Universidad de San Andrés

Departamento de Economía

Maestría en Economía


# Crime Dynamics in Buenos Aires: Evidence from a Quasi-Experimental Design


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Tesis de Maestría en Economía de

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## Dinámica criminal en Buenos Aires: Evidencia de un diseño cuasi-experimental


**Resumen**

En julio de 2018, el Gobierno de la Ciudad de Buenos Aires reorganizó los distritos policiales de la recién creada Policía de la Ciudad de Buenos Aires, reduciendo el número de comisarías de policía de 54 a 43 y remodelando sus límites para adecuarlos a los límites de las comunas y barrios. El nuevo esquema, a diferencia de antes, implica en muchos casos que varios de los barrios de la ciudad pasaron a estar patrullados por una sola comisaría.
Este artículo utiliza la variabilidad exógena introducida por la reforma para estudiar el impacto de la reestructuración policial y la reducción del números de comisarías en la dinámica del crimen en Buenos Aires durante el período 2017-2019. Dado que los límites de las comunas y los barrios responden a cuestiones administrativas y políticas no relacionadas con el crimen, y dado que la nueva distribución de los distritos policiales ocurrió solo en algunos barrios, este documento utiliza un enfoque de diferencias en diferencias para evaluar el efecto potencial de la reforma sobre cinco categorías diferentes de delitos a nivel de barrio y segmento de calle.
Los resultados muestran que la modificación de los distritos de las comisarías y la reducción en el número de comisarías provocó una disminución del 16,4 % en el número de hurtos cometidos en los barrios tratados, junto con un aumento del hurto de vehículos del 11,3 % en comparación con barrios pertenecientes al grupo de control. El impacto negativo de la intervención se mantiene cuando se analizan los resultados a nivel de segmento de calle.



**Palabras clave**: distritos policiales, crimen, diferencias en diferencias, diseño cuasi-experimental.


## Crime Dynamics in Buenos Aires: Evidence from a Quasi-Experimental Design




**Resumen**

In July 2018, Buenos Aires City Government reorganized police districts of the recently created Buenos Aires City Police, reducing the number of police stations from 54 to 43 and reshaping its borderlines to match them with the boundaries of the *comunas* and neighborhoods. The new districts, unlike before, do not have in many cases multiple police stations simultaneously patrolling one neighborhood.
This paper utilizes the exogenous variability introduced by the reform to study the impact of the police district restructuring and the police station downsizing on crime dynamics in Buenos Aires. Given that the boundaries of *comunas* and neighborhoods were drawn from administrative and political issues not related to crime, and since the new distribution of police districts happened only in some neighborhoods, this papers uses a difference-in-differences approach to evaluate the potential effect of the intervention on five different types of crime at a neighborhood and street segment level in City of Buenos Aires during the 2017-2019 period.
The results show that modifying police station districts and the number of police stations led to a decrease of 16.4 % in the number of thefts committed in the treated neighborhoods, together with an increase of car thefts of 11.3 % when compared with control neighborhoods. The negative impact of the intervention holds when analyzing results at a street-segment level.



**Keywords**: police districts, crime, difference-in-differences, quasi-experimental design.

**JEL Codes**: C50, C51, C55, D02, D04, K42.

# Crime Dynamics in Buenos Aires: Evidence from a Quasi-Experimental Design *

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**This version:** December 17, 2020

**Abstract**

In July 2018, Buenos Aires City Government reorganized police districts of the recently created Buenos Aires City Police, reducing the number of police stations from 54 to 43 and reshaping its borderlines to match them with the boundaries of the *comunas* and neighborhoods. The new districts, unlike before, do not have in many cases multiple police stations simultaneously patrolling one neighborhood.

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# 1 Introduction

Police capacity to deter crime has been has been widely studied (Braga et al., 2001; Nagin, 2013; Sherman and Weisburd, 1995; Sherman and Eck, 2002; Weisburd and Eck, 2004). The mechanisms through which police can deter crime are apprehension of criminals and also by their presence (Nagin, 2013). These two mechanisms depend both on the number of police officers and on their deployment tactics. There is abundant literature with evidence on how increasing endowment of police personnel and its allocation in the street deters crime (Nagin, 2013; Klick and Tabarrok, 2005; Draca et al., 2011; DeAngelo and Hansen, 2008). The more convincing evidence comes from those papers where there was an abrupt variation in police presence in the street that impacted crime (Nagin, 2013). In the case of Argentina, Di Tella and Schargrodsky (2004) used the impact of a terrorist attack to show that police presence deters car robberies in the City of Buenos Aires in small radius but significantly in amount (a 75% reduction on car thefts on treated blocks). Studies analyzing abrupt variations in police presence due to exogenous shocks have been made in London (Draca et al., 2011) and Washington D.C. (Klick and Tabarrok, 2005) with results in the same direction, showing that police presence in the streets deters crime. Another way to prove this causal mechanism with exogenous variations can be found in Levitt (2002) -using electoral hiring cycles of police officers-, Evans and Owens (2007) -using hiring cycles-, and Corman and Mocan (2000) -using lag variables as instruments. Regarding police deployment tactics, there is also abundant literature showing its impact on crime (Spelman and Brown, 1981; Nagin, 2013; Braga et al., 2011; Sherman and Weisburd, 1995; Weisburd and Eck, 2004). In Argentina, Cafferata (2011) showed that redeployment of federal security forces and different tactics in the south of the City of Buenos Aires, caused by the South Belt Unit Program in 2011, diminished crime and had diffusion effects. Certain police deployment tactics, such as hotspot policing or focus deterrence, improve the police apprehension capacities increasing the chance of criminal apprehension (Nagin, 2013). Moreover these tactics also deter crime by improving police "sentinel" capacity, averting crime just by being there, as stated by Braga et al. (2011); Nagin (2013); Cohen and Felson (1979).

The problem of police districting is extremely complex and a matter of importance as the goal of these areas are optimizing crime prevention, criminal apprehension, law enforcement, order maintenance, public services, and traffic enforcement (Hale, 1980; Barros, 2007). Police manpower and deployment tactics operate with an anchor, the police station, and within a radius of action, the district (Curtin et al., 2010). Police departments of a city are usually organized in police command and patrol areas where amount of personnel, the number of car patrols, deployment tactics and other issues are operated. The district sets the limit of action where police personnel of certain police station has to work and could be held accountable to in terms of their performance (Hancock and Simpson, 2009; Cordner and Scarborough, 2010). Citizens access to police services depends also on these districts, as they delimit the distance for rapid-response to emergency calls, crime registration and other bureaucratic services. Commonly, a city is divided into police command areas (e.g., precincts, districts, divisions, etc.) and patrol areas (beats, sectors, reporting areas, etc.), where the first usually manage and supervise the latter operations (Larson, 1978; Moonen, 2005).

There are some studies that have analyzed how police district modification could improve its performance (Camacho-Collados and Liberatore, 2015; Curtin et al., 2010). Smart design of police districts reduces the response times to citizen calls, improves the chances of catching offenders, identifies and locates witnesses by the police, provides immediate gathering of physical evidence and provides immediate lifesaving first aid. All these actions might enhance the reputation of the police department and could improve citizens' satisfaction with the police (Hancock and Simpson, 2009; Cordner and Scarborough, 2010). It is not usual to start the design of police district from a scratch, as historically the police geographic boundaries were hand-drawn based on an officer's or administrator's knowledge of the total area to be patrolled by the police force and the availability of police resources (Mitchell, 1972; Taylor and Huxley, 1989). In some cases districts have been drawn such as to respect natural boundaries, focus on hot spots of crime, or they conform in some way to other administrative boundaries -such as census tracks, neighborhoods, etc.- (Curtin et al., 2010; Curtin and Hayslett-McCall, 2006). The City of Buenos Aires had until July 2018 the number of police stations and district structure that was inherited from the Argentine Federal Police[1], overlapped with the one the Metropolitan City Police had[2]. When the Government of the City created the Buenos Aires City Police (BACP) by merging both forces in 2015, it took them 3 years to implement a reorganization of police station boundaries and the total number of police stations.

