Conditional Cash Transfers and Crime: Higher Income but also Better Loot

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Abstract: We analyze the impact of conditional cash transfer programs on crime. We present evidence that welfare payments in cash significantly increase criminal activities. We exploit the exogenous increase in the payment and the number of beneficiaries given by a major reformulation of the CCT program in Uruguay. The increase in crime is exclusively observed in property crime suggesting the impact is driven by economic reasons. Our findings suggest that more cash available in the streets improves the loot from crime and thus increases the incentives for criminal activities.

Keywords: Conditional cash transfers, crime, income effect, loot.
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1. Introduction

Since the end of the nineties, conditional cash transfer (CCT) programs spread allover the world. According to World Bank (2009), more than 30 countries have implemented CCT programs in which families receive government payments upon fulfillment requirements on schooling and health status checks. Uruguay was not an exception and the government introduced a CCT program in April 2005 targeted to people with income below the extreme poverty line (roughly 6 percent of the total number of households). In January 2008, after a reformulation of the CCT program the number of beneficiaries and the amount of money given was significantly expanded: the cash payment doubled for a typical Uruguayan family and the number of beneficiaries increased by 15 percent.

In this paper we exploit this exogenous increase in the payment given by the 2008 reformulation of the program in order to analyze the impact of the CCT programs on crime. We present evidence that welfare cash payments significantly increase criminal activities. The increase in crime is exclusively observed for offenses that have a financial motivation (property crimes such as thefts and robberies) and not for other types of offenses (non-property crimes such as assaults and domestic violence) suggesting the impact is driven by economic reasons.

Becker (1968) postulates that agents decide whether to engage in criminal activities by comparing the financial reward from crime and the return from legal activities. Under this framework, the welfare transfer produces a positive income effect that allows households to purchase goods and thus it reduces the incentive to engage in economically motivated crimes. Alternatively, welfare payments may precipitate crime by encouraging recipients to expend their resources prematurely, leading them to turn to commit crime to supplement their income for the remainder of the month (Foley 2011).

At the same time, welfare recipients who have just cashed the money represent especially attractive targets for potential offenders in the streets (Wright and Decker 1997). The rationale is straightforward: the higher the loot the more attractive the criminal activity. More cash available in the streets improves the loot from crime and thus increases the incentives for criminal activities. Cash usually plays a relevant role in fueling street crime due to its liquidity and transactional anonymity. Criminologists argued that street crime is motivated by a perceived need for cash to finance hedonistic activities (Wright and Decker 1994 and 1997; Shover 1996). The value of the liquidity and transactional anonymity of cash are critical to the functioning of the underground economy (Varjavand 2011).

Previous empirical evidence on the impact of welfare payments on crime suggests that the positive income effect on potential offenders is relevant to reduce crime rates. DeFronzo (1996, 1997), Zhang (1997), Hannon and DeFronzo (1998), and Jacob and Ludwig (2010), report that welfare payments significantly decrease arrests in the US. In the same line, Camacho and Mejía (2013) and Chioda et al. (2012) find a negative impact of the CCT program on crime in Colombia and Brazil respectively. In all these cases the welfare transfer was delivered as a credit in individual accounts. In sharp contrast, in Uruguay the welfare payment is given in cash. Our results suggest that better loot in the streets outperforms the positive income effect associated to the welfare payment, and therefore, it has a positive impact in the aggregate crime rates. In the same line, recent evidence suggests that less cash available in the streets, in response to the change in the delivery of welfare transfers from cash to debit cards, significantly reduced crime rates in the US (Wright et al. 2014).

More generally, our paper contributes to the literature on the economic and social effects of the CCT programs. In addition to the natural impact of reducing the number of household below the poverty line and improving the income distribution, CCT programs usually have positive impacts on health care and school enrollment rates (Schultz 2004; Rawlings and Rubio 2005; Fiszbein and Schady 2009; Amarante et al. 2011). CCT programs may also have undesired social consequences such as reduction on the incentives to work in the formal sector due to the fear of losing the conditional transfer. According to the empirical evidence, this is not true in several experiences in Latin America (Fiszbein and Schandy 2009; Alzúa et al 2013). However, Borraz and González (2009) find negative effects on the labor market in the urban areas of Uruguay. These results are consistent with Amarante and Vigorito (2010) who also find that beneficiary households have a lower probability of contribution to social security. In the same line, Marluccio and Flores (2005) find a significant negative impact on hours worked by adult men in Nicaragua. CCT programs also have political effects. Manacorda et al. (2011) find that the CCT program in Uruguay significantly increases the political support for the government that implemented it relative to the previous government.

