Can Conditional Cash Transfers Reduce Poverty and Crime? Evidence from Brazil

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Abstract

Conditional Cash Transfers (CCT) programmes are deemed to be effective measures at reducing poverty and income inequality in many developing countries. Another possible important consequence is its effect on criminal behaviour. This paper analyses a panel data set on crime rates and the Brazilian *Bolsa Familia*, the largest CCT programme in the world, in order to investigate these relationships and estimate the effect of these policies on crime rates. The related existing economic literature analysing general welfare programmes generally ignores the crucial endogeneity involved in the relationship between crime rates and social welfare policies, through poverty. Temporal heterogeneity in the implementation of the programme across the states is used to identify the causal impact of CCT programmes on poverty and criminality. States that reached the level of cash transfers expenditures proposed by the guidelines of the programme more promptly had a more significant reduction in poverty rates. Similar, but less robust results are found for crime rates as robbery, theft and kidnapping, while no significant effects were found for homicide and murder, indicating that property crime would be more sensitive to CCT programmes.

Key words: Criminal Behaviour, Poverty, Conditional Cash Transfers.
JEL Classification: K40, I38, H53, C23.

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1 Introduction

Crime is a central theme in the discussions of the main public issues of developing countries. Many of these countries have recently implemented policies based on conditional behaviour that are aimed at vulnerable people: Conditional Cash Transfers (CCT) Programmes, where the recipients receive a monthly benefit that represents a significant increase in their initial income. These policies have been the main device used by governments of countries such as Brazil (*Bolsa Família*), Mexico (*Oportunidades*) and Chile (*Chile Solidário*) to reduce poverty.[1] It is a stylised fact that higher levels of income inequality and poverty are associated with increased criminal behaviour, and these welfare programmes are deemed to be effective to mitigate these social problems.[2] A natural question would be whether those policies have also affected crime rate levels and how effective this kind of policy is when compared to increases in law enforcement.

This paper uses a panel data set to analyse the impact of CCT programmes on crime rates in the Brazilian States, a relationship that still has not been investigated by formal theoretical or empirical analyses. Unlike the related literature that studies the effect of general social welfare, the channels through which this relationship occurs are analysed in some detail.[3] Here the analysis is deepened by verifying the specific impact of conditional cash transfer programmes on crime levels. By accomplishing this task, it will be possible to shed some light on the effects on crime rates of this kind of policy originally aimed at reducing poverty and income inequality through minimum income policy and a conditional component.

Another pivotal difference is that the existing literature on unconditional programmes generally ignores the crucial endogeneity involved in the relationships among poverty, income inequality and social welfare programmes. If it is present and not taken into account, the estimates are biased and inconsistent. Temporal heterogeneity in the implementation of the programme across the states is used in this paper to identify the causal impact of CCT programmes on poverty and criminality.

CCT programmes have also the advantage of providing significant changes in social expenditures. The Brazilian CCT programme started in all 27 States in December 2003, adding up to the existing unconditional programme Continuous Cash Benefit (CCB), aimed at elderly and disabled poor people that started to operate in 1995. Figure 1.1 shows the trend in homicide rates, cash transfers and law enforcement expenditures per capita between 2001

[1]Other countries that adopted CCT programmes in the recent years are: India, Indonesia, Nigeria, Turkey and most Latin American countries. For further discussion on CCT programmes, see Medeiros, Brito, and Soares (2008) and Fiszbein and Schady (2009).

[2]As show Rawlings and Rubio (2003), Skoufias and Maro (2008) and Resende and Oliveira (2008).

[3]All papers in this area focus on aggregate social welfare or specific unconditional programmes: Johnson, Kantor, and Fishback (2007), Lindvall (2004) and Worrall (2005, 2009).

and 2008. It is possible to observe the relevance of the change in the cash transfers in 2004 with the beginning of the Bolsa Familia programme.[4] A sharp decrease in the homicide rate in the same period is also observed.

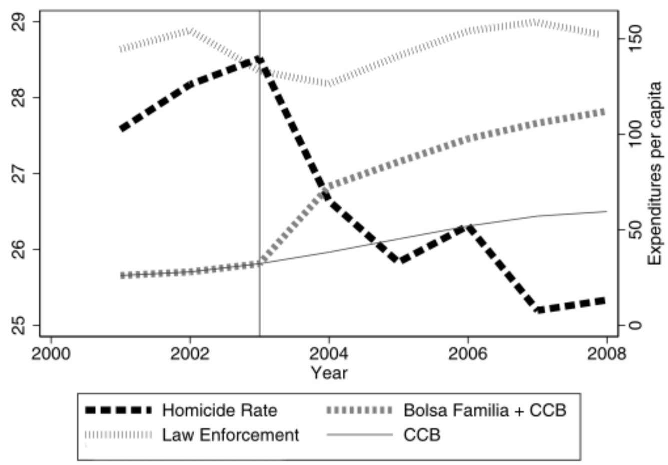


Figure 1.1: Cash Transfers, Law Enforcement (per capita, adjusted for inflation) and Homicide Rate (100,000 inhab.) in Brazil

The discussion of effect of social policies on crime is present in the texts of the first economists, but since the seminal paper of Becker (1968), economists consider formally the possible effects of socioeconomic variables on criminal behaviour. However, just recently the specific discussion of the effect of welfare programmes on criminal behaviour has been formalised. The literature that formally models the specific effect of social welfare programmes on crime is restricted to three papers: Benoit and Osborne (1995), Zhang (1997) and Imrohoroglu, Merlo, and Rupert (2000).

Empirical evidence, usually restricted to homicide rates, is provided by Chamlin, Cochran, and Lowenkamp (2002), Burek (2005) and Worrall (2005, 2009). Ambiguous effects are found. Results are frequently plagued by endogeneity issues and not always properly addressed.

The effect of CCT programmes on legal income have some features that may intensify their effects on crime when compared with general welfare programmes. Firstly, this type of policy is more extensive than other welfare programmes (in Brazil it reaches about 1/4 of population, which represent the vast majority of the poor population), which makes one more likely to affected by the programme, directly or indirectly; Secondly, the conditional aspect (incentivise children's education & health care) would affect the expected income and the decision to engage in the illegal market; Another distinguishing aspect would be a social

[4]It can also be seen that CCB expenditures were also increasing, even after inflation is taken into account. This shows the effect of the approach of the new government that proposed to reach more vulnerable people.

altruism effect, where recipients of the benefit increase their sensation of social protection, making them more inclined to tolerate higher levels of poverty and income inequality.

In summary, because of its conditional component and extensive coverage, policies of this kind should also affect the expected income of individuals on the edge to commit a crime as well as their attitude towards society and government.

In the following section I discuss the links between CCT programmes and criminal behavior. The data used is described in section 3. The forth and fifth sections analyse the relationships among CCT, Poverty and Crime. The effect of CCT on crime in provided in section 6 and section 7 concludes.

2 Context

The sign and the magnitude of the effect of CCT programmes on crime is a relevant question for the policy maker. Welfare policies in general and specifically CCT programmes are not explicitly aimed at crime reduction, however, its likely effect on income distribution, especially poverty could also affect the decisions involved in the criminal behaviour.

2.1 Conceptual Framework

The decision of an individual to commit a crime results from a expected utility maximization process, in which the individual would face, on one hand, the potential net gains arising from the criminal action, the value of punishment and the likelihood of arrest and conviction and, on the other hand, the opportunity cost of committing a crime represented by alternative wage in the legal labour market.[5]

Theoretical models and empirical findings in economics of crime point out poverty and income inequality to be major causes of crime.[6] In the economic theory of crime, areas with higher inequality place poor individuals who have low returns from market activity next to high-income individuals who have goods worth taking, thereby increasing the returns to time allocated to criminal activity. Faced with the relative success of others around them unsuccessful individuals feel frustration at their situation. A rise in inequality may also have a crime-inducing effect by reducing the individual's risk aversion and moral threshold to commit a crime (envy effect).

