"Police-Monitored Cameras and Crime"

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Police-Monitored Cameras and Crime[*]

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Abstract: We study the impact of police monitoring on crime. We exploit detailed information on location and date of installation of police-monitored surveillance cameras coupled with data at the street-segment level on all reported crimes in the city of Montevideo, Uruguay. We find that the introduction of police-monitored surveillance cameras reduces crime by about 20 percent in monitored areas relative to a pure control group located outside of the city. We further report that unmonitored areas of the city also benefit from a reduction in crime, thus indicating the presence of positive spillovers effects.

Keywords: Monitoring cameras; police; crime.

JEL Code: K42.

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I. Introduction

A growing number of cities from all around the world are relying on surveillance cameras as a tool for preventing crimes and supporting investigations and prosecutions. Still, not enough is known about the effect of surveillance cameras on crime, and in particular, little is known about whether cameras reduce crime or simply relocate criminal activity to other areas.

In this paper we study the impact of a large-scale introduction of police monitored cameras in Montevideo (the capital city of Uruguay, 1.5 million of inhabitants). In 2013 the Ministry of the Interior of Uruguay started to install surveillance cameras in some areas of the city. These cameras are continuously monitored by police officers located in a monitoring center that combines video surveillance technology with the action of police patrol response. In order to study the impact of this policy on crime, we take advantage of a really unique database that includes the universe of reported crime in the entire city of Montevideo, by street segment, for the three-year period January 2012 to December 2014, and the location and the time of the installation of all police monitoring cameras in the city.

Our difference-in-differences estimates indicate that the presence of police monitoring cameras is associated with a reduction of about 20 percent in crime in treated areas of the city. Which is the rationale behind these results? In principle, the effect of police monitoring on crime could potentially work through deterrence (police presence makes criminal activity less attractive) and incapacitation (police officers apprehend criminals leaving fewer of them around to commit future crimes). Even though there is anecdotal evidence of arrest made by police patrols alerted by officers in the monitoring center,[1] our results are unlikely to reflect changes in the numbers of

[1] As an example, in May 2015 the newspaper El País report a case in which surveillance cameras captured a robbery. Police officers in the monitoring center called a patrol in the area and nine minutes later two police officers apprehended the offender. In court the suspect denied everything, without being aware that the surveillance cameras

incarcerated criminals. Thus, we believe that our estimates should be interpreted as a deterrent effect of police monitoring on crime.[2]

It is well known that, potentially, the reduction in crime in areas with police monitoring may be compensated by an increase in crime somewhere else—a "displacement" effect.[3] Thus, we explore potential displacement effects and we do not find evidence of such effects. Indeed, we report the presence of positive spillover effects, since unmonitored areas of the city were also benefited from a reduction in crime relative to the pure control areas outside the city.

Our paper is related to the literature on the impact of police monitored cameras on crime.[4] In particular, the effect of surveillance cameras on crime is ambiguous in the literature.[5] Welsh and Farrington (2009) present a review of the empirical literature, which is mainly concentrated on small-scaled experiences and focuses on partial equilibrium effects.[6] In addition, only a few papers address the causality problem between the installation of cameras and crime. Exceptions include King et al. (2008), Hayes and Downs (2011), and La Vigne and Lowry (2011), Priks (2014), Priks

had registered the crime scene. The video recording was used as probative material in court and the offender was sentenced to prison.

[2] Gómez-Cardona et al. (2017) report no significant effects on apprehensions following the installation of surveillance cameras in Medellín, Colombia. Unfortunately, we cannot formally test the impact of surveillance cameras on apprehensions rates because there is not information available.

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

[4] There is also an important and related literature on the effects of police monitoring on crime. See, for example, Levitt (1997), Di Tella and Schargrodsky (2004), Klick and Tabarrok (2005), Poutvaara and Priks (2009), and Draca et al. (2011).

[5] Brown (1995), Skinns (1998), Armitage et al. (1999), Ditton and Short (1999), Blixt (2003), Griffiths (2003), Welsch (2004), King et al. (2008), La Vigne et al. (2011), Hayes and Downs (2011), McLean et al. (2013), Piza et al. (2014), Priks (2014), Priks (2015), van Ours and Vollaard (2016) and Gomez-Cardona et al. (2017) find reductions on crime following the installation of surveillance cameras. However, Winge and Knutsson (2003), Gill (2006), Farrington et al. (2007), Ratcliffe et al. (2009) and Lim and Wilcox (2016) find no conclusive results.

