Hot Spots, Patrolling Intensity, and Robberies: Lessons from a three-year program in Uruguay

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15 July 2022

Hot Spots, Patrolling Intensity, and Robberies:

Lessons from a three-year program in Uruguay

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July 2022

Abstract

We study the effects of increasing police presence on crime by exploiting the quasi-experimental nature of a large-scale hot spots intervention in a Latin American country that had experienced a significant increase in crime over the last 30 years. We match geocoded data on crime and GPS data that signals the presence of police to 200x200 meters cells covering Montevideo, Uruguay. Employing a difference-in-differences (DiD) approach, our results suggest that the program effectively increased police presence in the designated areas and reduced crime. We found an overall elasticity of 0.47 - a 10% increase in police presence is associated with a decrease of 4.7% in robberies. This three-year intervention allows us to investigate heterogeneous effects by year of intervention and contexts. The program presented greater effects during the first year of the intervention; during 2017, a period associated with significant legal changes in the country's criminal policy, the program did not affect crime. In 2018, we observed positive results in police presence and crime reduction but at a reduced level. We associated this reduction in outcomes with program fatigue which could impact the sustainability of this type of intervention. This study may help policymakers identify the conditions under which hot spots policing programs work and the degree to which they are replicable and scalable.

Keywords: Crime; Robberies; Police; Patrolling; Hot spots; Georeferenced; GPS; Difference-in-differences; Uruguay; Latin America.

JEL codes: K42, O17, J48.

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†Acknowledgements.
We are grateful to the staff of Ministerio del Interior for providing access to the data and feedback in several meetings to discuss our results. Financial support from the Agencia Nacional de Innovación e Investigación (ANII) through the Fondo Sectorial de Seguridad Ciudadana (2018), grant FSSC_1_2018_1_147810, is greatly appreciated.

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1. Introduction

Several empirical studies have examined the relationship between increasing police presence and reducing crime. While some have used the increase in terms of police officers available for patrol (Levitt 1997; Machin and Marie 2011; Chalfin et al. 2022), others have studied the impact of exogenous changes (Di Tella and Schargrodsky 2004; Draca, Machin and Witt 2011). Evidence suggests that crime is responsive to many forms of increases in police presence (Chalfin and McCrary 2017). Since potential offenders seem to be more aware of changes in street policing than incarceration policy, focused deterrence efforts that result in highly visible police presence like hot spots policing may lead to significant decreases in offending.

A robust body of scientific literature indicates that crime - particularly robbery - is spatially concentrated into a relatively small number of geographic units (Weisburd, Morris and Groff 2009; Weisburd et al. 2004). This previous research has fostered the development and implementation of a variety of hot spots policing strategies, in which police focus their limited resources on the highest-risk crime spots in a city.

Hot spots policing consists of a reallocation of existing resources. It is a strategy in which police forces are disproportionately deployed to areas in a city that appear to attract disproportionate levels of crime. This strategy supposes two prior facts. First, crime is sufficiently concentrated in a relatively small number of zones, and second, this concentration is stable in time, so the pattern is predictable.

As Weisburd et al. (2017) mentioned, robberies are a good choice to study the effects of hot spots policing. Their work provides a theoretical framework where location is of particular interest in the decision to commit a robbery. Robbers are attracted to places with exposed, accessible, and profitable targets. Opportunity theories (e.g. Durlauf and Nagin 2011; Lee and McCrary 2017), state that there is a supply of individuals in the population who are open to committing crimes. Potential offenders decide to act based on the characteristics of a given situation, such as the suitability of targets and the amount of guardianship. Suitable targets for street robbery must be visible and available, and the potential criminal must perceive that they have something of value. Potential robbers consider the risks and rewards. They are rational offenders that face a gamble (Becker, 1968). Other individuals at the same place and time affect the potential offenders' perception of risk. The supply of offenses will fall as the probability of apprehension rises.

Policymakers should consider whether the potential offender's risk perception (the individual's perceived risk of being apprehended and punished) mirrors reality. Durlauf and Nagin (2011) develop a model that includes the probability of apprehension. These authors note that if the perceived probability of detection is very low, even small changes in the perceived probability (e.g., due to hot spots implementation) may have large effects. Apel (2013) provides an in-depth review of the perceptual-deterrence literature. "Deterrence is important not only because it results in lower crime but also because, relative to incapacitation, it is cheap. Offenders who are deterred from committing a crime in the first place do not have to be identified, captured, prosecuted, sentenced, or incarcerated" (Chalfin and McCrary 2017, p. 5).

Focusing on small geographic areas can make police more effective and efficient in several ways. First, it concentrates police attention on places where crime is most likely to occur - approximately half of the crime occurs at 5% or less of a city's addresses and intersections (e.g., Sherman, Gartin and Buerger 1989; Weisburd et al. 2009; Weisburd et al. 2004). Second, police can establish a more visible presence and generate more significant deterrence effects in the small space than over more extensive areas like a patrol beat or a complete jurisdiction (Ariel, Sherman and Newton 2020; Sherman and Weisburd 1995).

However, the same factors that make hot spot policing effective could potentially reduce its impact in the long term. Deploying a high number of police officers daily to a single location during a fixed period may create a highly visible but somewhat predictable police response. Ariel and Partridge (2017) conclude that hot spots policing may backfire when offenders can systematically predict police behavior. This leads to a reasonable concern that concentrating police in high-crime areas may shift crime, creating displacement to non-intervened areas rather than reducing crime.

Although assessments of hot spots policing strategies have produced evidence supporting this type of intervention – Braga et al (2019) offer a recent systematic review –, and meta-analyses suggest a diffusion of benefit to nearby areas, recent findings challenge those results. In contrast to the consensus, studies in Latin American countries like Colombia (Blattman et al. 2021; Collazos et al. 2020) and Argentina (Chainey et al. 2022) reported mixed results.

Since most previous research on hot spot policing against violent crime was conducted in developed countries, further research is needed to understand developing countries' crime patterns and policy capacity[1]. In particular, the conditions under which hot spots policing programs work and if they are replicable, scalable, and sustainable over time. Further research can shed light on the importance of context when implementing hot spots policing and the adequacy of their design.

Latin America has the highest level of reported violent robberies in the world (Muggah and Aguirre Tobón 2018). While North Americans report 71 robberies per 100,000 inhabitants in 2015, Latin America reports 400. Victimization surveys report that 36% of all Latin Americans claim to have been victims of a crime in 2016, placing their countries into a different context.

A second issue less explored in the literature is the fidelity to the original design of the program and officer compliance with patrol routes. In their study, Chainey et al. (2022) mention that the mixed results found in Argentina could be due to the difference in deployment strategies and project management of the implementation in the different regions of the country. For instance, in one of these regions, qualitative evidence revealed several issues with the involvement of certain parties, which caused a lack of clear management and supervision of patrol deployments to hot spots. Chainey and colleagues suggest that this may have undermined the impact of the intervention in that region.

Few studies have addressed crime elasticity under regular patrolling conditions using a disaggregated and precise measurement of police presence. Blanes I Vidal and Mastrobuoni (2018) provide estimates for the effects of Operation Insight, a low-intensity patrol program that targeted areas where burglaries were likely to occur using officers' GPS signals, and found that these increases in patrolling were not accompanied by decreases in crime.

Lastly, despite the impressive number of hot spots impact evaluations – Braga et al., (2019) identify 65 studies –, there are no evaluations of hot spots against violent crime in developing countries that cover more than eight months.

In this work, we contribute to this literature by evaluating the effect of PADO (*Programa de Alta Dedicación Operativa*, Operative Program with Exclusive Dedication), a police intervention focused on crime hot spots, applied in Montevideo (the capital city of Uruguay) in the period 2016-2018. Uruguay is a Latin American country especially attractive to test policing strategies against robberies since its rate of victimization coincides with the region's average rate, and the rate of robberies per 100,000 inhabitants increased from less than 100 in 1989 to 909 in 2018 (Ministerio del Interior 2019). This figure would place Uruguay third in the regional ranking of robberies per 100,000 inhabitants (Muggah and Aguirre Tobón 2018). The effects of the first implementation of PADO – i.e., from April to December 2016 – were assessed by Chainey, Serrano and Veneri (2021). They employed a difference-in-differences strategy comparing zones treated by PADO with not treated zones and found that PADO reduced 23% the rate at which robberies occur. Also, they found that PADO does not seem to result in a spatial displacement of crime into areas immediately

[1] To our knowledge, there is a limited number of studies in developing countries (Blattman et al. 2021; Chainey et al. 2021; Chainey et al. 2022; Collazos et al. 2020).

surrounding targeted locations. Since that first evaluation, the program has evolved and experienced several changes. Our study provides further evidence about the long-term impact of the program and its different versions. We provide proof regarding program compliance using real-time GPS data collected by police officer radios to evaluate the fidelity of the program design.

Our work fills several gaps in the literature. We provide the first three-year term estimation in a developing country of the effect of hot spots policing on robberies. In addition, to our knowledge, we are the first to measure the intensity of the change of police presence caused by hot spots policing strategy in a developing country at a disaggregated level -only a handful of hot spots studies have ever measured police presence at all: Ariel, Weinborn and Sherman (2016); Barnes et al. (2020); Rosenfeld et al. (2014); Sherman and Weisburd (1995); Telep et al. (2014); Williams and Coupe (2017). Using GPS data that shows real-time police presence, our research offers the program's impact on increasing police presence in the designated areas (our results show that the program was effectively implemented: PADO caused a sharp increase in police presence since the program was introduced). Finally, by matching GPS data on police presence with geocoded microdata on crime, our study provides estimates for crime elasticity (our results suggest an overall elasticity of 0.47, meaning that a 10% increase in police presence is associated with a reduction of 4.7% in robberies).

We organize our work as follows. In section 2, we describe the PADO program. In sections 3 and 4, we describe the data about police presence and crime. In section 5, we present our estimates and additional exploratory analysis. Finally, we discuss our results in section 6 and conclude in section 7.

2. The intervention

Montevideo is the capital of Uruguay. With a population of about 1.5 million, half the country's population, it is the largest city in the country. It is disproportionally affected by crime: eighty percent of robberies occur in Montevideo (Ministerio del Interior 2019). In April 2016, the governmental authorities (the Ministry of Interior) implemented PADO – a hot spots policing strategy – in Montevideo and two adjacent cities. The program focuses explicitly on reducing robberies (IDB & Ministry of Interior of Uruguay 2017, p. 101), defined by the Uruguayan penal code in Article 344 as "incident in which someone steals -or intents to steal- an object that is in possession by a person or persons, by force or by threats of employing force." Thus, the difference between robberies and thefts is the use of force.

Before PADO, Uruguayan authorities had already experimented with using predictive policing software to identify at-risk areas ("PREDPOL program") and redistributing patrols into groups of street blocks after studying past data and consulting officers ("Critical Areas program"). However, those strategies had to cope with significant difficulties.

