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 the paycycle unfolds, and later-paid households are roughly 12% more likely to revolve credit-card debt and 16% more likely to default. 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 two testable hypotheses: (i) credit card usage and financial distress rise over the course of the paycycle; and (ii) households paid later in the month rely more on credit cards and are more prone to financial distress. The two effects answer different questions. One is about the within-cycle dynamics of a fixed household, while the other is about persistent level differences between households paid early versus late.

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 well into their paycycle, 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. First, 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 also rises along the paycycle: by the middle of the cycle, the probability of default is roughly 0.8 percentage points higher and the probability of holding an overdraft line about 0.15 percentage points higher than just after payday, with both effects continuing to grow further into the cycle.

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$70 higher, conditional on borrowing. These households are also more financially fragile: their delinquency rates are 1.2 percentage points larger (on a base of 10 percent), and their default rates are 0.8 percentage points higher (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). This intra-month liquidity cycle is not merely an accounting phenomenon: Carvalho, Meier and Wang (2016) show that the financial pressure of being late in the paycycle alters economic decision-making among low-income households, reinforcing the view that the position of a household within its cycle is an economically consequential state. Our timing results can be read as the credit-market counterpart of this mechanism.

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. In doing so we contribute to a growing literature on the financial lives of the poor in developing economies, where credit and payment frictions

shape how households manage scarce liquidity. Bachas, Gertler, Higgins and Seira (2021) show that the primary payment infrastructure available to low-income households are debit cards, which lower the cost of holding and accessing balances. In turn, reliance on debit cards materially changes saving and liquidity management behavior. We document a complementary point on the timing dimension: holding the level and frequency of income fixed, the calendar placement of payments shapes how much costly credit these households use and how often they fall into distress, which makes the design of the payment calendar itself a lever over financial outcomes.

The closest to our work is Baugh and Wang (2024), who exploit differences in the time between paychecks to show that households experience financial shortfalls during longer paycycles, establishing the gap between paydays as a source of liquidity strain. We build on this insight, and formalize testable hypothesis about income timing alone. Their identifying variation comes from the length of the gap between paychecks, while we hold the time between paychecks identical across income timing groups. This isolates the relative placement of income within the month, a distinct margin. Additionally, the last-NIS-digit quasi-random assignment of pay dates lets us separately identify the transient within-household paycycle effect and the persistent cross-household timing effect.

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.

The rest of the paper proceeds as follows. Section 2 presents the theoretical framework. Section 3 describes the data and institutional setting. Section 4 outlines the empirical strategy. Section 5 measures paycycle effects, and section 6 measures timing effects. Section 7 examines the underlying mechanism of sticky expense timing. Section 8 discusses robustness checks. Section 9 concludes.

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 τ within the paycycle, the consumer chooses consumption C_τ to maximize time-separable log utility with present bias. At each day τ, the consumer solves the quasi-hyperbolic dynamic program:

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

subject to a standard budget constraint, where $\beta \leq 1$ is the present-bias parameter and $\delta \leq 1$ is a standard exponential discount factor. The starred terms C_k^* denote the consumption of future selves, which the current self takes as given and best-responds to: the consumer is sophisticated, correctly anticipating future behavior rather than controlling it.

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, $u'(C_{k+1}^*) > u'(C_k^*)$, 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 collapses to a single, infinitely repeatable paycycle of length D. Within this finite cycle we normalize the daily exponential discount factor to $\delta = 1$, leaving the present-bias parameter β as the only source of im-

patience. The consumer's intra-month problem thus becomes the repeatable paycycle problem subject to the within-paycycle budget constraint $Y = \sum_{s=1}^{D} C_s^*$:

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

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. Because the present-biased consumer optimally exhausts this credit line each cycle, the repayment due at payday absorbs αY of the incoming paycheck, leaving $(1-\alpha)Y$ in liquid balances at payday alongside the αY of credit again available for the new cycle. 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). This is consistent with limited evidence of households adjusting committed 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 described case, 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:

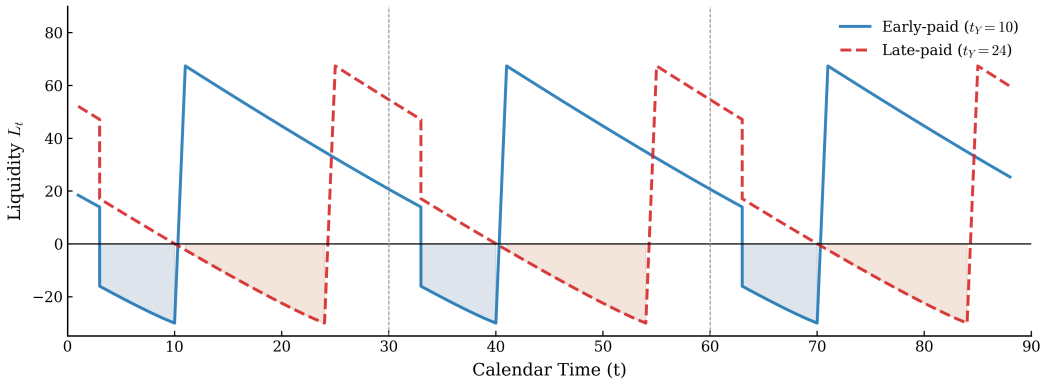
$$\begin{aligned} C_i^* &= A_i \times (Y - E) \\ A_1 &= \frac{1}{1 + (D-1)\beta} \\ A_i &= \frac{1}{1 + (D-i)\beta} \prod_{j=1}^{i-1} \frac{(D-j)\beta}{1 + (D-j)\beta} \qquad , \qquad i \in \{2, 3, \ldots, D\} \end{aligned} \tag{2}$$

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.

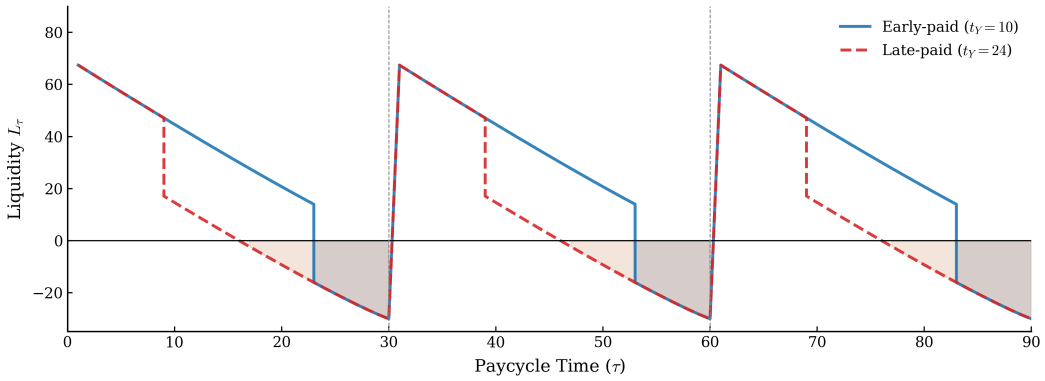
Liquid Balances. Let $m \equiv (t_E - t_Y) \bmod D$ denote the position of the fixed expense within the paycycle. Because each household finances the same expense E from the preceding paycheck, the optimal policy functions A_i are identical across households. However, the observed liquidity paths differ. For a household with expense location m, liquidity carried into the start of day $\tau + 1$ (equivalently, the balance at the end 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



(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.

and maintain higher liquidity throughout the month. Let $\mathbf{1}\{L_\tau < 0\}$ indicate that the household carries a negative liquid balance at cycle position τ—that is, draws on the revolving line to bridge the gap between income and committed expenditure. Note that a necessary condition for borrowing to depend on the timing of income is a binding liquidity constraint. However, in steady state this is a planned, fully anticipated use of credit and not a sign of distress.

Implications. This structure delivers two main predictions, illustrated in Figure 1, that map directly onto the empirical analysis that follows. Both fix the parameters

$\{\beta, Y, E, t_E, \alpha\}$, which pin down the optimal consumption path $\{C_i^*\}_{i=1}^D$ and hence the deterministic liquidity path L_τ. We track two objects that mirror our empirical outcomes: (i) the indicator $\mathbf{1}\{L_\tau < 0\}$ that the household draws on the revolving line, and (ii) the amount drawn, $b_\tau \equiv \max\{-L_\tau, 0\}$. For a single household both are deterministic functions of cycle position. When averaged over a population of households the indicator becomes the share that borrows, $\Pr(L_\tau < 0)$, the counterpart of our extensive-margin estimates. Because an average of non-decreasing functions is itself non-decreasing, any monotonicity we establish household by household carries over to these population shares.

Prediction 1 (Paycycle Effects)**.** Holding the parameters fixed, liquidity is drawn down monotonically along the cycle, $L_{\tau+1} < L_\tau$ for every τ, so both margins of borrowing are non-decreasing in paycycle position:

$$\frac{\Delta\, \mathbf{1}\{L_\tau < 0\}}{\Delta\tau} \;\geq\; 0 \qquad \text{and} \qquad \frac{\Delta\, b_\tau}{\Delta\tau} \;\geq\; 0.$$

A household therefore borrows more, on both margins, the further it stands from its last payday.

Prediction 2 (Income Timing Effects)**.** Consider two households with identical parameters $\{\beta, Y, E, t_E, \alpha\}$, and hence the same consumption path $\{C_i^*\}_{i=1}^D$, that differ only in their paydates. This, in turn, generates variation in within-cycle position of the fixed expense, $m' < m$. Their liquidity paths are ordered: the later-paid household, whose expense falls earlier (m'), holds weakly lower liquidity at every cycle position, and strictly lower over the positions that lie between the two expense dates,

$$L_\tau(m') \;\leq\; L_\tau(m) \quad \text{for all } \tau.$$

They, therefore, borrow weakly more at every position, and strictly more on average, on

both margins. Because a common expense date makes $m = (t_E - t_Y) \bmod D$ fall as the pay date t_Y rises, this orders borrowing by pay timing. Households paid earlier in the calendar month borrow less:

$$\frac{\Delta \mathbf{1}\{L_\tau < 0\}}{\Delta m} \leq 0 \qquad \text{and} \qquad \frac{\Delta b_\tau}{\Delta m} \leq 0.$$

From borrowing to distress. The borrowing margins above describe planned, fully anticipated credit use in a steady state without shocks. Distress arises when an unanticipated shock cannot be absorbed, pushing the household past its credit limit or into delinquency. Let $P(\text{distress})$ denote the probability of such an event, and suppose it decreases the liquidity buffer, $\partial P(\text{distress})/\partial L < 0$, since a thinner buffer leaves less room to accommodate a shock. This single assumption carries both comparative statics from borrowing over to fragility: liquidity falls along the cycle (Prediction 1) and is lower for later-paid households at any given position (Prediction 2), so positions later in the cycle and households paid later in the month both face a higher $P(\text{distress})$ when shocks arrive.

Scope of the framework. The model is deliberately stylized: it isolates the single channel we can identify in the data: how the calendar alignment of a fixed income and a fixed obligation maps into the within-cycle liquidity path. Among the several margins that real households also use to manage liquidity, three are worth naming explicitly. First, the model does not consider the household's lifecycle: it has no precautionary savings buffer and no borrowing between cycles, so households enter each cycle with only the revolving line as slack. Allowing a precautionary stock would let some households self-insure against the timing mismatch, dampening the mapping from low liquidity to credit use and distress. It would attenuate our predicted gradients but not reverse their sign, since the buffer is still drawn down faster for later-paid households.

Second, the model abstracts from informal support networks (transfers from family

or neighbors) and from informal or alternative credit. To the extent these substitute for formal revolving credit, they again attenuate the formal-credit responses we measure, so our estimates are best read as a lower bound on the total liquidity management response to timing.

Third, the model takes labor income as fixed and exogenous, ruling out an intra-month labor-supply response (e.g., taking on extra informal work when liquidity is tight). We believe this is a reasonable approximation, but where labor supply is more elastic it would provide an additional adjustment margin that, once more, works against finding timing effects. Each omitted margin is a way for households to undo the timing mismatch. Their omission therefore biases the model toward overstating effects relative to a world with these margins.

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



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).

(maximum 96 BRL).[1]

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) and to reductions in local crime (Chioda, De Mello and Soares 2016). Recent work documents the impact of BF in the local economy, by stimulating demand and increasing formal labor market participation (Gerard,

[1]These amounts and eligibilities refer to our sample period (2018-2019). They have since changed.

Naritomi and Silva 2025).

BF benefits are disbursed monthly through the public bank *Caixa Econômica Federal*, accessible via its 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.

We define credit card balances as the sum of household's current statement balance and any balance carried from prior months. Installment card financing is recorded and analyzed separately and is excluded from this measure. The corresponding extensive margin is an indicator for a positive balance, and the intensive margin is the balance conditional on holding one. Because the measure includes the current statement balance, it reflects total reliance on card credit at the snapshot and does not, on its own, distinguish cardholders who repay in full at the due date from those who revolve. Delinquency and default are household-level statuses computed across all credit products (not specific to credit cards) and are nested: the 30-day indicator captures households at least 30 days past due on any product (and thus also includes the up-to-89-day and default cases), while default denotes 90 or more days past due. The overdraft indicator marks a positive drawn overdraft balance.

A natural concern with month-end registry snapshots is that observed delinquency might partly reflect reporting conventions rather than genuine repayment difficulty. Any fixed reporting convention (e.g., a common month-end cutoff, a uniform classification rule) shifts the level of measured delinquency identically for all ten NIS groups observed in a given month and is differenced out by the rotation. For a reporting artifact to generate our results it would have to move delinquency or credit differentially across paycycle positions and do so consistently as the calendar reshuffles groups month to month, which is precisely the pattern a genuine liquidity mechanism, rather than a mechanical convention, would produce.

		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 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$).

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 panel of 1,236,179 households who are enrolled in the program for 24 months. The last digit of the NIS with the fewest 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 bal-

ances 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.

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 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.