[6] Alexandrie (2017) reviews recent studies that rely on random assignment and natural experiments in order to address some of the methodological shortcomings of previous literature.

(2015), van Ours and Vollaard (2016), and Gomez-Cardona et al. (2017).[7] Thus, our first contribution to the literature is to study the causal impact of a larger-scaled introduction of police monitored cameras compared to previous literature.

Our second contribution is to explore general equilibrium effects. Evidence on general equilibrium effects from anti-crime policies is scarce. Pricks (2015) analyzed the effects of surveillance cameras on crime in the Stockholm subway system. He presents evidence that the introduction of the cameras reduced crime by approximately 25 percent, and reports some evidence on local displacement. In a recent contribution, van Ours and Vollaard (2016) studies the impact of the introduction of the electronic engine immobilizer in the European Union. This anti-theft device reduced car theft on new (protected) cars. They also report some displacement to older (un-protected) cars. Our results suggest that crime displacement may depend on the particular setting of the policy implemented.

The paper continues as follows: Section II presents the data and describes the intervention; Section III presents the empirical strategy and reports results; Section IV concludes.

II. Intervention and data

To investigate the effect of police monitoring on crime we use two sources of data: a database with the date and location of the installations of surveillance cameras and a database on reported crime.

The first database was provided by the Ministry of the Interior of Uruguay and includes information on the date of installation and location of all surveillance cameras installed in Montevideo since 2013.

[7] Priks (2014) presents evidence that surveillance cameras reduce unruly behavior inside soccer stadiums. Gomez-Cardona et al. (2017) find that total crime reports are 24 percent lower within the coverage zone following the installation of a camera relative to the average baseline level of crime reports.

Surveillance cameras in Montevideo are exposed to everyone's view and they are continuously monitored by police officers located in a monitoring center with more than a hundred employees. When police officers in the monitoring center observe a crime, they contact a mobile patrolling the area and ask them to go immediately to the crime scene. In those cases where the police officers in the monitoring center see a suspicious movement, they can follow the suspect through cameras (able to zoom in and rotate up to 360 degrees) before deciding whether to contact or not the mobile patrolling the area. According to Montevideo police authorities, the average response is about five minutes.[8] When that happens, and the police officers arrest the offender, the video recording becomes part of the probative material.[9]

We divide Montevideo in 10,868 street segments by considering the geographical latitude and longitude of all the streets of the city. We define a treated street segment as an area under strict police monitoring. Each treated street segments can be protected by more than one camera in order to ensure a clear visual recognition of potential offenders. At the end of our sample period there were 277 street segments in Montevideo monitored with surveillance cameras.

The second database was provided by the Police Department of Montevideo and includes monthly information on the universe of criminal incidents reported in Montevideo, between January 2012 and December 2014 (273,700 offenses). The database is geo-located, i.e. each criminal incident recorded includes information on the exact location through its geographical coordinates (latitude and longitude). For a subset of crimes (robberies and thefts) we also have monthly data at the jurisdiction level for all the country.

[8] El Observador, "*Los robos en Ciudad Vieja y un sistema de cámaras al que exhiben como exitoso*", 26 May 2015.

[9] Supreme Court surveyed 20 criminal judges in Montevideo and all of them reported that they rely on video surveillance cameras as an investigative tool (see El Observador, 26 May 2015). In fact, since the beginning of the program 288 prosecutions relied on images from surveillance cameras (see El Observador, 5 January 2016).

Figures 1 and 2 summarize the geographical distribution of the areas monitored by surveillance cameras, the variability in the installation dates across different street segments, and crime incidence in Montevideo in October 2012, before the beginning of the program. As usual, crime is clustered in small areas that include not only the street segments covered by police-monitored cameras, but also other areas all around the city.

Reported crime is classified by the Police Department in more than 130 different types of offenses. In the period of analysis (2012-2014), 6 categories account for 92 percent of total crime: thefts represent 50 percent of total reported crime, robberies 14 percent, assault 12 percent, domestic violence 9 percent, damage 7 percent, and murder 0.2 percent.[10]

In the Uruguayan Penal System, in line with international standards, theft is defined as depriving a person of property without the use of violence. Robbery is defined as depriving a person of property with the use of violence or threat of violence. Assault is an intentional physical attack or threat against another person excluding domestic violence. Domestic violence is defined as a pattern of abusive behavior (physical, sexual, emotional, economic, or psychological actions or threats of actions) in any relationship that is used by one partner against an intimate partner. Damage is an act of vandalism involving deliberate destruction of or damage to public or private property. Murder implies causing the death of another person without extreme provocation or legal justification.