Since July 2018, police stations were reorganized in two different groups with differential hierarchies: communal police stations and neighborhood police stations. The first ones are 15 and match with the administrative boundary of the *comunas*[3], which are the first unit of Government with administrative capacities and political elected authorities. Each communal police department is in charge of controlling crime in their own territory and seeks solutions through their own means and through interaction with authorities and institutions outside their structure. The neighborhood police stations add up to 28, they match the *barrios*, and they are dedicated to smaller procedures, such as to receive neighbors' complaints and questions and coordinate the police force agents before they are deployed in the territory. Counting both sets of police stations gives a total of 43 police stations. As it can be appreciated from Figure 1, many of the former police department jurisdictions cut the neighborhoods in two halves (mainly in big avenues) which the new police department boundaries do not. Moreover, some small neighborhoods where subdivided into different stations jurisdictions while some large ones did not. A total of 18 neighborhoods did not have any redistricting or

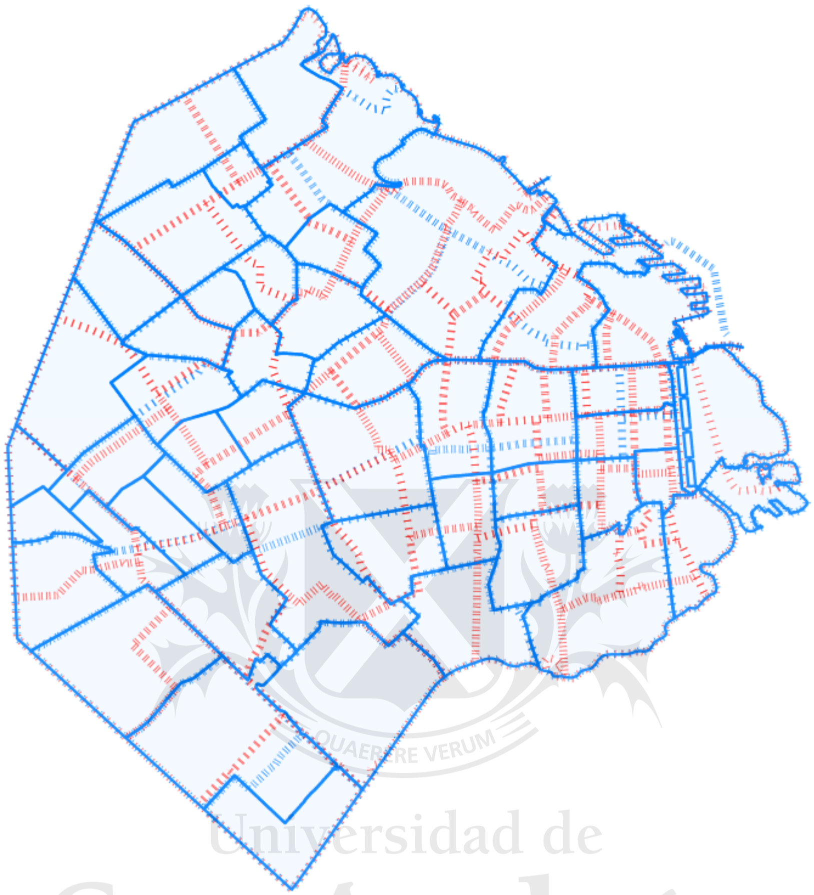
[1]The Argentine Federal Police created this structure in 1945 and subsequently modified it until 1999, where it ended with 54 police stations and a unclear district structure subsequently design by historic police administrative changes

[2]A smaller force operating in 3 neighborhoods that was created 2008 by the Law 2.894

[3]The Comunas were created by the Organic Law 1.777 of the year 2005 and their current limits where established by law 2650 of the year 2008. They are and administrative and political units within the city.

downsizing while 23 did, as Table 8 in the appendix shows.

**Figure 1:** Old and new divisions of police stations



**Source**: authors' own elaboration

**Note**: red dotted lines are the limits of the old division of police stations. Blue dotted lines are the limits of the new division. Blue full lines are neighborhood limits.



Redistricting also implied a downsizing the number of police stations from 54 to 43. The impact of police station closures on crime is not an usual topic in the empirical literature. Blesse et al. (2019) found that centralizing police services and closing police station diminish crime deterrence which cause an increase in certain crimes (overall theft did not increase, but car robberies and home burglaries did). Less police stations implied less deterrence capacity and more expected crime. Criminal opportunity theory states that with less capable guardians, more criminal opportunities emerge for the convergence on time and space of a suitable target and a motivated offender (Cohen and Felson, 1979) . These offenders perceived a decreased risk of sanctions and an increase of expected returns due to the police station closures that follow the reorganization (Blesse et al., 2019). Although informative to the analysis, it is no similar to the study presented here. Not only the City of Buenos Aires downsized the number of police stations, but also reshaped its districts to match them with the political and administrative boundaries of its *comunas* and *barrios*.

Through a quasi-experimental design, this paper finds evidence at two different levels, neighborhood and street segment. The intervention decreased monthly thefts by 15.3% at a neighborhood level. On the other hand, car thefts increased 11.3%, but only statistically significant at 10% showing that there was some negative effect of the intervention. When analyzed at a street-segment level, only the negative impact remains, indicating that there might be some potential issues at macro-level data.

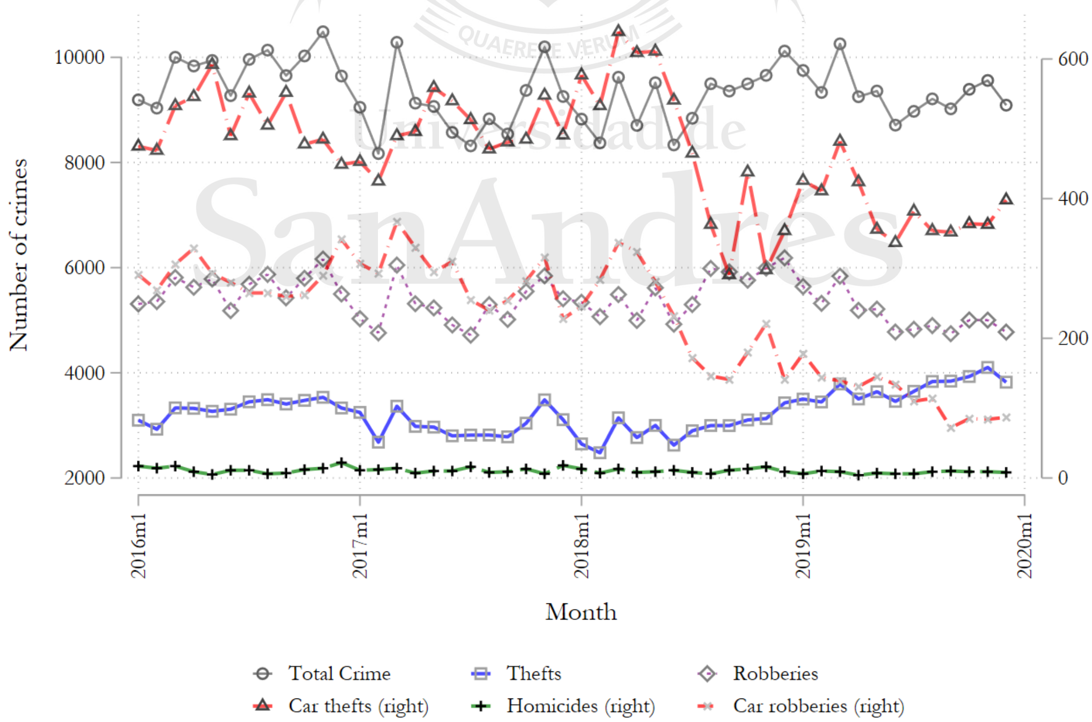
These findings are interpreted as a shock over capable guardianship of police in their districts. Among the reasons that might potentially explain results, improvement of police operations by redistricting, an increasing accountability of police staff by *comunas* political authorities for their performance, and an increasing awareness of law abiding citizens and criminal of police patrolling areas can be mentioned. The downsize of police stations might have altered the perceived risk of sanctions and increased the expected returns of criminals in certain crimes, as car thefts seem to increase at neighborhood level, in line with Blesse et al. (2019) hypothesis. Further research need to be done to regarding the behaviour micro-units of analysis, street-segments, to understand them more thoroughly.

