Debt Accumulation of Poor CCT Beneficiary Households: Evidence from Brazil using a novel rich administrative dataset

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Abstract

Using rich Brazilian administrative data, we investigate the effect of conditional cash transfers (CCT) on poor households' debt accumulation by exploring a beneficiary status discontinuity around the adulthood year of the youngest child. Debt accumulation and delinquency rates response to CCT depend on whether credit supply is sensitive to the benefit. Moreover, credit card expenditures increase in response to the loss of CCT, indicating it works as a substitute for cash transfers. The expenditure increase comes partially from higher labor income.

JEL Codes: G50, G51, I32, I38.

Keywords: access to credit, conditional cash-transfer, debt accumulation.

Introduction

Conditional cash transfers (CCT) programs seek to improve the welfare of low-income families by alleviating current poverty and increasing the human-capital accumulation across generations in developing countries[3]. Although many studies provide evidence of its impact on poor households' educational, health, and life conditions, its relation to credit outcomes and financial inclusion is not explored. In particular, there is still no evidence about the effects of CCT on the accumulation of debt of poor households. We address this gap by estimating the impact of losing CCT on debt accumulation and delinquency rates, exploring a a discontinuity on households' probability of being CCT beneficiaries in Brazil.

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[3] Such as Brazil, Mexico, Colombia, Jamaica, Bangladesh, Chile, Honduras, and Zambia.

This paper documents the effects of CCT on a new set of outcomes related to credit and labor while describing the differential behavior of beneficiary households depending on the characteristics of the local credit market. We show that credit card expenditures substitute cash transfers. Also, we show that losing the cash transfer impacts formal labor employment. The benefit correlates with a higher delinquency rate, suggesting that the supply of credit lines targeting the poor might be sensitive to the transfer.

The source of identification is a discontinuity in a Brazilian CCT program eligibility rule for low-income families with at least one child. The law limits the age of the children at the beginning of the year such that poor households whose youngest child completed 18 years old in the given year will lose the cash grant the following year, while those whose child did not will continue receiving it. The central identification assumption is that the unobservable characteristics are not systematically different between adults in households whose youngest child reaches the age threshold for eligibility momentarily before the beginning of the year (e.g., in December) and those of households whose youngest child reaches the eligibility age threshold soon after the beginning of the year (e.g., in January). The assumption's reasonability derives from the randomness in determining one's child's birth date. In this setting, households could anticipate losing the benefit since the information is publicly available. Arguably they might not do so due to a lack of sophistication. We also complement a fuzzy regression discontinuity specification, which gives the average effect of having CCT for one year more, comparing households close to the threshold, with a difference in differences (DID) that provides a visualization of the gradual effect of losing the CCT. The DID identifying 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 this assumption of extended treatment effect in a dynamic specification and find no evidence of pre-existing trends.

We contribute to the literature that investigates conditional cash transfer effects[4] by presenting evidence on the patterns of debt accumulation of beneficiary households.[5] Additionally, we con-

[4]like Rawlings and Rubio (2005), Rasella et al. (2013) and Parker and Todd (2017)

[5]It also relates to the one that investigates the impact of productive microcredit and grants on household wealth,

tribute to the literature on the labor market effects of the grant, showing potential positive effects of losing CCT on young adults' formal job supply [6]. Our results are also linked to the literature on the real effects of consumer debt accumulation and default (Mian et al. (2017); Gomes et al. (2019); Mian et al. (2020)), as we show that default rates can be positively or negatively associated with CCT depending on local credit market characteristics. Moreover, it connects to the literature on consumption response to anticipated income shocks (Jappelli and Pistaferri (2010)) and consumption patterns of poor households (Aguiar et al. (2020)). We present novel evidence that poor households use credit card expenditures to maintain a baseline consumption.

The rest of the paper is organized as follows. In section 1, we present the conceptual framework, followed by a description of *Bolsa Família*, the CCT Program of Brazil, and the difference microcredit market in Ceara and Minas Gerais, in section 2. Next, in section 3, we explain the data used. In section 4, we present the identification strategy and in section 5 we present the results followed by the discussion, in section 6. Finally, we state the conclusions of the paper.

1 Conceptional Framework

We present separately the conceptualization of two hypotheses explored in the paper. First, we describe the behavior of poor households facing an anticipated income shock. Second, we present to explore the possible effects of CCT on credit supply.

1.1 Anticipated Income Shock and Habits

According to the permanent income hypothesis, assuming a concave utility function, a rational household would not abruptly change its consumption given an anticipated income change.[7] So, considering the event of losing a CCT according to the existing law, households would save to smooth consumption, and there would not be effects on credit card behavior. Alternatively, they

such as Kaboski and Townsend (2011) and Fiala (2018).

[6]Contrasting with the evidence found by Fruttero et al. (2020) which find a positive impact of CCT on entry in the formal labor market for younger cohorts

[7]for a review of the literature on consumption response to income changes, see Jappelli and Pistaferri (2010)

could have present bias, discounting too much future over present consumption and not saving in anticipation.[8] However, they can adapt their use of credit cards to keep the same baseline level of consumption; that is, borrowing may be a way to keep the same consumption after losing the benefit. That's the case if their marginal utility to consume in the present is greater than the discounted marginal utility to consume in future periods.

Various studies investigate the effects of retirement on consumption. Like our setting, retirement is an anticipated negative income shock. Note that credit constraint is not a potential problem in this case. That's because households that expect an income decline would have saved to smooth consumption and not borrow as in the case of an anticipated income increase. Studies on retirement consumption effects find evidence of substantial drops in consumption.[9] Contrasting to our setting, retirement, which is the traditionally studied setting of anticipated income declines impact on consumption, coincides with a decrease in labor supply. The young child beneficiary households are entering the labor market since they are around adulthood, and their labor supply can respond to the CCT lost income. [10] One impediment comes from one conditionality of Bolsa Família, which request beneficiary households' children to attend a school. Once the households lose the benefit, the youngest child is naturally more inclined to leave school and has a higher propensity to work. Moreover, the parents are potentially still at an economically active age and could try to compensate for the cash transfer lost from the CCT by increasing their labor supply. That's why one could expect household credit card expenditures to increase, reflecting a gradually higher labor income.

[8] One could argue that poor households often lack financial literacy and do not have access to a proper saving mechanism.

[9] Using repeated cross-sectional data drawn from the UK Family Expenditure Survey (FES), Banks et al. (1998) found a substantial drop in consumption after retirement. Bernheim et al. (2001), using US Panel Study of Income Dynamics (PSID), also found evidence of a reduction in consumption, noting a sharper decrease for households with lower income replacement rate and less wealth.

[10] Relatedly, Attanasio et al. (2005) shows how the female labor supply works as an insurance mechanism against unexpected income shocks within the family.

1.2 CCT as a Pseudo Pleadgeable Income

In addition, given the tendency of poor households to be informal workers, a CCT can be considered a pseudo-pledgeable income, potentially increasing beneficiary households' credit intensive and extensive margins and reducing interest rates. In the case of productive microcredit concessions, credit agents are responsible for collecting a poor household' information in person before granting the credit, which might heighten the role of CCT as a pseudo-guarantee.[11]

In special, there are two more possible ways CCT can affect debt and delinquency. First, CCT can serve as a pseudo-pledgeable income since, even though the bank cannot legally confiscate it in case of default, it is a known steady income flow for beneficiary households. Low-income families have difficulty accessing credit due to a lack of collateral. Additionally, most have informal jobs and high turnover in the labor market, failing to prove their ability to pay loans and financing. So, CCT reduces the bank risk by reducing uncertainty about the borrower's income. Indeed, poor indebted households may use the residual income to pay debts such as loan installments; hence, CCT can help reduce their probability of default. [12] On the other hand, this can also affect the Bank's credit supply for these households, making CCT potentially increase debt accumulation (and leverage). Second, alternatively, such a constant income stream can also reduce poor households' need for credit. So, all else equal, losing CCT can either increase or decrease poor households' debt accumulation and delinquency rates (due to supply and demand channels).

[11] Furthermore, Bianchi and Bobba (2013) and Gertler et al. (2012) find that a Mexican CCT *Oportunidades*, significantly increased entry into entrepreneurship and cash transfer households received went to productive activities. Bianchi and Bobba (2013) find evidence that for the higher rate of entrepreneurship among beneficiaries households comes from the relaxation of liquidity constraints but also from households' increased willingness to bear risk. Ribas (2014) find similar effects for BF.

[12] CCT beneficiary households consume around 80 and 90 percent of transfers in Brazil (Resende and Oliveira (2008)), Colombia (Angelucci and Attanasio (2009)), and Mexico (Gertler et al. (2012)). The residual income was found to increase household savings (Rubalcava et al. (2009)) and investments in productive assets (Angelucci and De Giorgi (2009); Todd et al. (2010)) and, in urban areas, to be used to pay off debts (Angelucci et al. (2012)) in Mexico. Angelucci et al. (2012) finds that the transfer is used to reduce the number and value of loans.

2 Institutional Background

2.1 Bolsa Família: CCT Program in Brazil

In Brazil, *Programa Bolsa Família* (BF) was 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[13] - the last month of our sample -, to be eligible to receive a BF grant, families must 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.[14]

There are two main groups of *Bolsa Família* beneficiary households: extremely poor and poor. While extremely poor households[15] receive a baseline grant regardless of their family composition, poor households[16] receive the benefit conditional on having a minor child that fulfills the conditionalities being above a reasonable level of school attendance. So, when the year the youngest child completes 18 years old ends, poor households stop receiving the value of R$ 48,00 per month. We explore this discontinuity by using a difference-in-differences regression discontinuity approach.

