borrow when they run out of funds, according to our model. We then run our specification on the daily simulated data, estimating coefficients on dummies for income groups and for paycycle time simultaneously, using an indicator of whether consumer i is spending out of debt in day t.

Our theoretical model predicts the patterns in Figure 6: (i) within-cycle deterioration in liquidity and increasing credit use (δ_k rising in k), and (ii) higher average credit

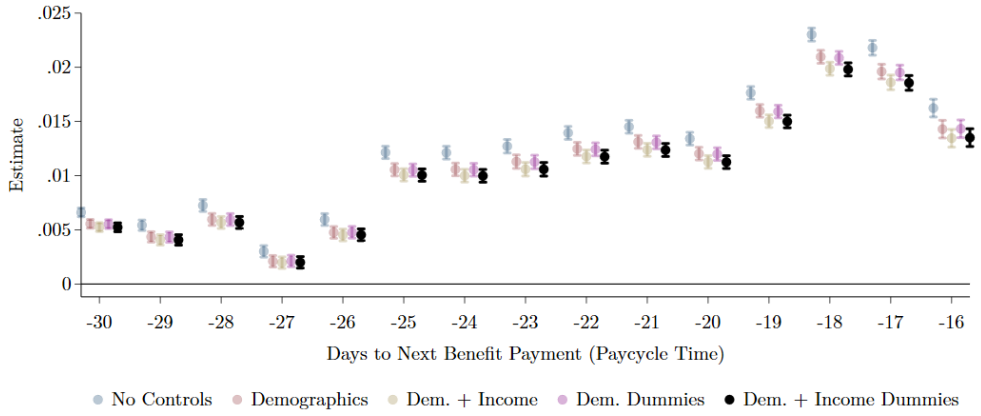
utilization for later-paid households (γ_d rising in lateness). Estimating (3) jointly provides a direct empirical test of both predictions. The δ_k trace the intra-cycle pattern holding timing composition constant, while the γ_d capture persistent timing effects net of cycle position. Given the rotation of payment dates across months, these two sets of coefficients correspond to the causal paycycle and timing effects under the calendar randomization.

5 Credit Card & Distress in the Paycyle

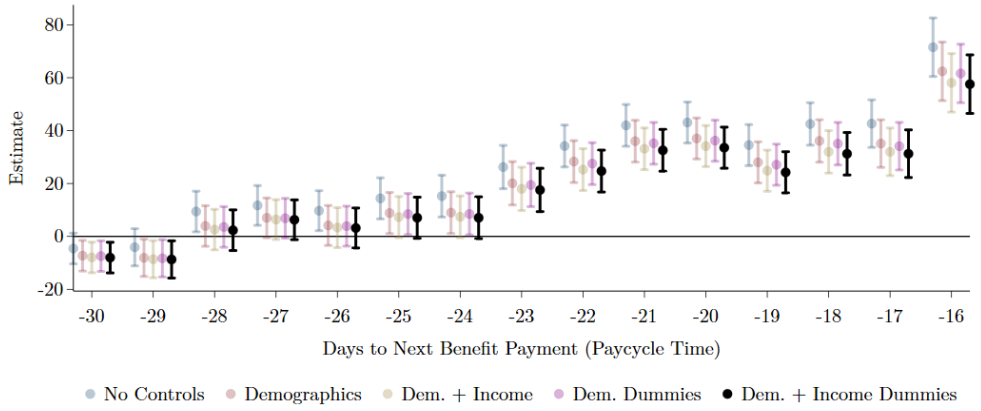
We begin by testing the first prediction of our theoretical framework: as liquidity declines within the paycycle, households increasingly rely on short-term credit and face a higher risk of delinquency. The Bolsa Família calendar offers random assignment of households to different paycycle positions at the month-end snapshot, enabling identification of the *paycycle effect*, the change in financial outcomes as the time since the last payment grows.

At the end of each month, households paid earlier have gone longer without income, while those paid later remain near the beginning of their paycycle. If liquidity constraints bind, we expect the need to use credit cards to arise as the distance from payday increases: propensity to carry credit card balances, and balances themselves should rise. Absent such frictions or under perfect expense adjustment, credit outcomes would remain flat along the cycle.

We document these patterns nonparametrically by estimating Equation (3) and plotting the series $\{\delta_k\}$ to trace the empirical profile of credit card borrowing through the cycle. As shown in Figure 5, paycycle times of -31 to -16 are identified by more than one of the NIS groups. The estimates we report use zero days to next paycheck as the ommitted category. Thus, the magnitues are relative to outcomes of households who we observe on the day they are paid.



(a) Propensity to Carry Credit Card Balance



(b) Credit Card Balance

Figure 7: Use of Credit Along the Paycycle This figure shows extensive (in panel (a)) and intensive (in panel (b)) margin estimates of credit card utilization in the paycycle. We progressively estimate Equation (3) with no controls, demographic controls, demographics and income, demographic non-parametric dummies, and demographic and income non-parametric dummies. All specifications contain municipality fixed effects. Robust standard errors are clustered by household.

Figure 7 presents the empirical paycycle profiles for credit card borrowing. Panel (a) plots the extensive margin, or the probability that a household carries a revolving balance. Panel (b) plots the intensive margin: the balance amount conditional on borrowing. Both outcomes display a clear, monotonic pattern: credit use rises steadily as the number of days since the last benefit payment increases.