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

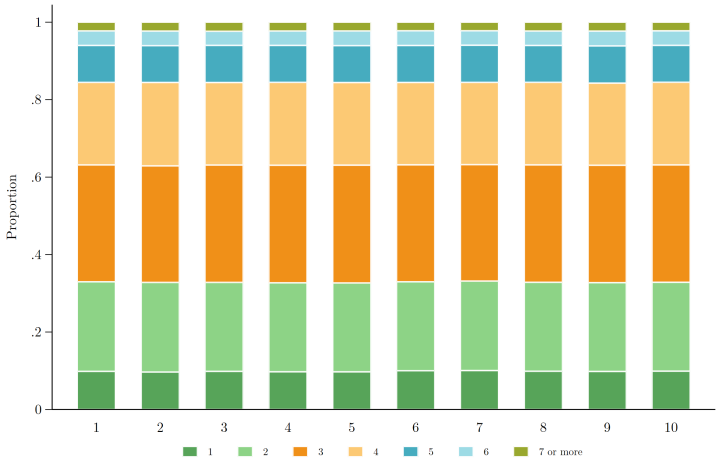
	Last NIS Digit									
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**0**
Avg. Age in Household										
Mean	35.4	35.4	35.5	35.4	35.4	35.5	35.4	35.4	35.4	35.4
St. Dev.	9.3	9.3	9.3	9.3	9.3	9.4	9.4	9.3	9.3	9.3
Formal Income per Capita										
Mean	39.8	39.8	40.1	39.7	39.8	39.7	40.1	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. NIS group 0 (last digit zero) is the latest-paid group. In the regression analysis it is coded as group 10.

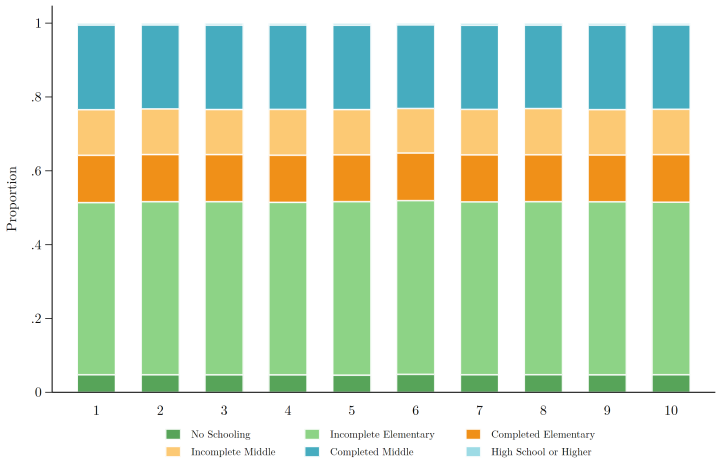
of number of people in a household, and the educational attainment of the head of household are also similar across groups.

In principle, with daily data for credit and distress outcomes, one could separately identify two distinct objects: (i) the paycycle effect: how a given household's credit use and financial distress evolve as liquidity decays between paydays (within-household dynamics), and (ii) the timing effect: the persistent cross-household level difference by which households paid later in the month carry higher credit use and distress, holding paycycle position fixed.

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 eighteen days after payday and NIS 9 households three days after payday. Thus, within a single month, timing and paycycle position are



(a) Household Composition by NIS Last Digit

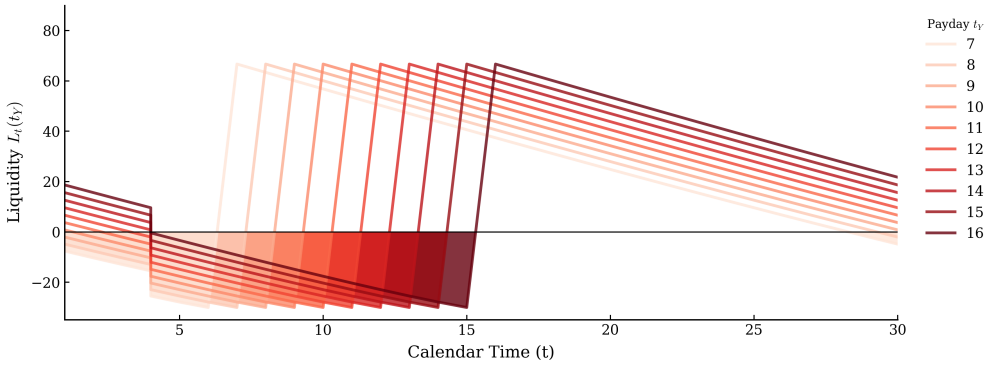


(b) Head of Household Educational Attainment by NIS Last Digit

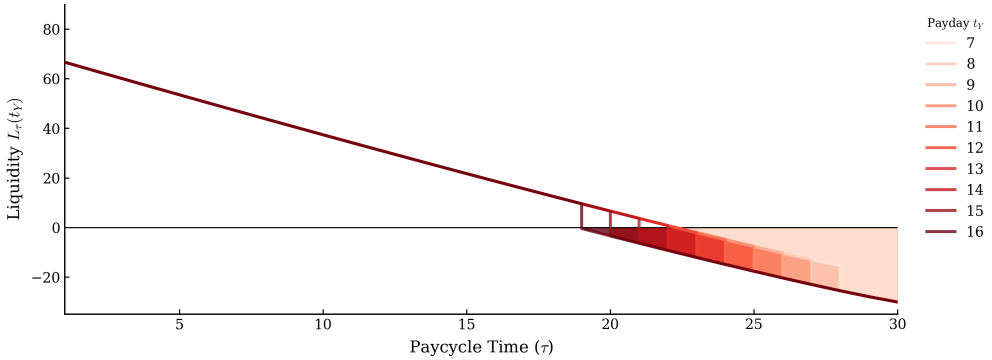
Figure 3: Household Composition and Literacy by NIS Last Digit. This figure presents distributions of number of people in the household (in panel (a)), and the educational attainment of the head of household (in panel (b)) by NIS last digit.

collinear.

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 face a fixed expense of 15. Those who would otherwise run negative use credit to bridge the gap, up to a



(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 $\beta = 0.9$, $Y = 100$, $\alpha = 0.3$, $E = 15$, and $t_E = 3$. Shaded areas illustrate credit card usage.

limit of 30% of their income, and repay any borrowing 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

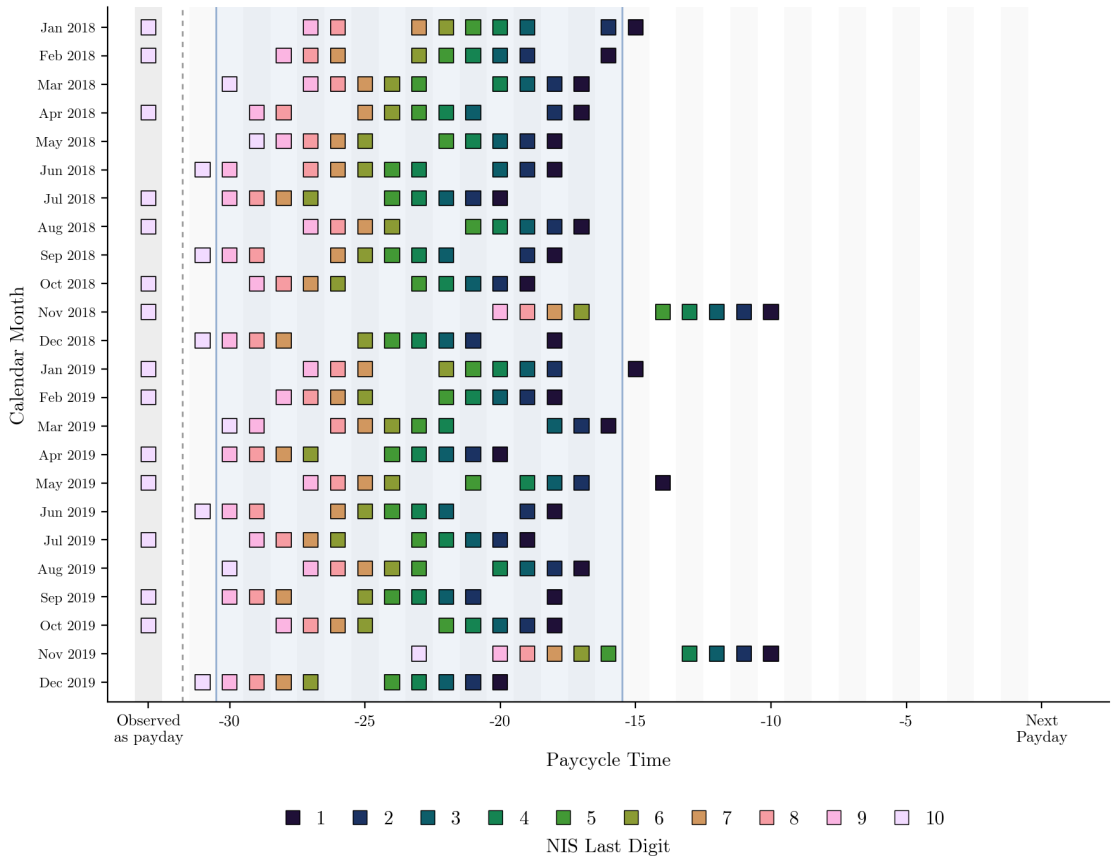


Figure 5: Identification of Paycycle and Timing Variation. This figure plots, for each calendar month from January 2018 to December 2019 (rows), the paycycle position occupied by each NIS last-digit group at the end-of-month snapshot. The horizontal axis measures paycycle time as the number of days until the next benefit payment: the next payday sits at the right edge, and month-ends that themselves coincide with a payday are shown separately in the leftmost column ("Observed as payday"). Each colored square marks the position of one NIS group, colored by its last digit. Because the Bolsa Família calendar fixes the ordering of NIS payment days but rotates their exact calendar dates across months, a given NIS group appears at different paycycle positions across months, and each paycycle position is occupied by different NIS groups. The shaded band (-30 to -16) marks the region of the cycle in which more than one NIS group is observed. This overlap provides the variation that separately identifies paycycle effects (δ_k) from timing effects (γ_d).

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.

Figure 5 makes this rotation visible: each month the ten NIS groups tile distinct paycycle positions, and over the first half of the paycycle (-30 to -16) more than one NIS last digit is observed at the same paycycle time, which is the variation we exploit. Appendix Figure 1 further documents the distributions of income-receipt days and of paycycle time at the time of observation. We compute paycycle time as days until next

paycheck so as to normalize months with different lengths.

4.1 Baseline Specification

Let $NIS_i \in \{1, \ldots, 10\}$ denote the household i's payment group, and define paycycle time, PCT_{im}, as the number of days from the month m's-end snapshot to the next benefit payment of household i, signed so that it equals zero on the payday and is negative earlier in the cycle:

$$\text{PCT}_{im} \equiv -\big(\text{days until the next payment at the month-end snapshot}\big).$$

A household observed just after payday, with a full cycle still to run, has $\text{PCT}_{im} \approx -D$, whereas one deep into its cycle, close to the next payday, has PCT_{im} near zero. Paycycle time therefore increases as the household moves through the cycle, so that a larger (less negative) PCT corresponds to more days elapsed since the last payment. A larger k denotes a later point in the paycycle, and all figures plot k along the horizontal axis ("days to next benefit payment"). 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). 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 household level.

The coefficients δ_k capture the paycycle effect: the pattern of credit use as liquidity declines over the cycle for the average individual of a fixed icnome timing group. The coefficients γ_d capture the timing effect: a persistent cross-household level difference be-

tween households paid early and those paid late at the same paycycle position. Because a household's NIS digit fixes its pay date in every month, this is a standing attribute the household carries across all of its cycles rather than a transient state.

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.[2] 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.

Equation (3) deliberately omits month-year fixed effects.[3]. A month shock is, by construction, common to all ten NIS groups observed that month. It shifts the level of that month's entire cross-section uniformly and cannot, on its own, tilt outcomes across paycycle positions or across NIS groups within the month.

We simulate a daily dataset, where 150 individuals are randomly assigned to 10 paydates (15 for each group), preserving the relative income timing order between groups,

[2]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.

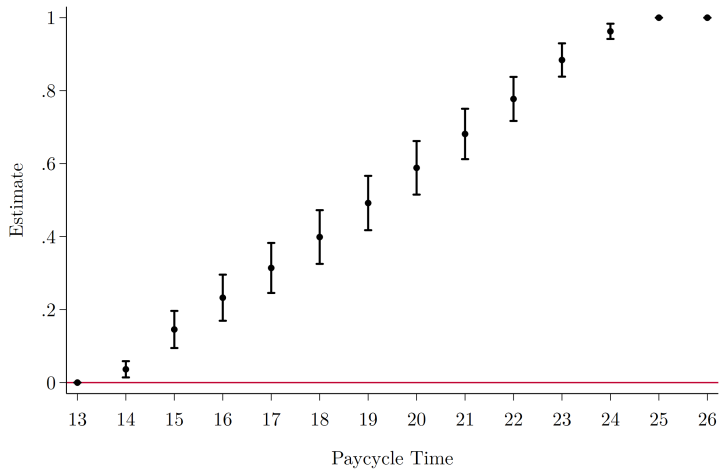
[3]This is the calendar analogue of the age-period-cohort identification problem: paycycle position plays the role of age, the NIS group that of cohort, and the month-year that of period. As in age-period-cohort, the three are collinear within a month. In our setting, what allows for identification is that BF calendar rotates the NIS-to-paycycle mapping nonlinearly across months.

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 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.

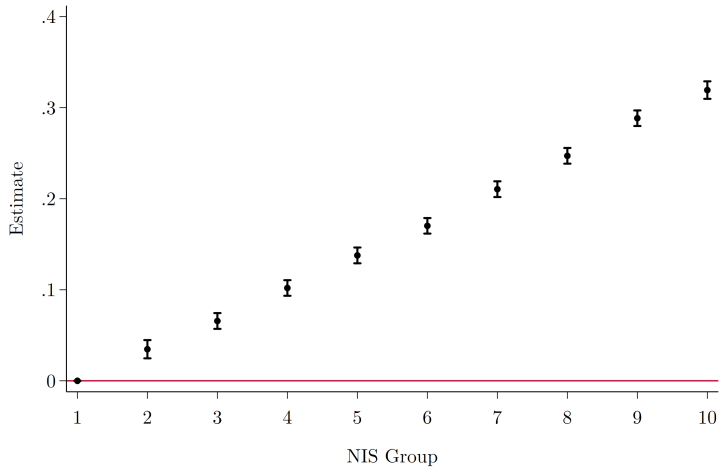
Our theoretical model predicts the patterns in Figure 6: (i) within-cycle deterioration in liquidity and increasing credit use (δ_k rising in k), and (ii) higher average credit utilization for later-paid households (γ_d rising in lateness). Estimating (3) jointly provides a direct empirical test of both 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 and Distress in the Paycycle

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.



