

Cash and Crime*

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Abstract: We analyze the impact of the elimination of cash payments on crime. We exploit a legal modification that prohibits the use of cash during the night in gas stations in Montevideo (the capital of Uruguay, 1.5 million inhabitants). We use detailed information on the location of stores with regular use of cash coupled with data on all reported geo-referenced crime geographical coordinates level. We present evidence of large and statistically significant effects. The elimination of cash is associated with a decrease on the rate of robberies of between 30 - 50% in treated areas. The reduction in crime is observed in property crime and not in other forms of violent offense, suggesting the action is motivated by economic reasons. We do not detect evidence of temporal or geographical displacement effects. Results are robust to alternative definitions of the control groups and estimation methods.

Keywords: Cash, crime, displacement.

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I. Introduction

In this paper, we provide evidence of a significant reduction in crime associated with the elimination of cash payments. We take advantage of a recent legal restriction imposed on the use of cash in Montevideo (the capital city of Uruguay with 1.5 million inhabitants and roughly 20,000 US dollars of annual per capita income).

After a major public alarm was provoked by the murder of two workers in gas stations, the Uruguayan government regulated the payments in cash in all gas stations of the city in order to prevent crime. In Uruguay, gas station's workers are who manipulate the pump machines (there is no consumer handling) and they are also who receive the payments. Since May 15, 2016, people cannot pay in cash in gas stations between 10pm and 6am.

According to the *National Association of Gas Stations*, the enforcement of the new law was rigorous and there were no exceptions. Daily revenues for an average gas station ranged from 10,000 to 15,000 US dollars of which about 30 percent was paid in cash. Therefore, the potential loot of robbing a gas station was between 3,000 and 5,000 US dollars. The imposed legal restriction eliminated it.

Gas stations are strictly regulated in Uruguay. The price of oil is fixed by the government and it is the same in all gas stations with no possibility of individual modifications. This is a relevant fact in order to disregard potential increases in oil prices as a response of the elimination of cash payments.

We present evidence that the elimination of cash significantly reduced criminal activities. Our difference-in-differences estimates show a reduction of between a half and a third on the robbery rate in the treated areas of the city. Offenses that have a financial motivation such as robberies were the only type of crime that was observed to decrease and

this did not happen with other types of violent crimes such as domestic violence. Additionally, we explore geographical and temporal displacement effects and we do not find supportive evidence of any of them. Thus, according to our results, the elimination of cash payments on certain locations and at certain hours of the day produced localized reductions on crime that were not offset by increases in nearby or other moments of time crime. Thus, the policy's net effect on crime was positive.

The rationale behind these results is straightforward. For a given level of the expected costs of crime —the same probability of apprehension, probability of prosecution given apprehension, and the probability of sentencing given prosecution— the elimination of cash payments reduces the potential benefit of criminal activities. Besides this direct effect, there is also an indirect positive externality in nearby locations since criminals that were heading to a certain gas station might also rob consumers passing by. Therefore, the elimination of cash available in the streets reduces the incentive for criminal activities not only in the gas station but in the area as well.

Cash plays a relevant role in fueling street crime due to its liquidity and transactional anonymity, critical to the performance of underground economy (Varjavand, 2011). In a recent article in the *Journal of Economic Literature*, Wallace (2018) comments Rogoff's (2016) book that emphasizes the importance of cash payments in the underground economy. Criminologists argue that street crime is sometimes motivated by a perceived need for cash to finance hedonistic activities (Shover, 1996; Wright and Decker 1994; Wright and Decker 1997). Studies based on interviews and observations of active street criminals state that cash is a necessary and functional component of the etiological cycle that drives street crime (Topalli, Wright and Fornango 2002; Wright and Decker 1994; Wright, Topalli and Jacques 2013;

Wright and Topalli 2011). Taking all this into consideration, a decrease in the amount of cash in circulation should produce a concomitant decrease in crime rates.

We also analyze potential displacement effects which is critical in order to design public policies aimed to fight crime. Here we analyze both geographical and temporal displacement. Naturally, the reduction of crime in certain areas at night without available cash may be compensated by increases in crime in different areas of the city and at other times of the day. In other words, there would be geographical displacement if the reduction in crime in the treated areas produced a concomitant increase in crime nearby. Time displacement would be present if there were changes in the hourly distribution of crime and increases of it in those hours where cash payments to gas stations were not prohibited.

