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THE IMPACT ON CONSUMPTION OF MORE CASH IN CONDITIONAL CASH TRANSFER PROGRAMS

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Abstract

This paper evaluates the impact of an increase in the value of the cash transfer paid to families by the Brazilian *Bolsa Família* program. The existence of a similar program in the state of Ceará, *Bolsa Cidadão*, that increases the value received by a sub-group of families, provides a unique dataset, enabling us to evaluate the effect of a higher value of transfer on the spending of comparable households. There is a significant increase in consumption, but it is smaller than the increment in the income, suggesting that the consumption of the households is not properly declared.

Keywords: Poverty; Cash Transfer Programs; Policy Evaluation.

Resumo

O presente artigo avalia o impacto de um aumento no valor do benefício do programa Bolsa Família. Isso é possível pela existência no Estado do Ceará de um programa semelhante, Bolsa Cidadão, que na prática aumenta o valor do Bolsa Família para um destas famílias, possibilitando avaliar o efeito de um maior valor de transferência sobre os gastos de famílias comparáveis. É observado um efeito significativo no consumo das famílias. No entanto, a elevação é menor do que o incremento na renda, o que sugere que o consumo das famílias não é corretamente declarado.

Palavras-chave: Pobreza; Programas de Transferência de Renda; Avaliação de Política.

JEL classification: I38, H75, H81.

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1 Introduction

Bolsa Família is the largest conditional cash transfer in the world and it is now a consolidated mechanism with favorable evaluations of its impact on poverty in Brazil.[1] The debate over its validity and effectiveness has been now directed to its improvement and expansion. A simple but not trivial question emerges from this discussion: Should additional resources be allocated to the program in order to extend its coverage or to increase the value of the benefit?

The Brazilian state of Ceará provides a unique situation to allow us to evaluate the effect of an increase in the value of *Bolsa Família* due to the existence of a similar and complementary program called: *Bolsa Cidadão*. The state government transfers resources to its 41 poorest municipalities in the state, where the poorest families receive a monthly stipend that is added to the *Bolsa Família*. This program allows us to compare families in similar circumstances receiving *Bolsa Família* for different values.

To our knowledge, this is the first attempt to use data of this type to estimate the effects of higher values of cash transfers on consumption of comparable units.[2] It is important to highlight that, by performing an evaluation under these circumstances, some of the most common and difficult problems to resolve when dealing with matching and impact evaluation are significantly mitigated: self-selection and selection bias.

As in the *Bolsa Família* program from the federal government, *Bolsa Cidadão* program unifies the actions of all programs of cash transfer existing in the state. It is a benefit that provides an additional amount of cash to the recipients of the *Bolsa Família* program, ranging from R$ 5 to R$ 25, which represented, on average, a 20% increase in the *Bolsa Família* benefit and 7.1% increase in the initial income.[3]

In order to carry out the proposed evaluation, we use a dataset extracted from the administrative file (*Cadastro Único*) provided by the Ministry of Social Development (*Ministério do Desenvolvimento Social — MDS*) through the Secretariat of Labor and Social Development of Ceará State (Secretaria do Trabalho e Desenvolvimento Social), which contains the information of all individuals enrolled in federal and state welfare programs.

In this official database are recorded information upon the family and its members with monthly per capita income of up to half the Brazilian minimum wage.[4] Information included in the official database includes characteristics relative to the household and the individual, such as educational qualification, profession, income and monthly expenses, among many other relevant variables.

From this dataset we performed an impact evaluation analysis of the families that receive both the *Bolsa Família* and *Bolsa Cidadão* benefits, using the methodology of matching with propensity score, in order to mitigate a likely selection bias in the determination of the recipients of the additional benefit. A statistically significant effect on the level of household consumption is

[1] Some of those papers are Resende & Oliveira (2008), Soares et al. (2009) and Duarte & Silveira (2008).

[2] Filmer & Schady (2010) use a sharp regression discontinuity design to identify the effect of higher values of cash transfers on school attendance in Cambodia.

[3] The average value received by the families in November 2007 was R$16.00 (About US$9.00). For more detailed figures, see Tables A.2 and A.3 in the Appendix.

[4] Income per person at the date of inclusion in the program.

found when the income of families who receive the additional cash transfer and families who receive only the *Bolsa Família* are compared. However, the increase in consumption is smaller than the increase in income, suggesting that the consumption of the households is not properly declared.

In the following section, the program coverage is defined, as well as the sample used in the analysis. In section 3, the methodology used is described, while section 4 discusses the effects of participation in the program on consumption. The fifth section concludes.

2 Sample Delimitation, Program Coverage and Descriptive Statistics

2.1 Sample Delimitation

In the *Cadastro Único* database for the state of Ceará, there were more than 5 million and 800 thousand individuals in November 2007. In order to enable more consistent and reliable estimates, the dataset were constrained to the entries updated between January and November 2007, in order to avoid distortions, especially in monetary variables.[5]

When we also constrain the database only to people living in the 41 poorest municipalities where the *Bolsa Cidadão* was provided, the sample size is reduced to 695.027 people, which represents 78% of the total population of those municipalities.

Table A.1 in the Appendix shows the rates of inclusion in *Cadastro Único* database, as well as participation in *Bolsa Família* and *Bolsa Cidadão* by municipality. The percentage of the total population in the official database is very high. This is partially explained by the fact that those municipalities are the ones with the highest social vulnerability in the state.[6]

2.2 Program Coverage

The percentage of coverage of the *Bolsa Família* is quite high, with most of the municipalities with more than 80% of registered people receiving the benefit. For the *Bolsa Cidadão* program, the percentage of coverage is not quite as high, just over 15% in the 41 municipalities with recipients of this additional benefit.