BF is generally considered a well-targeted CCT program (Lindert et al. (2007)).[17] Moreover, various studies indicate that BF has had a positive impact on the reduction of income inequality and poverty in Brazil [18], as well as on school attendance of children whose families are beneficiaries [19].

[13] Before July of 2018, the income thresholds where R$ 85,00 and R$ 170,00.

[14] *Ministério da Cidadania*: August 13th, 2020.

[15] those with per capita income below R$ 90

[16] those with per capita income between R$ 90 and R$ 178

[17] Both in terms of income range and conditionality compliance. Suppose a beneficiary family with children does not comply with the conditionalities. Following a government investigation, a warning postponement of payment is followed by a two-month suspension of benefits and, ultimately, cancellation.

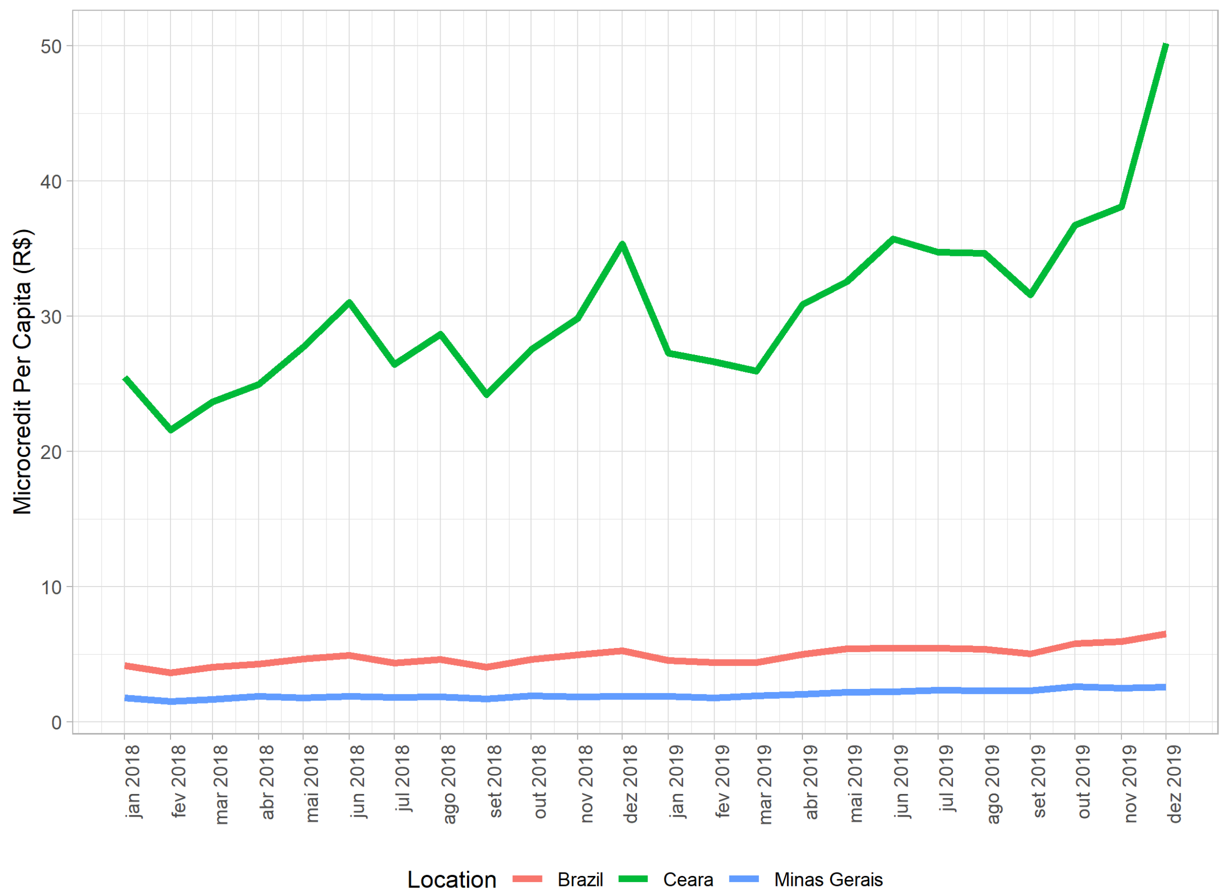
[18] For instance, Barros et al. (2007a), Barros et al. (2007b), Soares et al. (2009) and Cury et al. (2010)

[19] See, for example, Cardoso et al. (2004), and Glewwe and Kassouf (2012)

2.2 Microcredit Market: The Particular Case of Ceara

Microcredit is a subsidized credit type designed for poor individuals. CCT beneficiary households would generally prefer microcredit to other types since it tends to have better conditions in terms of interest rate, size, and term. On the supply side, a credit agent collects the information of potential household borrowers to assess whether they should receive the credit. All else equal, one might expect that the additional grant (such as CCT) would increase the credit agent's willingness to grant microcredit. On the demand side, the constant income flow of CCT can reduce the cost of distress by reducing the permanent consumption loss associated with default. Furthermore, it can increase the ability to meet basic needs after repayment during bad times. Since the discontinuity on the probability of poor households having CCT at the youngest child threshold is independent of location, we can assess the sensibility of productive microcredit concessions by comparing the results on the effects o CCT on credit terms in two locations that differ in the size of their microcredit market.

Figure 1: Microcredit Balance Per Capita (R$)



Source: Cadastro Unico and SCR. Jan-2018/Dec-2019.

Our sample consists of households from two States: Ceara and Minas Gerais. Ceara is a north-eastern state characterized by an active market of productive microcredit for poor individuals (see Figure 1), driven by public banks, in special *Banco do Nordeste*. Minas Gerais is the closest State to Brazil regarding income, ethnicity, demography, religion, education, and political preferences.

3 Data

This section describes the data sources used in the paper. We match CadÚnico, the Brazilian Credit Registry data (SCR), Relação Anual de Informações Sociais (RAIS) and Receita Federal (RF) 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. In 2017, the families included in CadÚnico represented 39% of microcredit operations by volume of resources, concentrated almost entirely in the Northeast region.[20]. SCR stores the information on all credit operations carried out throughout Brazil by persons and firms with a total liability of at least R$ 200. We use information household 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, an employer-employee matched database that includes employment information and wages for all formally employed workers in Brazil, and RF for information on formalized entrepreneurs. Data is aggregated at the household level such that the credit is the sum of every type of credit (productive microcredit, broad microcredit, rural credit, etc) received by every member and default is an indicator of whether any member is on default, according to BCB's definition[21], at a particular month. We also have a dummy indicating if there is any formal employee as well as the sum of formal salary and the number of formal entrepreneurs at the household level in each month. The dataset is at the household-quarter-year level, with matched information from *CadÚnico*, *SCR*, RAIS, and RF. The sample period goes from January 2018 to December 2019.

4 Identification Strategy

Endogeneity is a major problem when observing the relation between debt accumulation and labor behaviors of conditional cash transfers because beneficiaries are generally in a worse social and economic situation than non-beneficiary households. So, various unobserved characteristics might affect the outcomes of interest and beneficiary status. In other words, individuals self-select into BF based on unobserved characteristics that affect credit and labor outcomes.

Then, the identification strategy explores the discontinuity in the probability of having a BF

[20]Data from *Cadastro Único* December/2017 and *Sistema de Informações de Crédito* accumulated 2017

[21]Credit in arrears for more than 90 days

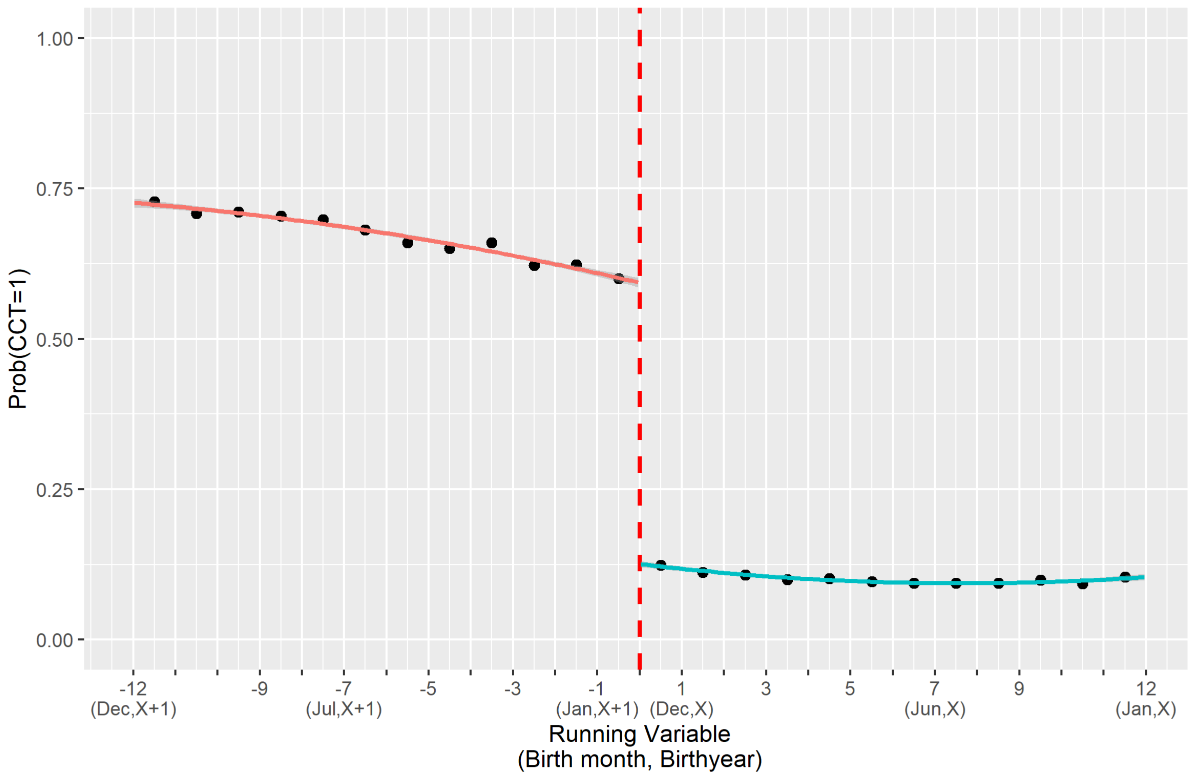
cash transfer at the end of the year the youngest child completes 18. Under the assumption that households are reasonably indistinguishable around the eligibility threshold, using the threshold as an instrument can allow for identifying the effect of CCT on debt accumulation, delinquency, and labor outcomes.

