The Effects of Conditional Cash Transfer Programmes on Adult Labour Supply: An Empirical Analysis Using a Time-Series-Cross-Section Sample of Brazilian Municipalities*

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Resumo: Neste trabalho, estimamos os efeitos dos programas condicionais de transferência de renda (PCTR) no Brasil sobre a oferta de trabalho de mulheres e homens adultos. Para tanto, utilizamos o painel de municípios que são continuamente cobertos pela Pesquisa Nacional por Amostra de Domicílios (PNAD/IBGE) durante o período entre 2001 e 2005. Os efeitos dos PCTR brasileiros são estimados tanto sobre a taxa de participação, quanto sobre o número médio de horas trabalhadas. Como a PNAD não investiga diretamente a participação das famílias em PCTRs, utilizamos um procedimento indireto, o qual é baseado nos valores típicos dos benefícios dos programas que são transferidos às famílias. Nossos resultados indicam que os efeitos de interesse não são significativos tanto do ponto de vista estatístico, como em termos de magnitude.

Abstract: In this paper, we estimate the effects of the Conditional Cash Transfer (CCT) programmes in Brazil on the labour supply of adult males and females. We employ the panel of municipalities that are continuously investigated by the Pesquisa Nacional por Amostra de Domicílios (PNAD/IBGE) over the years 2001-2005. The effects of the Brazilian CCT programmes are estimated both on the participation rate and the mean number of hours worked. Since PNAD does not ask directly surveyed families about PCTR programme participation, we use an indirect procedure, which is based on the typical values of the programmes' benefits that are transferred to families. Our results indicate that the effects of interest are not significant both on statistical grounds and in terms of magnitude.

JEL: I38, J22, C33.

1 Introduction

In recent years, there has been a widespread diffusion of Conditional Cash Transfers (CCT) programmes in Latin America. As implied by their name, these programmes provide monetary grants to poor families conditional on the fulfilment of a set of requirements, such as keeping children at school and bringing them to regular visits to health clinics. In general, the stated objective of this type of programme is twofold. The first is alleviation of current poverty, a goal that is pursued through the regular payments of benefits to recipient families. The second goal, which is based on the programmes' conditionalities, seeks to foster human capital accumulation of children so as to reduce long-term structural poverty. By now, CCT programmes are seen by many scholars and policy makers as a model of social safety-nets for the developing world.[1]

In trying to accomplish their objectives, CCT programmes may affect beneficiary families in many dimensions. These include the level and patterns of consumption, the health conditions of family members, investments in physical and human capital, and the labour supply of children and adults. In this paper, we focus on the effects of CCT programmes on the supply of labour of adults. Specifically, our objective is to measure CCTs' effects on the participation rate and number of hours worked by male and female adults in Brazil. Without denying that the most relevant effects of CCTs are likely to pertain to their impacts on children, we believe this is still an important issue for at least one reason. There is a general belief that CCT programmes (or transfer programmes more broadly) lead adults to work less, which is an outcome considered socially undesirable. However, this belief needs to confirmed, for the direction of the effect has not been uniquely established neither on theoretical nor on empirical grounds.

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[1]Looking at the experience of the main CCT programmes implemented in Latin America and the Caribbean, Handa and Davis (2006) discuss some of the strengths and weaknesses of this type of programme. See also Rawlings and Rubio (2003, 2005) for an overall assessment of the evaluations results for some of the main CCT programmes that have been implemented in developing countries.

In fact, from a standard, static model of family labour supply, the sign of the effect can either negative or positive (or nil). On the one hand, the additional income of the programmes' transfers allows beneficiary families to afford more of all goods. Hence, assuming leisure is a normal good, the effect of the cash transfers would be to increase leisure, which, by definition, should decrease the supply of labour of the family as a whole. On the other hand, given that the majority of the programmes' conditionalities are linked to children school attendance, child work may be reduced, which could lead the adult members of the family to substitute for their work. In theory thus, the sign of the overall effect of CCT programmes on adult labour supply can be ambiguous.

There are many different empirical strategies that can be used to investigate the effects of CCT programmes on adult labour supply. Ideally, one would like to count on a social experiment to compare the labour supply behaviour of the treatment and control groups. However, this is not available for most countries where CCT programmes have been implemented, including Brazil.[2] Non-experimental methods must then be used. In general, studies that rely on these methods employ individual data to find a comparison group that resembles the treatment group had the latter not received the programme. Our empirical method is also non-experimental, but instead of searching for a single comparison group we exploit the time-series, cross-section variation from a reasonably large sample of Brazilian municipalities to assess the effects of interest. Specifically, based on micro-data from a national, cross-section household survey (*Pequisa Nacional por Amostra de Domicílios - PNAD*), we calculate sample means at the municipal level for our outcome variables of interest (the participation rate and number of hours worked) and for a set of covariates, including a measure we develop for CCT programme participation. To obtain variation over time, we benefit from the fact that PNAD is annually fielded in the same set of municipalities between census years (only households are randomly sampled across years). Our sample period is 2001-2005.

To the best of our knowledge, there is no study that uses aggregate data to assess the effects of CCT programmes on labour supply. However, there are some that employ individual/family level data. Parker and Skoufias (2000) use experimental micro-data from PROGRESA to estimate the effect of the programme on the participation rate of male and female adults at different points in time for distinct age groups, categories of workers, and definitions of the eligibility criteria. Point estimates were mostly positive for males and negative for females. However, except for some age groups and points in time, most estimates were not significant on statistical grounds. They then conclude that there is no evidence that PROGRESA affects the labour force participation of adults. Ferro and Nicollela (2007) use micro-data from PNAD 2003, which contained two specific questions on CCT programme participation: one for whether families were signed-up for any of the existing programmes at the time of the survey, and another for whether they were already receiving the programmes' transfers. The utilise these two pieces of information to create a treatment group (those receiving the benefits) and a control group (those enrolled but still not receiving the benefits). The authors estimate the effects of the Brazilian CCT programmes on both the participation rate and number of hours worked by male and female adults in urban and rural areas.[3] Their estimates of the programmes' effect on the participation rate are small in magnitude and statistically nil for both males and females in urban and rural areas. As for the estimates on hours worked, the results show a negative effect for males in urban and rural areas (but only statistically significant for the former area), a positive impact for urban women, and a negative effect for females in rural areas.

This paper is organised as follows. In the next section we provide a description of the Federal CCT programmes that have been implemented in Brazil in the last decade. The third section is dedicated to describe the data we use, including the procedure we adopt to identify CCT beneficiaries. In section four, we briefly discuss how CCT programmes may affect the labour supply of adults. Since there are no aggregate models that connect the effects of CTT programmes on labour supply, we base our discussion on standard labour supply theory at the family level. Section five presents the empirical methodology, which is based on different linear regression models that are typically used in the time-series cross-section literature. Results are presented in section six and are obtained separately by gender for two distinct samples: one that includes all individuals, and another that only contains those individuals whose family per capita income is below the median family per capita income of the municipalities they live in. In the last section we present the main conclusions.

[2] One important exception is the case of PROGRESA in Mexico, where some communities were initially randomly assigned to participate in the programme.

[3] For the second outcome variable, they employ a Heckman two-step procedure.

2 Programmes' Description[4]

Before October 2003, there existed five Federal CCT programmes in Brazil. The oldest was the *Programa de Erradicação do Trabalho Infantil (PETI)*, which was launched in 1996, and whose aim was to eradicate child labour. It was targeted to families with children aged 7 to 15 years who were working (or at risk to work) in activities considered to be harmful for their health. The value of the programme's benefit was R$25 (US$ 37 PPP) per child in rural areas and R$40 (US$ 59 PPP) per child in urban areas. The programme also provided funds to participant municipalities to allow the extension of the school day. The programme's conditionalities required that children under 16 years of age did not work and maintained at least 75% school attendance.

Three programmes were created in 2001. The Federal *Bolsa Escola* programme had as its target population those families with children aged 6 to 15 years and whose per capita income was less than R$90 (US$97 PPP). Its transfer was R$15 (US$16) per child, up to a maximum of three children, that is, with an upper limit of R$45. The programme's conditionality stipulated that participant children had to attend school at least 85% of the school year. The *Bolsa Alimentação* programme had as its goal the reduction of infant mortality in families whose per capita income was below half the value of the prevailing minimum wage. The transfer was R$15 (US$16 PPP) per child under 6 years old, or pregnant woman, cumulative up to R$45. The conditionalities involved immunisation of young children and regular visits to health centers for pregnant and breast-feeding women. The last programme launched in 2001 was the so-called *Auxílio-Gás*. Targeted to families whose per capita income was lower than R$90 (US$97 PPP), it provided R$7.50 (US$8 PPP) as a subsidy to buy cooking gas. *Auxílio-Gás* only required that beneficiary families were registered in the so-called Federal government's *Cadastro Único* (Unified Register).

In the beginning of 2003, the *Cartão Alimentação* programme was created for families with per capita income below half the minimum wage. It transferred R$50 (US$54) to beneficiary families with the aim to reduce hunger to very low levels. The programme's grant had to be spent on food only.

In October 2003, the Federal government launched the *Bolsa Família* programme. It unified all previous CCT programmes, which were run by different agencies, had their separate information systems, and their own financing. Its target population consists of two groups of families. Families in extreme poverty (per capita income below R$50 (US$42 PPP)) receive a fixed transfer of R$50. If there are children under 15 years old or pregnant women, these families also get R$15 (US$13 PPP) per child or pregnant woman, up to a maximum of R$45. The maximum amount is therefore R$95. The second group consists of families in moderate poverty (per capita income between R$50 (US$42 PPP) and R$100 (US$85 PPP)). Families in this group only receive the benefits if there are children under 15 years of age or pregnant women in the household. The transfer is the same as the variable part of the previous group, i.e. R$15 per child or pregnant woman, also cumulative up to R$45. For this group, the maximum amount is R$45. In terms of conditionalities, the programme requires 85% school attendance for school-age children, immunisation of children under 6 years old, and regular medical check-ups for pregnant and breast-feeding women.

3 Data

All data we use in the empirical analysis come from the *Pesquisa Nacional por Amostra de Domicílios - PNAD* (National Household Survey). PNAD is fielded on a yearly basis (usually in October) and gathers information on demographic and socioeconomic characteristics of every household member. We use data for the period 2001 to 2005.[5]

PNAD is a cross-section survey, so we cannot follow households/individuals over time. However, its sampling scheme allows the construction of a time-series of cross-sections of municipalities in Brazil. This is because the municipalities that enter the sample are selected at the beginning of every decade and, though sampled households change across years, the same set of municipalities is kept constant within that decade.[6] We take advantage of this feature of the survey to construct our panel of municipalities.[7]

[4] This section is based on Soares et al. (2007) and Soares et al. (2008).

[5] Up to 2004 the rural area of the North region of the country was not covered by PNAD. For this reason we excluded all observations of the rural area of the North region for the years 2004 and 2005.