Table 1 presents the coverage of *Bolsa Cidadão* and *Bolsa Família* programs in municipalities taking into account two criteria. The coverage with respect to the total population of the municipality and coverage with respect to the population registered in the *Cadastro Único* database. It is worth noting that there is not a large reduction in the coverage of both programs when considering the total population of the municipality as a reference instead of the

[5]Another advantage of this approach is to improve the quality of information. As highlights Loureiro (2007), the *Cadastro Único* Databasehas some difficulties that were progressively mitigated by MDS.

[6]It should be noted also that some percentages exceed 100%. There are at least two causes for this fact. First, the values of population size are estimates, which may be underestimated. Second, it is well know that in the Brazil, especially in the Northeast region, there are people from towns of neighboring municipalities who seek to enroll in a different municipality because the registration office is closer. In this situation, they either incorrectly declare that their town belongs to a different municipality or simply lie about it.

population registered in the *Cadastro Único* database. This indicates the high level of poverty in these locations.

Table 1: Bolsa Família and Bolsa Cidadão Coverage in the 41 municipalities

	Bolsa Família	Bolsa Cidadão
Total Population	890,926	890,926
People in Cadastro Único database	695,027	695,027
Population not receiving the benefit	133,580	585,219
Population receiving the benefit	561,447	109,808
Program Coverage (Total Population)	63.02%	12.33%
Program Coverage (Cadastro Único database)	80.78%	15.80%

Note: Information in November — 2007. Data Source: Cadunico/MDS.

2.3 Descriptive Statistics

Aiming a better understanding of the characteristics of people included in the database in the 41 municipalities which have benefited families with the *Bolsa Cidadão* program, some descriptive statistics concerning the households, such as educational level, school attendance and condition in the labor market are presented below. The following statistics are related to all families registered in the database, regardless of whether or not they are receiving the benefits. Table 2 below shows the school attendance of people between 7 and 17 years of age who were registered in the municipalities under analysis. It can easily be noticed that the percentage of people in this age group who is not attending school is just over 11%. Furthermore, it is interesting to note that over 87% of the students are enrolled in public schools, with the great majority of the pupils attending schools under municipal administration. It is worth noting that less than 1% of them are enrolled in private schools.

Table 2: School Attendance of the population in the database between 7 e 17 years of age

School Attendance	%
Municipal Public	81.50
State Public	5.69
Federal Public	0.01
Private	0.62
Other	0.15
Not enrolled at school	11.53
N/A	0.49
Total	100.00

Note: Information in November — 2007.
Data Source: Cadunico/MDS.

Table 3 shows the distribution of individuals with respect to the situation in the labor market of the population in the database in working age. More than 54% of the population between 15 and 65 years of age that are registered in *Cadastro Único* database do not work. The second most frequent category is that of rural workers, followed by to retirees and pensioners. It is also notable the participation of people with formal employment, which reaches less than 1% of people registered in the database.

Table 3: Situation in the Labor Market of the population in the database in working age

Situation in the Labor Market	%
No Job	54.9
Rural Worker	31.1
Retiree/Pensioner	5.0
Autonomous	0.9
Employee with formal contract	0.9
Employee without formal contract	2.9
No reporting/Other	4.3
Total	100.00

Information in November — 2007. Data Source: Cadunico/MDS.

Another important aspect regards the source of income (excluding benefits) of households. Table 4 displays the share of each source of income among the people included in *Cadastro Único* database, which shows that almost 50% of people that have a source of income obtain it from labor. Note also that retirement and pensions benefits are the other main sources of income.

Table 4: Sources of Income of households in the database

Sources of Income	%
Labor	49.8
Retirement/Pension	32.7
Unemployment Benefit	0.1
Alimony	0.6
Other Income	16.8
Total	100.00

Information in November — 2007. Data Source: Cadunico/MDS.

As important as the information about the source of income of the potential benefit recipients is the destination of such income. Table 5 below shows the destination of the expenditure of people in the sample, where the food spending dominates the family budget, making up more than 64% of total expenditure. The second largest expenditure of the families is cooking gas, followed by medicines and electricity.

Table 5: Destination of the Expenditures of households in the database

Destination of the Expenditures	%
Food	64.2
Rent	2.1
Housing Financing	0.2
Water	2.3
Electricity	6.5
Transport	2.7
Medicines	6.9
Cooking Gas	10.1
Other Expenditures	5.0
Total	100.00

Information in November — 2007. Data Source: Cadunico/MDS.

3 Empirical Framework

In order to assess the impact of a family receiving an additional direct income transfer, we restricted the sample only to families that are *Bolsa Família* recipients.[7] Because this is also a condition for a family to receive the *Bolsa Cidadão* benefit, this procedure does not eliminate any of those families from the sample. This procedure also significantly mitigates the problem of *selection bias*.[8]

However, even after that, it is still possible (in fact likely) that a family will participate in the *Bolsa Cidadão* program if it has some specific characteristics. In order to mitigate this problem we will use matching based on propensity score in order to estimate the causal effects of the treatment. In the present study, this method will be employed to evaluate the effects of the *Bolsa Cidadão* benefit on expenditures of beneficiary families which comprise consumption in items such as food, housing, clothing, education and other expenses.