Half a paycycle later, consumers are between 1 and 2 percentage points more likely to carry a credit card balance and hold balances roughly 60 to 80 reais higher than

otherwise identical households observed near payday. These magnitues compare to a baseline propensity to have a credit card balance of 15%, and an average balance of roughly R$1,300. These gradients remain remarkably stable across specifications that sequentially add demographic, income, and non-parametric controls, confirming that they are not driven by compositional or income differences across NIS groups.

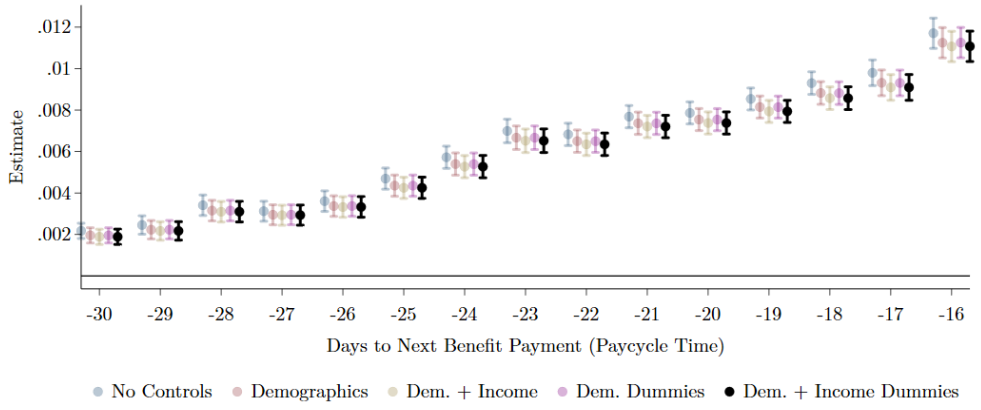
The estimates provide direct evidence of the paycycle mechanism predicted by the model: as liquidity declines between paydays, households increasingly resort to revolving credit to smooth consumption.

Our model, being a steady-state depiction of consumer choices does not explicitly predict financial distress. However, as the paycycle progresses, liquidity levels are lower, and the household's ability to mitigate unanticipated shocks diminishes. Hence, our prediction is that financial distress should increase during the paycycle.

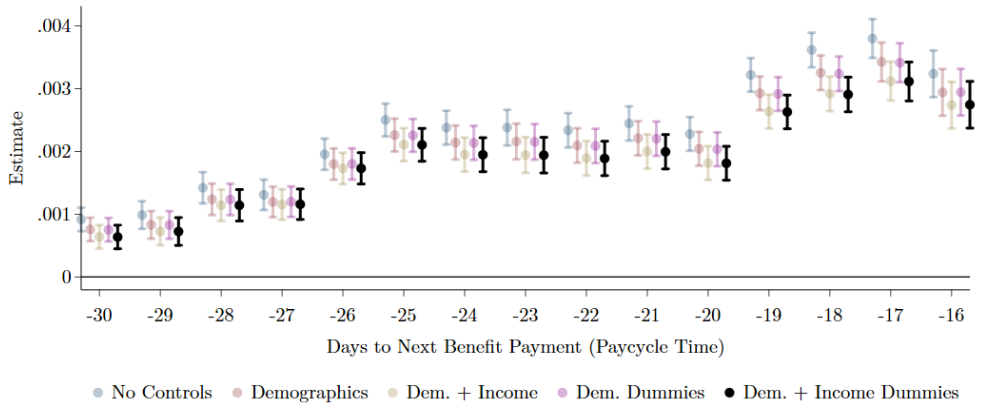
Figure 8 displays the estimated paycycle profiles for two distress indicators. In panel (a), we study the propensity for a household to have a loan in default, and in panel (b), we plot incidence of overdrafts. Both outcomes exhibit a pronounced upward slope, mirroring the pattern observed for credit card balances.

Households observed later in the paycycle are substantially more likely to be in default and to use overdraft credit. Relative to households observed on payday, the probability of default increases by roughly 1.5 percentage points, and the likelihood of holding an overdraft line rises by about 0.7 percentage points. These effects are sizable given baseline default rates near 5% and overdraft usage around 2%.

The estimates remain consistent across specifications with progressively richer controls, indicating that they are not driven by differences in demographics, income, or NIS composition. Taken together, these results confirm that liquidity depletion within the paycycle not only induces greater credit use but also amplifies financial fragility.



(a) Propensity to Default



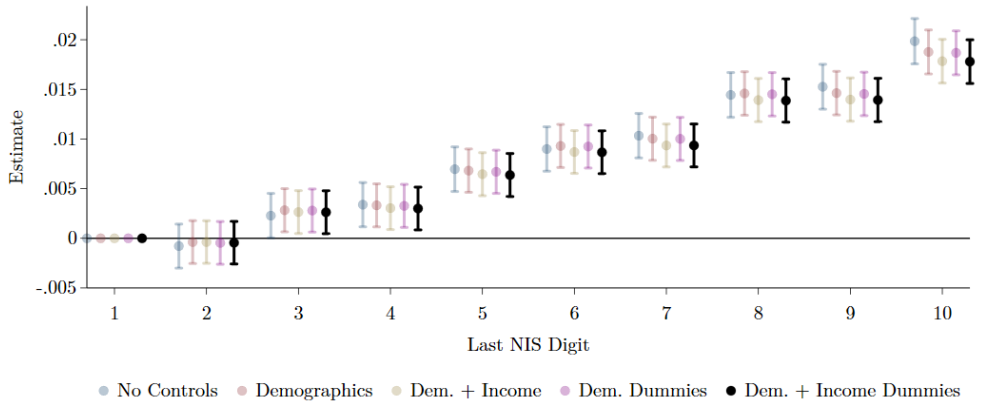
(b) Propensity to Have an Overdraft Line