The paper continues as follows. Section II describes the data and presents the statistical methods. Section III reports the results. Section IV concludes.

2. Data and Methods

Data

We exploit the database of the Police Department, which includes the universe of criminal incidents recorded in Montevideo: more than 550,000 offenses reported between April 2005 and December 2010. We focus on the three most frequent types of crime: theft, robbery, and assault. This subset of crimes comprises 77 percent of the total number of police-recorded offenses in Montevideo. Theft is defined as depriving a person of property without the use of violence (60 percent of the offenses), whereas robbery is defined as depriving a person of property with the use of violence or threat of violence (10 percent of the offenses). Assault is an intentional physical attack against another person (7 percent of the offenses). We label theft and robbery as property crimes and assaults as non-property crimes.

We also gather information from *Banco de Previsión Social* (the public agency responsible of the payment of the CCT program) and the *Instituto Nacional de Estadística* (the bureau in charge of socioeconomic statistics) on the date and the amount of the payment of every CCT in Montevideo between 2005 and 2010.

Finally, the socioeconomic information on each beneficiary household such as schooling, labor income and housing characteristics come from the annual Uruguayan household survey conducted by *Instituto Nacional de Estadística*.

Montevideo (1.5 million inhabitants) is divided into 24 police jurisdictions. Each of these jurisdictions corresponds to the union of several neighborhoods in the city. Since Montevideo has an area of 540 square kilometers, the police jurisdictions have an average area of 22.5 square kilometers, or a square of 47 city blocks on each side. Although these regions are fairly large, most of the economic activity in each police jurisdiction is concentrated in a much smaller area. Since 60 percent of Montevideo is rural, the effective size of each police jurisdiction is much smaller than the 22.5 square kilometers mentioned above.

In Table 1 we present the summary statistics for the data. All the variables are defined at the police jurisdiction level from April 2005 to December 2010. Therefore we have a panel data set with 1,656 observations (68 months in 24 police jurisdictions). The variable beneficiary indicates the number of beneficiaries of the CCT program in thousands at each police jurisdiction (mean is a simple average). We observe an important difference between the mean and the median of beneficiaries. This can be explained by the concentration of household beneficiaries in police jurisdictions. In particular seven out of ten beneficiaries are concentrated in six police jurisdictions. Property crime and non-property crime is defined at the police jurisdiction level; population is defined at the police jurisdiction level and measured in hundred thousands of inhabitants; per capita income is defined at the police jurisdiction level and measured in October 2014 constant Uruguayan pesos (simple average); the unemployment rate is also at the jurisdictional level (simple average).

Table 1. Summary statistics

	Mean	Median	St. Dev	Min.	Max.	Obs.
Beneficiaries (thousands)	4.37	1.20	4.83	0.24	17.49	1,656
Property Crime	242.55	238.00	105.59	4.00	657.00	1,656
Non-property Crime	22.55	20.00	14.12	0.00	11.00	1,656
Population (thousands)	50.67	49.12	26.15	6.10	114.56	1,656
Per Capita Income (thousands of Oct-2014 UR$)	10.73	8.94	7.96	2.19	40.23	1,656
Unemployment Rate	8.68	8.36	2.84	0.88	19.99	1,656

Methods

We analyze the effect of welfare cash transfers on crime. The main identification concern of the causal effect of cash transfers on crime is that the CCT programs are targeted to vulnerable socioeconomic neighborhoods, which, in turn, can be positively correlated with crime. Poorer neighborhoods have higher transfer coverage and also higher crime rates. To deal with this problem, we exploit an exogenous variation in the number of beneficiaries and in the amount of the transfer of the CCT program in Uruguay.

In Uruguay, the first stage of the CCT program (called *Ingreso Cuidadano*) was implemented in order to reduce extreme poverty rates observed after the 2002 crisis when the GDP decreased by more than 10 percent. A monthly cash transfer per household of $56 (expressed in 2005 US dollars, the amount of money needed to purchase a basic food basket) was given to the beneficiaries conditioned on school attendance and regular health status control for each child of the household.[2]

This program was in effect for only two years and a half, as the government did not want to be perceived as a one that gives money without counterparts as long as there was no effective control on school attendance and regular health status checks.[3] However, because of political reasons the government did not want to eliminate the subsidies.[4]