Under the usual policing model, Montevideo is organized into precincts with different territorial jurisdictions. In contrast, PADO program had a centralized organization and faced no territorial limits (precincts) within the city. Regular territorial jurisdictions faced at least three coordination challenges. First, the demand for personnel to cover other police-related tasks removed officers from targeted areas, since on-foot patrolling was one of several tasks in the job description. In addition, there were two barriers to a better deployment of officers: one related to time and the other to space. Shifts were organized with fixed starting and end times, following administrative reasons rather than matching the personnel needs for peak crime hours. Authorities could not reassign personnel freely, especially to the time windows that concentrated more crime (from 5:00 PM to 01:00 AM) – police officers did not receive incentives to apply for riskier time windows or strategies, preferring the morning (quieter) shift. Second, previous strategies deployed officers to areas of high crime concentration, not in exact street segments monitored live by GPS. Within those high crime zones, police officers decided where exactly to patrol. Anecdotal evidence suggests that officers tended to relocate to less risky zones within the assigned group of street blocks. PADO design aimed to solve all these difficulties, as we will explain.

It is not mandatory to work in the PADO program. Police officers who opted to participate in PADO received a monthly bonus that could amount up to 25% of the nominal salary for the lowest ranking officers (IDB & Ministerio del Interior de Uruguay 2017). The police officers accepted into the program work exclusively for PADO, thus limiting the first challenge of the usual policing model. Moreover, the extra payment required flexible hours from police officers: they could work the afternoon shift for one week, and then change to the night shift if it was required by displacement of crime throughout the day. In most cases, officers admitted to PADO remain in the program, and few of them abandoned the program.

During the first version of the program, most PADO officers were recruited from two special forces known as the *Guardia Republicana* (GR or Republican Guard) and the *Grupo de Reserva Táctica* (GRT or Tactic Reserve Group). The GR, created in 2010, receives special training and has access to armored vans, tactical equipment, and specialized firearms. The GRT personnel is trained specially for critical situations and public turmoil. Regular police officers who previously worked in precincts and were trained in mainly reactive strategies, working with victim and witness assistance, reporting crimes in progress, etc., complete the human resources devoted to PADO. The group was not bounded by historic police precincts and would patrol the most violent streets regardless of their location in the city.

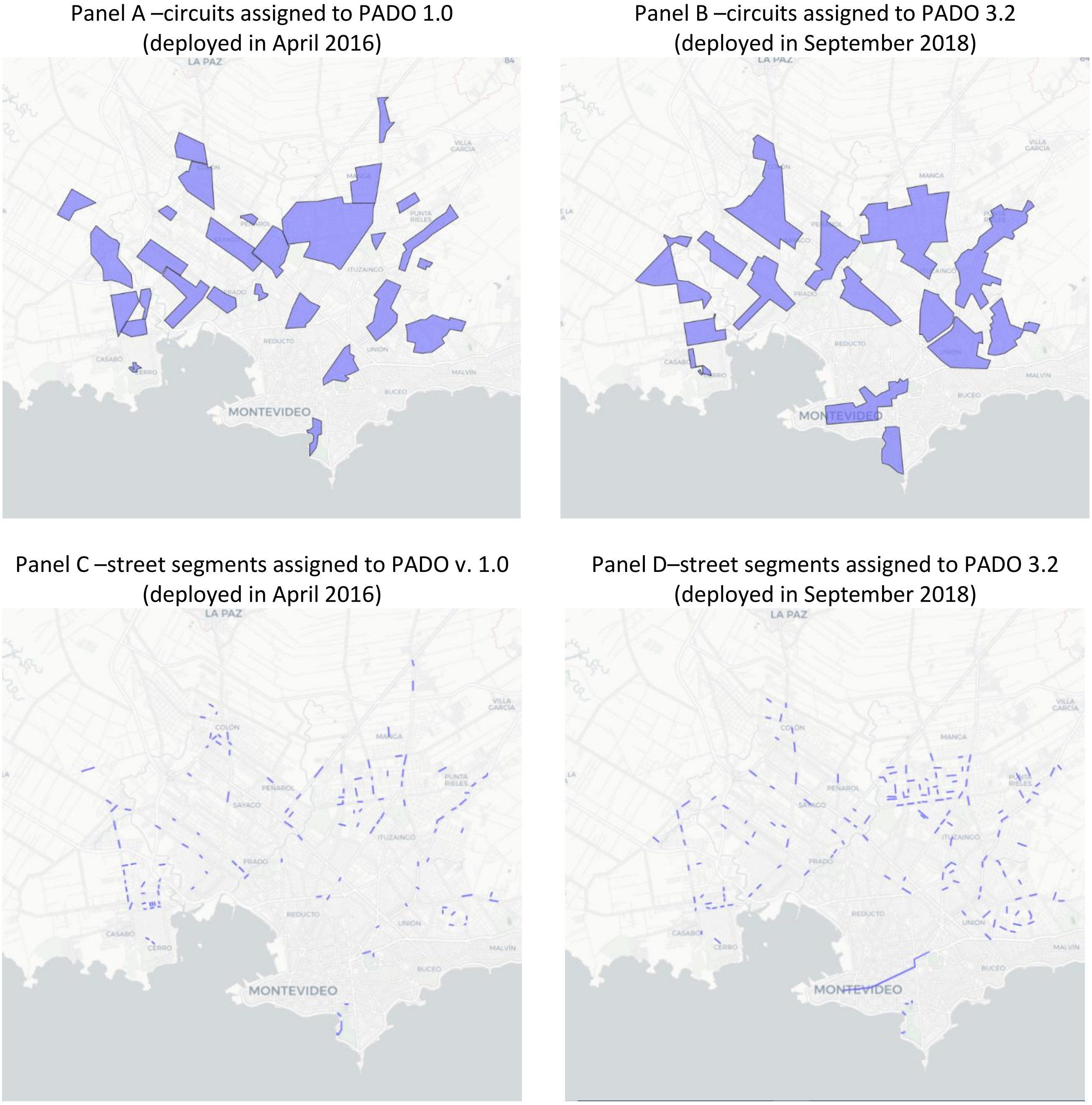
Authorities designed the intervention to maintain a constant police presence, monitoring officers' compliance using GPS technology. The definition of hot spots for on-foot patrolling was not implemented in an aggregate area but in very specific street segments (i.e. two street blocks with high pre-treatment crime patrolled for one 8 hours shift).

Although officers in the program had to be patrolling at specific spots, they had to respond to two types of crimes outside the assigned segment if they were the closest to the scene: crimes in progress or emergency calls in nearby areas. In the meantime, a patrol from the nearest police station was deployed to maintain the police presence in the PADO zone. Thus, PADO officers worked at assigned street segments, as we will show with GPS data, and only exceptionally (for emergencies) did they leave the targeted intervention zones. Anecdotal evidence suggests that coordination worked well, especially in 2016, and it was more difficult in 2017 and 2018.

The program is organized into street segments and circuits (see Figure 1). Patrol segments consist of contiguous street segments (between 50 to 250 meters each) with high pre-treatment crime levels. Two PADO officers were assigned to patrol on foot, exclusively in those precise meters. Compliance is measured with GPS technology. According to authorities, this prevented one of the previous program's weaknesses, where officers could move to safer places within a larger assigned area. Thus, the PADO program was customized in detail and focused on the higher criminal street segments. Their usual activities are mostly preventive (walking through targeted streets), but they also conduct background checks on people and vehicles.

Segments were organized in circuits for supervision and logistic purposes (i.e. the same van or truck deploying the officers' pairs, from the police station to the hot spots, at the beginning of the shift). Additionally to street segments with two on-foot officers, aggregate circuits were patrolled by two to four motorbikes and a patrol car with an officer that acts as circuit supervisor. Our primary focus will be the street segments with intense and direct patrolling.

Figure 1 – Areas assigned to PADO: two examples out of ten versions

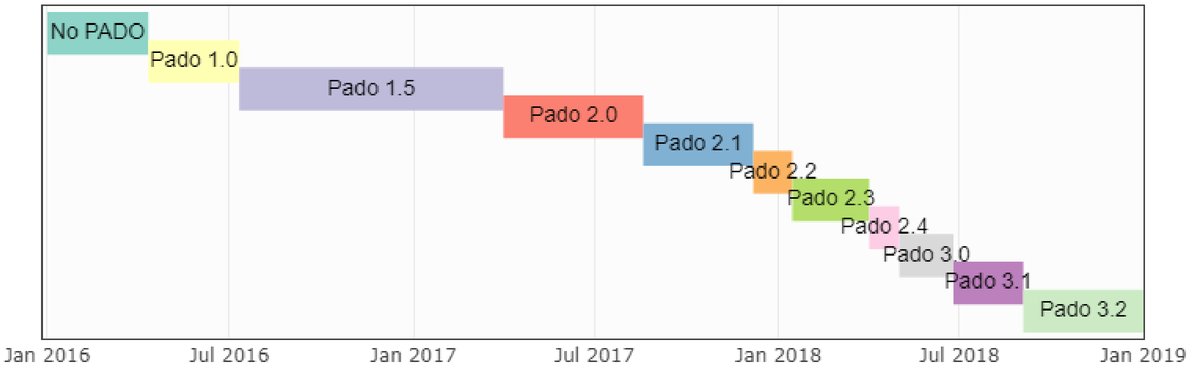


Notes: Street segments and circuits assigned to PADO. Police patrols were deployed to street segments organized in circuits. Source: Authors own visualizations based on microdata provided by the Ministry of Interior.

Treated zones and segments changed over time. Panel A of Figure 1 depicts the circuits of PADO of version 1.0 (deployed in April 2016), while Panel B shows the circuits of the last version of PADO in our study period (deployed in September 2018). Panel C and Panel D present the areas assigned to the program at the street segment level. This comparison shows that some areas entered the PADO program, others left the program at different versions, and others remained.

To select areas covered by the intervention, police officers from the Crime Analysis Unit identified areas with high crime concentration employing georeferenced crimes for the pre-intervention year 2015. For the first iteration of the program (April 2016), patrols were deployed in 120 street segments (Fig. 1, panel C) organized in 28 circuits (Fig. 1, panel A). The Crime Analysis Unit was additionally tasked with measuring compliance and monitoring the evolution of crime to suggest adjustments to the program. Between 2016 and 2018, they implemented ten versions of the program, changing segments and zones assigned to treatment. They also suggested changes in the hour of the day where the program should start in each zone. Figure 2 shows the duration of the different program versions. Patrols may be redeployed in each version, and segment or circuit changes.

Figure 2 – Different versions of PADO in 2016-2018



Notes: Each version implied patrol routes, segments, and circuit modification. The naming and version number reflect Ministry of Interior records. Source: Authors based on Ministry of Interior.

3. Data

We study the effects of hot spots policing on robberies by exploiting the quasi-experimental nature of PADO intervention. To do so, we employ two primary sources of data, both made available by the Police (Ministry of Interior)[2] under strict confidentiality agreements.

1. Police crime reports for 2015-18. We use detailed data for reported crimes recorded in the SGSP (*Sistema de Gestión de Seguridad Pública*), the main database from the Uruguayan Police.
2. Patrol data for 2015-18. We used the information generated by the global positioning system (GPS) associated with the radios worn by police officers on foot patrol and police vehicles. In addition, PADO Patrol routes -defined as segments and polygons- were used to determine the treatment areas.

From the crime reports, we first identify events within Montevideo city limits. We focus on robberies: they were the main objective of PADO and the reason for creating the program. In addition, for each report, we used the date reported by the victim as the time the crime took place and created dates variables: day of the week, year, and approximate hour (e.g., if the victim reported a crime as 19:20, the hour registered would be 19:00).