The criminology literature has a long history in recognizing the complexity of measuring geographical displacement effects.¹ The effect of police surveillance is a good example. Whereas there are several conclusive studies that document a positive direct effects of police surveillance in crime (Draca, Machin and Witt 2011; Machin and Marie 2009; Klick and Tabarol 2005; Di Tella and Schargrodsky 2004), the empirical studies that analyze the associated geographical displacement of crime are scarce and inconclusive. There are various empirical studies finding significant displacement effects (Waples, Gill and Fisher 2009; Priks 2015; van Ours and Vollaard 2016) and, at the same time, there are other empirical studies that find no displacement effects (Draca, Machin and Witt 2010; Munyo and Rossi 2019).

There is also literature on time displacement but unfortunately, it is very scarce (Guerette and Bowers 2009). Temporal displacement is a common evasive strategy that

¹ See, for example, Weisburd and Green (1995) that analyse the tension between research designs for measuring direct (or partial equilibrium) effects and displacement effects. In particular, they suggest that the usual design generates a potential bias toward the null hypothesis of no displacement. In this line, Braga et al. (1999) examined the effects of problem-oriented policing interventions on urban violent crime problems in Jersey City (New Jersey, US) and found positive local effects and no evidence for displacement.

requires less effort from the potential offender compared to other strategies such as a change in tactics. Vollaard (2017) provides evidence for temporal displacement of illegal discharges of oil from shipping in response to a monitoring technology that features variation in the probability of conviction by time of day. Using data from surveillance flights above the Dutch part of the North Sea during 1992-2011, he gave evidence of a sudden increase in illegal discharges right after sunset across the year. Their results reveal that even a minimal chance of being caught and a mild punishment can have a major impact on behavior.

The empirical references closest to ours analyze the impact on crime given by the transition from cash to electronic payments. Wright et al. (2017) present evidence that converting payments from cash to debit card is associated with a significant decrease in the overall street crime rate.² Moving from a check-based system to electronic benefit transfer in counties in the state of Missouri (U.S.) and counties in the states bordering Missouri between 1990 and 2011 effectively reduced the amount of cash available on the streets to be stolen or used for illegal purposes. They find that the overall crime rate decreased by 9.2 percent in response to the electronic benefit transfer program. In the same line, Armeiy et al. (2014) analyze a sample of 71 countries in order to show that the global spread of electronic financial transaction technology plays an important role in reducing crime and enhancing physical security. They present evidence of a negative and significant statistical relationship between access to electronic payments and the incidence of crime. They find that an increase in POS (point of sale, used for credit/debit card payments) of 1 per 1000 people leads to a reduction in robbery of 2-6 percent. As presumed, they also find that electronic transactions do little to reduce the incidence of non-economic crimes such as homicide and rape. More recently,

² The authors argue that the changes to the way welfare payments are distributed (from paper checks to an electronic payment method) were done in a random manner.

Pridemore et al. (2018) study the effect of less cash on crime with data from the Global Financial Inclusion database. In a cross-section analysis in a country level, they find a significant reduction for robberies.

Similar to us, these papers evaluate the impact on crime when programs aimed to reduce the use of cash are implemented. The difference is that they were based on county or country level observations. In all the cases mentioned, this makes it harder to differentiate the specific incidence of the use of cash among other interacting factors. Our data and empirical strategy allow a much more precise estimation of the effects on crime as we can identify the precise point in the city where the amount of cash reduced. This enables us to separate the effect of the cash from the effect of the majority of other changes that could have occurred in the city at the same time.

More generally, our paper is related to the literature focused on the impact of welfare programs on crime. The welfare transfer produces a positive income effect that allows households to purchase goods and thus reduces the incentive to engage in economically motivated crimes. At the same time, welfare payments may precipitate crime by encouraging recipients to expend their resources prematurely, leading them to resort to crime to supplement their income for the remainder of the month (Foley, 2011).

Empirical evidence of the impact of welfare payments on crime suggests that the positive income effect on potential offenders outperforms other incentives for criminal activities. Several empirical studies report that welfare payments significantly decrease arrests in the U.S. (DeFronzo, 1996; DeFronzo, 1997; Hannon and DeFronzo, 1998; Zhang, 1997). Similar results are also found in Colombia and Brazil (Camacho and Mejía, 2013; Chioda et al., 2016). There is a key determinant that could affect the impact on crime rates: the welfare

transfer is usually delivered as a credit in individual accounts, not in cash. More cash available on the streets would improve the potential loot from crime and thus increases the incentive for criminal activities.