## 2 Data

Data on crime was gathered from the government public open source platform named Crime Map[4], an official website from the Government of the City of Buenos Aires. This platform provides information with a daily frequency of every crime committed and registered in the city with geo-coded information for five different types: homicides, thefts, car thefts, robberies, and car robberies. Geo-located data include latitude and longitude, neighborhood, and commune where the crime occurred. Information is available from January 2016 until December 2019.

A data set at a monthly frequency was built with a total number of 448,212 crimes committed between 2016 and 2019, having a panel database with a total of 2,304 observations. Figure 2 provides an overview of these data. The period of analysis was restricted only to years 2017, 2018 and 2019, covering exactly the 18 months before the intervention and the 18 months after it and having a total of 331,034 crimes. Additionally, geo-coded information of crimes was used to impute each crime to a street-segment[5]. After identifying every existent street-segment in Buenos Aires, each crime was linked to the closest segment, thus providing a street-segment ID to each of such 331,034 crimes.

**Figure 2:** Crime Dynamics 2016-2019




**Source**: author own elaboration

[4] Crime Map.

[5] Street-segments are defined as the two block faces on either side of a street between two intersections.

Due to a law enacted in 2005, all socio-demographic information through the city's official web portals is provided at a communal level and not at the neighborhood level. This issue did not allow to enrich the analysis using additional controls such as gender, age, or poverty data.

To determine the exact moment in which the change in the jurisdictions of the new police stations became effective, this paper refers to the government resolution that gave effect to such restructuring. Additionally, various officials linked to the city's security area were consulted, and with this information it was confirmed that on July 1, 2018 the new police organization came into effect.

Information is available for five different types of crime, which are essentially the main outcomes of interest. Adding up the number of each of these specific crimes committed, a total crime variable was built, which is the sixth relevant outcome. The analysis only limited to these crime categories because data on other types of crime in not publicly available. However, according to official information, these crimes constitute approximately 60% of crimes committed in the City of Buenos Aires, so the analysis provided here is quite comprehensive since it covers a large proportion of the criminal acts committed in the city[6].

Analysis is limited to two types of neighborhoods. On the one hand, those neighborhoods that were patrolled by several police stations and that later came under the control of only one police station (this is the treatment group, which is made up of a total of 23 neighborhoods). On the other hand, a second group of neighborhoods was contemplated that was previously patrolled by several police stations and then remained under the influence of more than one police station (this is the control group, which is made up of a total of 16 neighborhoods). Table 8 and Table 9 provide a good overview of the data by treatment an control group, as well as by neighborhood. In this way, those neighborhoods (9 in total) that were originally patrolled by only police station and later came under the influence of several police stations or that were patrolled by one police station both before and after the police redistricting were excluded from the analysis. These 9 neighborhoods add up a total of 20,035 crimes during the 2017-2019 period, thus representing a 6.05% out of the total 331,034 crimes of such period.

Two alternative approaches were taken to address the analysis. Firstly, a second definition of treatment and control groups was applied, using the percentage change in the number of police stations. In this case, neighborhoods are considered as treated if the decrease in the number of police stations is over 50%. Under this new definition of groups, treatment groups is made up of a total of 21 neighborhoods, while the control group is made up of 18 neighborhoods. 4 neighborhoods move from the control group to the treatment group (Balvanera, Flores, Palermo and Recoleta), while 6 neighborhoods moves from the treatment group to the control group (Chacarita, Liniers, Mataderos, Parque Avellaneda, Saavedra, Villa Devoto, and Villa Ortuzar). Secondly, in a similar way, treatment variable was segmented in

[6] Aggregated data by year for Buenos Aires is available in the statistics official website. Specifically, homicides, thefts and robberies accounted for the 58.4% of the total crime in 2018 and for the 51.4% in 2019

different treatment arms according to the previous existent number of police stations prior to the reform (in this case, the original treatment condition is hold, that is, being patrolled by many police stations before and by only one after the reform). Under this strategy, those neighborhoods that previously were patrolled by 6, 5 or 4 police stations belong to the same treatment arm, those patrolled by 3 police stations belong to the second treatment arm, and those patrolled by only 2 police stations belong to the third treatment arm. In this way, first treatment groups is made up of 6 neighborhoods, second one is made up of 10 neighborhoods, and third treatment group is made up of 7 neighborhoods.

A total number of 28,209 street-segments were identified in Buenos Aires, as Table 1 shows. Of this total, in around 80% of them at least one crime was committed during the period of study. This figure increases to almost 87% if crimes committed during 2016 are taken into account. Between 2016 and 2019, over 25% of total crime was just concentrated in only 2.5% of all existent street-segments, that is, around 700 street-segments. Out of the total number of 28,209 street-segments in the city, 24,803 of them belong to the neighborhoods used in the analysis (the rest of the segments belong to the neighborhoods excluded from the sample).

**Table 1:** Descriptive statistics of street segments and crime

| Year | Total Crime | Number of SS | Mean crime | Std. dev. | Min. # of crimes | Max. # of crimes |
|---|---|---|---|---|---|---|
| 2016 | 117,178 | 28,209 | 4.15 | 9.5 | 0 | 397 |
| 2017 | 108,785 | 28,209 | 3.86 | 8.2 | 0 | 276 |
| 2018 | 110,344 | 28,209 | 3.91 | 8.2 | 0 | 314 |
| 2019 | 107.909 | 28,209 | 3.69 | 9.4 | 0 | 407 |

Note: all figures are expressed in terms of crime per street segment.

After identifying each of the existent street-segments in the city, each crime was linked to the closest segment, thus providing a street-segment ID to each of the 331,034 crimes of the 2017-2019 period. This process allowed the possibility of using crime data with a higher level of disaggregation, and thus perform the same analysis using street-segments instead of neighborhoods as the basic unit of analysis. The final result is a new database at monthly frequency with 24,803 street-segments observed during 36 months, having a total number of 892,908 observations.

## 3 Research design

Given that reforms implemented by the local authorities can be understood in a context in which the limits of the new police stations respond to administrative issues and where they seek to adapt them to the limits of the neighborhoods, the restructuring gives rise to a quasi-experimental design where some neighborhoods that previously were under the influence of more than one police station are now controlled by a single police station. In effect, the very nature of these changes meant that some of the neighborhoods were treated, and that another portion of them continued to be patrolled by more than one police station, thus belonging to the control group. In this context, since the reform of police districts is not related to crime in each observation unit, this exogeneity is used through a difference-in-differences approach, a method that will allow to analyze the causal effect of the reforms on crime in the treated neighborhoods and in the street-segments within them. This method relies essentially on the parallel trends assumption in the outcomes of both treated and untreated groups, and is needed to ensure internal validity of the results. Since this assumption cannot be directly tested, next section provides a visual inspection of the trends of the six outcomes of interest.

The basic unconditional effects of the intervention at a neighborhood level will be estimated using the following equation:

$$Y_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 P_{it} + \beta_3 T_{it} \times P_{it} + \mu_i + \delta_t + \epsilon_{it}, \tag{1}$$

where Y is the outcome of interest (crime) occured in the neighborhood $i$ in period $t$, $T$ is the treatment indicator, which takes a value of 1 the neighborhood came to be patrolled by only one police station when before was being patrolled by more than one, $P$ is dummy for the post period and $\epsilon$ is the error term. The coefficient associated to the interaction term between $T$ and $P$ is the difference-in-differences estimator, so $\beta_3$ captures the causal effect of the intervention, or the "intent-to-treat" (ITT) effect. The specification also includes temporal fixed effects at monthly-yearly level ($\delta_t$), as well as neighborhood fixed effects ($\mu_i$).

The main outcomes will consist on the number of total crime in each neighborhood, as well as the number of crimes disaggregated by category, that is, thefts, car thefts, robberies, car robberies, and homicides.

A second round of analysis will evaluate the effect of the intervention on street-segments, that is, going to a micro-level of analysis within the neighborhood. The basic unconditional effects of the intervention at the street-segment level will be estimated using the same equation as before:

$$Y_{sit} = \beta_0 + \beta_1 T_{sit} + \beta_2 P_{sit} + \beta_3 T_{sit} \times P_{sit} + \mu_i + \delta_t + \epsilon_{it}, \tag{2}$$

where Y is the outcome of interest (crime) in the street-segment $s$ for neighborhood $i$ in period $t$, $T$ is the treatment indicator, which takes a value of 1 if the street-segment is in the neighborhood $i$ and is now patrolled by only one police station when before was being patrolled by more than one, $P$ is dummy for the post period and $\epsilon$ is the error term. The interaction term between $T$ and $P$ is the difference-in-differences estimator, so again $\beta_3$ captures the causal effect of the reform. The specification includes again temporal fixed effects at monthly-yearly level ($\delta_t$), as well as neighborhood fixed effects ($\mu_i$).

