Felipe Goulart Tomkowski

Essays on Credit and Cash Transfer Policies

Tese apresentada ao programa de Doutorado em Economia dos Negócios como requisito parcial para obtenção do título de doutor em Economia

Orientador: Prof. Dr. Marco Bonomo

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Abstract

This thesis investigates the effects of government benefit payments and conditional cash transfers (CCT) on the financial behaviors of low-income households through three studies. The first study examines how the timing of benefit payments impacts credit usage, revealing that later payments increase reliance on credit and delinquency rates. The second study explores the effects of unexpected cash transfers on credit outcomes, finding that such transfers boost credit card usage and improve credit terms for the poorest households. The third study analyzes the impact of losing CCT benefits, showing a temporary rise in credit card expenditures following the loss but no significant change for those below the extreme poverty line. These findings provide insights into how cash transfers influence financial stability and credit access, offering guidance for policies aimed at enhancing financial inclusion for vulnerable populations.

Keywords: conditional cash transfers, credit constraint, financial inclusion, low-income households

Resumo

Esta tese investiga os efeitos dos pagamentos de benefícios governamentais e das transferências condicionais de renda (CCT) no comportamento financeiro de famílias de baixa renda por meio de três estudos. O primeiro estudo examina como o momento dos pagamentos de benefícios impacta o uso de crédito e a inadimplência, revelando que pagamentos tardios aumentam a dependência de crédito e as taxas de inadimplência. O segundo estudo explora os efeitos das transferências inesperadas de dinheiro nos resultados de crédito, descobrindo que tais transferências aumentam o uso de cartão de crédito e melhoram os termos de crédito para as famílias mais pobres. O terceiro estudo analisa o impacto da perda dos benefícios de CCT, mostrando um aumento temporário nos gastos com cartão de crédito após a perda, mas sem mudança significativa para aqueles abaixo da linha de extrema pobreza. Esses achados fornecem insights sobre como as transferências de renda influenciam a estabilidade financeira e o acesso ao crédito, oferecendo orientações para políticas voltadas à ampliação da inclusão financeira para populações vulneráveis.

Palavras-chave: transferências condicionais de renda, restrição de crédito, inclusão financeira, famílias de baixa renda

CHAPTER 1

Introduction

Government benefit payments such as conditional cash transfers (CCT) can potentially influence low-income households' financial behaviors and credit outcomes. This thesis investigates the credit dynamics of CCT beneficiary households through three independent yet interrelated studies, each providing insights into how varying aspects of cash transfers affect credit consumption, financial stability, and economic inclusion among impoverished populations.

The first study examines the impact of within-month variation in the timing of government benefit payments on low-income households' credit intake and delinquency rates. By leveraging a fixed cash transfer payment schedule, the paper provides evidence that households with later benefit days are more likely to rely on credit to smooth consumption despite the predictability of the payment schedule. The analysis highlights that these households often turn to consumption credit to meet their needs and, as a result, exhibit higher default rates. This study offers valuable insights into how the timing of benefit payments can affect low-income households' financial behavior and stability.

The second paper examines the effects of unexpected cash transfers on the credit outcomes of impoverished households, utilizing data from the Brazilian credit registry linked with a social registry for government programs. Through a difference-in-differences design, the study reveals that unexpected cash transfers significantly influence credit behaviors. Beneficiary households exhibit increased credit card usage and higher rates of credit origination. Moreover, extremely poor households benefit from improved credit terms, such as lower interest rates and better credit conditions. These findings underscore the potential of cash transfers to reduce household credit risk, enhance credit access, and foster financial inclusion among vulnerable populations. It also highlights the importance of policies promoting financial literacy, as incurring expensive credit types can be harmful to poor households.

The third study investigates the consequences of losing CCT benefits on the credit outcomes of economically disadvantaged households. Employing a comprehensive administrative dataset and a difference-in-differences approach, the research shows that households that exit the program at a pre-disclosed date experience a temporary increase in credit card expenditures following the cessation of CCT benefits. This study provides evidence that access to credit does not diminish after the loss of CCT benefits, aligning with a habit formation model where households fail to anticipate benefit loss.

Together, these studies offer a comprehensive understanding of how government benefit payments and CCTs impact low-income households' financial behaviors and credit outcomes. By exploring different dimensions of cash transfers—from scheduled payments to unexpected inflows and benefit cessations—, this thesis contributes valuable insights into the mechanisms through which financial assistance programs influence credit access for economically disadvantaged populations. The findings have important implications for policymakers aiming to design effective interventions that promote financial inclusion and mitigate the adverse effects of credit and liquidity constraints among the poor and financial planning.

CHAPTER 2

Timing Matters: Unintended Consequences of Government Benefit Schedules[1]

Abstract: Government benefit payments are often paid according to a pre-determined schedule that may or may not align with beneficiaries' financial needs. Exploiting a fixed cash transfer payment schedule, we studied the impact of within-month variation in the benefit payment day on credit intake and delinquency of low-income households. Our findings reveal that households rely more on credit when facing a later benefit day, even with predictable schedules. In particular, they often use consumption credit to meet their needs and present higher default rates.

JEL Codes: G51, G53, I32, I38.

Keywords: CCT, liquidity constraint; CCT pay timing, financial inclusion

1. In coauthorship with Marco Bonomo (Insper), Filipe Correia (Univesity of Georgia), and Lucas Teixeira (Brazilian Central Bank)

2.1 Introduction

Cash transfers typically aim to assist impoverished households that rely on each paycheck to meet their needs. This is particularly true in developing countries where the transfer often constitutes a significant portion of these households' income. In turn, the timing of cash transfer payments is frequently organized according to specific dates under the implicit assumption that it doesn't affect beneficiary household financial behavior. However, does the timing of these payments impact how beneficiaries manage their budgets? Understanding how variations in cash transfer payment schedules affect the financial behavior of agents is crucial for designing effective support systems. Moreover, it further advances the understanding of supply and demand dynamics of liquidity provision for vulnerable households. This paper addresses these issues and provides insights into how the timing of these transfers can impact the effectiveness of such programs, which, if not considered, could generate unintended inequalities between the beneficiary households.

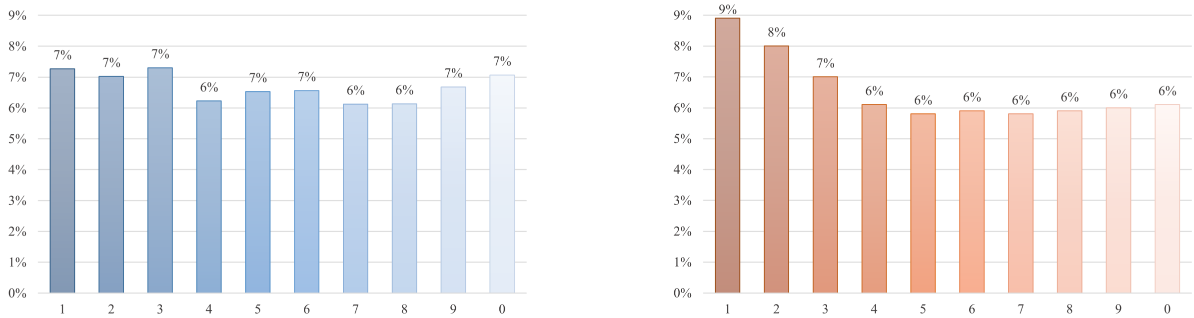
Payments for the Brazilian conditional cash transfer program, Programa Bolsa Família (PBF), are made according to a schedule. We exploit the random number assigned to each beneficiary household that determines when the beneficiary household receives the transfer to investigate whether the timing of the pay relative to financial obligations changes how these households use credit to manage their monthly budgets. Our investigation is divided into four different specifications. Firstly, we perform a difference-in-differences analysis by comparing households that receive the latest transfers with those that receive the earliest, considering only new beneficiaries in the first six months. Next, we perform a specification to capture the effect of mismatch within specific payment schedule groups, defined by the random digit.

Our findings reveal a significant effect of the timing households receive the transfer on the reliance on borrowing among households. Specifically, households that receive the transfer later in the month face a significantly higher likelihood of borrowing to fulfill their financial obligations. In particular, this effect comes when the income payment is received after the due date of a financial obligation. Hence, the results suggest that households use credit to smooth consumption, even with a predictable calendar of transfer cash flows consistent with Baugh and Wang (2018) findings.

The evidence supports the idea that when households have to pay an installment before they get the benefit, they face a liquidity restriction that makes them rely more on credit. By knowing that a mismatch between benefits and obligations affects delinquency rates and the need for credit, not only might the government rethink the way benefit scheduled payments are made, but banks can also better design financial products that are more adapted to households' financial needs.

Hence, exploring the exogenous nature of the calendar schedule and the availability of the information on the day an installment is due, our paper contributes to the literature by presenting further evidence on the effects of benefit payment schedules on credit. We present causal evidence of the impact of payment schedules by utilizing quasi-experimental settings and exploiting a random digit assignment that generates the exogenous variation in benefit payment timing.

Figure 2.1: Proportion of Households with Installment Payment on the 20th day by Last NIS Digit



(a) New Beneficiaries Households

(b) All Beneficiary Households

Notes: These graphs show the percentage of households with an installment payment due on the 20th day of the month among those who have an installment due that month. The New Beneficiary Households category refers to those who have recently started receiving cash transfers on that specific month. Meanwhile, the All Beneficiary Households category includes all beneficiary households in any month.

In Figure 2.1, we see the breakdown of households with an installment due and the proportion of those with a payment day on the 20th based on their last NIS digit, which is the random digit that defines the payment schedule of each group, from the earliest receiver (group 1) to the latest receiver (group 0). While there is no significant difference between the last NIS digit groups for households who just started receiving the benefit in the given month, for the all-beneficiary sample, those with a later cash transfer benefit day in the month are less likely to have their payment day fall on the 20th. This is because the latter group has a higher chance of receiving the benefit only after the 20th. Thus, they have the incentive to postpone the installment to a later date. This adaptive behavior highlights the importance of timing cash transfer benefits around the day poor households' obligations are due. We leverage rich administrative datasets to track payment schedules and due dates of obligations.

Our research explores two primary datasets. The first, known as the *Cadastro Único*, comprises household-level information such as the status of being a beneficiary of the

Conditional Cash Transfer program, per capita income, household composition, illiteracy, and highest education level attained by a member. The second dataset is sourced from a credit registry and provides information on household-level credit balances across different credit balances and origination types. Additionally, this dataset includes information on delinquency rates. By leveraging these two datasets, we can gain comprehensive insights into household finances.

This paper contributes to the extensive body of literature that explores the impact of income on borrowing and consumption. For example, Baker (2018) finds that heterogeneity in consumption elasticity among households with varying levels and types of debt can be explained entirely by credit and liquidity. Aydin (2022) exploit a field experiment that constructs a randomized credit limit shock. Using online financial service data, Kuchler and Pagel (2021) finds that they fail to adhere to their self-set debt paydown plans, which indicates present bias. Jones and Michelmore (2019) find evidence that credit card and unsecured debt holding reflects the timing of the earned income tax credit - a tax credit towards low-income households - among households eligible for the benefit, which presents low debt levels at the time of tax relative to other months.

Moreover, our investigation is closely aligned with previous studies investigating the connection between the timing of government benefits and household spending. Stephens Jr (2003) finds a significant rise in the likelihood of increased consumption among households receiving social security benefits immediately following the payment. Wilde and Ranney (2000), Shapiro (2005), and Mastrobuoni and Weinberg (2009) documented the cyclical food consumption among recipients of SNAP (Supplemental Nutrition Assistance Program) and Social Security benefits. At the same time, Hastings and Shapiro (2018) shows that changes in quality or prices do not drive the reduction in food expenditures among these beneficiaries. Olafsson and Pagel (2016) shows that even consumption of high liquidity households declines over the pay cycle. Two papers are more closely related to our investigation. First, Bos, Le Coq, and Santen (2016), which exploits a transfer system that randomly assigns the number of days between paydays to Swedish social welfare recipients, finds that tighter budget constraints lead to higher default risk and debt servicing costs, indicating that economic scarcity further exacerbates poverty conditions. Baugh and Wang (2018), which finds that longer pay periods and a mismatch between income and expenditure commitments increase the likelihood of financial shortfalls. On the other hand, studying beneficiary households from the Mexican CCT program, Prospera, Angelucci et al. (2024) finds evidence that there is no significant change in food consumption before or after the transfer payment date. Moreover, they discovered that it is not costly for these households to manage their consumption and expenses despite the timing of the transfer payment. That is, there was no evidence that smoothing consumption around the payment day had an adverse impact on their assets, labor supply, or child labor. Our paper contributes to the literature by providing further evidence on the impact of cash transfer timing on the financial health of beneficiary households. The results inform policies aimed at improving the design of transfer programs.

Finally, it connects to the literature on consumer credit supply (e.g., Bertola, Disney, Grant, et al. 2006, Ramcharan, Verani, and Van den Heuvel 2016, Benmelech, Meisenzahl, and Ramcharan 2017, Jensen and Johannesen 2017) and demand (e.g., Telyukova 2013).

Our results indicate that beneficiaries rely more on credit for consumption smoothing over the month when they receive late benefits. We find effects on debt accumulation from the cash transfer benefit date variation in relation to payment day within a specific household payment group. In particular, when experiencing a month when the withdrawal day is later than the installment payment date, households have a higher probability of using credit cards (0.5%) and installment cards (0.9%), as well as revolving credit (0.9%), overdraft (0.4%), and having to pay any interest rate (0.6%). In these months, households have a 0.4% higher probability of default.

The rest of the paper is organized as follows. First, we describe the PBF, the CCT program in Brazil, and its calendar payment schedules. Next, we detail the datasets used. Then, we present a conceptual framework to formalize the mechanism behind beneficiary households' expected financial behavior, followed by a description of the identification strategies. Finally, we present the results and conclusion.

2.2 CCT in Brazil

Programa Bolsa Família (PBF) is a Brazilian means-tested conditional cash transfer (CCT) program designed to provide financial aid to poor families while promoting human capital accumulation for future generations. The program aims to enhance the welfare of impoverished households through cash grants, coupled with conditionalities such as children's school attendance and vaccination, and it is considered a well-targeted CCT program both in terms of income range and conditionality compliance (Lindert et al. 2007). Until December 2019,[2] the eligibility criteria for receiving a BF grant required families to have a per capita income of up to 89.00 BRL monthly or between 89.01 BRL and 178.00 BRL monthly if they had children aged 0 to 18 years old.[3]

The PBF primarily serves two groups of beneficiary households: extremely poor and poor. Extremely poor households[4] receive a baseline grant of 89 BRL, regardless of their family composition, while poor households[5] receive the benefit conditional on having a minor child who meets the required level of school attendance. So poor and extremely poor households receive 48 BRL for each minor child. Once the year a child turns 18 ends, both groups cease to receive the respective monthly benefit of 48 BRL. Various studies indicate that PBF has had a positive impact on the reduction of income inequality and poverty in Brazil,[6] as well as on school attendance of children whose families are beneficiaries.[7]

2. Before July 2018, the income thresholds were set at 85 and 170.00 BRL.

3. https://www.gov.br/cidadania/pt-br/acoes-e-programas/bolsa-familia, *Ministério da Cidadania*: August 13th, 2020.

4. those with a per capita income below 89.01 BRL

5. those with a per capita income between 89.01 and BRL 178

6. For instance, Barros et al. (2007), Barros, Cury, and Ulyssea (2007), Soares et al. (2009) and Cury et al. (2010)

7. See, for example, Cardoso, Souza, et al. (2004), and Glewwe and Kassouf (2012)

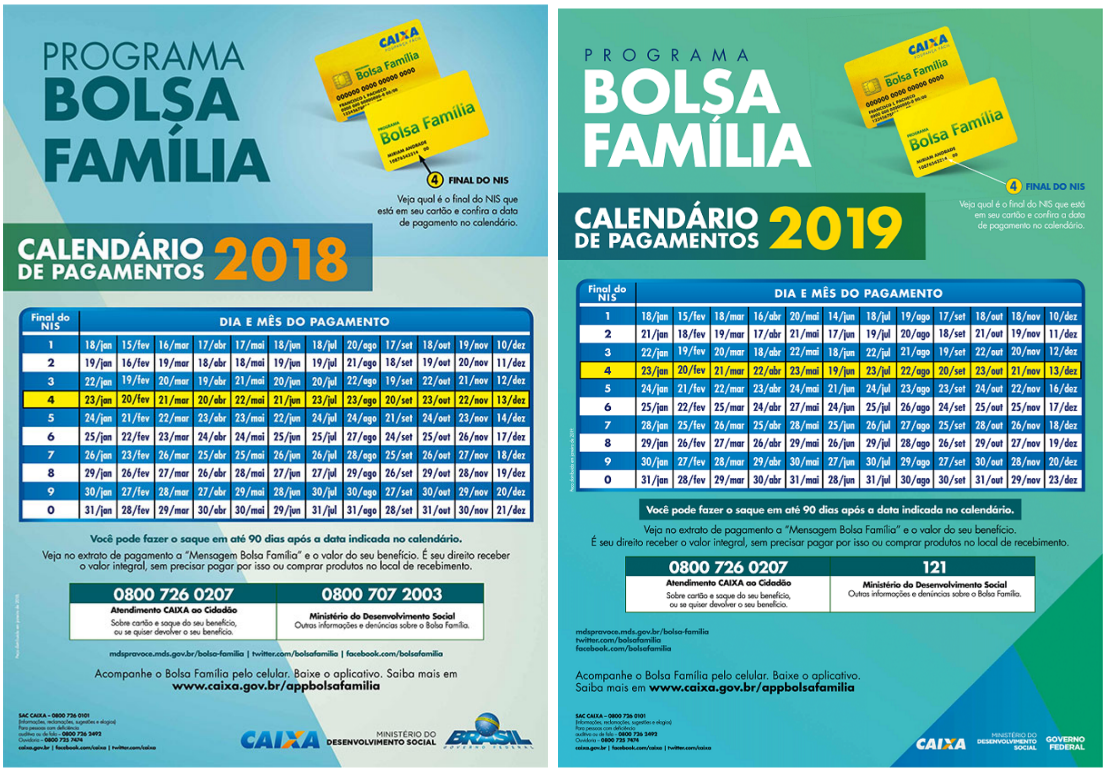


Figure 2.2: *Bolsa Família* Payment Schedule according to Last NIS Digit

Households can withdraw the PBF cash transfer in any CAIXA ECONOMICA FEDERAL bank agency, ATMs, lottery outlets, and accredited commercial establishments, respecting a national payment calendar. The calendar defines the day when a given beneficiary household will be able to withdraw the money in each given month, according to the last digit of the household's identification number in *Cadastro Único*, named NIS - *Número de Identificação Social*.[8] Figure 2.2 shows the actual payment calendar (for 2019) that was disclosed to the public at the end of the previous year (2018). The payment occurs in the last 15 days of the month, except for December. As depicted in Figure 2.3, our sample includes an almost equal number of beneficiary households for each last NIS digit. The last NIS digit is random and uniformly distributed across the ten digits (0-9), causing an exogenous variation in cash transfer payment day exploited in the identification strategy.

8. In English: "Social Identification Number"

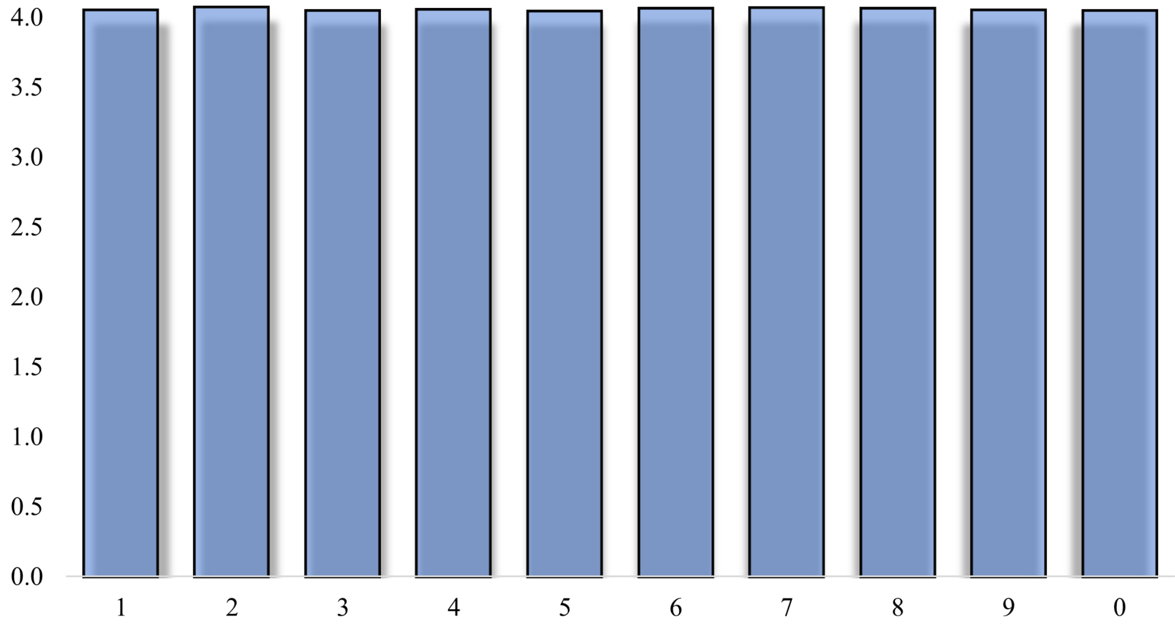


Figure 2.3: Number of *Bolsa Família* Beneficiary Households by Last NIS Digit (in Millions)

2.3 Data

This section provides an overview of the data sources utilized in the study. We combine data from multiple sources, including *Cadastro Único* (henceforth, CadÚnico),[9] the Brazilian Credit Registry (SCR), and *Relação Anual de Informações Sociais* (RAIS).[10]

Managed by the Brazilian Ministry of Citizenship, CadÚnico is the main instrument for selecting and including low-income families in federal programs, including the PBF. SCR stores comprehensive information on credit operations carried out throughout Brazil by individuals and firms with a total liability of at least 200 BRL. In our analysis, we utilize household-level information from CadÚnico, including variables such as the average adult age, the number of people in the family, household income, and credit and default status from SCR. Additionally, we incorporate data from RAIS, a database that provides

9. *Cadastro Único para Programas Sociais do Governo Federal.* In English: Single Registry for Federal Government Social Programs

10. In English: Annual Social Information Report

employment information and wages for all formally employed workers in Brazil.[11]

The dataset is aggregated at the household level for various types, such as credit card expenditure, revolving credit, and productive microcredit. Moreover, there is information on default rates, which indicates whether any household member is in default, based on the definition provided by the Brazilian Central Bank (BCB), which refers to credit in arrears for more than 90 days within a particular month. We also include a dummy variable indicating the presence of any formal employee, the sum of formal salary and the number of formal entrepreneurs at the household level each month.

To determine the monthly recurring payment schedule, we rely on two main variables: the next payment due and its corresponding date. These variables are linked to recurring credit installments, including installment cards, personal credit, and microcredit. By analyzing the next payment due date, we can identify households with payments due in a particular month and on a specific day.

The dataset is structured at the household-month-year level, with matched information from CadÚnico, SCR, and RAIS. The sample period spans from January 2018 to December 2019 and comprises households from two States: Ceara and Minas Gerais.

2.4 Timing of Payment and Mismatch

Poor households often have limited financial resources, and the timing of income can significantly impact their financial situation. Figure A1 displays the expense distribution of the poorest Brazilians, revealing that most of their budget is allocated to food and housing. The timing of benefit payments can be particularly critical for CCT beneficiary households, which often lack assets and have only informal income sources that are difficult to verify.

11. Many influential papers used RAIS; for instance: Van Doornik et al. 2018 studies the effects of access to credit on labor market outcomes; Fonseca and Van Doornik 2022, which estimates the increased access to bank credit on the employment and wages; and Ulyssea 2018 which developed an equilibrium model to study the relationship between informality and firms productivity.

A key factor here is the "mismatch effect," which arises when there is a misalignment between the days a household receives its benefit payment and when installment payments are due. This mismatch can create a significant liquidity constraint for households that receive their benefit after an installment is due. As a result, these households may be more likely to rely on credit to meet their needs and smooth consumption. Additionally, they may face a higher risk of delinquency due to the increased likelihood of missing or delaying installment payments.

This mismatch effect highlights the importance of timing in benefit disbursement. When households receive their benefits after a critical payment deadline, they are forced to navigate a more constrained financial environment, leading to increased borrowing, potentially on less favorable terms, and higher rates of missed payments.

In the following section, we describe the identification strategies used to estimate the impact of this mismatch effect.

2.5 Identification Strategy

Our empirical investigation is divided into two parts, allowing us to estimate the effect of the mismatch between cash transfers and observable installments due. This is made possible by the random variation in the payment schedule of cash transfers.

First, through a difference-in-differences setting, we begin by examining the differential effects on credit outcomes experienced by groups that receive the benefit later in the month compared to those who receive it earlier in their initial month as beneficiaries. This specification allows us to capture the effect of liquidity from different monthly disbursement dates when households first start receiving the benefit. Next, since the difference between installment payment and benefit payment days changes from month to month, we can analyze a "within" last NIS digit differential effect on credit behavior. Specifically, to increase the statistical power to capture the impact of interest, we select the last NIS digit groups with the highest variation in terms of receiving the benefit before or after a payment is due. In this way, we can see if payment timing occurring sporadically after a payment is due also affects credit behavior. This last identification allows us to have further causal evidence of the mismatch effect on credit.