To group the events into comparable units, we divided the city into a 200x200 meter grid (as in Veneri 2019) and assigned a grid ID to each crime committed within the city's limits. We assigned each GPS ping to a cell using the same grid and created a variable to serve as a proxy for police presence. Due to the high frequency of the information generated by the GPS devices and the fact that multiple police officer could potentially be together in the same place, we created 5 minutes bins and considered that police was present in the area if at least one ping was reported within the cell.

We intersected PADO patrol routes and circuits with the cell grid to identify cells treated by the intervention. We consider that a cell belongs to a circuit if it overlaps with the polygons that define the PADO

[2] In Uruguay, Police answers to the Ministry of Interior.

circuit. Our primary treatment is PADO foot patrol, and we define cells as treated if they intersect with the segments assigned to PADO routes. There are 301 average cells across program versions, corresponding to 124 average street segments; thus, a basic program unit intersects with an average of 2.4 cells.

We combine the generated datasets into balanced panels with different frequencies using the cells as our analysis units. Our main variables are the number of robberies and police presence within the hour, day, or month.

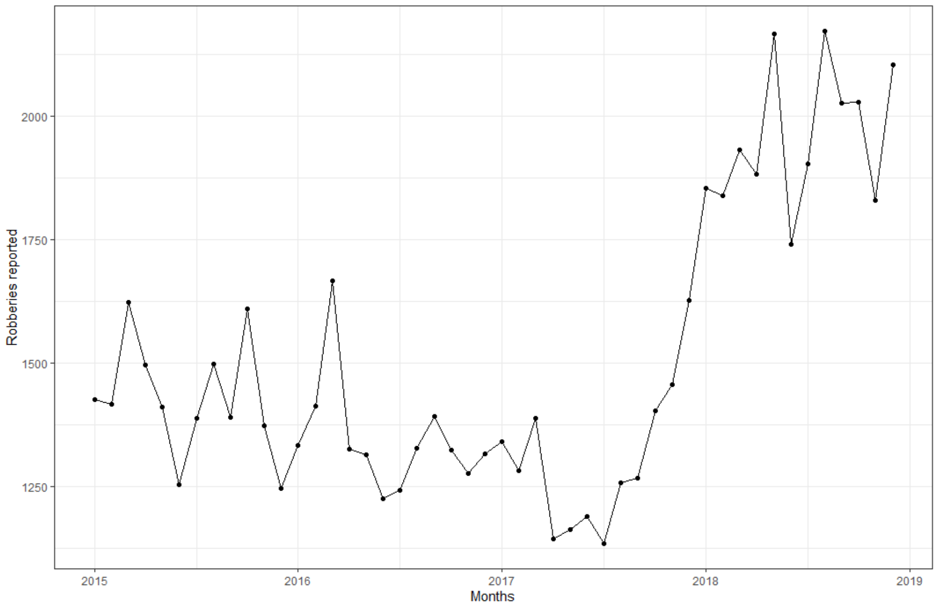
4. Summary Statistics.

In this section, we present summary statistics for our data. First section 4.1 presents some stylized facts about robberies in Montevideo, and section 4.2 offers summaries of police presence. Section 4.3 presents the intervention statistic at a grid level, while section 4.4 presents the summary statistics for the balanced panel used for the DiD analysis.

4.1. Robberies trends and concentration.

During the studied period, the number of robberies decreased in 2016, coinciding with the first implementation of PADO, and then experienced a sharp increase in 2018 (Figure 3)**.** On November 1, 2017, Uruguay implemented a new penal code. Díaz and Titiunik (2019) explore the potential effects of this new Code of Penal Procedure (CPP), which may account for 26%-31% of the average annual increase in crime.

Figure 3 –Robberies reported in Montevideo, 2015-2018



Notes. The figure displays the monthly evolution of the number of robberies in Montevideo.

The fact that a small percentage of areas tend to concentrate a large portion of crime has been previously established in geographic studies of crime (Weisburd 2015). This fact has also been corroborated for Latina American cities (Jaitman and Ajzenman 2016; Chainey et al. 2019). Results even suggest that crime tends to be more concentrated in Latin America than in Western countries (Chainey et al. 2019). Veneri (2019) describes the evolution of violent robberies and spatiotemporal behavior in Montevideo during 2013-2018. Veneri's results show that violent robberies have a high concentration level and tend to cluster in space and time. "Once a crime is committed, it is likely that another is committed at a small distance and in a short period of time. This may be because some areas are more attractive to the offenders (an endemic mechanism), and there is a pattern of contagion to nearby areas (an epidemic mechanism)" (Veneri 2019).

As in Veneri (2019), we present summary statistics for crime concentration in Montevideo at grid level by year in Table 1. During the 2015-2018 period, there was a 37.3% increase in robberies, notwithstanding the decrease observed in 2016 and 2017 (Column A). This increase in crime is associated with the rise in places that report at least one robbery (Column B). The Gini index (Column D) confirms this pattern, as the distribution of crimes improves towards the end of the study period. Columns E and F present the percentage of cells that accumulate 25% and 50% of crime per year, respectively, a standard measurement in geographic concentrations study. In 2015, 4.54% of the cells concentrated 50% of the crime, which increased to 5.29% towards the end of the period. This concentration of crime phenomenon is accompanied by a positive spatial autocorrelation as measured by the Moran index (G), where positive values indicate that cells with higher crime counts tend to cluster together in space.

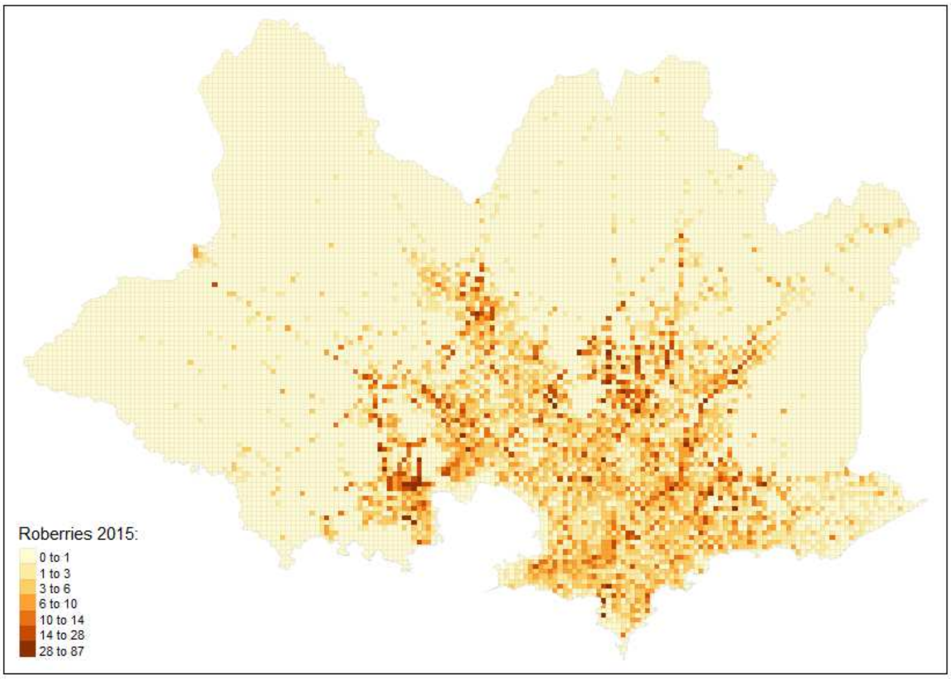
Table 1 – Summary Statistics by cells.

	(A)	(B)	(C)	(D)	(E)	(F)	(G)
	Total robberies	% of cells affected by robberies	Average robberies by cell	Gini	% of cells concentrating 25% of crime	% of cells concentrating 50% of crime	Moran Index
2015	17141	25.50%	1.2479	0.8687	1.40	4.54	0.3387
2016	16166	25.54%	1.1769	0.8633	1.62	4.91	0.3894
2017	15662	25.48%	1.1402	0.8647	1.55	4.80	0.3607
2018	23490	28.44%	1.7101	0.8520	1.73	5.29	0.3429

Source: Author's calculation using robberies reports from the *Sistema de Gestión de Seguridad Publica* (SGSP) provided by the Ministry of Interior, Uruguay. Note: Moran index computed using queen distance.

Figure 4 presents the distribution of robberies reports from 2015 -just before the PADO launch- and evidences the high concentration of robberies in some areas of Montevideo.

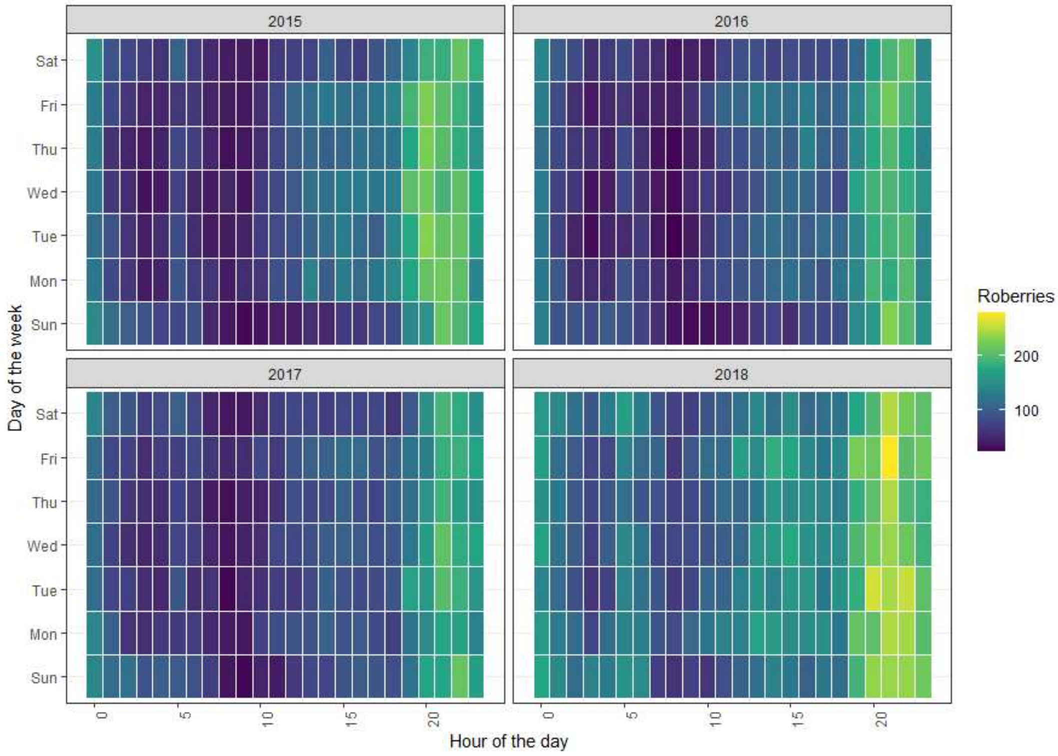
Figure 4 – Spatial distribution of robberies in Montevideo (2015)



Notes: Bins were chosen manually to illustrate spatial autocorrelation and the percentage of cells affected by crime. The first bin accounts for cells with no incidents, and the remaining bins are selected according to percentiles (50th, 75th, 80th, 90th, 99th, and 100th). Source: Author's calculation using robberies reports from the Sistema de Gestión de Seguridad Publica (SGSP) provided by the Ministry of Interior, Uruguay.