There is increasing literature on the economic and social effects of Conditional Cash Transfer (CCT) programs. These programs have the natural impact of reducing the number of households below the poverty line and improving income distribution. In addition, CCT programs usually have a positive impact not only in health care and school enrollment rates (Amarante et al., 2011; Fiszbein and Schady, 2009; Rawlings and Rubio, 2005; Schultz, 2004) but also in domestic violence (Hidrobo and Fernald 2013; Hidrobo et al. 2014; Borraz and Munyo 2019). CCT programs may also have undesired social consequences such as reducing the incentives to work in the formal sector due to the fear of losing the conditional transfer (Marluccio and Flores 2005; Borraz and Gonzalez 2009; Amarante and Vigorito 2010) and increasing political support for the government that implemented it compared to the previous government (Manacorda et al. 2011).

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

II. Data and Methods

Data

We use two sources of data: a database on reported crime and a database with the location of all gas stations in Montevideo, as well as other shops that deal with cash (such as supermarkets and pharmacies) to be used as controls.

Firstly, we employ detailed data on criminal activity for the city of Montevideo provided by the Ministry of the Interior (in charge of police forces). The data is geo-referenced at the coordinates level (latitude and longitude), and includes information about the type of crime reported.

We specifically consider two types of violent crimes: robbery and domestic violence. In the Uruguayan Criminal System, in line with international standards, robbery is defined as depriving a person of property with the use of violence or threat of violence. Domestic violence is described as a pattern of abusive behavior (physical, sexual, emotional, economic, or psychological actions or threats of actions) in any relationship enacted by one person against their intimate partner. In Figure 1, we present the heat maps of violent offenses (robbery and domestic violence) in Montevideo. Both types of violent crimes spread all over the city.

Secondly, we gather information on the exact location of the universe of gas stations (234) in Montevideo (Figure 2). As control groups we considered rings around each gas station and 169 artificial controls after a matching methodology that is explained below (Figure 3). We also consider the exact location of 313 shops that usually manage cash such as supermarkets and pharmacies (Figure 4).

The enforced policy (the elimination of cash), which is our treatment, was put forward after a random event of violence. Treatment was not implemented in the gas stations with higher property crime so we can consider that gas stations and controls similar in terms of observed and not observed characteristics. Additionally, the location of gas stations, supermarkets and pharmacies were set before the policy was announced.

Methods

The implementation of the new regulation provides a quasi-experimental framework ideal for policy evaluation. Alternative areas surrounding the gas stations conform the treatment groups. We define a ball of radius 50 meters, centered at each gas station, as the main treated area.³ We consider three alternative control groups: (i) balls in areas of the city without gas stations inside them that have the same pre-treatment evolution in property crime, (ii) rings around the balls of the gas stations,⁴ and (iii) balls around shops that usually use substantial amounts of cash (supermarkets and pharmacies). Graphically, panel A of Figure 5 illustrates the first and third mapping and Panel B the second.

For the first control group we started from a 10,000 points grid of the city of Montevideo (150 meters apart each). Then, we restricted the set of potential controls to those that were between 100 and 1,300 meters away from any gas station. Thus, we dropped points that are too close or too far away. We end up with 3,018 possible artificial controls. The matching was conducted so that the control group reflected the pre-treatment evolution of property crimes measured weakly. Thus, using 50 weekly summary variables of property crime we implemented a propensity score matching, choosing one artificial control per gas station – with reposition- and discarding those stations that were not in the common support region. This guaranties that in the pre-treatment there is a parallel trend between treated and matched controls.

Table 1 presents daily summary statistics. We have 667,850 observations corresponding to 703 days (352 days before the treatment and 351 after the legal modification after the beginning of the treatment on May 15, 2016) times 950 areas (234 treated and 716 controls). The average daily robbery rate is 0.003209 equivalent to a monthly rate of 0.09627 (1 in 10

³ In robustness tests, we expand the area of the balls.

⁴ We define a ring as the area between two concentric circles. The 50-100 meters ring is the area of the city that is between 50 and 100 meters away from the gas station.

reported a robbery every month). The corresponding statistics for domestic violence are lower. The daily average rate is 0.000806 corresponding to a monthly rate of 0.02418 (1 in 40 areas report domestic violence every month).