2.5.1 Difference-in-differences

By comparing new receivers, we can better capture the effects of late benefits. We select only households that started receiving the PBF during the sample period. Then, we keep those who were in the sample for at least three periods before receiving the benefit so that we can observe the outcomes of interest before the "treatment" period and keep receiving the benefit (without being excluded from the program due to for instance, registry checks and not following child school attendance conditionalities) for at least the following five months. Figure 2.4 illustrates the graph for the selected sample, where t represents the number of months since receiving the cash transfer.

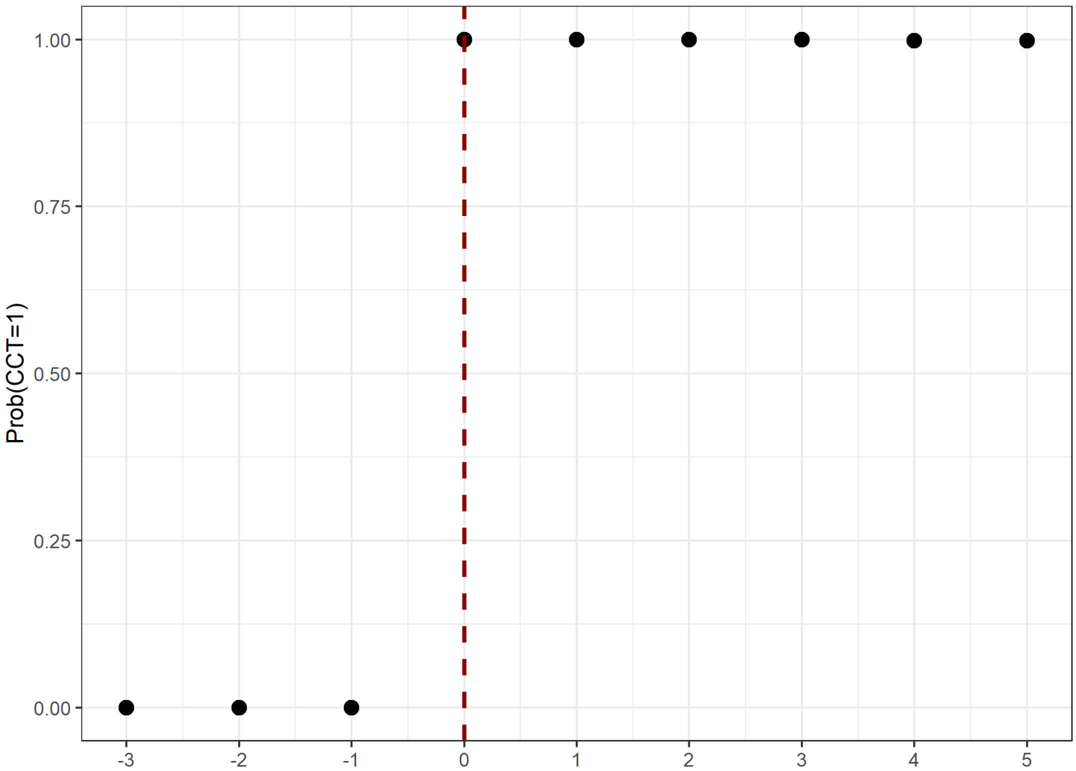


Figure 2.4: CCT Overtime

Then, we select those that at period t=0, when they started receiving the cash transfer, had a payment due day of 15 to 25,[12] and set the treatment group as those whose last NIS digit was 9 or 0, and the control group as those whose last NIS digit was 1 or 2. So, the treatment group will only be able to withdraw the benefit later in the month and usually only after the payment is due.

Table 2.1 shows the percentage of cash transfer over total household income, of installment over cash transfer, of installment over total household income, total household income from Cadunico, and also total income adding formal labor income in the first month. There is no statistically significant difference noted in any of these variables between the two treatment and control groups, revealing no systematic distinction in debt, income, and the importance of the cash transfer when they start receiving the benefit. The cash transfer represents, on average, roughly 50% of households' total income, and the installment due is close to 36% of the cash transfer. The estimated total income of households is 1,159 BRL.

12. We select more flexible payment dates to increase the sample size given that many households only enter the sample when they start receiving the benefit

Table 2.1: New Beneficiary Households the month receiving the transfer: Installment

Last NIS Digit	1|2	9|0	p-value
CCT / HH Income	0.26 (0.30)	0.26 (0.29)	0.997
Installment / CCT	1.79 (2.08)	1.77 (2.03)	0.881
Installment / HH Income	0.50 (0.83)	0.51 (0.96)	0.829
Total Income (Cadúnico)	576 (431)	568 (402)	0.712
Total Income	1113 (1043)	1205 (1256)	0.151

Notes: This Table shows the descriptive statistics for the installment due according to the SCR database and income and cash transfer according to *Cadastro Único* (and RAIS), in the month households started receiving the cash transfer. Total Income estimated as follows: Per capita income x Number of People + Cash Transfer + Formal Salary. Cash transfer, in turn, is estimated as: Number of young children x R$ 49 (+ R$ 85 if the household is extremely poor, i.e., it has a per capita income below R$ 89. Household Income (Cadunico) follows the same formula but without the formal salary. While the first tends to overestimate the true household income, since formal salary may be included in Cadunico's estimate, the latter tends to be an underestimate because it is self-reported. Standard errors are in parenthesis.

Table B1 shows no statistical difference between group credit, household socio-economic, and employment characteristics at timing "-1" the month before households started receiving the transfer. Notably, roughly 56% and 40% of households had positive balances on their credit cards and revolving credit, respectively, with associate mean balances of around 525 BRL and 156 BRL. Over 80% of households were paying some interest, with an annual average interest rate of more than 80%. Additionally, the statistics reveal that only 33% of households had a formal employee, and 9% had a formalized entrepreneur. The installment due the following month is roughly 220 BRL.

The difference-in-difference specification is then:

$$Y_{i,t} = \alpha \times \mathbb{1}\{\text{Last NIS}_i\text{= n}\} + \lambda_t + \beta \times Post_{i,t} \times \mathbb{1}\{\text{Last NIS}_i \in 9,\, 0\} + \epsilon_{i,t} \tag{2.1}$$

where $Y_{i,t}$ is the outcome of interest for household i, in period t, with the last NIS Digit equal to n, $Post_{i,t}$ is a dummy signaling if household i already receives the benefit in period t, and $\mathbb{1}\{\text{Last NIS} = 9, 0\}$ is an indicator whether it has a last NIS digit of 9 or 0. β capture the causal effect of receiving the transfer later in the month after the due day of an installment. To provide evidence of parallel trends, we also estimate the following extended specification:

$$Y_{i,t} = \omega \times \mathbb{1}\{\text{Last NIS}_i = \text{n}\} + \psi_t + \sum_{s \neq -1}^{5} \beta_s \times \mathbb{1}\{t_i - t = s\} \times \mathbb{1}\{\text{Last NIS}_i \in 9,\ 0\} + \eta_{i,t} \quad (2.2)$$

where t_i is the period household i starts receiving the benefit, and β_s captures the effect of having a last NIS digit of 9 or 0 in relation to those to 1 and 2 over the first 6 months of receiving the cash transfer; that is, the effect of receiving the transfer only later in the month.

The identification assumption is that treatment and control groups would have followed parallel trends if there was no difference in the day the transfer could be withdrawn between the two. Figures B2, B3, and B5 present visual evidence of parallel pre-trends.

2.5.2 Within Household Payment Timing Effect

To provide further causal evidence for the mismatch mechanism, we exploit the variation in the payment date within a given last NIS Digit effects on a household's financial behavior. In particular, we select those last NIS digit groups with the most variation in the variable LB - late benefit: receiving the benefit after a payment is due - when having payment due on day 20. These groups happen to be 2, 3, and 4.

We use as the explanatory variable the difference between the date the benefit is received and the payment date to investigate whether receiving the benefit after the payment day makes a difference within a given group:

$$Y_{i,t} = \nu \times \mathbb{1}\{\text{Last } NIS_i = \text{n}\} + \beta \times \{\text{Mismatch}_{i,t} = \tau\} + \eta_{i,t} \tag{2.3}$$

Now to get the late benefit effect with an alternative specification, let $PostiveMismatch =$ $\mathbb{1}\{\text{Cash Transfer Benefit Day}_{\text{ Last NIS Digit}_i,t} \text{ - Installment Payment Day} > 0\}$, where Cash Transfer Bene is the benefit payment day for last NIS digit group of household i in period t. The estimated regression is:

$$Y_{i,t} = \gamma \times \mathbb{1}\{\text{Last } NIS_i = \text{n}\} + \rho \times PositiveMismatch_{i,t} + \epsilon_{i,t} \tag{2.4}$$

where ρ is the coefficient of interest, capturing the effect of receiving the transfer after the payment in a particular period t.

The identification assumption is that the variation of benefit day around the installment payment day is generated by the last NIS digit (through the benefit payment calendar) and not by household characteristics or other factors affecting credit outcomes.

2.6 Results

First, we show the difference-in-differences results, providing evidence for the effect in the first months after receiving the benefit. Then, we present the results for the within specification, through which we estimate a specification that allows us to follow specific payment schedule groups and to understand whether receiving the benefit after the installment is due increases borrowing.

2.6.1 Cash Transfer Later in the Month

Table 2.2: Effects of Being a Late New Receiver on Credit Outcomes Intensive and Extensive Margins

	Panel A: Extensive Margin		
	Total Credit	Installment Card	Interest Rate
LB x Post	0.020	0.056***	0.049*
	(0.024)	(0.020)	(0.025)
Control Mean	0.81	0.21	0.64
Last NIS FE	Yes	Yes	Yes
N	8,755	8,755	8,755
R^2	0.031	0.007	0.019

	Panel B: Intensive Margin		
	Total Credit	Installment Card	Interest Rate
LB x Post	638.83**	99.31	-5.54
	(289.59)	(120.37)	(7.19)
Last NIS FE	Yes	Yes	Yes
N	7,539	1,986	6,120
R^2	0.00	0.01	0.00

Notes: This Table presents the results for the difference-in-differences specification of having a late benefit in the first six months of CCT reception on both intensive and extensive margin outcomes. Panel A displays the results for extensive margin outcomes, while Panel B displays those for the intensive margin outcomes. Standard errors are in parentheses and clustered at the household level.

Table 2.2 shows the regression result for the difference in differences specification for a selection of credit outcomes intensive and extensive margins.[13] At the extensive

13. See Appendix Table B2 for all difference-in-differences results.

margin, presented in Panel A, households that receive the benefit later in the month are 5.6% more likely to use an installment card - credit in installments financed by the card issuer, incurring financial charges - than those that receive it earlier in the month. Also, these late-receiver households present a 4.9% higher chance of paying any interest rate - which corresponds to the intensive margin on interest rates - in the first six months as beneficiaries. In turn, as shown in Panel B, the total credit balance of these households is also greater by 639 BRL. Figure B4 shows the average conditional total credit balance for the control and treatment groups plotted over time. The graph highlights that the later benefit group's higher credit usage comes from variation in the control group, which experienced a steeper decrease in the first month. This suggests that households that receive the benefit later in the first month still need to rely on credit to manage the increased liquidity constraints. Both groups follow parallel trends with a gradual increase in total credit after receiving the benefit.

2.6.2 Within Household Variation

Let's now consider the effects of the variation of the benefit day around the payment date for the Last NIS digits 2, 3, and 4, which presents a considerable time-series variation.

Table 2.3 and Figure C3 show the regression analysis results focusing on the within variation. Panels A and B display the extensive and intensive margin outcomes of the credit outcomes of interest. Panel A shows that households who had an installment due before receiving the payment of the transfer are 1.2% more likely to have a credit origination. Additionally, these households have a higher chance of using a credit card or installment card by 0.5% and 0.9%, respectively. They also have a higher chance of having a revolving credit or overdraft by 0.9% and 0.4%, respectively. Furthermore, the probability of having to pay any interest rate increases by 0.6%. Table 2.4 indicates that, in these cases, households have a 0.4% higher chance of defaulting. Panel B shows that, at the intensive margin, credit origination is 85.58 BRL larger in late benefit months.

Table 2.3: Within NIS Effect on Extensive and Intensive Margins

	Panel A: Extensive Margin								
		Credit Origination	Consumption Credit	Credit Card	Installment Card	Revolving Credit	Overdraft	Installment Due	Interest Rate
Mismatch		0.012***	0.005**	0.005**	0.009***	0.009***	0.004***	-0.012***	0.006***
		(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)
Last NIS FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N		80,971	80,971	80,971	80,971	80,971	80,971	80,971	80,971
R^2		0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000
	Panel B: Intensive Margin								
	Total Credit	Credit Origination	Consumption Credit	Credit Card	Installment Card	Revolving Credit	Overdraft	Installment Due	Interest Rate
Mismatch	-7.24	85.58***	10.53	-7.76	15.78	-11.52	-24.98	0.87	0.13
	(49.50)	(27.65)	(13.54)	(12.39)	(13.07)	(11.87)	(19.79)	(8.17)	(0.66)
Last NIS FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	78,332	22,743	36,678	33,735	15,801	26,917	5,852	73,983	71,602
R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: This Table shows the estimated results for Equation 2.4, which captures the effect of the payment schedule variation within each NIS on credit extensive and intensive margin outcomes. To analyze transfer withdrawal day variation around day 20, we consider all beneficiary households with payment day 20 and the last NIS Digit 2, 3, or 4. This captures households that exhibit the most variation in their withdrawal patterns in relation to their payment day. Standard errors are in parentheses.

These results suggest that the variation in withdrawal dates impacts the debt accumulation of poor households with a given last NIS digit.

Table 2.4: Within NIS Effect on Delinquency Rates

	Default	Any Delay	Up to 90	Up to 60	Up to 30
Mismatch	0.004**	0.0003	-0.003	-0.002	0.001
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Last NIS FE	Yes	Yes	Yes	Yes	Yes
N	80,971	80,971	80,971	80,971	80,971
R^2	0.000	0.000	0.000	0.000	0.000

Notes: This Table shows the estimated results for Equation 2.4, which captures the effect of the payment schedule variation within each NIS on delinquency rates. To analyze transfer benefit day variation around day 20, we consider all beneficiary households with payment day 20 and the last NIS Digit 2, 3, or 4. This captures households that exhibit the most variation in their benefit payment patterns in relation to their installment payment day. Standard errors are in parentheses.

Conclusion

This paper examines the impact of predictable cash transfer payment timing on households' financial behavior by investigating the influence of cash transfer intra-month timing in Brazil. We exploit an exogenous variation in the payment time over the month, which causes beneficiary households from a Brazilian CT program to randomly receive the benefit earlier or later according to the last digit of a random identification number.

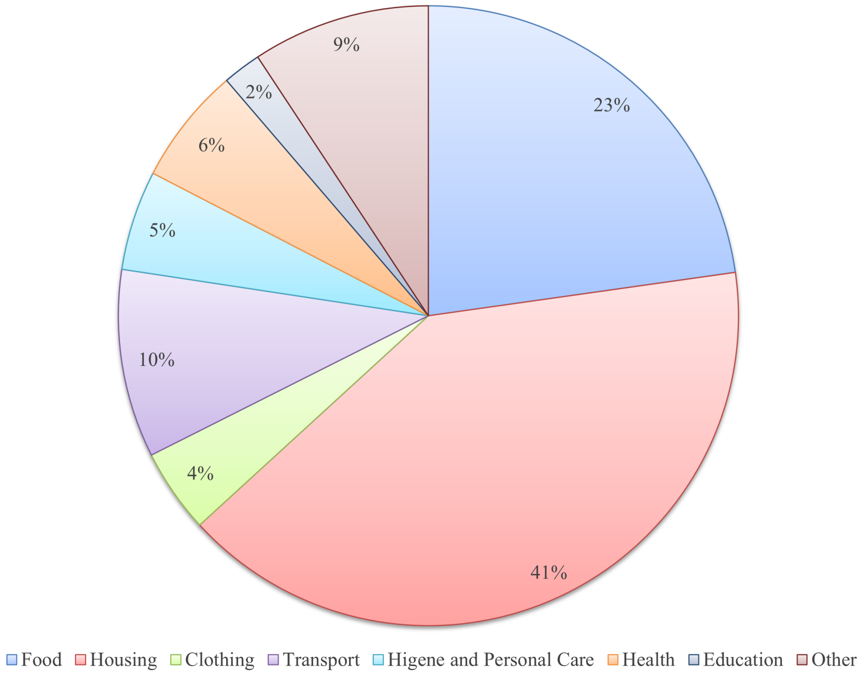
We documented the impact of cash transfer payment schedules on credit behavior, particularly focusing on the mismatch between benefit payment days and installment due dates. This mismatch creates a liquidity shock, prompting households to demand more credit to meet their obligations. When benefits are disbursed after an installment is due, households are more likely to rely on credit, indicating that the delayed benefit exacerbates liquidity constraints, forcing households to use credit to smooth consumption.

Using a difference-in-differences strategy to identify the impact for new beneficiary households, we find that it materializes in the first months the households receive the transfer. Also, we provide evidence that the mismatch effect is relevant even when considering within payment schedule group variation.

We contribute to enhancing the effectiveness of social welfare programs by highlighting that cash transfer timing can significantly influence households' financial outcomes. These findings should guide the design and implementation of social welfare policies that optimize cash transfer payment schedules, better aligning them to expenditures to maximize positive impacts on beneficiaries' financial well-being and not create undesirable inequalities between households. Future studies should investigate what types of expenses are more affected by heterogeneous payment schedules.

2.7 Appendix A: Descriptive Statistics

Figure A1: Poorest Brazilian Households Current Expenses by Type



Notes: The graph displays the proportion of different types of expenses among households in Brazil with a total income of up to 1908 BRL. This data is taken from the "Family Budget Research"[a] conducted by the Brazilian Government in 2017 and 2018.

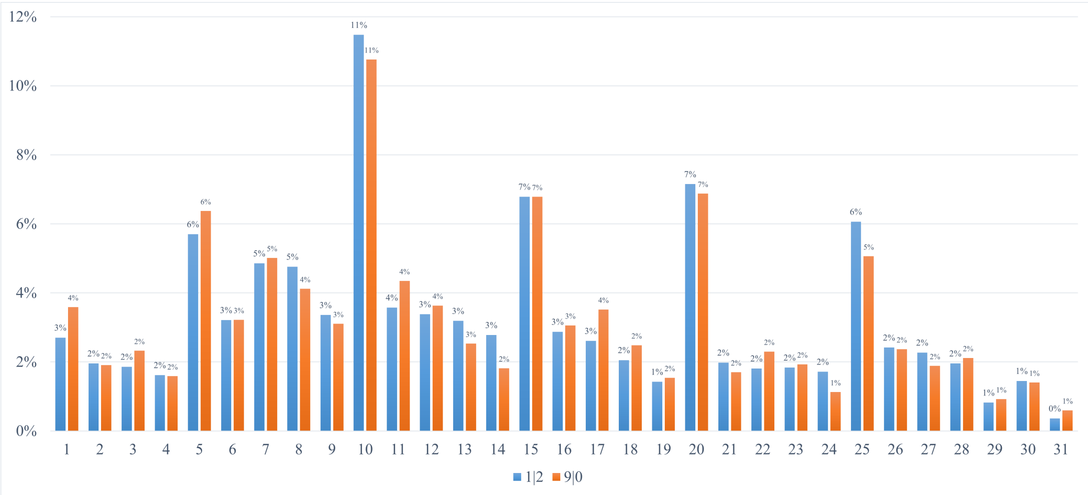
a. *Pesquisa de Orçamentos Familiares*

Table A1: Conditional Cash Transfer Actual Withdrawal Day Distance in days from Schedule Day

Last NIS Digit	Median
1	0.00
2	0.00
3	0.00
4	0.00
5	0.00
6	0.00
7	0.00
8	0.00
9	0.00
0	0.00

Notes: This table shows the median number of days between the actual withdrawal date and the date on which each group of Last NIS Digit was permitted to withdraw according to the payment schedule. The data was obtained from the Brazilian Government's *Portal da Transparência* for January 2018.

2.8 Appendix B: DID



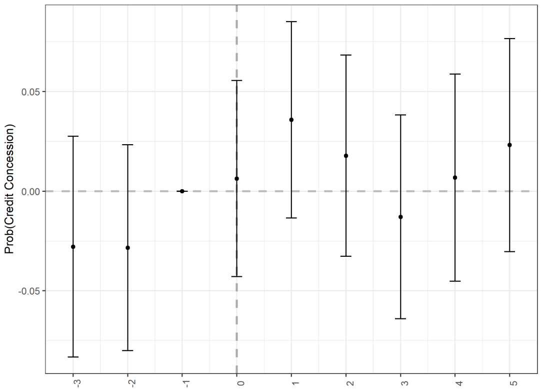
Notes: This Figure shows the proportion of installment payment days considering households in the treatment (Last NIS Digit 9|0) and the control group (Last NIS Digit 1|2) over the Post periods (when all were already indeed beneficiaries). We use only those with payment days between 15 and 25 for the estimation.

Table B1: New Beneficiary Households the month before first receiving the transfer

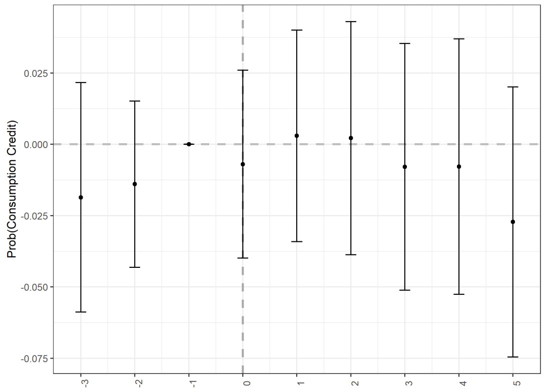
Last NIS Digit	*1/2*	*9/0*	p-value
N	N=650	N=648	
Female Head	0.94 (0.23)	0.94 (0.23)	0.893
Household Income	193 (161)	198 (178)	0.595
Number of People	2.95 (1.12)	2.86 (1.05)	0.136
Mean Adult Age	34.8 (8.76)	34.8 (8.87)	0.912
Number of Active Bank Accounts	1.49 (0.66)	1.49 (0.66)	0.933
Income according to Bank	1276 (744)	1330 (746)	0.219
Any Formal Employment	0.35 (0.48)	0.36 (0.48)	0.614
Formal Salary	477 (843)	580 (1137)	0.064
Formalized Entrepreneurs	0.09 (0.29)	0.10 (0.32)	0.404
Maximum Education Attained = 0	0.01 (0.09)	0.02 (0.13)	0.087
Maximum Education Attained = 1	0.29 (0.45)	0.26 (0.44)	0.25
Maximum Education Attained = 2	0.11 (0.32)	0.11 (0.31)	0.806
Maximum Education Attained = 3	0.15 (0.35)	0.14 (0.35)	0.708
Maximum Education Attained = 4	0.43 (0.50)	0.44 (0.50)	0.701
Maximum Education Attained = 5	0.02 (0.13)	0.04 (0.19)	0.042
%			
Total Credit	1.00 (0.04)	1.00 (0.00)	0.318
Interest Rate	0.84 (0.37)	0.85 (0.36)	0.778
Credit Card	0.52 (0.50)	0.56 (0.50)	0.219
Revolving Credit	0.37 (0.48)	0.39 (0.49)	0.466
Installment Card	0.31 (0.46)	0.27 (0.44)	0.134
Overdraft	0.05 (0.22)	0.07 (0.26)	0.083
Personal Credit	0.10 (0.30)	0.09 (0.29)	0.465
Microcredit	0.08 (0.28)	0.08 (0.28)	0.987

Table B1: New Beneficiary Households the month before first receiving the transfer

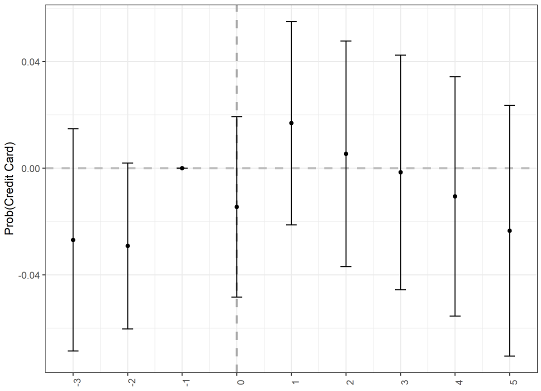
Last NIS Digit	*1/2*	*9/0*	p-value
Credit Concession	0.32 (0.47)	0.33 (0.47)	0.694
Installment Due	1.00 (0.04)	1.00 (0.00)	0.318
Default	0.03 (0.16)	0.04 (0.19)	0.422
	R$		
Total Credit	2423 (5757)	2060 (2780)	0.148
Interest Rate	81.3 (98.7)	79.5 (104)	0.749
Credit Card	513 (910)	566 (976)	0.306
Revolving Credit	154 (504)	165 (396)	0.666
Installment Card	148 (369)	127 (410)	0.327
Overdraft	25.6 (175)	30.9 (150)	0.557
Personal Credit	167 (690)	111 (458)	0.084
Microcredit	133 (618)	190 (841)	0.163
Credit Concession	268 (841)	276 (785)	0.866
Installment Due	221 (253)	250 (308)	0.066



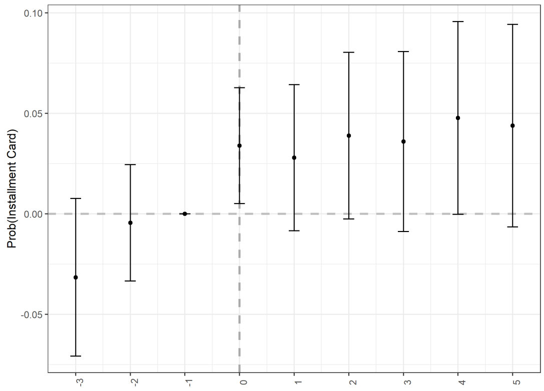
(a) Credit Concession



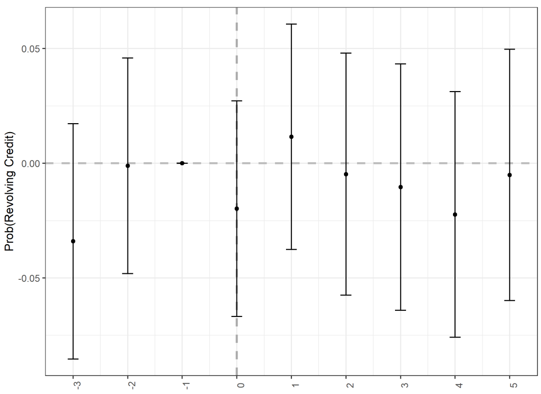
(b) Consumption Credit



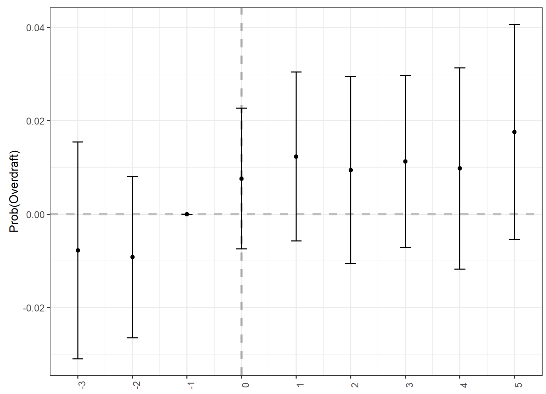
(c) Credit Card



(d) Installment Card

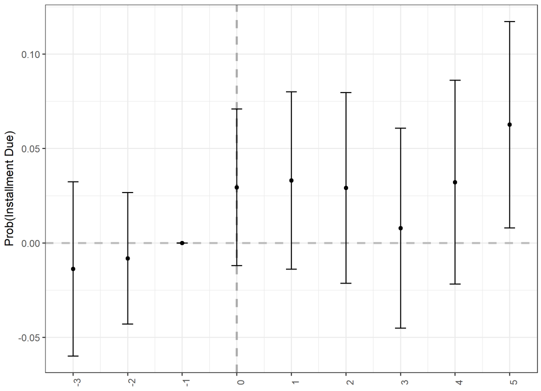


(e) Revolving Credit

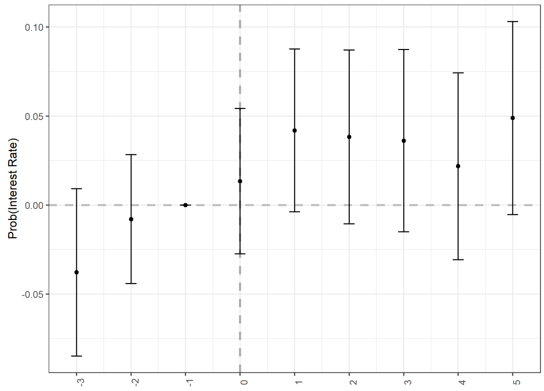


(f) Overdraft

Figure B2: Extensive Margin



(g) Installment Due



(h) Interest Rate

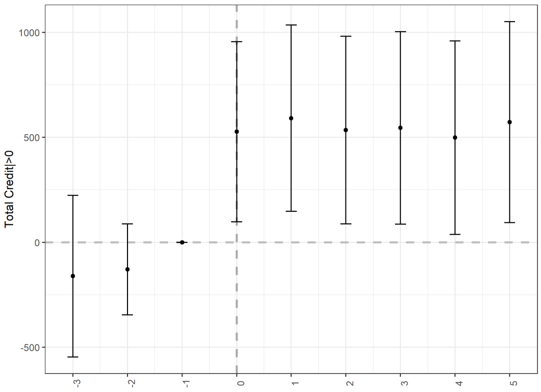
Figure B2: Extensive Margin (cont.)