[6] The sample of municipalities is chosen so as to be representative for whole country. See Silva et al. (2002) for a description of PNADs' sample design.

[7] It should be pointed out that the names of the municipalities are not available in PNAD's data sets. This implies that we cannot

For the current decade, PNAD's sample contains 817 municipalities that can be partitioned in three groups: 139 are situated in metropolitan areas, 134 are not in metropolitan areas but have large populations, and 544 are smaller municipalities. Because the number of individual observations for some municipalities were small, we decided to join municipalities with less than 100 observations in one of these groups to a municipality that belonged to the same group in the same state of the country. Altogether there were 11 municipalities in this situation, so we work with 806 municipalities that are followed over five years (total of 4030 time-series cross-section observations)[8]. Table 1 displays the average, the minimum and the maximum number of individual observations across this set of municipalities over the sample period.

Table 1: Average, Minimum and Maximum Number of Individual Observations in PNAD's Municipalities Across the Years

Year	Average	Minimum	Maximum
2001	458	107	11221
2002	466	106	12050
2003	465	104	11782
2004	470	103	11520
2005	483	103	12338

All variables that we use in the regression analysis are mean sample values at the municipal level. This implies that our variables are subject to sampling error, a fact that potentially creates measurement error problems. We return to this issue in section 5.

The PNADs' data sets contain sampling weights for individual observations. We use these weights to compute descriptive statistics for the whole country. We also use these weights to compute the population size in each municipality for each year of our data. The total population of each municipality across the years is used as a fixed weight in all regressions we run.

Before presenting descriptive statistics of the variables used in the regression analysis, there is one important issue related to the way we identify individuals that receive CCT programmes in PNAD. We discuss it in the following subsection.

3.1 Identifying Beneficiaries of CCT Programmes

In the main questionnaire of PNAD, there are no specific questions that explicitly ask whether interviewed households receive CCT programmes. In the lack of such direct information, we therefore created a procedure that tries to indirectly identify the beneficiaries of these programmes across the years.

PNAD's main questionnaire contains a set of questions in which the values of the different income sources a household may have are recorded. One of these questions refers to the value of household income that is obtained from both financial assets (e.g. interests and stock market shares) and transfers from social programmes. Note that income from both sources are reported together. However, one should expect that those households that derive income from financial assets tend not to receive benefits from social programmes. Based on this hypothesis, we use the information provided in this specific question to identify CCT beneficiaries. Specifically, our procedure makes use of the typical values of the benefits of CCT programmes to identify households that are (potentially) beneficiaries of these programmes. Table 2 presents the values typically transferred by each CCT programme.[9] Since a household may receive the benefits from more than one of these programmes, our procedure also uses the combination of these values to identify the beneficiary households. All values that were not equal to the typical values and their combinations were treated as income from financial assets or from non-CCT programmes.

In order to validate our procedure, we take advantage of the fact that the 2004 version of PNAD included a special questionnaire that directly asked households whether or not they were recipients of the Federal CCT programmes. Using the information provided by this special questionnaire as a reference, we check if our procedure is consistent. Specifically, we calculate the proportion of recipients and non-recipients individuals of CCT programmes according to the special questionnaire and to our procedure. The results are presented in Table 3.

match other municipal data sets with PNAD's.

[8] Although we have aggregated some municipalities, we keep using the term *municipality* to refer to our unit of analysis.

[9] It should be noted that in practice we use the values of R$7 or R$8 to capture the *Auxílio-Gás* programme. This is due to the fact that monetary values with decimal digits are not captured by PNAD.

Table 2: Typical Values of Benefits Transferred by CCT Programmes

Programme	Benefit Value (R$)
PETI (per child)	
Rural	25
Urban	40
Bolsa Escola	15
	30
	45
Bolsa Alimentação	15
	30
	45
Auxílio-Gás	7.50
Cartão Alimentação	50
Bolsa Família	15
	30
	45
	50
	65
	80
	95

Source: Barros et al. (2007, Table 6).

There are four main results that can be extracted from Table 3. Firstly, around 96% (18,4+77,7) of individuals were identically classified by both criteria. Secondly, around 8% (1,7/(1,7+18,4)) of those individuals identified as recipients by the special questionnaire were not classified as such by our procedure. In other words, approximately 92% of recipients were correctly identified by our proposed procedure. Thirdly, around 3% (2,2/(2,2+77,7)) of those classified as beneficiaries by our procedure were not identified by the special questionnaire. Finally, Table 3 also reveals that programme participation is only slightly overestimated by our procedure. Indeed, while our procedure classifies 20,6% (18,4+2,2) of the population as beneficiaries, this proportion is 20,1% (18,4+1,7) according to the special questionnaire.

Table 3: Proportion of CCT Beneficiaries: Comparison between the Special Questionnaire and the Procedure of Typical Values - (%)

		Special Questionnaire	
		Recipient	Non-recipient
Typical Values	Recipient	18.4	2.2
	Non-recipient	1.7	77.7

Source: Based on microdata from PNAD 2004.

Figures 1 and 2 present complementary evidence on the accuracy of our procedure. Still based on PNAD 2004, Figure 1 presents the proportion of individuals in each percentile of the family per capita income distribution that are recipients of CCT programmes. One of the curves in this Figure is based on our procedure, while the other is calculated from the information of the special questionnaire.[10] Apart from revealing that the Brazilian CCT programmes were reasonably well targeted to the poor, Figure 1 evinces that our procedure seems to consistently classify the recipients of CCT programmes along almost the entire income distribution. As it may be expected, our procedure tends to slightly overestimate programmes' participation for richer individuals.

As a final validation test of our procedure, we exploit two facts that are related to the historical evolution of CCT programmes in Brazil. The first is that all CCT programmes but one (namely *PETI*) started operating after 2001 (see Table 2). Hence, if our procedure is correct we should expect to detect fewer CCT individuals before that year. The second fact is that the coverage of CCT programmes progressively increased since 2001, so our procedure should be capable to detect this movement as well. Figure 2, which is solely based on our procedure, presents the evolution of the percentage of individuals along the family per capita income distribution for a set of years since 1999.[11,12] As it can be seen from this Figure, the two historical facts previously mentioned seem to be reasonably well captured by our proposed method: (1) the line corresponding to 1999 is almost flat; and (2) the lines corresponding to the years after 1999 are basically overlapped.

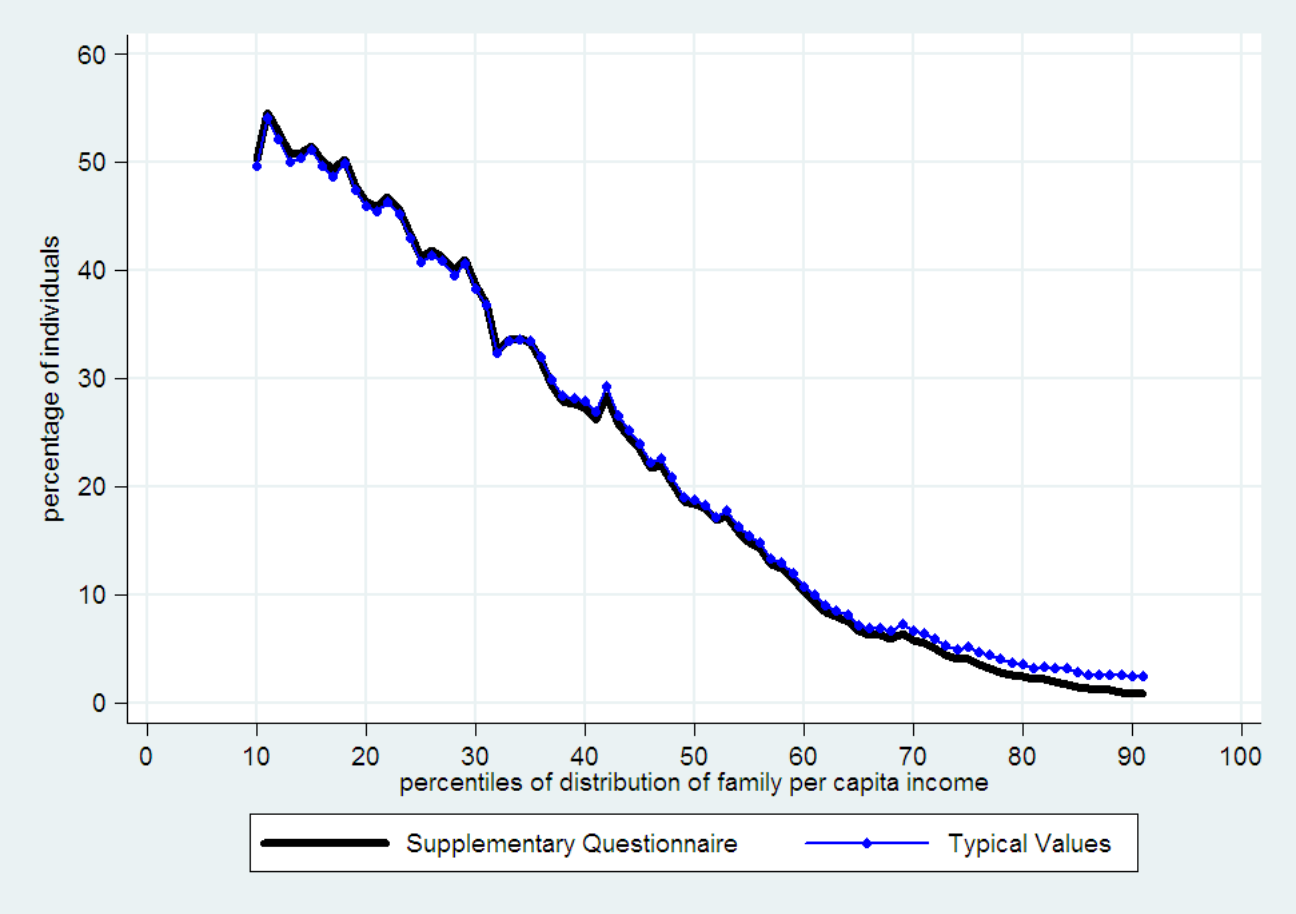
Overall, we believe that the evidence presented in this subsection indicates that our proposed procedure is sufficiently accurate to measure CTT programme participation over time. Thus, in our regression analysis, the variable that we use to measure programme participation is based on this procedure.

[10] In order to smooth these curves, they are depicted as a moving average of ten percentiles. For example, the point corresponding to the 10^{th} percentile represent the average of the 1^{st} to the 10^{th} percentiles.

[11] The PNAD questionnaire of 1999 is the same as that used in the following years.

[12] As in Figure 1, the lines depicted in Figure 2 are also moving averages of ten percentiles.