(a) Paycycle Effects (δ_k)

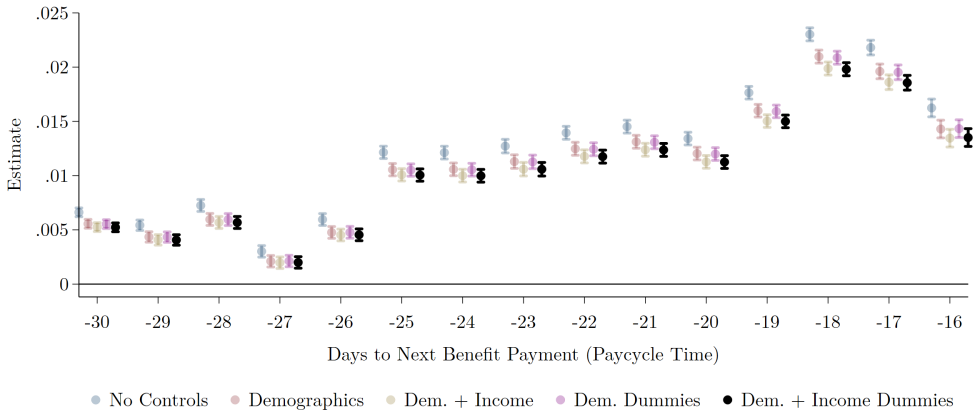


(b) Timing Effects (γ_d)

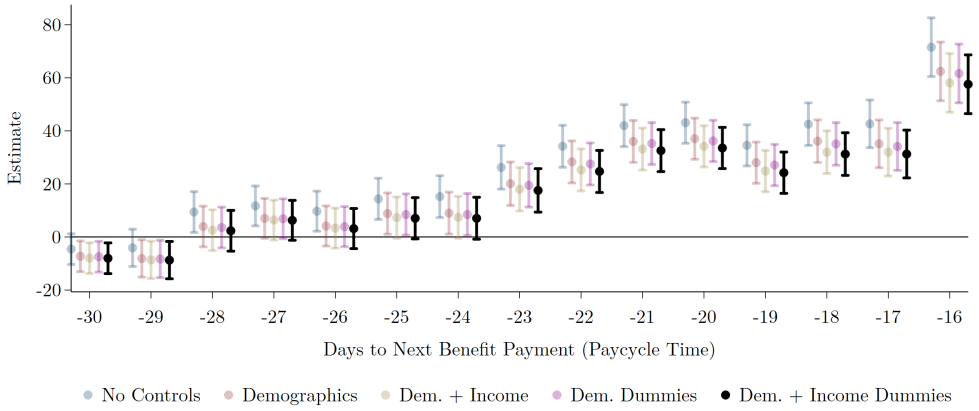
Figure 6: Simulated Data. This figure shows coefficients from a single regression of an indicator for carrying credit card debt on paycycle-time dummies (panel (a)) and income-timing-group dummies (panel (b)), estimated jointly on simulated data.

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: both the propensity to carry a credit card balance and the balance amount 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 plot-



(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. The plotted coefficients are reported in Appendix Tables 1 and 2.

ting the series $\{\delta_k\}$ to trace the empirical profile of credit card borrowing through the cycle. As shown in Figure 5, paycycle times of -30 to -16 are identified by more than one of the NIS groups. The estimates we report use zero days to next paycheck as the omitted category. Thus, the magnitudes are relative to outcomes of households who we observe on the day they are paid.

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 bal-

ance. 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.

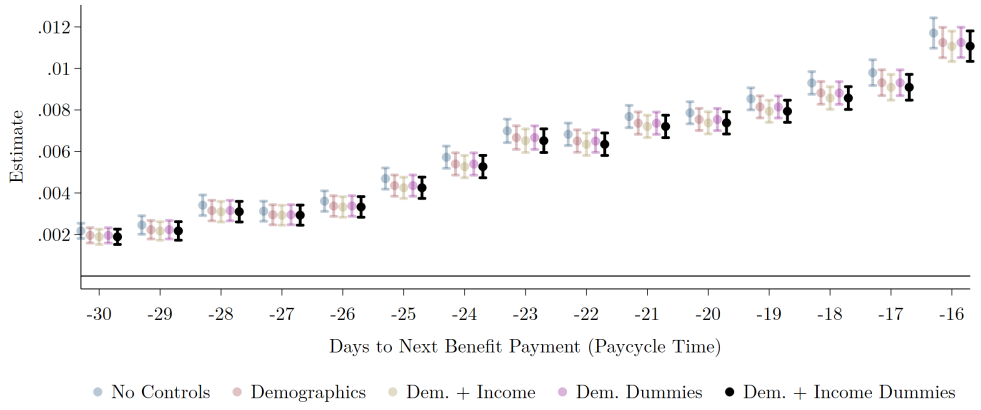
Half a paycycle later, consumers are between 1 and 2 percentage points more likely to carry a credit card balance and hold balances roughly 60 to 70 reais higher than otherwise identical households observed near payday. These magnitudes compare to a baseline propensity to have a credit card balance of 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.

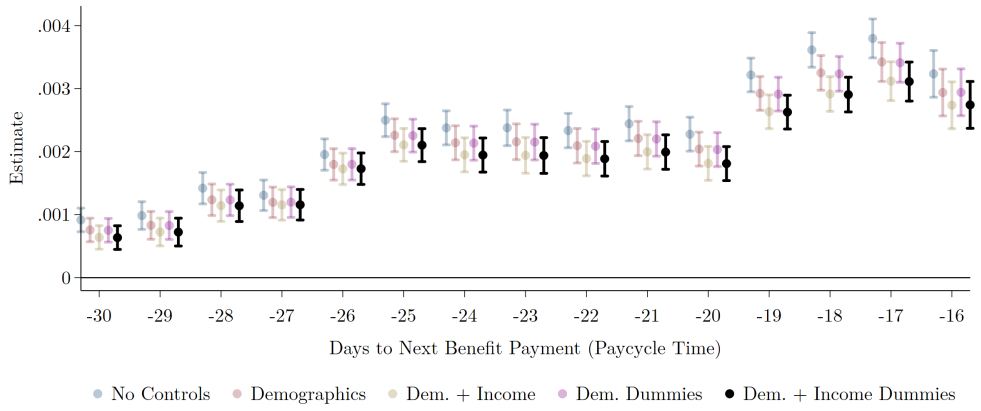
As the paycycle progresses, the model implies thinner liquidity buffers, and so the household's ability to absorb unanticipated shocks diminishes. We therefore expect financial distress to rise alongside credit card usage as households move further from their last paycheck.

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. By the middle of the cycle, relative to households observed on payday, the probability of default is roughly 0.8 percentage points higher and the likelihood of holding an overdraft line about 0.15 percentage points higher, with both effects continuing to grow as households approach their next payday. These effects are sizable given baseline default rates near 5% and overdraft usage around 2%.



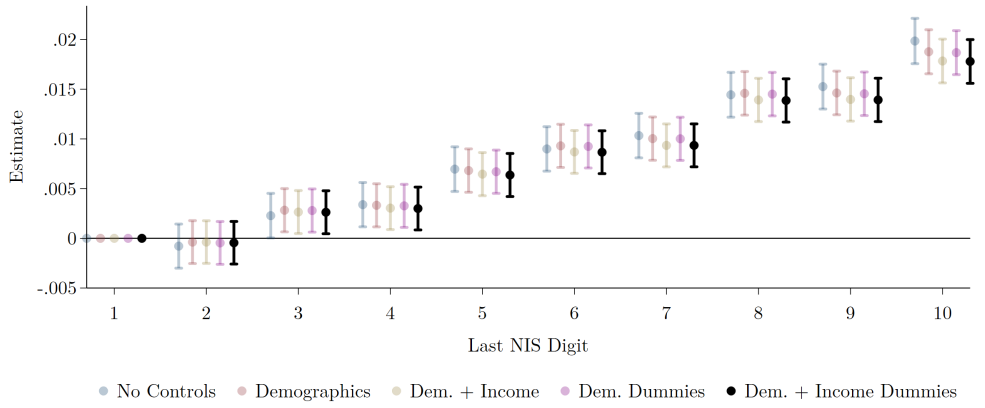
(a) Propensity to Default



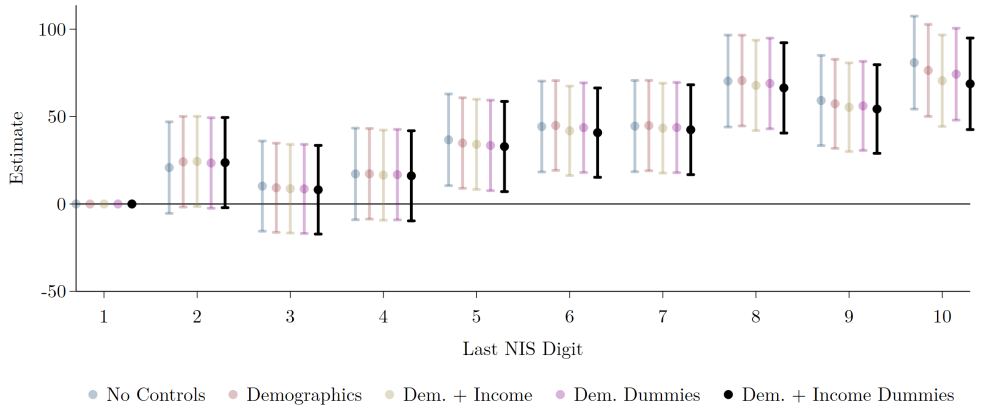
(b) Propensity to Have an Overdraft Line

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. The plotted coefficients are reported in Appendix Tables 3 and 4.

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 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. The plotted coefficients are reported in Appendix Tables 1 and 2.

6 Timing Matters: Credit Card and 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 the transient liquidity depletion a household passes through between paydays, this section tests for a persistent cross-household level difference arising from the timing of income

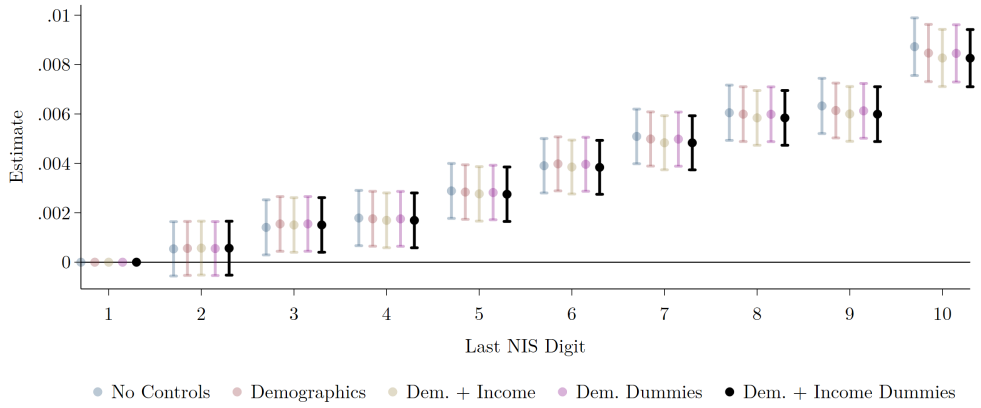
within the month: because the NIS digit fixes a household's pay date in every month, later-paid households meet fixed expenses early in the cycle month after month, leaving them at a higher level of credit use that they carry across all of their cycles.

The key insight is that late-paid households repeatedly encounter fixed expenses (such as rent or utility bills) earlier in their paycycle. These households should therefore 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.

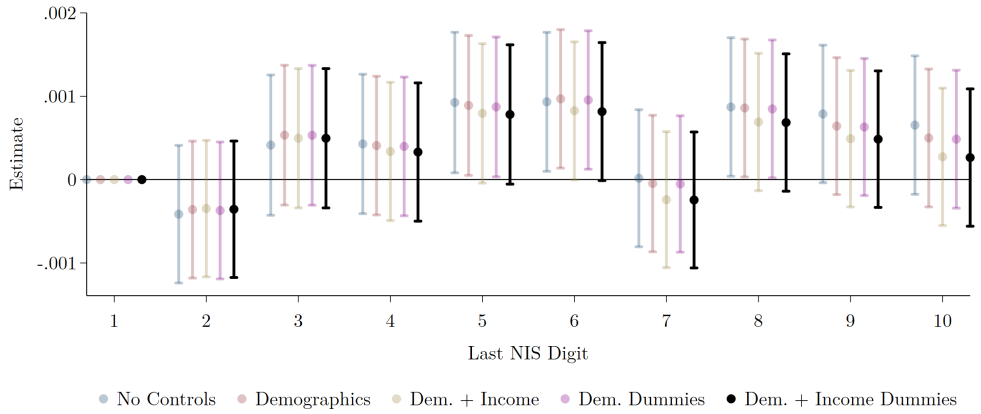
To test this prediction, we estimate Equation (3) focusing on the coefficients $\{\gamma_d\}$ associated with the ten NIS groups, which correspond to distinct calendar payment timings. Because we jointly estimate $\{\gamma_d\}$ and $\{\delta_k\}$, the timing coefficients are purged of transitory paycycle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

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 1.75 percentage points, and average balances increase by around 70–80 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



(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. The plotted coefficients are reported in Appendix Tables 3 and 4.

patterns again mirror the credit findings. Later-paid households are about 0.8 percentage points more likely to be in default, but we find no detectable differences in propensities to use an overdraft line across income timing groups. Overdraft lines are rare, and much of the variation is absorbed by the included controls and fixed effects. 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.

7 Mechanism: Sticky Expense Timing

Our evidence this far is consistent with liquidity being the channel trough which income timing affects borrowing and distress. However, the interpretation of our timing results rests on a single behavioral assumption: that liquidity-constrained households face calendar-fixed obligations whose dates they cannot, or choose not to, realign with their income. This assumption is what turns the random rotation of pay dates into random variation in the alignment between income and expenses. In this section, we explicitly test the empirical validity of this assumption.