Robberies in Montevideo are highly concentrated during some hours and days of the week. Higher crime counts are associated with evenings (Figure 5). From these descriptive analyses, we hope to illustrate the context and logic behind PADO implementation that focuses on (i) micro places and (ii) specific time windows where crime is highly concentrated.

Figure 5 – Distribution of robberies by day of the week (rows) and hour of the day (columns), 2015-2018.

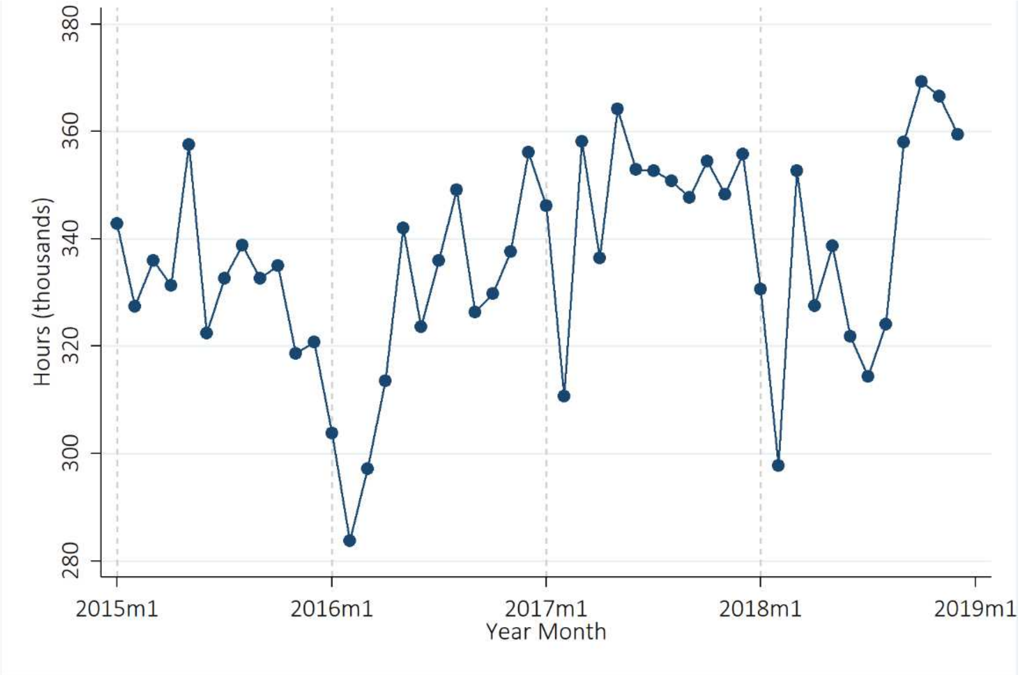


4.2. Police Presence and crime

The Uruguay police have equipped every officer and vehicle with a GPS tracking device that records their location every few seconds. We use this dataset to construct a measure of patrolling intensity by matching the signals to the cells of 200 x 200 meters as we do for crime data. We consider that police were present at the cell if a ping was transmitted within a 5-minute bin from that specific cell.

Figure 6 depicts the monthly evolution of the patrolling presence in Montevideo – there is a substantial increase in 2016, the year of the launching of PADO. In the average month, there were 336.000 hours of police presence in the city; this represents 11.000 hours of patrolling per day or 1.400 police officers in 8 hours shifts. There is some variation from month to month. The valleys correspond to the holiday season.

Figure 6 – Evolution of patrolling intensity, 2015-2018



Notes: The figure depicts the number of hours of police presence. GPS devices worn by police officers transmit georeferenced data that indicates police presence. We assigned these data to 200 x 200 meters cells. For each month, the total number of hours of police presence is the sum of the hours that each cell had at least one officer. Source: Authors own calculation using GPS data provided by the Ministry of Interior, Uruguay.

4.3. Intervention summary at the grid level.

Table 2 shows the number of 200x200 meters cells assigned to PADO during 2016-2018. Out of 13.736 cells covering Montevideo, 827 different cells (6%) were assigned to PADO at some point.

After identifying hot spots, officers from the Crime Analysis Unit monitored crime trends continuously to suggest modifications to patrol segments and circuits. There were ten versions of the program in the period of analysis. When the program was launched in April 2016, we identified 257 cells incorporated into PADO. In July 2016, the program was extended to cover 43 new cells. The first major revision occurred in April 2017, when 190 cells left the program, 159 new ones were added, and 110 remained unchanged. The following versions (2.1-2.3) only extended the program to new segments, while the remaining versions, 2.4 onward, removed some segments from the intervention. On average, 301 cells were patrolled across all versions of the program. We will exploit the timing of cells entering or leaving the program for our difference-in-differences analysis.

Table 2 – Cells (200x200 meters) assigned to PADO during 2016-2018)

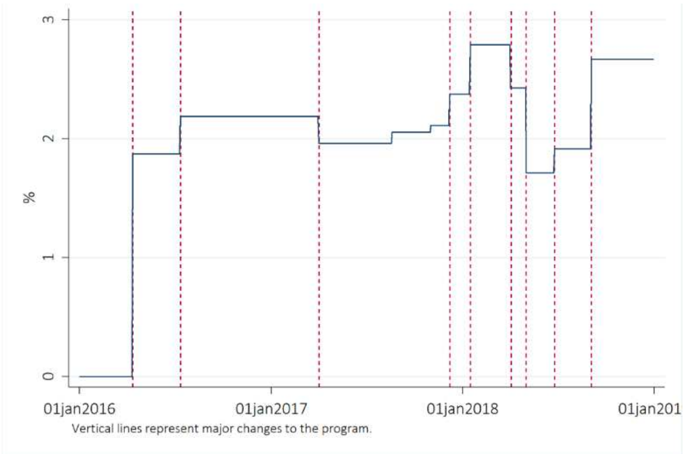
PADO version	Starting date	Days active	Number of cells			
			remains	enters	leaves	currently in PADO
1.0	11-Apr-16	91	-	257	0	257
1.5	11-Jul-16	264	257	43	0	300
2.0	1-Apr-17	140	110	159	190	269
2.1	19-Aug-17	110	269	13	0	282
2.2	7-Dec-17	39	290	36	0	326
2.3	15-Jan-18	77	326	57	0	383
2.4	2-Apr-18	30	202	131	181	333
3.0	2-May-18	54	138	97	195	235
3.1	25-Jun-18	70	221	42	14	263
3.2	3-Sep-18	119	149	217	114	366
Total			1,962	1,052	694	3,014

Notes: A cell is treated if it intersects with a PADO segment. PADO version name reflects naming by the Crime Analysis Unit. We set the last day of version 3.2 to December 31, 2018, the last day of our study period (not the last day of the program).

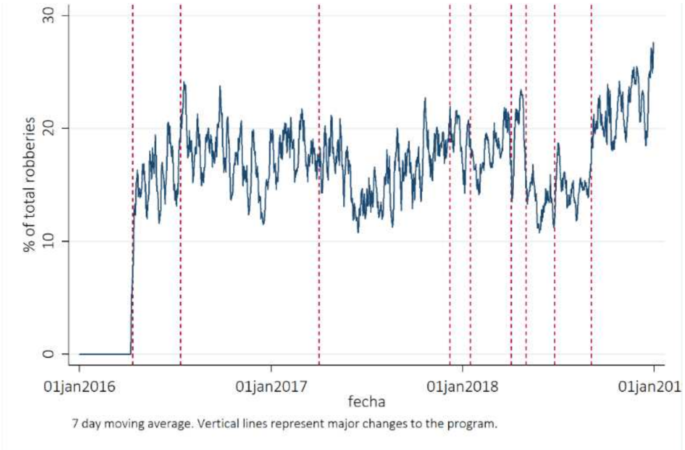
Figure 7 presents the extension of the program measured as the percentage of cells treated as a proxy for city coverage (Panel A), the crime that occurs within treated cells (Panel B), and average police presence (Panel C). During the first iteration of the program, the 257 cells treated represent less than 2% of the total surface of the city (Figure 7, Panel A) but concentrated 15% of the robberies in Montevideo (Figure 7, Panel B). If we consider only the cells with at least one robbery in the pre-treatment years of 2014 and 2015 (excluding rural or “super-safe” areas), then an average of 6% of the city was covered by PADO. Finally, Panel C of Figure 7 offers a visualization of the magnitude of police presence in PADO street segments and circuits compared to areas of the city not assigned to PADO. During the first version of the program, a treated cell received on average 390 minutes of policing per day (6.5 hours), while a cell in the rest of the city received an average of 41 minutes. The increase in police presence, as measured by GPS signals, was substantial for treated cells.

Figure 7 – Summary statistics of PADO cells.

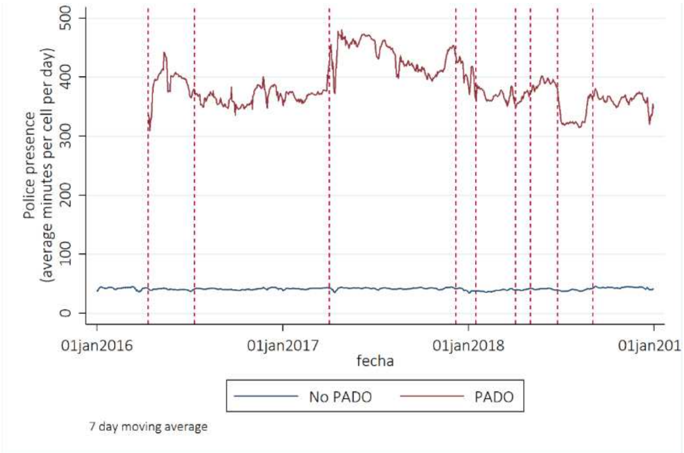
Panel A – Surface of PADO (% of the city) by version of the program



Panel B- Robberies in PADO Cells



Panel C - Police presence in PADO cells.



Notes: Panel A represents the percentage of the cells in which we divided the city (13.736) that overlap with a street PADO segment for each program version. For example, on April 11, 2016, 257 cells (of 200 x 200 meters) were assigned to on-foot patrolling in the program. Panel B shows the number of robberies in those 200x200 cells. Panel C is constructed with real-time data from GPS devices worn by police officers with signals in those cells. Source: Authors own calculations using SGSP (Sistema de Gestión de Seguridad Ciudadana) and GPS data, provided by the Ministry of Interior, Uruguay.

4.4. Summary Statistics for the balanced panel

We collapsed the data into a daily panel to implement our difference-in-differences strategy. The panel consists of 13,740 cells (200 x 200-meter grid) observed over four years.

We present its summary statistics in Table 3. The first four lines offer daily counts, while the last lines show yearly aggregates. On average, most cells did not report having any crime in a given day. The maximum number of robberies in a given cell and day was 5.