Notes: This figure shows the plots of the difference-in-difference coefficients of equation 2.2 capturing the effects of later benefit on extensive margin outcomes. The dashed vertical line denotes the period when households started receiving the transfer.

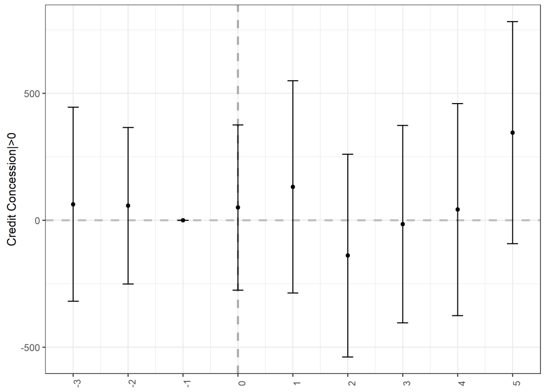
Table B2: Difference-in-differences - Credit Outcomes Intensive and Extensive Margins

	Panel A: Extensive Margin								
	Credit Concession	Total Credit	Consumption Credit	Credit Card	Installment Card	Revolving Credit	Overdraft	Installment Due	Interest Rate
LB x Post	0.025	0.020	-0.0001	0.011	0.056***	0.007	0.009	0.039	0.049*
	(0.018)	(0.024)	(0.022)	(0.022)	(0.020)	(0.023)	(0.010)	(0.027)	(0.025)
Control Mean	0.24	0.81	0.47	0.43	0.21	0.35	0.04	0.65	0.64
Last NIS FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8,755	8,755	8,755	8,755	8,755	8,755	8,755	8,755	8,755
R^2	0.004	0.031	0.006	0.007	0.007	0.0003	0.002	0.067	0.019
	Panel B: Intensive Margin								
	Credit Concession	Total Credit	Consumption Credit	Credit Card	Installment Card	Revolving Credit	Overdraft	Installment Due	Interest Rate
LB x Post	-92.47	638.83**	72.72	-51.44	99.31	79.12	-156.14	-1.69	-5.54
	(101.03)	(289.59)	(95.95)	(80.28)	(120.37)	(80.78)	(144.47)	(16.44)	(7.19)
Last NIS FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,333	7,539	4,368	4,101	1,986	3,131	447	6,478	6,120
R^2	0.00	0.00	0.01	0.01	0.01	0.01	0.07	0.01	0.00

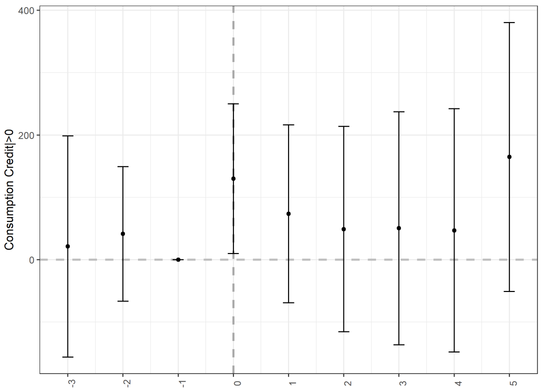
Notes: This Table presents the results for the difference-in-differences specification of having a late benefit on both intensive and extensive margin outcomes. Panel A displays the results for extensive margin outcomes, while Panel B displays the for intensive margin outcomes. Standard errors are in parentheses and clustered at the household level.



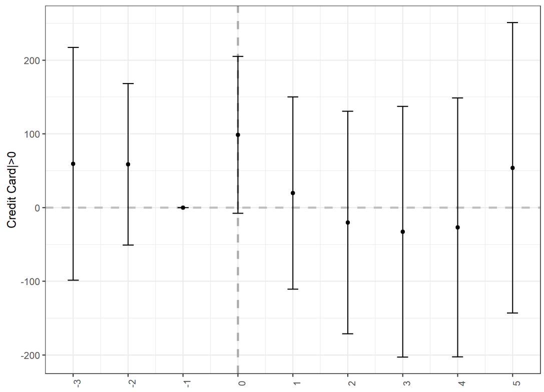
(a) Total Credit



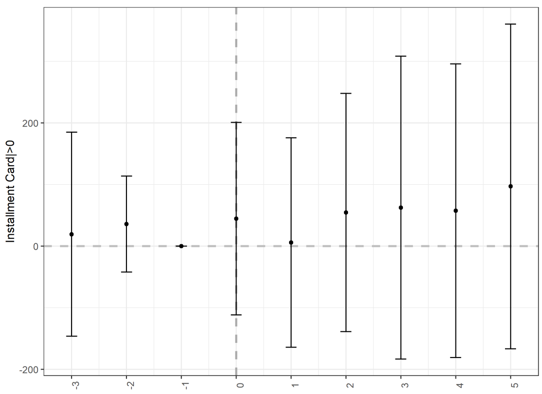
(b) Credit Concession



(c) Consumption Credit

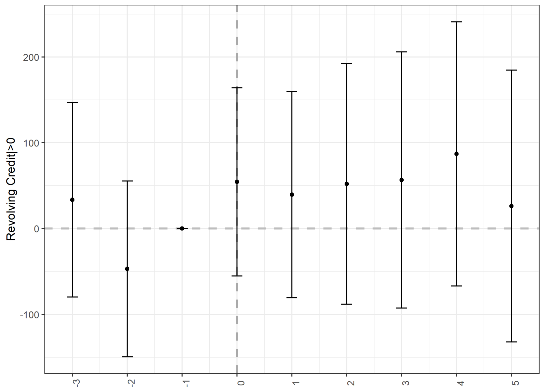


(d) Credit Card

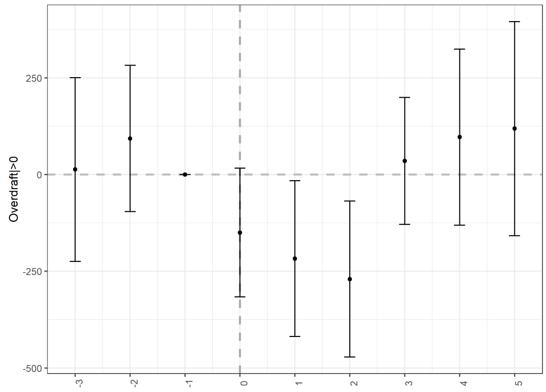


(e) Installment Card

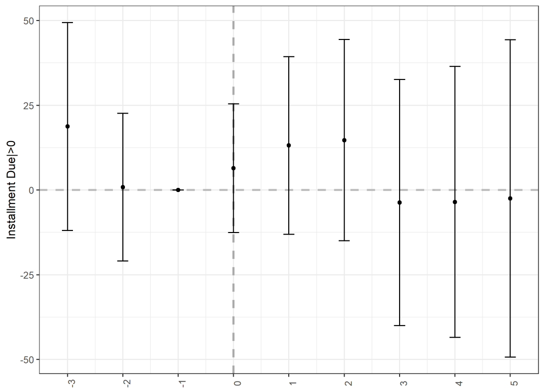
Figure B3: Intensive Margin



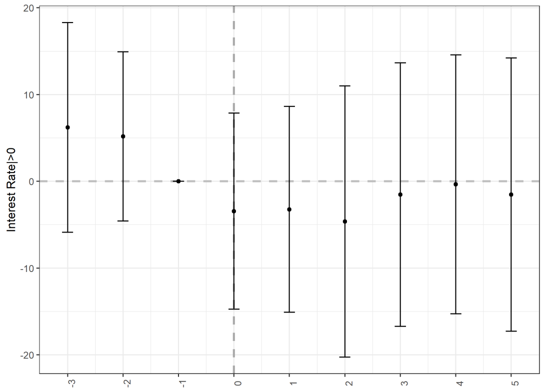
(f) Revolving Credit



(g) Overdraft



(h) Installment Due

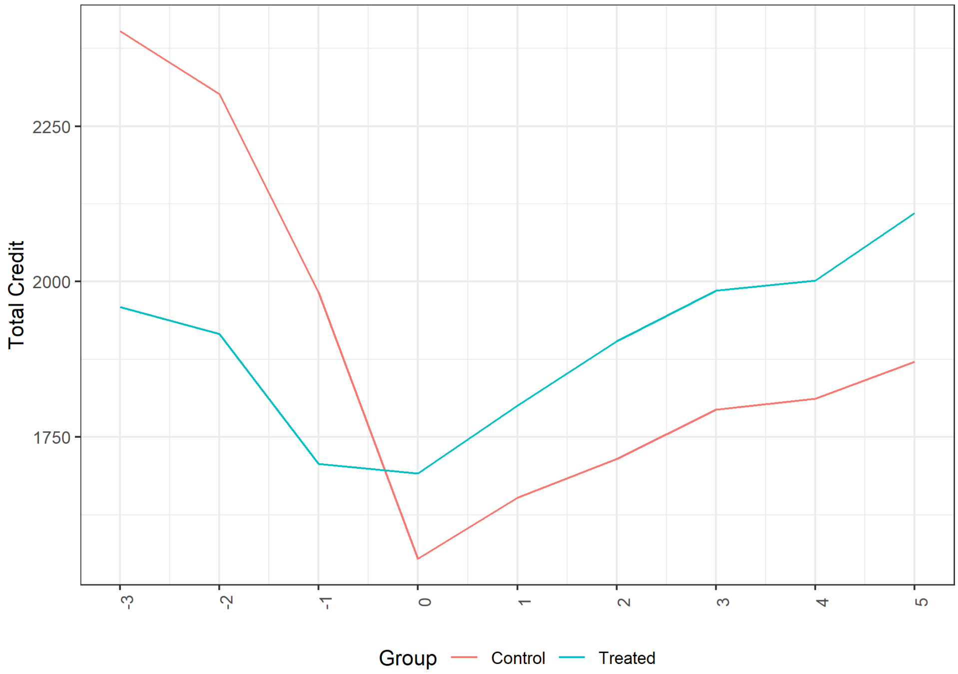


(i) Interest Rate

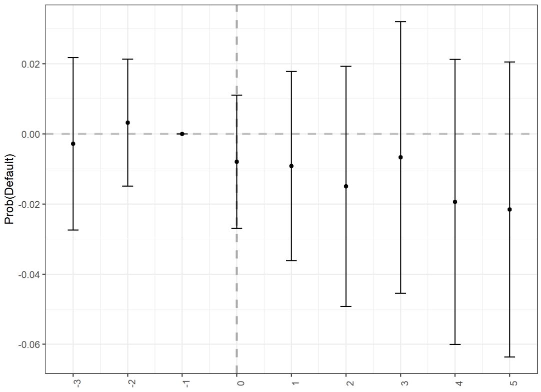
Figure B3: Intensive Margin (cont.)

Notes: This figure shows the plots of the difference-in-difference coefficients of equation 2.2 capturing the effects of later benefit on intensive margin outcomes. The dashed vertical line denotes the period when households started receiving the transfer.

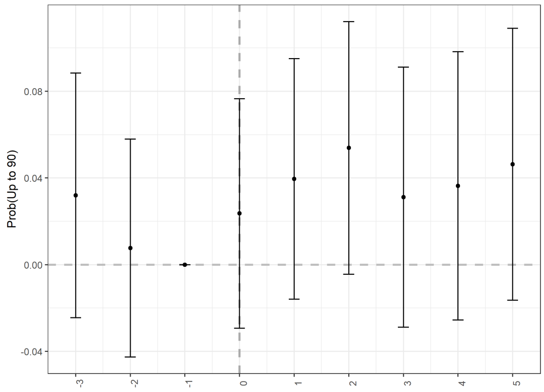
Figure B4: Control vs Treatment - Total Credit



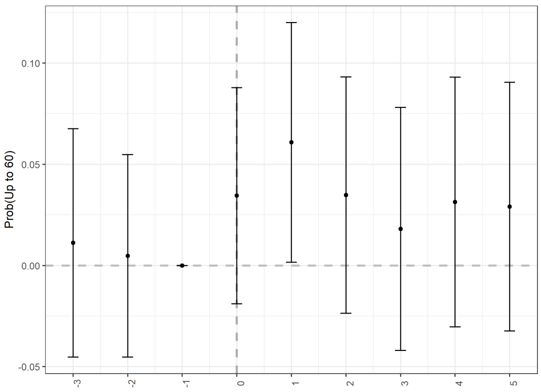
Notes: This figure displays the average Total Credit balance in BRL for both treatment and control groups of new beneficiaries in relation to the period they first receive the benefit in our sample. The treatment group consists of households whose last NIS digit is 9 or 0, and they receive the benefit latest in the month. Meanwhile, the control group comprises those with the last NIS digit of 1 or 0, and they receive cash transfers the earliest in the month.



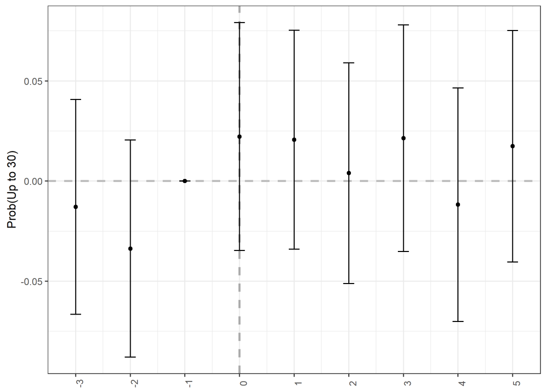
(a) Default



(b) Delay up to 90 days



(c) Delay up to 60 days



(d) Delay up to 30 days

Figure B5: Delinquency Rates

Notes: This figure shows the plots of the difference-in-difference coefficients of equation 2.2 capturing the effects of later benefits on delinquency rates. The dashed vertical line denotes the period when households started receiving the transfer.

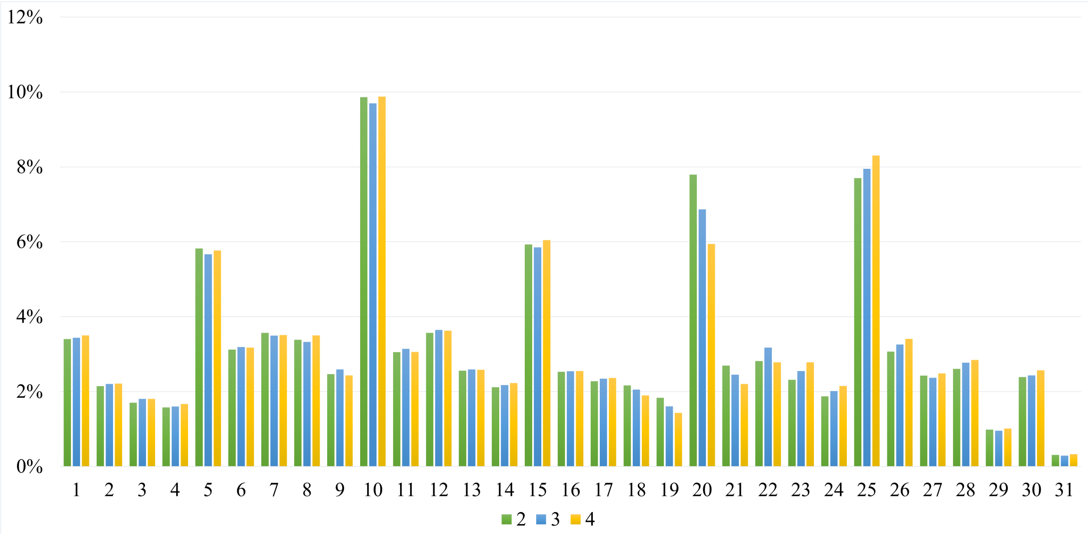
Table B3: Difference-in-differences regressions result: Late Withdraw on Delinquency Rates

	$\mathbb{1}\{\text{Last NIS} \in (9, 0)\} \times Post$
Default	-0.008
	(0.020)
Any Delay	0.017
	(0.026)
Up to 90	0.025
	(0.025)
Up to 60	0.030
	(0.023)
Up to 30	0.030
	(0.020)
Last NIS Digit FE	Yes

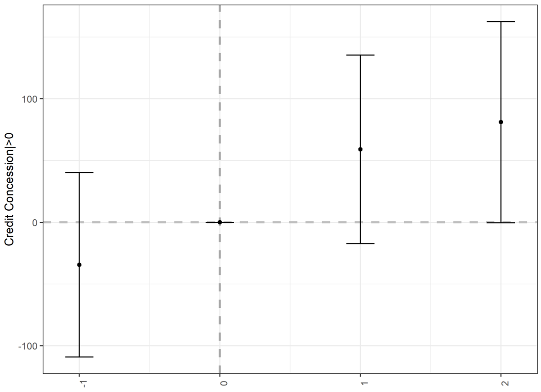
Notes: This Table presents the results for the difference-in-differences specification of having a late benefit on delinquency rates. Standard errors are in parentheses and clustered at the household level.

2.9 Appendix C: Within Effect

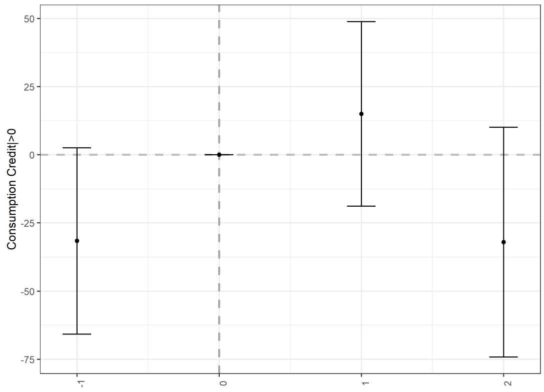
Figure C1: Proportion of Installment Payment Days by Last NIS Digit (All Beneficiaries Sample)



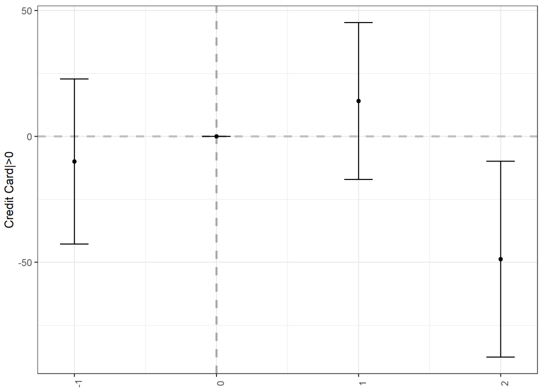
Notes: This figure displays the distribution of installment payment days for households with Last NIS Digits 2, 3, and 4, within the context of all beneficiary households.



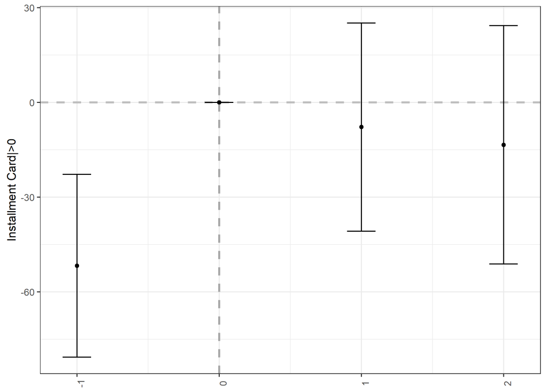
(a) Credit Concession



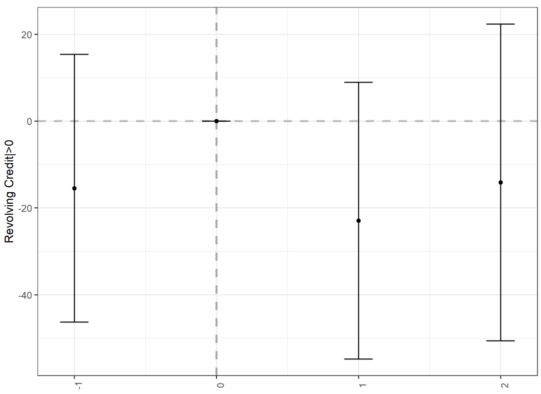
(b) Consumption Credit



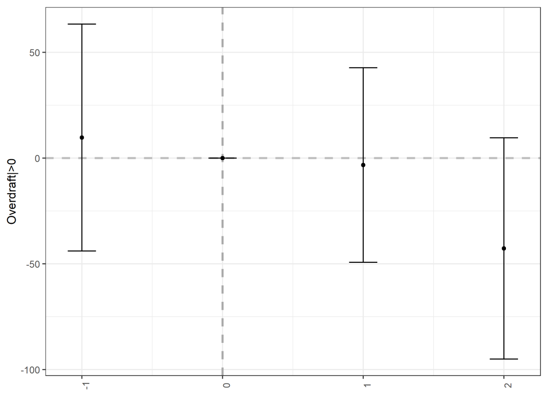
(c) Credit Card



(d) Installment Card



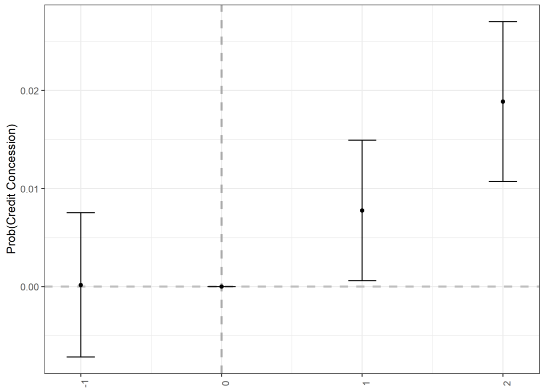
(e) Revolving Credit



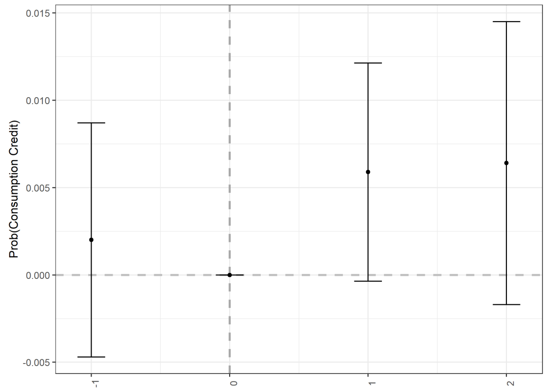
(f) Overdraft

Figure C2: Within Last NIS Digit Effects on Intensive Margin

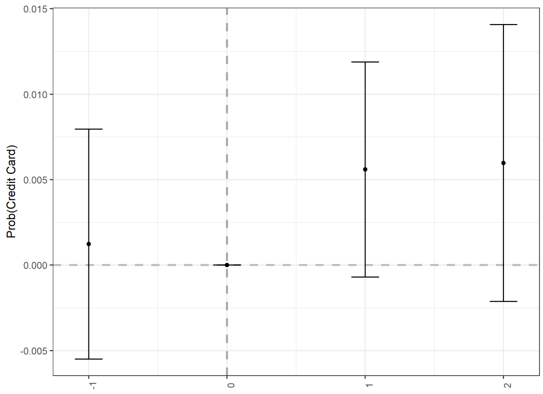
Notes: This figure presents the plots for the coefficients of equation 2.3, which captures the effects of getting the transfer a specific number of days before/after a payment is due in a given month on the intensive margin of credit outcomes. The dashed vertical line denotes the case where the transfer withdrawal could be made on the same day the payment was due.