The largest recurring obligations of low-income households are anchored to the calendar rather than to the household's idiosyncratic pay date. Rent payments are contractually fixed to a date of the month, utility billing cycles are set by the provider, and bunch on round-number due dates. A household wishing to undo a timing mismatch would have to renegotiate rent due dates, or restructure its consumption calendar, each of which carries transaction, search, or contractual costs that are high relative to the modest liquidity gain, and several of which are simply not under the household's control.

Our exercise thus 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 ex-

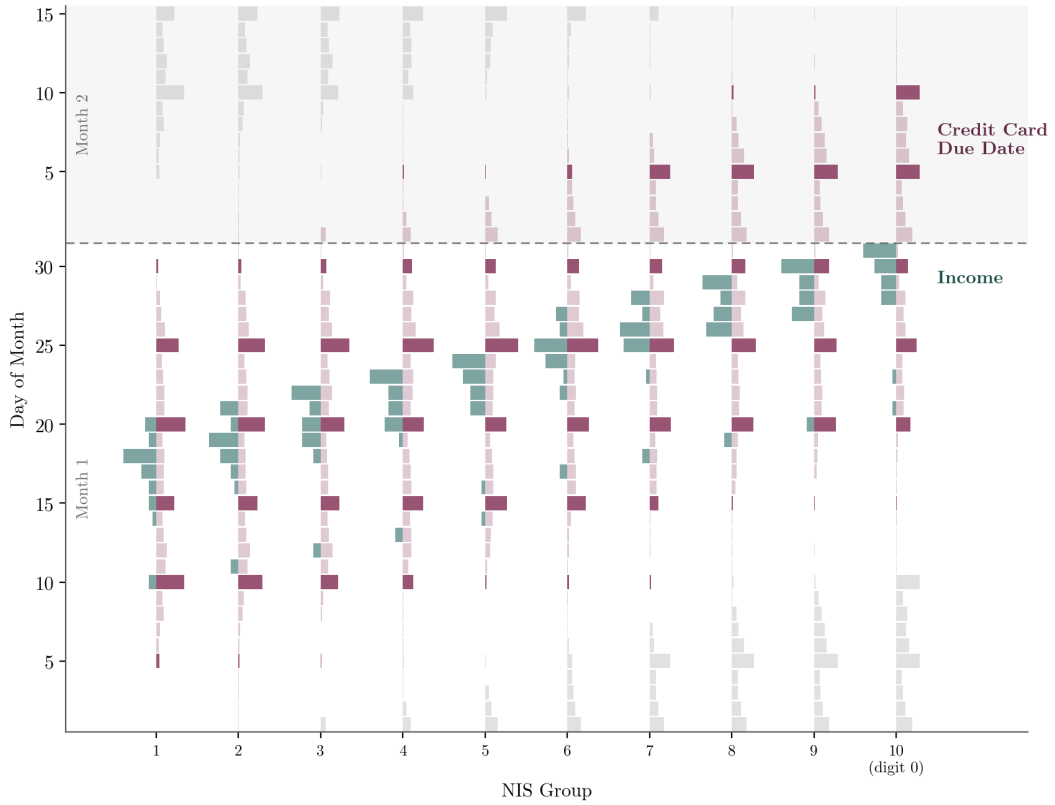


Figure 11: Credit Card Due Dates and Income Timing. Each column shows one full pay cycle for a NIS group, vertically centered on that group's benefit pay date. Green bars (left) are the within-group distribution of benefit receipt days. Red bars (right) are the distribution of first credit card due dates, with round-number days (5, 10, 15, 20, 25, 30) highlighted and the remaining due-date mass shown in faded grey as it repeats into the neighbouring cycle. Time runs upward, wrapping from the end of one month ("Month 1") into the next ("Month 2").

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

Figure 11 makes this stickiness visible in the raw distributions, before any estimation. Each NIS group is drawn over a single pay cycle centered on its benefit date, so the variation across columns is the calendar position of income. As the last NIS digit increases, the benefit date rotates steadily up the month, by construction. Credit card due

dates do not follow: in every group they bunch on the same round-number days (the 5th, 10th, 15th, 20th, 25th, and 30th), and the highlighted bars sit at the same calendar dates regardless of when the household is paid. Were households re-timing their cards to their income, the due-date mass would climb the diagonal alongside the benefit date. Instead, it remains pinned to the calendar. The bunching on multiples of five is itself telling: due dates appear to be chosen by round-number convention rather than tailored to each household's pay schedule.

This pattern reproduces a broader literature finding that the timing of consumption commitments is governed by the calendar rather than by the timing of income (Vellekoop 2018; Baugh and Wang 2024). For our purposes, the non-adjustment of due dates is precisely the condition that makes the mismatch test below valid: because due dates barely respond to income while income timing rotates quasi-randomly across the calendar, the gap between a household's pay date and its credit card due date is effectively randomly assigned.

To test whether expense dates have a prominent role in explaining the patterns we observe, we exploit the mismatch between credit card due dates and benefit receipt. This test is necessarily run on the subsample of credit card holders, since an individual must hold a card to have a credit card due date. Within this subsample we focus on financial distress rather than card usage itself: once we condition on cardholders, the relevant question is no longer whether a household borrows but whether the calendar alignment of its obligations pushes it into delinquency. The variation we exploit comes from two sources working together: the random assignment of income timing across households, and the stickiness of credit card due dates from month to month. Because due dates barely move while benefit dates rotate across the calendar, the gap between the two shifts quasi-randomly, letting us ask whether being paid just before versus just after a due date affects distress. We augment our specification with 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, together with dummies for the calendar day of the month on which the card is due:

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

where DUE_{im} is the calendar day of the month on which the first credit card payment of individual i is due, MIS_{im} is positive when the benefit arrives after the due date and negative when it arrives before, 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 specification conditions on the NIS timing dummies $\{\gamma_d\}$, the paycycle dummies $\{\delta_k\}$, and the due-date day dummies $\{\lambda_j\}$. Conditional on a household's NIS group and on the calendar day its card is due, the variation that remains in MIS_{im} comes from the month-to-month rotation of benefit payment dates across the calendar: the same household, with the same due date, is paid closer to or farther from its obligation purely because of the payment schedule. The sequence of coefficients $\{\phi_s\}$ thus measures effects on financial distress, net of paycycle and persistent timing effects, comparing months in which a household is paid right after its credit card due date versus right before it. If individuals adjusted credit card due dates to track their income, the mismatch would carry no information and we would expect $\{\phi_s\}$ to be zero.

In Figure 12, we show that, net of paycycle effects, the relative position of credit card due dates and income significantly impacts delinquency on credit. Because the specification conditions on the NIS group and on the due-date day itself, the estimated $\{\phi_s\}$ are identified from the calendar rotation of benefit dates within NIS groups and should be read as the effect of calendar alignment between income and obligations on distress. The differences are larger for benefit dates exactly around credit card due dates

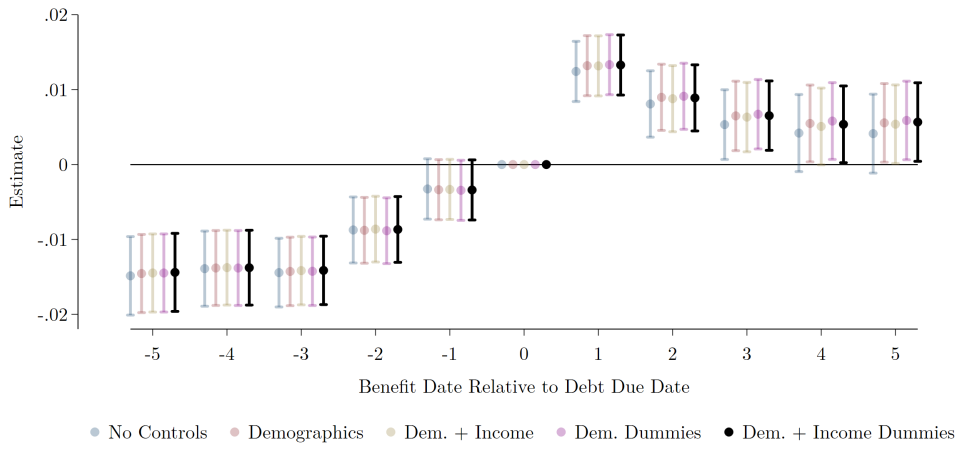
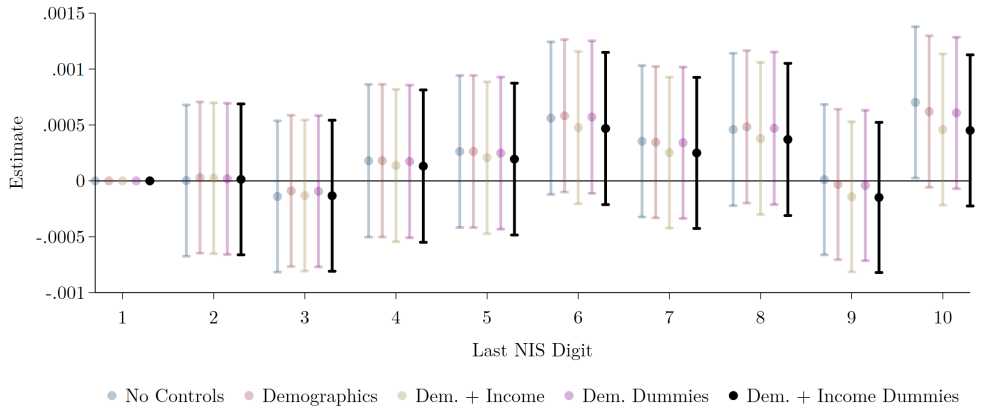


Figure 12: Mechanism: Expense Timing This figure shows coefficients on an indicator of 30-day delinquency on dummies for days between income receipt and credit card due dates. We progressively estimate Equation (4) with no controls, demographic controls, demographics and income, demographic non-parametric dummies, and demographic and income non-parametric dummies. All specifications contain municipality fixed effects as well as NIS-group, paycycle, and due-date day-of-month dummies. Robust standard errors are clustered by household. The plotted coefficients are reported in Appendix Table 5.

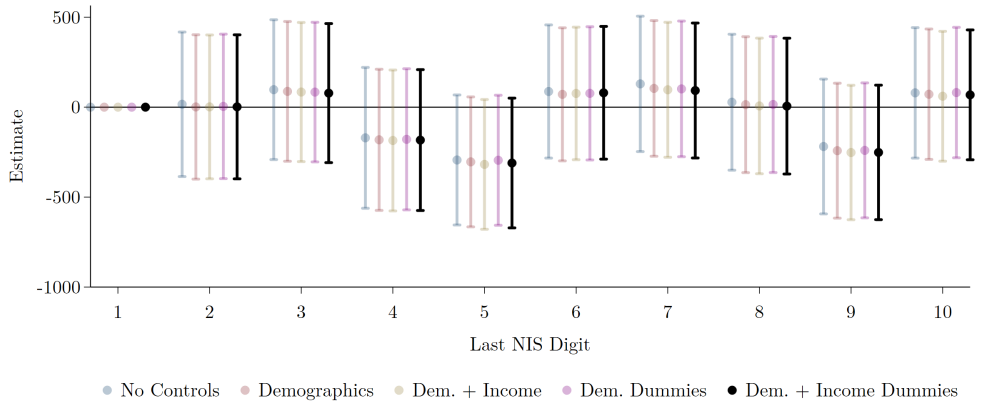
($s \in [-2, 1]$). We interpret this as evidence that households do not adjust their expense timing to their income, and that such sticky obligations matter for liquidity management under constraints. Because credit card due dates are among the most easily adjustable obligations a household faces, a delinquency jump around zero mismatch even here suggests that less flexible obligations, such as rent, are at least as sticky.

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



(a) Propensity to Carry Auto Loan Balance



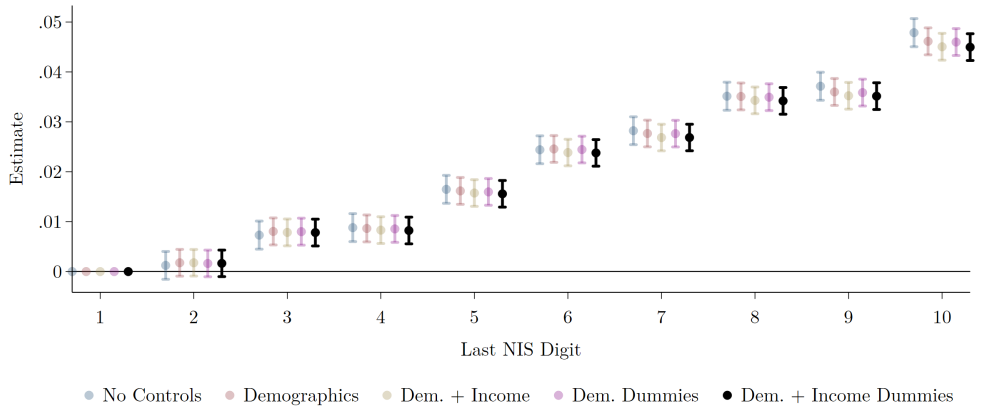
(b) Auto Loan Balance

Figure 13: Robustness: Auto Loans and Income Timing This figure shows extensive (in panel (a)) and intensive (in panel (b)) margin estimates of auto loan holdings by income timing (NIS last digit). 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 plotted coefficients are reported in Appendix Tables 6 and 7.

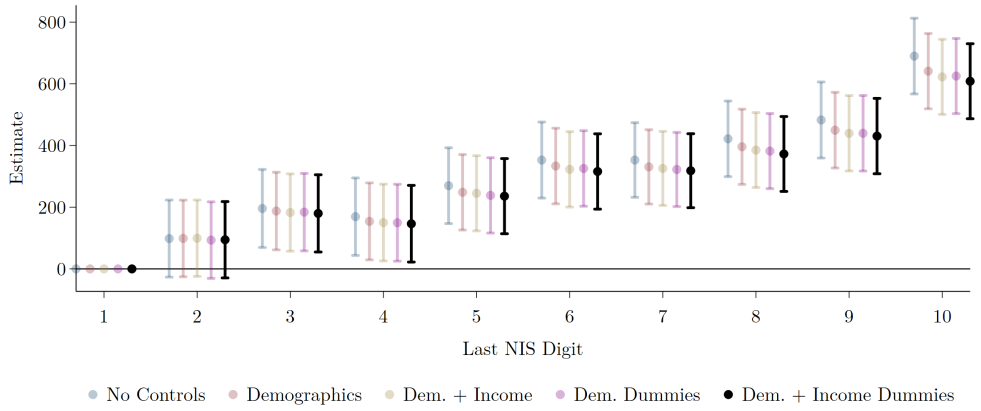
more immediate measures of financial distress.