Summary statistics are reported in the top panel of Table 1. In the top panel, the unit of observation is the street segment and the data correspond to the whole city of Montevideo. On average, there is one reported crime per street segments every 45 days (0.66 crimes per month and street segment), being theft the most prevalent type of crime. Table 2 provides additional summary

[10] The share of these 6 categories in total crime is quite stable though time: 92 percent in 2012, 92 percent in 2013, and 91 percent in 2014.

statistics, distinguishing between eventually treated areas (i.e., those areas that at some point in the sample period are under surveillance) and untreated areas. As expected, crime is higher in eventually treated areas relative to untreated areas.

In the bottom panel of Table 1 we report summary statistics for all the country. For all the country we have monthly data at the jurisdiction level for robberies and thefst, which together represent approximately 65 percent of total crime.

III. Empirical strategy and results

To identify the effect of police monitored cameras on crime we use a difference-in-differences approach that exploits the variability over time and space in the introduction of the cameras.

The installation of surveillance cameras targeted five specific areas of the city and occurred simultaneously with other actions followed by the Police Department. Specifically, a continuous patrolling of the targeted areas was implemented in order to reduce police response time. The presence of other anti-crime initiatives in Montevideo may potentially affect our identification strategy, especially if the introduction of such policies were collinear to the introduction of monitoring cameras. Even though we do not have police patrolling information, after a series of meetings with key authorities we confirmed that the path followed in police patrolling was orthogonal to the date of installation of each camera. We also confirm with the authorities that the concentration of policing efforts across the targeted segments does not imply lower police surveillance in the street segments without monitoring cameras. Nonetheless, our findings should be interpreted as the joint effect of the cameras and the increased presence of police. This is important since a general increased police presence could imply that the effect of the cameras is different than it would have been without a general increase in police presence.

Formally, we estimate the following difference-in-differences equation,

$$Y_{it} = \beta T_{it} + \alpha_i + \mu_t + \varepsilon_{it} \quad (1)$$

where Y_{it} is crime in street segment i at month t, T_{it} is a dummy variable that takes the value one for treated street segments (those with a police-monitored surveillance camera at month t) and zero for control street segments, α_i is a street-segment fixed effect, μ_t is a month fixed effect (36 months in our sample period), and ε_{it} is the usual error term. The parameter of interest is β.

In a first empirical strategy we restrict the sample to eventually treated street segments (277). In this sample, the control group includes those street segments that are untreated at time t but eventually treated at some point in the future (during the sample period). In this strategy, identification exploits the variability in the installation dates across different street segments. Given that the installation procedure relied on operational decisions and that installation sites were not prioritized, then the order in which the cameras were installed can be considered exogenous to crime trends, thus providing a source of variability that can be exploited in order to identify causal effects.[11]

Column (1) in Table 3 reports difference-in-differences estimates of the impact of surveillance cameras on crime, using the sample of eventually treated street segments. Standard errors are clustered at the street-segment level. The estimated coefficient on Police monitoring is negative and statistically significant at the 1 percent level. The result is not only statistically significant but also relevant: the incorporation of police-monitored surveillance cameras reduces

[11] The period 2012-2014 was active in terms of new policies implemented by the Police Department. The government (Ministry of the Interior) increased the wages of the police force and the number of police officers, upgraded the equipment of the police, trained police officers with seminars given by well-known criminologist such as Lawrence Sherman, and even signed a cooperation agreement with the New York Police Department. Even though these policies affect the general effectiveness level of the police and have the potential to affect crime rates in Uruguay they do not invalidate our identification strategy as their effects should be captured by the time dummies.

crime 19 percent in monitored areas relative to unmonitored areas that will be eventually monitored.[12] [13]

In a second strategy we use all street segments in the city of Montevideo. As reported in Column (2) in Table 3, the coefficient on Police monitoring is negative and statistically significant at the 1 percent level, thus providing further evidence that the installation of surveillance cameras has an important effect in reducing crime in monitored areas relative to unmonitored areas.[14]

Even though the differences are not statistically significant, the smaller estimated coefficient in the eventually treated sample compared to the estimated coefficient when we use the whole city of Montevideo suggests the presence of positive spillovers. This may happen since, in the eventually-treated sample, control and treatment street segments are geographically near each other and criminals may avoid all areas close to the cameras. This implies a question mark on the validity of the control group in the sample of eventually treated street segments.