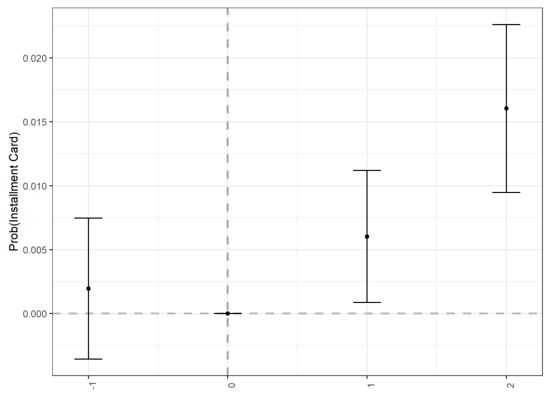
(a) Credit Concession



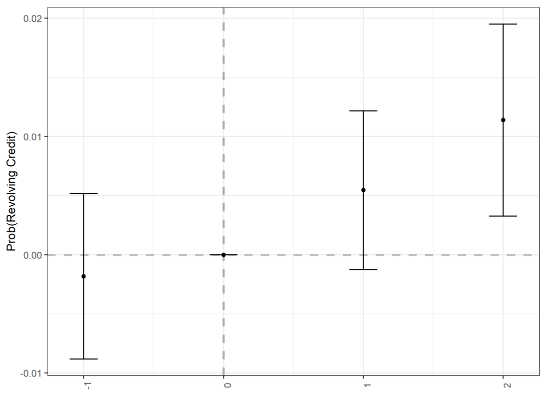
(b) Consumption Credit



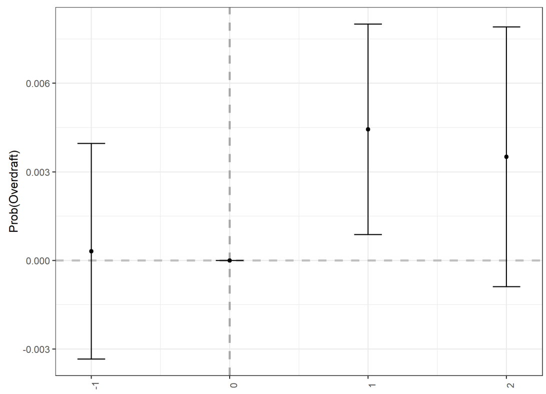
(c) Credit Card



(d) Installment Card



(e) Revolving Credit



(f) Overdraft

Figure C3: Within Last NIS Digit Effects on Extensive Margin

Notes: This figure presents the plots for the coefficients of equation 2.3, which captures the effects of getting the transfer a specific number of days before/after a payment is due in a given month on the extensive margin of credit outcomes. The dashed vertical line denotes the case where the transfer benefit occurred on the same day the payment was due.

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CHAPTER 3

Beyond Poverty Alleviation: Estimating the Causal Effect of Cash Transfers on Credit Dynamics in Brazil using Rich Administrative Datasets[1]

Abstract: How does receiving a cash transfer affect the credit outcomes of impoverished households? This paper investigates the impact of unexpected cash transfers on the credit outcomes of these households, utilizing a unique dataset from the Brazilian credit registry linked with a social registry for government social programs. Employing a difference-in-differences design that compares newly eligible households to those marginally above the new income threshold, we provide robust evidence that receiving unexpected cash transfers greatly influences credit outcomes. Specifically, we find that beneficiary households increase credit card usage and experience a higher rate of credit origination. Furthermore, extremely poor households benefit from improved credit terms, including lower interest rates and more favorable credit conditions. These findings suggest that cash transfers can effectively reduce household credit risk, enhance credit access, and improve overall credit conditions, thereby promoting financial inclusion and economic stability among vulnerable populations.

JEL Codes: G50, G51, I32, I38.

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Keywords: household debt, access to credit, conditional cash transfer, debt accumulation

3.1 Introduction

Many of the poorer world population lack access to credit and financial services. For example, despite significant progress in recent years, Brazil's poorer population's financial inclusion still has a long way to go. In December 2019, only 20% of the people in the households that received conditional cash transfers had a credit balance, compared to 65% of those in households other than beneficiaries who are not registered in the *Cadastro Único* social benefit registry. In turn, conditional cash transfer (CCT) programs are designed to enhance the well-being of low-income families by mitigating immediate poverty and fostering human capital development across generations in various countries.[2] Studies have highlighted the positive effects of CCTs on education, health, and overall living conditions (Rawlings and Rubio 2005, Rasella et al. 2013, Parker and Todd 2017). When it comes to the benefits of financial inclusion, a branch of the economic literature provides causal evidence that access to financial services enables poor households to cope with shocks, invest in labor market activities, accumulate wealth, improve financial stability, and save more (Bruhn and Love 2014, Célerier and Matray 2019, Fonseca and Matray 2022, Bachas et al. 2021). We tied both branches by studying how receiving the benefit affects the credit intake and conditions for newly eligible beneficiary households.

According to the Global Financial Index Survey, in 2021, of the 40% poorest Brazilians, 82% had a bank account, 52% borrowed money, 62% made a digital payment, and 39% saved any money. In a new context of increasing financial inclusion, understanding how CCTs influence household financial dynamics is indispensable for policymakers and practitioners seeking to enhance the efficacy of these programs. In particular, the financial inclusion of households receiving CCT is directly linked to how the transfers affect this population's supply and demand for credit. However, it is not clear how the transfer affects credit demand and supply. The reason is that the beneficiary status could indicate that households are struggling financially. On the other hand, these households

2. including Brazil, Mexico, Colombia, Jamaica, Bangladesh, Chile, Honduras, and Zambia

are comparatively better off than otherwise, as the transfer makes them richer and with less volatile income. We address this gap by estimating the impact of CCT on credit intake and debt accumulation, exploring discontinuities in households' probability of being CCT beneficiaries in Brazil. We explore exogenous law changes in the income eligibility range of *Bolsa Família*, a Brazilian CCT program, which allows us to infer the causality of entering and exiting the program on credit outcomes.

The identification strategy is based on a legal change in the interval determining which households are considered (extremely) poor and eligible to receive the cash transfer. A decree of May 30th, 2018,*Decreto Nº 9.396* enacted 90 days later, changed the eligibility income threshold from 170 BRL to 178 BRL for poor households and from 85 BRL to 89 BRL for extremely poor households. So, households who had updated their registry before the announcement date and whose per capita income information was between the new eligibility limits had a discontinuity in the probability of receiving the benefit in July 2018.[3] Here, under a difference-in-differences specification, the identification assumption is that households above and below the new threshold follow parallel trends in the outcomes of interest. In this setting, households do not anticipate receiving the benefit, and the income shock is unexpected. We provide evidence for the assumption of parallel trends using extended treatment effects in a dynamic specification and find no evidence of pre-existing trends.

We use two rich administrative datasets containing information about credit and social registry. The first dataset, called the *Cadastro Único*, contains information about households, including their status as beneficiaries of the CCT program, per capita income, household composition, illiteracy, and the highest education level attained by a member. The second dataset is obtained from a credit registry and provides information on household-level credit balances across different types of credit. This dataset also includes information on delinquency rates and interest rates. Using these two datasets, we

3. In the Appendix 3.8.1, we demonstrate that in July 2018, there were no observable systematic differences between those who updated their registry and those who did not.

observe various aspects of household finances over time.

Our findings suggest that after becoming CCT beneficiaries, households have more access to credit under better conditions. Notably, our analysis demonstrates that receiving CCT unexpectedly increases credit card usage by more than 11%, underscoring the relevance of these financial instruments in the lives of these households. Furthermore, we find evidence of a critical dimension of the relationship between CCT programs and credit supply to households in extreme poverty. This group experiences a remarkable 76% surge in the probability of credit origination. Moreover, the rise in credit utilization among new CCT beneficiaries is not accompanied by an increase in delinquency rate, while being associated with a reduction in the balance weighted average interest rate.

Our results have significant policy implications. They suggest policymakers should consider tailoring CCT programs to alleviate immediate poverty and foster financial inclusion. By recognizing the role of credit as a financial tool, policymakers can design more holistic and effective social welfare strategies that empower low-income households to navigate the complexities of their financial lives. In this context, policies aiming to increase beneficiaries' financial literacy gain importance.

Our contributions to the literature are twofold. First, we provide novel evidence of the effects of a cash transfer on financial inclusion. In particular, we provide evidence that new beneficiaries have more credit originations. Hence, we contribute to the literature that investigates CCT programs effects (e.g., Rawlings and Rubio 2005, Rasella et al. 2013, Parker and Todd 2017, Bianchi and Bobba 2013, Gertler, Martinez, and Rubio-Codina 2012, Bianchi and Bobba 2013).[4] Angelucci and De Giorgi (2009), for instance, find evidence of indirect CCT programs effects on the local economy as credit and insurance markets make non-beneficiary households increase consumption by receiving more gifts and loans and reducing savings. Also, through an incomplete markets model with heterogeneous agents facing idiosyncratic risk, Berriel and Zilberman (2012) find suggestive

4. It also relates to the one that investigates the impact of credit and grants on household wealth, such as Kaboski and Townsend 2011 and Fiala 2018.

evidence that the welfare gains of cash transfer programs increase in proportion to the cost of accessing financial markets.

Our results are also linked to the literature on consumer debt accumulation.[5] Moreover, it connects to the literature on consumption response to income shocks,[6] and on consumption patterns of poor households (Aguiar, Bils, and Boar 2020), as we find that consumption credit increases after households receive the benefit. Our empirical exercise - which exploits the new income eligibility range - is directly related to the literature that studies the effects of positive income shocks on credit behavior. For instance, exploiting the fact that rebates had a random timing across families and were expected, Agarwal, Liu, and Souleles (2007) find that after-tax rebates, consumers use the money to increase credit card payments while increasing their credit card expenses afterward, which contradicts the life-cycle/permanent income model. On the other hand, Andersen, Johannesen, and Sheridan (2021), exploiting lottery-like variation in gains across investors with similar portfolio characteristics, encounter that spending responses to stock market gains are immediate and persistent, which is compatible with the permanent income hypothesis. Also, Agarwal and Qian (2014) find that consumers tend to spend approximately 80 cents out of every dollar they receive due to an exogenous unanticipated income shock from a fiscal stimulus. Moreover, they find that spending rose primarily in the small, durable goods category, including electronics, computers, home or office furnishings, and appliances. This aligns with one valid interpretation of our results that suggests an increase in credit card spending is most likely related to durable goods that are small enough to be purchased by the expected future cash transfer income. That is, the credit card is utilized to distribute the payment of the lump sum value of the durable good over an extended period. Our investigation also relates to the literature on the effects of social

5. Bornstein and Indarte 2020; Indarte 2022; Mian, Sufi, and Verner 2017; Gomes, Grotteria, and Wachter 2019; Mian, Sufi, and Verner 2020

6. For instance:Carroll 1997;Parker 1999; Shapiro and Slemrod 2003; Souleles 2002; Stephens Jr 2008; Johnson, Parker, and Souleles 2006; Agarwal, Liu, and Souleles 2007; Stephens Jr and Unayama 2011; Broda and Parker 2014, Parker 2017, Andersen, Johannesen, and Sheridan 2021. See Jappelli and Pistaferri 2010 for literature review.

security expansion on vulnerable households' access to credit and performance (Bornstein and Indarte 2020, Gross and Notowidigdo 2011, Finkelstein et al. 2012, Barcellos and Jacobson 2015, Hu et al. 2018). For example, Bornstein and Indarte (2020) shows that Medicaid, a US health insurance targeting the poorer population, increased credit card borrowing.

Our second contribution is to provide evidence that the constant income stream from cash transfers improves credit conditions.[7] Hence, we also contribute to the literature on both the provision (Bertola, Disney, Grant, et al. 2006; Ramcharan, Verani, and Van den Heuvel 2016; Benmelech, Meisenzahl, and Ramcharan 2017; Jensen and Johannesen 2017) and demand (Telyukova 2013) of consumer credit. Beneficiary households often do not have formal labor income and assets, and we find that receiving a constant income stream from the government increases the beneficiary's ability to borrow. Regarding the effects of financial services on poor households' behavior, Angelucci, Attanasio, and Di Maro (2012) has more direct overlap with our study. In their research, they exploit the expansion of Mexico's CCT Program, known as Oportunidades, and highlight how CCTs are utilized to repay debts, thereby reducing the number and value of loans. In contrast, our investigation primarily focuses on the use of credit given a long-lasting, unexpected positive income shock.

The rest of the paper is organized as follows. In section 4.2, we describe the CCT program in Brazil and the Brazilian credit market to the Beneficiary and non-beneficiary populations. Next, in section 4.4, we explain the data used. In section 4.5, we present the identification strategy, and in section 4.6, we present the results, followed by an economic interpretation in 3.6, where we explore a reasonable framework behind the effects of the unexpected income increase from becoming a CCT beneficiary household. Finally, we state the conclusions of the paper.

7. Since virtually all beneficiary households tend to immediately withdraw all the cash - 99% of beneficiaries withdraw the transfer on the day or the following day it became available in January 2018 -, the effects on bank behavior are not necessarily easy to infer

3.2 Institutional Background

3.2.1 Bolsa Família: CCT Program in Brazil

In Brazil, *Bolsa Família* (BF) is a means-tested CCT program providing financial aid to poor families while also encouraging families with children to invest in human capital accumulating for the next generation. It aimed to improve poor households' welfare through a cash grant while promoting human capital accumulation with conditionalities such as children's school attendance and vaccination. Until December of 2019[8] - the last month of our sample -, to be eligible to receive a BF grant, families should have per capita income of up to 89.00 Brazilian Reais (BRL) monthly or between 89.01 BR and 178.00 BRL monthly, provided they have children from 0 to 18 years old.[9] In 2019, the average monthly transfer, considering all BF beneficiaries households, was 173 BRL.[10] Those two main groups of *Bolsa Família* beneficiary households are designated as "extremely poor" and "poor." While extremely poor households[11] received a baseline grant (89,00 BRL) regardless of their family composition, poor households[12] received the benefit of 48.00 BRL conditional on having a minor child that fulfills the conditionalities like being above a reasonable level of school attendance. We exploit the changed income eligibility range that generated a discontinuity in the probability of being a CCT beneficiary household for newly eligible households to estimate the grant's impact on these households' credit outcomes.

3.2.2 CCT and Credit in Brazil

Households benefiting from cash transfer programs are expected to exhibit distinct credit utilization patterns compared to their non-beneficiary counterparts. This diver-

8. Before July of 2018, the income thresholds were 85,00 BRL and 170,00 BRL.
9. *Ministério da Cidadania*: August 13th, 2020.
10. *Portal da Transparência*: October 23rd, 2023.
11. Those with per capita income below 90 BRL
12. Those with per capita income between 90 BRL and 178 BRL

Table 3.2.1: Proportion of Individuals Aged 18 to 100 using Credit Lines by Household Beneficiary Status

	CCT Beneficiary	**Non-beneficiary (Cadúnico)**	**Non-beneficiary**
Any Credit	20.9%	16.0%	65.1%
Credit Card	12.2%	9.1%	47.7%
Revolving	9.3%	7.0%	27.7%
Overdraft	2.6%	4.0%	17.8%
Microcredit	1.5%	0.2%	0.5%
Personal	2.5%	4.1%	11.3%
Payroll	0.6%	8.6%	15.5%
Rural	0.4%	0.2%	0.9%
Automotive	0.8%	0.5%	7.9%
Housing	0.4%	0.2%	5.8%

Notes: This table shows the proportion of adults between 18 and 100 years old in CCT Beneficiary and non-beneficiary households with a positive balance in the respective credit line. These statistics are categorized and presented based on Beneficiary Status for December 2019. The non-beneficiary group is divided into the ones that are registered in Cadúnico and those that are not.

gence in behavior primarily stems from the economic disparity between the two groups, with beneficiary households experiencing higher levels of poverty. From the bank's perspective, these households pose a greater risk as they often rely on unstable and informal sources of income that cannot be verified or confiscated in the event of a default. Banks view households with unstable and informal sources of income as riskier borrowers because these households lack the predictability and stability of more formal income sources. As a result, these households face greater challenges in providing the necessary documentation to verify their income, making it more difficult for banks to assess their creditworthiness. Furthermore, in the event of a default, these households often lack assets that can be confiscated to repay the loan, leaving the bank with a higher risk of loss.

Table 3.2.1 shows the proportion of individuals aged 18 to 100 according to the CCT beneficiary status of their household using each credit type. We consider three different CCT Beneficiary Status groups: beneficiaries, non-beneficiaries registered in a social registry, and non-beneficiaries not in the social registry. The registry is "Cadastro Único," also known as *Cadúnico*. It is an information collection instrument the Brazilian govern-

Table 3.2.2: Credit Type Percentage of Total Balance by Household Beneficiary Status

	CCT Beneficiary	**Non-beneficiary (Cadúnico)**	**Non-beneficiary**
Credit Card	1.2%	1.1%	0.9%
Revolving	0.8%	1.2%	0.4%
Overdraft	0.4%	0.2%	0.2%
Microcredit	4.0%	4.1%	1.5%
Personal	1.9%	2.4%	2.3%
Payroll	7.7%	8.1%	4.9%
Rural	30.0%	44.3%	61.0%
Housing	40.7%	24.7%	23.4%
Automotive	13.2%	13.9%	5.3%
Total	100%	100%	100%

Notes: This table shows the percentage participation of each credit type in the total credit balance by Beneficiary Status for December 2019. We consider adults between 18 and 100 years old in CCT Beneficiary households and non-beneficiary households. The non-beneficiary group is divided into the ones that are registered in Cadúnico and those that are not.

ment uses to identify and characterize low-income families in the country. The information provided in the *Cadúnico* is used to select and include families in social programs, such as Bolsa Família, Benefício de Prestação Continuada (BPC), Minha Casa, Minha Vida, among others.

Credit card corresponds to purchases made with credit cards, in cash or interest-free installments, by retailers. Revolving credit is a financing operation for the remaining debt balance after partial payment of credit card bills. Includes cash withdrawals using the card in the credit function. Overdraft is a credit operation linked to current accounts using a pre-established credit limit without prior communication to the financial institution. Includes advances to depositors and guaranteed account operations aimed at the individual segment. Microcredit is credit mostly to small individual entrepreneurs by public banks under subsidized conditions. Personal credit is a loan to individuals, not linked to the acquisition of goods or services, by making resources available to the borrower for free use. Payroll credit is an operation with payroll deductions tied to formal salary or pension. Automotive are loans to individuals intended to finance the purchase of motor vehicles, where the financed asset is sold on a fiduciary basis as a guarantee for the operation.

In December 2019, adults from 18 to 100 years old who were in a household that received CCT (Beneficiary) had 12% probability of using any credit card, in comparison to non-beneficiary households - either those that are in a social beneficiary registry and very likely had previously received a governmental benefit before - "Non-beneficiary (Cadúnico)" -, or those that are not in this registry - 'Non-beneficiary" - that presented 9% and 48% chance of using it. While wealthier adults who do not rely on governmental benefits use credit cards more frequently, those registered in Cadúnico but do not receive any transfers use them less.

Table 3.2.3: Credit Conditions by Type and Household Beneficiary Status

	Balance	**Concession**	**Interest Rate**	**Term**	**Default**
Any Credit					
CCT Beneficiary	BRL 4,807.27	BRL 439.06	44%	113	20.0%
Non-beneficiary (Cadúnico)	BRL 9,454.29	BRL 887.02	47%	74	11.9%
Non-beneficiary	BRL 27,794.35	BRL 1,669.26	23%	156	10.0%
Credit Card					
CCT Beneficiary	BRL 1,419.39	BRL 210.16	0%	58	0.1%
Non-beneficiary (Cadúnico)	BRL 1,358.29	BRL 148.46	0%	84	0.0%
Non-beneficiary	BRL 3,959.05	BRL 329.94	0%	73	0.0%
Revolving					
CCT Beneficiary	BRL 1,009.47	BRL 120.94	182%	42	28.3%
Non-beneficiary (Cadúnico)	BRL 1,438.66	BRL 687.33	109%	38	16.3%
Non-beneficiary	BRL 1,948.90	BRL 434.06	152%	48	10.6%
Overdraft					
CCT Beneficiary	BRL 465.33	BRL 121.72	269%	18	16.3%
Non-beneficiary (Cadúnico)	BRL 287.20	BRL 99.30	283%	28	7.2%
Non-beneficiary	BRL 1,056.99	BRL 437.68	264%	32	3.6%
Microcredit					
CCT Beneficiary	BRL 4,893.20	BRL 1,202.53	36%	9	3.9%

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Table 3.2.3: Credit Conditions by Type and Household Beneficiary Status (continued)

	Balance	Concession	Interest Rate	Term	Default
Non-beneficiary (Cadúnico)	BRL 5,137.19	BRL 1,224.95	36%	11	3.4%
Non-beneficiary	BRL 6,669.89	BRL 1,387.69	33%	15	2.1%
Personal					
CCT Beneficiary	BRL 2,342.82	BRL 237.41	187%	28	26.5%
Non-beneficiary (Cadúnico)	BRL 2,980.19	BRL 267.58	236%	36	14.5%
Non-beneficiary	BRL 9,955.18	BRL 1,112.02	76%	45	12.6%
Payroll					
CCT Beneficiary	BRL 9,355.62	BRL 897.36	26%	75	6.7%
Non-beneficiary (Cadúnico)	BRL 10,054.78	BRL 591.45	25%	73	4.4%
Non-beneficiary	BRL 21,426.22	BRL 1,628.18	23%	81	3.1%
Rural					
CCT Beneficiary	BRL 36,273.53	BRL 1,069.30	5%	94	18.0%
Non-beneficiary (Cadúnico)	BRL 54,939.78	BRL 1,340.46	5%	90	4.9%
Non-beneficiary	BRL 266,375.94	BRL 8,759.57	7%	67	8.9%
Housing					
CCT Beneficiary	BRL 49,154.98	BRL 441.44	6%	353	5.2%
Non-beneficiary (Cadúnico)	BRL 30,574.00	BRL 196.51	7%	297	1.5%
Non-beneficiary	BRL 102,090.87	BRL 1,258.25	8%	344	1.7%
Automotive					
CCT Beneficiary	BRL 16,006.27	BRL 1,122.62	25%	47	10.5%
Non-beneficiary (Cadúnico)	BRL 17,196.36	BRL 991.05	23%	47	4.0%
Non-beneficiary	BRL 22,931.88	BRL 1,505.09	20%	46	6.2%

Continued on next page

Table 3.2.3: Credit Conditions by Type and Household Beneficiary Status (continued)

	Balance	Concession	Interest Rate	Term	Default

Notes: This table provides a comprehensive overview of credit conditions, encompassing various key factors, including Balance (in BRL), Concession (in BRL), Interest Rate (in % a.r.), Term (in months), and Default Rate (%). Interest rate is in annual percentage rate terms and % a.r. stands for annual percentage rate. These statistics are categorized and presented based on Beneficiary Status for December 2019. We consider adults between 18 and 100 years old in CCT Beneficiary households and non-beneficiary households. The non-beneficiary group is divided into the ones that are registered in Cadúnico and those that are not.

Table 3.2.3 also shows the credit conditions (New Credit Size, Interest Rate, Term), balance, and default rate for these individuals according to household CCT Beneficiary Status for every credit type. We can see that individuals from households receiving benefits show a 20% delinquency rate, compared to 11.9% and 10% among those in non-beneficiary cadúnico households and non-beneficiary households. Also, adults from CCT beneficiary households receive a smaller personal credit loan size, with a shorter term and a higher interest rate, compared to those from non-beneficiary households not listed in *Cadúnico*. At the same time, those in *Cadúnico* but not in beneficiary households receive credit under higher interest rates, although longer terms.

This peculiarity in credit behavior and conditions among cash transfer beneficiaries raises an important research question: does the transfer of cash itself play a transformational role in influencing the credit usage dynamics and associated conditions within these households? This paper addresses this question by investigating the impact of cash transfers on credit utilization patterns and the terms under which credit is granted to beneficiary households, shedding light on the broader implications for poverty alleviation and financial inclusion initiatives. In the following section, we will explore the economic underpinnings that drive households' expected behavior when receiving the CCT benefits, as well as the bank's perspective on the households' new creditworthiness. This encompasses not only the bank's willingness to extend credit to CCT-receiving households but also its readiness to offer more favorable credit terms.