This impact is identified in the literature of impact assessment as Average Treatment Effect (ATE). This concept emerges from a framework based on the idea of *counterfactual*, where the impact of a treatment is evaluated by comparing the effect of the treatment on an outcome variable between two situations: the situation of an individual with the treatment and status of that same individual, if he had not received treatment.[9]

Denoting the consumption of the families with the additional benefit by Y_1 and Y_0 the consumption of families without treatment, it is clear that a family cannot be in both situations simultaneously. To measure the treatment effect, we should look for the difference between results with and without treatment, $Y_1 - Y_0$. Note that this difference remains a random variable. Considering the

[7] It is not unusual the situation in which there is more than one family in a given household. In this paper, we use the two words interchangeably to denote the entity with a common head.

[8] This session is based on Wooldridge (2002, chap. 18) and Lee (2005). For a recent survey on the propensity score matching literature, see Caliendo & Kopeinig (2008).

[9] The literature of impact evaluation is based on the seminal papers of Rubin (1974), Rosenbaum & Rubin (1983), Heckman (1991), Heckman et al. (1997), Imbens & Angrist (1994) and Angrist et al. (1996).

average difference between the families under analysis, which may include a set of covariates as controls (x), we have the average treatment effect:

$$ATE = E(Y_1 - Y_0|x) \tag{1}$$

ATE is the expected effect of treatment on a family selected at random from a population. A more common alternative measure in the literature would be the average treatment effect in the treated (ATT), that is, for those who actually participated in the program ($w = 1$, otherwise, $w = 0$). It is often denoted by:

$$ATT = E(Y_1 - Y_0|w = 1, x) \tag{2}$$

One must bear in mind that those procedures are only valid under randomization and some other assumptions.[10] In this case, a simple statistical test of comparison of averages would be sufficient. However, as in the great majority of the situations in social sciences, a randomized sample is not only difficult to carry out, but very unlikely to be accepted by the candidate recipients or policy makers.

In the present case, programs such as *Bolsa Família* and *Bolsa Cidadão* use some specific eligibility criteria so that there is a selection bias if outcomes between recipients and non-recipients are considered. Moreover, what also usually happens is the phenomenon known as self-selection into treatment. That is, individuals determine, at least partially, if they will receive treatment. Nevertheless, because the criteria used are the same, and every *Bolsa Cidadão* recipient is also a *Bolsa Família* recipient, most of these issues are resolved when a comparison between these two groups is carried out.

However, it is still possible to argue that even in the case of comparable households, some selection bias will emerge in the process of determination of the additional benefit. In order to mitigate this problem, the propensity score methodology is implemented.

3.1 Selection on Observable Variables: The Propensity Score

As mentioned earlier, in the case where participation is not drawn randomly, a simple comparison between families participating and not participating in the program could lead to misleading conclusions, due to, at least, two reasons. First, ex-post differences of the results could simply reflect differences that existed before the program. Second, the effect of the program may be a function of background variables (education of the head of the family, number of children, etc.) that may differ between treatment and control groups. These problems can be mitigated by using the method of matching with propensity score.[11]

To deal with the problem of pairing, Rosenbaum & Rubin (1983) developed a method known as propensity score matching. These authors showed that the matching procedure can be implemented through a single control variable, the propensity score. The propensity score $p(x)$ is defined as the conditional probability of a family receiving the treatment given their observable characteristics x. That is, $p(x) = Prob(w = 1|x)$.

[10] In the case of a randomized experiment ATE and ATT are equal. For further detail, see Wooldridge (2002, chap. 18) and Lee (2005).

[11] See Attanasio et al. (2004) to further details.

Rosenbaum & Rubin (1983) show that in equation 2, x can be replaced by $p(x)$, thus:

$$E(Y_1 - Y_0|w = 1, p(x)) = E(Y_1|w = 1, p(x)) - E(Y_0|w = 0, p(x)) \tag{3}$$

If the treatment and outcomes are independent conditional on pre-treatment variables, these are also independent conditional on the probability of receiving treatment given to observable characteristics, i.e., conditional on propensity score.[12]

$$(Y_0, Y_1 \perp w|p(x)) \tag{4}$$

However, as Rosenbaum (2002) points out, the propensity score methodology solves only two of the three likely sources of bias in the estimation of the ATT, the common support bias and the overt bias (generated by observed factors). A third source of bias, the covert bias (generated by unobserved factors), may be reduced by this procedure, but not completely eliminated. As it will be discussed, there are some reasons to believe that the bias stems basically from observable factors.

3.2 Unobserved Heterogeneity: Covert Selection Bias

When we consider the existence of unobserved factors (u) influencing the probability of being a *Bolsa Cidadão* recipient and we explicitly consider those variables to each family i, the propensity score can now be denoted by:

$$p_i = p(x_i, u_i) = Prob(w_i = 1|x_i, u_i) \tag{5}$$

That implies that two families with exactly the same values for the covariates x can have different probabilities of receiving the treatment. That would be the case if, for example, families were more likely to receive the additional benefit if they knew someone working in the municipal administration. Rosenbaum (2002) showed that the ATT only maintain its causal interpretation if unobserved factors caused the relative likelihood of treatment to differ between treatment and control groups with similar observed characteristics by a quantity within reasonably high bounds.[13] The analysis is performed by expressing the treatment propensity in terms of odds. In the present case, the odds of treatment are given by $\frac{p_i}{1-p_i}$ and inform the relative likelihood that a family will receive the additional benefit. For two families i and j, the ratio of their odds is given by

$$\frac{\frac{p_i}{1-p_i}}{\frac{p_j}{1-p_j}} = \frac{p_i\left(1-p_j\right)}{p_j\left(1-p_j\right)} \tag{6}$$

In the present case, the odds ratio reflects the relative and ex ante likelihood of treatment for an actually treated individual relative to an untreated

[12] Another important assumption is *common support*, that is, for any given x, both treated and control individuals have propensity scores within the $(0,1)$ interval.