Indeed, for these difference in differences strategies to be valid, the control group should (1) have a similar crime trend as the treatment group in absence of treatment (the parallel trends assumption), and (2) the crime levels in the control group should not be affected by the treatment (the Stable Unit Treatment Value Assumption, SUTVA, assumption). Below we check the validity of these two assumptions.

Parallel trends assumption

While the parallel trend assumption cannot be tested, it is possible to check whether crime trends in treated street segments and control street segments were the same in the pre-treatment period. If time trends are parallel in the pre-treatment period, then it is likely that they would have

[12] We estimate the percentage change relative to the mean of Total crime in treated areas in the pre-treatment period.
[13] We obtain similar results using daily data instead of monthly data. And when we exclude month fixed effects and street fixed effects. All results mentioned and not shown are available from the authors upon request.
[14] The significance of all coefficients reported in Table 3 remains unchanged if standard errors are clustered at the jurisdiction level.

been continued being parallel in the post-treatment period in the absence of the treatment. To test the parallel-trend assumption we ran an alternative specification with "leads" and "lags." Formally,

$$Y_{it} = \sum_{k=q-}^{q+} \beta^k \ T_{it}^k + \alpha_i + \mu_t + \varepsilon_{it} \quad (2)$$

where T_{it}^k is a dummy variable taking the value 1 if treatment took place k periods ago, q^- is the pre-period furthest back, and q^+ is the post-period furthest after the installation of the cameras. In this way, β^k measures the effect k periods after treatment took place. If k is negative then β^k measures the effect k periods before the treatment.

Table 4 reports estimates of Equation (2) for Total crime, for the 2 alternative samples (we set k=6). As observed in Table 4, in the main empirical strategy reported in Column (1) all pre-event dummies are individually (and jointly) equal to zero thus providing confidence on the difference-in-differences parallel-trends assumption.[15] In Figure 2 we plot the sequence of β^k (and confidence bands) corresponding to the specification in Column (1) against the event time line.

Column (2) reports estimates of Equation (2) for the whole city of Montevideo. In this specification, 5 out of 6 coefficients associated to the pre-event dummies are individually equal to zero providing additional support for the difference-in-differences parallel-trends assumption.

The specification in Equation (2) also allows us to examine the dynamic pattern following the installation of the cameras. The effect on crime is already observed the first month following the installation of the cameras, and the effect is relatively stable over time.

SUTVA assumption

As explain above, a second assumption is that the crime levels in the control group should not be affected by the treatment. If this assumption is violated, results from the difference in differences strategies may be biased. If the introduction of cameras induced criminals to move to

[15] The p-value for the joint test that all six "leads" coefficients are equal to zero is 0.60.

control street segments, crime levels in the control group would go up, thereby biasing the effect downwards. The effect would instead be upward biased if the introduction of cameras in the treatment street segments caused crime to go down also in the control group.

In order to account for the potential violation of the SUTVA assumption, we need a pure control area that is not affected by potential spillover effects. Under the assumption that potential spillovers only occurs within Montevideo, we use jurisdictions outside Montevideo as the pure control group. In this way, the potential contamination of the control group can be addressed by comparing the evolution of crime in the treated area vis a vis the evolution of crime in the pure control area. That is, we divided the country in 3 areas: the first group includes all treated areas in Montevideo. The second group includes all untreated areas in Montevideo (this area is the most likely area to be exposed to spillovers or displacement effects). The third group includes all areas outside Montevideo (this is a pure control group that we assume is not exposed to spillovers or displacement).

As described in Section II, for those jurisdictions outside Montevideo there is only monthly information at the jurisdiction level. In column (1) of Table 5 we report difference in differences estimates using the pure control group.[16] The value of the coefficient indicates that the introduction of police-monitored surveillance cameras reduces crime 20 percent in monitored areas relative to the pure control group area. This result is similar to the one obtained with street-segment data and where the control group was constructed with all untreated areas within Montevideo.

Overall, our results indicate that the introduction of surveillance cameras is associated to an important decrease in crime.

Displacement

[16] We consider as treated any area in which a surveillance camera was installed during that month.

In the absence of evidence of the presence or not of displacement effects, little can be learnt from finding that the increase of police monitoring in certain areas reduces crime relative to unmonitored areas. Policy action requires understanding whether the reduction in crime in monitored areas is compensated or not by a similar increase in other areas of the city. Indeed, the discussion on general equilibrium effects of policy interventions is a critical topic now-days, encompassing not only policy interventions on criminal activity but also other policy interventions economists are interested in.[17]

Thus, having established a link between surveillance cameras and crime, we now explore whether the introduction of surveillance cameras in certain areas of the city is displaced towards other areas of the city.