8.1 Auto Loans as Placebo

In Figure 13, 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



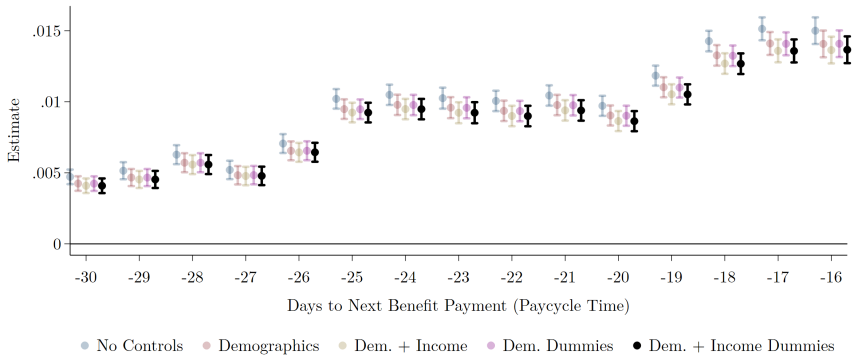
(a) Propensity to Carry a Credit Balance



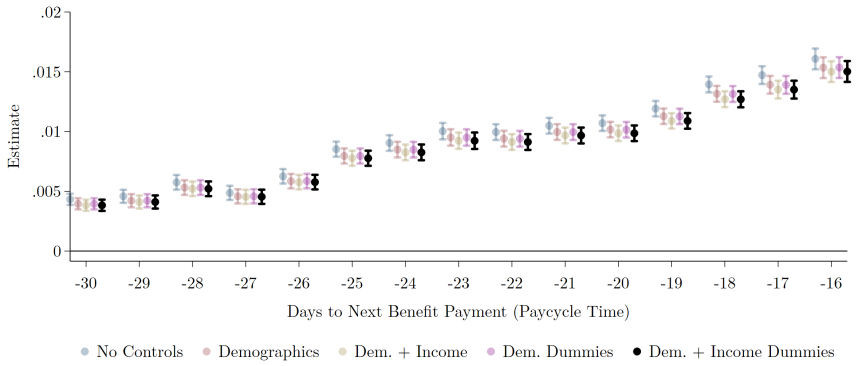
(b) Total Credit Balance

Figure 14: 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. The plotted coefficients are reported in Appendix Tables 8 and 9.

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 effect. The flat profiles 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) 30 Days Past Due



(b) Up to 89 Days Past Due

Figure 15: Robustness: Short-term Delinquency in the Paycycle This figure shows estimates for 30- (in panel (a)) and up to 89 days past due (in panel (b)) 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 plotted coefficients are reported in Appendix Tables 10 and 11.

8.2 No Substitution: Total Credit

In Figure 14, 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 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.

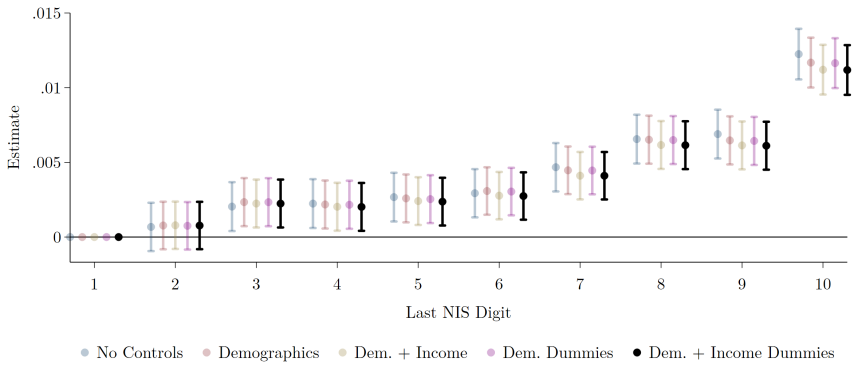
8.3 Short-Term Delinquency

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-day 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.

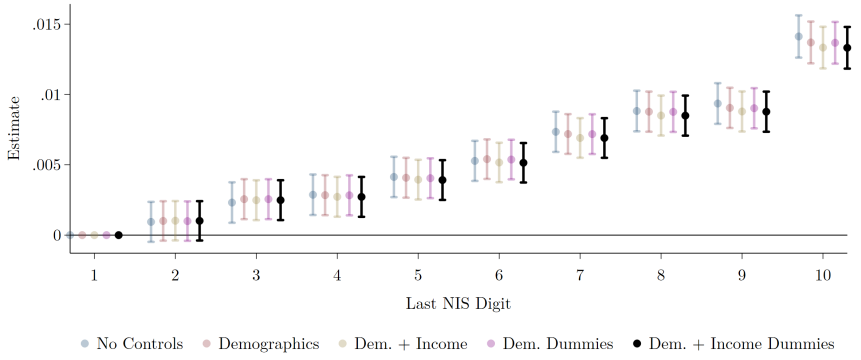
Figure 15 presents the estimated paycycle profiles for short-horizon delinquency. Both indicators display the same monotonic upward slope observed in our main results: as the time since the last benefit payment increases, delinquency rates rise steadily.

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 16. The findings are consistent with the remainder of the paper whereby consumers who are paid later in the calendar month encounter fixed calendar expenses earlier in their paycycle, which depletes their liquidity levels and makes them more vulnerable to unexpected shocks. The magnitudes are similar to those observed for default, and economically sizeable.



(a) 30 Days Past Due



(b) Up to 89 Days Past Due

Figure 16: Robustness: Short-term Delinquency and Income Timing This figure shows estimates for differences in 30- (in panel (a)) and up to 89 days past due (in panel (b)) 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. The plotted coefficients are reported in Appendix Tables 10 and 11.

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 liquidity constraints and fixed-date obligations. They 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.

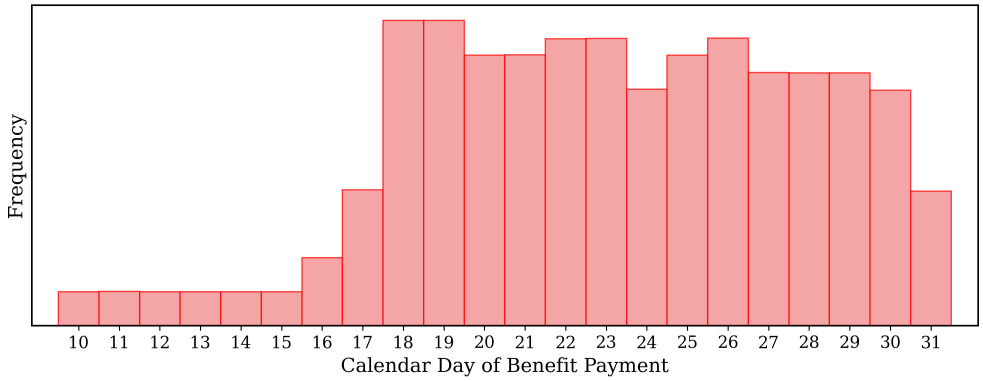
The evidence closely matches the model. Along the paycycle, the probability of revolving credit card debt and the conditional balance amount increase monotonically with time since last payment, and short-horizon delinquency rises in parallel. Across NIS groups, later-paid households are persistently 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.

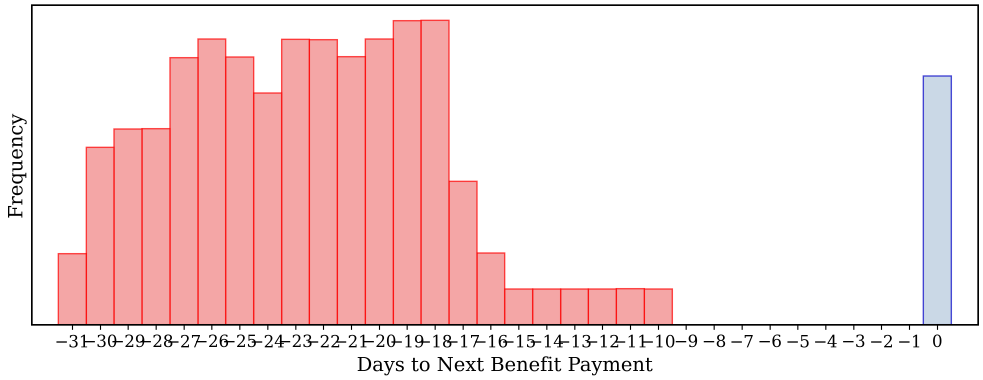
Intra-month timing is not a second-order detail for liquidity-constrained households. It shapes how identical income is transformed into liquidity, debt, and ultimately finan-

cial stability. Designing income calendars with this margin in mind can meaningfully improve household welfare in scalable, low-cost ways.

A Appendix Figures



(a) Distribution of Income Days (t_Y)



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

Appendix Figure 1: 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).

B Appendix Tables

Propensity to Carry a Credit Card Balance (p.p.)										
	(1) No Controls		(2) Demographics		(3) Dem.+Inc.		(4) Dem. Dum.		(5) Dem.+Inc. Dum.	
Panel A. Paycycle effects δ_k (days to next benefit payment)										
16	1.62***	(0.04)	1.43***	(0.04)	1.35***	(0.04)	1.43***	(0.04)	1.35***	(0.04)
17	2.18***	(0.03)	1.96***	(0.03)	1.86***	(0.03)	1.95***	(0.03)	1.86***	(0.03)
18	2.30***	(0.03)	2.10***	(0.03)	1.99***	(0.03)	2.09***	(0.03)	1.98***	(0.03)
19	1.76***	(0.03)	1.60***	(0.03)	1.50***	(0.03)	1.59***	(0.03)	1.50***	(0.03)
20	1.34***	(0.03)	1.20***	(0.03)	1.13***	(0.03)	1.20***	(0.03)	1.13***	(0.03)
21	1.45***	(0.03)	1.31***	(0.03)	1.24***	(0.03)	1.31***	(0.03)	1.24***	(0.03)
22	1.40***	(0.03)	1.25***	(0.03)	1.18***	(0.03)	1.24***	(0.03)	1.18***	(0.03)
23	1.27***	(0.03)	1.13***	(0.03)	1.06***	(0.03)	1.13***	(0.03)	1.06***	(0.03)
24	1.21***	(0.03)	1.06***	(0.03)	1.00***	(0.03)	1.05***	(0.03)	1.00***	(0.03)
25	1.21***	(0.03)	1.06***	(0.03)	1.01***	(0.03)	1.05***	(0.03)	1.01***	(0.03)
26	0.60***	(0.03)	0.48***	(0.03)	0.45***	(0.03)	0.48***	(0.03)	0.45***	(0.03)
27	0.30***	(0.03)	0.21***	(0.03)	0.20***	(0.03)	0.21***	(0.03)	0.20***	(0.03)
28	0.73***	(0.03)	0.60***	(0.03)	0.57***	(0.03)	0.60***	(0.03)	0.57***	(0.03)
29	0.54***	(0.02)	0.44***	(0.02)	0.41***	(0.02)	0.43***	(0.02)	0.41***	(0.02)
30	0.66***	(0.02)	0.56***	(0.02)	0.53***	(0.02)	0.55***	(0.02)	0.52***	(0.02)
Panel B. Timing effects γ_d (last NIS digit)										
2	−0.08	(0.11)	−0.04	(0.11)	−0.04	(0.11)	−0.05	(0.11)	−0.04	(0.11)
3	0.23**	(0.11)	0.28**	(0.11)	0.26**	(0.11)	0.28**	(0.11)	0.26**	(0.11)
4	0.34***	(0.11)	0.33***	(0.11)	0.30***	(0.11)	0.33***	(0.11)	0.30***	(0.11)
5	0.70***	(0.11)	0.68***	(0.11)	0.65***	(0.11)	0.67***	(0.11)	0.64***	(0.11)
6	0.90***	(0.11)	0.93***	(0.11)	0.87***	(0.11)	0.92***	(0.11)	0.87***	(0.11)
7	1.03***	(0.11)	1.00***	(0.11)	0.93***	(0.11)	1.00***	(0.11)	0.94***	(0.11)
8	1.44***	(0.12)	1.46***	(0.11)	1.39***	(0.11)	1.45***	(0.11)	1.39***	(0.11)
9	1.53***	(0.12)	1.46***	(0.11)	1.40***	(0.11)	1.45***	(0.11)	1.39***	(0.11)
10	1.98***	(0.12)	1.88***	(0.11)	1.78***	(0.11)	1.87***	(0.11)	1.78***	(0.11)
Munic. FE	Yes		Yes		Yes		Yes		Yes	
N	28,432,117		28,310,048		28,310,048		28,310,048		28,310,048	
R^2	0.038		0.081		0.090		0.083		0.091	