3.3 Data

This section describes the data sources used in the paper. We match *Cadastro Único para Programas Sociais do Governo Federal* (*CadÚnico*), the Brazilian Credit Registry data (SCR), and Relação Anual de Informações Sociais (RAIS) datasets. Managed by the Brazilian Ministry of Citizenship (MC), the *Cadastro Único para Programas Sociais do Governo Federal* (*CadÚnico*) is the main instrument of the Brazilian State for the selection and the inclusion of low-income families in federal programs, which must be used to grant the benefits of the Bolsa Família Program among others. SCR stores information on all credit operations carried out throughout Brazil by persons and firms with a total liability of at least 200 BRL. We use household information on the age of the youngest member, the number of people in the family, household income from *CadÚnico*, and the information on credit and default status from *SCR*. We also use RAIS, a database that includes employment information and wages for all formally employed workers in Brazil. Data is aggregated at the household level such that the credit is the sum of every type of credit received by every member. Default indicates whether any member is on default, according to BCB's definition,[13] at a particular month. We also have a dummy indicating if there is any formal employee, the sum of formal salary, and the number of formal entrepreneurs at the household level each month. The dataset is at the household-month-year level, with matched information from *CadÚnico*, *SCR*, and RAIS. The sample period goes from January 2018 to December 2019, encompassing two years. Our dataset is drawn from the State of Minas Gerais, a region that closely mirrors the socioeconomic characteristics of Brazil as a whole.

13. Credit in arrears for more than 90 days

3.4 Identification Strategy

The purpose of our investigation is to understand the impact of conditional cash transfers on poor individuals' debt accumulation and credit intake. In simple terms, we would like to estimate the following equation:

$$y_{it} = \alpha_i + \gamma_t + \beta \times CCT_{it} + \epsilon_{it} \tag{3.1}$$

where CCT_{it} is a dummy of whether the household i receives the transfer or not in period t, β is the coefficient of interest which represents the effect of having a CCT on a specific credit outcome y_{it}. α_i and γ_t are household and year-month fixed effects, respectively. However, endogeneity poses a significant challenge when examining the relationship between CCT and credit outcomes primarily because beneficiaries typically find themselves in more precarious social and economic circumstances than non-beneficiary households. Consequently, various unobserved factors may influence the outcomes of interest intertwined with the beneficiary status, some of which are not properly controlled by the traditional time and household fixed effects. In simpler terms, individuals often self-select into CCT participation based on unobservable characteristics that can, in turn, affect credit outcomes. Hence, endogeneity reflects in the error term ϵ_{it} of Equation 4.1 such that:

$$\mathbb{E}[\epsilon_{it}|\alpha_i, \gamma_t] \neq 0 \tag{3.2}$$

To tackle this issue, we explore a discontinuity in CCT beneficiary status that enables us to estimate the causal effects of interest by performing difference-in-difference specifications. The change is related to the eligibility threshold for the CCT program. It enables us to estimate the impact of receiving the cash transfer without any anticipation. Households were unaware they would receive the benefit as their registry was last updated before the new income threshold law was announced, and two months later, it was enacted.[14] The identification assumption is that the control and treatment would have followed parallel trends, meaning that whatever affected the control group in the interval before and after the intervention would also have affected the treatment group in the absence of the intervention.

3.4.1 Unexpectedly Becoming a CCT Beneficiary

First, let us ponder the complex relationship between cash transfers and credit utilization. Receiving cash transfers provides households with a stable income source. This financial stability, in turn, may influence households' decisions regarding credit usage, as they might use credit to anticipate income for consumption of durable goods, given the long-lasting nature of the cash transfer shock, or reduce since now they have the liquidity that would otherwise be provided by credit. Furthermore, from a financial institution's perspective, households receiving regular cash transfers are perceived as less risky borrowers, given the verifiable source of income, potentially affecting the credit conditions offered and the Bank's willingness to grant credit. This introduction sets the stage for our identification strategy, where we endeavor to estimate the impact of cash transfers on credit behavior, overcoming the endogeneity problem highlighted by Equation 4.2, shedding light on how these transfers influence households' financial decisions.

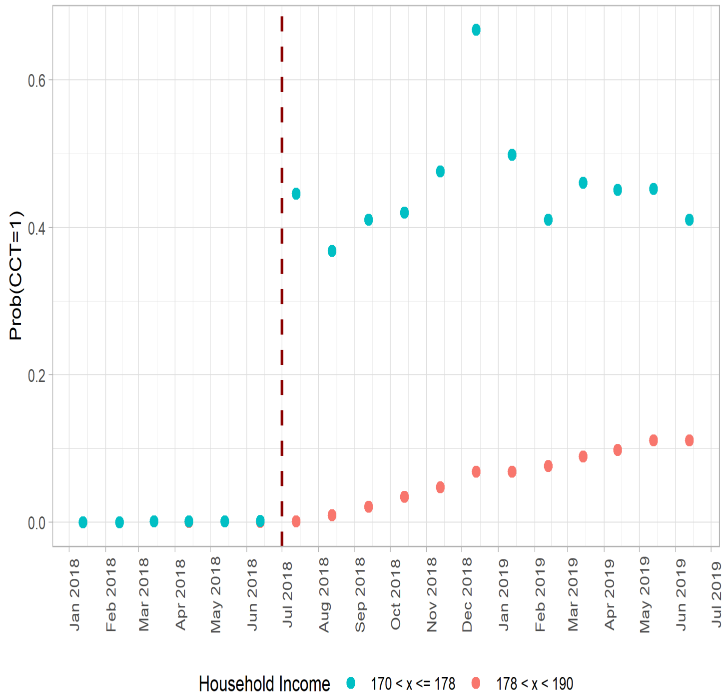
To address the identification challenge, we exploit the changes in BF income eligibility thresholds. In July 2018, extremely poor and poor households' per capita income thresholds changed from 80 BRL to 89 BRL and 170 BRL to 178 BRL, respectively. We select households with a registry update before May 2018 - the month the changes in eligibility threshold were announced - in July 2018 - the month it was enacted. In this way, the household head in the selected sample could not have manipulated its income declaration in their *Cadunico* update to be strictly below the new eligible range.

14. We weight all observations by performing a propensity score matching in the baseline period, using the following variables: (1) female household head; (2) maximum household education attained; (3) number of people; (4) indicator variable, if any households member used any credit card; (5) households total credit balance; and (6) household total formal salary.

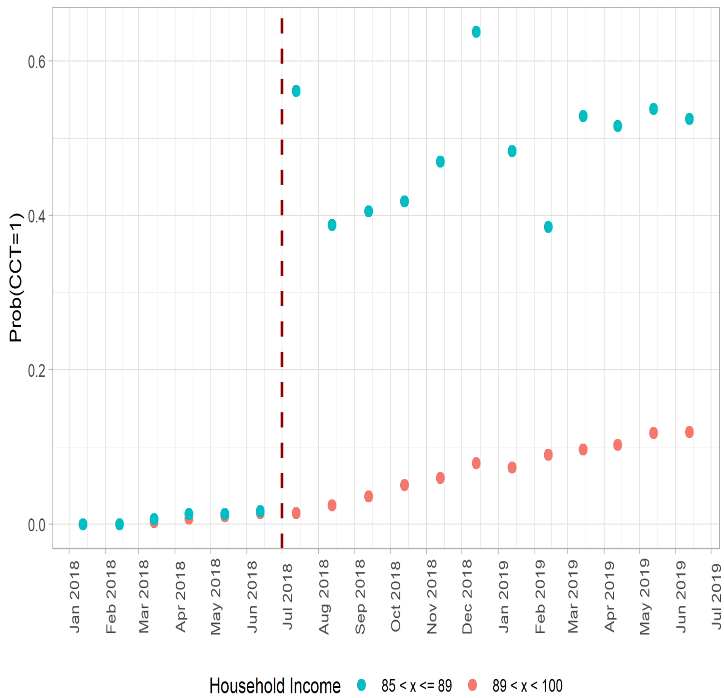
We ran difference-in-difference specifications separately to identify the effect of receiving the cash transfer for each group. For extremely poor households, we selected households without children who, hence, were not receiving any cash transfer amount, and those in the treatment would become eligible to receive 89.00 BRL, roughly 100% of their per capita income. In turn, we select the sample of poor households with children, whose treatment group became eligible to receive a cash transfer that amounts to close to 30% of their per capita income, in case they had, for instance, one child only.[15]

15. the calculations here are simply : (I) basic benefit for households in extreme poverty/income per capita upper limit of extreme poverty line = BRL 89/ BRL 89 = 1; youth variable benefit/income per capita upper limit of poverty line = 48/178=.27

Figure 3.4.1: Changes in Eligibility Income Range and CCT Status Over Time



(a) Poor Households



(b) Extremely Poor Households

Notes: These Figures depict the proportion of households that are CCT beneficiaries (CCT=1) over time for considering those that are in the newly eligible income range or just above it. Subfigure (a) shows the graph for the poor households group and Subfigure (b) for the extremely poor group.

Figure 3.4.1 shows the proportion of extremely poor households with no minor child that are beneficiary households over time. In July 2018, there was an increase in the probability of households in the treatment group having CCTs. This is an unexpected income change since we only select households who had updated their information in the registry before the changes in income threshold were announced. Table **??** shows the descriptive statistics for each group. The groups are similar in most credit and social variables. In particular, they have no statistically significant differences in all credit balances. To further ensure comparability of treatment and control groups, we also perform a matching before running the regressions the month before the law was enacted, and the balancing results can be seen in Figure A1.

Recall that one cannot directly estimate the effects of CCT through Equation 4.1 due to the endogeneity of CCT and households' unobserved characteristics, not captured by the traditional time and individual fixed effects, that would affect credit outcomes. Hence, we exploit the condition of having per capita income under the newly eligible range as an instrument for the CCT status. The first-stage regression is then:

$$CCT_{it} = \alpha_i + \gamma_t + \lambda \times \text{Newly Eligible}_i \times Post_t + \epsilon_{it} \tag{3.3}$$

where CCT_{it} is the household's i CCT Status at time t, Newly Eligible_i is a dummy equal to one if the household's i per capita income is within the new eligibility range, and $Post_t$ is a dummy equal to one if the year-month t is at or after July 2018, the month the new eligibility range law was enacted. α_i and γ_t are household and time-fixed effects.

Now, we can capture the causal effect of receiving CCT by regressing the outcomes of interest on the variation in CCT Status coming only from the new eligible status and captured from the fitted values of Equation 3.3, as the following specification:

$$Y_{it} = \iota_i + \theta_t + \beta \times \widehat{CCT_i} + \nu_{it} \tag{3.4}$$

where $\widehat{CCT_i}$ is the instrumented CCT Beneficiary Status from the first-stage.

Table 3.4.1: Descriptive Statistics - New Eligible vs Above Eligibility Threshold

	Panel A: Poor			Panel B: Extremely Poor		
	New Eligible	178 <x <190		New Eligible	89<x<100	
	N=6247	N=4652	p-value	N=695	N=293	p-value
Female Head	0.94 (0.23)	0.95 (0.22)	0.185	0.82 (0.39)	0.78 (0.41)	0.252
Household Income	185 (10.6)	175 (8.67)	0	93.7 (17.4)	87.2 (8.15)	<0.001
Number of People	4.38 (1.07)	4.07 (1.25)	<0.001	2.30 (1.14)	2.47 (1.14)	0.039
Number of Active Bank Accounts	1.89 (0.93)	1.78 (0.95)	<0.001	1.71 (1.01)	1.80 (1.11)	0.262
Total Credit	4092 (11614)	4064 (11956)	0.903	2689 (9293)	2821 (8744)	0.832
Interest Rate	40.7 (97.4)	38.3 (99.5)	0.218	26.2 (71.7)	23.9 (66.8)	0.626
Credit Card	403 (1047)	391 (1021)	0.545	267 (810)	369 (1167)	0.175
Revolving Credit	145 (700)	148 (633)	0.798	149 (993)	99.8 (392)	0.268
Credit Concession	184 (895)	186 (946)	0.904	136 (752)	94.8 (464)	0.296
Installment Due	254 (1007)	263 (1167)	0.681	263 (1117)	262 (937)	0.985
Default	0.10 (0.30)	0.09 (0.29)	0.484	0.07 (0.26)	0.09 (0.29)	0.268
Income According to Bank	1670 (1019)	1703 (1059)	0.26	1593 (1001)	1790 (1136)	0.125
Any Formal Employment	0.69 (0.46)	0.60 (0.49)	<0.001	0.40 (0.49)	0.38 (0.49)	0.479
Formal Salary	1178 (1206)	1045 (1224)	<0.001	645 (1011)	700 (1179)	0.49
Formalized Entrepreneur	0.09 (0.32)	0.11 (0.33)	0.071	0.07 (0.29)	0.11 (0.37)	0.142
Installment over Accounts	58.0 (228)	63.3 (284)	0.29	113 (506)	108 (413)	0.866
max education 0	0.01 (0.09)	0.01 (0.08)	0.387	0.06 (0.23)	0.02 (0.15)	0.01
max education 1	0.40 (0.49)	0.37 (0.48)	0.014	0.58 (0.49)	0.57 (0.50)	0.807
max education 2	0.12 (0.32)	0.13 (0.33)	0.216	0.08 (0.27)	0.10 (0.30)	0.257
max education 3	0.12 (0.33)	0.13 (0.34)	0.178	0.07 (0.25)	0.06 (0.23)	0.565
max education 4	0.33 (0.47)	0.34 (0.47)	0.359	0.20 (0.40)	0.23 (0.42)	0.381
max education 5	0.02 (0.15)	0.02 (0.15)	0.912	0.02 (0.14)	0.02 (0.14)	0.856

Notes: This table shows the descriptive statistics for "newly eligible" and just above the threshold of eligibility households in May 2018, the month the new eligibility range was announced. In Panel A, the per capita income range of New Eligibles is $85 < x \leq 89$ and for Panel B, it is $178 < x < 190$. Standard errors are in parentheses.

To provide visual evidence for the parallel trends assumption, we also perform the dynamic specification as follows:

$$Y_{it} = \alpha_i + \gamma_t + \sum_{s=-5, s\neq -1}^{11} \beta_s \cdot \text{Newly Eligible}_i \cdot I(t = s) + \epsilon_{it} \tag{3.5}$$

We omit (and hence set it as the baseline) the period one month before households from the treatment group are expected to start receiving the CCT ($t = -1$). β_s captures the "intention-to-treat" effect of receiving CCT.

3.5 Results

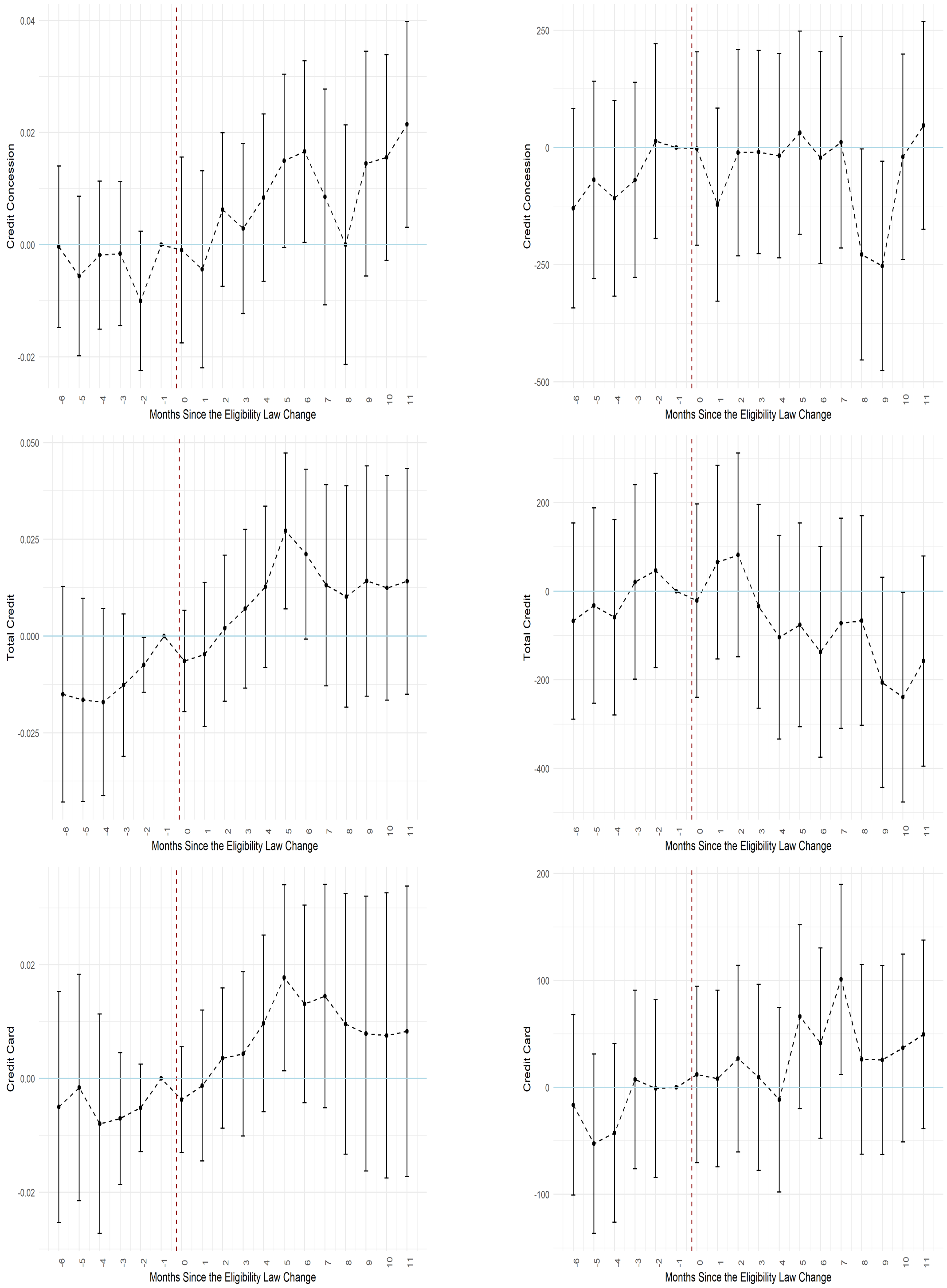
In this section, we present the results and economic interpretations of the findings. First, we explore the details of the unexpected gain of CCT impact on credit outcomes. Then, we provide an economic interpretation of the results in the following section.

Table 3.5.1 shows the first-stage regression results from Equation 3.3. After the new eligibility income threshold law was enacted, poor households have a 32%, and extremely poor ones have a 37% higher chance of being CCT beneficiaries. In Figure 3.5.1, we observe the timing intention-to-treat effects on credit origination. We use the terms credit concession and credit origination interchangeably. The plots indicate that although there is no apparent effect on the intensive margin of these outcomes, poor households' likelihood of obtaining credit, maintaining a positive total credit balance, and using credit cards gradually rises after they start receiving CCT benefits. This likelihood reaches a peak roughly 6 to 7 months after they first receive the benefit.

Table 3.5.1: Being within the New Eligibility Range on CCT Beneficiary Status

	Prob(CCT=1)	
	Poor	Extremely Poor
Newly Eligible x Post	0.327***	0.371***
	(0.003)	(0.011)
Household FE	Yes	Yes
Year-Month FE	Yes	Yes
N	141,746	10,124
R^2	0.579	0.576

Notes: This Table shows the first stage regression of being in the newly eligible income range on receiving conditional cash transfer after the new law was enacted. The first column displays results for Poor Households, while the second shows for the Extremely Poor Households. Standard errors are in parenthesis.



(a) Extensive Margin (b) Intensive Margin

Figure 3.5.1: Effects of Receiving CCT Unexpectedly on Selected Credit Outcomes (Poor Households)

Notes: This Figure shows the effect of receiving CCT on the different credit types for poor households, captured by the β_s coefficients from Equation 3.5. Panel A displays the effects on the extensive margin, which is a binary variable that equals one if the household has a positive balance on the relevant credit type and zero otherwise. Panel B shows the impact on the intensive margin, taking into account the balance for households that use the respective credit type in the given month.

Table 3.5.2: Effects of Receiving CCT Unexpectedly on Total Credit of Poor Households

	Panel A: Extensive Margin		
	Total Credit	Credit Origination	Interest Rate
CCT	0.067***	0.033***	0.040***
	(0.009)	(0.009)	(0.009)
Control Mean	0.49	0.18	0.4
Household FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
N	141,746	141,746	141,746
R^2	0.779	0.603	0.734
	Panel B: Intensive Margin		
	Total Credit	Credit Origination	Interest Rate
CCT	-140.39	116.00	5.71
	(165.12)	(169.01)	(4.36)
Control Mean	7529.15	1001.60	93.83
Household FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
N	76,883	27,483	64,518
R^2	0.97	0.45	0.77

Notes: This table shows how receiving CCT unexpectedly affects credit balance on an intensive margin from equation 3.4, where the Beneficiary Status (whether the household is receiving CCT or not) is instrumented with the condition of having a per capita income falling in the new eligibility threshold. Panel A displays results for the extensive margin, while Panel B shows results for the intensive margin of outcomes. The term "Interest Rate" at the extensive margin indicates whether a household needs to pay interest on any credit during the current month. The standard errors are shown in parentheses and are clustered at the municipality level.

Table 3.5.2 shows the effects of unexpectedly receiving CCT on general credit outcomes. Panel A presents the results for the extensive margin, while Panel shows the intensive margin. Poor households had a higher chance of having any credit (Total Credit) by 13.7%, while there is no statistically significant difference for total credit balance at the intensive margin.[16] The probability of credit origination increases by 18%, with the size of the credit origination not changing, as shown in column two of Panel B. Similarly, there is an increase in the change of a poor household paying interest rates of 10%, but not on the average interest rate (weighted by the size of the particular credit balance over the total credit balance).

16. Here, the estimate for the variation is calculated as the coefficient value over the control mean in the pre-treatment period (baseline). For the extensive margin of total credit balance: 0.067/0.49=0.137.

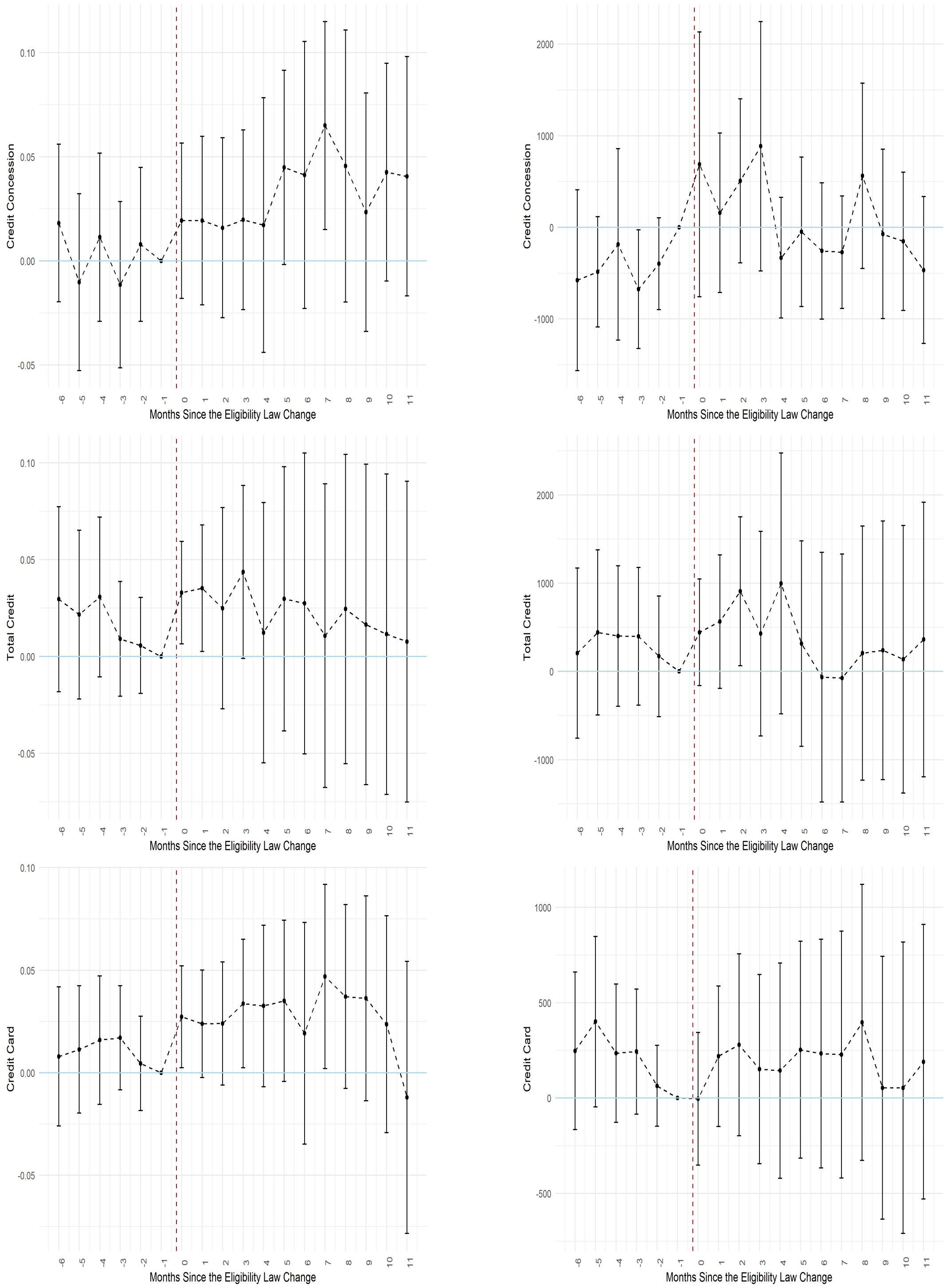
Table 3.5.3: Effects of Receiving CCT Unexpectedly on Credit Cards of Poor Households

	Panel A: Extensive Margin		
	Credit Card	Revolving Credit	Installment Due
CCT	0.035***	0.008	0.049***
	(0.008)	(0.009)	(0.009)
Control Mean	0.3	0.18	0.32
Household FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
N	141,746	141,746	141,746
R^2	0.785	0.621	0.722
	Panel B: Intensive Margin		
	Credit Card	Revolving Credit	Installment Due
CCT	175.25***	-70.74	150.47*
	(66.65)	(86.22)	(84.13)
Control Mean	1452.64	819.54	730.10
Household FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
N	45,754	29,040	53,39
R^2	0.77	0.71	0.75

Notes: This table shows how receiving CCT unexpectedly affects credit outcomes on an extensive margin from equation 3.4, where the Beneficiary Status (whether the household is receiving CCT or not) is instrumented with the condition of having a per capita income falling in the new eligibility threshold. Panel A displays results for the extensive margin, while Panel B shows the intensive margin of outcomes. "Installment Due" refers to the date when a household is required to make a payment for an installment in the upcoming month. Standard errors are in parentheses and clustered at the municipality level.