4.1 Fuzzy Regression Discontinuity Design: LATE of CCT

We use a fuzzy regression discontinuity design to estimate the effect of CCT. To do so, we explore a discontinuity on the probability of having CCT. This allows us to estimate the local average treatment effects of receiving the benefit for one year more on various outcomes. We use a sample of all *Cadúnico* households in the states of Ceara and Minas Gerais.

As compliance is imperfect, that is, some poor households did not receive the benefit even when they had a minor child, and also some few did have it even when they had no longer an adolescent child, our empirical strategy is analogous to an instrumental variable design where CCT status is instrumented with the time threshold of the year the young child completes 18 years old. The running variable is the birth date distance to the end of the beginning of the year for negative values and the end of the year for positive values. After the year of adulthood of the youngest children, there is a discontinuity in the probability of being a beneficiary of the program, as it is clear in Figure 2.

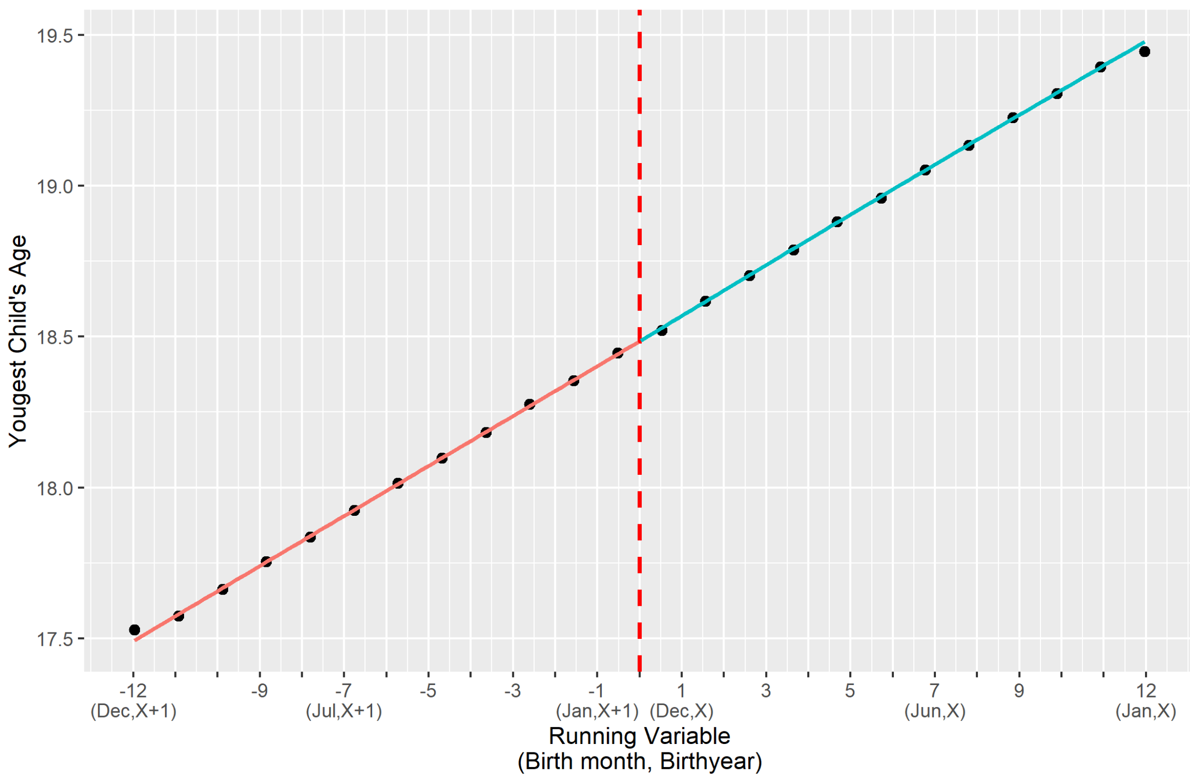
Figure 2: Probability of Being a CCT Beneficiary along Birth Year (and birthday anniversary)



Notes: We fit a polynomial regression on each threshold side, generating analogous predictions to a first-stage parametric specification. Source: Cadastro Unico and SCR. Jan-2018/Dec-2019.

In the limit, considering the year 2019, for instance, we are comparing a poor household whose youngest child was born on January 1st of 2001 (and continues to receive the benefit) with one whose youngest child was born on December 31st of 2000 (and hence loses the benefit). So we'll be comparing the behavior of households that have different conditional cash transfer statuses (beneficiary or not) only because the date of birth of their youngest child is slightly different (see Figure 3).

Figure 3: Youngest Child Adulthood Age along the Running Variable



Under a parametric setting, the first stage can be expressed as follows:

$$CCT_{it} = \alpha + \psi I\{z_{it} \geq 0\} + \sum_{1}^{p} \lambda^p z_{it} I\{z_{it} \geq 0\} + \sum_{1}^{p} \gamma^p z_{it} + \varepsilon_{it} \tag{1}$$

where CCT_i is whether the household i receives the transfer, $alpha$ is a constant, z_{it} is the running variable, $I\{z_{it} \geq 0\}$ is an indicator for the time being after the household's threshold of youngest child adulthood at year-month t. And the second stage regression becomes:

$$Y_{it} = \zeta + \beta \widehat{CCT}_{it} + \sum_{1}^{p} \iota^p z_{it} I\{z_{it} \geq 0\} + \sum_{1}^{p} \kappa^p z_{it} + \varepsilon_{it} \tag{2}$$

Y_{it} is the outcome of interest, $I\{z_{it} \geq 0\}$ is the excluded instrument. $\widehat{CCT}_{it}$ is the fitted value of the first stage regression. Here, the coefficient of interest, β, gives the Average Treatment Effect on the Treated (ATET) at $z = 0$ for the compliers (those whose CCT beneficiary status changes after the threshold) is δ.

Following recent advances in RDD estimation (Cattaneo et al. (2017)), we perform the FRDD using a non-parametric local linear polynomial procedure.

As depicted in Figure 2, we can safely reject the hypothesis that the instrument is weak because, for households with an average income between R$ 90 and R$ 178, there is a solid relationship between being in a period after the end of the year of adulthood of the youngest child and losing its CCT grant. Households that lose the cash transfer lose exactly R$ 48 per month - the amount poor BF beneficiary households receive for each adolescent child.

Table 1: Manipulation of the Assignment Variable (McCrary Test)

Bandwidth	**Z <0**	**Z >= 0**	**p-value**
0.900	9,261	9,185	0.580
1.200	11,429	11,289	0.360
1.500	14,957	15,049	0.600
1.800	17,842	18,142	0.110
2.100	20,913	20,697	0.290

Notes: Z refers to the running variable. Column 2 and 3 show the number of households in each side of the threshold. Estimates are obtained following Cattaneo et al. (2019).

McCrary (2008) provides a formal test for the existence of manipulation of the assignment variable in a regression discontinuity design. The marginal density of the running variable should be continuous without manipulation, and thus, there should be no discontinuities in the density around the threshold. As expected, Table 1 shows that the McCrary manipulation test fails to reject the null hypothesis of discontinuities around the threshold for various bandwidth sizes. Hence, as expected, there is no evidence of manipulation around the threshold (households picking their child's exact date of birth).

Table 2: Household Characteristics - Before vs. After the Threshold

	Ceara		Minas Gerais	
	T = 0	*T = 1*	*T = 0*	*T = 1*
Covariates	N=3542	N=3394	N=6433	N=6371
Female Head	0.94	0.95	0.92	0.92
	(0.27)	(0.23)	(0.28)	(0.27)
Household Income	126	130	133	131
	(26.1)	(26.1)	(25.5)	(25.6)
Max Education Level	2.13	2.26	1.80	1.86
	(1.32)	(1.41)	(1.24)	(1.25)
Number of People	2.90	2.98	2.98	3.01
	(1.04)	(1.06)	(1.01)	(0.99)

Notes: This table presents the means of household covariates before and after the threshold under a bandwidth of one month.

Table 2 shows the means of household characteristics before and after the threshold under a bandwidth of one month. In the limit, both groups are very similar regarding female household heads, household per capita income, maximum education (between household head or partner)[22], and the number of people.

4.2 Difference in Differences: Gradual Effects of Losing CCT

While the FRDD specification gives the average effect over a year of receiving the CCT for one more year (in comparison to those that have already lost it), a difference in differences specification enables us to check the robustness of the FRDD results to observe whether the effects are gradual

[22]Max Education Level: 0 - No Formal Education; 1 - Incomplete Primary Education; 2 - Complete Primary Education; 3 - Incomplete Secondary Education; 4 - Complete Secondary Education; 5 - Incomplete Higher Education or More.

or abrupt. So, in this second part of the identification strategy, we define the treatment group as those households whose youngest child was born in 2000 and the control those whose youngest child was born in 2001, 2002, 2003, 2005, or 2006. By controlling for the youngest child's age, we expect to capture only effects related to CCT status. We include household fixed effects to control for time-invariant heterogeneity and municipality x month fixed effects to control for all time-varying geographic variation. Here, we instrument the loss of the CCT status (ex-CCT) by the youngest child's birth year.