Regarding police presence, the average cell received 48 minutes of police presence during the period, with a significant standard deviation. The maximum daily police presence is 1,440, corresponding to 24 hours of policing in those cells and to cells with precincts or other types of round-the-clock police activity (embassies, official buildings, etc.). A deeper look into the distribution shows that police presence is skewed, with a long right tail. The 25th percentile of cells reported 0 minutes of police presence while the cell at the 75th percentile reported 40 minutes. The cell in the 90th percentile reported 150 minutes per day (2.5 hours). Finally, on an average day during the implementation period, 2.18% of the city cells were part of the program.

Table 3 – Descriptive statistics 2015-18

		mean	sd	min	max
Daily Counts	Robberies	0.00	0.06	0	5
	Police presence (minutes)	48.24	120.42	0	1440
	PADO treatment*	0.02	0.15	0	1
Yearly Counts	Robberies in 2015	1.25	3.53	0	87
	Robberies in 2016	1.18	3.13	0	67
	Robberies in 2017	1.14	3.08	0	63
	Robberies in 2018	1.71	4.41	0	98
	Observations		20,068,296		

Note: PADO treatment consists of cells treated that day, beginning in 2016 (April 11), and following years. Source: Authors own calculations using SGSP (Sistema de Gestión de Seguridad Ciudadana) and GPS data, provided by the Ministry of Interior, Uruguay.

5. Methodology and results.

For our analysis, we implement a difference-in-differences approach. First, we present estimates of the effect of the program in terms of police presence (section 5.1) and robberies (section 5.2), comparing outcomes between PADO areas and non-PADO ("NOPADO") before and after there was a change implemented.

Our main specification consists of an event study pooling the ten significant changes in the program's implementation. We identify the change date and collapse the information into weekly counts, considering four weeks before and after the patrols changed. We normalize the time variable across changes by setting the week where the intervention changed as $t = 0$. Hence, we index observations as being t ($t = \{-4,..,0,\dots 3\}$) periods way or from the program change.

We evaluate the impact using a difference-in-differences approach by estimating,

$$Y_{itmy} = \beta_0 + \beta_1 T_{imy} + \sum_{t=-4}^{3} \alpha_t D_t + \sum_{t=-4}^{3} \delta_t D_t * T_{imy} + \gamma_m + \theta_y + \mu_i + R_{i\,2015} + \varepsilon_{itmy} \quad (1.1)$$

Where Y_{itmy} denotes the outcomes of interest in the i-th cell at t periods away or from PADO implementation, on month *m* and year *y*. For Section 5.1, the outcome considered is police presence measured in minutes, and for Section 5.2 we consider the total number of robberies in that cell and week. Our main covariates are a set of dummy variables (D_t) that indicates the distance to and from the implementation of PADO and a treatment dummy (T_{itmy}) that indicates whether the unit enters the program in that period. The model parameter δ_t captures the difference-in-differences estimation, which is associated with the interaction of the covariates indicating time and treatment. As additional controls, we consider models that accounted for the total number of robberies for the i-th cells in the pre-intervention year($R_{i\,2015}$), fixed effects for moth (γ_m), year (θ_y) and/or specific cells fixed effects (μ_i).

We considered year and month fix effects to account for yearly trends or seasonal effects, while robberies in 2015 aim to control crime's pre-intervention level. Our most broad model considers cell fixed effects to capture all unobservable associated with each cell. Following opportunity theory, some cells might present more attractive characteristics to offenders (i.e., economic activity, bus stops, distance to the city center or a police station, etc.). In the cell fixed effects estimation, the pre-intervention number of robberies at the cell level is absorbed in the fixed effect, as all the characteristics of the zone that do not change in the period under consideration.

A second version of equation (1.1) considers the *average* post-treatment effect, instead of the effect for the individual weeks. We replace the weekly dummy variables (D_t), in equation (1.2) with a single dummy indicating the post-treatment period ($Post_t$), and run the following regression:

$$Y_{itmy} = \beta_0 + \beta_1 T_{imy} + \delta_t\ Post_t * T_{imy} + \gamma_m + \theta_y + \mu_i + R_{i\ 2015} + \varepsilon_{itmy} \quad (1.2)$$

In additional specifications, we considered daily counts of crime, pre and post-intervention. We followed a similar approach, but for a shorter period, taking 14 days from and to the change. This secondary specification includes fixed effects for the day of the week. Results using daily panels are consistent with the more aggregate or parsimonious weekly specifications and are available upon request.

While sections 5.1 and 5.2 provide average estimates for three years of the program, section 5.3 provides estimates of heterogeneous effects by year of the program.

PADO treatment effects are estimated using program changes, where units enter, remain, or leave the program. Section 5.4 presents the program's effect by assessing the impacts on units entering or leaving. At each version of the program, we identify four types of cells, (i) cells that remained PADO, meaning those that were assigned in a previous period and remained active during the 56-day window under consideration for pre/post intervention, (ii) cells that enter PADO, meaning those that were not yet assigned for patrol but became active after the change, (iii) cells that were active before the change in the program but left the program with the current change, and (iv) cells that remained inactive in terms of the program before and after the change was implemented. Hence, for the models in section 5.4, we created two additional indicator variables for cells entering the program (E) or leaving the program (L).

We use a difference-in-differences approach using Eq 2.1 and Eq 2.2

$$Y_{itmy} = \beta_0 + \beta_1 E_{imy} + \sum_{t=-4}^{3} \alpha_t\ D_t\ + \sum_{t=-4}^{3} \delta_t\ D_t * E_{imy} + \gamma_m + \theta_y + \mu_i + R_{i\ 2015} + \varepsilon_{itmy} \quad (2.1)$$

$$Y_{itmy} = \beta_0 + \beta_1 L_{imy} + \sum_{t=-4}^{3} \alpha_t\ D_t\ + \sum_{t=-4}^{3} \delta_t\ D_t * L_{imy} + \gamma_m + \theta_y + \mu_i + R_{i\ 2015} + \varepsilon_{itmy} \quad (2.2)$$

Equation 2.1 is estimated using cells (i), (ii), and (iv), meaning that in this equation δ_t depicts the difference-in-differences estimator for units entering PADO using as controls units that remained PADO and those which remained inactive in the study window. In the case of equation 2.2, estimation is done using cells (i), (iii), and (iv), and in this case δ_t depicts the difference-in-differences estimator for units leaving PADO using as controls cells that remained PADO or were not treated during that study window.

As before, we use several specifications as robustness checks and present estimates by year of introduction (section 5.5).

In all our implementations, we limited the sample to cells that reported at least one robbery during 2015, the pre-intervention year, to filter out rural areas and have more comparable zones to PADO areas. This results in considering 25% of the total cells for our approach, going from 13.736 to 3.503 cells. Results considering the whole sample are quantitatively similar and are available in the Appendix.

5.1. Effect of PADO on police presence 2016-2018.

We first focus on the program's impact on increasing police presence in the designated areas. Only a handful of other authors have addressed police officer compliance with the intervention, which is vital to understanding the mechanism behind the intervention.

Table 4 reports the estimates of Eq. 1 (Panel A) and Eq. 2 (Panel B), presenting different fixed effects specifications as controls. Under most of our specifications, there was no statistical difference in the pre-treatment period, pointing to the validity of the no pre-trends assumption in the DiD models. The only exception is one coefficient (that may be due to chance), showing a statistically significant difference the week before the program patrols were scheduled. Estimated coefficients for the fixed effect specification (Column 5) are also presented visually in Figure 8.

Table 4 – DiD estimates of police presence, 2016 – 2018

	Police Presence				
	(1)	(2)	(3)	(4)	(5)
A) By week (treatment in t=0)					
-3	-35	-35	-36	-35	-35
	(57)	(57)	(57)	(60)	(34)
-2	42	39	37	37	38
	(58)	(58)	(58)	(60)	(36)
-1	84	81	76	77	78**
	(59)	(59)	(59)	(60)	(35)
0	661***	658***	647***	648***	648***
	(59)	(59)	(59)	(60)	(36)
1	778***	775***	763***	764***	764***
	(60)	(60)	(60)	(60)	(36)
2	879***	876***	870***	871***	872***
	(60)	(60)	(61)	(60)	(37)
3	911***	908***	897***	899***	901***
	(62)	(62)	(62)	(61)	(38)
B) Average treatment effect					
Post Treatment	785***	783***	775***	775***	776***
	(30)	(30)	(30)	(30)	(19)
Mean T in pre-treatment weeks	1,599				
Year FE	NO	YES	YES	YES	YES
Month FE	NO	NO	YES	YES	YES
Robberies in 2015	NO	NO	NO	YES	NO
Cell FE	NO	NO	NO	NO	YES
Observations	280,240	280,240	280,240	280,240	280,240

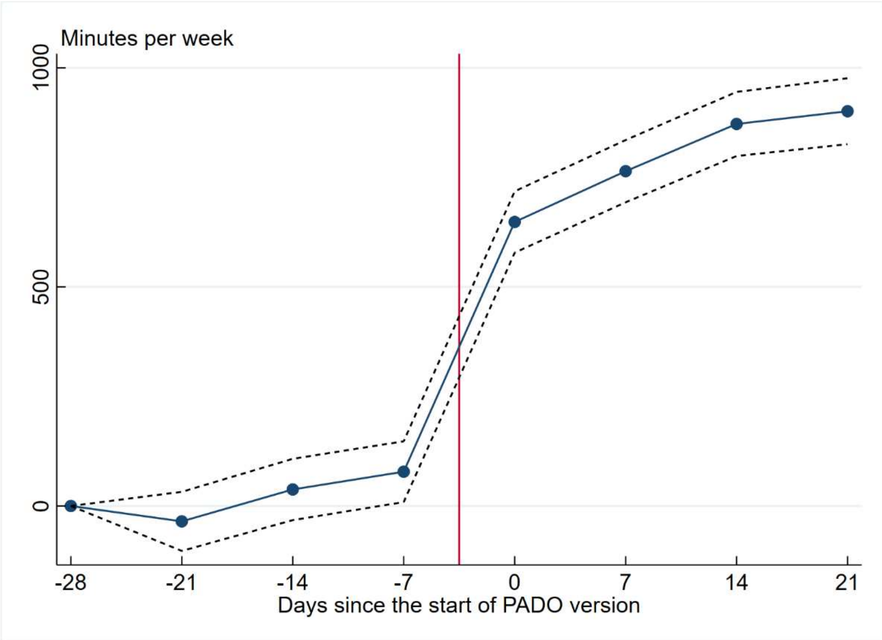
Notes: The difference-in-differences captures the change in Police Presence in the areas of Montevideo treated with PADO before and after the PADO intervention relative to the change in the non-PADO areas, following the specifications from equation 1 (Panel A results) and equation 2 (Panel B results). Source: Authors own calculations using GPS data, provided by the Ministry of Interior, Uruguay.

Our result shows a sharp increase in police presence once a change in patrol routes is introduced. On average, PADO cells receive 776 minutes, approximately 13 hours, of additional police presence per week during the post-treatment period, compared to NONPADO cells (i.e. cells not assigned to PADO). This estimate is smaller than the dose proposed in the program design for two reasons. First, PADO cells were already receiving police attention since they were crime hot spots. Second, multiple cells may share the same officers assigned for patrol in a shift, since a policing route overlaps with an average of 2.44 cells (200x200 meters) used to construct our panel data structure. This first result shows that the program was effectively implemented, as measured by GPS data of police officers deployed on the ground.