Two alternative approaches are also taken to address the analysis. Firstly, a second definition of treatment and control groups was applied, using the percentage change in the number of police stations. In this case, neighborhoods are considered as treated if the decrease in the number of police stations is over 50%. Under this new definition of groups, treatment groups is made up of a total of 21 neighborhoods, while the control group is made up of 18 neighborhoods. 4 neighborhoods move from the control group to the treatment group (Balvanera, Flores, Palermo and Recoleta), while 6 neighborhoods moves from the treatment group to the control group (Chacarita, Liniers, Mataderos, Parque Avellaneda, Saavedra, Villa Devoto, and Villa Ortuzar). In this case, both equations remain exactly as before.

The second approach consists on a segmented treatment variable in different treatment arms according to the previous existent number of police stations prior to the reform. As it was already mentioned, the original treatment condition is hold, that is, being patrolled by many police stations before and later by only one station after the restructuring. Under this strategy, those neighborhoods that previously were patrolled by 6, 5 or 4 police stations belong to the first treatment arm, those patrolled by 3 police stations belong to the second treatment arm, and those patrolled by only 2 police stations belong to the third treatment arm. The selection of the thresholds to determine each of the treatment arms was mainly based on the distribution of the number of police stations previous to the reform in the treatment group. Using this criterion, the number of neighborhoods in each group is notably balanced and has sense in terms of how group neighborhoods according to the number of stations. Following this strategy, the basic unconditional effects of the intervention at a neighborhood level will be estimated using the following equation:

$$\begin{aligned} Y_{it} = \beta_0 &+ \beta_1 T1_{it} + \beta_2 T2_{it} + \beta_3 T3_{it} \\ &+ \beta_4 P_{it} + \beta_5 T1_{it} \times P_{it} + \beta_6 T2_{it} \times P_{it} \\ &+ \beta_7 T3_{it} \times P_{it} + \mu_i + \delta_t + \epsilon_{it} \end{aligned} \tag{3}$$

The analysis performed at the street-segment level follows the same equation.

## 3.1 Verification of parallel trends assumption

In order to verify the parallel trends assumption for the outcomes of interest, a graphical analysis was performed using data for the pre-treatment period comparing the dynamics of the total number crimes and each specific felony separately for both the treated and the untreated group, using the neighborhoods as unit of analysis. The following figures show that, with the exception of homicides, variables display very similar trajectories when comparing both groups. Given that the evolution of these variables was certainly erratic in some cases, they were smoothed using a spline function in such a way as to capture their trend component.

## Parallel trends for treated and untreated groups

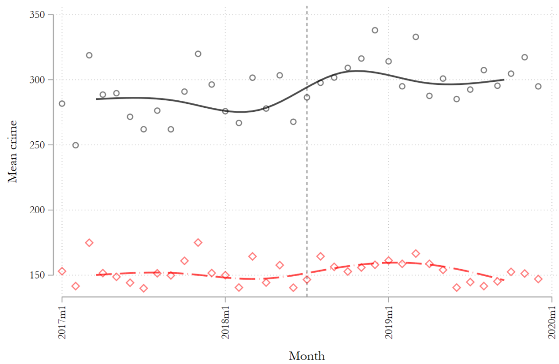



**Figure 3:** Total crime

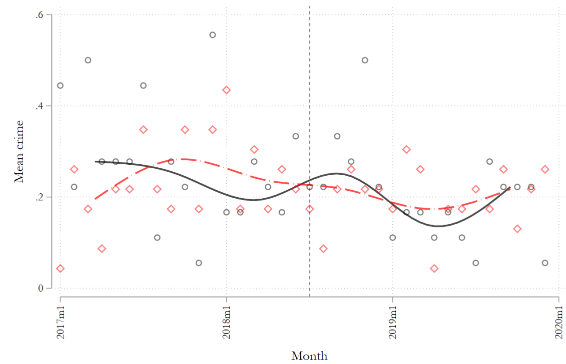



**Figure 4:** Homicides

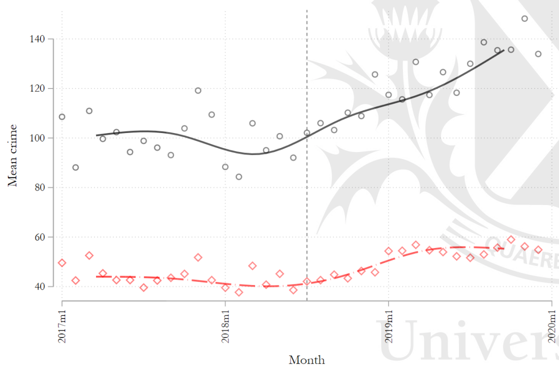



**Figure 5:** Thefts

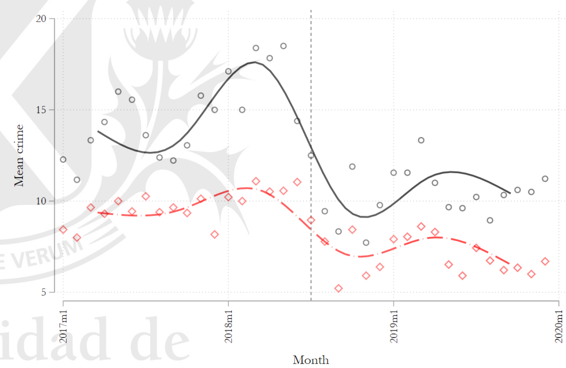



**Figure 6:** Car thefts



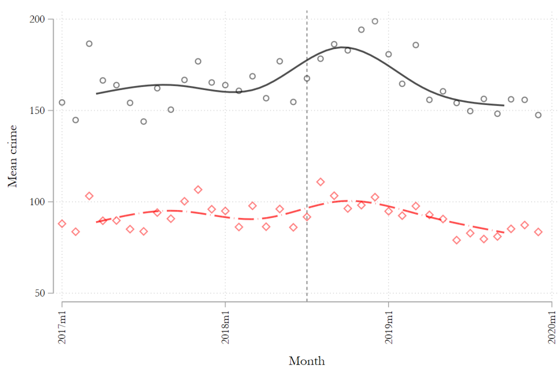



**Figure 7:** Robberies

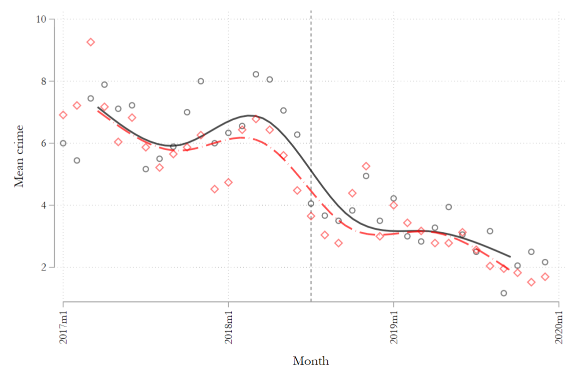
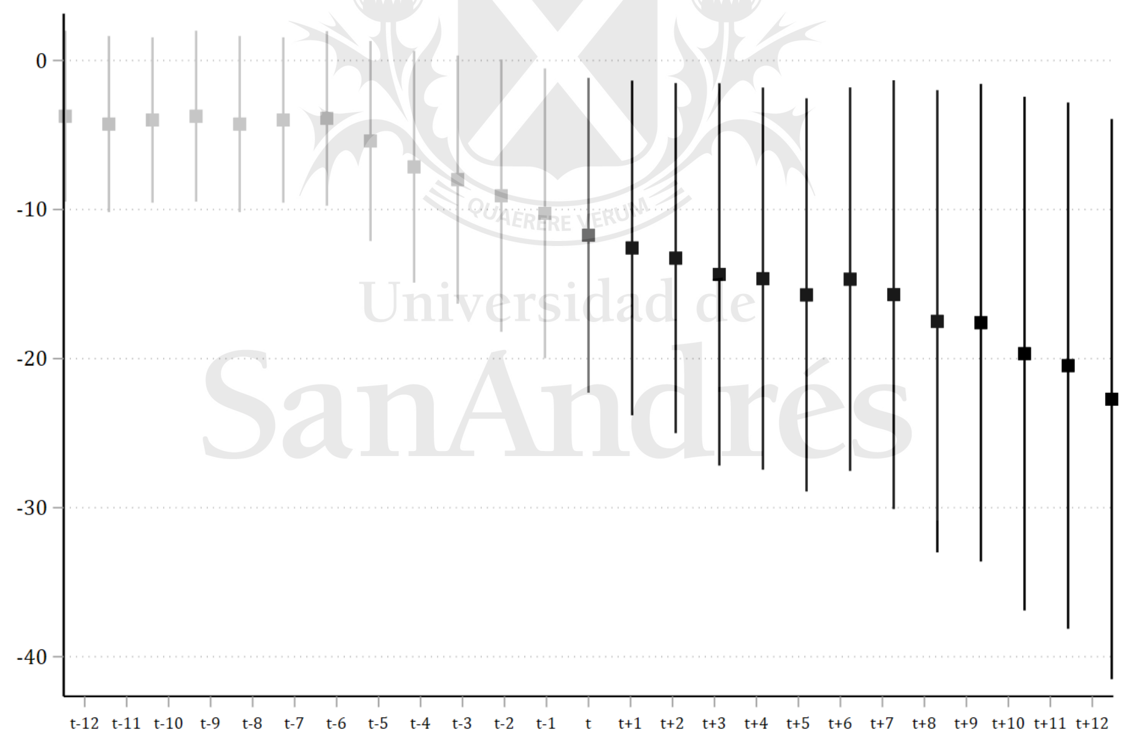