In Table 2 we compare the evolution of the average levels of violent crime (robbery and domestic violence) before and after the new regulation took effect (May 15, 2016) in the treatment and control groups considered all together. Back of the envelope calculations, based on the numbers sated in Table 2, initially suggest that the elimination of cash in gas stations have a relevant impact on crime. The difference in daily means of reported violent crime in treated relative to control groups before and after the new regulation presents a clear contrast between robberies and domestic violence. Difference-in-difference estimates are: -0.001123 in the case of robberies (a reduction of 25 percent relative to pre-treatment levels in treated units) and -0.000016 in the case of domestic violence (a reduction of 3 percent relative to pre-treatment levels in treated units).

To check the statistical significance of the treatment given by the elimination of cash in certain hours from the gas stations, we follow a simple difference-in-difference approach. The methodology controls are not only based on selection bias due to observable characteristics, but are also based on unobservable characteristics that remain constant over time (Abadie 2005; Athey and Imbens 2006; Donald and Lang 2007).

We estimate the following equation:

$$Y_{st} = \alpha T_{st} + \mu_s + \mu_t + \mu_{st}$$

Where Y_{st} represents robberies for ball s at time t , T_{st} is a dummy variable that takes the value of 1 for treated segments (balls around gas stations after May 15, 2016) and 0 otherwise, μ_s is dummy for each street segment to capture fixed effects, μ_t is a dummy per day for time

effects and μ_{st} is the error term, which varies across geographical segments over time. Our parameter of interest is α , as it captures the causal effect of the use of cash on crime. We also estimate the equation (1) with domestic violence as the dependent variable. We expect to find a negative and significant impact in robbery and no effect in domestic violence that acts as a placebo test.

III. Results

Parallel trends

The first order of business is to check for parallel trends. As seen in Figure 6, there is a clear change in the behavior after the treatment. Whereas the trends were similar before the legal modification, the reduction in robberies is much stronger in the treated group than in any of the controls. The same conclusion comes true for all three alternative controls.

Main results

In Table 3, we present the main results. There is a significant reduction in robberies after the implementation of the policy. The result is not only statistically significant but also economically relevant.

To address the relative size of marginal effects we need to keep in mind the base rate. The base rate shows the average amount of violent crimes that happened on each location on the whole period, regardless of it being treated or not. We also report the relative effect defined as the ratio between the marginal effect of the treatment and the base rate. This shows the estimated percentage variation of the crime rate as a result of the new policy implemented.

Finally, in all controls used, we find negative and significant effects of the policy in the case of robberies without finding any significant effects for domestic violence. In the case of

the artificial controls, there is an estimated reduction on the robberies rate of about 46 percent,⁵ while it is about 30 percent for the rings and for the shops.⁶ In the case of the artificial controls (matching), there was no requirement for these balls to include a shop; they simply had to have a similar amount of robberies compared to the gas stations.

Robustness

Given that the independent variables take discrete values and are strongly skewed to the right with a large number of zeros (there are many days with a relatively low count of criminal incidents), we specify a Poisson regression model for the number of crimes committed. An advantage of a Poisson specification is that fixed effects can be included without creating an incidental parameters problem (Cameron and Trivedi 2012). Another important property of the Poisson model is that the arrival process is not required to distribute Poisson in order to obtain consistent maximum likelihood estimates of the parameters (Cameron and Trivedi 1986). Reported standard errors are based on variance estimates robust to over-dispersion.⁷ In Table 4, we present the results that are similar to the ones obtained before (OLS estimates): negative and significant effect of the elimination of cash on property crime.

Moreover, alternative robustness checks include using weekly data instead of daily data, offenses exclusive to shops (eliminating crimes to nearby individuals) and a bigger radius for all the segments (balls and rings). In Table 5, we show that the effects are negative and significant on almost every scenario with the only exception being the case of the ball of 100 meters' radius where the effect has the expected sign but is not statistically significant.

⁵ In the estimation using the artificially created controls we have a base rate of daily robberies of 0.0045. This implies 0.135 probability of being robbed every month (1 out of 7 balls is robbed every month). The marginal effect is -0.00206. This implies that the elimination of cash reduced robberies by 46 percent.

⁶ The estimations using the rings and the shops as controls show a robbery base rate of 0.003 implying that every month 1 out of 10 balls report a robbery. The marginal effect is -0.00099, thus, the implied reduction in robberies is of 30 percent.

⁷ Results are robust to using an alternative Negative Binomial model (not reported, available from the author upon request).