To formally explore potential displacement effects we perform a difference-in-difference exercise in which the "treated" units are the unmonitored jurisdictions in Montevideo. The pure control units are all jurisdictions outside Montevideo. The "intervention" is the introduction of cameras in the monitored area of Montevideo (a dummy variable that takes the value one in the unmonitored areas of Montevideo in the post intervention period). Under the hypothesis of displacement, we should observe an increase of crime in the unmonitored area of Montevideo relative to pure control jurisdictions upon the introduction of cameras in the city. Under the hypothesis of positive spillovers effects, we should observe a decrease of crime in the unmonitored area of Montevideo relative to pure control jurisdictions upon the introduction of cameras in the city.

Results from this difference-in-differences exercise are presented in Column (2) in Table 5. The coefficient on the "intervention" variable is negative and significant, indicating the presence

[17] Crépon et al. (2013), for example, report experimental evidence of the existence of displacement effects in labor market interventions.

of positive spillovers effects. Even though the reduction in crime is smaller than the reduction observed in monitored areas, this finding suggests that surrounding areas are also benefited from protection provided by the increase in monitoring.

Additional results

According to police authorities from Montevideo, theft and robbery are the type of crime that are more likely to occur outdoors and, because of that, they are also the type of crime more likely to be prevented by means of surveillance cameras. On the other hand, assault and domestic violence are the type of crime more likely to occur indoors and, therefore, less likely to be prevented by surveillance cameras. We follow the authorities' classification and we construct two variables: Outdoor crime (thefts and robberies) and Indoor crime (assaults and domestic violence).

Table 6 reports regressions for Indoor crime and Outdoor crime as the dependent variables. For indoor crime surveillance cameras should not have an impact, or at least they should have a much smaller impact.[18] This is exactly what we find: there is no impact of surveillance cameras on Indoor crime.[19] In addition, when we use Outdoor crime as the dependent variable the estimated coefficients on Police monitoring are negative and statistically significant, and with similar values (in terms of percentage change) to the ones reported in Table 3.[20]

IV. Conclusions

This paper presents new evidence on the aggregate effects of police monitoring on crime. First, we find that the installation of police-monitored surveillance cameras significantly reduces

[18] It is possible to argue that even for indoor crimes surveillance cameras can deter criminal behavior by providing potential evidence against aggressors.
[19] We estimate the models with leads and lags (not reported) and, considering the four cases, most pre-event dummies (from 24 coefficients corresponding to 6 pre-event coefficients for 4 specifications, 22 of them are not significant) are individually (and jointly) equal to zero, thus providing confidence on the difference-in-differences identifying assumption.
[20] The fact that most of the impact from the introduction of cameras is on outdoor crime validates the use of outdoor crime to perform the spillover analysis above.

street crime in monitored street segments relative to unmonitored street segments. Second, we move to understanding aggregate effect and we find evidence of positive spillover effects.

Given the nature of the intervention, our findings should be interpreted as the joint effect of the cameras and the increased presence of police. This is important since a general increased police presence could imply that the effect of the cameras is different than it would have been without a general increase in police presence. In addition, given that our data are on reported crime, it can be argued that the installation of surveillance cameras may affect the willingness to report crime. If this were the case, and assuming that reporting increases with the installation of surveillance cameras (for example, because victims believe that offenders are more likely to be apprehended), our estimates can be interpreted as lower-bound estimates on the effect of surveillance cameras on crime.

A simple cost-benefit analysis shows that introducing police-monitored surveillance cameras is a very efficient policy. On the one hand, government authorities estimate that the total cost of the program (including cameras, software, and police agents) was about USD 350,000. This program reduces around 35 offenses per month (or 420 per year) in monitored areas of Montevideo. Therefore, the estimated cost for each offense avoided is USD 830. On the other hand, the Inter-American Development Bank (2017) estimates that the total expenditure in citizen security and crime prevention in Uruguay is 2.2 percent of GDP (or USD 1,592 in current US dollars).[21] Given the total number of offenses reported per year in Uruguay, the cost incurred by the private sector and the government translates into USD 4,200 per offense. This amount is five times higher the estimated cost for each offense avoided with police-monitored surveillance cameras.

[21] See Soares (2015) for details on the simple economic model followed to analyse the conceptual content underlying the estimates of the costs of crime.

Our findings have important policy implications: surveillance cameras seem to be an adequate instrument to keep certain areas of the city with low crime.