CCT programmes, as some other welfare policies, provide a boost in the income of the poorest individuals, generally deemed to be more likely to get involved in criminal activity,

[5] For an extensive critical literature review, see Dills, Miron, and Summers (2008).

[6] See Bourguignon (1998) for discussion. Huang, Laing, and Wang (2004) propose a search model analysis on the relation between poverty and crime. Multiple equilibria are found.

because of their lower opportunity costs. These programmes help individuals to reach a more acceptable subsistence income and also promotes income redistribution, reducing inequalities and the associated "envy effect". These effects raise the opportunity cost of the recipients of these programmes, which affects the probability of an individual committing a crime. Because the involvement in illegal activities may result in the loss of the benefit if arrested, recipients have an additional increase in the opportunity cost.

Therefore, the major effect of CCT programmes on criminal behaviour would come from the effect on poverty levels and income inequality. However, this type of policy generally follows a natural rule to provide more resources in regions with higher levels of poverty. This is especially true in the Bolsa Familia programme, which has a formal law to determine the amount spent in each state. The amount of resources that should be spent in each state was based on the levels of poverty obtained by the Census carried out in 2000. This rule creates a relevant source of endogeneity in the estimation of the effect of CCT on poverty.

Unlike most welfare programmes, CCT programmes make the payment of the benefit conditional on health and educational attainments, which implies not only a higher short term income, but also a higher expected income for the family, given the programme would provide opportunities for higher levels of education.[7] Because CCT programmes generally have a considerable magnitude, a possible additional effect is a situation of social altruism, in which the individuals that receive the benefit have a real perception of the government action, with the approval of the political elite, creating an environment/sensation of social protection. This effect would raise the "moral" opportunity costs of committing an illicit act for some individuals.[8]

2.2 Welfare Payments and Crime Literature

The number of papers that investigate the relationship between social welfare spending and crime is more restricted and more recent than those that analyse similar issues like the effects of law enforcement on criminality. Moreover, there is no empirical evidence on this issue for developing countries, where the different economic environment may lead to contrasting results.

The existing theoretical literature that formally model this specific issue is restricted to three articles. In general, they suggest that expenditures on welfare programmes have a negative effect on crime rates, as discussed by Benoit and Osborne (1995), Zhang (1997) and

[7] Lochner and Moretti (2004) and Stephen Machin and Vujić (2010) provide empirical evidence in this direction.

[8] Sickles and Williams (2008) propose and estimate a dynamic theoretical model where "social capital" is a relevant aspect to influence criminal behaviour while Buonanno, Montolio, and Vanin (2009) estimate the effect of several measures of social capital on crime rates.

Imrohoroglu, Merlo, and Rupert (2000).[9] The idea behind this negative effect is that the welfare spending would impact the model with a reduction in incentives to commit a crime by raising the opportunity costs of the potential criminal.

In Benoit and Osborne (1995), under a theoretical setting, a formal model is developed in order to integrate spending on social assistance in the economic model of crime. Consideration is given to how individuals in society behave in order to decide the optimal amount of investment in police and welfare payments needed to reduce crime. Under some specific assumptions, income redistribution reduce crime rates.

Zhang (1997) establishes a simple economic model in which, under some assumptions, criminal behaviour is reduced when policies aimed at redistribution are emphasised. This prediction is confirmed by his empirical findings for the US economy (Cross-sectional data for States). Reverse causality between Welfare Payment and crime is tested by using the amount of federal aid to the state governments and the percentage of the elderly in the population as instruments. No endogeneity problem in this sense is identified with these data.

In Imrohoroglu, Merlo, and Rupert (2000), a general equilibrium model is built in order to explain the relationship between public expenditures and criminality. The amount spent on police and income redistribution are determined endogenously through majority voting. In addition to the theoretical analysis, the authors consider the effects of increases in public spending on social welfare and in police over crime rates through calibration. Based on this structural model, it is found that the effect of the redistribution varies according to the characteristics of each region. However, as the authors emphasise, due to the fact that the model estimated is static, all possible dynamic aspects are ignored in these estimates.

Empirical evidence that find a negative effect of welfare programmes on crime rates is provided by Pratt and Godsey (2002) (Homicide only), Johnson, Kantor, and Fishback (2007), Savage, Bennett, and Danner (2008) and Worrall (2009) (Homicide only).

Pratt and Godsey (2002) use a panel data of 46 countries to estimate the relationship between social support (% of GDP spent on health care and education) and homicide. The percentage of people immunized for measles is used as instrumental variable. A negative effect is found and relatively robust. Alternative policies (law enforcement expenditures) are not considered.

Johnson, Kantor, and Fishback (2007) explore a panel data set for 81 large American cities is built in order to estimate the effect of the relief effort during the great depression. By using instrumental variables (mean of percentage voting for the Democratic Party and months of extreme wetness) the authors find a negative effect of public welfare spending on

[9] A few other papers, as Burdett, Lagos, and Wright (2003) and Merlo (2003), consider the role of redistribution on crime in general terms.

crime rates.

Savage, Bennett, and Danner (2008) analyse a panel data set of 25 countries for 13 years to explore the relationship between crime and social welfare spending. After unobserved heterogeneity and dynamic aspects are considered, a negative and curvilinear (by adding a quadratic term) relationship is found. Short run and long run results vary in sign and statistical significance. Endogeneity issues are not mentioned. Alternative policies (law enforcement expenditures) are not considered.

Worrall (2009) re-estimates the model considered in Worrall (2005) taking the likely endogeneity issues into account. A Panel data from California counties is used in order to assess the effect of welfare spending on homicide. The lagged welfare spending is used as instrument. A negative effect is found, but it is not robust to different econometric approaches and specifications. Once again alternative policies (law enforcement expenditures) are not considered.

The other papers on this issue find little or no evidence of the effect of social welfare spending on criminal behaviour, as argued by Chamlin, Cochran, and Lowenkamp (2002) (except homicide), Burek (2005) (less serious crimes) and Worrall (2005). Some of them predict no relationship between those variables or even a positive relationship when endogeneity issues are not taken into account and others do not encounter any effect even when the appropriate econometric models are considered.[10]

As discussed below the econometric estimation of the relationship between welfare payments and crime is complicated by the likely presence of problems of endogeneity via poverty. It may also be argued that the welfare expenditures are intensified in places and/or in periods of higher economic hardship or poverty. Section 5 provides some empirical evidence on this issue. It is therefore not surprising to find that crime in its various forms is positively correlated with the spending on welfare. This problem may be controlled for by using the appropriate econometric methods.

2.3 Conditional Cash Transfer Programmes: The *Bolsa Familia* Case

Conditional Cash Transfer (CCT) programmes are political mechanisms aimed at reducing poverty by making welfare programmes conditional upon the receivers' actions. The government only transfers the money to individuals/families that meet specific criteria. In addition, after these agents have engaged in the programme and in order to keep the benefit

[10] Witte and Witt (2001) also provides an extensive discussion on the government role to reduce crime rates.

they must follow some educational and health requirements.[11]

This kind of policy provides emergency assistance, while the conditionalities (requirement to the families) promote long-term investments in human capital. This kind of policy addresses the problem of underinvestment in human capital not only by compensating individuals in the short-term for the real costs of investing in health, nutrition, and education, but also by adding requirements for households to use services that have long-term payoff in these areas.[12]

CCT programmes have some important features that distinguish them from other welfare programmes. Firstly, they have eligibility requirements and conditionalities over the recipients' actions. Additionally, the grant is paid in cash, providing a minimum income. Another distinguishing feature is that the responsible individual for the benefit is almost always a woman (In the Bolsa familia programme, this number is around 95%).