Displacement

After establishing a link between cash and crime, we now explore whether the elimination of cash payment in gas stations at night displaces crime towards other areas or towards daily hours.

We analyze time displacement by considering the potential variation in crime close to the time window affected by the new regulation. The sample consists of 234 treatments (gas stations from 10pm to 6am) and 234 controls (the same gas stations from 6am to 22pm) and 703 days (352 days before the treatment and 351 after it) centered in May 15, 2016, with all periods normalized to last 8 hours (the amount of crimes counted in the control group was divided by two as it lasted 16 hours per day).

We follow again a difference-in-difference approach. In other words, we estimate the same equation presented above, using as controls the same balls where the gas stations are located but at daylight when the use of cash was not banned. A non-significant parameter would imply that the effect of the policy did not produce time displacement of crime. A negative coefficient would suggest displacement.

Results in Table 6 suggest that the crime relation between day and night did not suffer any kind of variation, as both treatment coefficients are not significant. As we showed that the new policy reduced the crime at night, this means that taking the cash away generated a positive externality: reducing the crime rates during the day.

Geographical displacement is trickier. If there was no geographical displacement, there should not be any change in crime in closer or further away zones. If there is local displacement we should observe an increase in crime in nearby segments that does not

happened further away. On the other hand, if there was a positive local externality we should observe a reduction on the crime rate close to the gas stations.

To test this idea, we analyze the rings around the treatments (gas stations) and controls (artificial controls and shops controls). These rings cover the area closest to the location without including the ball already defined (all the area between 50 and 100 meters away from it). In theory, the rings have not been treated; the idea is to check if there was any effect from the treatment on the rings around the gas stations. If there was no geographical displacement, estimating the equation mentioned at the beginning but with the locations described above should show no effect of the policy. If the rings around the gas stations show a negative treatment effect, this would mean that there was a reduction on the amount of crimes in the nearby areas thanks to the policy. This would be a positive externality. Nevertheless, a positive and significant effect would imply local displacement.

Table 7 shows no robust evidence. In the estimations using rings around the artificial controls we have no significant effects. However, we find a negative coefficient in robberies when we consider shops as a control group indicating the presence of a positive externality close to the focal point. This implies that the reduction of the amount of cash near the gas stations discourage criminals from actually going to the area.

IV. Conclusion

This paper presents evidence that the elimination of nightly cash payment in gas stations significantly reduced street crime relative to untreated control units in the city. Additionally, we find no displacement effect after the intervention. Neither geographical nor temporal displacement was found in our estimates.

Although the policy was successful, it remains the question if it was efficient. To deal with a cost-benefit analysis is a complex issue in this case. It is necessary to measure not only monetary and non-pecuniary (the value of the violence, human harm and even potential loss of human life avoided) gains and costs associated with robberies, as well as the fee paid to the banks to use credit and debit cards. The Inter-American Development Bank (2017) estimates that the total expenditure in citizen security and crime prevention in Uruguay, but unfortunately do not discriminate for robberies.⁸ This opens a different avenue for research.

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⁸ See Soares (2015) for an analysis of the conceptual content underlying the estimates of the cost of crime”?

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Tables

Table 1. Daily summary statistics

	Mean	St. Deviation	Min.	Max.	Obs.
Robbery	0.003209	0.057449	0	3	667,850
Domestic Violence	0.000806	0.028582	0	2	667,850

Notes: The sample includes 234 50-meter-centered-balls treated units and 716 controls (234 rings, and 50-meter-centered-balls around 169 artificial locations and 313 shops). The sample considers 703 days, 352 days before the treatment and 351 after it (May 15, 2016)

Table 2. Before and after means

		Treatment	Control
Before	Robbery	0,004456	0,003071
	Domestic Violence	0,000522	0,000857
After	Robbery	0,003202	0,002941
	Domestic Violence	0,000572	0,000923

Notes: The sample includes 234 50-meter-centered-balls treated units and 716 controls (234 rings, and 50-meter-centered-balls around 169 artificial locations and 313 shops). The sample considers 703 days, 352 days before the treatment and 351 after it (May 15, 2016)