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Table 1. Summary statistics

	Mean	Standard deviation	Min.	Max.
	Montevideo (street segment)			
Total crime	0.6675	1.5635	0	86
Assault	0.0801	0.3421	0	17
Theft	0.3314	0.9013	0	31
Domestic violence	0.0604	0.3057	0	23
Damage	0.0462	0.2405	0	13
Murder	0.0012	0.0347	0	2
Robbery	0.0937	0.3847	0	25
Indoor crime	0.1405	0.5143	0	36
Outdoor crime	0.4251	1.0770	0	50
Police monitoring	0.0064	0.0800	0	1
	All the country (jurisdiction)			
Outdoor crime	215.93	217.37	5	1,645
Theft	185.06	192.31	5	1,424
Robbery	30.41	37.87	0	242

Notes: Indoor crime includes Domestic Violence and Assaults. Outdoor crime includes Theft and Robbery. The period is January 2012 to December 2014 (36 months). In Montevideo the data is at the street-segment level (10,868 street segments). In all the country the data is at the jurisdiction level (42 jurisdictions).

Table 2. Summary statistics: eventually treated and not treated areas in Montevideo

	(1) Untreated areas Mean	(2) Eventually treated areas Mean
Total crime	0.6408	1.6864
	(1.5252)	(2.4293)
Indoor crime	0.1378	0.2440
	(0.5122)	(0.5785)
Outdoor crime	0.4072	1.1094
	(1.0477)	(1.7494)
Theft	0.3147	0.9702
	(0.8691)	(1.6029)
Robbery	0.0925	0.1392
	(0.3838)	(0.4157)
Domestic violence	0.0602	0.0675
	(0.3063)	(0.2821)
Assault	0.0775	0.1765
	(0.3373)	(0.4810)
Damage	0.0441	0.1244
	(0.2348)	(0.3943)
Murder	0.0012	0.0009
	(0.0348)	(0.0332)

Notes: Indoor crime includes Domestic Violence and Assaults. Outdoor crime includes Theft and Robbery. Standard Errors are shown in parenthesis. The period is January 2012 to December 2014 (36 months). The total number of street segments is 10,868. In all cases the mean is calculated using observations for the whole period of analysis (before and after the treatment).

Table 3. Difference in differences results

	(1) Total crime	(2) Total crime
Police monitoring	-0.3351*** (0.1019)	-0.5305*** (0.0598)
Percentage change	-18.72	-29.64
Street segments	277	10,868
Observations	9,972	391,248

Notes: Standard errors clustered at the street-segment level are shown in parentheses. All regressions include street-segment dummies and month/year-combination dummies (36 months). Column (1) shows results restricted to eventually-treated street segments. Column (2) shows results using the whole city of Montevideo. Percentage change is calculated relative to the mean of Total crime in treated areas in the pre-treatment period (1.79). *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

Table 4. Pre-treatment trends and dynamic patterns

	(1) Total crime	(2) Total crime
t6 before	-0.0290	-0.1006
	(0.1067)	(0.0878)
t5 before	-0.1249	-0.2111**
	(0.1162)	(0.0857)
t4 before	0.0300	-0.0853
	(0.1133)	(0.0808)
t3 before	0.1073	0.0640
	(0.1358)	(0.0994)
t2 before	0.0922	0.0628
	(0.1241)	(0.0853)
t1 before	0.0773	0.0569
	(0.1498)	(0.1062)
t	0.0936	-0.0342
	(0.1447)	(0.1066)
t1 after	-0.3528**	-0.5144***
	(0.1566)	(0.0875)
t2 after	-0.2930*	-0.4478***
	(0.1665)	(0.1020)
t3 after	-0.3583**	-0.5117***
	(0.1782)	(0.0900)
t4 after	-0.4320**	-0.5988***
	(0.1998)	(0.1054)
t5 after	-0.6375***	-0.7485***
	(0.2249)	(0.1366)
t6 or more after	-0.5153**	-0.6929***
	(0.2239)	(0.0771)
Street segments	277	10,868
Observations	9,972	391,248

Notes: Standard errors clustered at the street-segment level are shown in parentheses. All regressions include street-segment dummies and month/year-combination dummies (36 months). Column (1) shows results restricted to eventually-treated street segments. Column (2) shows results using the whole city of Montevideo. Pre-treatment mean of Total crime in treated areas is equal to 1.79. *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

Table 5. Results using data at the jurisdiction level

	(1) Outdoor crime	(2) Outdoor crime
Police monitoring	-43.2767*** (12.3622)	-33.3725*** (11.9686)
Percentage change	-20.44	-17.91
Jurisdictions	28	32
Observations	984	1,128