In the last few years the Brazilian government has significantly boosted cash transfers policies to poor people. Two major welfare programmes are now being carried out in Brazil: Continuous Cash Benefit (CCB) and *Bolsa Familia* (BF).

CCB is a cash transfer programme implemented in the country in 1995 and aimed at individuals over 65 and/or with severe disabilities. In both cases the income per capita in the family must be below 1/4 of the minimum wage.[13]

Bolsa Familia is a conditional cash transfer programme that took place in all 27 Brazilian states in the end of 2003 targeted at families with low income.[14] It is mainly aimed at poor families with children and establishes education and health requirements.[15]

In 2009 Bolsa Familia was considered the largest conditional cash transfer programme in the world, though the Mexican programme *Oportunidades* was the first nation-wide programme of this kind. I compare the figures related to the cash transfers programmes in Brazil in Table 2.1.

[11] For further details on CCT programmes, see Fiszbein and Schady (2009).

[12] Several empirical papers address these issues, as Gertler (2004), Glewwe and Kassouf (2008) and Reis (2010). In general they provide evidence that CCT programmes are effective to boost recipients' health and education.

[13] It should not be confused with a pension or retirement benefit. This confusion is common even among recipients of this benefit.

[14] Bolsa Familia was a programme that provided additional income to most poor families in Brazil. Nevertheless, there were previous programmes of smaller magnitude that were absorbed into the new programme, like *Bolsa Escola*, *Vale Gas* etc. Data on those programmes were not included in this paper. However, this omission will only underestimate any effect found.

[15] For further discussion on cash transfer programmes in Brazil, see Medeiros, Brito, and Soares (2008).

Table 2.1: Bolsa Familia and CCB's Figures - Jan-Dec - 2009

	Bolsa Familia	**CCB**
Amount Spent	US$ 6,610,220,967	US$ 9,917,301,532
Families receiving the benefit	12,472,540	3,166,845
People receiving the benefit	51,636,316	13,110,738
Average Benefit per person per year	US$ 529.98	US$ 3,131.60
Percentage of Federal Social Expenditures	37.26%	57.01%
Percentage of National Social Expenditures	33.53%	51.32%
Percentage of Federal Total Expenditures	0.76%	1.16%
Percentage of GDP	0.33%	0.51%

Source: Calculated by the author with data from the National Treasury Secretariat and Ministry of Social Development

Notes: Monetary figures converted from *Real* (R$)

People receiving the benefit and derived quantities are estimates.

Social welfare policies are accomplished by the three levels of government.[16] Nevertheless, unlike other areas as spending on police, the percentage that each level of government applies in welfare programmes varies considerably across states and between years. The amount the Federal Government spends on welfare represents about 90% of the whole expenditure in the states. In 2009 those two programmes represented about 94% of all federal spending on social welfare. Expenditure on *Bolsa Familia* is approximately 50% smaller than the amount spent on Continuous Cash Benefit, although the former covers 4 times more families. Another relevant fact is that such expenditures account for less than 2% of the federal budget. It should be also noticed that, unlike many developing countries, all resources for funding *Bolsa Familia* and CCB expenditures come from federal tax revenue, with insignificant contribution from foreign aid.

The *Bolsa Familia* benefit is paid directly to the final recipient by the federal government. However, the municipality government also participates in the process by registering the potential receivers of the benefit. The participation of the state government is restricted to the administrative and technical support to the local governments.

[16]In Brazil, the governmental attributions are carried out by federal, state and municipality administrations.

3 Data

A new data set is created by linking aggregate variables I constructed from the state representative socioeconomic micro data from annual Brazilian house survey of PNAD (National Survey of Household Sample by the IBGE - Brazilian Institute of Geography and Statistics) with the criminal registers from the Public Security national agency, from 2001 to 2008.

3.1 Criminal Data

I use data from SENASP - National Secretariat of Public Security, agency of the Ministry of Justice, which compiles information from the State Secretariats of Public Security, and indicators of the incidence of crime in the Brazilian states the following indices: murder rate per 100 thousand inhabitants, total rate of robberies per 100 thousand inhabitants, total rate of theft per 100 thousand inhabitants and extortion through kidnapping rate per 100 thousand inhabitants. The data are to be used annually to all 27 states of Brazil and covering the period 2001 to 2008.[17] Alternative measures of homicide rates are also calculated using data from the Ministry of Health, that provides state level data.[18]

3.2 Expenditures on Cash Transfers and Law Enforcement

As mentioned before, the two main federal welfare programs are direct cash transfer: *Bolsa Familia*, aimed at poor people, especially those with young children and Continuous Cash Benefit, which is primarily aimed at elderly and disabled people. The variable used in this paper is the sum spent on both programmes per capita and corrected for inflation. Data come from the Ministry of Social Development (MDS).

Information about the law enforcement spending and revenue of the states was obtained from the Bulletin of Public Finance of Brazil, prepared by the Secretariat of the National Treasury (STN). Such information relates to all public expenditure made of state governments and the Federal District within the respective units of the federation. The variables used were corrected for inflation using INPC index from IBGE with 2007 as the base year.

Like the other public expenditures in Brazil, law enforcement is run by all the three levels of government: Federal, State and Municipality governments. However, as usually happens for all kind of expenditures in Brazil, the main responsibility lies with one of these levels. Law enforcement is a primary duty of state governments. In fact, the total amount spent on police in the Brazilian States in 2007 is about 88% made by the state governments.

[17] The national agency decided not to make public the figure for property crimes for some states after 2005. For that reason, this type of crime will be analysed over the period between 2001 and 2005.

[18] Murder are always intentional crimes whereas homicide comprises both voluntary and involuntary killing.

3.3 Poverty Rates and other Explanatory Variables

Poverty Rates and the other explanatory variables were constructed by aggregating state representative micro data of PNAD (National Survey of Household Sample by the IBGE - Brazilian Institute of Geography and Statistics) from 2001 to 2008. Besides poverty rates and extreme poverty rates, other poverty related measures are calculated. Poverty lines were determined as a function of minimum consumption levels.[19] The other variables considered are income inequality (GINI index), years of schooling, average labour income, unemployment rate, % of one-parent households, percentage of young males, informality degree in the labour market. I correct all the monetary variables for inflation using INPC index from IBGE with 2007 as the base year. Table A.1 in the appendix summarizes the description of each variable used in the estimates, and the origin of the data.

4 Empirical Framework

In this section I present the empirical relationships of interest. However, the main purpose of the following paragraphs is to discuss the inherent problems of estimating the effect of welfare programmes on crime rates.

The basic assumption is that CCT programmes affect poverty rates, as described by:

$$Pov_{it} = \alpha_i + \pi_t + \mathbf{w}'_{it}\sigma + \rho CCT_{it} + \tau_{it} \tag{4.1}$$

where Pov_{it} represents the poverty rate in each state i in a specific year t, CCT_{it} represents the amount per capita spent in cash transfers, $\mathbf{w}_{it}$ is a vector of covariates, α_i and π_t are respectively state and year fixed effects.