Figure 1: Percentage of CCT Beneficiaries across Percentiles of the Per Capita Income Distribution: Special Questionnaire and Method of Typical Values



3.2 Descriptive Statistics

As the labour supply effects of CCT programmes may be different for males and females, our analysis is implemented separately by gender group. In addition, since the effects of interest may also vary across the different parts of the income distribution, results are obtained separately for the overall samples of the sexes and for the samples of males and females whose family per capita income is below the median family per capita income of each municipality in our data (henceforth called below-median samples).[13]

The sample mean and standard deviation of the variables used in our regression analysis are presented in Table 4. Columns (2) and (3) display these statistics for the overall samples of females and males respectively, while columns (4) and (5) contain the estimates respectively for the below-median samples of females and males. Statistics are presented for all years combined (2001-2005). Almost all estimates are calculated for individuals of each gender group above the age of 15 years. The exceptions are: (1) the proportion of children under 14 years old, for which there is no distinction between the sexes; (2) the proportion of beneficiaries of CCT programmes, which includes individuals of all ages and genders; and (3) the unemployment rate, which is calculated for individuals older than 15 years of both sexes together.

The first two rows of Table 4 display the estimates of the two response variables used in the regression analysis: the labour market participation rate (Row (1)) and the mean number of hours worked during the reference week of the survey (Row (2)).[14] On average, women have lower participation rates and work fewer hours than men. This is observed for both the overall and the below-median samples. Also noticeable is that the participation rate and hours worked of poorer women tend to be smaller than those of the overall female sample. Interestingly, this

[13] The reason for establishing the threshold at the median is that the sample size for some municipalities is not very large.

[14] According to the concepts used in PNAD, an individual is considered employed if he/she works at least one hour in the reference week of the survey; an individual is considered unemployed if he/she did not work during the reference week but searched for a job in that week. In the calculation of the mean number of hours worked we included all jobs an individual may have and incorporated all individuals with zero hours.

Figure 2: Percentage of CCT Beneficiaries across Percentiles of the Per Capita Income Distribution: Method of Typical Values - Selected Years

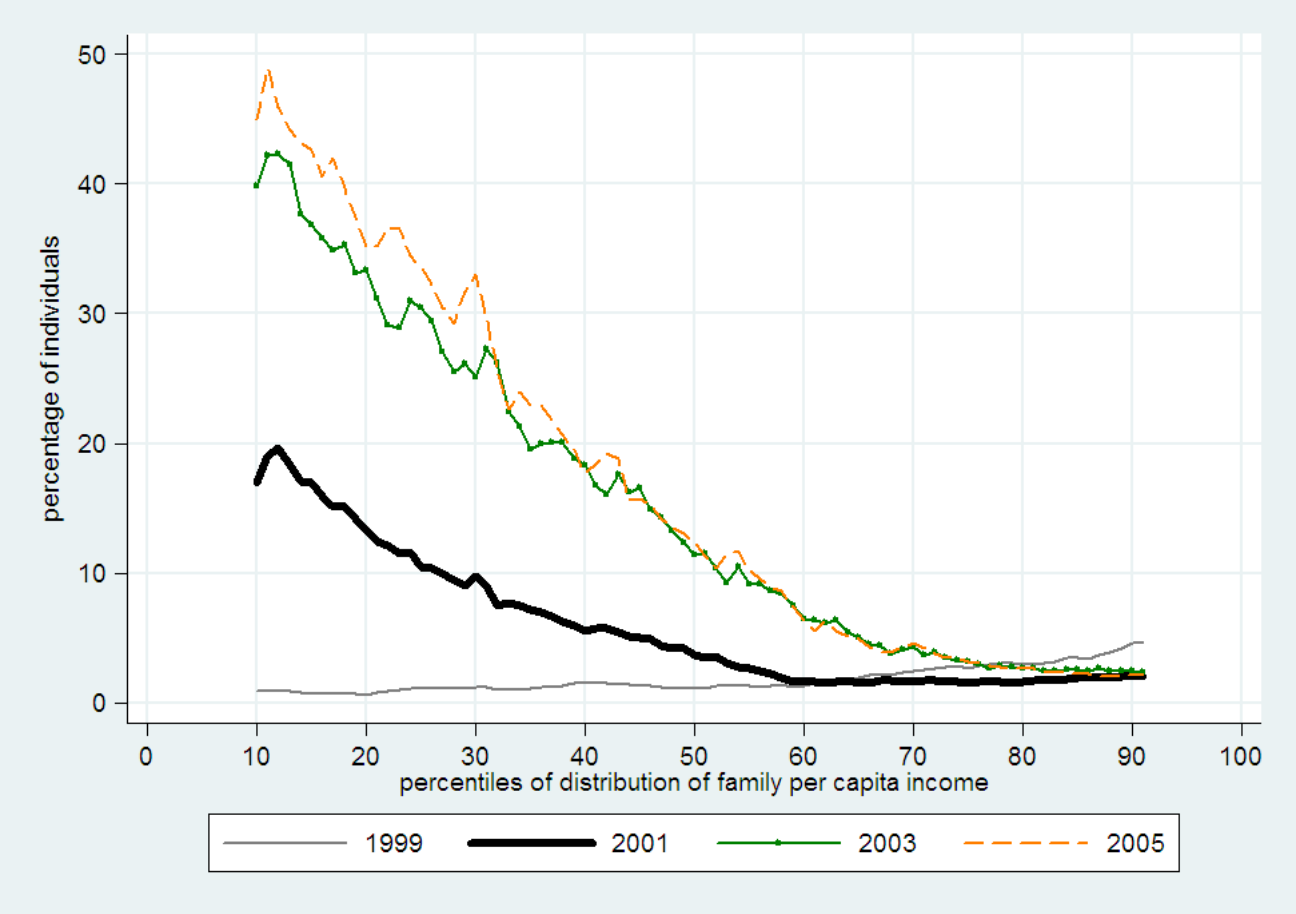


Table 4: Descriptive Statistics: Mean of Variables for All Years (2001-2005)

Variables	Overall Sample		Below-Median Sample	
	Females	Males	Females	Males
	(2)	(3)	(4)	(5)
1. Participation Rate	55.8	81.0	52.6	80.7
	(9.1)	(6.0)	(11.8)	(7.6)
2. Hours Worked	17.7	33.9	14.5	31.9
	(3.7)	(4.4)	(4.3)	(5.4)
3. Proportion of Beneficiaries	13.6	13.6	19.4	19.4
	(16.0)	(16.0)	(22.1)	(22.1)
4. Labour Earnings	194.0	464.3	31.8	85.3
	(123.3)	(253.5)	(20.1)	(39.9)
5. Non-Labour Earnings	91.2	102.4	14.4	12.4
	(56.7)	(74.1)	(8.6)	(9.5)
6. Unemployment Rate	9.5	9.5	15.1	15.1
	(5.4)	(5.4)	(8.9)	(8.9)
7. Proportion of Children Under 14	27.5	27.5	36.4	36.4
	(5.2)	(5.2)	(6.5)	(6.5)
8. Age	38.7	37.4	35.5	35.0
	(2.7)	(2.3)	(3.0)	(2.6)
9. Schooling	6.7	6.5	5.4	5.1
	(1.6)	(1.9)	(1.3)	(1.5)
10. Proportion of Married	52.0	56.0	53.2	59.0
	(7.3)	(5.7)	(9.3)	(7.7)
11. Proportion of Whites	54.0	51.8	45.9	44.3
	(24.1)	(24.3)	(24.2)	(24.2)
12. Proportion of Urban Population	85.3	83.7	82.1	80.5
	(21.3)	(22.8)	(24.5)	(25.9)
13. Proportion in Adm. Occupations	11.6	6.2	6.3	4.2
	(6.6)	(4.0)	(6.1)	(3.9)
14. Proportion in Service Occupations	31.0	11.9	44.5	14.1
	(10.9)	(5.8)	(18.1)	(9.1)
15. Proportion in Comm. Occupations	12.1	9.1	11.4	8.9
	(5.8)	(4.5)	(8.0)	(6.0)
16. Proportion in Other Occupations	45.2	72.7	37.8	72.8
	(16.0)	(11.0)	(23.6)	(14.8)

Notes: Based on microdata from PNAD. The below-median samples (columns (4) and (5)) refer to individuals whose family per capita income is below the median family per capita income of their respective municipalities. All variables are mean sample values weighted by the sampling weights provided by PNAD. Standard-deviations in parentheses. Rows (4) and (5) are measured in R$ of September 2005 (deflator: Índice de Preços ao Consumidor Amplo (IPCA/IBGE) - Consumer Price Index).

is only observed for the number of hours worked in the case of males.

Row (3) displays the estimates for our variable of interest: the proportion of individuals that received benefits of CCT programmes. These estimates are based on the procedure described in subsection 3.1. As it can be seen, on average, around 14% of the population in all years of our sample were beneficiaries of CCT programmes. This figure increases to around 19% of the population that live in families whose per capita income falls below the median family per capita income of their respective municipalities.

Rows (4) and (5) shows the estimates of mean labour and non-labour income respectively.[15] Labour earnings of women is substantially lower, on average, than that of men (ratio of around 0.43 for the overall sample, and approximately 0.38 for the below-median sample). Interestingly, this gap is not so high in terms of non-labour income. In fact, women in the below-median sample seem to get slightly more than men in this part of the distribution.

Row (6) shows that the unemployment rate of females is substantially higher than that of males for both samples we use. Also noticeable is that the incidence of unemployment is much higher for poorer males and females.

Rows (7) shows that children under 14 years old represent around 28% of the overall population and approximately 36% of population below the median per capita income. Rows (8) and (9) show that women are slightly older and more educated than men. This is observed for both types of samples we are working with. Row (10) indicates that a lower proportion of women is married as compared to men. This difference is due to the larger size of the female population. As shown in Row (11), the proportion of white females is higher than that of males for the overall population, but this difference is smaller for those below median per capita income. Row (12) shows that the proportion of women living in urban areas is higher than that of men for both types of samples we are considering.

Rows (13) to (16) present the occupational composition for females and males. As it can be seen, the proportion of females in the first three categories (specially in service occupations) is higher than that of males.[16]

4 Some Theoretical Considerations

We are interested in the effects of CCT programmes on the labour supply of adults. Though our estimation of these effects is based on aggregate data, labour supply models at the individual/family level can provide useful insights about our effects of interest.[17] In what follows, we use the reasoning of simple, static models of labour supply at the micro level.

In a standard model of individual labour supply, the effect of programmes's transfers constitute a pure income effect: the extra income from programmes's grants allows individuals to afford more of all goods. According to theory, the income effect should increase the demand for all normal goods, including both consumption and leisure (assuming the latter is a normal good). Hence, with adults allocating their time only between work and leisure, the standard individual model predicts that the effect of CCT programmes is unambiguously negative on the labour supply of adults.

However, given that CCT programmes are targeted to household units and impose conditionalities that restrict the time use of (some of) its members, a labour supply model at the family level seems more appropriate than the individual model to enhance the understanding of our effects of interest. Indeed, in family models, the decisions on the supply of labour of each household member take into account the restrictions on and the inter-dependencies between the time allocation of all household members.