The first stage can be written as follows:

$$\text{ex-}\widehat{CCT}_{it} = \alpha_i + \lambda_{tm} + \phi \cdot I(BirthYear_i = 2000) \times Post_t + \nu_{it} \tag{3}$$

where ex-$\widehat{CCT}_{it}$ is again a dummy variable indicating whether the household does not receive the CCT in period t, $alpha_i$ and λ_t are household and municipality 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.[23]

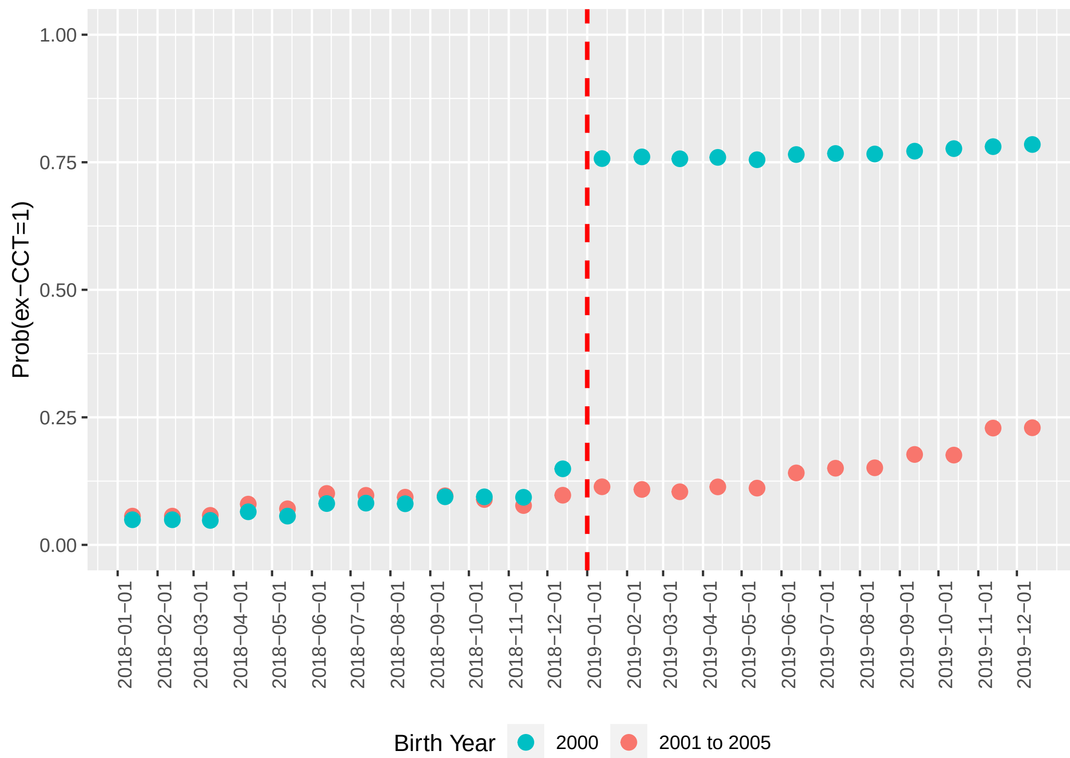
The second stage is then:

$$Y_{it} = \alpha_i + \lambda_{tm} + \beta \cdot \text{ex-}\widehat{CCT}_{it} + \varepsilon_{it} \tag{4}$$

where Y_{it} is the outcome of interest and ex-$\widehat{CCT}_{it}$ 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, analogous to the FRDD estimates. Since we are comparing households within each municipality, the standard errors of the point estimates are clustered at the municipality level. Figure 4 shows the proportion of households in the treatment and control groups that CCT beneficiaries and gives visual evidence of the instrument's relevance (youngest child born in 2000) for explaining the treatment status after December 2019.

[23]Table A1 in the appendix presents the first stage DID results.

Figure 4: Loss of CCT Status over time according to Youngest Child Birth Year



Notes: This Figure depicts the proportion of households that are CCT beneficiaries over time for the group whose youngest child was born in the year 2000 and the one whose youngest child was born after 2000.

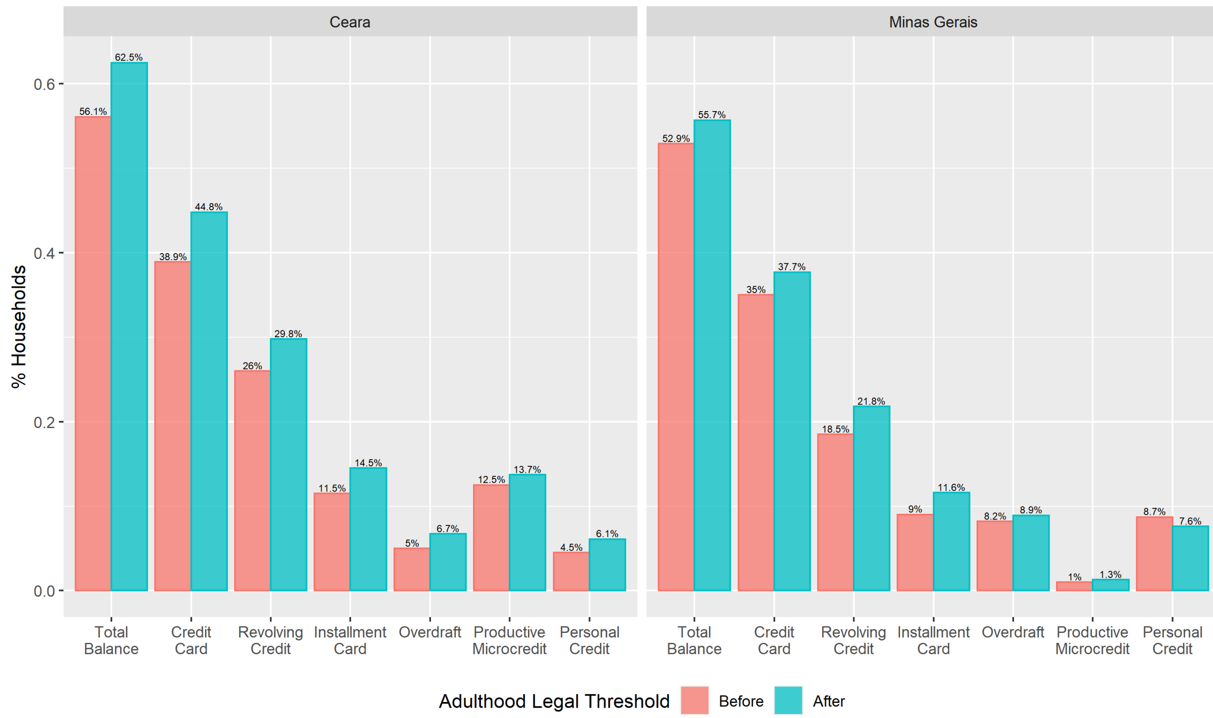
Additionally, we extend perform a direct dynamic specification:

$$Y_{it} = \alpha_i + \alpha_{mt} + \sum_{s=-12, t\neq -3}^{11} \beta_s \cdot I(BirthYear_i = 2000) \cdot I(t = s) + \varepsilon_{it} \tag{5}$$

We omit (and hence set it as the baseline) three months before households from the treatment group are expected to lose the CCT. β_s captures the effects of losing the cash transfer in January 2019 on various outcomes in relation to their levels in December 2018.

4.3 Descriptive Statistics

Figure 5: Percentage of Households with Specific Credit Type Before and After Threshold



Proportion of households with a positive balance of various credit lines before and after the threshold. Source: Cadastro Unico and SCR. Jan-2018/Dec-2019.

Figure 5 shows the most important credit types for poor households before and after the considered threshold. These are credit card [24], revolving card[25], installment card[26], microcredit, overdraft, and personal credit.

5 Results

We replicate our empirical strategies in the two States. First, we examine households' debt accumulation patterns by analyzing the effects of losing the CCT on the probability and balance of

[24] Is the amount represented by purchases made with credit cards without financial charges.