[13] Other relevant empirical and methodological contributions for this particular aspect were given by Aakvik (2001), DiPrete & Gangl (2004) and Becker & Caliendo (2007).

individual. If the probability of treatment is assumed to follow a logistic[14] distribution, expressed in terms of its cumulative distribution function

$$p_i = F(\beta x_i + \gamma u_i) = \frac{1}{1 + e^{-(\beta x_i + \gamma u_i)}} \tag{7}$$

where β and γ are vectors of coefficients that capture respectively the sensitivity of the probability of treatment to observed and unobserved factors.

Using equation 7 into equation 6 and rearranging leads to:

$$\frac{e^{\beta x_i + \gamma u_i}}{e^{\beta x_j + \gamma u_j}} \tag{8}$$

For a pair of two matched families i and j that consequently share the same vector of observable covariates, the odds ratio is a quantity independent of x:

$$\frac{\frac{p_i}{1-p_i}}{\frac{p_j}{1-p_j}} = e^{\gamma(u_i - u_j)} \tag{9}$$

The odds ratio is different from one unless the unobservable factors are negligible to determine the probability of treatment ($\gamma = 0$) and/or the unobserved values for both matched individuals are identical ($u_i = u_j$), in which case there is no hidden or covert selection bias. For example, if the odds ratio is greater than one, a treated individual was, ex ante, more likely to receive the treatment relative to an untreated individual even after controlling for the observable characteristics.

We follow the literature and assume that the unobserved factor is a dichotomous variable: $u_i \in \{0, 1\}$ and denote $e^{\gamma} = \Gamma$. Rosenbaum derived the following bounds for the odds ratio:

$$\frac{1}{\Gamma} \leq \frac{\frac{p_i}{1-p_i}}{\frac{p_j}{1-p_j}} \leq \Gamma \tag{10}$$

If $\Gamma = 1$, two matched families (one treated and one untreated) with similar propensity scores have the same probability of receiving the additional benefit and there is no covert bias. If $\Gamma = 2$, even though two matched families share similar observable characteristics, the family with the extra benefit was ex ante 2 times more likely to receive the treatment when compared to a similar family that did not receive the benefit.

If the difference between treated and untreated families is statistically significant, even for low values of Γ, the hypothesis of covert bias affecting the results cannot be rejected. Nevertheless, it must be emphasized that the Rosenbaum bounds represent a worst case scenario.

3.3 Calculating the ATT

There are several alternatives of matching methods to calculate the average treatment on the treated (ATT), established in the program evaluation litera-

[14]That is the usual distribution in the literature. One of the main reasons for its use is that it greatly simplifies the exposition.

ture.[15] We will focus on four methods of calculating the ATT: Nearest Neighbour, Radius (Nearest Neighbour with more than one neighbor), Stratification and Kernel.

The method of pairing the nearest neighbor, as the name suggests, selects the non-treated individuals to be compared to a treated one when they have the propensity score closest to each other. We follow the notation adopted in the impact evaluation literature and define T to be the set of treated units and C the set of control units, and Y^T and Y^C the results of those treated and control, respectively. Denoting $C(i)$ as the set of control individuals matched with the treated individual i with an estimated propensity core p_i. Thus, we have:

$$C(i) = min\|p_i - p_j\|, i \neq j \tag{11}$$

It is worth noting that $C(i)$ is a singleton set unless there are multiple nearest neighbors. The Radius estimator allows all individuals j within a certain radius r to be controls for a treated individual i:

$$C(i) = \left\{p_j \mid \|p_i - p_j\| < r, i \neq j\right\} \tag{12}$$

The ATT estimator for both cases above is given by:

$$ATT^{NN} = ATT^{R} = \frac{1}{N^T}\sum_{i\in T}\left(Y_i^T - \sum_{j\in C(i)} w_{ij}Y_j^C\right), \tag{13}$$

with the corresponding $C(i)$ for each estimator and $w_{ij} = \frac{1}{N_i^C}$ if $j \in C(i), w_{ij} = 0$ otherwise.

The method of stratified matching is performed by dividing the variation in the propensity scores into intervals such that each of treated and control units have on average the same propensity score. Then, in each interval, the difference in average scores between groups of participants and nonparticipants is calculated. The ATT is finally obtained by the weighted average of these differences, with the weights being determined by the distribution of units between the treated blocks. In the stratified matching method, the observations in the blocks that have no treatment or control are discarded. Defining q as the index of the blocks defined in the range of propensity score within each block is computed, we have:

$$ATT_q^S = \frac{\sum_{i\in I(q)} Y_i^T}{N^{T_q}} - \frac{\sum_{j\in I(q)} Y^{T_i}}{N_q^C} \tag{14}$$

where $I(q)$ represents all the units in block q, while N_q^T and N_q^C represent the amounts of treated and control units in block q, respectively.

The Kernel matching estimator assigns weights on each controls decreasing on the distance (in terms of the propensity score) to the treated individual:

$$ATT^K = \frac{1}{N^T}\sum_{i\in T}\left\{Y_i^T - \frac{\sum_{j\in C} Y^{C_j}\, G\left(\frac{p_j - p_i}{h}\right)}{\sum_{k\in C} G\left(\frac{p_k - p_i}{h}\right)}\right\} \tag{15}$$

[15]This session is based on Becker & Ichino (2002).

where $G(\cdot)$ is a kernel function and h is the bandwidth. It can be interpreted as a particular version of the Radius method.