Figure 8: Financial Distress Along the Paycycle This figure shows default (in panel (a)) and overdraft (in panel (b)) intensity estimates in the paycycle. We progressively estimate Equation (3) with no controls, demographic controls, demographics and income, demographic non-parametric dummies, and demographic and income non-parametric dummies. All specifications contain municipality fixed effects. Robust standard errors are clustered by household.

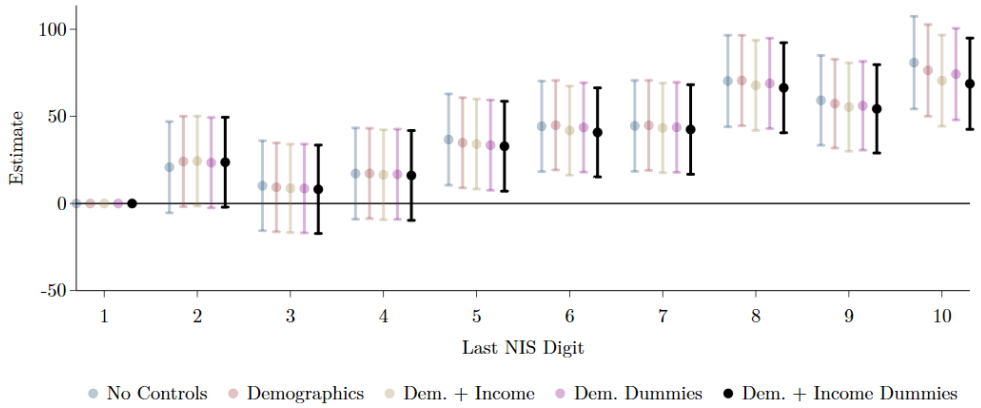
6 Timing Matters: Credit Card & Distress

The second prediction of our framework is that households who are systematically paid later in the calendar month, while facing identical income and expenses, accumulate higher credit balances on average. Unlike the paycycle effect, which captures temporary liquidity depletion between paydays, this section tests for persistent level differences arising from the timing of income within the month.

The key insight is that late-paid households repeatedly encounter fixed expenses



(a) Propensity to Carry Credit Card Balance



(b) Credit Card Balance

Figure 9: Income Timing and Use of Credit This figure shows extensive (in panel (a)) and intensive (in panel (b)) margin estimates of credit card utilization differences due to income timing. We progressively estimate Equation (3) with no controls, demographic controls, demographics and income, demographic non-parametric dummies, and demographic and income non-parametric dummies. All specifications contain municipality fixed effects. Robust standard errors are clustered by household.

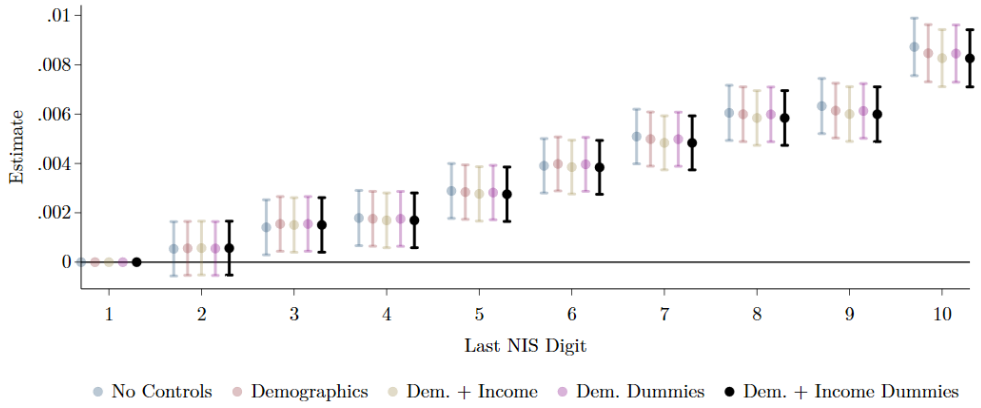
(such as rent or utility bills) earlier in their paycycle. These households rely more heavily on revolving credit. As shown in our theoretical model, this structural mismatch leaves them with lower steady-state liquidity and a thinner buffer to absorb shocks. Consistent with the findings of Baugh and Wang (2024) that income-expense mismatch leads to higher incidence of overdrafts and bounced checks, we hypothesize that later paid households in our setting are more vulnerable to shocks and more likely to experience financial distress, therefore more likely to be delinquent on their credit obligations.

To test this prediction, we estimate Equation (3) focusing on the coefficients $\{\gamma_d\}$ associated with the ten NIS groups, which correspond to distinct calendar payment timings. Because we jointly estimate $\{\gamma_d\}$ and $\{\delta_k\}$, the timing coefficients are purged of transitory paycycle effects—each γ_d reflects the persistent difference in credit outcomes between earlier- and later-paid households, evaluated at comparable points in their cycle.