Table 3.5.3 shows the effects of unexpectedly receiving CCT on outcomes related to credit cards. Panel A shows that the probability of using credit cards increased by BRL 175.25 or more than 11% relative to the baseline control mean, while panel B shows that the balance of credit cards increased by 12%. At the same time, there is no significant difference both at the extensive and intensive margins of revolving credit, signaling that the increase in credit cards is not followed by a lack of ability to pay the minimum value of the credit card bill, which is the main reason an individual's account automatically triggers a revolving credit line. In turn, the chance of having an installment due the following month increases by 15%, while the size of installments due increases by 20%. Note that the installment due is typically associated with making fixed payments for a specific item using a credit card. It is also possible to make installment payments directly through the store selling the item, in this case, we can only observe the amount owed on the credit card balance but not on the installment due.

Figure 3.5.2 shows the timing intention-to-treat effects on credit origination size, total credit balance, and credit card balance for extremely poor households. The extensive margin plots suggest an increased likelihood of having a positive credit card balance and total credit balance in the first month of becoming a CCT beneficiary household. In contrast, the increase in credit origination is more gradual. The intensive margin plots show that the effects on credit cards and total credit balance occur in the same month households start receiving the grant and gradually diminish, with credit cards showing a more lasting impact.



(a) Extensive Margin (b) Intensive Margin

Figure 3.5.2: Effects of Receiving CCT Unexpectedly on Selected Credit Outcomes (Extremely Poor Households)

Notes: This Figure shows the effect of receiving CCT on the different credit types for extremely poor households, captured by the β_s coefficients from Equation 3.5. Panel A displays the effects on the extensive margin, which is a binary variable that equals one if the household has a positive balance on the relevant credit type and zero otherwise. Panel B shows the impact on the intensive margin, taking into account the balance for households that use the respective credit type in the given month.

Table 3.5.4 shows the effects on total credit, credit origination, and interest rates for extremely poor households. Contrary to what Figure 3.5.2 suggests, there is no statistically significant effect on total credit balance at the intensive and extensive margins. At the same time, the occurrence of credit origination increases by 53%, while the size of those who get it increases by 126%. The probability of incurring any interest (extensive margin of interest rate) increases by 26%, while the interest rate at the intensive margin (i.e. average concession interest rates, weighted by the respective amounts disbursed) decreases by 38%. This reduction could be partially explained by a change in the composition of credit balances, from more expensive to less expensive credit types, as well as a greater willingness of banks to grant credit under better conditions once households have CCT as a stable income source.

Table 3.5.4: Effects of Receiving CCT Unexpectedly on Total Credit of Extremely Poor Households

	Panel A: Extensive Margin		
	Total Credit	Credit Origination	Interest Rate
CCT	0.007	0.069***	0.082***
	(0.027)	(0.026)	(0.029)
Control Mean	0.42	0.13	0.33
Household FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
N	10,124	10,124	10,124
R^2	0.798	0.566	0.731
	Panel B: Intensive Margin		
	Total Credit	Credit Origination	Interest Rate
CCT	113.95	1,554.13***	-24.10**
	(549.13)	(554.39)	(12.22)
Control Mean	6512.74	1232.74	63.59
Household FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
N	4,570	1,468	3,631
R^2	0.95	0.39	0.80

Notes: This table shows how receiving CCT unexpectedly affects credit balance on an intensive margin from equation 3.4, where the Beneficiary Status (whether the household is receiving CCT or not) is instrumented with the condition of having a per capita income falling in the new eligibility threshold. Panel A displays results for the extensive margin, while Panel B shows results for the intensive margin of outcomes. The term "Interest Rate" at the extensive margin indicates whether a household needs to pay interest on any credit during the current month. The standard errors are shown in parentheses and are clustered at the municipality level.

The results for the credit card, revolving credit, and installment due for extremely poor households are displayed in Figure 3.5.5. Panel B indicates no statistically significant effect of receiving CCT on the intensive margin of these outcomes. In Panel A, it is shown that while there is no effect on the probability of having an installment due the following month, extremely poor households that start receiving the cash transfer have a 13% higher chance of using credit cards and a 73% higher probability of having a revolving credit. This suggests difficulty in paying the minimum credit card monthly bill.

Table 3.5.5: Effects of Receiving CCT Unexpectedly on Credit Cards of Extremely Poor Households

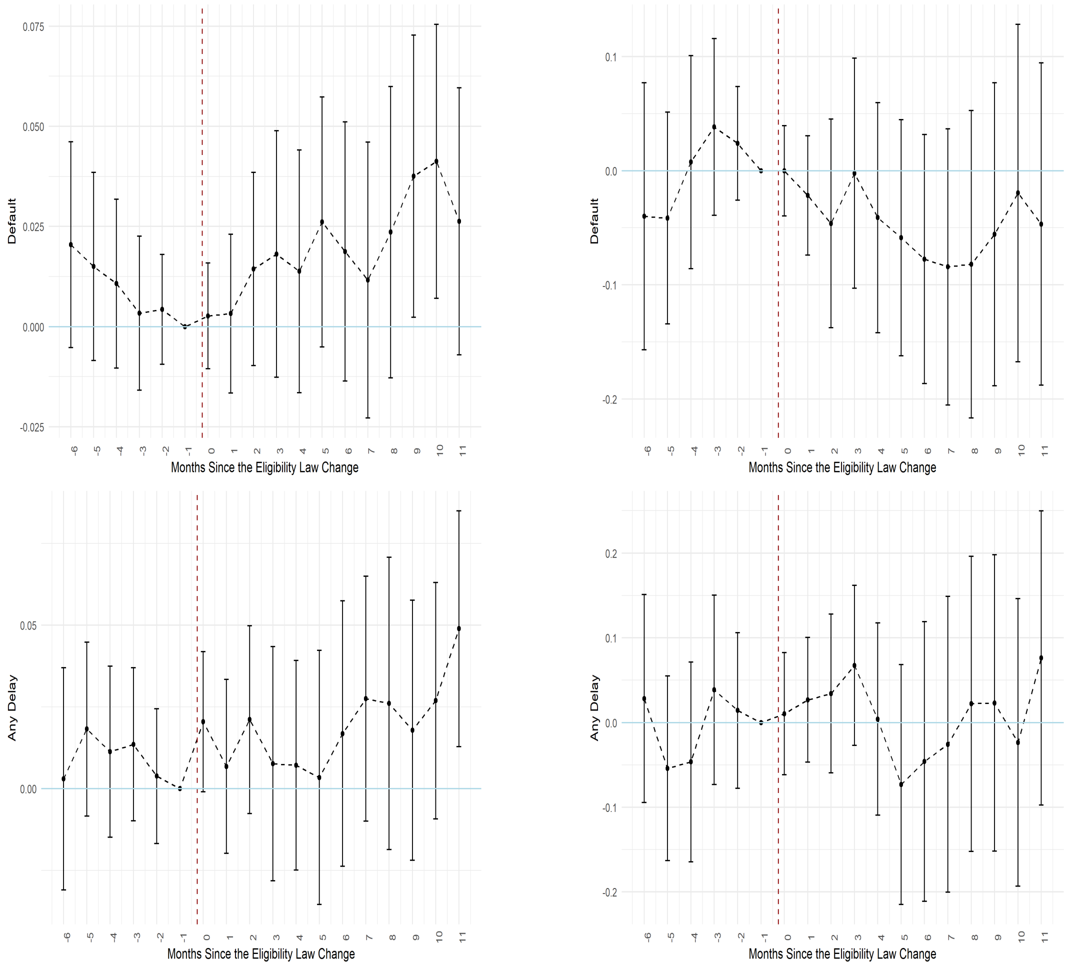
	Panel A: Extensive Margin		
	Credit Card	Revolving Credit	Installment Due
CCT	0.036*	0.110***	-0.019
	(0.021)	(0.026)	(0.027)
Control Mean	0.26	0.15	0.28
Household FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
N	10,124	10,124	10,124
R^2	0.829	0.597	0.741
	Panel B: Intensive Margin		
	Credit Card	Revolving Credit	Installment Due
CCT	-207.34	31.74	287.04
	(232.04)	(162.38)	(385.96)
Control Mean	1911.13	617.36	1088.89
Household FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
N	2,695	1,585	3,251
R^2	0.77	0.94	0.69

Notes: This table shows how receiving CCT unexpectedly affects credit outcomes on an extensive margin from equation 3.4, where the Beneficiary Status (whether the household is receiving CCT or not) is instrumented with the condition of having a per capita income falling in the new eligibility threshold. Panel A displays results for the extensive margin, while Panel B shows for the intensive margin of outcomes. "Installment Due" refers to the date when a household is required to make a payment for an installment in the upcoming month. Standard errors are in parentheses and clustered at the municipality level.

Table 3.5.6: Effects of Receiving CCT Unexpectedly on Delinquency Rates

	Panel A: Poor		
	Default	Any Delay	Up to 90
CCT	0.017	0.021	0.029
	(0.039)	(0.042)	(0.037)
Control Mean	0.20	0.40	0.29
Household FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
N	76,883	76,883	76,883
R^2	0.587	0.583	0.464
	Panel B: Extremely Poor		
	Default	Any Delay	Up to 90
CCT	-0.100	0.034	0.127
	(0.127)	(0.136)	(0.140)
Control Mean	0.15	0.33	0.28
Household FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
N	4,570	4,570	4,570
R^2	0.580	0.575	0.485

Notes: This table shows the effects of receiving CCT unexpectedly affects delinquency rates from equation 3.4, where the Beneficiary Status (whether the household is receiving CCT or not) is instrumented with the condition of having a per capita income falling in the new eligibility threshold. Considering households with a positive total credit balance, Panel A displays results for Poor Households, while Panel B shows Extremely Poor Households. Standard errors are in parentheses and clustered at the municipality level.



(a) Poor Households (b) Extremely Poor Households

Figure 3.5.3: Effects of Receiving CCT Unexpectedly on Delinquency Rates

Table 3.5.6 shows the effects on delinquency rates, considering households with a positive total credit balance. Panels A and B reveal no significant effects on the probability of default, incidence of any delays, or delays of up to 90 days for both poor and extremely poor households after they begin receiving the benefit.

3.6 Economic Interpretation

The results presented in this study indicate a significant impact of receiving CCT on credit behavior among poor and extremely poor households. To interpret these findings, we explore possible economic mechanisms for the impact of CCTs on credit demand and on bank credit supply for households in a vulnerable financial condition.

3.6.1 CCT and Credit Demand

Under an intertemporal framework, a rational household confronted with an unexpected and sustained increase in income is expected to adjust its consumption and saving behavior to optimize utility over time, increasing expenditures especially when its marginal utility of consumption is high, as it is in the case of poor households. Given that the increase in immediate consumption of non-durable goods can be done using physical cash or other payment instruments such as debit cards, there is no expectation of an increase in credit usage. Also, the positive income shock from CCTs enables households to reduce their reliance on borrowing, as suggested by Angelucci, Attanasio, and Di Maro 2012, and even increase precautionary savings. Deleveraging of debts and the use of payment instruments to pay for an increase in non-durables would reduce credit usage. On the other hand, a rise in durable goods that were previously not attainable without the cash transfer but whose total cost is still not affordable upfront would justify an increase in credit utilization.

Our findings indicate a 13.7% increase in the probability of poor households having any form of credit (Total Credit), an 18% rise in credit origination, and an 11% increase in credit card usage among poor households. This shift suggests that households leverage their stable CCT income to facilitate planned purchases of durable goods, in line with the findings of Agarwal and Qian 2014, which are able to observe increases in different consumption categories. Thus, given that the cash transfer is not big enough to afford large, durable goods consumption such as vehicles (as Parker et al. 2013 find for US consumers), it is probable that they are increasing their consumption of small, durable goods.

The significant increase in installment-due payments for poor households further supports the notion that households are now capable of making larger, planned purchases.

This behavior indicates access to credit facilities that require regular installment payments. Interestingly, the absence of a significant increase in revolving credit suggests that households are not relying on credit cards to cover short-term cash flow issues but are instead using them for planned purchases.

3.6.2 CCT and Credit Supply

The potential effect of CCTs on credit supply, in turn, can be substantial. Banks, recognizing the stable income CCTs provide, may reassess the credit risk associated with these households, loosening the household credit constraint. The substantial increase in credit origination for extremely poor households, by 53%, suggests that Banks view the CCT income as reducing the default risk, thereby enhancing the households' creditworthiness.

Moreover, the significant reduction in average interest rates for extremely poor households indicates that banks are willing to offer better credit terms. The 38% decrease in average interest rates can be attributed to the perceived lower risk associated with a stable income stream. This shift towards more favorable credit conditions highlights the positive impact of CCTs on the credit supply side, enabling households to access larger loan amounts under better terms.

The findings illustrate that CCTs not only enhance credit access but also improve the conditions under which credit is extended. Poor and extremely poor households, many of whom engage in informal employment with very volatile income sources, now supplied with a stable income, can engage more confidently with the formal financial system. This increased engagement is evident in the rise in credit card usage and the improved terms of credit origination.

Conclusion

This paper provides robust empirical evidence on the impact of cash transfers on financial inclusion among impoverished households in Brazil. By leveraging a quasi-experimental design and a difference-in-differences methodology, we estimate the causal effects of unexpectedly becoming a Conditional Cash Transfer (CCT) beneficiary on various credit outcomes.

Our findings reveal that newly eligible households significantly increase their credit card utilization and access to credit following the commencement of cash transfers. This behavior likely reflects households' use of CCT income to finance the purchase of durable goods by enabling the payment of installments. Additionally, extremely poor households receiving larger transfer shocks benefit from improved credit terms, indicating a reduction in perceived financial risk and an enhancement in creditworthiness.

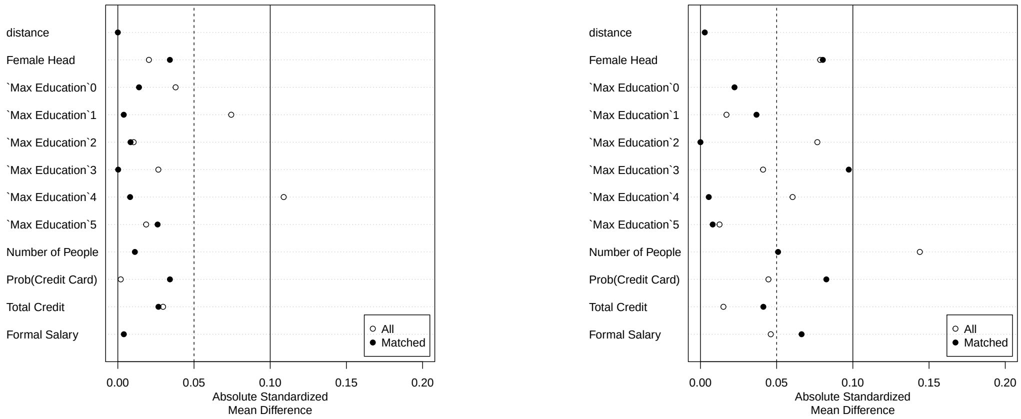
These results underscore the potential of cash transfer programs in promoting financial inclusion in marginalized communities. By facilitating access to formal financial services, cash transfers not only alleviate immediate financial constraints but can also contribute to long-term economic stability and resilience. Future studies could track beneficiaries over an extended period to assess whether the initial improvements in credit access and terms persist and how they influence broader economic outcomes such as income, employment, and asset accumulation.

The implications of our findings for policy are noteworthy. Policymakers should consider cash transfer programs as valid instruments to foster inclusive economic growth. Tailoring these interventions to target specific demographic groups and incorporating insights from rigorous empirical research can enhance the effectiveness of cash transfer policies. Such refined approaches will optimize the potential of cash transfers to advance financial inclusion and support sustainable socioeconomic development.

In particular, the investigation highlights the critical role of CCTs in promoting the integration of impoverished and extremely impoverished households into formal credit markets. The empirical results suggest that by providing a reliable income source, CCTs reduce credit constraints and improve creditworthiness, fostering greater access to credit. In summary, the findings highlight the significance of stable income support programs in advancing financial inclusion and improving the economic prospects of underprivileged populations.

3.7 Appendix

3.8 Appendix A: Receiving CCT



(a) Poor Households (b) Extremely Poor Households

Figure A1: Matching Plot - Group Diffenrences

3.8.1 Descriptive Statistics: Households that Updated Cadunico Registry between Announcement and Enactment

The following table presents descriptive statistics comparing households within the new eligible range for Bolsa Família that have updated their Cadúnico registry between the law announcement and its enactment. The purpose is to determine whether there are systematic differences between households that were included in the analysis (those that did not update their registry) and those that were left out (those that updated their registry).

Table A1: Descriptive statistics comparing households within the new eligible range that have updated their Cadúnico registry between the law announcement and its enactment

	Poor Households					
Income within the New Eligible Range?	Yes			No		
Updated Cadúnico Registry ?	Yes	No		Yes	No	
	N=27	N=943	p-value	N=35	N=1159	p-value
Femela Head	0.93 (0.27)	0.86 (0.34)	0.25	0.89 (0.32)	0.83 (0.38)	0.309
Household Income	175 (1.40)	175 (1.33)	0.179	184 (3.17)	183 (3.01)	0.574
Number of People	2.74 (1.72)	2.72 (1.30)	0.949	2.66 (1.33)	2.75 (1.44)	0.676
Mean Adult Age	41.1 (11.7)	38.7 (10.9)	0.322	42.9 (12.3)	39.2 (11.2)	0.087
Prob (Credit Card)	0.37 (0.49)	0.38 (0.49)	0.898	0.43 (0.50)	0.40 (0.49)	0.752
Prob (Revolving Card)	0.41 (0.50)	0.30 (0.46)	0.281	0.40 (0.50)	0.32 (0.47)	0.365
Prob (Installment Card)	0.15 (0.36)	0.17 (0.38)	0.741	0.14 (0.36)	0.18 (0.39)	0.516
Total Credit (BRL)	2004 (3563)	3226 (8945)	0.109	3511 (13171)	3621 (9940)	0.961
Interest Rate (%; a.r.)	26.1 (55.7)	31.2 (73.3)	0.642	35.9 (77.4)	33.0 (82.0)	0.828
Credit Card (BRL)	849 (1556)	489 (1264)	0.244	410 (980)	497 (1194)	0.613
Revolving Credit (BRL)	108 (399)	151 (869)	0.604	36.5 (132)	132 (703)	0.002
Installment Card (BRL)	33.1 (172)	81.4 (610)	0.217	55.9 (319)	70.0 (391)	0.8

Notes: Descriptive statistics comparing households within the new eligible range that have updated their Cadúnico registry between the law announcement and its enactment for poor households. Standard errors are in parentheses.

Table A1, which focuses on poor households, several key characteristics were examined. The proportion of female-headed households is slightly higher among those who updated their registry compared to those who did not; however, this difference is not statistically significant (p-values of 0.25 and 0.309 for the two groups, respectively). Household income and the number of people per household are virtually identical across groups, with p-values well above the threshold for statistical significance (0.179 and 0.949, respectively). Similarly, the mean adult age does not show a significant difference between groups, with p-values of 0.322 and 0.087. These consistent similarities across various demographic metrics indicate that there is no systematic demographic difference between households that updated their registry and those that did not.

Credit-related variables also show no significant differences between the groups. The probability of having a credit card, revolving credit, or installment card is similar across groups, with p-values all above 0.1. Total credit amount and specific credit types (credit card, revolving credit, installment card) do not show significant differences, except for revolving credit in the "No" new eligible range group, where a significant difference was noted (p-value of 0.002). Interest rates across groups are also statistically similar, indicating no significant difference in the cost of credit between those who updated and did not update their registry.

Table A2: Descriptive statistics comparing households within the new eligible range that have updated their Cadúnico registry between the law announcement and its enactment

	Extremely Poor Households					
Income within the New Eligible Range?	Yes			No		
Updated Cadúnico Registry ?	Yes	No		Yes	No	
	N=9	N=293		N=30	N=695	
Femela Head	0.67 (0.50)	0.78 (0.41)	0.501	0.83 (0.38)	0.82 (0.39)	0.822
Household Income	87.0 (0.50)	87.1 (0.75)	0.482	92.9 (3.16)	92.9 (2.94)	0.999
Number of People	2.56 (1.01)	2.47 (1.14)	0.812	2.20 (1.19)	2.31 (1.14)	0.638
Mean Adult Age	41.6 (7.39)	38.3 (10.1)	0.232	39.4 (11.1)	40.1 (11.4)	0.726
Prob (Credit Card)	0.22 (0.44)	0.32 (0.47)	0.527	0.33 (0.48)	0.32 (0.47)	0.877
Prob (Revolving Card)	0.22 (0.44)	0.24 (0.43)	0.913	0.20 (0.41)	0.20 (0.40)	0.97
Prob (Installment Card)	0.11 (0.33)	0.14 (0.35)	0.805	0.10 (0.31)	0.15 (0.36)	0.393
Total Credit (BRL)	314 (681)	2998 (8779)	0.001	2906 (8048)	2631 (9048)	0.857
Interest Rate (%; a.r.)	9.84 (20.9)	22.2 (59.3)	0.138	14.3 (30.0)	27.5 (76.2)	0.039
Credit Card (BRL)	268 (570)	393 (1236)	0.551	189 (441)	278 (846)	0.312
Revolving Credit (BRL)	6.48 (19.4)	107 (394)	0.001	2.85 (12.1)	161 (982)	0.001
Installment Card (BRL)	38.9 (117)	23.0 (143)	0.698	0.00 (0.00)	48.0 (353)	0.001

Notes: Descriptive statistics comparing households within the new eligible range that have updated their Cadúnico registry between the law announcement and its enactment for extremely poor households. Standard errors are in parentheses.

Table A2, focusing on extremely poor households, the findings are similar. The proportion of female-headed households does not significantly differ between those who updated their registry and those who did not (p-values of 0.501 and 0.822). Household income and the number of people per household are again statistically indistinguishable between groups, with p-values of 0.482 and 0.812, respectively. Mean adult age shows no significant difference, with p-values of 0.232 and 0.726. Exemptions are Interest Rate (%; a.r.), Installment Card (BRL), and Revolving Credit (BRL) for extremely poor households whose income is out of the new eligible range, which is probably coming from the very small sample size (9) of households that updated their registries during the period. The same reasoning applies to Revolving Credit (BRL) for extremely households whose income was in the new income-eligible range.

The lack of significant differences in these characteristics suggests that households that updated their Cadúnico registry between the law announcement and its enactment are comparable to those that did not update their registry in terms of demographic and credit-related variables. This supports the validity of the quasi-random experimental design, as it indicates that there is no systematic difference between the two groups that could bias the results. This strengthens the causal inference that can be drawn from the analysis, providing robust evidence for the study's findings.

3.8.2 Placebo

We perform a placebo test using alternative treatment and control groups defined over a given average household income range. Table A3 presents the results of a placebo test, comparing the alternative treatment group (individuals with a per capita income between 146 and 150) with the alternative control group (individuals with a per capita income between 140 and 145). The variable $Post_t$ is a binary indicator set to 1 for periods after July 2018.

Table A3: Unexpected Gain on Credit Outcomes (Placebo)

	Panel A: Extensive Margin					
	Total Credit	Credit Card	Revolving Credit	Credit Concession	Installment Due	Interest Rate
Treated x Post	0.017	0.014	0.011	-0.003	0.006	0.012
	(0.016)	(0.011)	(0.008)	(0.008)	(0.014)	(0.015)
Control Mean	0.39	0.22	0.14	0.13	0.25	0.32
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	105,338	105,338	105,338	105,338	105,338	105,338
R^2	0.773	0.763	0.610	0.575	0.706	0.723

	Panel B: Intensive Margin					
	Total Credit	Credit Card	Revolving Credit	Credit Concession	Installment Due	Interest Rate
Treated x Post	-140.39	175.25	-70.74	115.995	150.47	5.71
	(469.122)	(137.92)	(200.92)	(218.06)	(142.58)	(10.50)
Control Mean	7529.15	1452.64	819.54	1001.6	730.1	93.83
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	76,883	45,754	29,040	27,483	53,392	64,518
R^2	0.97	0.77	0.71	0.45	0.74	0.77

Notes: The table displays the results of the placebo test, which compares the alternative treatment group (individuals with per capita income between 146 and 150) with the alternative control group (individuals with per capita income between 140 and 145). The variable $Post_t$ is a dummy variable that equals 1 if the period is after July 2018. The standard errors are reported in parentheses and clustered at the municipality level for accuracy. Standard errors are in parentheses and clustered at the municipality level.

The placebo test results show that there are no statistically significant changes in credit outcomes for the alternative treatment group compared to the alternative control group. This indicates that any observed effects in the main analysis are likely due to the actual treatment (gain of CCT benefits) rather than random fluctuations or other unobserved factors.

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CHAPTER 4

Debt Accumulation of ex-CCT Beneficiary Households: Evidence using rich administrative credit and social datasets[1]

Abstract: This paper investigates the impact of Conditional Cash Transfer (CCT) loss on credit outcomes among economically disadvantaged households. Using a comprehensive administrative dataset, we employ a difference-in-difference approach to analyze households' credit behavior after the cessation of CCT benefits. Our results reveal that poor households experience a temporary increase in credit card expenditures following a CCT loss at a pre-disclosed date, consistent with the predictions of a habit formation model in which households do not anticipate the loss.