Furthermore, in order to pursuit principles of efficiency and fairness, the policymaker generally establishes a rule that assures more resources to the poorer regions. This fact establishes the following relationship:

$$CCT_{it} = \phi_i + \lambda_t + \mathbf{x}'_{it}\varrho + \theta Pov_{it} + \mu_{it} \tag{4.2}$$

where $\mathbf{x}_{it}$ is a vector of factors that can also affect the policy maker's allocation decisions, ϕ_i

[19]Poverty is measured here using the standard index (FGT index) suggested by Foster, Greer, and Thorbecke (1984): $P(\alpha) = (\frac{1}{N})\sum_{i=1}^{q}\left(\frac{z-y_i}{z}\right)^{\alpha}$, where N is the total number of households, y_i is the per capita income of the ith household, z is the poverty line, q is the number of poor individuals. With α=0, the FGT measure becomes the incidence of poverty index P(0) or simply the percentage of the population that is below the poverty line (poverty rate). With α=1 the FGT measure gives the poverty gap P(1), a measure of the average intensity of poverty. With α=2, the FGT index becomes the severity of poverty index.

and λ_t are respectively state and year fixed effects.

Consider now equation 4.3 that describes the determinants of crime rates[20], depending on expenditures on law enforcement[21], poverty rates and a vector with other control variables $\mathbf{z}_{it}$:

$$Crime_{it} = \psi_i + \omega_t + \mathbf{z}'_{it}\beta + \gamma Law_{it} + \delta Pov_{it} + \epsilon_{it}. \tag{4.3}$$

$Crime_{it}$ is one of the crime rates mentioned before: Murder, Homicide, Robbery, Theft and Kidnapping (per 100,000 inhabitants). Law_{it} is the total expenditure in law enforcement per capita, $\mathbf{z}'_{it}$ is a vector of socioeconomic variables, namely: income inequality (GINI index), years of schooling, average labour income, unemployment rate, % of one-parent households, informality degree in the labour market and ψ_i and ω_t are respectively state and year fixed effects.[22]

As discussed before, the underlying assumption is that individuals are maximisers of their respective expected utility, making rational choices in order to participate in the criminal sector in response to the costs and benefits of illegal activities, in relation to the alternative gain from the legal market. This specification attempts to capture the fact that the participation of an individual in criminal activities depends on the monetary return on these actions in relation to legal activities, the economic conditions under which the individual is living, their cultural and social condition (including the environment that he/she is surrounded) and the degree in which the police system is able to affect the likelihood of imprisonment and punishment.

One assuming exogeneity of the redistribution policy would ignore equation 4.2 and estimate the effect of cash transfers on crime rates after plugging equation 4.1 on equation 4.3. However, as it will be shown in the next section, an endogenous resources allocation should hold in most situations, leading to inconsistent estimates.[23]

Another confounding factor would raise if the cash transfers are assumed to affect crime rates directly (not only through poverty rates). That would account for any social altruism effect on the potential criminals, as the social program would make them perceive a real

[20]The theoretical and the empirical literature in the economics of crime converge for a similar specification. However, poverty rate is often omitted.

[21]Law enforcement itself must be endogenous due to the simultaneity with crime rates. This will be ignored for a while.

[22]There are at least three reasons to expect the presence of the terms of spatial and time unobserved heterogeneity ψ_i and ω_t. First, it is to be expected that there are unobserved heterogeneity such as cultural characteristics relatively stable over time, what makes some states to have higher crime rates than others. A second reason is to account for the presence of measurement error in the rates of crime. Time-specific effects common to all states, like changes in federal law, justifies the presence of ω_t.

[23]Another possibility would be to use CCT as an IV for Pov. That not only would generate inconsistent estimates as the measure of the effect of CCT on crime would be lost.

presence of the government in their lives. The benefit would then have an effect on the individuals' decisions beyond the monetary transfer. If this is the case, the error term in the equation 4.3 would be $\epsilon_{it} = \eta CCT_{it} + \zeta_{it}$. [24]

Therefore, in order to consistently estimate the effect of cash transfers on crime rates, these endogeneity problems must be taken into consideration.

5 Effect of Conditional Cash Transfer Programmes on Poverty

5.1 Will CCT always reduce Poverty?

The effect of CCT expenditures on Poverty is not obvious as it initially seems. One important reason is the simultaneity between poverty and this kind of policy. Poorer places often are focused in the distribution of resources, which creates a confounding factor in the analysis.

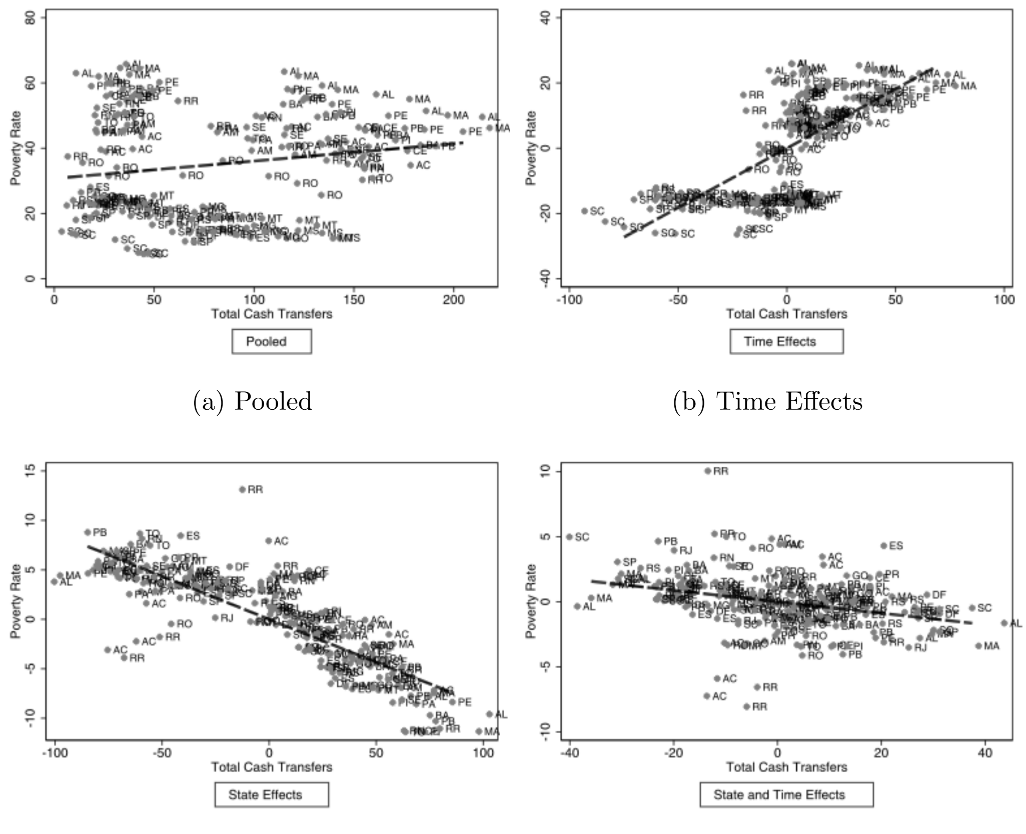
Another important issue is that more cash transfers may affect fertility and family formation decisions, diluting the expected reduction in poverty levels. It may also reduce the incentives to mothers to work, reducing the total income in the family. Although this type of governmental action will alleviate poverty, the additional resource will not necessarily make a poor family "non-poor" if it is very far below the poverty line.

5.2 A More Detailed Look on the Data

Figure 5.1 shows the correlations between CCT expenditures per capita and poverty rates across the Brazilian states between 2001 and 2008. By observing the very different correlations in each case, the reason for being careful in estimating the relationship becomes clear.

Figure 5.1a shows a positive correlation between cash transfers and poverty in the pooled data. When time effects are added, the relationship becomes stronger and with a higher slope (figure 5.1b). This suggests that once the time dimension is removed, higher poverty rates imply more money being spent on cash transfers.

[24] An alternative approach, where CCT is explicitly included in the crime equation, is also considered. Similar problems of endogeneity would arise.