Table 3. Main results

	Control: Matching		Control: Rings		Control: Shops	
	Robberies	Domestic Violence	Robberies	Domestic Violence	Robberies	Domestic Violence
Treatment	-0.00206*** (0.00055)	-0.00037 (0.00026)	-0.00099** (0.00041)	0.00007 (0.00018)	-0.00099*** (0.00037)	0.00008 (0.00017)
Observations	241,129	241,129	329,004	329,004	384,541	384,541
Standard Error	0.12132	0.26362	0.12258	0.27695	0.11664	0.24609
Baserate	0.0045	0.00097	0.00331	0.00063	0.00317	0.0007
Relative Effect	-0.45847***	-0.38277	-0.29949**	0.11461	-0.31156***	0.10658

Notes. The dependent variable includes offenses reported within a centered ball with radius of 50 meters. The matching was conducted so that the control group reflected the pre-treatment evolution of property crimes measured weakly. Rings are defined as the area between two concentric circles of radius 50 and 100 meters and centered at each specific location. Shops include supermarkets and pharmacies.

Table 4. Poisson Regression

	Control: Matching		Control: Rings		Control: Shops	
	Robberies	Domestic Violence	Robberies	Domestic Violence	Robberies	Domestic Violence
Treatment	-0.42619* (0.23625)	-0.30730 (0.38405)	-0.23790* (0.12331)	0.12285 (0.28007)	-0.23143** (0.11689)	0.12210 (0.25855)
Observations	168,720	168,720	329,004	329,004	384,541	384,541

Notes. The dependent variable includes offenses reported within a centered ball with radius of 50 meters. The matching was conducted so that the control group reflected the pre-treatment evolution of property crimes measured weakly. Rings are defined as the area between two concentric circles of radius 50 and 100 meters and centered at each specific location. Shops include supermarkets and pharmacies.

Table 5. Alternative Robustness

	Weekly data			Only offenses to shops			Ball with radius of 100 meters		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment	-0.01466*** (0.00390)	-0.00709** (0.00285)	-0.00693*** (0.00260)	-0.00076*** (0.00024)	-0.00038* (0.00020)	-0.00066*** (0.00018)	-0.00198*** (0.00066)	-0.00037 (0.00062)	-0.00169*** (0.00052)
Observations	34,300	46,800	54,700	241,129	329,004	384,541	241,129	329,004	384,541
Standard Error	0.12336	0.12289	0.11683	0.27847	0.24227	0.24194	0.09992	0.08063	0.08407
Baserate	0.03157	0.02318	0.02221	0.00087	0.00084	0.00073	0.00663	0.00765	0.00612
Relative Effect	-0.46415***	-0.30599**	-0.31197***	-0.87032***	-0.44631*	-0.89107***	-0.29798***	-0.04841	-0.27632***

Notes. Matching balls are the control in columns (1), (4) and (7). Rings around the ball are the control in columns (2), (5) and (8). Shops are the control in columns (3), (6) and (9).

Table 6. Temporal Displacement

	Robberies	Domestic Violence
Treatment	0.00067 (0.00049)	0.00030 (0.00024)
Observations	329,004	329,004
Standard Error	0.10066	0.20022
Baserate	0.00486	0.00121
Relative Effect	0.13879	0.2475

Notes: The dependent variable includes offenses reported within a centered ball with radius of 50 meters. Crimes committed at night are those that were carried out between 10 pm and 6 am while day crimes are those that were committed between 6 am and 10 pm. As the day period lasted twice as much as the night period, the day period was normalized to last 8 hours.

Table 7. Geographical Displacement

	Control: Matching		Control: Shops	
	Robberies	Domestic Violence	Robberies	Domestic Violence
Treatment	0.00009 (0.00038)	-0.00020 (0.00022)	-0.00070** (0.00036)	0.00014 (0.00020)
Observations	241,129	241,129	384,541	384,541
Standard Error	0.17669	0.3025	0.12142	0.20701
Baserate	0.00213	0.00072	0.00295	0.00098
Relative Effect	0.04042	-0.27848	-0.23847**	0.13959

Notes: We consider robberies and domestic violence in the ring around the 50-meter-radius ball as the dependent variable. Rings are defined as the area between two concentric circles of radius 50 and 100 meters and centered at each specific location. The matching was conducted so that the control group reflected the pre-treatment evolution of property crimes measured weakly. Shops include supermarkets and pharmacies.