JEL Codes: G50, G51, I32, I38.

Keywords: conditional cash transfer, debt accumulation, habit formation

1. In coauthorship with Marco Bonomo (Insper), and Lucas Teixeira (Brazilian Central Bank)

4.1 Introduction

Conditional Cash Transfer (CCT) programs alleviate the poverty of vulnerable households, helping them achieve minimum living standards. Given the transient nature of social programs, it becomes imperative to understand how these households react when confronted with the loss of such benefits. While the economic literature investigates the effects of financial inclusion (Bruhn and Love 2014, Célerier and Matray 2019, Fonseca and Matray 2022, Bachas et al. 2021), studies do not yet investigate the financial behavior of poor households when they lose the temporary benefit. We exploit a rule to estimate the effects of losing the benefit at a pre-disclosed date on the credit usage of ex-beneficiary households.

The source of identification is a discontinuity in the CCT program eligibility rule for low-income families with at least one child. The law implies that beneficiary households whose youngest child completed 18 years old in a year will lose the cash grant associated with the number of adolescent children the following year, while those whose child is younger will continue receiving it. We then implement a difference in differences (DID) that provides a visualization of the gradual effect of losing the CCT. The DID identification assumption here is that absent the treatment, the difference between treatment and control groups would have stayed the same; both groups would have followed parallel trends. We provide evidence for the assumption of parallel trends in a dynamic specification and find no evidence of pre-existing trends.

We combine two administrative datasets to get household-level data. One is a credit registry that displays credit balances across various types of credit; the other is a social registry that contains information such as education level, CCT beneficiary status, and other social information.

The results suggest that when beneficiaries lose the CCT, households with per capita incomes within the poverty range increase their credit card usage by approximately 30%.

This finding is consistent with a habit formation model tied to the non-anticipation of shock. Extremely poor households—which lose less than half of their transfer—do not substantially change their credit outcomes.

We contribute to the literature that investigates CCT programs' effects in increasing enrollment rates, improving preventive health care, raising household consumption (Rawlings and Rubio 2005), reducing child mortality (Rasella et al. 2013), promoting entrepreneurship (Bianchi and Bobba 2013), increasing investment and long-term living standard as a consequence (Gertler, Martinez, and Rubio-Codina 2012). Our contribution specifically consists of presenting evidence on the debt accumulation patterns in beneficiary households after they lose the benefit. We contribute to this literature by showing a temporary increase in credit card usage after the loss of the benefit for poor households exiting the CCT program. Our study also connects to the literature on consumption response to income shocks[2] and on consumption patterns of poor households. Aguiar, Bils, and Boar (2020), for example, models the consumption of poor households characterized by a "hand-to-month" behavior, suggesting they are relatively impatient and have a high inter-temporal elasticity of substitution. Likewise, various studies investigate the validity of the permanent income hypothesis prediction that household consumption will not be sensitive to predictable changes in income. The evidence is mixed, with some studies supporting the prediction (e.g., Browning and Collado 2001, Hsieh 2003) and many finding excess sensitivity of consumption to predictable income changes. (e.g., Shea 1995, Souleles 1999, Parker 1999, Stephens Jr 2003, Johnson, Parker, and Souleles 2006). closer to the second set of studies, our results suggest that poor households reduce consumption slower than their income after a predictable cash transfer loss using credit.

The rest of the paper is organized as follows. In Section 4.2, we provide a description of the CCT program in Brazil. In Section 4.3, we present the conceptual framework used to understand the economic implications of losing a cash transfer at a pre-disclosed

2. For instance:Carroll 1997;Parker 1999; Shapiro and Slemrod 2003; Souleles 2002; Stephens Jr 2008; Johnson, Parker, and Souleles 2006; Agarwal, Liu, and Souleles 2007; Stephens Jr and Unayama 2011; Broda and Parker 2014, and Parker 2017.

date. Section 4.4 covers the data sources used in the paper. We present the identification strategy in Section 4.5. In Section 4.6, we discuss the findings and their implications. Then, in Section 4.7, we extend the analysis for the case of extremely poor households, for which the loss corresponds to only a portion of their CCT. Finally, we state the conclusion remarks of the paper.

4.2 Institutional Background

4.2.1 Bolsa Família: CCT Program in Brazil

In Brazil, the *Bolsa Família* (BF) program operates as a means-tested Conditional Cash Transfer (CCT) initiative, offering financial assistance to impoverished families while incentivizing investments in human capital for the next generation. The program is designed to enhance the welfare of disadvantaged households through direct cash assistance, contingent upon fulfilling specific conditions such as ensuring children's school attendance and vaccination. Up until December 2019, which marks the conclusion of our data sample, eligibility for BF grants required families to have a monthly per capita income of up to 89.00 Brazilian Reais (BRL), or between 89.01 BRL and 178.00 BRL if they had children aged 0 to 18 years old.[3] In 2019, the average monthly transfer for all BF beneficiary households stood at 173 BRL.[4]

Beneficiary households of *Bolsa Família* fall into two primary categories: "extremely poor" and "poor." Those classified as extremely poor—defined as having a per capita income below 90 BRL—receive a fixed grant of 89.00 BRL, irrespective of family size. Conversely, poor households—with per capita incomes ranging between 90 BRL and 178 BRL—receive benefits provided they have minor children meeting the stipulated conditions, chiefly centered around school attendance. Upon the youngest child reaching 18 years of age, both categories of households cease to receive the additional 48 BRL monthly.

3. *Ministério da Cidadania*: August 13th, 2020.
4. *Portal da Transparência*: October 23rd, 2023.

We leverage this discontinuity to assess the impact of the grant on the accumulation of debt within these households.

4.3 Expected Outcomes: Losing the CCT at a Pre-disclosed Date

When households have a concave utility function in the intertemporal framework, they are not expected to change their behavior when an expected loss occurs. As households foresee the impending loss of a CCT or a portion thereof, which constitutes an anticipated negative income shock, they would save in anticipation in order to smooth consumption.[5] Consequently, one would anticipate no sudden alterations in their utilization of credit cards once the income shock materializes. However, it's crucial to acknowledge the possibility of present bias among households, where the inclination towards present consumption outweighs future-oriented saving behaviors, particularly prevalent among financially illiterate and resource-constrained households lacking access to appropriate saving mechanisms. Alternatively, in scenarios where loss is unanticipated, households adjust by scaling back consumption and limiting credit usage when the loss materializes. Moreover, within the internal habits framework, households' current consumption depends on past consumption. In such cases, households adapt their credit card usage to align with their established consumption patterns. In the absence of cash transfers, credit cards may be utilized to sustain spending habits, with households gradually adjusting consumption levels over time. Those not anticipating the event of the loss adapt their credit card usage, initially increasing and reducing credit utilization, thereby gradually realigning consumption patterns with a new lower baseline.

5. See Jappelli and Pistaferri 2010 for a review of the literature.

4.4 Data

This section outlines the data sources employed in the paper. We merge three datasets: the *Cadastro Único para Programas Sociais do Governo Federal* (*CadÚnico*), the Brazilian Credit Registry data (SCR), and the Relação Anual de Informações Sociais (RAIS). Administered by the Brazilian Ministry of Citizenship (MC), *CadÚnico* is the primary tool for identifying and enrolling low-income families in federal programs, including the BF Program. The SCR contains records of all credit activities conducted across Brazil by individuals and businesses with a liability of at least 200 BRL. Our analysis incorporates household-level information such as the age of the youngest member, family size, income sourced from *CadÚnico*, and credit and default status extracted from the SCR. Additionally, we utilize RAIS, a database encompassing employment details and wages for all formally employed individuals in Brazil. Data is aggregated at the household level, with total credit representing the sum of all types of credit received by each household member. Default status indicates whether any member has defaulted on credit, per the definition provided by the Central Bank of Brazil (BCB)—credit in arrears for more than 90 days—during a specific month. We also incorporate a binary variable indicating the presence of formal employment, the aggregate sum of formal salaries within each household on a monthly basis. Our dataset operates at the household-month-year level, drawing matched information from *CadÚnico*, SCR, and RAIS. From January 2018 to December 2019, our sample period encompasses two years. The dataset is sourced from the State of Minas Gerais, a region that closely mirrors the socioeconomic characteristics of Brazil as a whole.

4.5 Identification Strategy

The purpose of our investigation is to understand the impact of the loss of cash transfers on poor individuals' credit intake. We would like to estimate the following equation:

$$y_{it} = \alpha_i + \gamma_t + \beta \times \text{ex-}CCT_i + \epsilon_{it} \tag{4.1}$$

where ex-CCT_i is a dummy equal to one if the household i does not receive the transfer, β is the coefficient of interest which represents the effect of not having a CCT on a specific credit outcome y_{it}, α_i and γ_t are household and year-month fixed effects, respectively. However, endogeneity presents a substantial challenge in analyzing the association between CCT participation and credit outcomes. This challenge arises because beneficiaries often inhabit more vulnerable social and economic conditions than non-beneficiary households. Consequently, many unobservable factors may confound the outcomes of interest intertwined with the beneficiary status, some of which are not adequately addressed by conventional time and household fixed effects. In other words, individuals frequently self-select into CCT participation based on unobservable characteristics, which can subsequently impact credit outcomes. Hence, endogeneity is reflected in the error term ϵ_{it} of Equation 4.1 such that:

$$\mathbb{E}[\epsilon_{it}|\alpha_i, \gamma_t] \neq 0 \tag{4.2}$$

To tackle this issue, we explore discontinuities in CCT beneficiary status that enable us to estimate the effects of interest by performing difference-in-difference specifications. The discontinuity is a substantial reduction in the probability of receiving the portion of the cash transfer benefit that is tied to the number of adolescent children at the end of the year the child completes 18.[6] Hence, we use the youngest child's year and month of birth as an instrument to identify the effect of losing CCT on a disclosed date on credit outcomes - note here that the expected effect is Null.[7] The identifying assumption is that

6. Barbosa and Corseuil 2014 use the youngest child adulthood discontinuity to study *Bolsa Família* effects on labor informality in a regression discontinuity setting

7. We weight all observations by performing a propensity score matching in the baseline period, using the following variables: (1) female household head; (2) maximum household education attained; (3) number of people; (4) indicator variable if any households member used any credit card; (5) households total credit balance; and (6) household total formal salary.

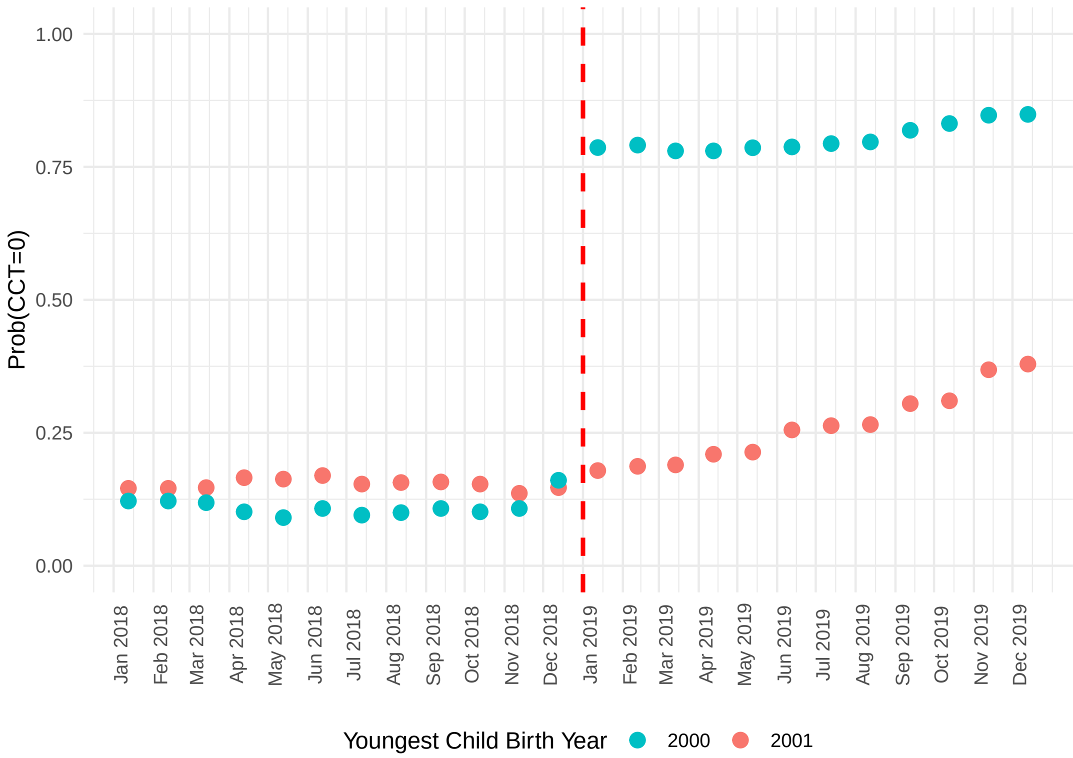
the control and treatment would have followed parallel trends, meaning that whatever affected the control group in the interval before and after the intervention would also have affected the treatment group in the absence of the intervention.

4.5.1 Losing the Cash Transfer at a pre-disclosed Date

An intriguing scenario arises when households, accustomed to relying on the steady income stream provided by the CCT, face the known cessation of this transfer on a specified date. In such circumstances, if households effectively incorporated all available information, they might adjust their consumption and credit behavior in anticipation of the impending loss. However, it remains uncertain whether households indeed anticipate this loss. In the absence of anticipation, coupled with the abrupt discontinuation of the CCT, there could be a temporary surge in credit usage as households endeavor to sustain their previous consumption levels. Over time, this heightened credit usage could enable a gradual decline in consumption, eventually settling at a new baseline with a concomitant reduction in credit balance.

Beneficiary households receive a grant specific to the number and age of their children. In particular, they receive 48 BRL for adolescents until the year they turn 18 years old ends. This transfer is the Youth Variable Benefit (*Benefício variável Jovem*). Hence, after the year of adulthood of the youngest children, there is a discontinuity in the probability of receiving the youth variable benefit, which, for the case of poor households, translates into a reduction in the probability of being a beneficiary of the program. Figure 4.5.1 shows the proportion of poor households whose youngest child was born in 2000 or 2001 that are CCT beneficiaries and gives visual evidence of the instrument's relevance (youngest child born in 2000) for explaining the treatment status after December 2018. In other words, we can see that the discontinuity in the probability of having CCT occurs precisely at the expected moment, which is the end of the year the youngest child completed 18 years old, for the sample of households whose youngest child was born in the year 2000. The probability of not being a beneficiary of the CCT program does not change from 0 to 1. This is because we observe the average household income over the 12 months prior to the last update in the Cadúnico Registry. Eligibility is determined based on the minimum value between the last month's income in the registry and the average household income. Therefore, it's possible for a household to remain eligible for the program, even after the youngest child turns 18 if their previous income was less than BRL 89.

Figure 4.5.1: Loss of CCT Status over time according to Youngest Child Birth Year



Notes: This Figure depicts the proportion of poor households that are not CCT beneficiaries (CCT=0) over time for the group whose youngest child was born in the year 2000 and the one whose youngest child was born after 2000. Poor Households are those that have a per capita income between R$ 90 and R$ 178.

This allows us to perform a difference-in-differences specification, exploring the fact that the discontinuity does not occur precisely at the adulthood of the youngest child but at the end of the year of adulthood. To avoid confusing the impact of losing the grant with the effects of age differences among the youngest household members, we ensure that the maximum difference between the treatment and control groups is no more than six months. Specifically, we identify the treatment group as households with the youngest child born in the last three months of 2000 who will lose the 48 BRL grant in 2001. For the control group, we select households with the youngest child born in the first three months of 2001. Table 4.5.1 shows the descriptive statistics for the sample used. To further guarantee that the groups are comparable, we perform a matching based on relevant social and credit variables at the baseline period. Figure A1 depicts the balancing between treatment and control groups before and after matching.

Table 4.5.1: Descriptive Statistics by Year of Birth of Youngest Child

	Poor Households		
	2001	*2000*	
	N=417	N=368	p-value
Female Head	0.94 (0.25)	0.93 (0.26)	0.743
Household Income	129 (23.9)	127 (23.1)	0.203
Number of People	2.95 (0.81)	2.93 (0.85)	0.703
Total Credit	2291 (8662)	1545 (6263)	0.164
Interest Rate	25.6 (74.4)	21.9 (69.5)	0.476
Credit Card	278 (909)	279 (927)	0.993
Revolving Credit	91.3 (576)	70.8 (502)	0.593
Credit Concession	90.5 (438)	80.5 (375)	0.731
Default	0.05 (0.22)	0.05 (0.22)	0.944
Any Formal Employment	0.20 (0.40)	0.19 (0.39)	0.693
Formal Salary	243 (594)	226 (575)	0.682
max education 0	0.03 (0.17)	0.02 (0.13)	0.237
max education 1	0.65 (0.48)	0.67 (0.47)	0.523
max education 2	0.11 (0.31)	0.10 (0.30)	0.918
max education 3	0.05 (0.22)	0.07 (0.25)	0.376
max education 4	0.15 (0.36)	0.13 (0.33)	0.345
max education 5	0.01 (0.11)	0.01 (0.12)	0.843

Notes: This table shows the descriptive statistics for households' youngest childbirth year in 2000 and 2001 in December 2018. Standard errors are in parentheses.

We estimate a monthly average treatment effect over the following 12 months after losing the cash transfer of 48 BRL from the youth variable benefit. We set households whose youngest child was born in 2000 as the treatment group and those whose youngest child was born in 2001 as the control group. We include household fixed effects to control for time-invariant heterogeneity and year-month fixed effects to control for all time-varying effects. Here, we instrument the loss of the CCT status (ex-CCT) by the youngest child's birth year for poor households. For households experiencing extreme poverty and continuously receiving a portion of the CCT grant, we employ an "intention-to-treat" identification. This entails exclusively estimating the regression of the outcome of interest regarding the birth of the youngest child in 2000 with $Post_{it}$. Hence, for poor households, the first stage can be written as follows:

$$\text{ex-}CCT_{it} = \alpha_i + \lambda_t + \phi \cdot I(BirthYear_i = 2000) \times Post_t + \nu_{it} \tag{4.3}$$

where ex-CCT_{it} is again a dummy variable indicating whether the household does not receive the CCT in period t (and is equivalent to $Prob(CCT = 0)$), α_i and λ_t are household and year-month fixed effects, $I(BirthYear_i = 2000)$ is a dummy indicating if the youngest child was born in the year 2000, and $Post_t$ is a dummy indicating if the period is after December 2018, the last month the treatment group is expected to receive the CCT.

The second stage, where the CCT status comes with the discontinuity coming from the adulthood of the youngest child, is then:

$$Y_{it} = \alpha_i + \lambda_{tm} + \beta \cdot \text{ex-}\widehat{CCT}_i + \epsilon_{it} \tag{4.4}$$

where Y_{it} is the outcome of interest and ex-$\widehat{CCT}_i$ is the instrumented ex-CCT status from the first stage. β is the coefficient of interest that captures the average effect of losing the CCT on the outcomes of interest over a year.

Additionally, we estimate a direct dynamic specification:

$$Y_{it} = \alpha_i + \alpha_{mt} + \sum_{s=-12, t\neq -1}^{11} \beta_s \cdot I(BirthYear_i = 2000) \cdot I(t = s) + \epsilon_{it} \tag{4.5}$$

We omit (and hence set it as the baseline) one month before households from the treatment group are expected to lose the CCT. So, $t = -1$ is in December 2018. β_s captures the "intention to treat" effect of losing the cash transfer in January 2019 on various outcomes.

4.6 Results

4.6.1 Losing CCT

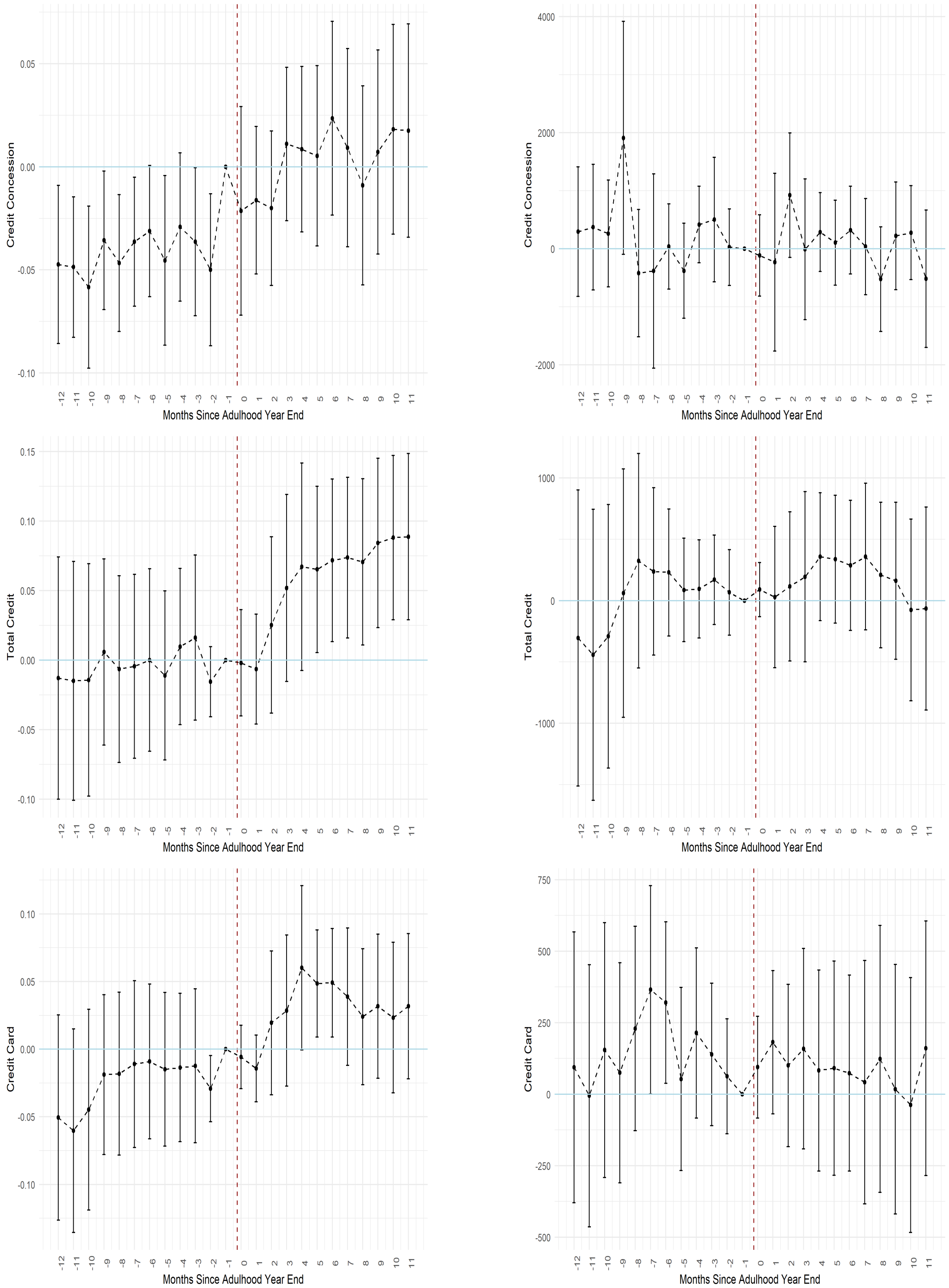
Table 4.6.1 presents the first-stage results using the sample with households in the poor income range. Poor households with the youngest child born in 2000 have a 67% greater chance of losing the CCT beneficiary status in 2019.

Table 4.6.1: Youngest Child Birth Year on CCT Beneficiary Status

	ex-CCT
I(Youngest Birth-Year=2000) x Post	0.671***
	(0.008)
Household FE	Yes
Year-Month FE	Yes
N	14,784
R^2	0.772

Notes: This Table shows the first stage regression (equation 4.3) of the age of the youngest child birthyear being 2000 on losing conditional cash transfer after 2019 for households whose per capita income falls within the poverty range (poor households). Standard errors are in parenthesis.

Figure 4.6.1 shows the timing intention-to-treat effects on credit origination, total credit, and credit card usage. The plot on credit origination shows a possible anticipation effect, with poor households increasing the probability of having a credit origination one month before they lose the benefit. After the cash transfer is lost, we observe an increase in total credit balance and credit card usage probabilities. In turn, these three outcomes have no observed effects at the intensive margins.



(a) Extensive Margin (b) Intensive Margin

Figure 4.6.1: Effects of Losing CCT on Credit Outcomes (Poor Households)

Table 4.6.2: Effects of Losing CCT on the Credit Outcomes Balance

	Panel A: Extensive Margin		
	Total Credit	Credit Card	Revolving Credit
ex-CCT	0.106**	0.076*	0.072***
	(0.048)	(0.039)	(0.028)
Control Mean	0.5	0.26	0.16
Household FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
N	14,784	14,784	14,784
R^2	0.721	0.709	0.552
	Panel B: Intensive Margin		
	Total Credit	Credit Card	Revolving Credit
ex-CCT	126.84	68.61	192.75
	(634.02)	(228.31)	(205.62)
Control Mean	8255.36	1392.97	622
Household FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
N	6,494	3,903	1,961
R^2	0.963	0.748	0.767

Notes: This Table reports the results for Equation 4.4 of losing CCT on the credit balance for the sample of households whose per capita income falls within the poverty range and for which the CCT Loss (ex-CCT) is instrumented by the year of birth of the youngest child interacted with a dummy equal to one in periods after December 2018 (Post). Panel A shows the results for the extensive margin, and Panel B for the intensive margin. Standard errors are in parentheses and clustered at the municipality level.