Appendix Table 1: Paycycle and Timing Effects: Propensity to Carry a Credit Card Balance. Estimates of Equation (3) for Propensity to Carry a Credit Card Balance. The paycycle (δ_k) and timing (γ_d) coefficients are jointly estimated in a single regression. Panels A and B report the two blocks of that one regression. Each column pair reports the coefficient and, in parentheses, the household-clustered standard error. Columns add progressively richer controls. All include municipality fixed effects. Panel A omits the payday category (zero days to next benefit payment). Panel B omits NIS group 1, and group 10 denotes last NIS digit 0 (latest paid). Only figure-window coefficients are shown. Coefficients and standard errors are in percentage points. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Credit Card Balance (R$)					
	(1) No Controls		(2) Demographics		(3) Dem.+Inc.	
	(4) Dem. Dum.		(5) Dem.+Inc. Dum.			
Panel A. Paycycle effects δ_k (days to next benefit payment)						
16	71.54***	(5.65)	62.42***	(5.65)	58.08***	(5.65)
	61.62***	(5.65)	57.57***	(5.65)		
17	42.66***	(4.59)	35.11***	(4.59)	31.98***	(4.60)
	34.12***	(4.59)	31.27***	(4.60)		
18	42.53***	(4.09)	36.11***	(4.10)	31.98***	(4.10)
	35.08***	(4.10)	31.25***	(4.10)		
19	34.54***	(3.97)	28.01***	(3.97)	24.86***	(3.97)
	27.13***	(3.97)	24.23***	(3.97)		
20	43.08***	(3.96)	37.05***	(3.96)	34.16***	(3.96)
	36.20***	(3.97)	33.55***	(3.96)		
21	41.99***	(4.03)	36.02***	(4.03)	33.15***	(4.03)
	35.22***	(4.04)	32.56***	(4.03)		
22	34.20***	(4.04)	28.30***	(4.04)	25.26***	(4.04)
	27.53***	(4.04)	24.70***	(4.04)		
23	26.23***	(4.19)	20.09***	(4.19)	17.99***	(4.18)
	19.47***	(4.19)	17.56***	(4.18)		
24	15.24***	(4.03)	9.00**	(4.03)	7.41*	(4.03)
	8.49**	(4.03)	7.06*	(4.03)		
25	14.39***	(3.97)	8.84**	(3.97)	7.31*	(3.97)
	8.45**	(3.97)	7.05*	(3.97)		
26	9.73**	(3.86)	4.15	(3.86)	3.35	(3.86)
	3.90	(3.86)	3.18	(3.86)		
27	11.72***	(3.84)	7.03*	(3.84)	6.38*	(3.83)
	6.87*	(3.84)	6.29	(3.83)		
28	9.42**	(3.92)	3.95	(3.92)	2.59	(3.92)
	3.59	(3.92)	2.34	(3.92)		
29	−4.09	(3.59)	−8.09**	(3.59)	−8.61**	(3.59)
	−8.27**	(3.59)	−8.72**	(3.59)		
30	−4.56	(2.96)	−7.29**	(2.96)	−7.94***	(2.96)
	−7.43**	(2.96)	−8.01***	(2.96)		
Panel B. Timing effects γ_d (last NIS digit)						
2	20.82	(13.37)	24.16*	(13.23)	24.36*	(13.17)
	23.45*	(13.22)	23.67*	(13.16)		
3	10.23	(13.17)	9.29	(13.01)	8.73	(12.94)
	8.63	(13.00)	8.14	(12.94)		
4	17.19	(13.37)	17.27	(13.22)	16.50	(13.16)
	16.79	(13.21)	16.10	(13.15)		
5	36.72***	(13.38)	34.87***	(13.22)	34.11***	(13.17)
	33.50**	(13.21)	32.86**	(13.16)		
6	44.29***	(13.27)	44.92***	(13.11)	41.87***	(13.05)
	43.67***	(13.09)	40.80***	(13.04)		
7	44.55***	(13.33)	44.86***	(13.18)	43.38***	(13.12)
	43.73***	(13.17)	42.47***	(13.11)		
8	70.31***	(13.42)	70.60***	(13.25)	67.82***	(13.19)
	68.94***	(13.24)	66.40***	(13.18)		
9	59.20***	(13.17)	57.29***	(13.01)	55.36***	(12.94)
	56.11***	(13.00)	54.31***	(12.94)		
10	80.86***	(13.58)	76.40***	(13.43)	70.52***	(13.37)
	74.26***	(13.42)	68.74***	(13.36)		
Munic. FE	Yes		Yes		Yes	
	Yes		Yes			
N	4,038,257		4,025,116		4,025,116	
	4,025,116		4,025,116			
R^2	0.018		0.038		0.046	
	0.039		0.046			

Appendix Table 2: Paycycle and Timing Effects: Credit Card Balance (R$). Estimates of Equation (3) for Credit Card Balance (R$). The paycycle ($\delta_k$) and timing ($\gamma_d$) coefficients are jointly estimated in a single regression. Panels A and B report the two blocks of that one regression. Each column pair reports the coefficient and, in parentheses, the household-clustered standard error. Columns add progressively richer controls. All include municipality fixed effects. Panel A omits the payday category (zero days to next benefit payment). Panel B omits NIS group 1, and group 10 denotes last NIS digit 0 (latest paid). Only figure-window coefficients are shown. Coefficients and standard errors are in reais (R$). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Propensity to Default (90+ Days Past Due) (p.p.)										
	(1) No Controls		(2) Demographics		(3) Dem.+Inc.		(4) Dem. Dum.		(5) Dem.+Inc. Dum.	
Panel A. Paycycle effects δ_k (days to next benefit payment)										
16	1.17***	(0.04)	1.12***	(0.04)	1.11***	(0.04)	1.13***	(0.04)	1.11***	(0.04)
17	0.98***	(0.03)	0.93***	(0.03)	0.91***	(0.03)	0.93***	(0.03)	0.91***	(0.03)
18	0.93***	(0.03)	0.88***	(0.03)	0.86***	(0.03)	0.88***	(0.03)	0.86***	(0.03)
19	0.85***	(0.03)	0.81***	(0.03)	0.79***	(0.03)	0.81***	(0.03)	0.79***	(0.03)
20	0.79***	(0.03)	0.75***	(0.03)	0.74***	(0.03)	0.75***	(0.03)	0.74***	(0.03)
21	0.77***	(0.03)	0.74***	(0.03)	0.72***	(0.03)	0.74***	(0.03)	0.72***	(0.03)
22	0.68***	(0.03)	0.65***	(0.03)	0.63***	(0.03)	0.65***	(0.03)	0.63***	(0.03)
23	0.70***	(0.03)	0.67***	(0.03)	0.65***	(0.03)	0.67***	(0.03)	0.65***	(0.03)
24	0.57***	(0.03)	0.54***	(0.03)	0.53***	(0.03)	0.54***	(0.03)	0.53***	(0.03)
25	0.47***	(0.03)	0.44***	(0.03)	0.43***	(0.03)	0.44***	(0.03)	0.43***	(0.03)
26	0.36***	(0.03)	0.34***	(0.03)	0.33***	(0.03)	0.34***	(0.03)	0.33***	(0.03)
27	0.31***	(0.02)	0.30***	(0.02)	0.29***	(0.02)	0.30***	(0.02)	0.29***	(0.02)
28	0.34***	(0.03)	0.32***	(0.03)	0.31***	(0.03)	0.32***	(0.03)	0.31***	(0.03)
29	0.25***	(0.02)	0.22***	(0.02)	0.22***	(0.02)	0.22***	(0.02)	0.22***	(0.02)
30	0.22***	(0.02)	0.20***	(0.02)	0.19***	(0.02)	0.20***	(0.02)	0.19***	(0.02)
Panel B. Timing effects γ_d (last NIS digit)										
2	0.05	(0.06)	0.06	(0.06)	0.06	(0.06)	0.06	(0.06)	0.06	(0.06)
3	0.14**	(0.06)	0.15***	(0.06)	0.15***	(0.06)	0.15***	(0.06)	0.15***	(0.06)
4	0.18***	(0.06)	0.18***	(0.06)	0.17***	(0.06)	0.18***	(0.06)	0.17***	(0.06)
5	0.29***	(0.06)	0.28***	(0.06)	0.28***	(0.06)	0.28***	(0.06)	0.28***	(0.06)
6	0.39***	(0.06)	0.40***	(0.06)	0.39***	(0.06)	0.40***	(0.06)	0.38***	(0.06)
7	0.51***	(0.06)	0.50***	(0.06)	0.48***	(0.06)	0.50***	(0.06)	0.48***	(0.06)
8	0.61***	(0.06)	0.60***	(0.06)	0.58***	(0.06)	0.60***	(0.06)	0.58***	(0.06)
9	0.63***	(0.06)	0.61***	(0.06)	0.60***	(0.06)	0.61***	(0.06)	0.60***	(0.06)
10	0.87***	(0.06)	0.85***	(0.06)	0.83***	(0.06)	0.85***	(0.06)	0.83***	(0.06)
Munic. FE	Yes		Yes		Yes		Yes		Yes	
N	28,432,117		28,310,048		28,310,048		28,310,048		28,310,048	
R^2	0.009		0.018		0.019		0.018		0.019	

Appendix Table 3: Paycycle and Timing Effects: Propensity to Default (90+ Days Past Due). Estimates of Equation (3) for Propensity to Default (90+ Days Past Due). The paycycle (δ_k) and timing (γ_d) coefficients are jointly estimated in a single regression. Panels A and B report the two blocks of that one regression. Each column pair reports the coefficient and, in parentheses, the household-clustered standard error. Columns add progressively richer controls. All include municipality fixed effects. Panel A omits the payday category (zero days to next benefit payment). Panel B omits NIS group 1, and group 10 denotes last NIS digit 0 (latest paid). Only figure-window coefficients are shown. Coefficients and standard errors are in percentage points. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Propensity to Have an Overdraft Line (p.p.)										
	(1) No Controls		(2) Demographics		(3) Dem.+Inc.		(4) Dem. Dum.		(5) Dem.+Inc. Dum.	
Panel A. Paycycle effects δ_k (days to next benefit payment)										
16	0.32***	(0.02)	0.29***	(0.02)	0.27***	(0.02)	0.29***	(0.02)	0.27***	(0.02)
17	0.38***	(0.02)	0.34***	(0.02)	0.31***	(0.02)	0.34***	(0.02)	0.31***	(0.02)
18	0.36***	(0.01)	0.33***	(0.01)	0.29***	(0.01)	0.32***	(0.01)	0.29***	(0.01)
19	0.32***	(0.01)	0.29***	(0.01)	0.26***	(0.01)	0.29***	(0.01)	0.26***	(0.01)
20	0.23***	(0.01)	0.20***	(0.01)	0.18***	(0.01)	0.20***	(0.01)	0.18***	(0.01)
21	0.24***	(0.01)	0.22***	(0.01)	0.20***	(0.01)	0.22***	(0.01)	0.20***	(0.01)
22	0.23***	(0.01)	0.21***	(0.01)	0.19***	(0.01)	0.21***	(0.01)	0.19***	(0.01)
23	0.24***	(0.01)	0.22***	(0.01)	0.19***	(0.01)	0.22***	(0.01)	0.19***	(0.01)
24	0.24***	(0.01)	0.21***	(0.01)	0.19***	(0.01)	0.21***	(0.01)	0.19***	(0.01)
25	0.25***	(0.01)	0.23***	(0.01)	0.21***	(0.01)	0.23***	(0.01)	0.21***	(0.01)
26	0.20***	(0.01)	0.18***	(0.01)	0.17***	(0.01)	0.18***	(0.01)	0.17***	(0.01)
27	0.13***	(0.01)	0.12***	(0.01)	0.12***	(0.01)	0.12***	(0.01)	0.12***	(0.01)
28	0.14***	(0.01)	0.12***	(0.01)	0.11***	(0.01)	0.12***	(0.01)	0.11***	(0.01)
29	0.10***	(0.01)	0.08***	(0.01)	0.07***	(0.01)	0.08***	(0.01)	0.07***	(0.01)
30	0.09***	(0.01)	0.08***	(0.01)	0.06***	(0.01)	0.08***	(0.01)	0.06***	(0.01)
Panel B. Timing effects γ_d (last NIS digit)										
2	−0.04	(0.04)	−0.04	(0.04)	−0.03	(0.04)	−0.04	(0.04)	−0.04	(0.04)
3	0.04	(0.04)	0.05	(0.04)	0.05	(0.04)	0.05	(0.04)	0.05	(0.04)
4	0.04	(0.04)	0.04	(0.04)	0.03	(0.04)	0.04	(0.04)	0.03	(0.04)
5	0.09**	(0.04)	0.09**	(0.04)	0.08*	(0.04)	0.09**	(0.04)	0.08*	(0.04)
6	0.09**	(0.04)	0.10**	(0.04)	0.08*	(0.04)	0.10**	(0.04)	0.08*	(0.04)
7	0.00	(0.04)	−0.00	(0.04)	−0.02	(0.04)	−0.01	(0.04)	−0.02	(0.04)
8	0.09**	(0.04)	0.09**	(0.04)	0.07	(0.04)	0.08**	(0.04)	0.07	(0.04)
9	0.08*	(0.04)	0.06	(0.04)	0.05	(0.04)	0.06	(0.04)	0.05	(0.04)
10	0.07	(0.04)	0.05	(0.04)	0.03	(0.04)	0.05	(0.04)	0.03	(0.04)
Munic. FE	Yes		Yes		Yes		Yes		Yes	
N	28,432,117		28,310,048		28,310,048		28,310,048		28,310,048	
R^2	0.005		0.014		0.019		0.014		0.019	

Appendix Table 4: Paycycle and Timing Effects: Propensity to Have an Overdraft Line. Estimates of Equation (3) for Propensity to Have an Overdraft Line. The paycycle (δ_k) and timing (γ_d) coefficients are jointly estimated in a single regression. Panels A and B report the two blocks of that one regression. Each column pair reports the coefficient and, in parentheses, the household-clustered standard error. Columns add progressively richer controls. All include municipality fixed effects. Panel A omits the payday category (zero days to next benefit payment). Panel B omits NIS group 1, and group 10 denotes last NIS digit 0 (latest paid). Only figure-window coefficients are shown. Coefficients and standard errors are in percentage points. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	30-Day Delinquency (p.p.)				
	(1) No Controls	(2) Demographics	(3) Dem.+Inc.	(4) Dem. Dum.	(5) Dem.+Inc. Dum.
Mismatch effects ϕ_s (benefit date relative to credit card due date)					
-5	−1.49*** (0.27)	−1.46*** (0.27)	−1.45*** (0.27)	−1.45*** (0.27)	−1.44*** (0.27)
-4	−1.39*** (0.26)	−1.38*** (0.26)	−1.38*** (0.26)	−1.38*** (0.26)	−1.38*** (0.25)
-3	−1.44*** (0.23)	−1.43*** (0.23)	−1.42*** (0.23)	−1.42*** (0.23)	−1.41*** (0.23)
-2	−0.87*** (0.22)	−0.88*** (0.22)	−0.86*** (0.22)	−0.88*** (0.22)	−0.87*** (0.22)
-1	−0.33 (0.21)	−0.34 (0.21)	−0.33 (0.20)	−0.34* (0.20)	−0.34* (0.20)
1	1.24*** (0.21)	1.32*** (0.20)	1.32*** (0.20)	1.33*** (0.20)	1.33*** (0.20)
2	0.81*** (0.23)	0.90*** (0.23)	0.88*** (0.23)	0.91*** (0.23)	0.89*** (0.23)
3	0.53** (0.24)	0.65*** (0.24)	0.63*** (0.24)	0.67*** (0.24)	0.65*** (0.24)
4	0.42 (0.26)	0.55** (0.26)	0.51* (0.26)	0.58** (0.26)	0.54** (0.26)
5	0.41 (0.27)	0.56** (0.27)	0.54** (0.27)	0.59** (0.27)	0.57** (0.27)
Munic. FE	Yes	Yes	Yes	Yes	Yes
NIS-group dummies	Yes	Yes	Yes	Yes	Yes
Paycycle dummies	Yes	Yes	Yes	Yes	Yes
Due-date dummies	Yes	Yes	Yes	Yes	Yes
N	2,506,842	2,499,065	2,499,065	2,499,065	2,499,065
R^2	0.032	0.040	0.041	0.040	0.042