Notes: Standard errors clustered at the jurisdiction level are shown in parentheses. All regressions include jurisdiction dummies and month/year-combination dummies (36 months). Column (1) uses eventually-treated jurisdictions and pure control jurisdictions. Column (2) uses untreated jurisdictions in Montevideo and pure control jurisdictions. Percentage change is calculated relative to the mean of Total crime in treated areas in the pre-treatment period (211.77 for Column (1); 186.27 for Column (2)). *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

Table 6. Indoor crime and outdoor crime

	(1) Indoor crime	(2) Indoor crime	(3) Outdoor crime	(4) Outdoor crime
Police monitoring	0.0155	-0.0009	-0.2606***	-0.4209***
	(0.0237)	(0.0123)	(0.0773)	(0.0440)
Percentage change	6.46	-0.36	-21.72	-35.08
Street segments	277	10,868	277	10,868
Observations	9,972	391,248	9,972	391,248

Notes: Standard errors clustered at the street-segment level are shown in parentheses. All regressions include street-segment dummies and month/year-combination dummies (36 months). Columns (1) and (3) show results restricted to eventually-treated street segments. Columns (2) and (4) show results using the whole city of Montevideo. Percentage change is calculated relative to the mean of Total crime in treated areas in the pre-treatment period (0.24 for Indoor crime; 1.2 for Outdoor crime). *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