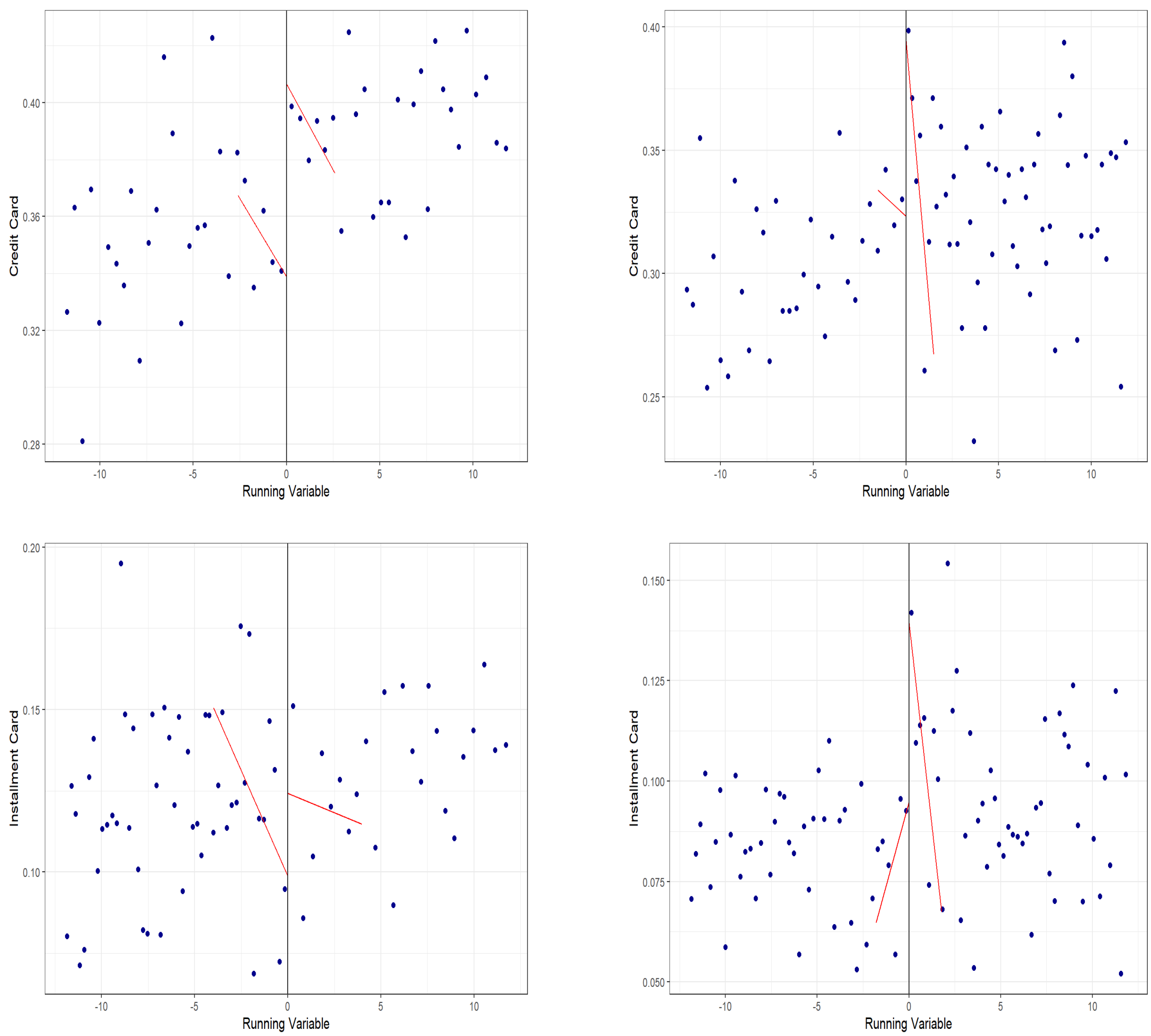
[25] Outstanding balance after the invoice is due, equivalent to the difference between the total amount of the invoice and the amount paid by the borrower, including the interest calculated until the end of the month.

[26] Installment credit financed by the card issuer, with finance charges. These operations can be linked to withdrawals, the installment of purchases, or the installment of credit card bills.

various credit outcomes. We also present the effects on formal employment and salary, formal entrepreneurial activity, and the number of bank accounts in the household. Then, we see the effects on delinquency rates. We are comparing households over all months, capturing an average local effect.

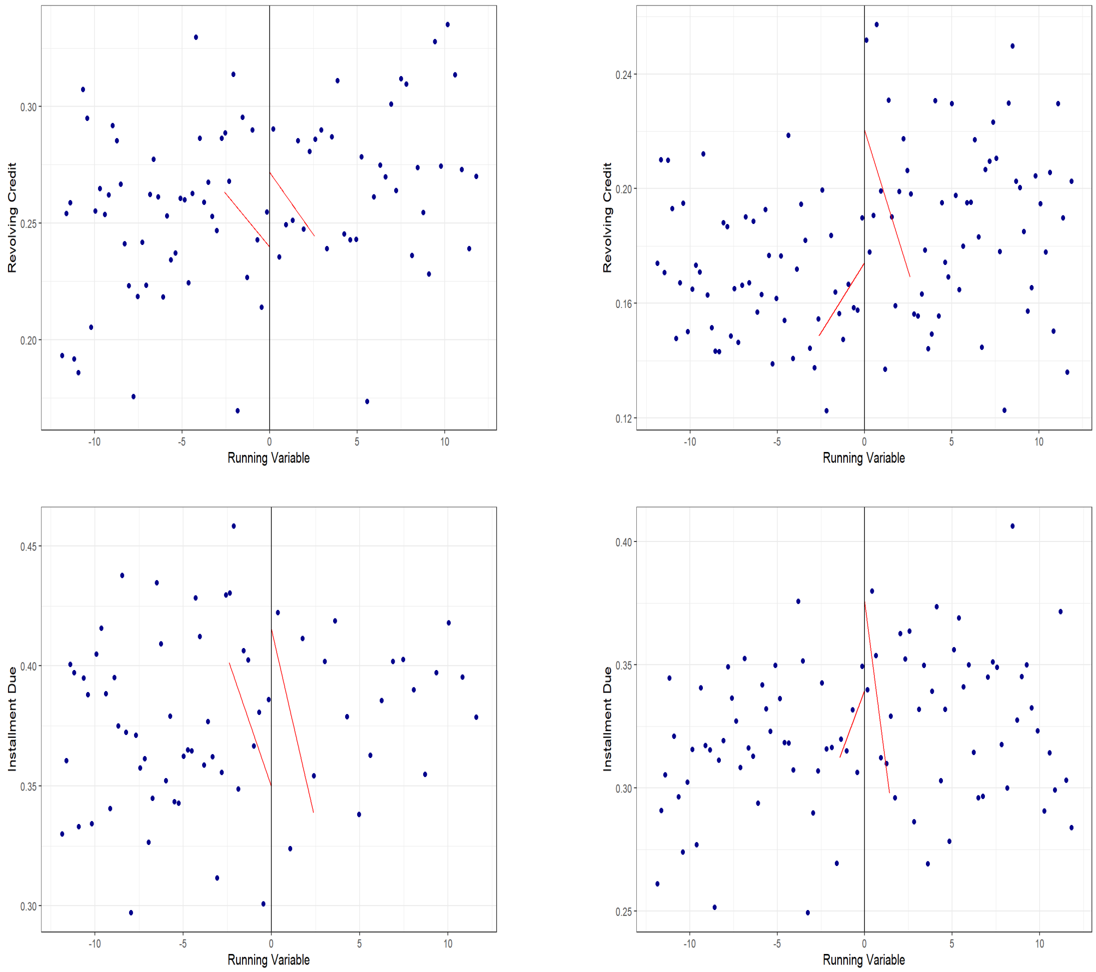
5.1 Accumulation of Debt of CCT Households

Table 3 shows the fuzzy rdd results of CCT on the probability of having credit lines.



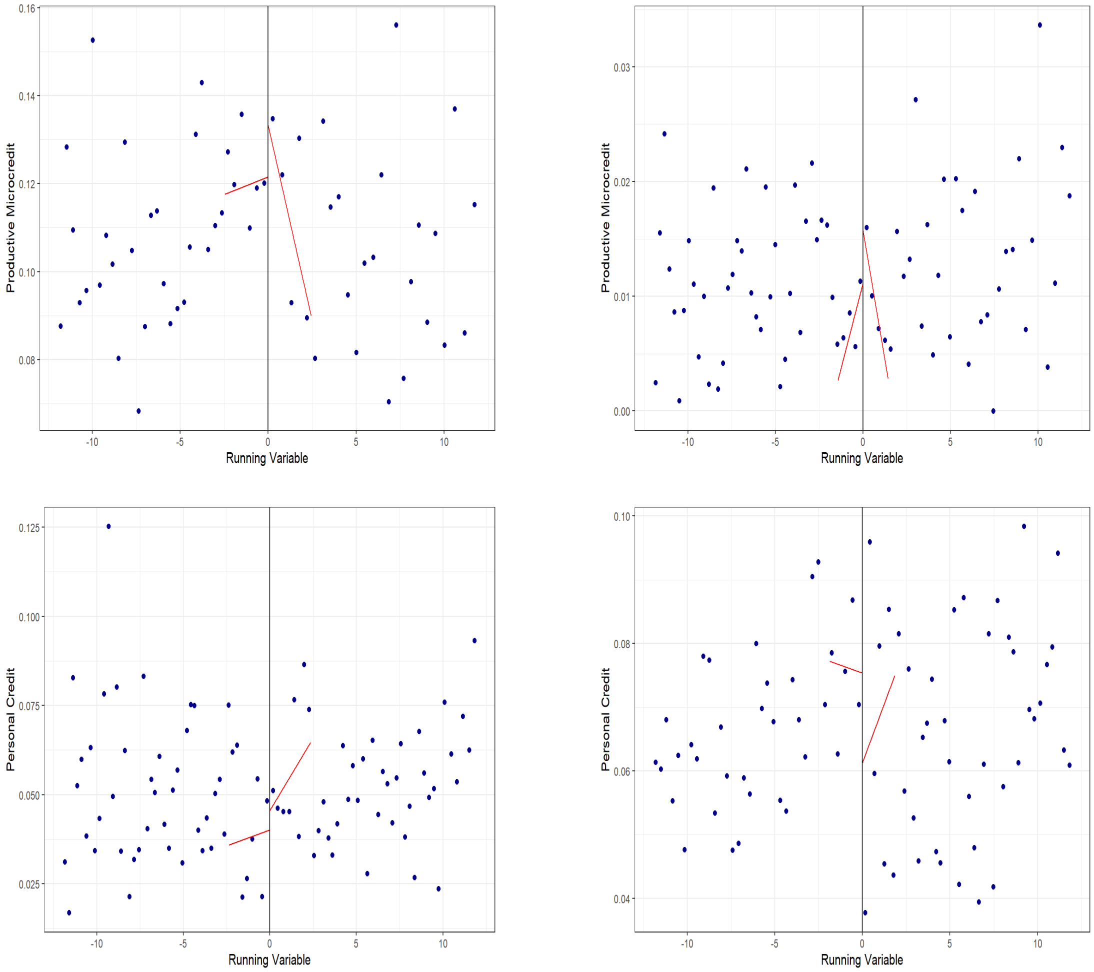
(a) Ceara (b) Minas Gerais

Figure 6: Poor Households - Probabilities - Consumption



(a) Ceará (b) Minas Gerais

Figure 7: Poor Households - Probabilities - Expensive Credit Line and Installment Due



(a) Ceará

(b) Minas Gerais

Figure 8: Poor Households - Probabilities - Credit Concessions

In Minas Gerais, results indicate that, before losing the CCT, poor households are less likely to have any credit concession (-13%), credit card expenditures (∼-20%), installment card expenditure (∼-10%), and revolving credit (∼-15%). Credit card is more closely related to daily consumption, while installment card relates more to the consumption of durable goods. Revolving credit increases after losing the CCT because poor households are not managing to pay the minimum credit card invoice payment, suggesting they use part of the cash transfer to pay part of the credit card invoice. Furthermore, CCT beneficiaries have a smaller probability of having vehicles financing (-4%), Microcredit (∼-4%), having to pay any interest rate (-12%), and installment due (-7%).