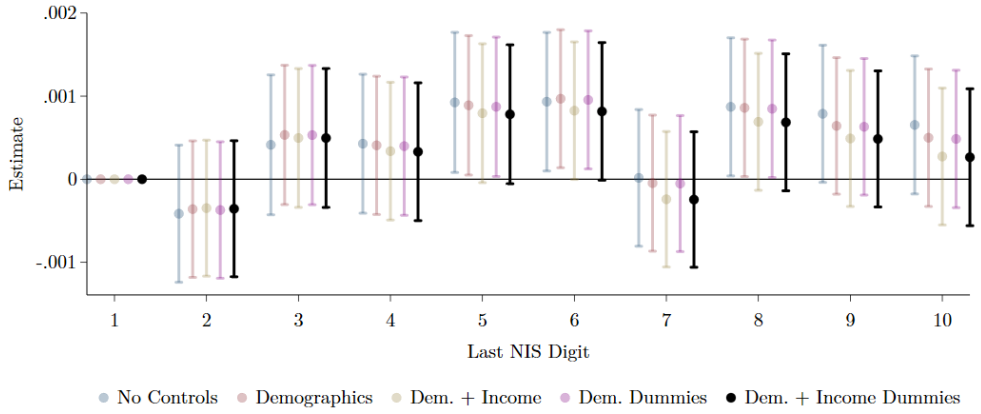
Figure 9 presents the estimated timing effects for credit card borrowing. Panel (a) reports the extensive margin (probability of carrying a balance) and Panel (b) the intensive margin (balance amount conditional on borrowing). Both exhibit clear positive slopes across NIS groups, indicating that later-paid households systematically borrow more. Moving from the earliest to the latest payment group (roughly 10-12 days), the propensity to hold a credit card balance rises by approximately 1.5 percentage points, and average balances increase by around 50–60 reais, relative to early-paid households. These effects are stable across all specifications with demographic and income controls.

In Figure 10 we study financial distress outcomes: default and overdraft usage. The patterns again mirror the credit findings. Later-paid households are about 1 percentage point more likely to be in default, but we find no detectable differences in propensities to overdraft across income timing groups. Overdraft lines are rare, and therefore much of the variation can be absorbed by other estimators. Importantly, the slope of the timing gradient in default remains intact after controlling for income and municipality fixed effects, confirming that the effects arise from structural liquidity timing rather than persistent household characteristics.

Our results demonstrate that timing matters. Even holding constant total income, frequency, and composition, the simple calendar placement of a household's pay date systematically affects both borrowing and distress. Households paid later in the month live persistently closer to their liquidity constraint, validating the model's prediction that the alignment of income and expenditure timing plays a first-order role in household liquidity management.



(a) Propensity to Default



(b) Propensity to Have an Overdraft Line

Figure 10: Income Timing and Financial Distress This figure shows default (in panel (a)) and overdraft (in panel (b)) intensity differences due to income timing. We progressively estimate Equation (3) with no controls, demographic controls, demographics and income, demographic non-parametric dummies, and demographic and income non-parametric dummies. All specifications contain municipality fixed effects. Robust standard errors are clustered by household.

7 Mechanism: Sticky Expense Timing

Our exercise takes for granted that liquidity constrained consumers have expenses with timing that they cannot or choose not to adjust, in the spirit of Baugh and Wang (2024). Unlike in the account aggregator data, we do not observe fixed-date expenses such as rent and utility payments. However, we can use the credit registry data and observe credit card due dates. Because in our population credit access is not abundant, we believe that the first credit card due date that credit card users encounter is an impor-

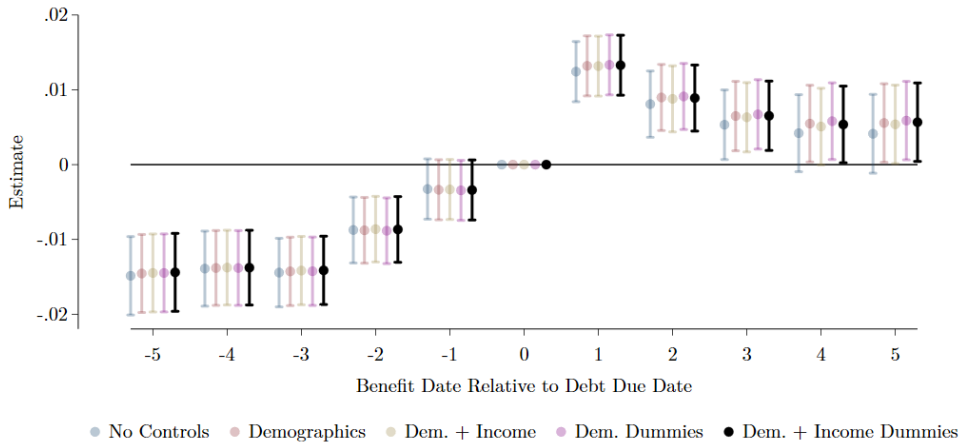


Figure 11: Mechanism: Expense Timing This figure shows coefficients an indicator of 30-day delinquency on dummies for days between income receipt and credit card due dates. We progressively estimate Equation (4) with no controls, demographic controls, demographics and income, demographic non-parametric dummies, and demographic and income non-parametric dummies. All specifications contain municipality fixed effects. Robust standard errors are clustered by household.

tant expense date. Additionally, credit card due dates are adjustable, in principle, but literature has shown consumers do not (perfectly) adjust expenditures, based on income profile (Vellekoop 2018).