(a) Pooled

(b) Time Effects

(c) State Effects

(d) State and Time Effects

Figure 5.1: Cash Transfers (per capita & adjusted for inflation) X Poverty Rate

However, when alternatively state specific effects are included, the relationship becomes negative, as show figure 5.1c. A similar result is obtained when both time and state effects are taken into account, but with a lower slope, as show figure 5.1d. This may indicate that once the state specific unobserved heterogeneity is removed more resources for cash transfers results in lower levels of poverty.

Table 5.1 presents the regression results for the cases illustrated, including average labour income as a control, in order to capture reductions in poverty due to improvements in the labour market. A negative and statistically significant coefficient prevails when time and state effects are considered.

Table 5.1: Effect of Cash Transfers on Poverty: State and Time Effects

	(1) Poverty	(2) Poverty	(3) Poverty	(4) Poverty	(5) Poverty	(6) Poverty
Cash Transfers	0.050**	-0.084***	-0.050***	0.361***	-0.042***	-0.029**
	(0.016)	(0.005)	(0.006)	(0.016)	(0.008)	(0.008)
Avg. Labour Income			-0.022***			-0.018***
			(0.008)			(0.004)
Constant	30.944***	41.965***	56.675***	-23.986***	39.358***	51.467***
	(1.971)	(0.544)	(3.015)	(2.513)	(1.101)	(4.196)
State Effects?	no	yes	yes	no	yes	yes
Time Effects?	no	no	no	yes	yes	yes
Observations	216	216	216	216	216	216
R^2	0.0251	0.6189	0.6033	0.5292	0.7598	0.6887

Notes: Standard errors robust to heteroscedasticity and clustering on state in parentheses.
p-values for the test for unobserved state, time and two-way effects, respectively: 0.0000 ; 0.0000; 0.0000.
Robust Hausman test rejects Random Effects: p-value=0.0001.
p-value test for heteroscedasticity = 0.0000. p-value of the test for strict exogeneity = 0.6597
Wooldridge test for autocorrelation in panel data does not reject H_0: no first-order autocorrelation: p-value=0.0894
*** p<0.01, ** p<0.05, * p<0.1

This analysis suggests that the association between cash transfers and poverty is negative and significant. The coefficients of the last equation correspond to elasticities of -0.0691 and -0.3929 for respectively Cash Transfers and Average Labour Income. However, as seen above, endogeneity is present in this relationship: because poorer states receive more cash transfers, this prevents any causal interpretation of the results. (In spite of the fact that fixed effects estimation may mitigate concerns about this problem as Besley and Case (2000)) argue.

Therefore, we need a source of exogenous variation to identify this effect. As shown in the next section, a specific characteristic in the timing of the distribution of the resources helps to identify the relationship between CCT spending and poverty rates.

5.3 Constructing exogenous variation of CCT programmes

As figure 5.2 show, some states had a more intensive change of total cash transfers (after Bolsa Familia Programme in 2004) than others. The guidelines of Bolsa Familia programme established that the amount of resources available for each state should be based on the poverty levels in 2000. However, by reasons unrelated to poverty levels and crime rates (as it will be shown below), some states were able to implement the programme to a greater extent more quickly than others.

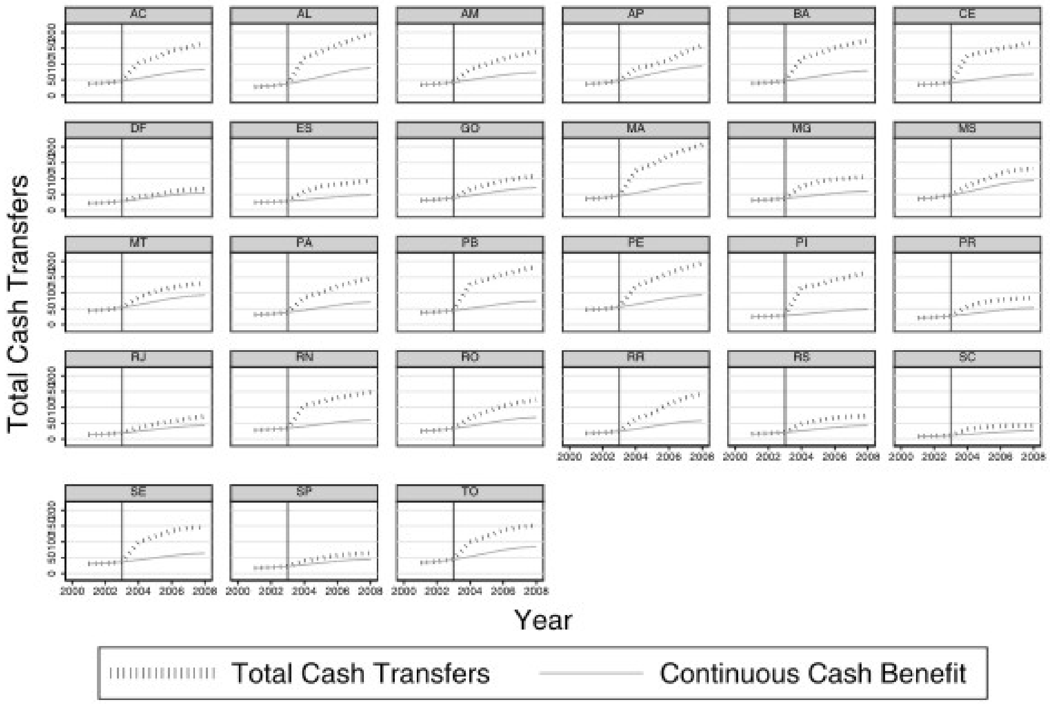
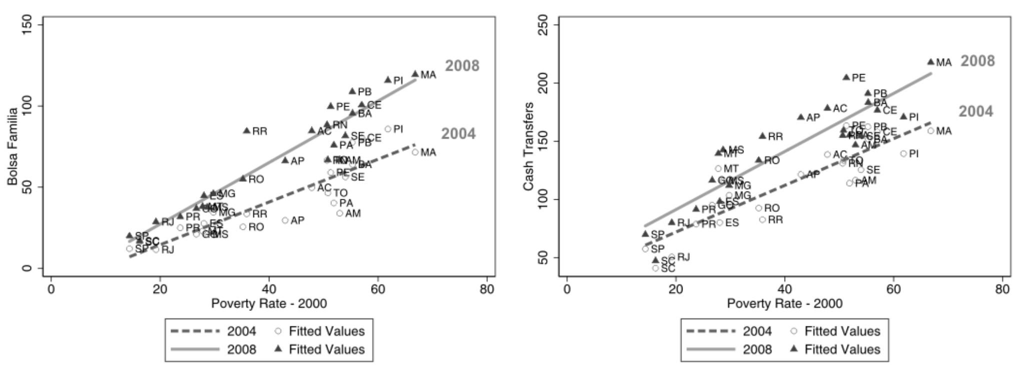


Figure 5.2: Total Cash Transfers over time by State

Another way to see this is to observe that some states had a significant increase in cash transfer spending in the 2004 with the beginning of *Bolsa Familia* programme. Those states had a smaller variation in cash transfers between 2004 and 2008 than the states that had a "late" start.



(a) Bolsa Familia

(b) Total Cash Transfers

Figure 5.3: Poverty Rates in 2000 X Cash Transfers Spending (per capita & adjusted for inflation)

Because the guidelines of the programme establishes that the amount of resources for each state depends on the poverty levels of the 2000 census, it is interesting to examine the relationship between poverty rates in 2000 and Cash Transfers expenditures in 2004 and 2008.

In a situation of perfect implementation of the programme according to its guidelines, this relationship would be a graph proportional to a 45 degrees line.[25] However, in 2004 many states spend less than they were supposed to be spending. The resources were available from the federal government, but because some states and local governments were not able to register all eligible recipients, the money was not fully spent. Note that in 2008 most states reach the full implementation of the programme.