The second stage of the CCT program (called *Plan de Equidad*) introduced in January 2008 was a reformulation of an old program (called *Asignaciones Familiares)* created in 1942 with a substantial increase in the cash payment from about $56 to $110 and an increase of 15 percent in the number of beneficiaries.[5] The amount given shifts from a lump sum to a variable payment according to the following formula: Cash transfer = $\$47*(\text{Number of kids})^{0.6} + \$14*(\text{Number of kids in high school})^{0.6}$. For example, for a family with two kids in primary school and one in high school the total payment equals to $\$105=(\$47(3)^{0.6} + \$14(1)^{0.6})$. Those households receiving the original transfer according to the April 2005 program were automatically transferred to the new extended CCT program.

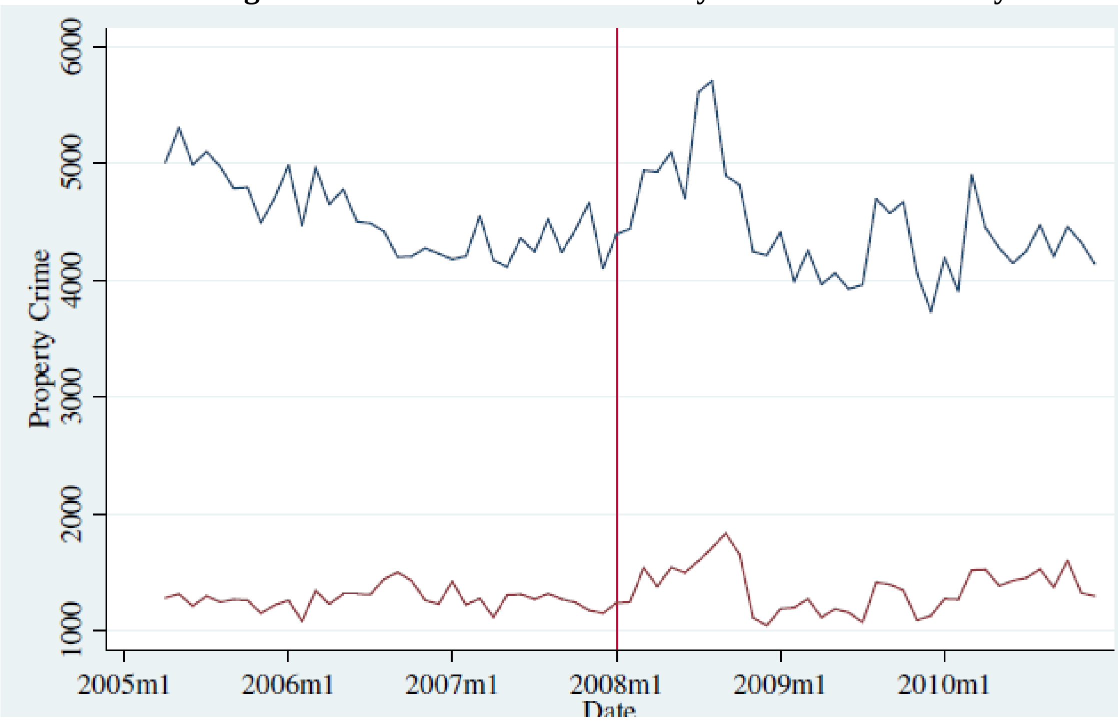
[2] For a complete description of the CCT program see Amarante et al. (2013) and Borraz and González (2009).
[3] According to Amarante et al. (2013) the conditionality's on school attendance and health checkups were not enforced.
[4] Manacorda et al. (2011) show the support to the government significantly increases after being one of the beneficiaries of the CCT program.
[5] In the case of disadvantaged kids the payment quadruples.

This significant change in the Uruguayan CCT program was not explained by economic variables. In fact, GDP per capita growth was more than six percent in 2007, a year before the extension of the program.

Additionally, the law 17.869 that create the first CCT program in 2005 clearly states that it was a temporary poverty relief program running from April 2005 to December 2007. Moreover, according to Amarante and Vigorito (2010), survey data (carried out from December 2006 to March 2007) show that 61 percent of the beneficiaries knew that the program will come to an end, 37 percent did not know and only 2 percent believed it would not finish.