To test whether expense dates have a prominent role in explaining the patterns we observe, or whether individuals in our sample are prone to adjust their expense profile, we exploit the mismatch between credit card due dates, and the benefit receipt. We do not study credit card usage, as individuals need a credit card to have a credit card due date. Instead, we focus on financial distress. We augment our specification, and add dummies for the number of days between the first credit card due date of individual i in month m, and their benefit receipt date determined by the benefit schedule:

$$Y_{im} = \sum_{d=1}^{10} \gamma_d \mathbf{1}(\text{NIS}_i = d) + \sum_{k \in \mathcal{K}} \delta_k \mathbf{1}(\text{PCT}_{im} = k) + \sum_{s \in \mathcal{S}} \phi_s \mathbf{1}(\text{MIS}_{im} = s) + \mathbf{X}'_{im}\theta + \mu_c + \varepsilon_{im} \tag{4}$$

where μ_c are municipality fixed effects, and $\mathbf{X}_{im}$ includes controls for household composition, formal labor indicators, and income. Standard errors are clustered at the household level. The sequence of coefficients $\{\phi_s\}$ measures effects on financial distress, net of paycycle and timing effects, comparing individuals in months in which they are paid

right after their credit card due date versus right before their credit card due date. If individuals adjust credit card due dates, then we expect to see a zero effect.

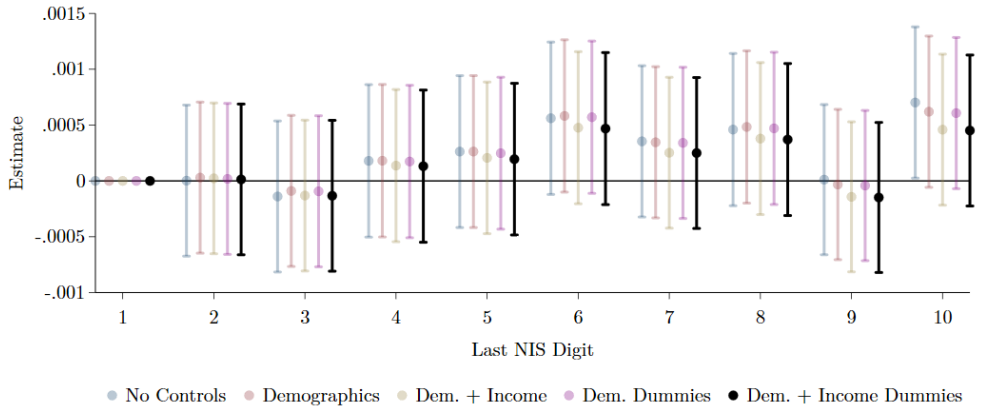
In Figure 11, we show that net of paycycle effects and income timing effects, the relative position of credit card due dates and income significantly impacts delinquency on credit. The differences are larger for benefit dates exactly around credit card due dates ($s \in [-2, 1]$). We interpret this result as evidence that both consumers do not adjust (even adjustable) expense timing, and that these sticky expenditures matter for household liquidity management under liquidity constraints.

8 Robustness Checks

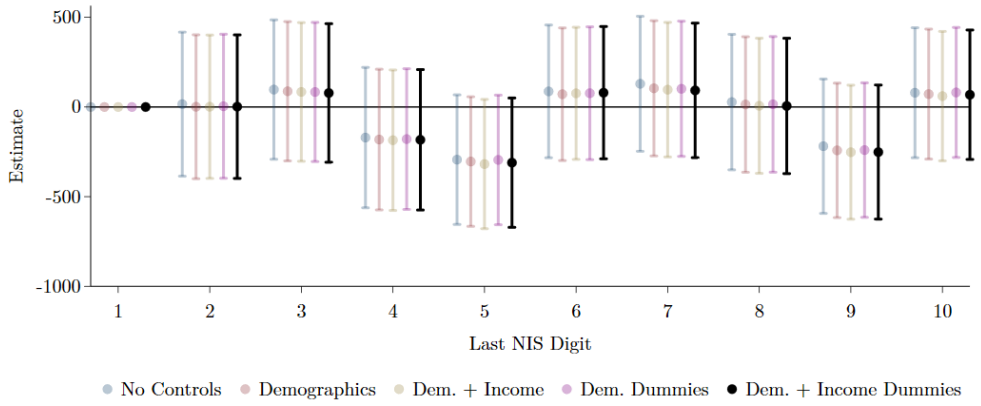
In this section, we run additional tests to lend credence to our main results. We start by running the same specifications for auto loans: because they are longer-term debt and with the purpose of a vehicle purchase, they should be less or not affected by household intra-month liquidity management. We also show that consistent with summary statistics, credit cards shape the total credit landscape of Bolsa Família beneficiaries, and that other types of credit do not offset the timing effects in credit cards. Next, we run the same tests for earlier financial distress outcomes: 30-, 60- and 89- day delinquency indicators. The small coverage of overdrafts, and the lag on the default indicator call for more immediate measures of financial distress.