Figure 1. Police-monitored areas and previous crime

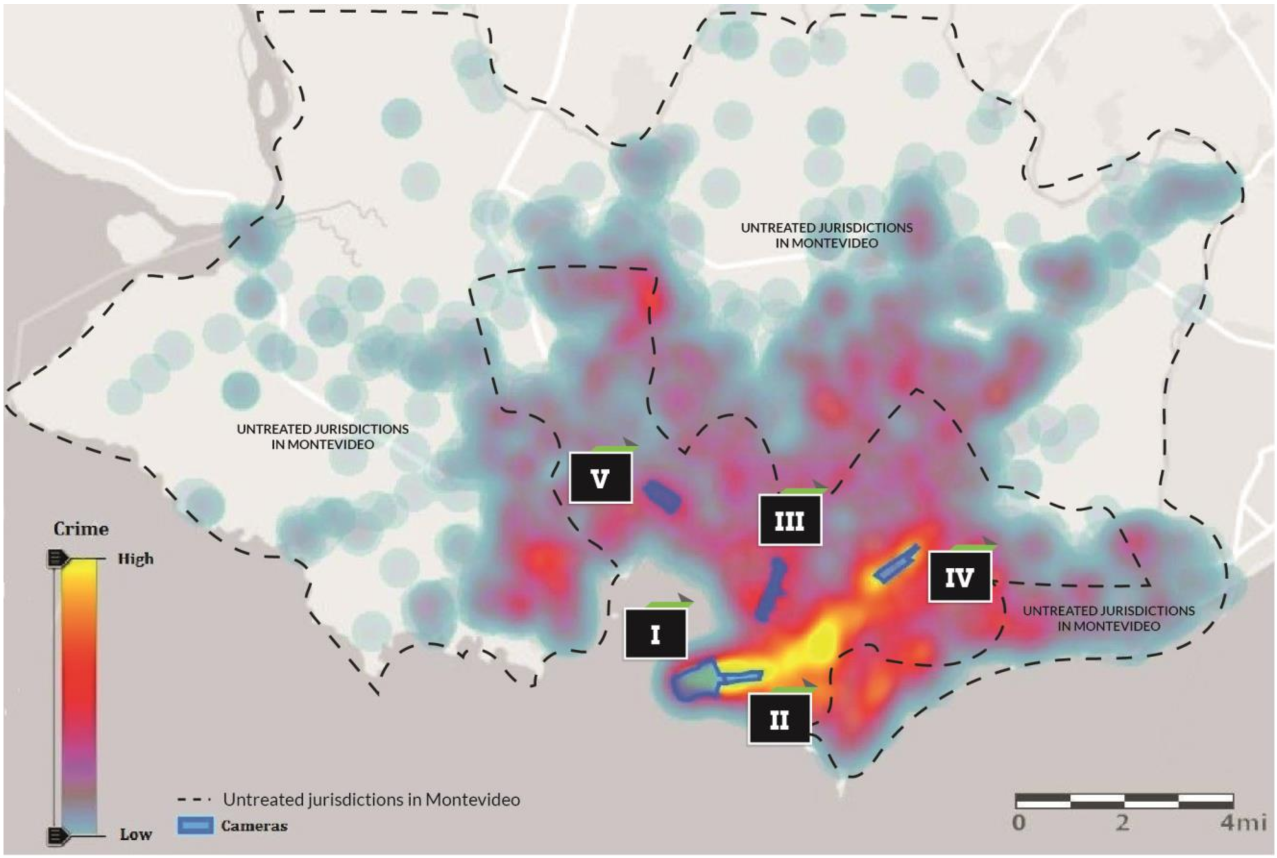

Figure 2. Date and place of installation of the cameras

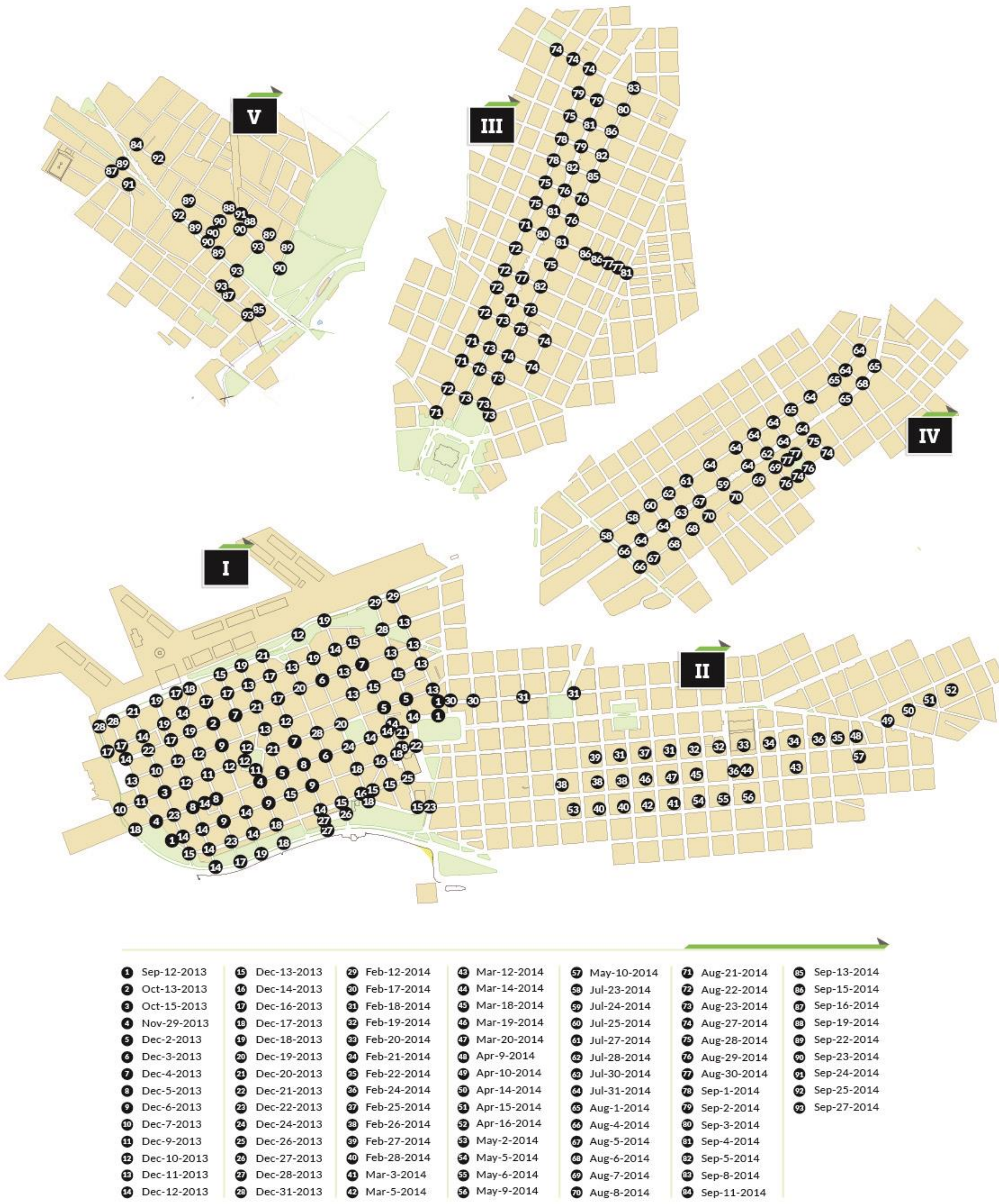

Figure 3. Sequence of β^k against the event time line