Figure 5.4 presents the distribution of variation in *Bolsa Familia* between 2004 and 2008. The variation in CCT spending between 2004 and 2008 was between 40% and 150% and 5 out of 27 states had variation above 100% or above the 75th percentile of the distribution.

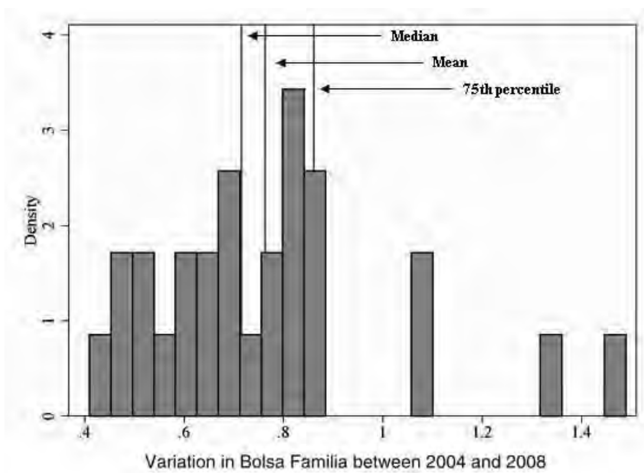


Figure 5.4: Distribution of variation in Cash Transfers between 2004 and 2008 (per capita, adjusted for inflation)

This heterogeneity results from different operational capabilities and efforts among states. On one hand, it is possible to argue that states with higher poverty rates would be more determined to implement the programme as soon as possible. On the other hand, it is likely that states with a higher relative number of poor individuals would face more difficulties to identify and register all eligible families. As it is discussed below, poverty rates do not seem to have played a significant role in the promptness of the execution of the programme. The efficiency of the local governments and political issues in the states were more likely to

[25]Strictly speaking, because the amount of money varies with the number and age of children in a family, the present graph would never be a perfect 45 degrees line. However, this is a good approximation to convey the idea of compliance.

determine the speed of the implementation.

In order to take advantage of this heterogeneous variation in the implementation in CCT to analyse its effect on poverty, define D_i as:

$$D_i = \begin{cases} 1, & \text{if } CCT \text{ gap in state } i \text{ in 2004 is below 75th percentile value (Low Gap)} \\ 0, & \text{otherwise (High Gap)} \end{cases} \tag{5.1}$$

And defining pov_1 to be the poverty rate before the beginning of the programme (2004) and pov_2 poverty rate to after the programme started, the differences-in-differences (DD) estimator in this context can be defined as:

$$\hat{\delta} = (pov_2^{lowgap} - pov_1^{lowgap}) - (pov_2^{highgap} - pov_1^{highgap}) \tag{5.2}$$

The DD estimate $\hat{\delta}$ can be obtained by estimating:

$$pov_{it} = \alpha + \beta D_i + \gamma 1(AfterProgramme)_t + \delta D_i \cdot 1(AfterProgramme)_t + \varepsilon_{it} \tag{5.3}$$

or equivalently:

$$pov_{it} = \alpha + \delta D_i \cdot 1(AfterProgramme)_t + \phi_i + \lambda_t + \varepsilon_{it} \tag{5.4}$$

where ϕ_i and λ_t are state and time effects, respectively.

A crucial assumption in the DD framework is that λ_t is common across "treated" and "untreated".[26] This assumption can be tested by running the following regression:

$$pov_{it} = \alpha + \delta D_i \cdot 1(AfterProgramme)_t + \psi_i t + \phi_i + \lambda_t + \varepsilon_{it} \tag{5.5}$$

In the case of poverty, significant values for ψ_i and and insignificant value for δ tell us that the dependent variable would be declining even without treatment. In any case, the pre-treatment data must establish a clear trend that can be extrapolated into the post-treatment period.

Table 5.2 displays the averages for the relevant variables for both high and low variation in CCT expenditures between 2004 and 2008.[27]

[26] See Cameron and Trivedi (2005) and Angrist and Pischke (2009) for further discussion.

[27] Imbens and Wooldridge (2008) highlight the importance of comparing descriptive statistics in this setting.

Table 5.2: Selected variables for different levels in the implementation of Bolsa Familia

	Whole Sample			2003-2004		
	Low Gap ($D_i = 1$)	**High Gap** ($D_i = 0$)	**t-test on diff.**	**Low Gap** ($D_i = 1$)	**High Gap** ($D_i = 0$)	**t-test on diff.**
Murder Rate	20.8405	28.4798	-4.52	19.9952	27.7501	-2.51
Homicide Rate (Health)	24.1419	34.1217	-5.72	23.7479	33.2542	-2.76
Robbery Rate	352.6788	379.1966	-0.54	341.8772	392.7397	-0.66
Theft Rate	1130.9132	1037.4245	0.74	1160.1571	1011.8172	0.67
Kidnapping Rate	0.3667	0.3482	0.17	0.3339	0.2698	0.47
Poverty Rate	0.3495	0.3573	-0.31	0.3894	0.3991	-0.18
Extreme Poverty Rate	0.1407	0.1356	0.36	0.1653	0.1634	0.06
Gini Index	0.5572	0.5447	1.85	0.5616	0.5488	1.23
Average Labour Income	742.1845	749.7728	-0.17	703.7415	716.9822	-0.16
Informality Labour Market	56.1774	55.7940	0.22	56.7759	56.7265	0.01
Single-Parent Households	0.2764	0.2877	-1.46	0.2763	0.28968	-1.08

Notes: High Gap and Low Gap as defined in equation 5.1.

Apart from murder and homicide rates, all other variables have no significant differences between the groups, corroborating the assumption that this variation was exogenous in this context.[28] Table A.2 in the appendix presents the regression of poverty rates in 2001 on the variation in CCT expenditures between 2004 and 2008. No statistical significance is found in the relationship, whereas a similar regression on the variation in the spending between 2003 and 2004 is positive and significant.[29]

5.4 Effect of CCT on Poverty

Figure 5.5 presents the effects of CCT on Poverty for different levels of variation. The reduction of poverty is slightly stronger for states that had a faster increase in total cash transfers after the program *Bolsa Familia*.

The estimation of differences-in-differences effect described by equation 5.3 is presented by table 5.3.[30]

[28] A possible variable related to this variation is the degree of efficiency or bureaucracy in each state, a priori, unconnected with the variables in consideration.

[29] Figure B.1 in the appendix presents the spatial distribution of these variables, which also corroborate this idea.

[30] One possible alternative would be to use $D_i * AfterProgramme_t$ as an instrumental variable for Pov_{it} in the crime equation. However, this approach would make the measure of the effect of CCT on crime to be lost.