Because programme grants are conditioned on children's school attendance, the family model would predict that the shadow price (or relative value) of school rises, whereas the relative value of all other activities declines (say, work and leisure). This should lead to an increase in time allocated to school and a decrease in time devoted

[15] The measure of non-labour income does not include the value of transfers of CCT programmes. It includes the values of all other types of transfers available in the survey questionnaire such as pensions, rents, private transfers, capital income and benefits received from non-CCT programmes. These last two components correspond to all non-typical values (and their combinations) of our procedure to identify beneficiaries of CCT programmes (see subsection 3.1).

[16] Due to a change in the occupational codes used in PNAD from 2002 on, we were only able to construct four different occupational categories that seemed compatible over time: administrative, service, commercial, and others. Because this last category includes the manufacturing industry, most males fall in that category.

[17] The extensive theoretical literature on labour supply is fairly well developed for both the individual and family units of analysis. However, the literature on more aggregate levels (e.g. municipalities, states, or countries) is scarce. See Killingsworth (1983) for a survey of first-generation models of labour supply, and Blundell and Macurdy (1999) for a review of more recent models.

to all other activities together. In principle, it is unclear what the new composition of time dedicated these other activities will be (Ravallion and Wodon, 2000). For instance, it is possible that there is no change in child labour, so the increase in schooling time comes at the expense of a reduction in children's leisure. However, if there is a decline in the time children spend working, then there will be less available labour within the household.[18] In that case, the relative price of labour inside the household tends to rise, which should lead to an increase in the labour supply of adults. Thus, given that the income effect operates in the other direction, the total effect of CCT programmes on adult labour supply becomes ambiguous.[19]

A potentially important aspect of CCT programmes is that they may engender general equilibrium effects. Indeed, if the (local) scale of the programmes is relatively large, one should consider the appearance of feedback responses from the programmes onto the (local) economy (labour market). For instance, if total programmes' transfers in a municipality are large relatively to the size of the local economy, one should expect to see a non-negligible increase in the demand for certain types of goods and services consumed in that community. In that case, it is likely that the demand for labour rises, which should lead to changes in wage rates and, as a result, in changes in labour supply. Hence, the implication is that part of the impacts of CCT programmes on the supply of labour may be due to general equilibrium effects brought about by the inter-relation between the programmes themselves and the economy. Clearly, this type of effect tends be more relevant in smaller communities. Figure 3, which displays the histogram of the proportion of CCT beneficiaries across our sample of municipalities for the years 2001-2005, provides some evidence that the size of CCT programmes is significant for a large set of municipalities. Indeed, around 55% (37%) of the municipalities in the sample have at least 10% (20%) of their respective populations as CCT beneficiaries.

5 Methodology

We use various linear regression models to investigate the effect of CCT programmes on adult labour supply. We use a time series of cross-sections of 806 Brazilian municipalities that are followed over five years. This panel of municipalities is constructed from microdata of the 2001-2005 versions of PNAD (see section 3).

The effect of interest is assessed on two different variables: the participation rate and number of hours worked. The response variables and the covariates are described in section 3. Results are obtained separately by gender group and for two types of samples: one in which all individuals of each sex are used to construct the sample means (overall sample), and another in which the sample means of the sexes are calculated only for individuals whose family per capita income is below the median family per capita income of their respective municipalities (below-median sample). It is important to point out that the use of sample means may create measurement error problems, an issue that is address through the application of instrumental variables methods.[20]

Consider the following equation for municipality $j = 1, ..., J$ at time period $t = 1, ..., T$:

$$y_{jt} = \alpha + p_{jt}\gamma + x'_{1jt}\beta_1 + x'_{2j}\beta_2 + \eta_j + u_{jt}, \tag{1}$$

where y represents the response variable, p measures the proportion of individuals who are CCT beneficiaries, (x_1, x_2) are vectors of time-variant and time-invariant control variables respectively, η denotes unobserved municipality-specific effects, and u is a mean zero disturbance term that is assumed to be uncorrelated across municipalities and time periods but whose variance may be clustered at the municipal level. The parameter α is an intercept, γ is our parameter of interest, and (β_1, β_2) are conformable vectors of parameters respectively associated with the control variables in (x_1, x_2).

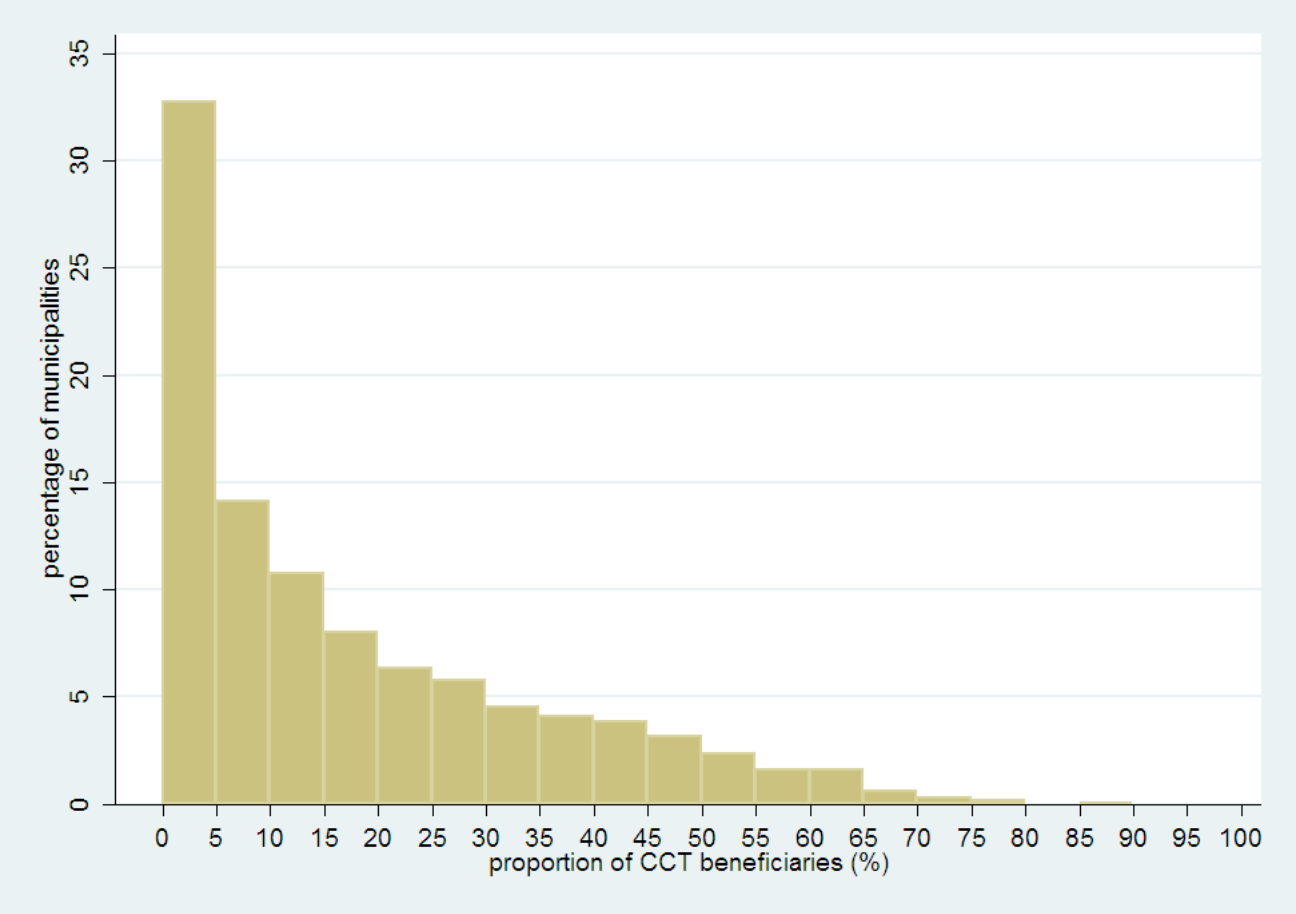
In total we estimate five different models. The first is pooled OLS. The second is the random effects model, which differs from pooled OLS in that it explicitly recognises the presence of municipality-specific effects, but

[18] Assuming that education and leisure are normal goods, the pure income effect from programmes' grants would produce a reduction in child work as well.

[19] It should be pointed out that CCT eligibility criteria could also affect labour supply decisions within the household. Indeed, for CCT programmes that include periodic checks on family income, it is possible that (some) adults choose to work less (or not to work at all) so as to meet the income eligibility criterion of programmes. Another point to be raised is that compliance with the programmes' conditionalities may also affect the allocation of time within the family. For instance, complying with periodic clinic visits and school attendance of children may decrease the labour supply of some family members, specially women.

[20] Another method to tackle error-in-variables problems in the context of time series of cross-sections has been proposed by Deaton (1985).

Figure 3: Histogram of the Proportion of CCT Beneficiaries at the Municipal Level



assumes that they are uncorrelated with all covariates. This last assumption is relaxed by the fixed effect model, which is our third model.[21] This model can be estimated through various methods, the most common of them being the within-groups transformation. Applied to equation (1), this transformation produces:

$$\tilde{y}_{jt} = \tilde{p}_{jt}\gamma + \tilde{x}'_{1jt}\beta_1 + \tilde{u}_{jt}, \tag{2}$$

where the tilde notation denotes: $\tilde{\omega}_{jt} = \omega_{jt} - \overline{\omega}_j$, with $\overline{\omega}_j = T^{-1}\sum_{t=1}^{T}\omega_{jt}$. Notice that all time-invariant elements of equation (1) are swept out by the within-groups transformation, including the municipality-specific effects, η_j. In a small-T setting as ours, the fixed effects estimator of γ and β_1 is consistent as long as there is strict exogeneity.[22]

Another common method used in the panel data literature is the first-differences transformation. Denoting $\Delta\omega_{jt} = \omega_{jt} - \omega_{jt-1}$, equation (1) can then be expressed in first-differences as:

$$\Delta y_{jt} = \Delta p_{jt}\gamma + \Delta x_{1jt}\beta_1 + \Delta u_{jt}. \tag{3}$$

Note that because of the first difference transformation we loose one time period, so now $t = 2, ..., T$. Note too that the first-difference transformation also sweeps out all time-invariant elements of equation (1). Our fourth and fifth models are based on equation (3). The fourth model simply estimates that equation under the assumption that there is strict exogeneity (see footnote 22). The fifth model relaxes strict exogeneity, allowing for the presence of correlation between the error term and the covariates.[23] Within our context, this type of correlation (endogeneity) may arise from two basic sources. The first has already been mentioned: it has to do with the error-in-variables

[21] We report the usual Hausman test to assess the appropriateness of the random effects specification.

[22] That is: $E[u_{js} \mid Z_{jt}] = 0$ for all j, and for all s and t, where $Z_{jt} = (p_{jt}, x_{1jt}, x_{2j})$.