**Figure 8:** Car robberies

**Source**: author own elaboration
**Note**. Black line: untreated. Red line: treated.

In the addition to this visual inspection, following Munyo and Rossi (2020), an alternative specification with leads and lags is presented using thefts as outcome variable, which is the one where significant results are found in the different rounds of analysis[7]. Using different hypothetical beginnings of the intervention, both before and after the real date of implementation, and once all the estimates were performed, coefficients were extracted and plotted together with their respective confidence intervals. Figure 9 displays the results for 12 lags and for 12 leads[8]. It can be seen that, despite only treatment and leads are statistically significant at the 5% level, pre-event dummies show a negative trend three or four months before the effective beginning of the intervention. This could be lead by the fact that, despite the restructuring was officially implemented on July, 2018, some administrative and logistic changes could have been performed during the transition to the new regime, and this may have had some effect on crime. However, it is worth emphasizing again that the lags are not statistically significant.

**Figure 9:** Average effects on **thefts** using different periods as beginning of intervention - neighborhood level data




**Source**: author own elaboration

[7]Same estimates for the rest of the outcomes variables are available in the Appendix.

[8]Table with all results of these estimates is available on request. Since the table and the graph presented would be showing exactly the same information, displaying both in the paper would be redundant.

## 4 Results

Results will be presented at neighborhood and street-segment level, first showing the findings on the impact of the intervention on the number of crimes disaggregated by category using the neighborhoods as basic unit of analysis, and then using data at street-segment level. The analysis was performed at a monthly frequency. Finally, a placebo test was performed when significant results were found.

### 4.1 Neighborhood-level analysis

Table 2 displays the estimated effect of the police station re-district on crime. Analysis includes monthly-yearly fixed effects, and standard errors were clustered at the neighborhood level. As can be seen, the effects of the intervention are negative for the total number of crimes, thefts, and robberies, and positive for crimes related to motor vehicles. In the case of homicides, the size of the coefficient is nearly zero. Statistically significant effects are only found on the number of thefts and the number of motor vehicle thefts, but not on the rest of the crimes. In the case of homicides, this is to be expected since the nature of this type of act is certainly different from that linked to property crimes. Treated neighborhoods perceived a reduction of 17.83 thefts by month, which is equivalent to a 16.4% decrease when compared with the control group.

**Table 2:** Difference-in-Differences estimates for the 2017-2019 period

| *Variables* | (1)<br>*All crimes* | (2)<br>*Homicides* | (3)<br>*Thefts* | (4)<br>*Car Thefts* | (5)<br>*Robberies* | (6)<br>*Car Robberies* |
|---|---|---|---|---|---|---|
| *Treatment* | -21.914 | 0.048 | -17.827** | 1.785* | -6.590 | 0.670 |
| | (13.651) | (0.064) | (7.128) | (1.025) | (7.763) | (1.058) |
| Observations | 1,404 | 1,404 | 1,404 | 1,404 | 1,404 | 1,404 |
| Data frequency | Monthly | Monthly | Monthly | Monthly | Monthly | Monthly |
| $R^2$ | 0.250 | 0.011 | 0.266 | 0.143 | 0.214 | 0.119 |
| Mean dep. var. control | 306.7 | 0.309 | 107.8 | 15.73 | 175.5 | 7.299 |
| SD dep. var. control | 192.5 | 0.687 | 80.09 | 11.01 | 113.7 | 6.710 |

Notes: mean and standard deviation for dependent variables are computed taking into account only neighborhoods which belong to the control group and considering only the pre-treatment period, that is, from January, 2017 to June, 2018. Clustered standard errors at neighborhood level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

It can be observed also an increase of 1.79 car thefts in those treated jurisdictions. This is equivalent to an increase of 11.3% over the control group. This result, although contrary to the former, is in line with findings documented by Blesse et al. (2019). It could be explained from the criminal opportunities created by the very nature of the implemented reform that reduce the number of police stations. Next table replicates the analysis at street-segment level.

### 4.1.1 Alternative definition of treatment and control groups

Table 3 shows the results obtained using a different definition of treatment and control groups based in the percentage change of the number of police stations. Under this approach, results do not hold and none of the coefficients is significant.

**Table 3:** Difference-in-Differences estimates for the 2017-2019 period at the neighborhood level (alternative definition of treatment and control groups)

| *Variables* | (1)<br>*All crimes* | (2)<br>*Homicides* | (3)<br>*Thefts* | (4)<br>*Car Thefts* | (5)<br>*Robberies* | (6)<br>*Car Robberies* |
|---|---|---|---|---|---|---|
| *Treatment* | 11.261 | -0.057 | 5.281 | -0.076 | 4.688 | 1.425 |
| | (13.651) | (0.064) | (7.128) | (1.025) | (7.763) | (1.058) |
| Observations | 1,404 | 1,404 | 1,404 | 1,404 | 1,404 | 1,404 |
| Data frequency | Monthly | Monthly | Monthly | Monthly | Monthly | Monthly |
| $R^2$ | 0.025 | 0.030 | 0.028 | 0.085 | 0.047 | 0.130 |
| Mean dep. var. control | 197.1 | 0.190 | 65.65 | 13.43 | 110.4 | 7.415 |
| SD dep. var. control | 115.3 | 0.492 | 50.18 | 9.820 | 68.32 | 6.630 |

Notes: mean and standard deviation for dependent variables are computed taking into account only neighborhoods which belong to the control group and considering only the pre-treatment period, that is, from January, 2017 to June, 2018. Clustered standard errors at neighborhood level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

### 4.1.2 Segmented treatment variable

Table 4 displays the results from the alternative analysis approach, where the treatment variable is segments. These findings are very interesting and are in line with the estimates from Table 2. Firstly, negative and statistically significant effects are found for thefts for all treatment arms. These effects are also economically meaningful. Curiously, the effect is larger in *T3*, the group that was previously patrolled by only two police stations. This treatment arm also displays statistically and economically significant effects for total crime. In these neighborhoods, total crime decreases by almost 37 crimes, which is equivalent to a 12.1% reduction compared to the control group.

Also similarly to the previous findings, coefficients associated to car thefts and car robberies are statistically significant for the second treatment arm. This finding is also interesting since it provides additional evidence on the dynamics of this specific type of crimes which deserve further attention in future research. The magnitude of the increase in car robberies is noticeably large, implying a 30% rise of these crimes in the second treated group over the control group.