Table 4.6.3: Effects of Losing CCT on Credit Origination, Installment Due and Interest Payment

	Panel A: Extensive Margin		
	Credit Origination	Installment Due	Interest Payment
ex-CCT	0.088***	0.078*	0.115***
	(0.020)	(0.040)	(0.040)
Control Mean	0.12	0.34	0.42
Household FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
N	14,784	14,784	14,784
R^2	0.511	0.632	0.667
	Panel B: Intensive Margin		
	Credit Origination	Installment Due	Interest Rate
ex-CCT	-29.530	-289.493	-6.336
	(335.434)	(428.373)	(16.002)
Control Mean	1334.96	1550.33	97.55
Household FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
N	2,161	4,208	5,030
R^2	0.362	0.850	0.691

Notes: This Table reports the results for Equation 4.4 of losing CCT on the extensive margin of credit outcomes for the sample of households whose per capita income falls within the poverty range and for which the CCT Loss (ex-CCT) is instrumented by the year of birth of the youngest child interacted with a dummy equal to one in periods after December 2018 (Post). Panel A shows the results for the extensive margin, and Panel B for the intensive margin. Standard errors are in parentheses and clustered at the municipality level.

Table 4.6.4: Effects of Losing CCT on Delinquency Rates

	Poor Households		
	Default	Any Delay	Up to 90
CCT	0.058	0.089	0.101**
	(0.057)	(0.057)	(0.054)
Control Mean	0.24	0.39	0.24
Household FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
N	6,494	6,494	6,494
R^2	0.535	0.564	0.403

Notes: This Table reports the results for Equation 4.4 of losing CCT on delinquency rates for the sample of households whose per capita income falls within the poverty range and for which the CCT Loss (ex-CCT) is instrumented by the year of birth of the youngest child interacted with a dummy equal to one in periods after December 2018 (Post). We select households that have a positive total credit balance. Standard errors are in parentheses and clustered at the municipality level.

In Panel A of Table 4.6.2, we can observe that poor households experienced a 21.2% increase in the chance of having any credit (Total Credit) compared to the control mean of 50%. Furthermore, they are 29.2% and 45% more likely to use credit cards and have revolving credit, respectively. Panel B indicates no statistically significant difference in poor households' balances intensive margin.

Table 4.6.3 shows that poor households experienced a 66.6% rise in the probability of having a credit origination. Their probability of having any installment due or paying any interest rose by 23% and 27.3%.[8] Panel B shows no statistically significant effects for credit concession and installment due sizes. Also, there is no effect on the cost of credit, which is captured by the intensive margin of the interest rate.[9] Table 4.6.4 shows the effects on delinquency rates. After losing the transfer, poor households with a positive credit balance have a 41% higher chance of experiencing delays up to 90 days after losing the cash transfer than the control mean of 24%. Still, they are not more likely to be in default.

The results indicate that poor households use credit cards to compensate for the CCT loss, acting according to a habit-formation model. The household may expect the youngest child to start contributing to the household income, and this expectation could be the reason why the household can maintain a steady level of consumption in anticipation of the wealth effect that comes from the increased labor supply. This is because one of the household members can now participate in the labor market without having to meet the requirement of minimum school attendance.

4.7 Extension: Poorer Households Losing a portion of the benefit

As an extension, we exploit the same threshold year for households whose youngest child was born in 2000 but now consider those with a per capita income that falls within the extreme poverty range. In 2019, this group lost BRL 48 related to the youngest child; however, its households still received BRL 89 such that they did not lose the entirety of the cash transfer. It is worth noting that these households are likely to be in worse

8. We are considering interest payments at the extensive margin. This refers to the condition of having to pay any interest on credit being used. This does not apply, for example, if a person is only using a credit card and paying the minimum amount every month, or if they are using an installment card payment. An installment card payment can be made through a financial institution or a retail company and is used to spread the payment for a good or service over time without incurring interest payments.

9. The interest rate in this case is a weighted average based on the proportion of balance of each credit type.

economic conditions than poor households. Consequently, they may have less access to financial services and are less likely to use credit.

4.7.1 Identification Strategy

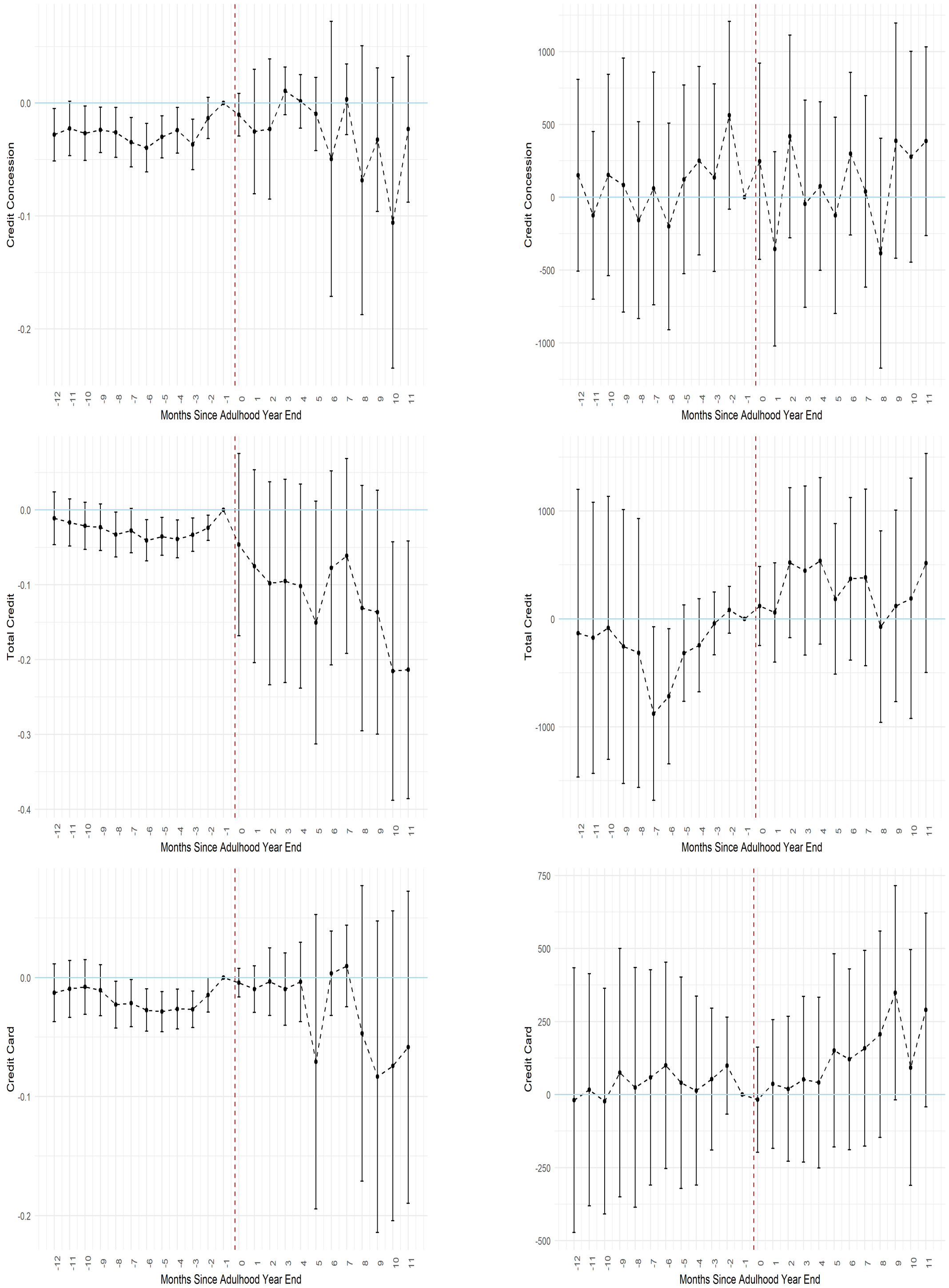
Our dataset contains only the CCT Status (1 if receiving and 0 if not), and we cannot directly observe the reduction in the transfer size for each household. So, even though there might be households that continue to receive the same amount even after the youngest child's adulthood threshold (as it happens for poor households, depicted in Figure 4.5.1), we estimate the intention-to-treat regression for the case of extremely poor households. In practical terms, this means we estimate the direct effects of the instrument on the outcomes of interest through the following regression:

$$Y_{it} = \alpha_i + \lambda_t + \beta \cdot I(BirthYear_i = 2000) \times Post_t + \epsilon_{it} \tag{4.6}$$

where again $I(BirthYear_i = 2000)$ is a dummy variable that indicates if the household's youngest child was born in 2000, and $Post_t$ indicates if the month is in 2019. The equation also includes household (α_i) and year-month (λ_t) fixed effects to control for unobserved heterogeneity across households and time.

4.7.2 Results

Figure 4.7.1 shows the results from the dynamic specification, and there are no statistically significant differences for credit origination (concession), total credit, and credit card at the extensive and intensive margins. Table 4.7.1 further validates this by showing no effects on total credit and credit cards at both margins. However, it shows a 15% increase in the probability of having a revolving credit (Panel A) and a 245 BRL larger revolving credit balance (Panel B). It is reasonable to assume that this increase comes from losing a portion of the CCT, reducing the ability to pay the minimum credit card payment that automatically triggers a revolving credit line.



(a) Extensive Margin (b) Intensive Margin

Figure 4.7.1: Effects of Losing CCT on Credit Outcomes (Extremely Poor Households)

Notes: This Figure shows the leads and lags regression coefficients as presented in equation 4.5. Standard errors are clustered at the municipality level.

Table 4.7.1: Effects of Losing CCT on Credit Outcomes

	Panel A: Extensive Margin		
	Total Credit	Credit Card	Revolving Credit
I(Youngest Birth-Year=2000)	-0.092	-0.012	0.020**
	(0.062)	(0.028)	(0.008)
Control Mean	0.55	0.21	0.13
Household FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
N	41,838	41,838	41,838
R^2	0.653	0.663	0.521
	Panel B: Intensive Margin		
	Total Credit	Credit Card	Revolving Credit
I(Youngest Birth-Year=2000)	527.70	84.08	245.60**
	(469.67)	(141.49)	(123.96)
Control Mean	6254.37	1142.63	750.73
Household FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
N	15,466	6,684	3,703
R^2	0.919	0.743	0.730

Notes: This Table reports the results of losing CCT on the credit balance for households with extremely low income who are under the CCT program and do not experience a complete loss of transfers. In this case, the coefficients reflect the intended treatment effects outlined in Equation 4.6. Panel A shows the results for the extensive margin and Panel B for the intensive margin. Standard errors are in parentheses and clustered at the municipality level.

Table 4.7.2 shows no statistically significant effects on credit origination, installment due, and interest payment. Similarly, Table 4.7.3 shows that losing part of the cash transfer does not affect delinquency rates of extremely poor households.

Table 4.7.2: Effects of Losing CCT on Credit Origination, Installment Due and Interest Payment

	Panel A: Extensive Margin		
	Credit Origination	Installment Due	Interest Payment
I(Youngest Birth-Year=2000)	-0.002	-0.087	-0.060
	(0.017)	(0.063)	(0.063)
Control Mean	0.13	0.41	0.48
Household FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
N	41,838	41,838	41,838
R^2	0.432	0.611	0.619
	Panel B: Intensive Margin		
	Credit Origination	Installment Due	Interest Rate
I(Youngest Birth-Year=2000)	-4.441	69.633	3.355
	(130.282)	(157.343)	(7.111)
Control Mean	1038.18	1613.63	94.1
Household FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
N	4,311	10,956	13,121
R^2	0.579	0.904	0.736

Notes: This Table reports the results of losing CCT on the extensive margin of credit outcomes for households with extremely low income who are under the CCT program and do not experience a complete loss of transfers. In this case, the coefficients reflect the intended treatment effects outlined in Equation 4.6. The outcomes "Installment Due" and "Interest Payment" refer to when a household must pay any installment in the upcoming month and any interest in the current month. Panel A shows the results for the extensive margin, and Panel B for the intensive margin. Standard errors are in parentheses and clustered at the municipality level.

Table 4.7.3: Effects of Losing CCT on Delinquency Rates

	Extremely Poor Households		
	Default	Any Delay	Up to 90
I(Youngest Birth-Year=2000)	0.039	0.049	0.020
	(0.027)	(0.032)	(0.026)
Control Mean	0.15	0.32	0.23
Household FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
N	15,466	15,466	15,466
R^2	0.525	0.541	0.425

Notes: This Table reports the results for Equation 4.6 of losing CCT on delinquency rates for households with extremely low income who are under the CCT program and do not experience a complete loss of transfers. We select households that have a positive total credit balance. Standard errors are in parentheses and clustered at the municipality level.

In summary, our findings indicate that the loss of the youth variable benefit associated with the youngest child has a greater impact on the credit outcomes of poor households compared to extremely poor households. This disparity may be attributed to the fact that extremely poor households continue to receive a portion of the benefit or because they already exhibit lower levels of financial inclusion, making them less likely to utilize credit.

Conclusion

We conducted a study to investigate how the loss of a cash transfer program (CCT) affects credit outcomes. In particular, we aimed to estimate the effects of CCT loss (or a portion of it) on credit intake. We did this by taking advantage of a unique aspect of a Brazilian CCT program, where households lose a portion of the cash transfer related to their adolescent child when he or she turns 18. This allowed us to use a difference-in-differences specification to analyze the impact of CCT loss on credit outcomes.

Our findings reveal that poor households exhibit a temporary increase in credit card spending when confronted with an anticipated CCT loss. This behavior aligns with the expectations of a habit formation model in the absence of anticipation. However, we observe no statistically significant effects for households whose per capita income falls below the extreme poverty line and who experience only a partial reduction in their cash transfer. It seems that households who still receive a portion of the cash transfers may not have to rely on increasing their credit card usage temporarily. Still, the reduction in cash transfers appears to be affecting their ability to pay their existing credit card bills, leading to a higher usage of revolving credit.

Future investigations could examine the differential impacts of CCT loss across various demographic groups, such as households with different levels of education or employment status, which could offer a nuanced understanding of the broader socio-economic implications. Additionally, exploring the mechanisms underlying households' responses to CCT loss, such as changes in savings behavior or reliance on informal financial sources, could provide further depth to our understanding. Lastly, exploring policy interventions aimed at mitigating the adverse effects of CCT loss and promoting financial resilience among vulnerable households could offer practical implications for policymakers and practitioners in social welfare and financial inclusion.

4.8 Appendix A: Losing CCT

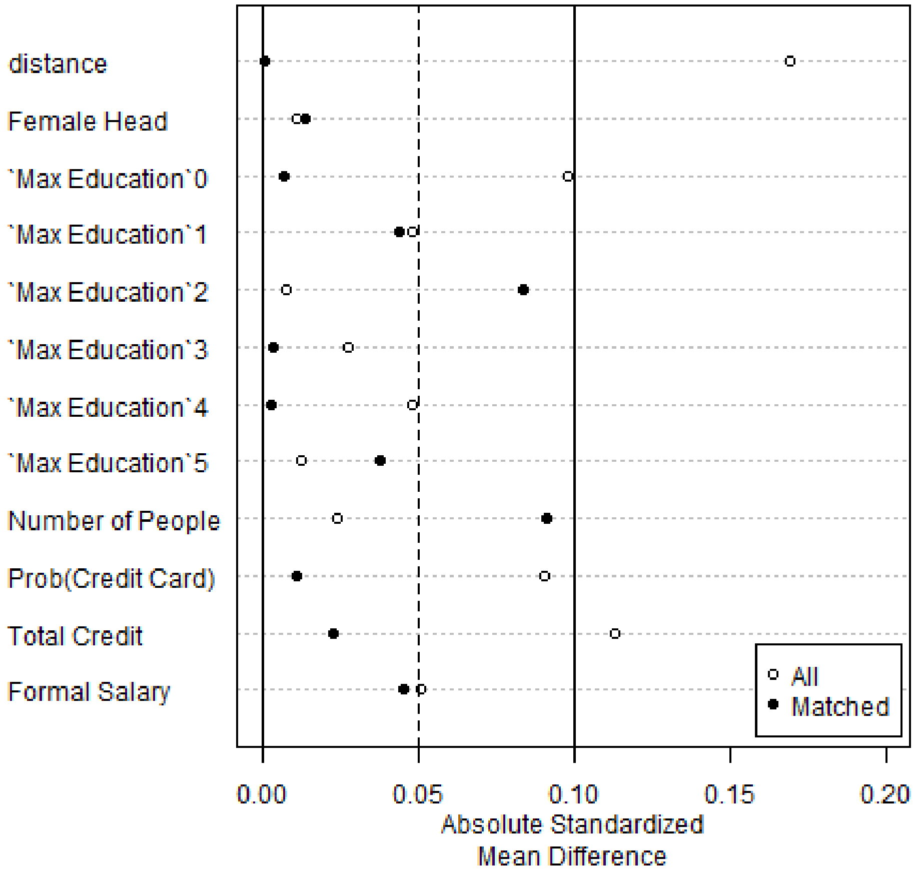


Figure A1: Matching Plot - Poor Households

4.8.1 Placebo

We perform a placebo test, comparing non-eligible households whose youngest child was born in the last three months of 2000 (treatment) with those whose youngest child was born in the first three months of 2001. In particular, we select households with per capita income between BRL 500 and BRL 1000 who never received the CCT over our sample period.

Table A1: Anticipated Loss (Placebo)

	Total Credit	Credit Card	Revolving Credit	Credit Concession	Installment Due	Interest Rate
	Panel A: Extensive Margin					
	Total Credit	Credit Card	Revolving Credit	Credit Concession	Installment Due	Interest Rate
I(Youngest Birth-Year=2000)	-0.044	-0.058	0.020	-0.003	0.036	0.004
	(0.041)	(0.042)	(0.036)	(0.034)	(0.045)	(0.041)
Control Mean	0.68	0.49	0.24	0.27	0.51	0.52
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,968	4,968	4,968	4,968	4,968	4,968
R^2	0.719	0.703	0.546	0.528	0.695	0.679
	Panel B: Intensive Margin					
	Total Credit	Credit Card	Revolving Credit	Credit Concession	Installment Due	Interest Rate
I(Youngest Birth-Year=2000)	566.779	46.232	-20.424	300.610	-49.214	-2.760
	(623.400)	(272.981)	(290.578)	(205.751)	(75.632)	(8.960)
Control Mean	8905.34	1879.34	870.79	995.71	601.3	71.14
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3,547	2,700	1,262	1,512	2,489	2,679
R^2	0.956	0.721	0.665	0.279	0.623	0.606

This Table reports the results for Equation 4.4 of losing CCT on the intensive margin of credit outcomes for the placebo sample consisting of households that have a per capita income between BRL 550 and BRL 1000 and never were CCT Beneficiaries in 2018 and 2019. Panel A shows the results for the Extensive Margin of outcomes. The results in Panel B for the Intensive Margin of Outcomes. Standard errors are in parentheses and clustered at the municipality level.

Table A1 indicates that post-2019 (post-period), being in the treatment group shows no effects. This suggests that the primary analysis' observed effects come from the CCT loss, not from any unobserved variation possibly linked to varying time trends based on the youngest child's birth year.

4.8.2 Internal Habits Model

In this section, following Jappelli and Pistaferri 2017, we describe a habit formation model. Assume that the utility of a given household in period t depends not only on consumption in that period but also on consumption in period $t-1$, a case of time non-separability known as internal habits: $u(c_t, c_{t-1})$. The sign of the cross-derivative $\frac{\partial^2 u(c_t, c_{t-1})}{\partial c_t \partial c_{t-1}}$ determines whether current and past consumption are complements or substitutes in utility. If $\frac{\partial^2 u(c_t, c_{t-1})}{\partial c_t \partial c_{t-1}} > 0$, current and past consumption are substitutes and the marginal utility of current consumption falls with c_{t-1}, whereas if $\frac{\partial^2 u(c_t, c_{t-1})}{\partial c_t \partial c_{t-1}} < 0$, they are complements. In general, consumption in periods s and t are complements if an increase in consumption in period s increases the marginal utility of consumption in period t. They are substitutes if the sign of the derivative is negative.

Consider the problem of a consumer with infinite horizon under uncertainty and a generic utility function $u(c_t, c_{t-1})$. The objective is to maximize:

$$\max E_t \sum_{\tau=0}^{\infty} (1+\delta)^{-\tau} u(c_{t+\tau}, c_{t+\tau-1}),$$

subject to the dynamic budget constraint:

$$a_{t+1} = (1+r)(a_t + y_t - c_t)$$

Note that in this case, there are two state variables: wealth and the level of past consumption (which determines the consumer's habits). The value function can therefore be written as:

$$V_t(a_t, c_{t-1}) = \max_{a_{t+1}, \alpha_t} u(c_t, c_{t-1}) + \frac{1}{1+\delta} E_t V_{t+1}(a_{t+1}, c_t),$$

subject to the constraint $a_{t+1} = (1+r)(a_t + y_t - c_t)$. The first-order conditions of the problem are:

$$\frac{\partial u_t}{\partial c_t} - \frac{1}{1+\delta}(1+r)E_t\frac{\partial V_{t+1}}{\partial a_{t+1}} + \frac{1}{1+\delta}E_t\frac{\partial V_{t+1}}{\partial c_t} = 0$$

$$\frac{\partial V_t}{\partial a_t} = \frac{1+r}{1+\delta}E_t\frac{\partial V_{t+1}}{\partial a_{t+1}},$$

where we use the notation $u_{t+\tau} = u\left(c_{t+\tau}, c_{t+\tau-1}\right)$ for every $\tau = 0, 1, \ldots$ As in the standard problem without habits, the last equation above implies that (when $r = \delta$) the marginal utility of wealth follows a martingale process even with habits. Taking the derivative of the objective function with respect to the second argument of the utility function, one obtains:

$$\frac{\partial V_t}{\partial c_{t-1}} = \frac{\partial u_t}{\partial c_{t-1}}.$$

Combining the last two equations, the first-order condition for consumption can be rewritten as:

$$\frac{\partial u_t}{\partial c_t} + \frac{1}{1+\delta}E_t\frac{\partial u_{t+1}}{\partial c_t} = \frac{\partial V_t}{\partial a_t}.$$

Considering the value of this last equation in period $t+1$ and taking expectation as of period t yields:

$$E_t\frac{\partial u_{t+1}}{\partial c_{t+1}} + \frac{1}{1+\delta}E_t\frac{\partial u_{t+2}}{\partial c_{t+1}} = E_t\frac{\partial V_{t+1}}{\partial a_{t+1}}.$$

And finally, multiplying both sides by $(1+r)(1+\delta)^{-1}$:

$$\frac{1+r}{1+\delta}\left[E_t\frac{\partial u_{t+1}}{\partial c_{t+1}} + \frac{1}{1+\delta}E_t\frac{\partial u_{t+2}}{\partial c_{t+1}}\right] = \frac{1+r}{1+\delta}E_t\frac{\partial V_{t+1}}{\partial a_{t+1}}.$$

Since the right-hand sides of the last two expressions coincide, one can equate the left-hand sides and obtain the following Euler equation:

$$\frac{\partial u_t}{\partial c_t} + \frac{1}{1+\delta}E_t\frac{\partial u_{t+1}}{\partial c_t} = \frac{1+r}{1+\delta}\left[E_t\left(\frac{\partial u_{t+1}}{\partial c_{t+1}} + \frac{1}{1+\delta}\frac{\partial u_{t+2}}{\partial c_{t+1}}\right)\right].$$

If preferences are intertemporally separable, $\frac{\partial u_{t+1}}{\partial c_t} = \frac{\partial u_{t+2}}{\partial c_{t+1}} = 0$, and equation above collapses to the standard Euler equation without habits.

To interpret this Euler equation, suppose that $\frac{\partial u_{t+1}}{\partial c_t} < 0$, that is, current utility decreases with past consumption so that levels of consumption in the two periods are substitutes in utility. In other words, having consumed a lot in period t reduces the utility of additional consumption in period $t+1$, so that when the consumer considers consuming more in period $t+1$, the total utility obtained is reduced by the high consumption of the previous period. Therefore, habits reduce the variability of consumption across time and ensure that individuals seek to maintain the same levels of consumption as in the past. While in the standard case the marginal utility of consumption follows a martingale, with habits it does not, so in this case the optimal consumption rule is more complex than under time separability. Whenever an individual chooses consumption, intertemporal choice involves more than just a sequence of two periods: consumption today depends on consumption yesterday, and by the same token also affects tomorrow's consumption decisions.

One implication of the model with habits is that the Euler equation no longer has the property that consumption innovations are independent of lagged variables. Depending on the number of lags in habits, in the case of time nonseparability, one must modify the orthogonality condition to account for lags that affect current consumption. To see this, consider the case with quadratic utility,

$$u\left(c_t, c_{t-1}\right) = a\left(c_t + \alpha c_{t-1}\right) - \frac{b}{2}\left(c_t + \alpha c_{t-1}\right)^2,$$

and assume $r = \delta = 0$. In this case, the "habit" Euler equation reduces to:

$$\alpha E_t \Delta c_{t+2} + \left(1 + \alpha^2\right) E_t \Delta c_{t+1} + \alpha \Delta c_t = 0.$$

If $\alpha = 0$, we obtain the standard random walk equation $E_t \Delta c_{t+1} = 0$. However, if $\alpha \neq 0$, changes in consumption are autocorrelated and are affected not only by past changes in consumption but also by the expectations of future changes. This example may be used to explain both a failure of the orthogonality test (because expected changes in consumption depend on past changes) and excess sensitivity of consumption changes to expected income changes (because the latter determines future consumption changes). Failure of the orthogonality test and excess sensitivity may, therefore, be signs that preferences are misspecified.

4.9 References

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