The increase in patrolling was significant. Before the intervention was modified, cells selected for treatment presented a weekly average of 1,599 minutes in the four weeks before the program started. Using this baseline, the increase associated with the program represents an increase of roughly 50% in police presence.

To understand what this represents in terms of additional patrolling, note that our regression considers 35.030 cells, 964 PADO and 34.066 NONPADO during eight weeks, four before and four after the changes. These 964 treated cells correspond to 10 versions of the program, thus in every single version there are on average 96.4 treated cells. Hence, the total number of additional patrol hours can be estimated to be 178 hours per day [3].

Figure 8 – DiD estimate by week of police presence



Notes: The figure depicts the coefficients of the interaction of a program dummy with weekly indicators, applying a fixed effects model –δ_t from equation (1.1) –, as reported in column 5, panel A, Table 4. The dependent variable is Police Presence measured in minutes. Dotted lines represent the upper and lower bounds of the 95% confidence interval. Source: Authors own calculations using GPS data, provided by the Ministry of Interior, Uruguay.

5.2. Effects of PADO on crime, period 2016-2018

Next, we focus our attention on the effect of PADO on crime. We follow the same approach as before by estimating several versions of Eq. 1 and Eq. 2. In this case, the variable of interest is robbery counts per week before and after the change in the program.

Table 5 presents the program's estimated effect on robberies, while Figure 9 plots the coefficients and confidence intervals corresponding to our preferred estimation (column 5, panel A). Our results show that there was no statistically significant difference between PADO and NONPADO areas before the program in terms of crime.

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[3] To arrive to this estimate we consider the average estimated additional patrolling hours associated with the program in the PADO cells. There are 776 additional minutes per week of policing, thus 111 minutes per day, or 1.85 additional hours in each of the 96.4 cells. This gives 178 additional patrolling hours per day in the city.

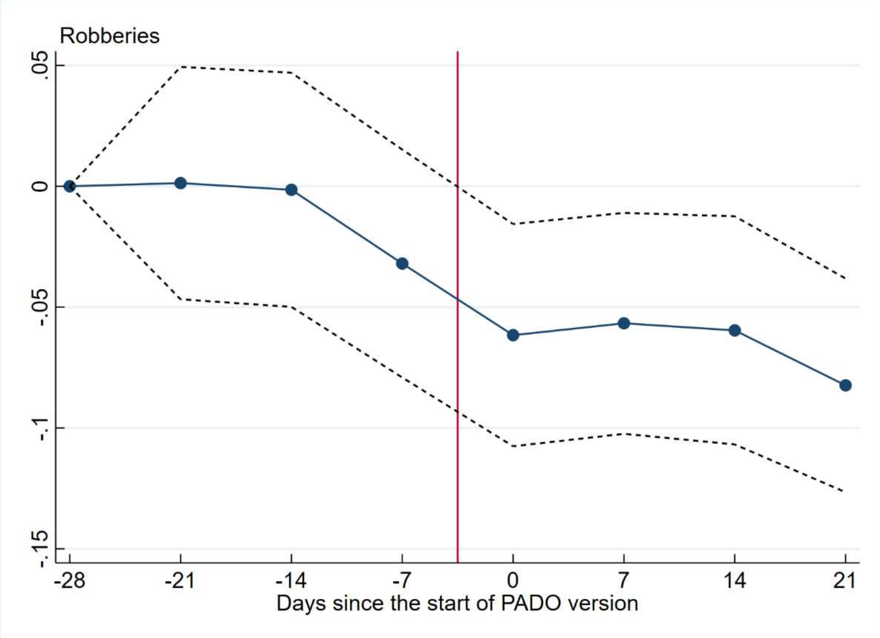
Table 5 - DiD estimates of robberies, 2016-2018

	Robberies				
	(1)	(2)	(3)	(4)	(5)
A) By week (treatment in t=0)					
-3	0.001	0.001	0.001	0.001	0.001
	(0.026)	(0.026)	(0.026)	(0.025)	(0.025)
-2	-0.002	-0.001	-0.002	-0.001	-0.001
	(0.026)	(0.026)	(0.026)	(0.025)	(0.025)
-1	-0.035	-0.033	-0.032	-0.032	-0.032
	(0.025)	(0.025)	(0.025)	(0.025)	(0.024)
0	-0.065***	-0.064***	-0.062**	-0.062**	-0.062***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.023)
1	-0.061**	-0.059**	-0.057**	-0.057**	-0.057**
	(0.024)	(0.024)	(0.024)	(0.024)	(0.023)
2	-0.063**	-0.062**	-0.060**	-0.060**	-0.060**
	(0.025)	(0.025)	(0.025)	(0.025)	(0.024)
3	-0.083***	-0.082***	-0.083***	-0.083***	-0.082***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
B) Average treatment effect					
Post Treatment	-0.059***	-0.058***	-0.057***	-0.057***	-0.057***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)
Mean T in pre-treatment weeks			0.247		
Year FE	NO	YES	YES	YES	YES
Month FE	NO	NO	YES	YES	YES
Robberies in 2015	NO	NO	NO	YES	NO
Cell FE	NO	NO	NO	NO	YES
Observations	280,240	280,240	280,240	280,240	280,240

Notes: The difference-in-differences captures the change in robberies in the areas of Montevideo treated with PADO before and after the PADO intervention relative to the change in the non-PADO areas, following the specifications from equation 1 (Panel A results) and equation 2 (Panel B results). Source: Authors own calculations using SGSP (Sistema de Gestión de Seguridad Ciudadana), provided by the Ministry of Interior, Uruguay.

After the change was implemented, our results suggest that the program was able to decrease crime by a statistically significant but economically moderate amount. On average, during the first four weeks after patrols were deployed, PADO cells presented a decrease of approximately -0.06 robberies. This result is consistent across the different model specifications. As before, we evaluated the magnitude of this decrease. The effect of the program represents a 23% decrease in robberies from the pre-intervention period.

Figure 9 –DiD estimate by week for robberies



Note: Figure depicts the coefficients of dummy variables that indicate the days, applying a fixed effects model –δ_t from equation (1.1) –, as reported in column 5, panel A, Table 5. The dependent variable is the number of robberies in each cell. Source: Authors own calculations using SGSP (Sistema de Gestión de Seguridad Ciudadana), provided by the Ministry of Interior, Uruguay.

Our results from these two sections can be used to perform a back-of-the-envelope calculation of the elasticity of crime to police presence. An increase of 49% minutes in terms of police presence resulted in a decrease of 23% in crime. This results in an elasticity of 0.47, meaning that a 10% increase in police presence would be associated with a reduction of 4.7% in robberies.

5.3. Effects of PADO by year of the program.

Next, we explore the effects of PADO patrols across different years. Change in the program efficacy could be due to changes to the program's original design, or endogenous behavior of offenders that adapt to this policing strategy may have jeopardized the effects of PADO. In our descriptive analysis, we identified a decrease in crime from 2015 to 2017 but an increase in 2018 (Table 1).

Table 6 presents the average treatment effects of PADO for police presence and robberies using our preferred cell fixed effect specification. Column 1 recaps results found in sections 5.2 and 5.1 (column 5, panel B from Tables 4 and 5), while columns two to four present the estimated yearly effects.

Our results show heterogeneous effects by year. The program significantly increased police presence in PADO cells. However, this effect on police presence decreased toward the end of the period. In 2016 PADO cells received additional 911 minutes of police presence (58% increase), 812 minutes in 2017 (48%), and 614 minutes in 2018 (39%). In terms of crime, the program showed the most considerable decrease in 2016, when the program started, presenting an average effect of -0.072 (-28%), followed by a non-significant reduction in 2017 of -0.0014 robberies on average (-8%) and lastly a significant average decrease of -0.06 robberies in 2018 (-22%).

Table 6. DiD estimates of the effect of PADO on police presence and robberies by year of the program.

	(1) 2016-2018	(2) 2016	(3) 2017	(4) 2018
Police presence	776***	911***	813***	615***
	(19)	(24)	(38)	(21)
Mean T in pre-treatment weeks	1,599	1,563	1,701	1,573
Robberies	-0.057***	-0.072***	-0.014	-0.060***
	(0.011)	(0.021)	(0.022)	(0.017)
Mean T in pre-treatment weeks	0.247	0.257	0.180	0.272
Observations	280,240	56,048	91,078	133,114

Notes: Estimates represent average treatment effects during the follow-up period using a fixed-effect model as in Columns 5 in tables 4 and 5. Source: Authors own calculations using SGSP (Sistema de Gestión de Seguridad Ciudadana) and GPS data, provided by the Ministry of Interior, Uruguay.

These results should be read in the context of institutional reform in 2017, when the code of penal process was changed. Anecdotal evidence collected in interviews suggests that police officers were uncertain regarding both the extent of the reform and its impact on police procedure. We will further discuss this implication in section 6.

5.4. Effect on cells entering and leaving PADO, 2016-2018

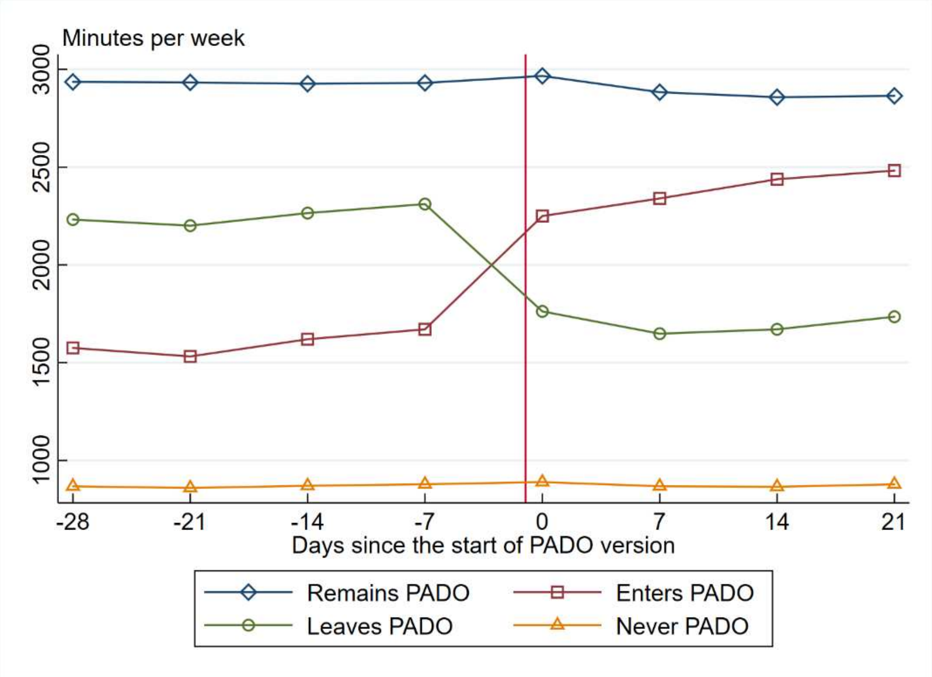
During our study period, the program experienced ten different versions (Table 2). Each version implied change in terms of new street segments that entered or left the program and changes in the circuits. In this section, we aim to study this source of heterogeneity.