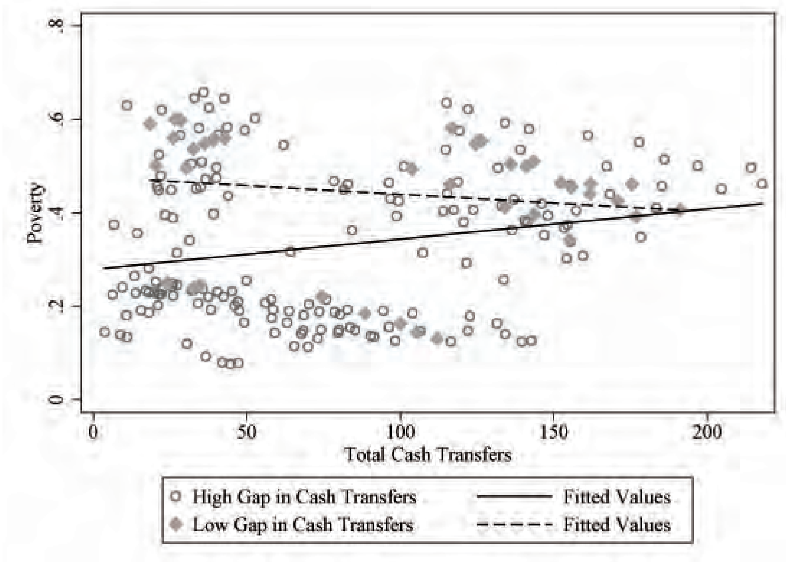


Figure 5.5: Poverty X Cash Transfers for different levels of variation in Cash Transfers

Table 5.3: Poverty Rates for different levels in the implementation of *Bolsa Familia* Program, before and after 2004

	Low Gap ($D_i = 1$) (i)	**High Gap** ($D_i = 0$) (ii)	Difference: (i) - (ii) (iii)
Poverty Rate **Before** 2004	0.3960***	0.3809***	0.0150
	(0.0213)	(0.0360)	(0.0437)
Poverty Rate **After** 2004	0.3217***	0.3378***	-0.0161
	(0.0159)	(0.0275)	(0.0223)
Change in Poverty	-0.0742***	-0.0430***	-0.0312***
	(0.0263)	(0.0452)	(0.0135)

Notes: Standard errors robust to heteroscedasticity and clustering at the state level in parentheses.
High Gap and Low Gap as defined in equation 5.1.
Similar results for D_i defined using mean and median as threshold.
Similar significance when standard errors are bootstrapped. Number of obs. before: 81, after: 135
Without considering groups, the total decline in poverty was -0.0672 (-6.72 perc. points).
*** p<0.01, ** p<0.05, * p<0.1

Table 5.4: Effect of Cash Transfers Programme: Alternative Specifications

Left hand side variable:	(1) Poverty	(2) Extreme Poverty
State-specific trends as controls	-0.0434**	-0.0255**
(Equation 5.5)	(0.0253)	(0.0132)
Median as threshold	-0.0306***	-0.0214***
	(0.0105)	(0.0098)
2003/2004 comparison	-0.0354*	-0.0283**
	(0.0184)	(0.0151)
Socio-economic variables as controls	-0.0216**	-0.0194**
	(0.0109)	(0.0088)
Intensity of Poverty as Control	-0.0312***	-0.0256**
(P(1) - Distance from Poverty Line)	(0.0127)	(0.0092)
Poverty in 2001 as Control (No Fixed Effects)	-0.0321**	-0.0199**
	(0.0141)	(0.0089)
Poverty in 2001/2003 as Control (Fixed Effects)	-0.0298**	-0.0201***
(Poverty in 2001 if year $\leq$ 2002, 2003 if year $\geq$ 2003)	(0.0142)	(0.0097)

Notes: Standard errors robust to heteroscedasticity and clustering at the state level in parentheses.
Similar significance when standard errors are bootstrapped.
"Poverty" reads "Extreme poverty" for control variables in column (2).
All controls used are significant at least at 0.05 level.
*** p<0.01, ** p<0.05, * p<0.1

The estimate of the relevant parameter δ is -0.0312. This 3.12 percentage points represents approximately an additional reduction of 7.5% in poverty rates in states that distributed the resources of CCT more quickly. It is a sizable magnitude, but it is even more significant if it is taken into consideration that the programme is also present in the "control" states. It is worth noting that poverty rates are not statistically different between the groups.[31]

Table 5.4 displays alternative procedures in the estimation of δ in order to check the robustness of the results.[32]

Similar effects are found when variations and percent variations are used, as well as other thresholds to define the levels of gap. The estimated δ does not vary significantly to

[31] It should be noticed that because the number of clusters is 27, the underlying statistical test can over-reject the significance of the coefficients. As suggested by Cameron, Gelbach, and Miller (2008), I use bootstrapped standard errors to mitigate this problem.

[32] Reporting a sensitivity analysis in this context is essential to the legitimacy of the results as pointed out by Angrist and Pischke (2010).

the addition of different covariates, providing additional evidence of the exogeneity of the variation of the CCT expenditures between 2004 and 2008 relative to poverty.

It is also possible to argue that these results are based on a convergence effect, where poorer states would improve faster anyway. In order to control for that, three strategies are considered. The first controls for intensity of poverty - P(1)[33], which is a measure of distance from poverty line. The second one uses poverty rates in 2001 as a control. However this has the downside of preventing the use of fixed effects, since it is a constant over time. To get around this issue a slightly different approach is considered. In this third way, a new variable is defined so that it assumes the values of 2001's poverty rates if the year is before 2002 (inclusive) and 2003's values if the year is after 2003 (inclusive). In all cases, the estimates of the effort of cash transfers on poverty rates are quite similar to the previous approaches.

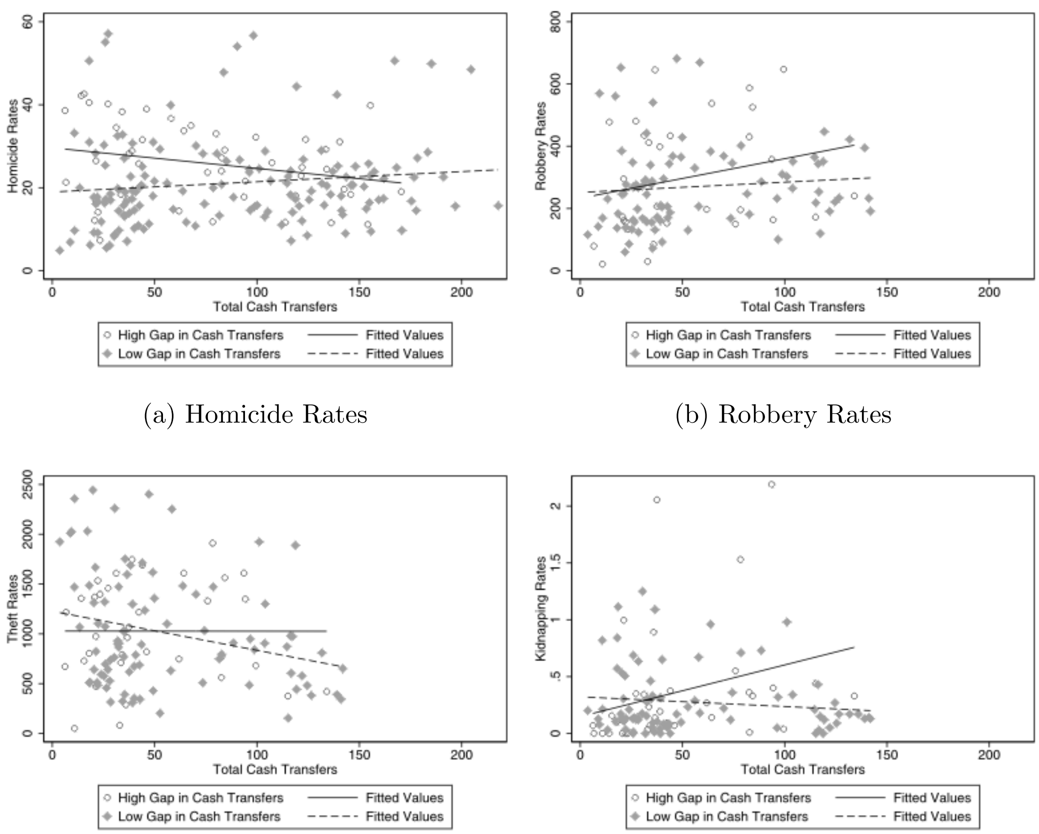
This relative robustness corroborates the assumption of random distribution of states into the different speeds of implementation of the program and consequently the causal interpretation of the estimates.

Because the values of extreme poverty are generally less than half of those of poverty and the estimated coefficient have similar sizes, the effect of CCT on extreme poverty is much more intense. This corroborates the hypothesis that many people are still poor even after receiving the benefit.