8.1 Auto Loans as Placebo

In Figure 12, we report the estimates for timing effects in auto loans. Panel (a) reports the probability of holding an auto loan, and Panel (b) shows outstanding balances among borrowers. We do not rely much on confidence bands as the sample size of auto loan users is substantially smaller and selected. However, in both cases estimates are statistically and economically insignificant, with no evidence of a clear timing. The flat profiles



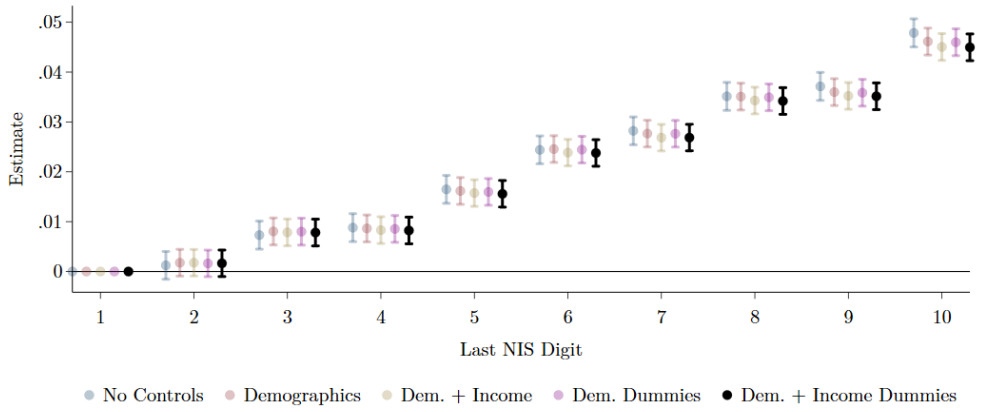
(a) Propensity to Carry Auto Loan Balance



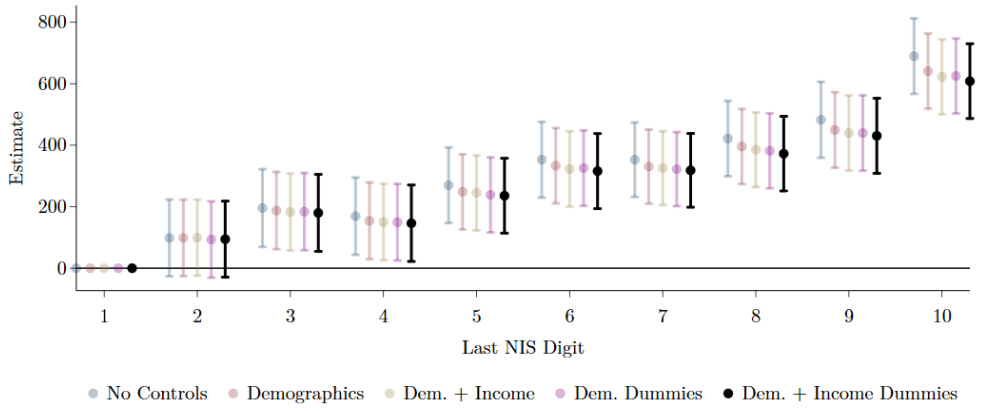
(b) Auto Loan Balance

Figure 12: Robustness: Auto Loans in the Paycyle This figure shows extensive (in panel (a)) and intensive (in panel (b)) margin estimates of auto loan in the paycycle. We progressively estimate Equation (3) with no controls, demographic controls, demographics and income, demographic non-parametric dummies, and demographic and income non-parametric dummies. All specifications contain municipality fixed effects. Robust standard errors are clustered by household.

contrast sharply with the strong positive gradients found for credit card borrowing and delinquency, reinforcing the interpretation that those effects stem from short-term liquidity depletion rather than general differences in credit demand or access. This null result also validates our research design: the random assignment of income timing affects only outcomes that are directly linked to liquidity management.