4 Program Participation and effects on Consumption

4.1 Additional Sample Delimitation

In the estimation of the propensity score, we need to define some variables that are likely to explain the participation in the *Bolsa Cidadão* program. However, as the following analysis will show, many relevant variables would be redundant, if we considered the whole sample (all individuals in all households). In order to avoid this problem, all information from the families was grouped, so that all individuals of one family have information that are common and linked to each member of the family. Therefore, only the heads of each family are kept in the data, and although information from the households is maintained, the problem of redundant information is overcome. Additionally, all observations with inconsistent levels of income and consumption were discarded.

4.2 Descriptive Statistics

Table 6 below shows the descriptive statistics for consumption per capita and the variables used in the estimation of the propensity score. The 57,523 observations refer to families in 41 municipalities covered by both programs. The variables of personal attributes such as age, race and sex refer to the head of the family. The first seven variables are continuous while the others are binary, taking 1 when they have the attribute in consideration and 0 otherwise. Since they are dichotomous variables, the average of these variables informs the proportion of the population in question that have the attributes. Still from Table 6, one can see that 11,556 households receive the additional benefit, which represents over 20% of households in the data.[16]

The households with the additional conditional cash transfer have a statistically significant higher level of consumption, even though the average income is not statistically different. However, this 4.78% higher consumption might be affected by observable variables. One of these variables seems to be the amount received from the *Bolsa Família* program in per capita terms. The amount paid for households with the *Bolsa Cidadão* program is significantly smaller than the per capita value received by families without the additional benefit.

Some other relevant conclusions may be taken from Table 6. More than 96% of the household heads are women. Besides, the average consumption per capita level is almost R$ 4 higher than the average income per capita, indicating, in general a certain degree of indebtedness.[17]

Figure 1 depicts the distribution of income and consumption per capita, letting clear the high degree of inequality among the poor and that almost the whole of both distributions are below R$ 100 per month per capita. Another relevant characteristic is the fact the consumption distribution is considerably

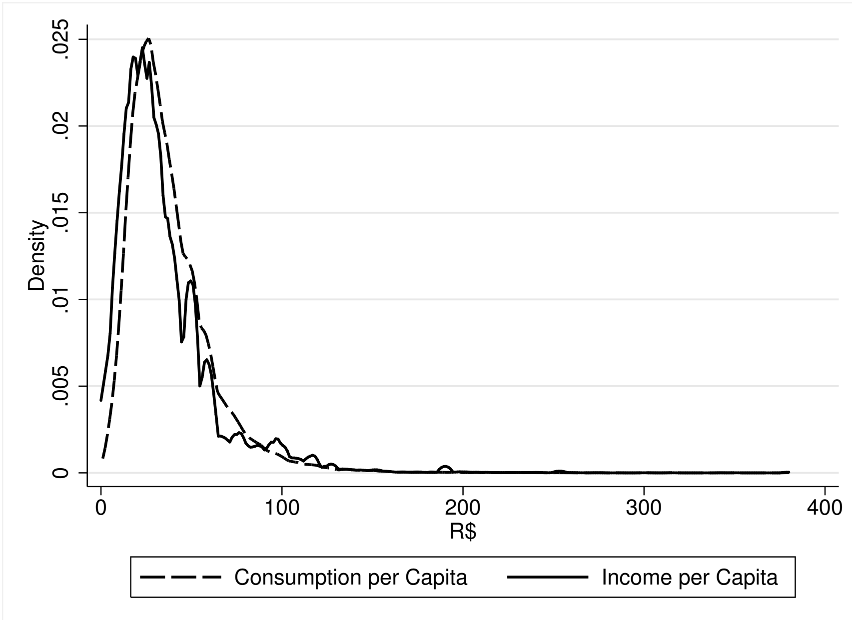
[16]Note that the difference between this number and presented in section 2 is due to the restrictions made in the sample.

[17]It is important to highlight that the income in this analysis does not include the cash transfers.

Table 6: Descriptive Statistics

Variable	*Bolsa Cidadão* and *Bolsa Família* Recipients				*Bolsa Família* only			
	Mean	S. Dev.	Min	Max	Mean	S. Dev.	Min	Max
Consumption per Capita	39.07	23.19	1.43	258	37.25	23.11	1.01	286
Income per Capita	34.68	28.97	0	380	34.69	27.30	0	380
Bolsa Família per capita	21.67	8.84	1.8	76	22.02	9.38	1.64	116
Age	37.22	10.90	17	94	37.48	11.07	16	92
Number of People in HH	4.30	1.78	1	15	4.26	1.77	1	16
Number of Rooms in HH	4.71	1.64	1	16	4.66	1.61	1	19
Male	0.03	0.17	0	1	0.04	0.19	0	1
Non-white	0.77	0.42	0	1	0.74	0.44	0	1
Married	0.73	0.44	0	1	0.72	0.45	0	1
Unemployed	0.31	0.46	0	1	0.34	0.47	0	1
Elementary School	0.15	0.36	0	1	0.15	0.36	0	1
High School	0.07	0.26	0	1	0.08	0.26	0	1
Urban	0.35	0.48	0	1	0.35	0.48	0	1
Brick Household	0.76	0.43	0	1	0.77	0.42	0	1
Appropriate Sewer	0.25	0.43	0	1	0.25	0.44	0	1
Crop Insurance Recipient	0.13	0.34	0	1	0.11	0.31	0	1
Number of Observations	11,556				45,967			

Data Source: Cadunico/MDS.



Data Source: Cadunico/MDS.