[23] More formally, it assumes that for all j:

$$E[u_{js} \mid Z_{jt}] \begin{cases} = 0 & \text{if } s > t \\ \neq 0 & \text{if } s \leq t \end{cases}. \tag{4}$$

where $Z_{jt} = (p_{jt}, x_{1jt}, x_{2j})$. Note that the assumption allows for contemporaneous correlation between the error term and the covariates.

problem. The second is not related to measurement issues, but to more substantial (economic) factors. For instance, if there are relevant omitted variables in equation (1), it is likely that the error term will be correlated with the included covariates.

A typical approach to deal with the presence of endogeneity is the use of instrumental variables. The main requirements for instruments to be valid are that they are correlated with the endogenous covariates and at the same time orthogonal to the error term in the equation. Hence, given our assumptions, valid instruments for $(\Delta p_{jt}, \Delta x_{1jt})$ are $(p_{j,t-2}, ..., p_{j1}; x_{1j,t-2}, ..., x_{1j1})$. Note that the use of lagged instruments at time period $t-2$ implies that the fifth model is estimated for $t = 3, ..., T$. Since $T = 5$, our model is over-identified, so we can apply the Sargan/Hansen test of over-identifying restrictions. The estimation method of the fifth model is the so-called two-step GMM, as proposed by Arellano and Bond (1991).[24]

All models we estimate include year dummies. The standard-errors of the models' coefficients are estimated through the usual sandwich-type robust/clustered (at the municipal level) method. Regressions are weighted by the municipal population summed over the years that are used in the corresponding models. F-tests for the joint significance of the models' coefficients are reported in the tables containing the regression estimates.

6 Results

We first present results for the participation rate and then for hours worked. For each sex, overall sample results are followed by below-median sample results.

6.1 Participation Rate

6.1.1 Females

Regression results for the participation rate of all females are presented in Table 5. The coefficient of interest is the one corresponding to the variable proportion of beneficiaries. As this Table shows, all point estimates of this coefficient are positive, though only for the OLS and the random effects we cannot reject the hypothesis that they are different from zero on statistical grounds. The Hausman test largely rejects the hypothesis that the random-effects specification is adequate. Indeed, as the following Tables will show, this hypothesis is strongly rejected by the Hausman test for both sexes, samples, and response variables we use. The Hansen test of over-identifying restrictions does not reject the null for the validity of the instruments used in the GMM model. This will also be observed in most of the following Tables.

To assess the magnitude of the effect of interest we can calculate its elasticity at the mean values of $(y,p) = (0.558,0.136)$. Taking the point estimates at face value, their average equals approximately 0.04, which gives an elasticity of around 0.01. This implies that the effect of a 10% increase in the proportion of CCT beneficiaries would rise the female participation rate in 0.1%, which is a small impact. Hence, we may conclude that the effect of the Brazilian CCT programmes on the female participation rate does not seem to be significant either in magnitude or on statistical grounds.

The effects of labour and non-labour income are respectively positive and negative, and statistically significant for both covariates across almost all models (the exception is the GMM estimate[25]). These are the expected signs. Indeed, there is abundant empirical evidence that shows that higher labour earnings affects positively the supply of labour (see e.g. Blundell and Macurdy (1999)). Also, higher non-labour earnings can be seen as a pure income effect, so we would expect a negative impact of this variable on labour supply.[26] Interestingly, higher unemployment rates seem to increase the participation rate of women. This may be due to women's decision to enter the labour force when their husbands become unemployed. Though not statistically significant, most estimates of the coefficient associated with the proportions of children in the municipality are negative. Hence, if anything, this may be indicating that children care activities inhibit women from participating in the labour market. Except for the GMM results, age seems to increase participation of women but at a decreasing rate. Similar

[24] It has been found in the panel data literature that the standard-errors of the two-step GMM may be inaccurately estimated in finite samples. To correct for that we apply the method put forward by Windmeijer (2005).

[25] Since instrumental variable estimation typically involves some loss of efficiency, it is not uncommon to lose statistical significance in this type of estimation.

[26] A recent study for Brazil (Reis and Camargo, 2007) shows that non-labour earnings from pensions impact negatively the participation rate of men and women.

Table 5: Effect of CCT Programmes on the Participation Rate of Females: Overall Sample

Covariates	OLS (2)	Random Effects (3)	Fixed Effects (4)	First Differences (5)	GMM (6)
Proportion of beneficiaries	0.0604***	0.0563***	0.0145	0.0066	0.0438
	(0.0224)	(0.0136)	(0.0165)	(0.0160)	(0.0629)
Labour income (1/10)	0.0037***	0.0049***	0.0047***	0.0026***	0.0009
	(0.0005)	(0.0003)	(0.0004)	(0.0003)	(0.0021)
Non-labour income (1/10)	-0.0034***	-0.0028***	-0.0016***	-0.0009**	-0.0027
	(0.0006)	(0.0004)	(0.0005)	(0.0004)	(0.0032)
Unemployment rate	0.1209***	0.1585***	0.2390***	0.0811***	0.0605
	(0.0448)	(0.0332)	(0.0358)	(0.0298)	(0.1992)
Proportion of children between 0-14	-0.0631	-0.0323	0.0471	0.0001	-0.1067
	(0.0667)	(0.0415)	(0.0472)	(0.0381)	(0.2745)
Age	0.0252***	0.0171***	0.0162***	0.0097***	-0.0466*
	(0.0059)	(0.0039)	(0.0042)	(0.0035)	(0.0255)
Age^2	-0.0003***	-0.0002***	-0.0002***	-0.0001***	0.0005*
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0003)
Schooling	0.0613***	0.0337***	0.0133	-0.0302*	-0.0484
	(0.0133)	(0.0091)	(0.0115)	(0.0175)	(0.0407)
$Schooling^2$	-0.0041***	-0.0024***	-0.0005	0.0026*	0.0044
	(0.0011)	(0.0007)	(0.0009)	(0.0014)	(0.0029)
Proportion married	-0.0581*	-0.0624***	-0.0743***	-0.0077	-0.0460
	(0.0307)	(0.0232)	(0.0277)	(0.0226)	(0.1606)
Proportion of whites	-0.1094***	-0.0730***	-0.0692***	-0.0303*	0.0069
	(0.0197)	(0.0139)	(0.0184)	(0.0163)	(0.1011)
Proportion of urban population	-0.0478**	-0.1223***	-0.1447***	0.0233	-0.0582
	(0.0227)	(0.0201)	(0.0463)	(0.0376)	(0.2466)
Proportion in administrative occupations	-0.3698***	-0.2363***	-0.1455***	-0.0464*	-0.0926
	(0.0357)	(0.0263)	(0.0266)	(0.0243)	(0.2081)
Proportion in service occupations	-0.3078***	-0.1895***	-0.0749***	-0.0470***	0.1903
	(0.0255)	(0.0188)	(0.0222)	(0.0164)	(0.1289)
Proportion in commercial occupations	-0.2698***	-0.1463***	-0.0425*	0.0023	-0.0136
	(0.0341)	(0.0238)	(0.0258)	(0.0206)	(0.1799)
F-test:	47.71	90378.07	35.84	1445.40	1.46
P-value	0.0000	0.0000	0.0000	0.0000	0.1030
Hausman test: χ^2			184.25		
P-value			0.0000		
Hansen test: χ^2					79.43
P-value					0.3414
Number of observations	4030	4030	4030	3224	2418

*Notes: All variables are mean sample values computed from micro-data from PNAD across the years 2001-2005. The dependent variable is the proportion of individuals in the labour force at the municipality level. Standard-errors are in parenthesis. Significance levels: *** = 1%, ** = 5%, * = 10%. The models in columns (2) and (3) contain an intercept and dummies for geographical regions and metropolitan areas. The GMM model is estimated in first-differences and uses as instruments the levels of covariates lagged twice and earlier. All models contain year dummies. Regressions are weighted by the municipal population summed over the years that are used in the regressions.*

results are observed for the schooling effect. Being married impacts negatively the labour force participation of females, a result that might be due to a lower necessity to work for married women. A higher proportion of white females appears to be associated with lower participation of women. To the extent that labour supply decisions of black women are affected by expectations of racial discrimination in the labour market, this result is unexpected. Some estimates of the effect of the proportion of females that live in urban areas are negative, whereas others are positive or statistically nil. In principle, the sign of this effect is ambiguous: on the one hand, urban areas tend to have more diversity in employment opportunities, which should lead to higher levels of labour force participation; on the other hand, rural individuals tend to help out in farm chores, a fact that should lead to higher participation levels in rural areas. As for the occupational composition, most estimates indicate that higher shares of women in administrative, service, or commercial occupations tend to decrease female labour market participation (as compared to the excluded miscellaneous occupational category).

Table 6 reports the results for the participation rate of the below-median sample of females. Overall, the estimates of the effect of interest are quite similar to those obtained for the sample of all females. This is observed both in terms of the magnitude of the point estimates and in terms of statistical significance. Using the average of the point estimates (approximately 0.04), the elasticity of the effect of interest [calculated at the mean values of $(y,p) = (0.526,0.194)$] is around 0.01, implying that a 10% increase in the proportion of CCT beneficiaries in Brazil would rise by 0.1% the participation rate of females whose per capita income is below the median family per capita income of the municipalities they live in. As in the case of all females, we may conclude that CCT programmes does not seem to significantly increase the participation rate of females below the median family per capita income of their respective municipalities.

The results for the rest of the covariates are also similar to those of the overall sample of females. What seems somewhat different is the higher magnitude of the impact of labour and non-labour income, and the unemployment rate.