**Table 4:** Difference-in-Differences estimates for the 2017-2019 period at the neighborhood level (segmented version of treatment variable)

| *Variables* | (1) *All crimes* | (2) *Homicides* | (3) *Thefts* | (4) *Car Thefts* | (5) *Robberies* | (6) *Car Robberies* |
|---|---|---|---|---|---|---|
| *T1* | -12.729 | 0.161 | -13.895* | 0.387 | 0.281 | 0.337 |
| | (14.236) | (0.120) | (7.886) | (1.187) | (8.186) | (1.127) |
| *T2* | -16.885 | -0.013 | -16.230** | 2.607** | -5.441 | 2.192** |
| | (15.569) | (0.071) | (7.804) | (1.034) | (8.751) | (0.875) |
| *T3* | -36.971** | 0.039 | -23.481*** | 1.809 | -14.120 | -1.219 |
| | (14.295) | (0.065) | (7.062) | (1.374) | (8.711) | (2.040) |
| Observations | 1,404 | 1,404 | 1,404 | 1,404 | 1,404 | 1,404 |
| Data frequency | Monthly | Monthly | Monthly | Monthly | Monthly | Monthly |
| $R^2$ | 0.025 | 0.030 | 0.028 | 0.085 | 0.047 | 0.130 |
| Mean dep. var. control | 306.7 | 0.309 | 107.8 | 15.73 | 175.5 | 7.299 |
| SD dep. var. control | 192.5 | 0.687 | 80.09 | 11.01 | 113.7 | 6.710 |

Notes: mean and standard deviation for dependent variables are computed taking into account only neighborhoods which belong to the control group and considering only the pre-treatment period, that is, from January, 2017 to June, 2018. T1 is made up of those neighborhoods that previously were patrolled by 6, 5 or 4 police stations (Barracas, la Boca, Boedo, Constitución, Parque Chacabuco, and Villa Crespo). T2 is made up of neighborhoods that were patrolled by 3 police stations (Coghlan, Colegiales, Parque Patricios, Paternal, Retiro, San Cristobal, San Telmo, Villa Gral. Mitre, Villa Santa Rita, and Villa Urquiza). Finally, T3 is made up of neighborhoods that were patrolled by only 2 police stations (Liniers, Mataderos, Parque Avellaneda, Saavedra, Villa Devoto, Villa Ortuzar, and Chacarita). Clustered standard errors at neighborhood level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.



### 4.2 Street-segment analysis

As Table 5 shows, street-segment analysis displays consistent results with the negative impact on thefts caused by the intervention. This coefficient sign is in line with neighborhood findings. Nevertheless, the positive effect on car thefts disappears when considering this level of analysis.

**Table 5:** Difference-in-Differences estimates for the 2017-2019 period at the street-segment level

| *Variables* | (1) *All crimes* | (2) *Homicides* | (3) *Thefts* | (4) *Car Thefts* | (5) *Robberies* | (6) *Car Robberies* |
|---|---|---|---|---|---|---|
| *Treatment* | -0.030 | 0.000 | -0.020* | 0.001 | -0.011 | -0.000 |
| | (0.020) | (0.000) | (0.011) | (0.001) | (0.011) | (0.001) |
| Observations | 892,908 | 892,908 | 892,908 | 892,908 | 892,908 | 892,908 |
| Data frequency | Monthly | Monthly | Monthly | Monthly | Monthly | Monthly |
| $R^2$ | 0.007 | 0.000 | 0.006 | 0.001 | 0.004 | 0.001 |
| Time FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean dep. var. control | 0.4150 | 0.0004 | 0.1460 | 0.0213 | 0.2380 | 0.0101 |
| SD dep. var. control | 1.063 | 0.0206 | 0.562 | 0.152 | 0.693 | 0.105 |

Notes: mean and standard deviation for dependent variables are computed taking into account only neighborhoods which belong to the control group and considering only the pre-treatment period, that is, from January, 2017 to June, 2018. Clustered standard errors at neighborhood level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

In this level of aggregation, the impact of the intervention on thefts implies a reduction of 13% of thefts at street level. This is a non-negligible result from a crime prevention perspective. It is also important to mention that, despite increasing sample size and keeping its sign, the impact of the intervention in car thefts is no longer statistically significant. This could be showing potential issues at the aggregation process or that some crimes present different patterns in their dynamics which needs further research.

### 4.2.1 Alternative definition of treatment and control groups

Table 6 shows the same results as in Table 3, but in this case at the street-segment level. Again, results do not hold and none of the coefficients is statistically significant, and are in line with the table at neighborhood level.

**Table 6:** Difference-in-Differences estimates for the 2017-2019 period at the street-segment level (alternative definition of treatment and control groups)

| *Variables* | (1)<br>*All crimes* | (2)<br>*Homicides* | (3)<br>*Thefts* | (4)<br>*Car Thefts* | (5)<br>*Robberies* | (6)<br>*Car Robberies* |
|---|---|---|---|---|---|---|
| *Treatment* | 0.023 | -0.000 | 0.016 | -0.002 | 0.009 | 0.001 |
| | (0.020) | (0.000) | (0.011) | (0.001) | (0.011) | (0.001) |
| Observations | 892,908 | 892,908 | 892,908 | 892,908 | 892,908 | 892,908 |
| Data frequency | Monthly | Monthly | Monthly | Monthly | Monthly | Monthly |
| $R^2$ | 0.008 | 0.000 | 0.004 | 0.001 | 0.008 | 0.001 |
| Time FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean dep. var. control | 0.269 | 0.000258 | 0.0897 | 0.0186 | 0.151 | 0.0103 |
| SD dep. var. control | 0.782 | 0.0163 | 0.411 | 0.143 | 0.516 | 0.105 |

Notes: mean and standard deviation for dependent variables are computed taking into account only neighborhoods which belong to the control group and considering only the pre-treatment period, that is, from January, 2017 to June, 2018. Clustered standard errors at neighborhood level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

### 4.2.2 Segmented treatment variable

Table 7 displays the last set of results. At the street-segment analysis, this approach shows additional findings which are in line with the analysis at the neighborhood level. While the positive effect of the intervention on crimes related to automobiles gets almost dissipated, the negative effects on theft and total crime strongly remain.

**Table 7:** Difference-in-Differences estimates for the 2017-2019 period at the street-segment level (segmented version of treatment variable)

| *Variables* | (1) *All crimes* | (2) *Homicides* | (3) *Thefts* | (4) *Car Thefts* | (5) *Robberies* | (6) *Car Robberies* |
|---|---|---|---|---|---|---|
| *T1* | -0.012 | 0.000 | -0.014 | -0.001 | 0.004 | -0.001 |
| | (0.022) | (0.000) | (0.014) | (0.002) | (0.013) | (0.001) |
| *T2* | -0.021 | -0.000 | -0.009 | 0.001 | -0.014 | 0.001 |
| | (0.026) | (0.000) | (0.015) | (0.001) | (0.013) | (0.001) |
| *T3* | -0.047** | 0.000 | -0.031*** | 0.003* | -0.019 | -0.001 |
| | (0.020) | (0.000) | (0.011) | (0.001) | (0.012) | (0.002) |
| Observations | 892,908 | 892,908 | 892,908 | 892,908 | 892,908 | 892,908 |
| Data frequency | Monthly | Monthly | Monthly | Monthly | Monthly | Monthly |
| $R^2$ | 0.007 | 0.000 | 0.006 | 0.001 | 0.004 | 0.001 |
| Time FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean dep. var. control | 0.4150 | 0.0004 | 0.1460 | 0.0213 | 0.2380 | 0.0101 |
| SD dep. var. control | 1.063 | 0.0206 | 0.562 | 0.152 | 0.693 | 0.105 |

Notes: mean and standard deviation for dependent variables are computed taking into account only neighborhoods which belong to the control group and considering only the pre-treatment period, that is, from January, 2017 to June, 2018. T1 is made up of those neighborhoods that previously were patrolled by 6, 5 or 4 police stations (Barracas, la Boca, Boedo, Constitución, Parque Chacabuco, and Villa Crespo). T2 is made up of neighborhoods that were patrolled by 3 police stations (Coghlan, Colegiales, Parque Patricios, Paternal, Retiro, San Cristobal, San Telmo, Villa Gral. Mitre, Villa Santa Rita, and Villa Urquiza). Finally, T3 is made up of neighborhoods that were patrolled by only 2 police stations (Liniers, Mataderos, Parque Avellaneda, Saavedra, Villa Devoto, Villa Ortuzar, and Chacarita). Clustered standard errors at neighborhood level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.