Figure 1: Distribution of Consumption and Income per capita

smoother than the income distribution, revealing a greater inconsistence in the declaration of the monthly amount of income.

4.3 Propensity Score Estimation

As discussed above, even with the comparison of two extremely similar groups, it is still possible that there is selection bias. In order to mitigate this problem, the propensity score model is estimated and presented in Table 7. The specification of the model that determines the likelihood of receiving the additional benefit was obtained, as usual, by observing the balancing property for all covariates. The use of a less parsimonious model is justified by the fact that the greater the number of variables included, the better the matching performed, since the higher the number of observable characteristics used, the more similar are the individuals in the treatment and control groups.[18]

In the estimated model, most control variables are statistically significant and have the expected effects, what suggests that the included factors are relevant to determine treatment. It is observed that the number of children in the household increases the likelihood of participation in the *Bolsa Cidadão* program. The fact that the head of household is unemployed, male or white decreases this probability. Married individuals, located in urban areas, in households with greater numbers of rooms are more likely to be eligible for the program. In addition, households made of brick are less likely to be selected, while families who participate in the Crop Insurance program are more likely to receive the *Bolsa Cidadão* benefit.

[18]Interactions between the variables are also included in the specification, but are omitted in the table.

Table 7: Propensity Score Estimation — *Bolsa Cidadão* Recipient

	Coeff.	Std. Error	t-test	p-value
Constant	−1.7292	0.2602	−6.65	0.000
Male	−0.5065	0.1435	−3.53	0.000
Non-white	0.0047	0.0599	0.08	0.938
Age	0.0666	0.0124	5.35	0.000
Age^2	−0.0019	0.0003	−6.50	0.000
Married	0.1452	0.0154	9.41	0.000
Income in the HH per Capita	−0.0052	0.0013	−3.90	0.000
Bolsa Família per capita	−0.0001	0.0010	−0.06	0.951
Unemployed	−0.1174	0.0137	−8.58	0.000
Elementary School	0.0366	0.0241	1.52	0.128
High School	−0.0549	0.0318	−1.73	0.084
Number of People in the HH	0.0021	0.0038	0.57	0.570
Number of Rooms	0.0054	0.0331	0.16	0.869
Urban	0.0253	0.0139	1.83	0.067
Brick Household	−0.1135	0.0723	−1.57	0.116
Appropriate Sewer in the HH	−0.0744	0.0636	−1.17	0.243
Crop Insurance Recipient	−0.0172	0.0278	−0.62	0.535

Data Source: Cadunico/MDS.

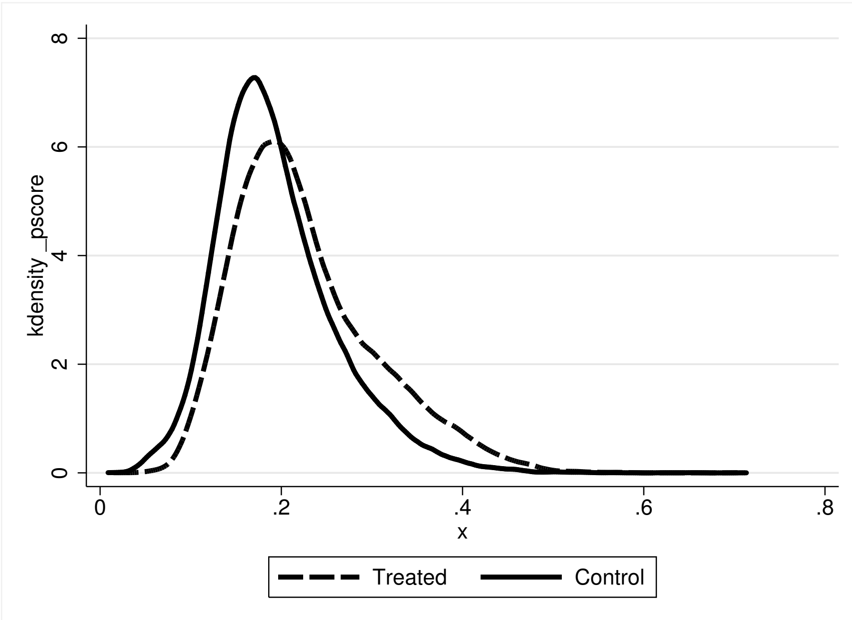
Figure 2 shows the nonparametric distribution of the propensity score comparing control and treatment groups. Interestingly, the distribution for treated and control groups do not differ significantly, as one might expect. This is likely due to the fact that we are only considering *Bolsa Família* recipients, what makes most households in our sample very homogeneous. Yet, we could expect significant differences if the supplementary program had prioritized a specific group of families. This evidence strongly suggests that the choice of the *Bolsa Cidadão* recipients was reasonably random among the families participating in the *Bolsa Família* program.

4.4 Estimation of Impact of a higher value of *Bolsa Família* on Consumption

Table 8 shows the estimates of the impact of *Bolsa Cidadão* benefit on the consumption per capita for the 41 non-contiguous municipalities using the estimated propensity score and the four matching methods described in the previous section: nearest neighbor, radius, stratification and kernel matching, with the nearest neighbor estimates being reported for 1 and 2 neighbours. In general, it is possible to identify a positive and statistically significant effect on consumption, if the family receives the additional cash transfer, which is around R$ 2.00 per month.[19]

The first part of the table displays the results of estimating the average treatment effect on the treated using matching by stratification method. To match the 11,556 families that received the additional benefit were generated 45,966 control families, with an ATT of 2.235.