Figures

Figure 1. Heat map of violent offenses in Montevideo

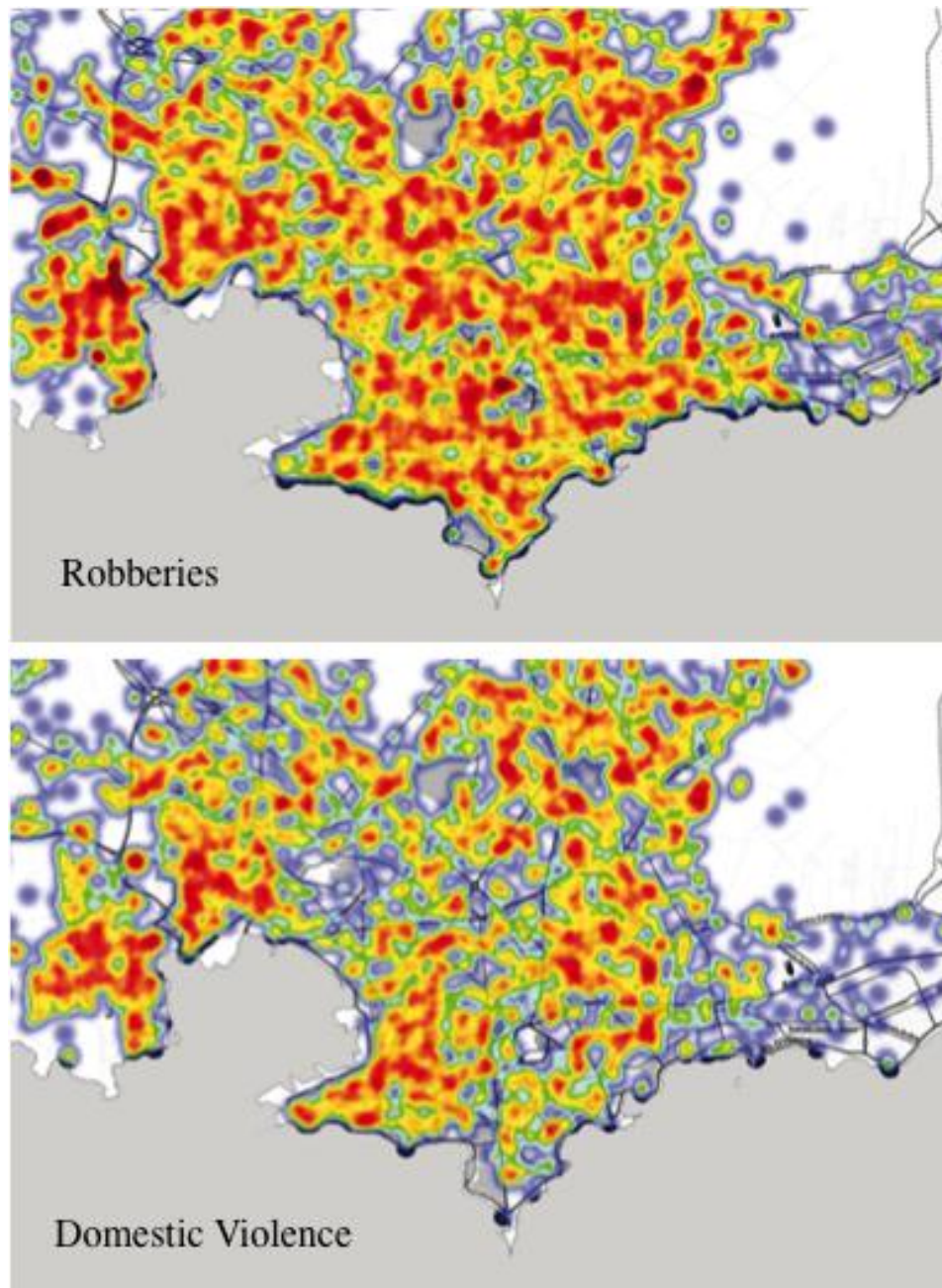


Figure 2. Gas Stations in Montevideo



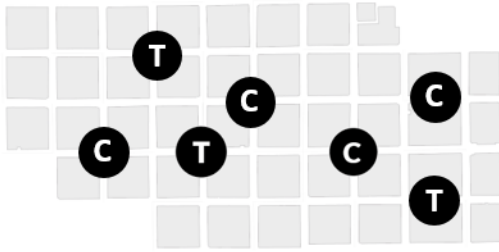
Figure 3. Matching Controls in Montevideo