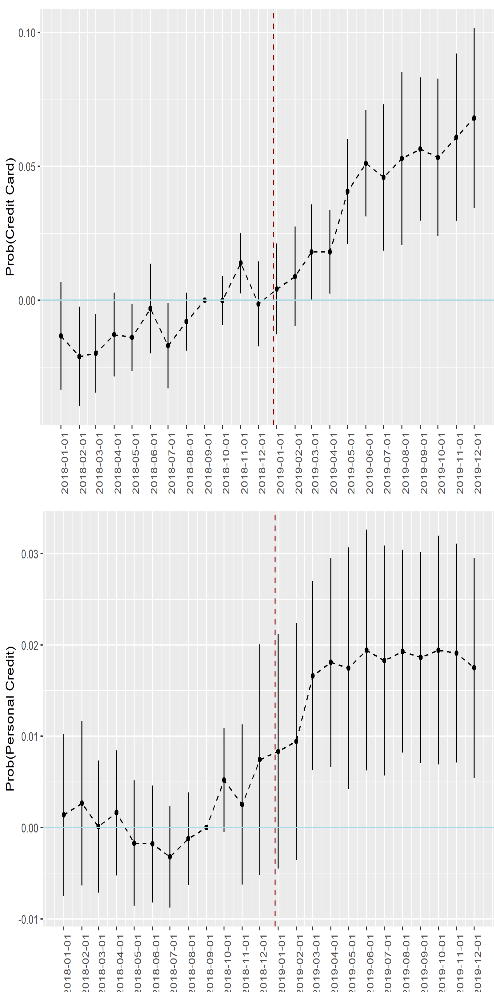
In Ceara, poor households, before losing the CCT, have a smaller probability of having a new credit concession (∼-4%), credit card expenditure (∼-14%) and installment card (-7%). They also have less chance of having revolving credit (∼-6%), overdraft (-8%), any interest rate (-7%), and installment due (∼ 23%). Furthermore, CCT beneficiaries have a greater probability of having vehicles financing (4%).

Table 3: Fuzzy RDD - CCT on Credit Outcomes - Probabilities

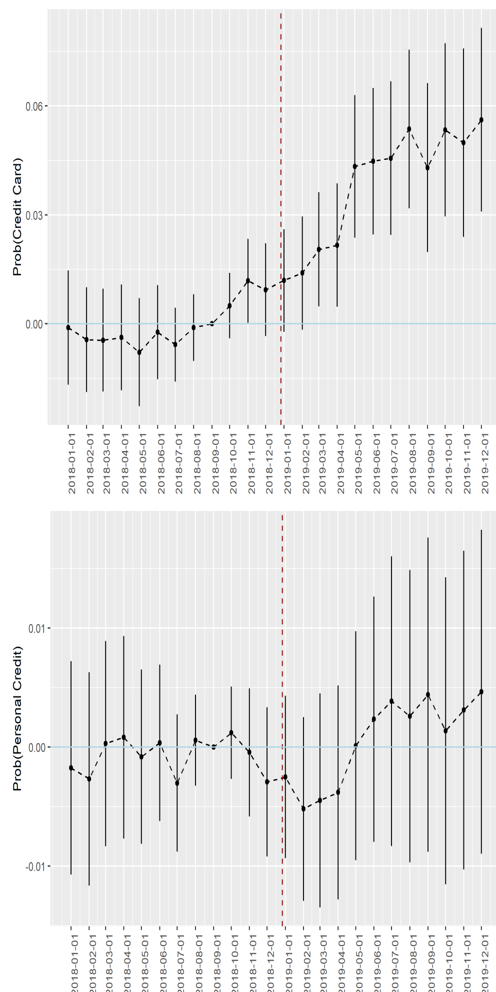
	Ceara			Minas		
Outcome	Control Mean	Bandwidth	Point Estimate	Control Mean	Bandwidth	Point Estimate
Credit Concession	0.04	2.34	-0.04	0.03	2.45	-0.025
			(0.036)			(0.023)
Credit Card	0.45	3.13	-0.126	0.37	1.71	-0.15
			(0.032)			(0.032)
Revolving Credit	0.31	2.35	-0.137	0.21	1.88	-0.076
			(0.036)			(0.026)
Personal Credit	0.06	1.83	0.03	0.07	2.28	0.073
			(0.023)			(0.016)
Productive Microcredit	0.14	2.57	-0.068	0.01	1.77	-0.008
			(0.025)			(0.007)
Installment Due	0.38	2.07	-0.251	0.40	1.09	-0.211
			(0.043)			(0.044)
Year-Month Fixed Effects		Yes			Yes	
Household Controls		Yes			Yes	
Formal Salary		Yes			Yes	

Notes: This table presents the coefficients of of the Fuzzy Regression Discontinuity using nonparametric local linear polynomial estimation. Point estimators are constructed using local polynomial estimators with triangular kernel; "robust p-values" are constructed using bias-correction with robust standard errors as derived, and bandwidth corresponds to the second generation data-driven MSE-optimal bandwidth selector proposed in Calonico et al. (2014). Standard errors in parenthesis.

Figure 9: Timing of Effect on Probability of Using Different Credit Types

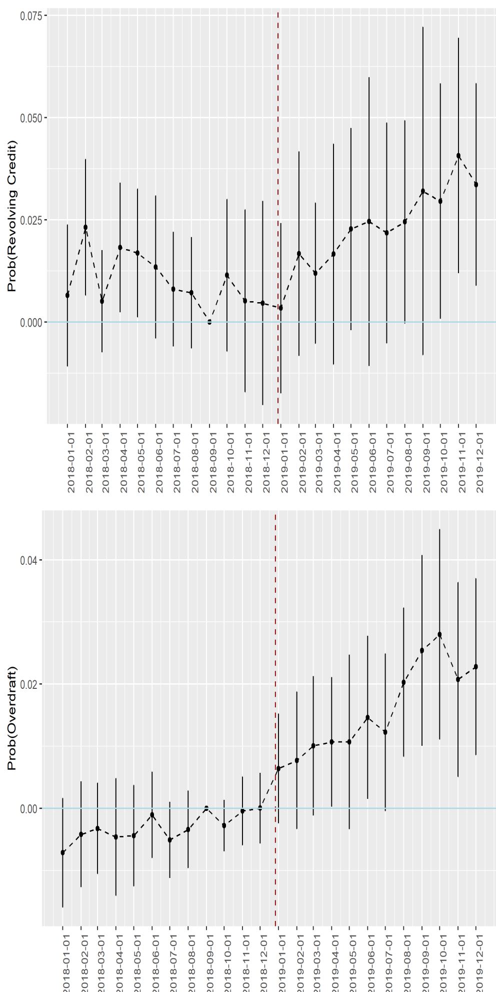


(a) Ceará

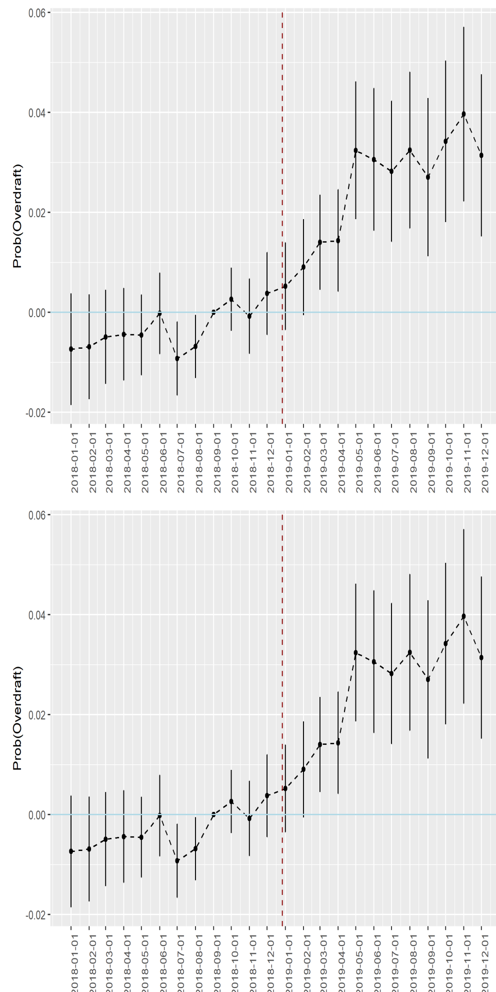


(b) Minas Gerais

Figure 10: All Households - Balance - R$



(a) Ceará



(b) Minas Gerais

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

Table 4: DID - Second Stage - CCT on Credit Outcomes

	Ceara	Minas		Ceara	Minas
Total Credit	-0.066	-0.076	Credit Concession	-0.072	-0.062
	(0.013)	(0.014)		(0.012)	(0.009)
Credit Card	-0.096	-0.080	Productive Microcredit	0.006	0.0001
	(0.012)	(0.012)		(0.007)	(0.003)
Installment Card	-0.036	-0.018	Personal Credit	-0.026	-0.006
	(0.012)	(0.009)		(0.008)	(0.007)
Revolving Credit	-0.033	-0.039	Installment Due	-0.038	-0.033
	(0.017)	(0.010)		(0.014)	(0.013)
Overdraft	-0.029	-0.045	Interest Rate	-0.042	-0.055
	(0.008)	(0.008)		(0.014)	(0.013)
Household FE	Yes	Yes		Yes	Yes
Year-Month FE	Yes	Yes		Yes	Yes
Observations	280,046	611,683		280,046	611,683

Notes: All columns report estimates of the second-stage coefficients (Equation 4) of CCT on Credit Outcomes instrumented by the year of birth of the youngest child 2000 and the period after December 2018 (Post) for each State. Observation is at the household-month-year level, and the bottom rows specify the fixed effects. Standard Errors, clustered at the municipality level, are reported in parentheses.