Table 6: Effect of CCT Programmes on the Participation Rate of Females: Bellow-Median Sample

Covariates	OLS (2)	Random Effects (3)	Fixed Effects (4)	First Differences (5)	GMM (6)
Proportion of beneficiaries	0.0765***	0.0603***	0.0160	0.0146	0.0120
	(0.0186)	(0.0124)	(0.0134)	(0.0123)	(0.0654)
Labour income (1/10)	0.0370***	0.0450***	0.0490***	0.0270***	0.0279*
	(0.0023)	(0.0023)	(0.0024)	(0.0020)	(0.0152)
Non-labour income (1/10)	-0.0104***	-0.0088***	-0.0081***	-0.0022	0.0015
	(0.0038)	(0.0031)	(0.0031)	(0.0024)	(0.0249)
Unemployment rate	0.1891***	0.2524***	0.3513***	0.1524***	0.3810*
	(0.0377)	(0.0267)	(0.0290)	(0.0243)	(0.2274)
Proportion of children between 0-14	-0.0415	0.0249	0.1098**	0.0132	-0.2617
	(0.0611)	(0.0426)	(0.0452)	(0.0367)	(0.2957)
Age	0.0301***	0.0192***	0.0135***	0.0092***	-0.0358
	(0.0051)	(0.0036)	(0.0035)	(0.0033)	(0.0284)
Age^2	-0.0004***	-0.0003***	-0.0002***	-0.0001***	0.0003
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0003)
Schooling	0.0279	0.0069	-0.0134	-0.0006	-0.0517
	(0.0172)	(0.0115)	(0.0133)	(0.0179)	(0.0464)
$Schooling^2$	-0.0020	-0.0010	0.0007	-0.0004	0.0048
	(0.0016)	(0.0011)	(0.0013)	(0.0017)	(0.0048)
Proportion married	-0.1180***	-0.0607***	-0.0261	0.0190	-0.1301
	(0.0302)	(0.0235)	(0.0252)	(0.0213)	(0.2014)
Proportion of whites	-0.1243***	-0.0620***	-0.0315*	-0.0109	0.1162
	(0.0197)	(0.0148)	(0.0168)	(0.0148)	(0.1205)
Proportion of urban population	-0.1131***	-0.1684***	-0.1090***	-0.0077	-0.3002*
	(0.0234)	(0.0198)	(0.0295)	(0.0254)	(0.1706)
Proportion in administrative occupations	-0.3820***	-0.2567***	-0.2126***	-0.0659**	0.0287
	(0.0401)	(0.0314)	(0.0300)	(0.0261)	(0.2953)
Proportion in service occupations	-0.2414***	-0.1721***	-0.0991***	-0.0532***	-0.0450
	(0.0194)	(0.0142)	(0.0159)	(0.0120)	(0.1154)
Proportion in commercial occupations	-0.2147***	-0.1214***	-0.0526**	-0.0109	-0.1398
	(0.0274)	(0.0226)	(0.0232)	(0.0181)	(0.1569)
F-test:	49.07	48281.49	43.30	897.82	1.57
P-value	0.0000	0.0000	0.0000	0.0000	0.0647
Hausman test: χ^2			224.05		
P-value			0.0000		
Hansen test: χ^2					90.85
P-value					0.1027
Number of observations	4030	4030	4030	3224	2418

Notes: See Table 5. The below-median sample refers to females whose family per capita income is below the median family per capita income of the municipalities they live in.

6.1.2 Males

Table 7 presents the results for the participation rate of all males. All point estimates of the effect of interest are positive and, except for the GMM case, also statistically different from zero at conventional levels. Calculated for the average of the point estimates (approximately 0.03) and at the mean values of (y,p) = (0.810,0.136), the implied elasticity here is around 0.005. This implies that a 10% increase in the proportion of CCT beneficiaries would rise the male participation rate by 0.05%. Though very small in magnitude, here we may conclude that the impact is positive and statistically significant.

The effects of labour and non-labour income are respectively positive and negative, though they seem to be smaller in absolute value than those obtained for all females. The unemployment rate seems to increase the participation rate of males, a result that has also been observed for women. In fact, the effects of the other covariates tend to be similar to what has been observed for the other gender group. The main exception is the variable proportion of married, whose effect seems to be positive in the case of males. This may be due to the fact that males feel more compelled to be in the labour force when they are married.

Table 8 displays the results for the participation rate of the below-median sample of males. Estimates of the effect of interest are similar to those of the overall sample of males: all point estimates are positive and, except for the GMM, also statistically significant. Using again the average of the all point estimates (approximately 0.04) and the mean values of (y,p) = (0.807,0.194), the elasticity is around 0.01, implying that a 10% increase in the proportion of CCT beneficiaries would lead to a 0.1% in the participation rate of males under the median family per capita income of the municipalities they live in. Though this impact is higher than that obtained for all males, it is still small.

Similar to the comparison between the two samples of females, here it is also noticeable that labour income, non-labour income, and the unemployment rate have higher impacts (in absolute value) than those observed for overall sample of males. The rest of the results are also similar between the two samples of males.

Table 7: Effect of CCT Programmes on the Participation Rate of Males: Overall Sample

Covariates	OLS (2)	Random Effects (3)	Fixed Effects (4)	First Differences (5)	GMM (6)
Proportion of beneficiaries	0.0390***	0.0391***	0.0193**	0.0274***	0.0146
	(0.0104)	(0.0076)	(0.0090)	(0.0102)	(0.0515)
Labour income (1/10)	0.0010***	0.0008***	0.0008***	0.0006***	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0005)
Non-labour income (1/10)	-0.0022***	-0.0020***	-0.0012***	-0.0005**	-0.0006
	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0014)
Unemployment rate	-0.0398	0.0174	0.1368***	0.0795***	0.0451
	(0.0264)	(0.0212)	(0.0232)	(0.0213)	(0.1457)
Proportion of children between 0-14	-0.0312	0.0107	0.0952***	0.0026	-0.2121
	(0.0376)	(0.0280)	(0.0352)	(0.0265)	(0.1977)
Age	0.0249***	0.0253***	0.0271***	0.0143***	0.0377**
	(0.0031)	(0.0024)	(0.0028)	(0.0021)	(0.0152)
Age^2	-0.0003***	-0.0003***	-0.0003***	-0.0002***	-0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)
Schooling	-0.0037	-0.0027	-0.0012	0.0450***	-0.0324
	(0.0044)	(0.0041)	(0.0062)	(0.0101)	(0.0234)
$Schooling^2$	-0.0004	-0.0001	0.0006	-0.0035***	0.0021
	(0.0003)	(0.0003)	(0.0005)	(0.0008)	(0.0016)
Proportion married	0.1404***	0.0979***	0.0381*	0.0373**	0.0591
	(0.0213)	(0.0172)	(0.0196)	(0.0174)	(0.1351)
Proportion of whites	-0.0387***	-0.0158*	-0.0360***	-0.0058	-0.0185
	(0.0099)	(0.0083)	(0.0117)	(0.0121)	(0.0723)
Proportion of urban population	-0.0657***	-0.0945***	-0.1326***	-0.0242	-0.0623
	(0.0097)	(0.0089)	(0.0222)	(0.0204)	(0.1672)
Proportion in administrative occupations	-0.0731**	-0.0462	-0.0163	0.0059	-0.0977
	(0.0361)	(0.0304)	(0.0314)	(0.0285)	(0.1979)
Proportion in service occupations	-0.1128***	-0.0618***	0.0155	-0.0798***	0.3057*
	(0.0208)	(0.0185)	(0.0199)	(0.0213)	(0.1622)
Proportion in commercial occupations	-0.1544***	-0.0987***	-0.0102	-0.0181	-0.2891*
	(0.0284)	(0.0226)	(0.0237)	(0.0206)	(0.1562)
F-test:	114.15	569505.77	31.74	6905.91	1.85
P-value	0.0000	0.0000	0.0000	0.0000	0.0195
Hausman test: χ^2			208.10		
P-value			0.0000		
Hansen test: χ^2					52.77
P-value					0.9760
Number of observations	4030	4030	4030	3224	2418

Notes: See Table 5.

6.2 Hours Worked

We now discuss the regression results for the case in which the response variable is the mean number of hours worked at the municipal level. It is important to recall that this variable has been measured including those individuals that worked zero hours (i.e. the unemployed and those out of the labour force). This implies that shifts in our measure of the mean number of hours worked are driven either by changes in the proportion of individuals with zero hours or by changes in the mean of strictly positive hours.

More formally, let h denote the individual labour supply of hours, π the proportion of individuals with $h = 0$, and $\mu^* = E[h \mid h > 0]$ the mean of the distribution of strictly positive hours. Then, the mean number of hours worked can be written as: $\mu = E[h] = \pi.E[h \mid h = 0] + (1 - \pi).E[h \mid h > 0] = (1 - \pi).\mu^*$. Thus, μ can be affected either by changes in π or in μ^*.

CCT programmes may directly affect both π and μ^*.[27] For example, π can vary because these programmes may make some of those who are out of the labour force to find a job. Also, μ^* can change because these programmes may directly affect the supply decisions of hours of those already employed. Moreover, changes in π can indirectly affect μ^*. For instance, using the previous example, if the group of newly employed individuals (i.e those who moved from out of the labour force) has average hours below (above) the initial μ^*, then we should observe a decrease (increase) in μ^*.

It is not straightforward to connect the effects of CCT programmes on the supply of hours and the participation rate. First, there is an intrinsic relationship between the proportion of individuals with zero hours of work and the participation rate.[28] Since CCT programmes may trigger movements of individuals across the different labour market statuses (employment, unemployment, and inactivity), it is possible that: (1) the participation rate and

[27] For simplicity we omit conditioning variables in the notation for π and μ^*. It should be understood, however, that $\pi = Pr[h = 0 \mid p, X]$ and $\mu^* = E[h \mid h > 0, p, X]$, where p denotes programme participation and X represent a vector of control variables.

[28] Denote by P the population over 15 years of age, and let it be partitioned into three groups: those who are employed (e), those who are unemployed (u), and those who are out of the labour force (f). Denoting the participation rate by r, we can thus write: $r = (e + u)/P$ and $\pi = (u + f)/P$, which clearly shows that two variables are inter-related.

Table 8: Effect of CCT Programmes on the Participation Rate of Males: Below-Median Sample

Covariates	OLS (2)	Random Effects (3)	Fixed Effects (4)	First Differences (5)	GMM (6)
Proportion of beneficiaries	0.0566***	0.0503***	0.0193**	0.0372***	0.0280
	(0.0082)	(0.0067)	(0.0081)	(0.0092)	(0.0491)
Labour income (1/10)	0.0100***	0.0108***	0.0131***	0.0079***	0.0033
	(0.0007)	(0.0006)	(0.0008)	(0.0008)	(0.0046)
Non-labour income (1/10)	-0.0265***	-0.0279***	-0.0236***	-0.0122***	-0.0134
	(0.0022)	(0.0023)	(0.0023)	(0.0018)	(0.0101)
Unemployment rate	0.0396*	0.0784***	0.1990***	0.1051***	0.0726
	(0.0205)	(0.0179)	(0.0216)	(0.0175)	(0.1174)
Proportion of children between 0-14	0.0084	0.0824***	0.1780***	0.0572**	0.1658
	(0.0313)	(0.0279)	(0.0330)	(0.0275)	(0.1878)
Age	0.0180***	0.0181***	0.0155***	0.0129***	0.0430***
	(0.0026)	(0.0024)	(0.0026)	(0.0023)	(0.0153)
Age^2	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)
Schooling	-0.0194***	-0.0111**	-0.0055	0.0486***	-0.0086
	(0.0052)	(0.0047)	(0.0064)	(0.0077)	(0.0255)
$Schooling^2$	0.0015***	0.0010**	0.0009	-0.0049***	0.0015
	(0.0005)	(0.0005)	(0.0006)	(0.0008)	(0.0024)
Proportion married	0.1327***	0.1044***	0.0831***	0.0272*	-0.0729
	(0.0178)	(0.0159)	(0.0185)	(0.0163)	(0.1118)
Proportion of whites	-0.0500***	-0.0297***	-0.0379***	-0.0204**	0.0168
	(0.0100)	(0.0087)	(0.0119)	(0.0103)	(0.0748)
Proportion of urban population	-0.0894***	-0.1099***	-0.1194***	-0.0386***	-0.1153
	(0.0089)	(0.0081)	(0.0161)	(0.0134)	(0.1154)
Proportion in administrative occupations	-0.0668*	-0.0672**	-0.0163	-0.0412	-0.0054
	(0.0365)	(0.0336)	(0.0350)	(0.0313)	(0.2100)
Proportion in service occupations	-0.0534***	-0.0359**	0.0119	-0.0586***	0.1881
	(0.0146)	(0.0146)	(0.0168)	(0.0167)	(0.1268)
Proportion in commercial occupations	-0.1326***	-0.1128***	-0.0333	-0.0265	-0.2972**
	(0.0226)	(0.0219)	(0.0237)	(0.0186)	(0.1399)
F-test:	96.02	424969.57	49.42	5397.55	2.31
P-value	0.0000	0.0000	0.0000	0.0000	0.0020
Hausman test: χ^2			157.90		
P-value			0.0000		
Hansen test: χ^2					63.20
P-value					0.8325
Number of observations	4030	4030	4030	3224	2418