However, one concern is that the expansion of the CCT program is explained for the increase in crime. It is possible that the government may have implemented the program to counteract crime to a certain degree even if people knew the program would come to an end. For example the Colombian CCT program (*Familias en Acción*) has a clear crime objective. We address this issue showing in Figure 1 data on trends in crime rate in high beneficiaries' areas (judicial sections 16 to 19, 21 and 24) and in the rest of the areas. We observe that in fact crime was decreasing in both areas before the extension of the program. In 2007, whereas the decrease in crime was 4 percent in the areas with high intensity of beneficiaries, the decrease was 1 percent in the areas with low intensity of beneficiaries.

Figure 1. Crime evolution in time by beneficiaries' density



Note: The blue line shows property crime in high beneficiaries' areas (judicial sections 16 to 19, 21 and 24). The red line shows property crime in low beneficiaries' areas. The red vertical line indicates when the program was expanded

For these reasons, this important change in Uruguayan CCT program can be considered as exogenous. Also relevant for our identification strategy, there were no legal modifications affecting the expected level of punishment for crime in 2008.

Therefore, in order to estimate the impact of CCT program on crime we follow an approach based on the idea that the second stage of the CCT program provides an exogenous source of variation in the distribution of beneficiaries across regions (police jurisdictions). Once this variable was computed, the following step was to analyze crime variations in police jurisdictions with different incidence of CCT beneficiaries before and after the second stage of CCT program. This difference-in-difference methodology that controls not only for selection bias due to observable characteristics but also to unobservable characteristics that remain constant along the time (Abadie 2005; Athey and Imbens 2006; Donald and Lang 2007) leads us to the following equation:

$$Y_{st} = \alpha_0 + \alpha_1\, Post2008_t + \alpha_2\, CCT_{st} + \alpha_3\, Post2008{*}CCT_{st} + \varphi\, X'_{st} + \mu_s + \mu_m + \mu_y + \varepsilon_{st} \qquad (1)$$

$$s = 1, \ldots, 24; \text{ and } t = \text{April 2005 to December 2010}$$

where Y_{st} is the outcome variables (in this case property crime and non-property crime) for police jurisdiction s, at time t; $Post2008_t$ is a dummy variable that takes the value of one in the second stage of the CCT program and zero otherwise; CCT_{st} is the number of beneficiary households in police jurisdiction s, at time t (it is useful to distinguish police jurisdiction that are sensible to CCT change from those who are not); $Post2008{*}CCT_{st}$ is the interaction of the last two variables; X'_{st} represents the control variables for police jurisdiction i, at time t (population, per capita income and unemployment rate); μ_s is a police jurisdiction fixed effect; μ_m is a month dummy (January to December); $\mu_{y\ is}$ year dummies (2005 to 2010), and, finally, ε_{st} is the error term, which varies across police jurisdiction and time. Our parameter of interest is α_3, and it captures the causal effect of the CCT program on property crime.

One concern of this strategy is the fact that the error term ε_{st} could be divided into a component that varies across police jurisdictions and another that varies at the police jurisdiction–time. In order to consider this error structure in the estimation of the standard error of our main estimator, we applied the commonly used robust-clustered standard errors at the police jurisdiction level.

As a robustness check we estimate placebo test and we estimate equation (1) with non-property crime as the dependent variable. We expect to find no impact of the CCT program on non-property crime.

3. Results

Table 2 presents the main regressions of our analysis. In each case, the dependent variable is property crime in police jurisdiction s at time t; the independent variables include the number of beneficiaries (in thousands) of the CCT program in police jurisdiction s in period t; population (in thousands), per capita income and the unemployment rate in police jurisdiction s in period t.[6] We estimate our empirical model using a panel fixed effect regression.

Table 2. Impact of the CCT program on property crime

Panel Data Fixed Effect Model Dependent variable: property crime					
Variables	(1)	(2)	(3)	(4)	(5)
Beneficiaries	-3.343	-3.872	-3.789	-4.028	-3.962
	(3.993)	(4.093)	(4.057)	(4.121)	(4.091)
Dummy Post 2008	-9.319	-8.791	-17.055	-33.788***	-18.777
	(10.783)	(10.870)	(13.265)	(10.821)	(12.738)
Beneficiaries * Dummy Post 2008	3.595***	3.708***	3.325**	3.677***	3.289**
	(1.219)	(1.249)	(1.287)	(1.253)	(1.290)
Population		-0.256	-0.237	-0.255	-0.236
		(0.159)	(0.161)	(0.159)	(0.160)
Per Capita Income			-0.003***		-0.003***
			(0.001)		(0.001)
Unemployment Rate				-0.390	-0.434
				(0.575)	(0.565)
Constant	267.891***	282.383***	292.916***	287.733***	298.910***
	(16.901)	(20.034)	(19.642)	(20.734)	(20.512)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year and Month Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,656	1,656	1,656	1,656	1,656
Number of jurisdictions	24	24	24	24	24

Clustered standard errors in parentheses at the jurisdiction level
* significant at 10 percent level; ** significant at 5 percent level; *** significant at 1percent level

[6] In order to concentrate on the main results, the dummy variables for year, months and jurisdictions effects are omitted from Table 2.