(a) Propensity to Carry a Credit Balance

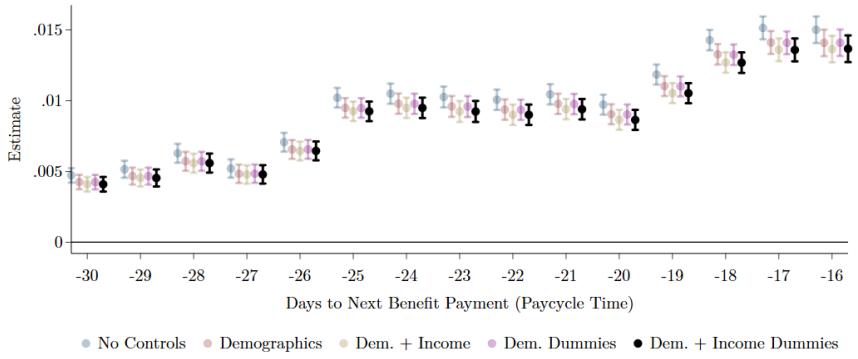


(b) Total Credit Balance

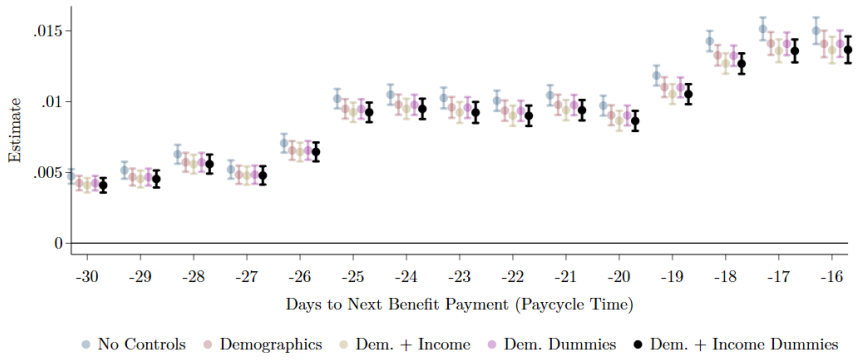
Figure 13: Robustness: Timing Effects in Total Credit This figure shows extensive (in panel (a)) and intensive (in panel (b)) margin estimates of total credit differences due to income timing. We progressively estimate Equation (3) with no controls, demographic controls, demographics and income, demographic non-parametric dummies, and demographic and income non-parametric dummies. All specifications contain municipality fixed effects. Robust standard errors are clustered by household.

8.2 No Substitution: Total Credit

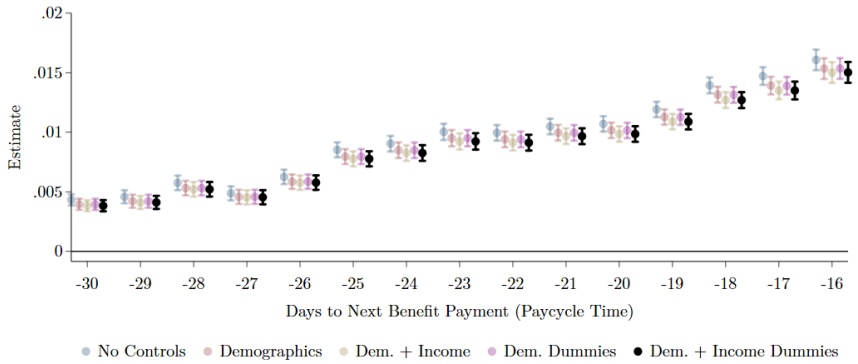
In Figure 13, we report estimates for timing effects in both the extensive (panel (a)) and intensive (panel (b)) margins of household total credit. Consistent with credit card patterns, we find a monotonic effect where later-paid households are more likely to have a credit balance, and those who have a credit balance, carry larger balances. Economically, compared with a baseline mean of 25% of recipients having a credit contract, the latest-paid households have a 4 percentage points larger propensity to have credit than



(a) 30 Days Past Due



(b) 60 Days Past Due



(c) Up to 89 Days Past Due

Figure 14: Robustness: Short-term Delinquency in the Paycycle This figure shows estimates for 30- (in panel (a)) 60- (in panel (b)), and up to 89 days past due (in panel (c)) along the paycycle. We progressively estimate Equation (3) with no controls, demographic controls, demographics and income, demographic non-parametric dummies, and demographic and income non-parametric dummies. All specifications contain municipality fixed effects. Robust standard errors are clustered by household.

the earliest-paid group. On the intensive margin the effect is around 600 reais between extremes, or 15% of the mean credit balance, and almost half of the median.

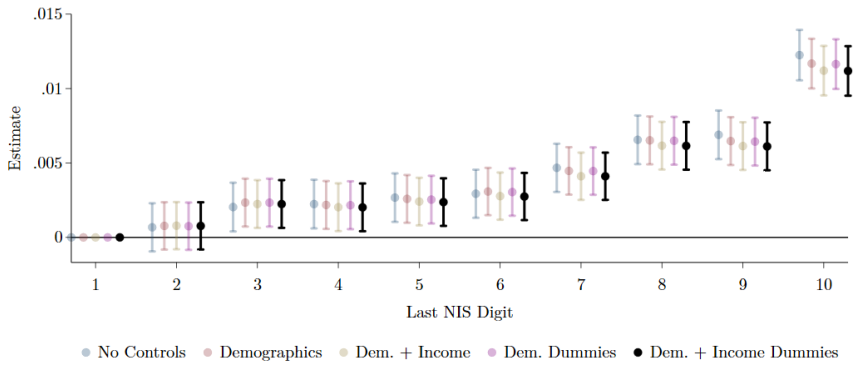
8.3 Short-Term Delinquency

Our baseline distress results focused on overdraft incidence and default (90+ days past due), which capture severe liquidity shortfalls but occur infrequently and with reporting lags. To assess whether the same dynamics appear earlier in the delinquency process, we replicate the analysis using indicators for 30-, 60-, and up to 89-day delinquency. These measures provide a more immediate view of repayment strain and are less affected by administrative delays in credit reporting.