[19]The estimate of the ATT is performed considering the use of common support for all observations and all standard error estimates are bootstrapped.



Data Source: Cadunico/MDS.

Figure 2: Propensity Score: Treated vs Control

In order to test the robustness of this result, the ATT was estimated by the method of matching of nearest neighbor with one and two neighbors. Like the stratification method estimate, the impact of the additional cash transfer in the estimates based on the nearest neighbor method is positive, significant and around R$ 2.00.[20]

Table 8: ATT Estimate: Nearest Neighbor, Radius, Stratification and Kernel Matching

Matching Method	Number of Treated	Number of Controls	ATT	Standard Error	t-test	Covert Bias Bounds (Γ)
Stratification	11,556	45,966	2.235	0.225	9.95	1.10 – 1.15
Nearest Neighbor (One neighbor)	11,556	45,966	2.194	0.345	6.35	1.15 – 1.20
Nearest Neighbor (Two neighbors)	11,556	45,966	1.966	0.294	6.67	1.03 – 1.04
Radius (caliper=0.0001)	11,352	44,516	2.239	0.248	9.02	1.02 – 1.03
Kernel	11,556	45,958	1.739	0.245	7.09	1.02 – 1.03

Note: The number of treated and controls refers to the effectively matched by the corresponding matching method. Bootstrapped standard errors.
Data Source: Cadunico/MDS.

The last two matching methods are the radius and kernel, generating ATTs of 2.239 and 1.739, respectively. Note that because of the restriction in the size of the radius, the number of treated and controls in the radius method were 11,352 and 44,516, respectively.

[20]The results do not change substantially when other matching methods were used, namely Radius Matching and Kernel Matching.

The increase in consumption varies from 4.67% (kernel) to 6.01% (stratification) when compared with the households that receive only the *Bolsa Família* benefit. Except for the kernel estimate, these figures are marginally higher than the 4.78% observed by the mean comparison, which would corroborate with the fact that poorer households are selected to the additional program. These numbers are also consistent with the fact that the *Bolsa Cidadão* program represents an income increase of 7.12% in the household per capita income.

Nevertheless, the narrow gap between the estimated ATTs and the difference between the treated and control before matching casts some doubt on the assumption that there was a selection to receive the *Bolsa Cidadão* benefit, based on observed characteristics of the families, like the level of income. This is despite the fact that there was considerable bias reduction after matching for all matching methods used, presented in Table A.1 in the appendix. The reduction in the mean absolute standardized bias between the matched and unmatched families varies between 73.4 and 86.2.

In order to consider the importance of the influence of unobserved factors, Table 8 also presents the sensibility of the results to the presence of covert bias, displaying the critical levels of Γ described in section 3.2. The small values indicate that unobserved factors, such as the fact that a family knows someone in the municipal administration, can play an important role in the results. Covert bias is a likely possibility as the critical levels of Γ in which the conclusion of an effect of the additional benefit is as little as 2% in the case of the radius and kernel matching methods and 20% in the nearest neighbor with one control for each treated unit.

Nevertheless, it must be taken into account that such sensitivity analysis represents a worst case scenario. DiPrete & Gangl (2004) emphasize that even in the cases in which the critical levels of Γ are very small, the ATT estimates would be inconsistent only if unobserved factors caused the odds ratio of treatment to differ between treatment and control groups by a small factor and if the effects of those confounding factors on the outcome variable were extremely strong. In the present case, if the confounding factors had a relevant effect on the likelihood of receiving the additional benefit but little influence on consumption levels, the ATT estimates would still be consistent.

5 Conclusion

This paper presents an analysis of the impact of an increase in the *Bolsa Família* program on the consumption of households by using a unique data set in Brazil. This was possible by comparing households that are recipients of both *Bolsa Família* and *Bolsa Cidadão* programs with households that receive only the former.

The methodology of matching based on propensity score is used in order to mitigate the selection bias in the determination of the recipients of the additional benefit. It was observed a statistically significant average increase on household consumption for those receiving the additional cash transfer benefit. This is in line with the percentage increase in income from the additional benefit. The analysis also showed that the additional benefit was concentrated in the poorer households, what helps to reduce the income inequality among the poor.

Nevertheless, a sensitivity analysis pointed out the possibility that unobserved factors could be driving the results. Moreover, as the marginal propensity to consume is assumed to be closer to one when we consider lower quantiles, one might expect a higher increase in the consumption. This could be related to a measurement error in the consumption basket referenced in *Cadastro Único* database, since the information is self-reported. This misreporting could be largely related to the fact that part of the extra resources generates an income effect that boosts the purchase of durable goods, which are generally paid in monthly installments, which people tend not to recognize as consumption.

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Appendix A

Table A.1: Situation in the Labor Market of the population in the database in working age

Matching Method	Mean Bias	| Δ Bias | %
Stratification	0.72	73.4
Nearest Neighbor (1)	0.81	77.3
Nearest Neighbor (2)	0.78	78.0
Radius	0.49	86.2
Kernel	0.54	84.6

Raw Sample Mean Bias: 3.56.
Data Source: Cadunico/MDS.