Table 4 shows the effects under the difference in differences specification for the effects of CCT on the probabilities of households using credit lines. Figure 9 shows the timing effects of being in the 2000 youngest birth year on the probability of various credit lines. The use does not increase abruptly but gradually and results are similar to those encountered in the FRDD specification.

DID results indicate that CCT negatively affects the likelihood of any installment due, and interest to pay is smaller. We get further evidence that credit card use increases with expensive credit lines such as overdraft and revolving credit after households lose the CCT. Similarly, there is no effect on productive microcredit in both States.

Table 5: Fuzzy RDD - CCT on Conditional Log Outcomes

	Ceara			Minas Gerais		
Outcome	**Control Mean**	**Bandwidth**	**Point Estimate**	**Control Mean**	**Bandwidth**	**Point Estimate**
Credit Concession	1571.27	3.13	0.503	1452.54	3.78	-0.383
			(0.273)			(0.267)
Credit Card	2135.42	4.04	-0.418	1651.11	2.62	-0.644
			(0.174)			(0.193)
Revolving Credit	931.45	2.7	1.327	788.62	2.77	0.068
			(0.435)			(0.427)
Overdraft	508.17	2.03	2.703	651.05	4.07	-1.016
			(1.025)			(0.585)
Personal Credit	1498.74	3.24	1.02	3518.42	4.19	-0.059
			(0.44)			(0.293)
Productive Microcredit	5718.37	2.53	1.044	4792.31	1.98	-3.595
			(0.265)			(0.828)
(Balance Weigheted) Interest Rate	87.14	2.43	-0.033	89.734	3.45	-0.03
			(0.238)			(0.152)
Min Interest Rate (Microcredit)	31.079	2.61	-0.318	32.96	2.05	-0.266
			(0.076)			(0.163)
Installment Due	909.011	2.82	0.187	3249.64	2.11	0.374
			(0.175)			(0.24)
HH Income according to Bank	859.63	2.38	-0.464	960.159	1.2	-0.465
			(0.089)			(0.147)
Income Commitment	0.645	2.45	0.25	0.819	2.52	0.955
			(0.174)			(0.223)
Year-Month Fixed Effects		Yes			Yes	
Household Controls		Yes			Yes	
Formal Salary		Yes			Yes	

Notes: This table presents the coefficients of of the Fuzzy Regression Discontinuity using nonparametric local linear polynomial estimation. Point estimators are constructed using local polynomial estimators with triangular kernel; “robust p-values” are constructed using bias-correction with robust standard errors as derived, and bandwidth corresponds to the second generation data-driven MSE-optimal bandwidth selector proposed in Calonico et al. (2014). Standard erros in parenthesis.

Table 6: Fuzzy RDD - CCT on Labor Outcomes and Bank Accounts - All Households

	Ceara			Minas Gerais		
Outcome	**Control Mean**	**Bandwidth**	**Point Estimate**	**Control Mean**	**Bandwidth**	**Point Estimate**
Bank Accounts	2.04	2.49	-0.189	2.12	1.75	-0.216
			(0.068)			(0.069)
P(Formal Entrepreneurs)	0.12	3.67	-0.067	0.12	2.2	-0.125
			(0.02)			(0.022)
P(Formal Employment)	0.40	2.44	-0.07	0.44	2.53	-0.201
			(0.029)			(0.027)
Formal Salary	600.54	2.88	-250.929	704.854	2.93	-260.824
			(55.131)			(53.243)
Year-Month Fixed Effects		Yes			Yes	
Household Controls		No			No	
Formal Salary		No			No	

Notes: This table presents the coefficients of of the Fuzzy Regression Discontinuity using nonparametric local linear polynomial estimation. Point estimators are constructed using local polynomial estimators with triangular kernel; robust standard errors reported in parenthesis, and bandwidth corresponds to the second generation data-driven MSE-optimal bandwidth selector proposed in Calonico et al. (2014).

In table 5, we can see the results on the log of the balance of credit outcomes. The first thing to notice is that CCT beneficiaries have a considerably bigger productive microcredit balance (104%) in Ceara but not in Minas Gerais where they have a smaller one (-359%).

As shown in the 2, Ceara has an intense Productive Microcredit market from subsidized credit operations granted through federal banks, in particular *Banco do Nordeste*. Microcredit is usually directed towards the poor population and granted by credit agents who might understand a CCT as a "pseudo" pledgeable income. Poor households, in turn, could recognize this and exploit the fact that there will be more credit supply while they still receive the transfer.

5.2 Effects of Losing the CCT on Labor Outcomes and Financial Inclusion

Table 6 shows the impact of CCT on labor outcomes and bank accounts. In both States, households present a lower probability of having any formal job and being a formal entrepreneur while receiving CCT. Part of the effect on credit might come from an increase in labor income. The effect should be higher for both States if we also observed the effects on informal labor.

5.3 CCT on Delinquency Rates

In Ceara, irrespective of the selected sample (all poor households, with a positive balance, and with positive installment), beneficiary households present a greater probability of default (see Table 7).

Table 7: Fuzzy RDD - CCT on Deliquency Rates - Ceara

Panel A - All Households						
Outcome	Bandwidth	Point Estimate	Bandwidth	Point Estimate	Bandwidth	Point Estimate
Default	3.26	0.04	2.69	0.04	2.48	0.04
		(0.018)		(0.02)		(0.021)
Any Delay	3.74	-0.03	1.9	-0.06	1.9	-0.06
		(0.022)		(0.033)		(0.033)
Up to 30	4.57	-0.05	2.39	-0.02	2.77	-0.03
		(0.015)		(0.023)		(0.02)
Panel B - Households with Positive Balance						
Outcome	Bandwidth	Point Estimate	Bandwidth	Point Estimate	Bandwidth	Point Estimate
Default	2.32	0.07	2.13	0.09	2.13	0.1
		(0.039)		(0.041)		(0.04)
Any Delay	3.24	0.03	2.76	0.04	2.6	0.05
		(0.042)		(0.046)		(0.047)
Up to 30	2.66	-0.02	2.29	0.02	2.68	0
		(0.038)		(0.042)		(0.038)
Panel C - Households with Positive Installment to Pay						
Outcome	Bandwidth	Point Estimate	Bandwidth	Point Estimate	Bandwidth	Point Estimate
Default	2.15	0.02	1.96	0.04	1.89	0.03
		(0.041)		(0.045)		(0.045)
Any Delay	3.17	-0.03	3.11	0	3.19	0
		(0.047)		(0.05)		(0.049)
Up to 30	3.07	-0.07	2.16	0.01	2.29	0
		(0.041)		(0.052)		(0.05)
Formal Employment		No		No		Yes
Household Controls		No		Yes		Yes
Year Month FE		No		Yes		Yes

Notes: This table presents the coefficients of of the Fuzzy Regression Discontinuity using nonparametric local linear polynomial estimation. Point estimators are constructed using local polynomial estimators with triangular kernel; "robust p-values" are constructed using bias-correction with robust standard errors as derived, and bandwidth corresponds to the second generation data-driven MSE-optimal bandwidth selector proposed in Calonico et al. (2014).

Table 8: Fuzzy RDD - CCT on Deliquency Rates - Minas

Panel A - All Households						
Outcome	Bandwidth	Point Estimate	Bandwidth	Point Estimate	Bandwidth	Point Estimate
Default	1.98	-0.01	1.59	-0.01	1.55	-0.01
		(0.016)		(0.019)		(0.019)
Any Delay	2.02	0	1.58	0.01	1.64	0.02
		(0.022)		(0.025)		(0.025)
Up to 30	2.44	0.02	2.36	0.03	2.26	0.03
		(0.014)		(0.014)		(0.015)
Panel B - Households with Positive Balance						
Outcome	Bandwidth	Point Estimate	Bandwidth	Point Estimate	Bandwidth	Point Estimate
Default	3.39	-0.03	3.14	-0.01	2.3	0.03
		(0.026)		(0.027)		(0.034)
Any Delay	2.39	0.1	3.63	0.01	3.85	0
		(0.042)		(0.032)		(0.032)
Up to 30	3.23	0.06	2.65	0.08	3.03	0.07
		(0.027)		(0.03)		(0.028)
Panel C - Households with Positive Installment to Pay						
Outcome	Bandwidth	Point Estimate	Bandwidth	Point Estimator	Bandwidth	Point Estimate
Default	2.87	-0.03	2.63	-0.01	3.29	-0.05
		(0.037)		(0.039)		(0.034)
Any Delay	2.42	0.11	1.89	0.12	1.91	0.13
		(0.055)		(0.063)		(0.064)
Up to 30	2.86	0.11	2.23	0.13	2.91	0.11
		(0.041)		(0.048)		(0.042)
Formal Employment		No		No		Yes
Household Controls		No		Yes		Yes
Year Month FE		No		Yes		Yes

Notes: This table presents the coefficients of of the Fuzzy Regression Discontinuity using nonparametric local linear polynomial estimation. Point estimators are constructed using local polynomial estimators with triangular kernel; "robust p-values" are constructed using bias-correction with robust standard errors as derived, and bandwidth corresponds to the second generation data-driven MSE-optimal bandwidth selector proposed in Calonico et al. (2014).