At each version of the program, we identify four types of cells, (i) cells that remained in the program, (ii) cells that entered PADO, (iii) cells that left PADO, and (iv) cells that remained inactive, never entering PADO during the eight-week period.

Figure 10 depicts the evolution of the weekly average of police presence four weeks before and after the change in the program across all ten versions, following the same idea of pooling versions depicted in the previous section.

On average, cells that remained PADO received a higher dose of police presence, about 6.6 hours per day, and did not experience a substantial change once the patrolling routes were modified. Cells that left the program did not stop receiving some police attention. Leaving the program implied a reduction of 25% in terms of police presence. Even if PADO was no longer assigned to those areas, other police officers might have conducted patrols and responded to emergency calls. Cells not previously assigned to PADO but who entered the program already were receiving police attention, on average less than PADO units. Once entering the program, they experience a 50% increase on average. These descriptive results indicate that the program increased police presence, and once cells left the program, they did not stop receiving police attention.

Figure 10 – Weekly average police presence per cell and type of cell, 2016-2018

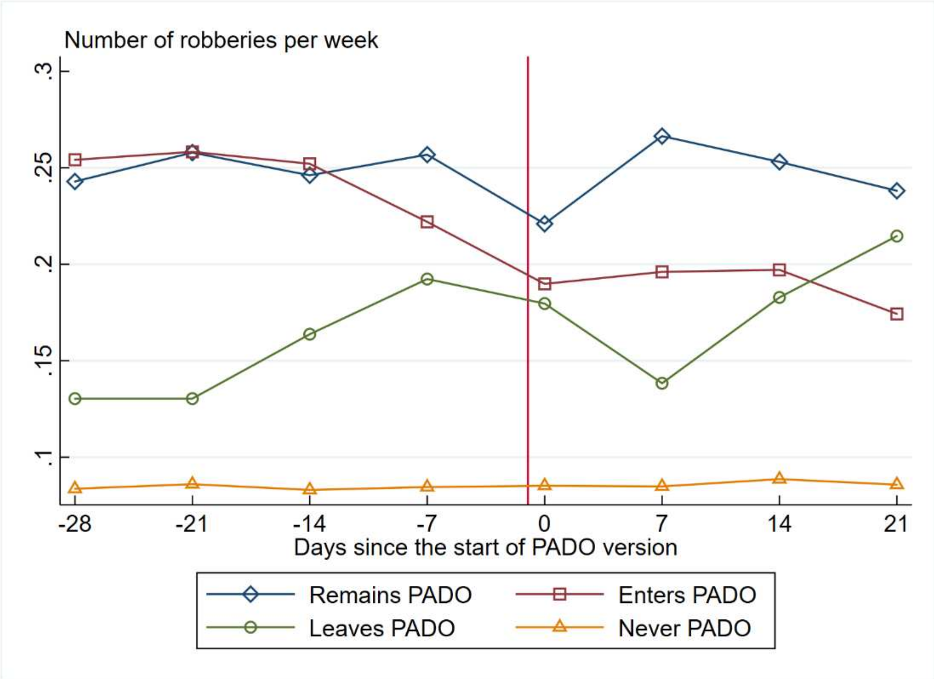


Notes: Evolution of weekly average police presence in four categories of 200x200-meters cells: (i). cells remained PADO; (ii) cells that entered the program; (iii) cells that left the program; (iv) cells that were not assigned to PADO). Only cells with one or more robberies in 2015 are considered. Source: Authors own calculations using GPS data, provided by the Ministry of Interior, Uruguay.

Figure 11 presents the weekly average evolution of robberies in the four categories previously described. The figure shows that zones of the city that entered the program had on average more robberies than the zones leaving the program and that zones that never entered. Conversely, zones selected to leave the program showed less crime than zones that remained in the program and zones that would enter.

Entering (leaving) the program was endogenous: police officers selected cells with high (low) crime concentration. Cells that were going to be treated had much higher crime rates than cells that remained out of the program. Moreover, they had a crime rate that was on average similar to hot spots. Perhaps surprisingly, those cells experienced a decrease in robberies in the pre-treatment week. For "entering cells", the average number of robberies per week was decreasing before entering the program and, after entering PADO, this trend disappeared. On the other hand, cells that were selected to leave PADO were (as expected) the ones with less than the average number of robberies. Also, perhaps surprisingly, they exhibited an increase in the number of robberies just before leaving the program. Both facts may be interpreted as a regression to the mean effect, if those cells were selected to enter or leave the program 28 or 21 days before the treatment, by selecting "the worst" and "the best" of their respective pools.

Figure 11 – Weekly average robberies per cell and type of cell, 2016-2018



Notes: Average number of robberies per cell per week in four categories of 200x200-meters cells ((i). cells remained PADO; (ii) cells that entered the program; (iii) cells that left the program; (iv) cells that were not assigned to PADO). Only cells with one or more robberies in 2015 are considered. Source: Authors own calculations using SGSP (Sistema de Gestión de Seguridad Ciudadana), provided by the Ministry of Interior, Uruguay.

Interestingly, Figure 11 does not show a dramatic increase in robberies when cells leave PADO, although there was an increasing pre-treatment trend. It is consistent with our previous finding: cells that left PADO experienced a decrease in police presence but not to zero – other police forces remained. Also, a possible explanation is that the areas that left PADO were endogenously selected (i.e., PADO segments and circuits with little chance of suffering an explosion in robberies in the absence of PADO). An additional explanation could be the existence of *residual* deterrence (distinguished from what can be called the *direct* deterrence of crime by visible police presence when it *is* present). Barnes et al. (2020) run an experiment that included random periods of up to 20 consecutive days in which individual hot spots remained without patrols. This design allowed Barnes and coauthors to measure how soon the residual deterrent effect wore off. They find that not until four days after the absence of patrols do the hot spots experience a termination of the residual deterrence.

Table 7 presents our estimated average treatment effect using the weekly panel under the fixed effects specification. A cautionary note should be made regarding the existence of pre-treatment trends that prevent us from considering these results causal but suggestive. Recall under Eq. 2.1 and Eq 2.2, the treatment effects for entering and leaving the program are measured with respect to those units that did not change their status, meaning remained PADO or were never PADO during the eight-week window.

Table 7 – Effects of PADO on police presence and robberies by type of cell.

2016-2018	PADO cells	
	Enters	Leaves
Police Presence	762***	-564***
	(19)	(23)
Mean T in pre-treatment weeks	1,599	2,252
Robberies	-0.056***	0.025**
	(0.011)	(0.012)
Mean T in pre-treatment weeks	0.247	0.154
Observations	275,208	272,528

Notes: Estimates represent average treatment effects during the follow-up period using a fixed-effect model as in Columns 5 in tables 4 and 5. Source: Authors own calculations using SGSP (Sistema de Gestión de Seguridad Ciudadana) and GPS data, provided by the Ministry of Interior, Uruguay.

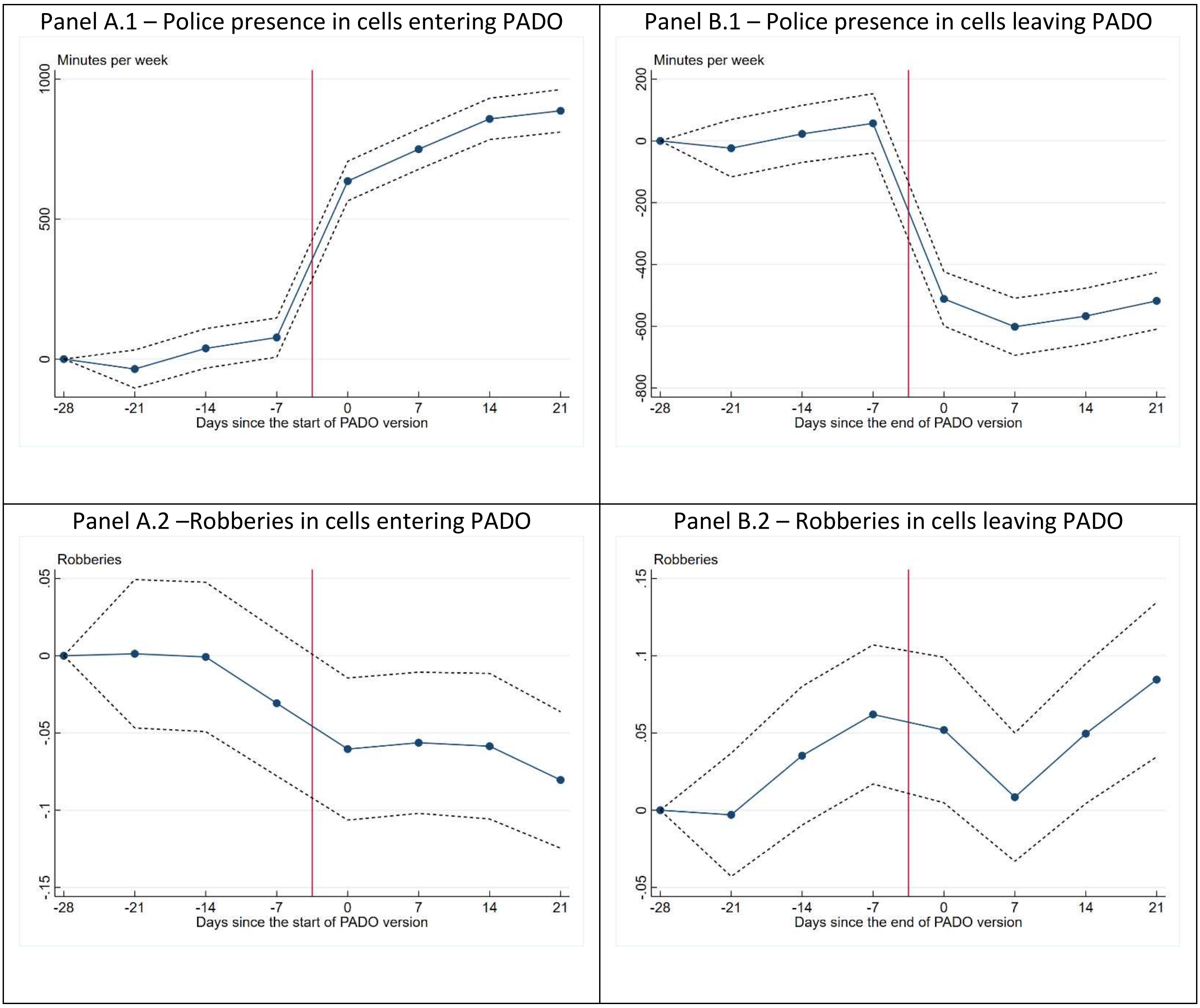
Our results show first that all the estimated coefficients have the expected sign: police presence as measured by GPS increased (decreased) in zones entering (leaving) the program, while robberies decreased (increased) respectively. Second, the increase in police presence is estimated on average at 762 minutes for cells entering the program, approximately 13 extra hours per week or two hours daily, above the baseline level for police presence before the program was modified. Leaving the program implied a decrease of approximately 564 minutes, slightly more than 9 hours weekly or one hour 20 minutes daily.

Entering the programs was associated with an average significant decrease of 0.056 robberies, while cells leaving the program experienced an increase of 0.025 on average. Our estimated impact from the program differs from those in Table 4 and 5 since there was a composition effects of units entering and leaving the program.