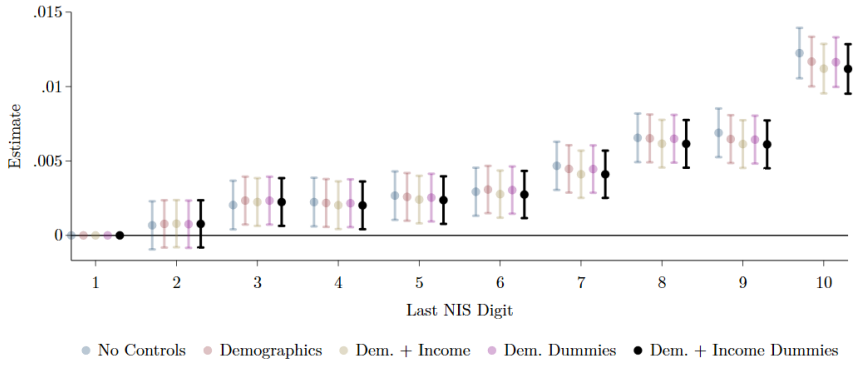
Figure 14 presents the estimated paycycle profiles for short-horizon delinquency. All three indicators display the same monotonic upward slope observed in our main results: as the time since the last benefit payment increases, delinquency rates rise steadily.

Households observed later in their paycycle are 0.5 to 1.2 percentage points more likely to be delinquent, relative to those observed near payday, depending on the horizon considered. These effects are economically meaningful given a baseline delinquency rate of roughly 8%-10%. The persistence of the pattern across delinquency horizons reinforces our interpretation that liquidity depletion within the paycycle directly translates into repayment difficulties. Rather than reflecting chronic default risk or long-run borrower heterogeneity, the evidence suggests that short-term liquidity management,determined by intra-month pay timing, drives delinquency.

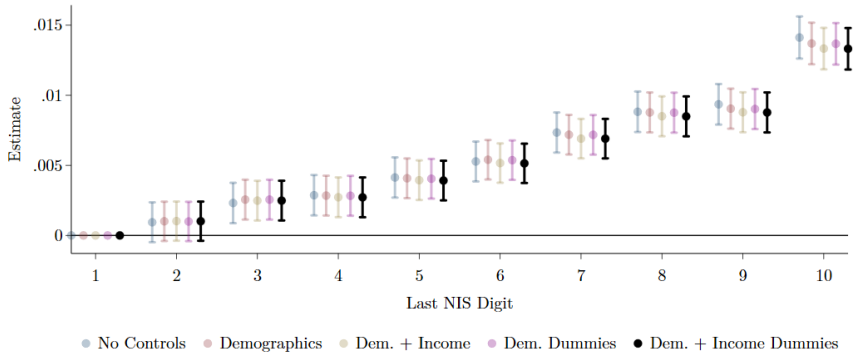
Lastly we show the timing effect in short-term delinquency in Figure 15. The findings are consistent with the remainder of the paper whereby consumers who are paid later in calendar month, encounter fixed calendar expenses earlier in their paycyle, which depletes their liquidity levels, and making them more vulnerable to unexpected shocks. The magnitudes are similar to those observed for default, and economically sizeable.



(a) 30 Days Past Due



(b) 60 Days Past Due



(c) Up to 89 Days Past Due

Figure 15: Robustness: Short-term Delinquency and Income Timing This figure shows estimates for differences in 30- (in panel (a)) 60- (in panel (b)), and up to 89 days past due (in panel (c)) due to income timing. We progressively estimate Equation (3) with no controls, demographic controls, demographics and income, demographic non-parametric dummies, and demographic and income non-parametric dummies. All specifications contain municipality fixed effects. Robust standard errors are clustered by household.

9 Conclusion

This paper shows that income timing has first-order consequences for household liquidity, borrowing, and financial distress, even holding income levels and frequency constant. We develop a simple steady-state model in which present-biased consumers face fixed-date obligations and can shift cash across days using revolving credit. The model delivers two main predictions: (i) credit use and distress rise as liquidity decays over the paycycle, and (ii) households paid later in the calendar month face those obligations earlier in their cycle, rely more on short-term credit, and are more fragile on average.

We test these predictions using administrative microdata linking Brazil's credit registry (SCR) to the Bolsa Família beneficiary registry (Cadastro Único). Identification exploits the institutional payment calendar that assigns benefit days based on the last digit of the NIS identifier. Within each month, NIS groups map one-to-one into paycycle positions at the end-of-month snapshot, but across months the schedule rotates calendar dates while preserving the NIS ordering. This rotation allows us to separately identify paycycle and timing effects from a single monthly measurement.

The evidence closely matches the model. Along the paycycle, the probability of revolving credit card debt and the conditional balance amount increase monotonically with time since last payment, and short-horizon delinquency rises in parallel. Across NIS groups, later-paid households are persistently more likely to revolve, carry larger balances, and default more often, consistent with operating closer to their liquidity constraint. These results are robust to rich controls and municipality fixed effects and are specific to short-term liquidity products. We find no timing gradients for long-term credit such as auto loans. Additional tests using 30-, 60-, and up-to-89-day delinquency confirm that the mechanism manifests early in the delinquency process, not only at default.

Two implications follow. First, the alignment of income and obligations is a policy

lever. Small adjustments to benefit or payroll calendars, such as shifting payments closer to common bill due dates or smoothing disbursements within the month, can reduce revolving credit use and financial distress among liquidity-constrained households at negligible fiscal cost. Second, program evaluation and consumer-credit policy should account for intra-month timing, not only income levels and frequencies, when forecasting debt dynamics or designing hardship mitigation.

Intra-month timing is not a second-order detail. It shapes how identical income is transformed into liquidity, debt, and ultimately financial stability. Designing income calendars with this margin in mind can meaningfully improve household welfare in scalable, low-cost ways.

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