6 Discussion

Households substitute cash transfers with credit card and installment card expenditures, indicating that they are not entirely credit-constrained and can substitute the purchasing power lost from CCT. On the other hand, losing the benefit increases revolving credit - a credit line automatically used when individuals fail to pay the minimum value of a credit card bill - which signals a possible worsening of their financial situation.

There are positive effects of losing CCT on formal labor supply. Given the positive results on formal employment and salary, we the increase in credit concessions and expenditure very likely comes partially from the increase in labor income. Even though the effects are robust to controlling for formal employment, we do not have information on the effects on the informal labor market. Hence, we are estimating a downward biased effect on the labor market.

We find evidence that CCT status increases debt accumulation when a positive elasticity of microcredit supply exists to cash transfers in the local market. In Ceara, distinguished by an active microcredit market, households present larger productive microcredit balances. Such a higher rate of indebtedness possibly relates to the observed higher probability of default before they lose the cash transfer.

Formal employment increases in Minas Gerais after losing the grant. However, the effects may also be positive for Ceara if we consider informal labor. One concern is that beneficiary households would omit formal employment since the federal government can check formal labor income and would exclude de facto ineligible families from the program. However, Barbosa and Corseuil (2014) find that the program has no impact on the occupational choice of beneficiaries between formal and informal posts.

Conclusion

This paper investigates the debt accumulation of CCT beneficiary households. We exploit the discontinuity of eligibility of poor households around the end of the year their youngest child completes 18 years old.

Households tend to substitute cash transfers with credit card consumption. After losing the benefit, households' likelihood of having a formal job and labor market dynamics at least partially drive the increases in credit card expenditures and credit increases of ex-CCT beneficiaries.

We contrast two Brazilian States where poor households face different market scenarios: Ceara, where there is an abundant supply of governmentally subsidized microcredit, and Minas Gerais, where the microcredit supply is much smaller. In Ceara, the productive microcredit balance is greater, and credit conditions are better, while households have the CCT at the same time correlating with higher rates of default.

References

M. A. Aguiar, M. Bils, and C. Boar. Who are the hand-to-mouth? Technical report, National Bureau of Economic Research, 2020.

M. Angelucci and O. Attanasio. Oportunidades: program effect on consumption, low participation, and methodological issues. *Economic development and cultural change*, 57(3):479–506, 2009.

M. Angelucci and G. De Giorgi. Indirect effects of an aid program: how do cash transfers affect ineligibles' consumption? *American economic review*, 99(1):486–508, 2009.

M. Angelucci, O. Attanasio, and V. Di Maro. The impact of oportunidades on consumption, savings and transfers. *Fiscal Studies*, 33(3):305–334, 2012.

O. Attanasio, H. Low, and V. Sánchez-Marcos. Female labor supply as insurance against idiosyncratic risk. *Journal of the European Economic Association*, 3(2-3):755–764, 2005.

J. Banks, R. Blundell, and S. Tanner. Is there a retirement-savings puzzle? *American Economic Review*, pages 769–788, 1998.

A. L. N. d. H. Barbosa and C. H. L. Corseuil. Bolsa família, escolha ocupacional e informalidade no brasil. 2014.

R. P. d. Barros, M. d. Carvalho, S. Franco, and R. S. P. d. Mendonça. A queda recente da desigualdade de renda no brasil. 2007a.

R. P. d. Barros, S. Cury, and G. Ulyssea. A desigualdade de renda no brasil encontra-se subestimada?: Uma análise comparativa com base na pnad, na pof e nas contas nacionais. 2007b.

B. D. Bernheim, J. Skinner, and S. Weinberg. What accounts for the variation in retirement wealth among us households? *American Economic Review*, 91(4):832–857, 2001.

M. Bianchi and M. Bobba. Liquidity, risk, and occupational choices. *Review of Economic Studies*, 80(2): 491–511, 2013.

S. Calonico, M. D. Cattaneo, and R. Titiunik. Robust nonparametric confidence intervals for regression-discontinuity designs. *Econometrica*, 82(6):2295–2326, 2014.

E. Cardoso, A. P. Souza, et al. The impact of cash transfers on child labor and school attendance in brazil. 2004.

M. D. Cattaneo, R. Titiunik, and G. Vazquez-Bare. Comparing inference approaches for rd designs: A reexamination of the effect of head start on child mortality. *Journal of Policy Analysis and Management*, 36(3):643–681, 2017.

M. D. Cattaneo, M. Jansson, and X. Ma. Two-step estimation and inference with possibly many included covariates. *The Review of Economic Studies*, 86(3):1095–1122, 2019.

S. Cury, A. E. Mori Coelho, I. Callegari, and E. Pedrozo. The impacts of income transfer programs on income distribution and poverty in brazil: an integrated microsimulation and computable general equilibrium analysis. 2010.

N. Fiala. Returns to microcredit, cash grants and training for male and female microentrepreneurs in uganda. *World Development*, 105:189–200, 2018.

A. Fruttero, A. R. Leichsenring, and L. H. Paiva. *Social Programs and Formal Employment: Evidence from the Brazilian Bolsa Família Program*. International Monetary Fund, 2020.

P. J. Gertler, S. W. Martinez, and M. Rubio-Codina. Investing cash transfers to raise long-term living standards. *American Economic Journal: Applied Economics*, 4(1):164–92, 2012.

P. Glewwe and A. L. Kassouf. The impact of the bolsa escola/familia conditional cash transfer program on enrollment, dropout rates and grade promotion in brazil. *Journal of development Economics*, 97(2): 505–517, 2012.

J. F. Gomes, M. Grotteria, and J. A. Wachter. Cyclical dispersion in expected defaults. *The Review of Financial Studies*, 32(4):1275–1308, 2019.

T. Jappelli and L. Pistaferri. The consumption response to income changes. *Annu. Rev. Econ.*, 2(1):479–506, 2010.

J. P. Kaboski and R. M. Townsend. A structural evaluation of a large-scale quasi-experimental microfinance initiative. *Econometrica*, 79(5):1357–1406, 2011.

K. Lindert, A. Linder, J. Hobbs, and B. De la Brière. The nuts and bolts of brazil's bolsa família program: implementing conditional cash transfers in a decentralized context. *World Bank social protection discussion paper*, 709, 2007.

J. McCrary. Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of econometrics*, 142(2):698–714, 2008.

A. Mian, A. Sufi, and E. Verner. Household debt and business cycles worldwide. *The Quarterly Journal of Economics*, 132(4):1755–1817, 2017.

A. Mian, A. Sufi, and E. Verner. How does credit supply expansion affect the real economy? the productive capacity and household demand channels. *The Journal of Finance*, 75(2):949–994, 2020.

S. W. Parker and P. E. Todd. Conditional cash transfers: The case of progresa/oportunidades. *Journal of Economic Literature*, 55(3):866–915, 2017.

D. Rasella, R. Aquino, C. A. Santos, R. Paes-Sousa, and M. L. Barreto. Effect of a conditional cash transfer programme on childhood mortality: a nationwide analysis of brazilian municipalities. *The lancet*, 382 (9886):57–64, 2013.

L. B. Rawlings and G. M. Rubio. Evaluating the impact of conditional cash transfer programs. *The World Bank Research Observer*, 20(1):29–55, 2005.

A. C. C. Resende and A. M. H. C. d. Oliveira. Avaliando resultados de um programa de transferência de renda: o impacto do bolsa-escola sobre os gastos das famílias brasileiras. *Estudos Econômicos (São Paulo)*, 38:235–265, 2008.

R. P. Ribas. Liquidity constraints, informal financing, and entrepreneurship: direct and indirect effects of a cash transfer programme. Technical report, Working Paper, 2014.

L. Rubalcava, G. Teruel, and D. Thomas. Investments, time preferences, and public transfers paid to women. *Economic Development and cultural change*, 57(3):507–538, 2009.

S. Soares, R. G. Osório, F. V. Soares, M. Medeiros, and E. Zepeda. Conditional cash transfers in brazil, chile and mexico: impacts upon inequality. *Estudios económicos*, pages 207–224, 2009.

J. E. Todd, P. C. Winters, and T. Hertz. Conditional cash transfers and agricultural production: Lessons from the oportunidades experience in mexico. *The Journal of Development Studies*, 46(1):39–67, 2010.

Appendix

Table A1: DID - First Stage Results

	Ex-CCT	
	Ceara	Minas Gerais
I(Birth Year = 2000) x Post	0.641	0.681
	(0.020)	(0.009)
Household FE	Yes	Yes
Year-Month x Municipality FE	Yes	Yes
Observations	367,046	653,155

Notes: Both columns report first-stage coefficients (Equation 3) of the instrumenting the loss of CCT beneficiary Status with the year of birth of the youngest child being 2000 and the period after December 2018 (Post) for each State. Observation is at the household-month-year level, and the bottom rows specify the fixed effects. We also control for the age of the youngest child interacting with a dummy variable for older than 18. Standard Errors, clustered at the municipality level, are reported in parentheses.