# 5 Conclusion

The paper found that police station redistricting and downsizing made by the Buenos Aires City Police in July 2018 had a negative impact on crime. Thefts decreased using a difference-in-difference design when testing it from two different levels of aggregation in the unit of analysis, the neighborhood and street-segments. The magnitude of thefts decrease is interesting in itself and it is aligned with the literature on police districting efficacy enhancing virtues (Camacho-Collados and Liberatore, 2015; Curtin et al., 2010). At the neighborhood level, car thefts increased by the intervention, in line with Blesse et al. (2019). However, this finding does not hold in the street-segment level of analysis. These opposite effects need for further research to understand the mechanisms behind them as there could be potential aggregation issues behind the results. While the alternative definition of treatment and control groups does not show any significant result, the segmentation of treatment group into three different arms provides evidence in line the first analysis. Finally, it should be noted that this paper innovates in the crime economics literature on many aspects by using two different units of analysis (neighborhood and street-segment) to test the impact of the intervention.

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# Appendix A Additional results

## Appendix A.1 Summary statistics and overview

**Table 8:** Crime by neighborhood, before and after intervention

| | | *Before* | | | | *After* | | | |
|---|---|---|---|---|---|---|---|---|---|
| | # SS | Accum. crime | Mean crime *Dai.* | Mean crime *Mon.* | # PS | Accum. crime | Mean crime *Dai.* | Mean crime *Mon.* | # PS |
| *Not treated (16)* | | | | | | | | | |
| Almagro | 541 | 6,664 | 12.21 | 370.2 | 4 | 7,436 | 13.54 | 413.1 | 2 |
| Balvanera | 555 | 9,961 | 18.24 | 553.4 | 6 | 13,101 | 23.86 | 727.8 | 2 |
| Belgrano | 906 | 5,242 | 9.6 | 291.2 | 4 | 5,810 | 10.58 | 322.8 | 3 |
| Caballito | 1069 | 7,871 | 14.42 | 437.3 | 4 | 7,326 | 13.34 | 407 | 2 |
| Flores | 1365 | 8,583 | 15.72 | 476.8 | 5 | 7,965 | 14.51 | 442.5 | 2 |
| Floresta | 448 | 2,225 | 4.08 | 123.6 | 3 | 2,209 | 4.02 | 122.7 | 2 |
| Monserrat | 362 | 3,998 | 7.32 | 222.1 | 5 | 4,591 | 8.36 | 255.1 | 3 |
| Monte Castro | 494 | 1,520 | 2.78 | 84.4 | 3 | 1,348 | 2.46 | 74.9 | 2 |
| Nueva Pompeya | 880 | 3,391 | 6.21 | 188.4 | 2 | 3,893 | 7.09 | 216.3 | 2 |
| Palermo | 1403 | 13,453 | 24.64 | 747.4 | 7 | 13,531 | 24.65 | 751.7 | 3 |
| Recoleta | 605 | 7,490 | 13.72 | 416.1 | 5 | 8,249 | 15.03 | 458.3 | 2 |
| San Nicolas | 365 | 7,733 | 14.16 | 429.6 | 4 | 9,124 | 16.62 | 506.9 | 2 |
| Velez Sarsfield | 471 | 1,708 | 3.13 | 94.9 | 2 | 1,495 | 2.72 | 83.1 | 2 |
| Villa Lugano | 1345 | 4,831 | 8.85 | 268.4 | 3 | 5,467 | 9.96 | 303.7 | 3 |
| Villa Luro | 442 | 1,619 | 2.97 | 89.9 | 4 | 1,360 | 2.48 | 75.6 | 2 |
| Villa del Parque | 601 | 2,035 | 3.73 | 113.1 | 4 | 1,909 | 3.48 | 106.1 | 2 |
| *Treated (23)* | | | | | | | | | |
| Barracas | 817 | 5,007 | 9.17 | 278.2 | 6 | 5,196 | 9.46 | 288.7 | 1 |
| Boca | 462 | 2,478 | 4.54 | 137.7 | 5 | 2,479 | 4.52 | 137.7 | 1 |
| Boedo | 393 | 2,744 | 5.03 | 152.4 | 5 | 2,696 | 4.91 | 149.8 | 1 |
| Chacarita | 326 | 2,289 | 4.19 | 127.2 | 2 | 2,084 | 3.8 | 115.8 | 1 |
| Coghlan | 230 | 723 | 1.32 | 40.2 | 3 | 743 | 1.35 | 41.3 | 1 |
| Colegiales | 366 | 1,993 | 3.65 | 110.7 | 3 | 2,132 | 3.88 | 118.4 | 1 |
| Constitucion | 291 | 4,468 | 8.18 | 248.2 | 4 | 5,078 | 9.25 | 282.1 | 1 |
| Liniers | 910 | 3,417 | 6.26 | 189.8 | 2 | 2,447 | 4.46 | 135.9 | 1 |
| Mataderos | 1242 | 3,811 | 6.98 | 211.7 | 2 | 3,687 | 6.72 | 204.8 | 1 |
| Parque Avellaneda | 690 | 2,533 | 4.64 | 140.7 | 2 | 2,531 | 4.61 | 140.6 | 1 |
| Parque Chacabuco | 691 | 3,626 | 6.64 | 201.4 | 4 | 3,458 | 6.3 | 192.1 | 1 |
| Parque Patricios | 430 | 2,975 | 5.45 | 165.3 | 3 | 2,815 | 5.13 | 156.4 | 1 |
| Paternal | 291 | 909 | 1.66 | 50.5 | 3 | 988 | 1.8 | 54.9 | 1 |
| Retiro | 332 | 3,785 | 6.93 | 210.3 | 3 | 5,348 | 9.74 | 297.1 | 1 |
| Saavedra | 1070 | 2,667 | 4.88 | 148.2 | 2 | 2,479 | 4.52 | 137.7 | 1 |
| San Cristobal | 297 | 2,856 | 5.23 | 158.7 | 3 | 2,805 | 5.11 | 155.8 | 1 |
| San Telmo | 166 | 2,303 | 4.22 | 127.9 | 3 | 2,335 | 4.25 | 129.7 | 1 |
| Villa Crespo | 659 | 4,128 | 7.56 | 229.3 | 4 | 4,603 | 8.38 | 255.7 | 1 |
| Villa Devoto | 1289 | 2,923 | 5.35 | 162.4 | 2 | 2,586 | 4.71 | 143.7 | 1 |
| Villa Gral. Mitre | 312 | 1,784 | 3.27 | 99.1 | 3 | 1,534 | 2.79 | 85.2 | 1 |
| Villa Ortuzar | 307 | 938 | 1.72 | 52.1 | 2 | 945 | 1.72 | 52.5 | 1 |
| Villa Santa Rita | 401 | 1,752 | 3.21 | 97.3 | 3 | 1,468 | 2.67 | 81.6 | 1 |
| Villa Urquiza | 961 | 3,693 | 6.76 | 205.2 | 3 | 3,622 | 6.6 | 201.2 | 1 |

Notes: *SS* means Street Segments. *Accum. crime* is the total accumulated number of crimes from January 1st, 2017 to June 30th, 2018, for the before-treatment period, and from July 1st, 2018 to December 31st, 2019 for the post-treatment period. *Mean dai.* and *mean mon.* crime are the mean daily and monthly crime in each neighborhood, respectively. *# PS* is the number of police stations involved in the patrolling of the neighborhood.

**Table 9:** Summary statistics - untreated versus treated neighborhoods

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Not treated | | Treated | |
| | *Before* | *After* | *Before* | *After* |
| Mean monthly number of total crimes | 283.36 | 304.26 | 152.22 | 153.12 |
| Mean monthly number of homicides | 0.27 | 0.20 | 0.23 | 0. 19 |
| Mean monthly number of thefts | 99.50 | 122.45 | 43.92 | 51.22 |
| Mean monthly number of car thefts | 14.77 | 10.46 | 9.73 | 7.07 |
| Mean monthly number of robberies | 162.08 | 167.96 | 92.14 | 91.67 |
| Mean monthly number of car robberies | 6.73 | 3.18 | 6.18 | 2.94 |

Note: control groups is composed by 16 neighborhoods, while treatment groups has 23 neighborhoods in total. 9 neighborhoods were excluded from the analysis since there were patrolled by one police stations both before and after the intervention. Number of police stations was reduced from 54 (under the Federal Police scheme) to 43 in 2018 (under the new scheme).