[33] As defined in subsection 3.3.

6 Estimating the Impact of CCT on Crime

The following figures show the association between crime rates and cash transfers for states with different speeds in the implementation of *Bolsa Familia* programme as defined by equation 5.1.



(a) Homicide Rates

(b) Robbery Rates

(c) Theft Rates

(d) Kidnapping Rates

Figure 6.1: Crime rates X Cash Transfers: Different levels of variation in Cash Transfers *Bolsa Familia*

Figure 6.1a shows a weak positive relationship between Homicide and Cash Transfers and no significant difference between high and low treatment.[34] There is also a positive association for Robbery, however with a significantly smaller slope for states with faster spending (Figure 6.1b).

In the case of theft and kidnapping rates, different relationships between crime and Cash Transfers for different levels of treatment emerge: increased cash transfers is associated with lower theft and kidnapping rates for states with lower gap in CCT (Figures 6.1c and 6.1d).

[34]Very similar picture for murder rates (not reported here).

The estimation of the effect of CCT on crime rates using the differences-in-differences (DD) framework used in the previous section is presented in table 6.1.

Table 6.1: Crime Rates for different levels in the implementation of *Bolsa Familia* Program, before and after 2004

	(1) Murder	(2) Homicide	(3) Robbery	(4) Theft	(5) Kidnapping
75th percentile as threshold in D_i	-0.739	-0.489	-39.525**	-43.685*	-0.066*
	(3.183)	(0.307)	(21.561)	(26.426)	(0.043)
Median as threshold in D_i	2.779	4.623	-16.809*	-37.849	-0.109**
	(2.779)	(2.955)	(9.033)	(55.590)	(0.062)
2003/2004 comparison	-0.328	-0.399	-52.581	-81.932	-0.701*
	(0.424)	(0.831)	(135.563)	(91.477)	(0.413)
Socioeconomic variables as controls	-1.125	-1.692	-8.511	-56.145*	-0.064
	(3.220)	(2.838)	(13.981)	(30.436)	(0.228)

Notes: Standard errors robust to heteroscedasticity and clustering at the state level in parentheses.
Similar significance when standard errors are bootstrapped.
All controls used are significant at least at 0.05 level.
*** p<0.01, ** p<0.05, * p<0.1

Significant negative effects are found for robbery, theft and kidnapping for some definitions of low gap in the implementation of the programme. However, they are not robust as different specifications are estimated.

7 Conclusions

Heterogenous implementation of *Bolsa Familia* programme is used in order to identify the effect of this CCT programme on poverty and crime rates. *Bolsa Familia* has a significant effect on poverty reduction. States that reached the level of cash transfers expenditures proposed by the guidelines of the programme more promptly had a more significant reduction in poverty rates. However, many recipients of the programme are still below the poverty line.

Some results suggest that CCT expenditures contribute to reduction in robbery, theft and kidnapping rates, while no significant effect was found for homicide and murder. These findings indicate that property crime would be more sensitive to CCT programmes. However, the results are not robust to different specifications. The positive or insignificant effect for the other types of crimes may suggest that the proposed approach is not efficient to correct the endogeneity problems in the crime equations.

Another possibility might be related to the fact that many people receiving the benefits are still poor or below a threshold of "acceptable" income, making the illicit activities still worth the risk. Moreover, two other parallel effects might dominate the relationships. More cash transfers may reduce willingness to work, increasing the probability of involvement with illicit activities. It may also positively affect informality to the detriment of formal labour, in the situations where the family would lose the benefit otherwise. This may put individuals in contact with people that commit petty crimes affecting their probability of involvement in criminal activities.

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A Additional Tables

Table A.1: Definition and Sources of Variables

Variable	Description	Source
Murder	Murder Rate (100,000 inhabitants)	SENASP
Homicide	Homicide Rate (100,000 inhabitants)	Health Ministry
Robbery	Robbery Rate (100,000 inhabitants)	SENASP
Theft	Larceny Rate (100,000 inhabitants)	SENASP
Kidnapping	Kidnapping Rate (100,000 inhabitants)	SENASP
Poverty	People below poverty line (%) (IPEA)	IPEA/PNAD
Extreme Poverty	People below extreme poverty line (%) (IPEA)	IPEA/PNAD
Gini	Income Gini Coefficient	IPEA/PNAD
Labour Income	Mean Per capita Household Income from Labour (INPC corrected - R$ 2007)	IPEA/PNAD
Education	Mean number of years of schooling (people aged 25 or more)	IPEA/PNAD
Young Male	Percentage of male aged between 15 and 24 in relation to all population	PNAD
Unemployment	Unemployment Rate	PNAD
Parent	Percentage of households with only one parent (Female Headed)	PNAD
Informality	Informality degree in the labour market (%)	PNAD
Law Enforcement	Per capita government expenditure on law enforcement (INPC corrected - R$ 2007)	STN
Cash Transfers	Per capita government expenditure on Bolsa Familia and Continuous Cash Benefit (INPC corrected - R$ 2007)	MDS, Portal da Transparência
Revenue	Per capita Tax revenue of the States (INPC corrected - R$ 2007)	STN

Notes: All variables constructed by the author with data from the mentioned sources.
SENASP - *Secretaria Nacional de Segurança Pública* (National Secretariat of Public Security)
IPEA - *Instituto de Pesquisa Econômica Aplicada* (Institute of Applied Economic Research)
PNAD - *Pesquisa Nacional por Amostra de Domicílios* (National Survey by Household Sampling)
STN - *Secretaria do Tesouro Nacional* (National Treasury Secretariat)
TSE - *Tribunal Superior Eleitoral* (Supreme Electoral Court)
MDS - *Ministério do Desenvolvimento Social e Combate à Fome*
(Ministry of Social Development and Hunger Eradication)

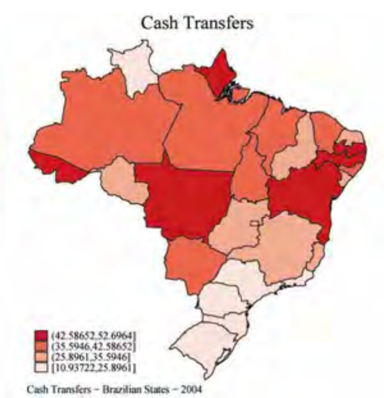
Table A.2: Effect of Poverty on the lag in the implementation

	CCT perc. var. 04/08	CCT perc. var. 04/08	CCT perc. var. 03/04	CCT perc. var. 03/04
Poverty in 2001	-0.4114		0.4489***	
	(0.3145)		(0.0907)	
Poverty		-0.2737		0.4029***
		(0.3748)		(0.0869)
Constant	0.9251***	0.8376***	0.3849***	0.4065***
	(0.1326)	(0.1128)	(0.0382)	(0.0363)
R^2	0.0266	0.0209	0.4944	0.4623

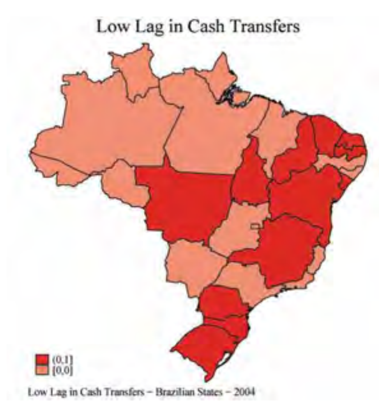
*** p<0.01, ** p<0.05, * p<0.1

B Additional Figures

(a) Poverty Rate



(b) Cash Transfers



(c) Gap in CCT Variation

Figure B.1: Poverty, Cash Transfers and lag in its variation in Brazil - 2004 (Classes based on quartiles)