Notes: See Table 5. The below-median sample refers to males whose family per capita income is below the median family per capita income of the municipalities they live in.

proportion of zero-hours individuals change in different directions; (2) one of them does not change at all; (3) they both change in the same direction.[29] Second, as discussed in the previous paragraph, the mean of strictly positive hours (μ^*) may be indirectly affected by changes in proportion of individuals with zero hours of work. In this sense, since the participation rate and the proportion of zero-hours individuals are intertwined, this channel also contributes to make the link between total labour supply of hours (i.e. μ) and the participation rate less direct. In fact, in order to investigate empirically the connection between the effects of CCT programmes on these two variables, it seems necessary to develop a method that is capable of isolating the programmes' effects on the set of all relevant variables that affect the total labour supply of hours. This task is beyond the scope of this paper, though.

6.2.1 Females

Table 9 reports the results for the overall sample of females. As it can be seen from this Table, all point estimates of the effect of interest are negative, with three out of five being statistically significant. In terms of magnitude, if we take the average of all estimates (approximately -1.6), the elasticity [calculated at the mean values of $(y, p) = (17.7, 0.136)$] is around -0.01. This implies that the impact of a 10% increase in the proportion of CCT beneficiaries would reduce in 0.1% the mean number of hours worked by females. Though negative, this appears to be a small impact.

It is interesting to note that the effects of the Brazilian CCT programmes on the mean number of hours worked and the participation rate of females seem to be different. Indeed, the evidence shows that the impact is approximately nil on the participation rate of women but negative on their supply of hours. As discussed before,

[29] The previous example can provide a case in which these variables move in opposite directions. Indeed, using the notation of footnote 28 and assuming that P is constant, a movement from part of f into e decreases π and increases r. Assuming again that P is constant, an example in which only one of these variable does not change value (namely r) would occur if there is movement between u and e with f fixed. Finally, if there is an expansion in P that leads solely to an increase in u, we should observe both r and π moving in the same direction (specifically they both increase).

Table 9: Effect of CCT Programmes on Hours Worked of Females: Overall Sample

Covariates	OLS (2)	Random Effects (3)	Fixed Effects (4)	First Differences (5)	GMM (6)
Proportion of beneficiaries	-1.4585**	-1.0271***	-0.6524	-2.6266***	-2.3830
	(0.6205)	(0.3617)	(0.5379)	(0.6191)	(2.0709)
Labour income (1/10)	0.1961***	0.2005***	0.2194***	0.1158***	0.1068
	(0.0210)	(0.0088)	(0.0170)	(0.0136)	(0.0793)
Non-labour income (1/10)	-0.1307***	-0.1075***	-0.0684***	-0.0400**	-0.0207
	(0.0202)	(0.0141)	(0.0184)	(0.0166)	(0.1163)
Unemployment rate	-18.5929***	-16.7559***	-15.2628***	-8.7690***	-16.2545**
	(1.5306)	(0.9785)	(1.0829)	(1.1643)	(8.0390)
Proportion of children between 0-14	-2.8796	0.9053	2.1828	3.3829*	-3.8405
	(2.3694)	(1.3244)	(1.6180)	(1.7691)	(10.7241)
Age	1.0411***	0.8222***	0.7663***	0.4442***	-1.3847
	(0.2005)	(0.1229)	(0.1464)	(0.1384)	(0.8700)
Age^2	-0.0141***	-0.0109***	-0.0099***	-0.0054***	0.0151
	(0.0022)	(0.0013)	(0.0016)	(0.0016)	(0.0096)
Schooling	3.0372***	1.2467***	0.1818	-4.4180***	-0.8848
	(0.4223)	(0.2603)	(0.4361)	(0.6282)	(1.2524)
$Schooling^2$	-0.2314***	-0.0860***	0.0171	0.3738***	0.0873
	(0.0350)	(0.0206)	(0.0339)	(0.0496)	(0.0905)
Proportion married	-5.0810***	-4.9810***	-5.6113***	-2.9856***	-4.9769
	(1.0301)	(0.7787)	(0.8706)	(0.9573)	(7.0995)
Proportion of whites	-0.6220	-0.9371**	-1.3794**	-1.1175**	0.1409
	(0.5693)	(0.4101)	(0.5537)	(0.5621)	(3.9200)
Proportion of urban population	0.5451	-1.7028***	-3.6178**	0.2405	6.3285
	(0.8091)	(0.5571)	(1.4299)	(1.4168)	(9.3572)
Proportion in administrative occupations	-9.1480***	-3.8009***	-1.6881*	-0.6317	-2.0769
	(1.2446)	(0.8515)	(0.9729)	(0.9999)	(6.8999)
Proportion in service occupations	-5.8759***	-0.0395	2.6156***	1.2695*	6.8951
	(0.8517)	(0.5300)	(0.7103)	(0.6481)	(4.3442)
Proportion in commercial occupations	-3.8321***	0.7889	2.4720***	1.5014*	5.9166
	(1.1287)	(0.7430)	(0.8385)	(0.8376)	(6.2977)
F-test:	64.35	2042.76	50.46	959.02	2.10
P-value	0.0000	0.0000	0.0000	0.0000	0.0057
Hausman test: χ^2			214.60		
P-value			0.0000		
Hansen test: χ^2					68.62
P-value					0.6851
Number of observations	4030	4030	4030	3224	2418

*Notes: All variables are mean sample values computed from micro-data from PNAD across the years 2001-2005. The dependent variable is the mean number of hours worked at the municipality level. Standard-errors are in parenthesis. Significance levels: *** = 1%, ** = 5%, * = 10%. The models in columns (2) and (3) contain an intercept and dummies for geographical regions and metropolitan areas. The GMM model is estimated in first-differences and uses as instruments the levels of covariates lagged twice and earlier. All models contain year dummies. Regressions are weighted by the municipal population summed over the years that are used in the regressions.*

since there are various different channels through which these two effects may be connected, it is difficult to offer an explanation for this result.

The signs of the effects of the other covariates are similar to those found for the participation rate. A noticeable exception is the unemployment rate, whose effect on hours is negative.

Table 10 contains the results for the below-median sample of females. All point estimates of the effect of interest display a negative sign, but only one of them is statistically significant at the 10% level.[30] From the average of the point estimates (approximately -0.47), the elasticity [calculated at the mean values of $(y, p) = (14.5, 0.194)$] is close to -0.01, implying that a rise in 10% in the proportion of CCT beneficiaries would lead to a reduction in -0.1% in the mean number of hours worked by females below the their respective municipalities' median per capita income. Once again, the impact is quite small. In contrast to the case of all females, here the effect of interest does not seem to be statistically different from zero. Hence, for this sample, the effects on both the participation rate and the supply of hours are not significant either statistically or in magnitude.

In terms of signs, the effects of the other covariates are in line with those obtained for the overall sample of females. The magnitude of the effects associated with labour and non-labour income is higher (in absolute terms) for the below-median sample of females. The opposite applies for the unemployment rate.

6.2.2 Males

Table 11 presents the results for hours worked for the overall sample of males. Apart from OLS, all other models' estimates of the effect of interest are positive. However, only one estimate is statistically different from zero at conventional levels. Taking the average of all estimates (approximately 0.73), the elasticity [computed at the mean

[30] Here, the validity of the orthogonality conditions of the GMM model is not rejected only at the 5% level by the Hansen test of overidentifying restrictions.

Table 10: Effect of CCT Programmes on Hours Worked of Females: Below-Median Sample

Covariates	OLS	Random Effects	Fixed Effect	First Differences	GMM
Proportion of beneficiaries	-0.2359	-0.0932	-0.1971	-0.8286*	-1.0153
	(0.5610)	(0.3043)	(0.4015)	(0.4226)	(1.7312)
Labour income (1/10)	1.7796***	2.0554***	2.2308***	1.2844***	1.3591***
	(0.0907)	(0.0511)	(0.0930)	(0.0860)	(0.4421)
Non-labour income (1/10)	-0.6066***	-0.5466***	-0.4880***	-0.0318	-1.1543*
	(0.1355)	(0.0864)	(0.0972)	(0.0964)	(0.6048)
Unemployment rate	-11.6967***	-9.3645***	-7.9904***	-3.9574***	-14.2965***
	(1.0357)	(0.7218)	(0.7478)	(0.8010)	(5.0715)
Proportion of children between 0-14	0.9797	4.1298***	5.3883***	3.9187***	2.2846
	(1.9722)	(1.1460)	(1.4268)	(1.3168)	(2.2126)
Age	1.0684***	0.5867***	0.4510***	0.2745**	0.5995***
	(0.1717)	(0.1058)	(0.1160)	(0.1140)	(0.1696)
Age^2	-0.0127***	-0.0076***	-0.0060***	-0.0032**	-0.0067***
	(0.0019)	(0.0012)	(0.0013)	(0.0013)	(0.0024)
Schooling	1.9203***	0.4189	0.0061	-1.3598**	-0.4065
	(0.5245)	(0.2821)	(0.4503)	(0.5877)	(0.6940)
$Schooling^2$	-0.1969***	-0.0731***	-0.0317	0.1164**	0.0358
	(0.0484)	(0.0275)	(0.0423)	(0.0557)	(0.0695)
Proportion married	-7.9715***	-4.4348***	-3.3059***	-0.3785	-6.7331***
	(1.0388)	(0.6575)	(0.8067)	(0.7410)	(1.8405)
Proportion of whites	-1.2109**	-0.3970	0.2897	-0.2827	-0.0106
	(0.5789)	(0.4033)	(0.4789)	(0.4838)	(0.7250)
Proportion of urban population	-1.6817**	-3.0585***	-1.3986	0.6730	-1.5359
	(0.7914)	(0.4893)	(0.9756)	(0.8464)	(1.3863)
Proportion in administrative occupations	-9.7746***	-4.2795***	-2.5795***	0.0624	1.9328
	(1.2427)	(0.9255)	(0.9756)	(0.9279)	(1.5897)
Proportion in service occupations	-5.0698***	-1.2654***	0.0039	0.2418	0.8091
	(0.5741)	(0.3762)	(0.4425)	(0.3984)	(0.6367)
Proportion in commercial occupations	-4.8685***	-1.5492***	-0.4474	0.3100	1.5322
	(0.8028)	(0.6006)	(0.6592)	(0.6192)	(1.0069)
F-test:	82.58	2990.05	76.99	615.18	9.13
P-value	0.0000	0.0000	0.0000	0.0000	0.0000
Hausman test: χ^2			188.41		
P-value			0.0000		
Hansen test: χ^2					106.24
P-value					0.0686
Number of observations	4030	4030	4030	3224	2418

Notes: see Table 9. The below-median sample refers to females whose family per capita income is below the median family per capita income of the municipalities they live in.