**Table 10:** Descriptive statistics on the crime dynamics per street segment, using different spans

| | N | Mean | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|---|
| *1 day* | | | | | |
| 2017-2019 | 314,576 | 1.05 | 0.26 | 1 | 19 |
| 2017 | 103,841 | 1.05 | 0.24 | 1 | 14 |
| 2018 | 104,212 | 1.06 | 0.28 | 1 | 19 |
| 2019 | 106,523 | 1.05 | 0.27 | 1 | 12 |
| *1 week* | | | | | |
| 2017-2019 | 273,056 | 1.21 | 0.66 | 1 | 23 |
| 2017 | 89,769 | 1.21 | 0.61 | 1 | 16 |
| 2018 | 91,204 | 1.21 | 0.63 | 1 | 19 |
| 2019 | 92,083 | 1.22 | 0.73 | 1 | 23 |
| *10 days* | | | | | |
| 2017-2019 | 262,746 | 1.26 | 0.77 | 1 | 26 |
| 2017 | 86,397 | 1.26 | 0.71 | 1 | 17 |
| 2018 | 87,779 | 1.26 | 0.73 | 1 | 26 |
| 2019 | 88,570 | 1.26 | 0.85 | 1 | 23 |

Table shows descriptive statistics on the number of crimes per street segment using different spans of time. First, we consider one day as the unit of time, and then we extend it to one week and 10 days.

## Appendix A.2 Additional tests for parallel trends for the rest of outcome variables

**Figure 10:** Average effects on **total crime** using different periods as beginning of intervention - neighborhood level data

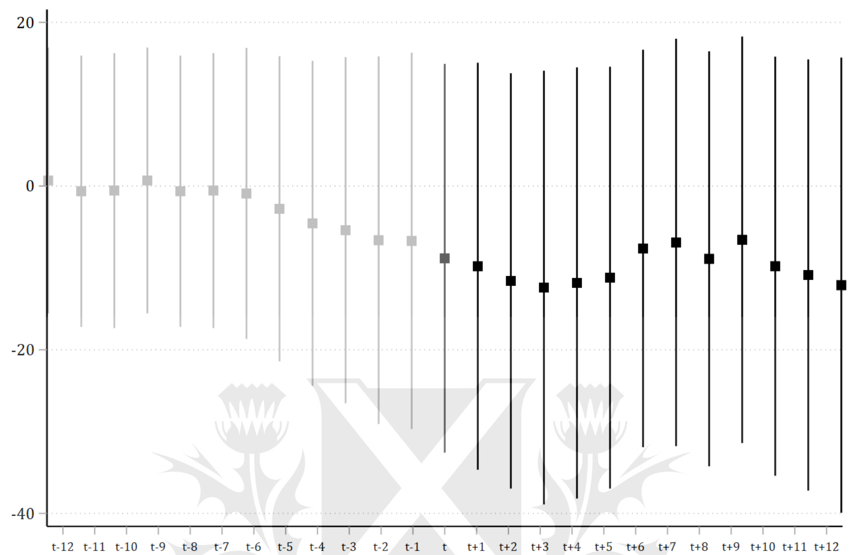


**Figure 11:** Average effects on **homicides** using different periods as beginning of intervention - neighborhood level data

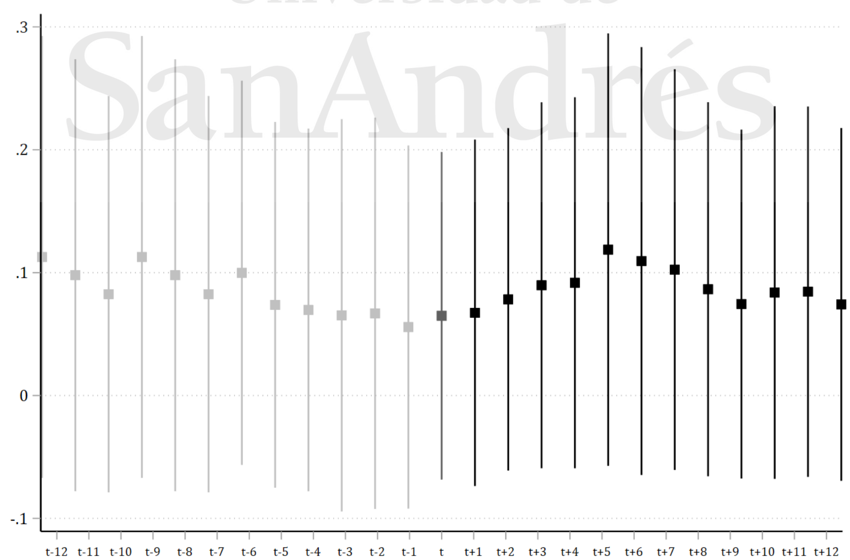

**Figure 12:** Average effects on **car thefts** using different periods as beginning of intervention - neighborhood level data

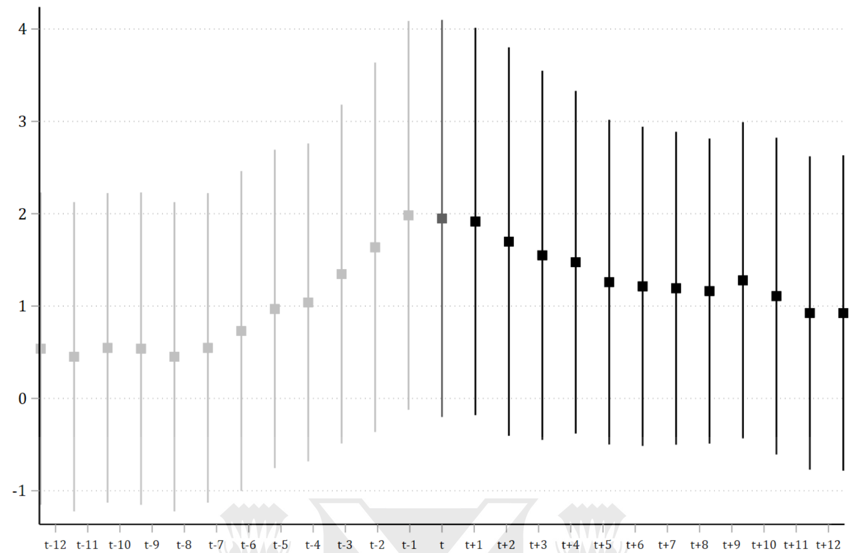


**Figure 13:** Average effects on **robberies** using different periods as beginning of intervention - neighborhood level data

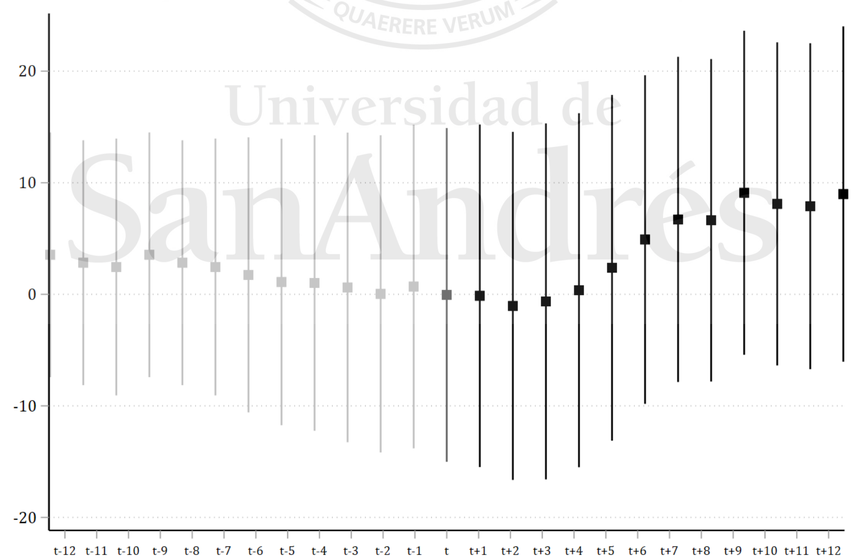

**Figure 14:** Average effects on **car robberies** using different periods as beginning of intervention - neighborhood level data