Appendix Table 5: Mechanism: Mismatch and 30-Day Delinquency. Estimates of Equation (4) for 30-day delinquency on the subsample of credit card holders. ϕ_s is the coefficient on the number of days between benefit receipt and the first credit card due date (MIS $>$ 0: benefit arrives after the due date). The omitted category is exact alignment (MIS $= 0$). Every column additionally conditions on NIS-group (γ_d), paycycle (δ_k), and due-date day-of-month (λ_j) dummies and municipality fixed effects, and adds progressively richer demographic and income controls. Each column pair reports the coefficient and the household-clustered standard error in parentheses. Only figure-window coefficients ($s \in [-5, 5]$) are shown. Coefficients and standard errors are in percentage points. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Propensity to Carry an Auto Loan Balance (p.p.)										
	(1) No Controls		(2) Demographics		(3) Dem.+Inc.		(4) Dem. Dum.		(5) Dem.+Inc. Dum.	
Panel A. Paycycle effects δ_k (days to next benefit payment)										
16	0.09***	(0.01)	0.07***	(0.01)	0.06***	(0.01)	0.07***	(0.01)	0.06***	(0.01)
17	0.06***	(0.01)	0.04***	(0.01)	0.03***	(0.01)	0.04***	(0.01)	0.03***	(0.01)
18	0.05***	(0.01)	0.04***	(0.01)	0.02***	(0.01)	0.03***	(0.01)	0.02**	(0.01)
19	0.05***	(0.01)	0.04***	(0.01)	0.03***	(0.01)	0.04***	(0.01)	0.02***	(0.01)
20	0.05***	(0.01)	0.04***	(0.01)	0.03***	(0.01)	0.04***	(0.01)	0.03***	(0.01)
21	0.05***	(0.01)	0.04***	(0.01)	0.03***	(0.01)	0.04***	(0.01)	0.03***	(0.01)
22	0.04***	(0.01)	0.03***	(0.01)	0.02**	(0.01)	0.03***	(0.01)	0.02**	(0.01)
23	0.04***	(0.01)	0.02***	(0.01)	0.01*	(0.01)	0.02***	(0.01)	0.01*	(0.01)
24	0.03***	(0.01)	0.02**	(0.01)	0.01	(0.01)	0.02**	(0.01)	0.01	(0.01)
25	0.03***	(0.01)	0.01	(0.01)	0.00	(0.01)	0.01	(0.01)	0.00	(0.01)
26	0.03***	(0.01)	0.02**	(0.01)	0.01*	(0.01)	0.02**	(0.01)	0.01*	(0.01)
27	0.03***	(0.01)	0.02**	(0.01)	0.01**	(0.01)	0.02**	(0.01)	0.01**	(0.01)
28	0.03***	(0.01)	0.01*	(0.01)	0.01	(0.01)	0.01*	(0.01)	0.01	(0.01)
29	0.02***	(0.01)	0.01	(0.01)	0.00	(0.01)	0.01	(0.01)	0.00	(0.01)
30	0.01*	(0.00)	−0.00	(0.00)	−0.01	(0.00)	−0.00	(0.00)	−0.01	(0.00)
Panel B. Timing effects γ_d (last NIS digit)										
2	0.00	(0.03)	0.00	(0.03)	0.00	(0.03)	0.00	(0.03)	0.00	(0.03)
3	−0.01	(0.03)	−0.01	(0.03)	−0.01	(0.03)	−0.01	(0.03)	−0.01	(0.03)
4	0.02	(0.03)	0.02	(0.03)	0.01	(0.03)	0.02	(0.03)	0.01	(0.03)
5	0.03	(0.03)	0.03	(0.03)	0.02	(0.03)	0.02	(0.03)	0.02	(0.03)
6	0.06	(0.03)	0.06*	(0.03)	0.05	(0.03)	0.06	(0.03)	0.05	(0.03)
7	0.04	(0.03)	0.03	(0.03)	0.03	(0.03)	0.03	(0.03)	0.03	(0.03)
8	0.05	(0.03)	0.05	(0.03)	0.04	(0.03)	0.05	(0.03)	0.04	(0.03)
9	0.00	(0.03)	−0.00	(0.03)	−0.01	(0.03)	−0.00	(0.03)	−0.01	(0.03)
10	0.07**	(0.03)	0.06*	(0.03)	0.05	(0.03)	0.06*	(0.03)	0.05	(0.03)
Munic. FE	Yes		Yes		Yes		Yes		Yes	
N	28,432,117		28,310,048		28,310,048		28,310,048		28,310,048	
R^2	0.003		0.008		0.011		0.008		0.011	

Appendix Table 6: Paycycle and Timing Effects: Propensity to Carry an Auto Loan Balance. Estimates of Equation (3) for Propensity to Carry an Auto Loan Balance. The paycycle (δ_k) and timing (γ_d) coefficients are jointly estimated in a single regression. Panels A and B report the two blocks of that one regression. Each column pair reports the coefficient and, in parentheses, the household-clustered standard error. Columns add progressively richer controls. All include municipality fixed effects. Panel A omits the payday category (zero days to next benefit payment). Panel B omits NIS group 1, and group 10 denotes last NIS digit 0 (latest paid). Only figure-window coefficients are shown. Coefficients and standard errors are in percentage points. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Auto Loan Balance (R$)									
	(1) No Controls		(2) Demographics		(3) Dem.+Inc.		(4) Dem. Dum.		(5) Dem.+Inc. Dum.	
Panel A. Paycycle effects δ_k (days to next benefit payment)										
16	455.02***	(73.91)	454.50***	(74.06)	446.38***	(74.15)	455.13***	(74.07)	447.54***	(74.14)
17	63.07	(59.43)	66.87	(59.60)	63.22	(59.69)	69.72	(59.57)	65.75	(59.65)
18	28.09	(49.41)	30.02	(49.59)	25.53	(49.70)	30.57	(49.60)	26.30	(49.69)
19	166.93***	(47.69)	168.04***	(47.78)	161.47***	(47.93)	169.14***	(47.78)	163.01***	(47.93)
20	250.71***	(48.25)	250.00***	(48.34)	245.41***	(48.48)	251.47***	(48.34)	246.98***	(48.47)
21	199.58***	(48.48)	199.60***	(48.60)	195.72***	(48.78)	200.38***	(48.61)	196.53***	(48.78)
22	166.52***	(50.37)	167.69***	(50.48)	162.99***	(50.61)	166.91***	(50.52)	162.61***	(50.63)
23	234.85***	(54.36)	232.95***	(54.46)	226.43***	(54.61)	232.13***	(54.50)	226.16***	(54.63)
24	123.36***	(47.78)	122.40**	(47.84)	119.20**	(48.01)	123.17**	(47.85)	120.20**	(48.01)
25	22.30	(47.24)	23.52	(47.35)	23.21	(47.41)	25.29	(47.35)	25.07	(47.40)
26	134.84***	(45.91)	134.23***	(46.01)	134.32***	(46.03)	135.21***	(46.03)	135.49***	(46.04)
27	185.14***	(46.53)	185.22***	(46.60)	187.66***	(46.66)	184.24***	(46.58)	187.13***	(46.64)
28	113.80**	(47.55)	115.79**	(47.63)	118.33**	(47.65)	115.24**	(47.63)	118.09**	(47.64)
29	−14.60	(39.45)	−10.87	(39.47)	−8.43	(39.45)	−11.32	(39.47)	−8.53	(39.45)
30	−65.92**	(31.53)	−66.87**	(31.57)	−64.18**	(31.61)	−66.31**	(31.54)	−63.45**	(31.58)
Panel B. Timing effects γ_d (last NIS digit)										
2	16.00	(204.93)	1.27	(204.70)	1.60	(203.96)	4.29	(204.94)	1.82	(204.19)
3	97.24	(198.29)	87.83	(198.15)	84.08	(197.31)	83.82	(197.98)	78.12	(197.12)
4	−170.53	(199.72)	−181.47	(200.15)	−185.12	(199.76)	−178.73	(200.13)	−182.92	(199.74)
5	−293.51	(184.37)	−304.05*	(184.28)	−318.06*	(183.94)	−295.02	(184.37)	−310.42*	(184.00)
6	87.13	(188.81)	71.27	(188.67)	76.31	(187.95)	76.80	(188.90)	79.87	(188.16)
7	129.38	(192.02)	104.31	(192.41)	96.58	(191.41)	101.55	(192.36)	92.50	(191.35)
8	27.49	(192.75)	13.94	(192.75)	6.87	(192.29)	14.76	(193.00)	5.77	(192.55)
9	−218.62	(191.15)	−241.79	(191.35)	−251.99	(190.67)	−240.24	(191.39)	−251.62	(190.70)
10	79.59	(185.00)	72.02	(184.93)	60.69	(184.15)	81.15	(184.93)	68.37	(184.13)
Munic. FE	Yes		Yes		Yes		Yes		Yes	
N	282,742		282,069		282,069		282,069		282,069	
R^2	0.077		0.078		0.083		0.078		0.083	

Appendix Table 7: Paycycle and Timing Effects: Auto Loan Balance (R$). Estimates of Equation (3) for Auto Loan Balance (R$). The paycycle ($\delta_k$) and timing ($\gamma_d$) coefficients are jointly estimated in a single regression. Panels A and B report the two blocks of that one regression. Each column pair reports the coefficient and, in parentheses, the household-clustered standard error. Columns add progressively richer controls. All include municipality fixed effects. Panel A omits the payday category (zero days to next benefit payment). Panel B omits NIS group 1, and group 10 denotes last NIS digit 0 (latest paid). Only figure-window coefficients are shown. Coefficients and standard errors are in reais (R$). $^{*}\,p < 0.10$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Propensity to Carry a Credit Balance (Total Credit) (p.p.)										
	(1) No Controls		(2) Demographics		(3) Dem.+Inc.		(4) Dem. Dum.		(5) Dem.+Inc. Dum.	
Panel A. Paycycle effects δ_k (days to next benefit payment)										
16	5.73***	(0.06)	5.45***	(0.06)	5.35***	(0.06)	5.46***	(0.06)	5.36***	(0.06)
17	5.48***	(0.05)	5.15***	(0.05)	5.03***	(0.05)	5.13***	(0.05)	5.02***	(0.05)
18	5.41***	(0.04)	5.10***	(0.04)	4.97***	(0.04)	5.08***	(0.04)	4.96***	(0.04)
19	4.73***	(0.04)	4.48***	(0.04)	4.37***	(0.04)	4.47***	(0.04)	4.36***	(0.04)
20	4.17***	(0.04)	3.96***	(0.04)	3.87***	(0.04)	3.95***	(0.04)	3.87***	(0.04)
21	4.05***	(0.04)	3.84***	(0.04)	3.76***	(0.04)	3.84***	(0.04)	3.75***	(0.04)
22	3.81***	(0.04)	3.59***	(0.04)	3.51***	(0.04)	3.58***	(0.04)	3.50***	(0.04)
23	3.66***	(0.04)	3.45***	(0.04)	3.37***	(0.04)	3.44***	(0.04)	3.36***	(0.04)
24	3.07***	(0.04)	2.85***	(0.04)	2.78***	(0.04)	2.84***	(0.04)	2.78***	(0.04)
25	2.63***	(0.04)	2.39***	(0.04)	2.34***	(0.04)	2.39***	(0.04)	2.33***	(0.04)
26	1.76***	(0.04)	1.60***	(0.04)	1.57***	(0.04)	1.60***	(0.04)	1.57***	(0.04)
27	1.28***	(0.04)	1.16***	(0.04)	1.15***	(0.04)	1.17***	(0.04)	1.15***	(0.04)
28	1.65***	(0.04)	1.47***	(0.04)	1.44***	(0.04)	1.47***	(0.04)	1.43***	(0.04)
29	1.31***	(0.03)	1.16***	(0.03)	1.13***	(0.03)	1.16***	(0.03)	1.13***	(0.03)
30	1.16***	(0.03)	1.00***	(0.03)	0.97***	(0.03)	1.00***	(0.03)	0.96***	(0.03)
Panel B. Timing effects γ_d (last NIS digit)										
2	0.12	(0.14)	0.18	(0.14)	0.18	(0.14)	0.16	(0.14)	0.16	(0.14)
3	0.73***	(0.14)	0.80***	(0.14)	0.78***	(0.14)	0.80***	(0.14)	0.78***	(0.14)
4	0.88***	(0.14)	0.86***	(0.14)	0.83***	(0.14)	0.85***	(0.14)	0.82***	(0.14)
5	1.65***	(0.14)	1.62***	(0.14)	1.57***	(0.14)	1.60***	(0.14)	1.56***	(0.14)
6	2.44***	(0.14)	2.46***	(0.14)	2.39***	(0.14)	2.45***	(0.14)	2.38***	(0.14)
7	2.82***	(0.14)	2.77***	(0.14)	2.69***	(0.14)	2.76***	(0.14)	2.69***	(0.14)
8	3.51***	(0.14)	3.51***	(0.14)	3.43***	(0.14)	3.49***	(0.14)	3.42***	(0.14)
9	3.71***	(0.14)	3.60***	(0.14)	3.52***	(0.14)	3.59***	(0.14)	3.52***	(0.14)
10	4.79***	(0.14)	4.61***	(0.14)	4.50***	(0.14)	4.60***	(0.14)	4.50***	(0.14)
Munic. FE	Yes		Yes		Yes		Yes		Yes	
N	28,432,117		28,310,048		28,310,048		28,310,048		28,310,048	
R^2	0.020		0.079		0.087		0.083		0.090	