Table 11: Effect of CCT Programmes on Hours Worked of Males: Overall Sample

Covariates	OLS	Random Effects	Fixed Effect	First Differences	GMM
Proportion of beneficiaries	-0.6309	0.2766	0.5778	1.6025**	1.8281
	(0.6899)	(0.5126)	(0.6402)	(0.6381)	(2.1012)
Labour income (1/10)	0.0827***	0.0611***	0.0563***	0.0473***	0.0457
	(0.0078)	(0.0063)	(0.0061)	(0.0066)	(0.0302)
Non-labour income (1/10)	-0.0932***	-0.0879***	-0.0481***	-0.0229	-0.0728
	(0.0145)	(0.0129)	(0.0130)	(0.0141)	(0.0806)
Unemployment rate	-27.7628***	-24.5796***	-19.7568***	-9.7300***	-30.4398***
	(1.6085)	(1.2719)	(1.3293)	(1.4121)	(7.7795)
Proportion of children between 0-14	-1.6475	0.6947	4.9978**	0.3146	1.8819
	(2.3585)	(1.7397)	(1.9476)	(1.8773)	(3.2170)
Age	1.9424***	1.7164***	1.6313***	0.7985***	1.7843***
	(0.1839)	(0.1423)	(0.1617)	(0.1547)	(0.2353)
Age^2	-0.0246***	-0.0219***	-0.0208***	-0.0105***	-0.0217***
	(0.0020)	(0.0015)	(0.0018)	(0.0017)	(0.0026)
Schooling	0.9259**	0.4320	-0.6429*	2.4243***	-0.8057
	(0.4092)	(0.3101)	(0.3641)	(0.6685)	(0.5156)
$Schooling^2$	-0.1620***	-0.0817***	0.0599**	-0.2161***	0.0826*
	(0.0319)	(0.0247)	(0.0296)	(0.0540)	(0.0451)
Proportion married	8.8246***	7.6752***	5.5037***	3.4944***	5.3435***
	(1.4599)	(1.1112)	(1.2113)	(1.1591)	(1.7212)
Proportion of whites	-0.6144	-0.3354	-1.4747**	0.6491	1.2221
	(0.6248)	(0.5302)	(0.6768)	(0.7562)	(0.9646)
Proportion of urban population	-2.6690***	-4.0697***	-5.3394***	1.3547	-4.6355**
	(0.6542)	(0.6137)	(1.3309)	(1.4253)	(1.8585)
Proportion in administrative occupations	-6.9284***	-5.1490***	-3.8760**	-0.2570	-3.1583
	(2.1265)	(1.7767)	(1.8579)	(1.9048)	(2.7311)
Proportion in service occupations	-3.1937**	-1.3307	2.0506*	-6.9829***	0.0742
	(1.2785)	(1.0607)	(1.1958)	(1.4229)	(1.7723)
Proportion in commercial occupations	-5.7593***	-2.8844**	-0.4422	-0.4121	-1.3148
	(1.6566)	(1.3667)	(1.3226)	(1.3163)	(2.0391)
F-test:	119.35	194570.28	57.08	2059.64	19.27
P-value	0.0000	0.0000	0.0000	0.0000	0.0000
Hausman test: χ^2			164.97		
P-value			0.0000		
Hansen test: χ^2					93.74
P-value					0.2665
Number of observations	4030	4030	4030	3224	2418

Notes: see Table 9.

values of $(y, p) = (33.9, 0.136)$] is less than 0.01. This implies that increases in the proportion of CCT beneficiaries in Brazil would have no (or negligible) effects on males' mean supply of hours.

Contrasting the effects' estimates for the participation rate and the mean supply of hours, there is a distinction as compared to the female case. There the former effect is basically nil, while the latter is negative; here the former effect is positive, while the latter is nil. Hence, in term of sign, it seems that the Brazilian CCT programmes do not change the labour supply of hours of males but increase their participation rate, whereas they decrease the supply of hours of females without affecting their participation rate. In all cases, however, it should be pointed out that, if any, the effects are quite small in magnitude.

As in the case of all females, the signs of the effects of the other covariates are similar to those found for the participation rate. Again, a noticeable exception is the unemployment rate, whose effect on hours is negative.

Table 12 displays the results for the sample of males whose per capita income is below the median family per capita income of the municipalities they live in. All five point estimates of the effect of interest are positive, but only one is significant on statistical grounds. The implied elasticity from the average of all estimates (approximately 1.43) and the mean values of $(y, p) = (31.9, 0.194)$ is around 0.01, implying that a 10% increase in the proportion of beneficiaries would rise the mean number of hours worked for this group of males in 0.1%. As in the case for all males, the results indicate that the Brazilian CCTs' increase the participation rate for this sample but have no (or negligible) effects on the their mean labour supply of hours.

Table 12: Effect of CCT Programmes on Hours Worked of Males: Below-Median Sample

Covariates	OLS (2)	Random Effects (3)	Fixed Effects (4)	First Differences (5)	GMM (6)
Proportion of beneficiaries	0.1889	0.5721	0.4952	1.9569***	3.9159
	(0.6241)	(0.3626)	(0.5378)	(0.6033)	(3.0073)
Labour income (1/10)	0.7198***	0.7960***	0.9192***	0.6193***	0.5107*
	(0.0464)	(0.0333)	(0.0504)	(0.0465)	(0.2670)
Non-labour income (1/10)	-1.4850***	-1.2628***	-1.0316***	-0.5550***	-1.5068**
	(0.1342)	(0.0916)	(0.1161)	(0.1078)	(0.6385)
Unemployment rate	-23.7888***	-19.2739***	-16.1634***	-7.2695***	-25.0366***
	(1.1812)	(0.8785)	(1.0346)	(1.0580)	(7.1113)
Proportion of children between 0-14	2.2966	7.3479***	10.9509***	3.5647**	2.4448
	(2.1057)	(1.4950)	(1.8815)	(1.7471)	(10.5554)
Age	1.0450***	0.8368***	0.7720***	0.5959***	0.8997
	(0.1660)	(0.1273)	(0.1516)	(0.1310)	(1.0601)
Age^2	-0.0120***	-0.0104***	-0.0100***	-0.0073***	-0.0130
	(0.0019)	(0.0015)	(0.0017)	(0.0015)	(0.0125)
Schooling	0.1290	-0.2306	-0.5773	2.8554***	-3.9238**
	(0.4372)	(0.2622)	(0.4201)	(0.5969)	(1.6795)
Schooling^2	-0.0775*	-0.0269	0.0336	-0.3153***	0.3835**
	(0.0403)	(0.0257)	(0.0390)	(0.0584)	(0.1533)
Proportion married	9.1814***	8.4658***	7.6056***	3.6438***	6.6646
	(1.1707)	(0.9111)	(1.1098)	(1.0218)	(6.6278)
Proportion of whites	-1.9426***	-1.5269***	-0.9816	-0.0553	2.4732
	(0.6133)	(0.4695)	(0.6410)	(0.6762)	(4.7626)
Proportion of urban population	-3.7431***	-5.4487***	-6.5568***	-0.3385	-4.0523
	(0.6359)	(0.4724)	(0.9724)	(0.8717)	(8.4539)
Proportion in administrative occupations	-8.5585***	-5.6829***	-3.5420**	-3.0668*	3.5352
	(1.9003)	(1.6951)	(1.7826)	(1.6932)	(15.5984)
Proportion in service occupations	-1.2544	0.1267	1.2425	-6.0490***	1.1845
	(0.9113)	(0.7978)	(0.9254)	(1.0356)	(8.5430)
Proportion in commercial occupations	-5.0585***	-3.1426***	-1.7711	-1.2735	-11.0825
	(1.3133)	(1.0440)	(1.2104)	(1.1060)	(9.0792)
F-test:	126.64	3939.71	98.42	1252.43	3.05
P-value	0.0000	0.0000	0.0000	0.0000	0.0000
Hausman test: χ^2			112.01		
P-value			0.0000		
Hansen test: χ^2					96.17
P-value					0.0504
Number of observations	4030	4030	4030	3224	2418

Notes: see Table 9. The below-median sample refers to males whose family per capita income is below the median family per capita income of the municipalities they live in.

Overall, the effects of the other covariates are similar to those obtained for all males. Main exceptions are the impacts of labour and non-labour income, which are higher in absolute terms.

7 Conclusions

In this paper, we estimated the effects of the Brazilian CCT programmes on the labour supply of adults. These effects were estimated from a time-series, cross-section sample of municipalities in the country. We constructed this data set from the *Pesquisa Nacional por Amostra de Domicílios - PNAD*, which is a national household survey that

is fielded annually in the same set of municipalities between census years (only households are randomly sampled across years). The outcome variables were the participation rate and the average number of hours worked at the municipal level. Since PNAD does not ask direct questions about CCT programme participation, our measure of programme assignment was indirect and based on the typical benefit values of the programmes. Results are obtained separately for all males and females and, in order to investigate whether the effects of interest differ for poorer individuals, we also obtain results for males and females that live in families whose per capita income falls below the median family per capita income of their respective municipalities. Methodologically, we employ various linear panel data models typically used in the literature.

Our results indicate that the impact of the Brazilian CCT programmes on the female participation rate is not significant either on statistical grounds or in terms of magnitude. This is valid for all females and for those below the median of the distribution of family per capita income of the municipalities they live in. As for males, there is evidence that the effect on the participation rate is positive, though very small in magnitude. Again, this is observed for all males and for those below the median of their respective municipal distribution of family per capita income. In terms of the supply of hours, the results indicate a small negative effect on all females but an insignificant impact on those that live below the median family per capita income of their municipalities. For both groups males, the results show insignificant impacts of the programmes both in size and on statistical grounds.

In sum, our results do not show particularly significant effects of the Brazilian CCT programmes on either the labour market participation or the supply of hours of men and women. Rather, our results seem to be compatible with a story that CCT programmes do not affect the labour supply of adult males and females. In fact, this contention seems to be in line with the empirical literature that uses individual data and compare treatment and control groups' outcomes.

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