Table A.2: Values and percentages of the benefits: *Bolsa Cidadão* X *Bolsa Família*

		Bolsa Cidadão							
		0	5	10	15	20	25	Total	%
	0	558664	145	445	270	105	58	559687	0.808
	18	4234	556	237	344	75	12	5458	0.008
	23	1	-	-	-	-	-	1	0
	26	115	77	11	3	1	-	207	0
	36	2670	82	361	123	173	43	3452	0.005
	38	1	-	-	-	-	-	1	0
	41	6	-	6	-	-	1	13	0
	44	29	-	21	4	-	1	55	0
	51	2	-	-	-	-	-	2	0
	54	1279	11	23	153	38	118	1622	0.002
	58	18472	29	3464	640	56	7	22668	0.033
	59	3	-	-	2	-	-	5	0
	61	5	-	-	-	-	-	5	0
	62	7	-	-	3	-	-	10	0
	64	1	-	-	-	-	-	1	0
	66	34	-	-	1	-	-	35	0
	72	2	-	-	1	-	-	3	0
	76	29421	524	1113	4432	732	76	36298	0.052
	77	2	-	-	-	-	-	2	0
	79	1	-	-	1	-	-	2	0
	81	3	-	-	-	1	-	4	0
	84	287	7	2	122	22	2	442	0.001
	91	2	-	-	-	1	-	3	0
	94	25382	18	533	1346	2569	574	30586	0.044
BF	96	1	-	-	-	-	-	1	0
	97	2	-	-	-	-	-	2	0
	99	44	-	-	-	9	1	54	0
	102	155	-	2	-	54	9	220	0
	108	4	-	-	-	-	-	4	0
	112	24943	48	180	518	759	4481	30929	0.045
	114	7	-	-	-	-	1	8	0
	115	4	-	-	-	-	-	4	0
	116	22	-	3	-	1	-	26	0
	117	29	-	-	-	-	6	35	0
	119	1	-	-	-	-	-	1	0
	120	206	-	-	-	-	112	318	0
	127	2	-	-	-	-	-	2	0
	134	3	-	1	1	-	-	5	0
	135	123	-	-	-	-	35	158	0
	142	1	-	-	-	-	-	1	0
	150	41	-	-	-	-	12	53	0
	152	16	-	-	-	-	-	16	0
	155	2	-	-	-	-	-	2	0
	165	7	-	-	-	-	-	7	0
	166	-	-	-	1	-	-	1	0
	188	18	-	-	-	1	-	19	0
	224	14	-	-	-	-	-	14	0
	240	1	-	-	-	-	-	1	0

Note: Information in November — 2007. Data Source: Cadunico/MDS.

Table A.3: Municipalities with *Bolsa Cidadão* recipients and participation in the programs

Municipality	Total Population	*Cadastro Único*	%	*Bolsa Família*	%	*Bolsa Cidadão*	%
Aiuaba	15500	11471	0.74	9877	0.861	677	0.059
Alcantaras	10349	7950	0.768	6522	0.82	1932	0.243
Apuiares	15111	8675	0.574	8063	0.929	523	0.06
Araripe	21474	21755	1.013	14585	0.67	4191	0.193
Arneiroz	7666	5785	0.755	4819	0.833	1110	0.192
Assare	21964	18062	0.822	13960	0.773	1432	0.079
Aurora	25816	19318	0.748	16654	0.862	1532	0.079
Barroquinha	14765	12515	0.848	9915	0.792	4138	0.331
Boa Viagem	52337	41158	0.786	33582	0.816	5074	0.123
Carire	19357	13540	0.699	11981	0.885	557	0.041
Caririacu	29487	23330	0.791	19130	0.82	7716	0.331
Carius	19186	15190	0.792	12756	0.84	1522	0.1
Catarina	18619	8133	0.437	7219	0.888	1846	0.227
Chaval	13526	10513	0.777	8407	0.8	849	0.081
Coreau	22035	16107	0.731	14116	0.876	1648	0.102
Farias Brito	22602	17199	0.761	13211	0.768	1709	0.099
Graca	15194	12316	0.811	10491	0.852	2011	0.163
Granja	54422	37826	0.695	32057	0.847	7740	0.205
Hidrolandia	17506	14570	0.832	12493	0.857	1073	0.074
Iraucuba	21605	18138	0.84	14704	0.811	6254	0.345
Itatira	16976	17596	1.036	12491	0.71	6632	0.377
Jardim	28497	21666	0.76	17814	0.822	972	0.045
Madalena	16738	14200	0.848	9853	0.694	1014	0.071
Massape	34578	26346	0.762	19532	0.741	2613	0.099
Miraima	12578	9462	0.752	7804	0.825	798	0.084
Mombaca	41540	33118	0.797	26784	0.809	1400	0.042
Moraujo	7704	6199	0.805	5266	0.849	1232	0.199
Morrinhos	20821	12978	0.623	11633	0.896	713	0.055
Mucambo	15392	11066	0.719	9033	0.816	902	0.082
Ocara	23077	17608	0.763	15076	0.856	6413	0.364
Parambu	34192	27918	0.816	22163	0.794	5860	0.21
Potengi	9980	6988	0.7	5761	0.824	1536	0.22
Quiterianopolis	19214	16414	0.854	13198	0.804	5283	0.322
Reriutaba	24557	15057	0.613	12556	0.834	1416	0.094
Saboeiro	16877	12642	0.749	10793	0.854	1525	0.121
Salitre	15013	15660	1.043	11244	0.718	4134	0.264
Santana do Acarau	29388	24103	0.82	18456	0.766	2005	0.083
Tarrafas	8448	7305	0.865	6361	0.871	2028	0.278
Tejucuoca	14977	10143	0.677	8745	0.862	649	0.064
Uruoca	12550	9349	0.745	8077	0.864	2001	0.214
Vicosa do Ceará	49306	43076	0.874	32710	0.759	6953	0.161
Total	890926	692445	0.777	559892	0.809	109613	0.158

Note: Information in November — 2007. Data Source: Cadunico/MDS.