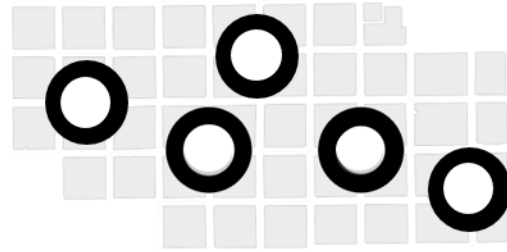
Figure 4. Shops (supermarkets and pharmacies) in Montevideo



Figure 5. Treatment and control groups as rings

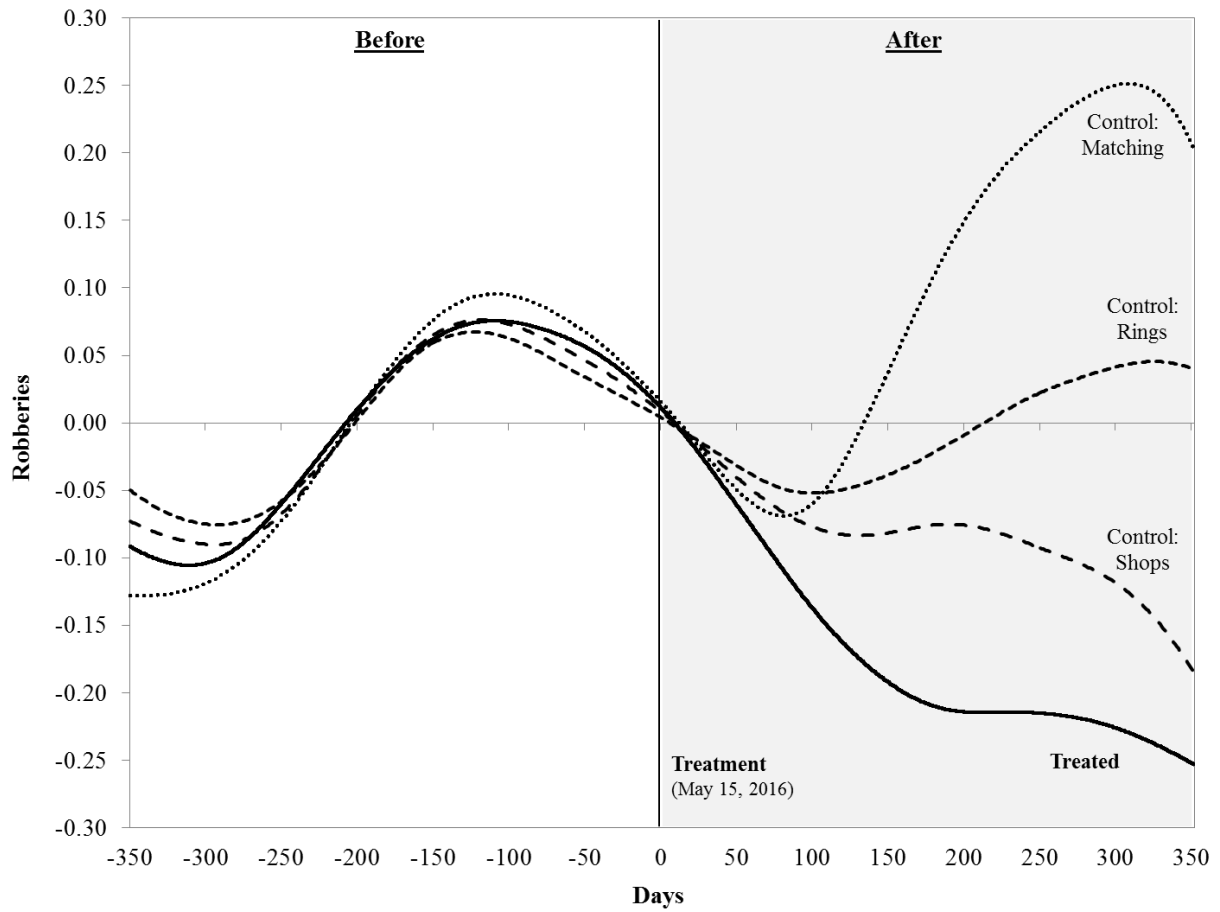


Panel A



Panel B

Figure 6. Detrended evolution of robbery rates for treatment and control groups



Notes. The treatment is the elimination of cash in gas stations between 10pm and 6am. The matching was conducted so that the control group reflected the pre-treatment evolution of property crimes measured weakly. Rings are defined as the area between two concentric circles of radius 50 and 100 meters and centered at each specific location. Shops include supermarkets and pharmacies.