Figure 12 presents the estimated weekly coefficients[4]. As expected from Figure 11 and the results from Table 7, police presence showed a significant increase (decrease) when a cell enters (leaves) the program. Moreover, parallel trends in police presence are a reasonable assumption. Regarding the impact of PADO on robberies, the coefficients, while they are imprecisely estimated, point in the right direction: a decrease for cells entering the program and an increase (albeit a pre-trend) when police presence decreased after the cells leave PADO.

[4] For brevity, we do not include the respective tables but are available upon request.

Figure 12 -DiD estimate by week and type of cells for police presence and robberies, 2016-2018



Source: Authors own calculations using SGSP (Sistema de Gestión de Seguridad Ciudadana) and GPS data, provided by the Ministry of Interior, Uruguay.

In summary, we find a significant effect of PADO on police presence and a reduction of crime in cells entering the program. The opposite occurs for cells leaving: a decrease in police presence and an increase in robberies, although it is worth noting that our estimate of crime increases two weeks after the cell left PADO and could be pointing towards a residual deterrent effect. Since these results consider the whole period (2016-2018) and we found heterogeneous effects by year of introduction (section 5.3), in the next section, we will briefly explore the effect of entering or leaving PADO by year.

5.5. Effect on cells entering and leaving PADO by year of modification.

In this section, we focus on the effects of entering and leaving the program by year. We are interested in understanding heterogeneous results by year of modification.

Table 8 reports the effects of cells entering and leaving PADO by year. Results show that the program had heterogeneous effects on police presence and crime. Across all year, PADO significantly increased the number of minutes of police presence in cells that entered the program. However, while in 2016, police presence was increased by 911 minutes, in the next two years, the increase was smaller: 785 minutes in 2017 and 601 minutes per week in 2018, (a 58%, 46% and 38% increase, respectively). Thus, we argue that the program lost approximately 40% of its intensity. This dilution of treatment - or program fatigue - is consistent with the increasing cost of sustaining an intervention at scale (the "voltage effect", in terms of List (2022)). Similarly, the effects of leaving the program were also less intense. While leaving the program in 2017 accounted for a decrease in 818 minutes (34%), this only amounted to 449 minutes in 2018 (20%), meaning those cells were still receiving significant police attention while they were deemed to be ready to leave the program.

The program was especially effective in reducing robberies during the first year of implementation (-0.072, or 28%, on average) but experienced somewhat mixed results in the following years. While in 2017, we did not find a significant effect for either leaving or entering the program on robberies, cells that entered the program in 2018 experienced a decrease in robberies, although smaller than in 2016 despite being a year with higher crime rates (Figure 3 and Table 1). Regarding cells that left the program, there was no change in crime in 2017, while in 2018 they experienced an increase in robberies of 17%.

Table 8 – DiD estimates of the effect of PADO on police presence and robberies by year of introduction

	(1)	(2)	(3)	(4)	(5)	(6)
	2016		2017		2018	
Pado Cells:	Enters	Leaves	Enters	Leaves	Enters	Leaves
Police Presence	911***	-	785***	-818***	601***	-449***
	(24)	-	(38)	(40)	(21)	(25)
Mean T in pre-treatment weeks	1,563	-	1,701	2,426	1,573	2,188
Robberies	-0.072***	-	-0.015	-0.002	-0.058***	0.032**
	(0.021)	-	(0.022)	(0.022)	(0.017)	(0.015)
Mean T in pre-treatment weeks	0.257	-	0.18	0.143	0.272	0.158
Observations	56,048	-	89,718	89,428	129,442	129,260

Notes: Estimates represent average treatment effects during the follow-up period using a fixed-effect model as in Columns 5 in tables 4 and 5. Source: Authors own calculations using SGSP (Sistema de Gestión de Seguridad Ciudadana) and GPS data, provided by the Ministry of Interior, Uruguay.

6. Discussion

PADO is the first large-scale police intervention in Latin America that focused on robberies hot spots and had dedicated police officers throughout its implementation. Our work covers the first three years of the program, allowing us to examine the long-run effects and shed some light on whether this type of program is replicable in Latin America and if they are sustainable over time.

While other authors found mixed results for similar programs in Colombia (Blattman et al. 2021; Collazos et al. 2020) and Argentina (Chainey et al. 2022), we verified the positive effects of PADO found by Chainey et al. (2021) and expanded upon those results.

Our results show that PADO effectively increases police presence in areas of Montevideo that experience above-average levels of robberies by a significant amount. During its first three-year run (2016-2018), PADO cells received an additional 13 hours of police presence per week during our four-week follow-up period compared to non-treated cells. As we mentioned before, these estimates are smaller than the proposed dosage of the program but confirm the program was implemented, as measured by GPS data of police officers deployed on the ground. This might explain the contrasting results to other interventions in

Latin America since, in PADO, police compliance was explicitly monitored and reported throughout the intervention.

In addition, the multi-year run allows us to investigate the program's sustainability and explore heterogeneous results, first in terms of the context during the implementation and second in terms of entering or leaving the program.

In 2016, units that entered the program received an additional dosage of 911 minutes per week, but the effects on police presence decreased in the following years. In 2017 units entering received 785 minutes, and it reduced to 601 minutes in 2018. Leaving the program reduced the level of police presence but did not eliminate it. Units still were cared for by other police programs, although with less emphasis. In 2017, leaving the program decreased police presence by 818, while in 2018, this was only 449 minutes.

We argue that this reduction in the effects of PADO on police presence may be associated with a dilution of the program, and that through the three years the program may have lost its intensity. Anecdotal evidence suggests that changes in the program may explain at least part of these results. In some versions of 2017, PADO authorities determined that PADO should work 24 hours in the most critical zones instead of the initial 8 hours. However, there was no equivalent increase in human and material resources, limiting the available resources to target more critical hours that concentrate crime. During our interviews, officers indicated that during the 2017-2018, PADO patrols were more frequently requested to assist in crime response outside PADO circuits than in 2016. In particular, during 2017-2018, domestic violence reports and the number of protective measures increased, demanding more resources, hence diminishing the resources devoted to other strategies like hot spots policing. Further research outside the scope of our current work is required to present evidence that validates these claims.

In terms of the effects of reducing crime, during the three years evaluated, PADO decreased crime by a statistically significant amount of 0.06 robberies on average per week during our follow-up period, representing a 23% decrease in robberies from the pre-intervention period.

We found heterogeneous effects both by year of the modification and if the cells entered or left the program. While in 2016, when no cell left the program, we observed the most significant decrease in robberies, a reduction of 0.072, followed by a non-significant decrease of 0.015 for cells entering the program and a significant reduction of 0.058 in 2018. In 2018 we observed that leaving the program was associated with a weekly average increase of 0.032 robberies.

The lack of effects in crime during 2017 and the sharp increase in robberies (Figure 3) may be partly due to the change in the penal process implemented that year. Díaz and Titiunik (2019) state that the change in the law may account for 26% to 31% of the increase in crime. We argue that changes in the context are relevant to any program's outcomes. In particular, the uncertainty generated by these changes may have affected how officers were deployed and what activities they carried out while on patrol (in February 2017, the police union publicly stated that 80% of police officers were not prepared to fulfill their tasks in the context of the new penal process and demanded training - "most officers do not know the norms of the new law and it is very difficult for them to understand the complex new relationship between police authorities and judges"[5]). The fact that there was a significant increase in policing in 2017 as measured by police officers' GPS information suggests that the deployment effectively happened, but we did not observe the expected deterrence effect.

Considering 2018 alone, which we may consider as business as usual in terms of legal changes, it is interesting to address the results for cells leaving PADO in more detail. While most research has focused on

[5] News at El Pais –Uruguayan daily newspaper_ titled: "Sindicato Policial Pide Capacitar para Nuevo Código", retrieved on June 27th 2022 from: https://www.elpais.com.uy/informacion/sindicato-policial-pide-capacitar-nuevo-codigo.html

the effect of increasing police presence on crime, few researchers have discussed the impact of reducing patrols after a hot zone has been cooled off. Even if we cannot establish a causal link, our results suggest that there was no drastic increase in crime after police presence is reduced, which we may characterize as residual deterrence.

Conversations with officers in charge of PADO may provide additional explanation for the dilution of PADO effects. They identified several obstacles that may have ended reducing the efficacy of the program. Robbery is characterized as an opportunistic crime carried out by non-organized criminals. In the worst hot spots, offenders may learn to exploit the precarious infrastructure that reduces the police capacity to pursue the offenders. "PADO may prevent the explosion of robberies in these contexts, but it is not able to significantly reduce robberies", suggested interviewed police officers.

This deficit in infrastructure, often associated with disadvantaged neighborhoods, is characterized by bad street lighting and narrow passages that do not allow proper patrolling. Even if hot spots policing programs like PADO may be able to cool down hot areas, complementary interventions may be determinant in producing long-lasting effects after police presence is reduced.

7. Conclusions

We evaluate the effect of PADO (*Operative Program with Exclusive Dedication*), a police intervention focused on crime hot spots, applied in Montevideo (the capital city of Uruguay) in 2016-2018. Our study is the first three-year term estimation in a developing country of the effect of hot spot policing on robberies. We used GPS data showing real-time police presence and matched these records with geocoded data of robberies over a 200x200 meters grid covering the city.

We first focus on the program’s impact on increasing police presence in the designated areas. Our results show that the program was effectively implemented: PADO caused a sharp increase in police presence. Next, we measure the effect of police presence on robberies, by comparing PADO cells with NOPADO cells, before and after modifications to the program. Our results show that the program contributed to the reduction in crime by a statistically significant but economically moderate amount. On average, after patrols were deployed, hot spot cells presented a decrease of -0.06 robberies. The program's effect represents a 23% decrease in robberies from the pre-intervention period. This results in an elasticity of 0.47, meaning that a 10% increase in police presence would be associated with a reduction of 4.7% in robberies.

Our research sheds light on the importance of context when implementing hot spots policing and the existence of program fatigue. Hot spot policing programs like PADO could be affected by a change in the fidelity to the program's original design, endogenous behavior of offenders that adapt to this policing strategy, and uncertainty introduced by legal changes outside the program's scope. These results can help policymakers identify conditions under which hot spots programs could work and be scalable.

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9. Appendix

Table A.1– DiD estimates of police presence and crime, for the full sample.

	(1)	(2)	(3)	(4)	(5)
Police Presence	766***	766***	763***	763***	763***
	(29)	(29)	(29)	(32)	(18)
Mean T in pre-treatment weeks			1,562		
Robberies	-0.052***	-0.052***	-0.051***	-0.051***	-0.051***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Mean T in pre-treatment weeks			0.231		
Year FE	NO	YES	YES	YES	YES
Month FE	NO	NO	YES	YES	YES
Robberies in 2015	NO	NO	NO	YES	NO
Cell FE	NO	NO	NO	NO	YES
Observations	1,098,880	1,098,880	1,098,880	1,098,880	1,098,880

Notes. This table consists of a replication of the main results (Panel B from Tables 4 and 5), estimated with the full sample. Results in the main text were calculated for cells that had at least one robbery in the pre-treatment year of 2015 (approx. 25% of the full sample of the city).