Appendix Table 8: Paycycle and Timing Effects: Propensity to Carry a Credit Balance (Total Credit). Estimates of Equation (3) for Propensity to Carry a Credit Balance (Total Credit). The paycycle (δ_k) and timing (γ_d) coefficients are jointly estimated in a single regression. Panels A and B report the two blocks of that one regression. Each column pair reports the coefficient and, in parentheses, the household-clustered standard error. Columns add progressively richer controls. All include municipality fixed effects. Panel A omits the payday category (zero days to next benefit payment). Panel B omits NIS group 1, and group 10 denotes last NIS digit 0 (latest paid). Only figure-window coefficients are shown. Coefficients and standard errors are in percentage points. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Total Credit Balance (R$)				
	(1) No Controls	(2) Demographics	(3) Dem.+Inc.	(4) Dem. Dum.	(5) Dem.+Inc. Dum.
Panel A. Paycycle effects δ_k (days to next benefit payment)					
16	806.68*** (17.27)	748.49*** (17.25)	740.23*** (17.27)	737.89*** (17.26)	730.70*** (17.27)
17	508.55*** (13.84)	454.58*** (13.84)	447.67*** (13.86)	441.73*** (13.85)	436.10*** (13.87)
18	461.74*** (12.36)	411.74*** (12.37)	401.17*** (12.39)	399.15*** (12.38)	390.03*** (12.40)
19	486.36*** (11.96)	441.49*** (11.94)	435.15*** (11.96)	430.83*** (11.95)	425.62*** (11.96)
20	507.85*** (12.12)	465.71*** (12.09)	460.07*** (12.11)	455.81*** (12.10)	451.14*** (12.11)
21	446.16*** (12.08)	406.22*** (12.04)	400.06*** (12.05)	397.15*** (12.05)	391.94*** (12.06)
22	392.19*** (12.16)	353.75*** (12.12)	347.10*** (12.13)	345.33*** (12.12)	339.58*** (12.13)
23	406.73*** (13.16)	367.18*** (13.10)	364.08*** (13.10)	359.39*** (13.09)	357.12*** (13.10)
24	282.94*** (11.74)	245.72*** (11.70)	243.53*** (11.70)	239.27*** (11.69)	237.76*** (11.70)
25	188.39*** (11.22)	155.83*** (11.17)	151.46*** (11.18)	150.86*** (11.17)	147.08*** (11.18)
26	194.69*** (10.66)	168.76*** (10.61)	167.48*** (10.61)	166.13*** (10.60)	165.09*** (10.60)
27	209.22*** (10.38)	187.23*** (10.32)	187.19*** (10.32)	185.44*** (10.32)	185.55*** (10.32)
28	162.41*** (10.60)	135.28*** (10.55)	131.86*** (10.55)	131.63*** (10.55)	128.68*** (10.55)
29	95.47*** (9.23)	75.16*** (9.18)	75.07*** (9.19)	73.25*** (9.18)	73.40*** (9.19)
30	43.60*** (7.43)	26.42*** (7.40)	24.88*** (7.40)	24.15*** (7.39)	22.90*** (7.40)
Panel B. Timing effects γ_d (last NIS digit)					
2	98.31 (63.73)	98.71 (63.41)	99.44 (63.19)	93.35 (63.32)	94.46 (63.12)
3	195.90*** (64.57)	187.54*** (64.20)	182.80*** (63.94)	184.02*** (64.12)	179.90*** (63.87)
4	169.34*** (64.11)	154.05** (63.71)	150.18** (63.50)	149.69** (63.62)	146.36** (63.41)
5	269.78*** (62.71)	248.40*** (62.41)	245.09*** (62.21)	238.41*** (62.33)	235.77*** (62.13)
6	352.90*** (62.91)	333.52*** (62.56)	322.75*** (62.36)	325.58*** (62.47)	315.79*** (62.27)
7	353.02*** (61.76)	330.69*** (61.48)	325.68*** (61.27)	322.28*** (61.39)	318.31*** (61.19)
8	421.75*** (62.56)	395.97*** (62.22)	385.28*** (62.00)	381.96*** (62.14)	372.52*** (61.93)
9	482.71*** (62.93)	449.70*** (62.61)	439.69*** (62.41)	439.68*** (62.52)	430.61*** (62.33)
10	689.89*** (62.66)	641.10*** (62.31)	622.53*** (62.11)	625.22*** (62.23)	608.39*** (62.04)
Munic. FE	Yes	Yes	Yes	Yes	Yes
N	7,090,588	7,067,677	7,067,677	7,067,677	7,067,677
R^2	0.046	0.060	0.066	0.062	0.068

Appendix Table 9: Paycycle and Timing Effects: Total Credit Balance (R$). Estimates of Equation (3) for Total Credit Balance (R$). The paycycle ($\delta_k$) and timing ($\gamma_d$) coefficients are jointly estimated in a single regression. Panels A and B report the two blocks of that one regression. Each column pair reports the coefficient and, in parentheses, the household-clustered standard error. Columns add progressively richer controls. All include municipality fixed effects. Panel A omits the payday category (zero days to next benefit payment). Panel B omits NIS group 1, and group 10 denotes last NIS digit 0 (latest paid). Only figure-window coefficients are shown. Coefficients and standard errors are in reais (R$). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	30 Days Past Due (p.p.)									
	(1) No Controls		(2) Demographics		(3) Dem.+Inc.		(4) Dem. Dum.		(5) Dem.+Inc. Dum.	
Panel A. Paycycle effects δ_k (days to next benefit payment)										
16	1.50***	(0.05)	1.41***	(0.05)	1.36***	(0.05)	1.41***	(0.05)	1.37***	(0.05)
17	1.51***	(0.04)	1.41***	(0.04)	1.36***	(0.04)	1.41***	(0.04)	1.36***	(0.04)
18	1.43***	(0.04)	1.33***	(0.04)	1.27***	(0.04)	1.32***	(0.04)	1.27***	(0.04)
19	1.18***	(0.04)	1.10***	(0.04)	1.05***	(0.04)	1.10***	(0.04)	1.05***	(0.04)
20	0.97***	(0.04)	0.90***	(0.04)	0.86***	(0.04)	0.90***	(0.04)	0.86***	(0.04)
21	1.04***	(0.04)	0.98***	(0.04)	0.94***	(0.04)	0.98***	(0.04)	0.94***	(0.04)
22	1.01***	(0.04)	0.94***	(0.04)	0.90***	(0.04)	0.94***	(0.04)	0.90***	(0.04)
23	1.03***	(0.04)	0.96***	(0.04)	0.92***	(0.04)	0.96***	(0.04)	0.92***	(0.04)
24	1.05***	(0.04)	0.98***	(0.04)	0.95***	(0.04)	0.98***	(0.04)	0.95***	(0.04)
25	1.02***	(0.04)	0.95***	(0.04)	0.92***	(0.04)	0.95***	(0.04)	0.92***	(0.04)
26	0.71***	(0.03)	0.66***	(0.03)	0.64***	(0.03)	0.66***	(0.03)	0.64***	(0.03)
27	0.52***	(0.03)	0.48***	(0.03)	0.48***	(0.03)	0.48***	(0.03)	0.48***	(0.03)
28	0.63***	(0.03)	0.57***	(0.03)	0.56***	(0.03)	0.57***	(0.03)	0.56***	(0.03)
29	0.52***	(0.03)	0.47***	(0.03)	0.45***	(0.03)	0.47***	(0.03)	0.45***	(0.03)
30	0.47***	(0.03)	0.42***	(0.03)	0.41***	(0.03)	0.42***	(0.03)	0.41***	(0.03)
Panel B. Timing effects γ_d (last NIS digit)										
2	0.07	(0.08)	0.08	(0.08)	0.08	(0.08)	0.08	(0.08)	0.08	(0.08)
3	0.20**	(0.08)	0.23***	(0.08)	0.22***	(0.08)	0.23***	(0.08)	0.22***	(0.08)
4	0.22***	(0.08)	0.22***	(0.08)	0.20**	(0.08)	0.22***	(0.08)	0.20**	(0.08)
5	0.27***	(0.08)	0.26***	(0.08)	0.24***	(0.08)	0.25***	(0.08)	0.24***	(0.08)
6	0.29***	(0.08)	0.31***	(0.08)	0.28***	(0.08)	0.30***	(0.08)	0.27***	(0.08)
7	0.47***	(0.08)	0.45***	(0.08)	0.41***	(0.08)	0.45***	(0.08)	0.41***	(0.08)
8	0.66***	(0.08)	0.65***	(0.08)	0.62***	(0.08)	0.65***	(0.08)	0.62***	(0.08)
9	0.69***	(0.08)	0.65***	(0.08)	0.61***	(0.08)	0.64***	(0.08)	0.61***	(0.08)
10	1.22***	(0.09)	1.17***	(0.09)	1.12***	(0.08)	1.16***	(0.09)	1.12***	(0.08)
Munic. FE	Yes		Yes		Yes		Yes		Yes	
N	28,432,117		28,310,048		28,310,048		28,310,048		28,310,048	
R^2	0.014		0.033		0.036		0.033		0.037	

Appendix Table 10: Paycycle and Timing Effects: 30 Days Past Due. Estimates of Equation (3) for 30 Days Past Due. The paycycle (δ_k) and timing (γ_d) coefficients are jointly estimated in a single regression. Panels A and B report the two blocks of that one regression. Each column pair reports the coefficient and, in parentheses, the household-clustered standard error. Columns add progressively richer controls. All include municipality fixed effects. Panel A omits the payday category (zero days to next benefit payment). Panel B omits NIS group 1, and group 10 denotes last NIS digit 0 (latest paid). Only figure-window coefficients are shown. Coefficients and standard errors are in percentage points. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Up to 89 Days Past Due (p.p.)					
	(1) No Controls	(2) Demographics	(3) Dem.+Inc.	(4) Dem. Dum.	(5) Dem.+Inc. Dum.	
Panel A. Paycycle effects δ_k (days to next benefit payment)						
16	1.61*** (0.04)	1.53*** (0.04)	1.50*** (0.04)	1.54*** (0.04)	1.50***	(0.04)
17	1.47*** (0.04)	1.39*** (0.04)	1.35*** (0.04)	1.39*** (0.04)	1.35***	(0.04)
18	1.39*** (0.03)	1.32*** (0.03)	1.27*** (0.03)	1.31*** (0.03)	1.27***	(0.03)
19	1.19*** (0.03)	1.13*** (0.03)	1.09*** (0.03)	1.13*** (0.03)	1.09***	(0.03)
20	1.07*** (0.03)	1.02*** (0.03)	0.99*** (0.03)	1.02*** (0.03)	0.99***	(0.03)
21	1.05*** (0.03)	1.00*** (0.03)	0.97*** (0.03)	1.00*** (0.03)	0.97***	(0.03)
22	1.00*** (0.03)	0.94*** (0.03)	0.91*** (0.03)	0.94*** (0.03)	0.91***	(0.03)
23	1.00*** (0.04)	0.95*** (0.04)	0.92*** (0.04)	0.95*** (0.04)	0.92***	(0.04)
24	0.90*** (0.03)	0.85*** (0.03)	0.83*** (0.03)	0.85*** (0.03)	0.83***	(0.03)
25	0.85*** (0.03)	0.80*** (0.03)	0.78*** (0.03)	0.80*** (0.03)	0.78***	(0.03)
26	0.63*** (0.03)	0.59*** (0.03)	0.58*** (0.03)	0.59*** (0.03)	0.58***	(0.03)
27	0.49*** (0.03)	0.46*** (0.03)	0.45*** (0.03)	0.46*** (0.03)	0.45***	(0.03)
28	0.58*** (0.03)	0.53*** (0.03)	0.52*** (0.03)	0.53*** (0.03)	0.52***	(0.03)
29	0.46*** (0.03)	0.42*** (0.03)	0.41*** (0.03)	0.42*** (0.03)	0.41***	(0.03)
30	0.43*** (0.02)	0.40*** (0.02)	0.38*** (0.02)	0.40*** (0.02)	0.38***	(0.02)
Panel B. Timing effects γ_d (last NIS digit)						
2	0.09 (0.07)	0.10 (0.07)	0.10 (0.07)	0.10 (0.07)	0.10	(0.07)
3	0.23*** (0.07)	0.26*** (0.07)	0.25*** (0.07)	0.26*** (0.07)	0.25***	(0.07)
4	0.29*** (0.07)	0.28*** (0.07)	0.27*** (0.07)	0.28*** (0.07)	0.27***	(0.07)
5	0.41*** (0.07)	0.41*** (0.07)	0.39*** (0.07)	0.40*** (0.07)	0.39***	(0.07)
6	0.53*** (0.07)	0.54*** (0.07)	0.52*** (0.07)	0.54*** (0.07)	0.51***	(0.07)
7	0.73*** (0.07)	0.72*** (0.07)	0.69*** (0.07)	0.72*** (0.07)	0.69***	(0.07)
8	0.88*** (0.07)	0.88*** (0.07)	0.85*** (0.07)	0.88*** (0.07)	0.85***	(0.07)
9	0.94*** (0.07)	0.90*** (0.07)	0.88*** (0.07)	0.90*** (0.07)	0.88***	(0.07)
10	1.41*** (0.08)	1.37*** (0.08)	1.33*** (0.08)	1.37*** (0.08)	1.33***	(0.08)
Munic. FE	Yes	Yes	Yes	Yes	Yes	
N	28,432,117	28,310,048	28,310,048	28,310,048	28,310,048	
R^2	0.012	0.027	0.030	0.028	0.030	

Appendix Table 11: Paycycle and Timing Effects: Up to 89 Days Past Due. Estimates of Equation (3) for Up to 89 Days Past Due. The paycycle (δ_k) and timing (γ_d) coefficients are jointly estimated in a single regression. Panels A and B report the two blocks of that one regression. Each column pair reports the coefficient and, in parentheses, the household-clustered standard error. Columns add progressively richer controls. All include municipality fixed effects. Panel A omits the payday category (zero days to next benefit payment). Panel B omits NIS group 1, and group 10 denotes last NIS digit 0 (latest paid). Only figure-window coefficients are shown. Coefficients and standard errors are in percentage points. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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