In the case without controls (see Table 2, column 1) we find a positive a significant effect of the number of beneficiaries of the CCT program on property crime. We estimate that per 1,000 beneficiaries in the neighborhoods of the police jurisdictions there are, on average, more than 3.5 new property crimes. Given that the average property crime is 243, the CCT program increases property crime by 1.4 percent (3.5/243*100).

This results remains almost unchanged when we include control variables (see Table 2 columns 2-5). We find that per capita income is significant and negatively correlated with crime, and population and unemployment rate are not significant.

In order to ensure the causal interpretation of the results, we run two placebo exercises. First, we run the same model for non-property-crime. As expected, we find no relationship between CCT beneficiaries and non-property crime in the panel date fixed-effect regression model without controls (see Table 3, column 1) and in the model including controls (see Table 3, columns 2-5).

Table 3. Impact of the CCT program on non-property crime

Panel Data Fixed Effect Model					
Dependent variable: non-property crime					
Variables	(1)	(2)	(3)	(4)	(5)
Beneficiaries	0.531	0.509	0.499	0.473	0.464
	(0.390)	(0.450)	(0.453)	(0.445)	(0.449)
Dummy Post 2008	-3.123***	-3.101***	-3.541***	-3.535***	-3.895***
	(0.839)	(0.827)	(1.109)	(0.865)	(1.163)
Beneficiaries* Dummy Post 2008	-0.033	-0.028	-0.016	-0.036	-0.024
	(0.146)	(0.149)	(0.150)	(0.151)	(0.153)
Population		-0.011	-0.013	-0.010	-0.013
		(0.041)	(0.041)	(0.040)	(0.041)
Per Capita Income			0.085		0.081
			(0.110)		(0.110)
Unemployment Rate				-0.091	-0.090
				(0.124)	(0.123)
Constant	25.629***	26.232***	25.672***	27.485***	26.923***
	(2.306)	(4.079)	(3.913)	(4.546)	(4.380)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year and Month Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,656	1,656	1,656	1,656	1,656
Number of Jurisdictions	24	24	24	24	24

Clustered standard errors in parentheses at the jurisdiction level
* significant at 10%; ** significant at 5%; *** significant at 1%

Second, we performed a placebo test changing the year of the expansion of the CCZ program from 2008 to a previous year (2007) and to one year advance (2009). Because we did not find coefficients statistically different from zero, our strategy was working properly (see Table 4).

Table 4. Impact of CCT program on property crime: Placebo test

Panel Data Fixed Effect Model	
Dependent variable: property crime	
Variables	
Beneficiaries * Dummy Post **2007**	0.489
	(0.349)
Beneficiaries * Dummy Post **2009**	1.555
	(1.121)
Control Variables	Yes
Fixed Effects	Yes
Year and Month Effects	Yes
Observations	1,656
Number of Jurisdictions	24
Clustered standard errors in parentheses at the jurisdiction level	
* significant at 10%; ** significant at 5%; *** significant at 1%	

As a final robustness check, we ran a *Poisson panel data model* to take into account the count nature of the dependent variable. The results are in line with those obtained in the main specification (the *Ordinary Least Squares Regression*): the CCT program has a positive effect on property crime.[7]

4. Conclusion

This paper sheds new light on the undecided consequences of the conditional cash transfer programs. We present evidence that welfare payment given in cash significantly increases criminal activities.

Our results contradict previous findings in the literature that suggest conditional cash transfer programs reduce crime rates. However, the fact that in the previous studies the

[7] The results are available upon request to the authors.

payment was not in cash, which is the case in Uruguay, suggests that our findings should not be surprising after all.

In fact, our results are in line with Wright et al. (2014) who present evidence that changing the cash payment to a debit card was associated with a significant decrease in the overall street crime rate. Moving from a check-based system to electronic benefit transfer in the US effectively reduced the amount of cash on the streets available to be taken or used for illegal purposes.

Finally, our findings have direct policy implications by highlighting the importance to avoid cash payments in welfare programs.

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