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Abstract: We exploit detailed information on the location and exact date of installation of police-monitored surveillance cameras plus daily data at the street-segment level on all reported crimes in the city of Montevideo, Uruguay, to study the impact of police monitoring on crime. The incorporation of police-monitored surveillance cameras reduces crime in 85 percent in monitored areas relative to un-monitored areas of the city. Results are robust to alternative definitions of the control group and to a series of robustness checks. We run a series of placebo experiments that reassure that the findings have a causal interpretation. When we analyze aggregate crime, however, we find that total crime remain unchanged, thus indicating that the reduction in crime in police monitored areas of the city is compensated by an increase in crime in other areas of the city.

Keywords: Monitoring cameras; theft; robbery; domestic violence.

JEL Code: K42.

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I. Introduction

In a very influential paper, Di Tella and Schargrodsky (2004) show evidence on the deterrence effect of observable police on crime. The reported effect is large, with a fall of 75 percent of car thefts in street segments where police was deployed relative to control street segments. The effect, however, is local, with no evidence that police presence in a given street segment reduces car thefts one or two street segments away from the protected ones. More importantly, the data used by Di Tella and Schargrodsky (2004) do not allow at looking at global or aggregate effects of the presence of police on crime. Given that they only have information on a limited number of street segments in the city, the reduction in crime in street segments with police presence may be compensated by an increase in crime somewhere else—the so called “displacement” effect.

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 control 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 global or 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.¹

In this paper we take advantage of a really unique database that includes daily reported crime in Montevideo (Uruguay), by street segment, for the three-year period January 2012 to December 2014. The data includes the location and the exact time of the allocation of all police monitoring cameras in the city, thus allowing the study of the impact of police monitoring on

¹ For example, Crépon et al. (2013) report experimental evidence of the existence of displacement effects in abor labor market interventions.
crime. More importantly, the fact that the data has information on the entire city of Montevideo allows us to study potential displacement effects.

In March 2013 the city of Montevideo started to install surveillance cameras in certain areas of the city. These cameras are continuously monitored by police officers located in a monitoring center. The monitoring center combines video surveillance technology with the action of police patrol response. 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 to a communication on a crime is about five minutes.\(^2\) When that happens, and the police officers arrive in time to arrest the offender, the video recording becomes part of the probative material.\(^3\)

The literature on the effect of surveillance cameras on crime is ambiguous. One the one hand, cameras could increase the expected costs of crime for potential offenders as long as these expected costs are internalized. On the other hand, cameras may increase crime by expanding the opportunity set for offenders by creating a sense of security among potential victims. It also may increase police-reported crime by reducing underreporting rates. Even though the deterrent effect seems to be stronger, at the end, the final outcome is an open empirical question. Welsh and Farrington (2009) present a review of the empirical literature, which is mainly concentrated on small-scaled experiences. Brown (1995), Skinns (1998), Armitage, Smyth, and Pease (1999), Ditton and Short (1999), Blixt (2003), Griffiths (2003), and Gomez, Mejía, and Tobón (2015) find reductions on crime following the installation

\(^3\) Supreme Court held a consultation to 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).
of surveillance cameras. However, Winge and Knutsson (2003) and Farrington, Bennett, and Welsh (2007) find increases on crime after the installation of surveillance cameras.

Our difference-in-differences estimates indicate that the presence of police monitoring cameras reduces crime in treated street segments in about 85 percent relative to control street segments. Results are robust to alternative definitions of the control group and to a series of robustness checks. We report a series of placebo experiments that reassure that the findings have a causal interpretation.

Since Becker (1968), crime is analyzed as a rational response to incentives. Thus, people engage in criminal behavior if the expected gains are large enough to offset the expected costs. Surveillance cameras increase the expected costs of crime through different channels: they increase the probability of apprehension, the probability of prosecution given apprehension, and the probability of sentencing given prosecution. Thus, the effect of police monitoring on crime could potentially work through two channels: 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, our results are unlikely to reflect changes in the numbers of incarcerated criminals, which should affect all city street segments and not just the few street segments in which monitoring cameras were installed. Thus, we believe that our estimates should be interpreted as the causal deterrent effect of police monitoring on crime.

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4 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 captured the offender. In court the suspect denied everything, without being aware that the surveillance cameras had registered the scene. The video recording was use as probative material in court and the offender was sentenced to prison.

5 Gómez, Mejía, and Tobón (2015) 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 data available on apprehensions.
When we explore the evolution of total crime, however, our results indicate that total crime in the city remain unchanged after the introduction of surveillance cameras, suggesting that the reduction in crime in monitored areas of the city is compensated by a similar increase of crime in un-monitored areas of the city. Thus, our results suggest that all the reported effects in partial equilibrium analysis of the impact of increasing police monitoring on crime are explained by displacement effects.

Our paper is also related to the recent and growing literature on hot spots. Recent literature suggests that strategies that deploy law enforcement resources after an offense has been committed (rapid response) can be less effective than targeted deployment of the police force to high-crime areas or “hot spots”. According to Nagin (2013), the apprehension risk perception for potential offenders is unlikely to be affected by improvement in the response. Hot spot policing is inspired in the observed fact that usually crime tends to be geographically and spatially concentrated. This stylized fact comes true from Minneapolis, US (Sherman at al. 1989) to Jersey City, US (Weisburd and Green 1995) and Medellín, Colombia (Chioda 2015). Even though the literature has long recognized significant decline in crime after hot spot policing (Braga 2008, García et al. 2013), the channel through which it operates—incapacitation at hot spots or general deterrence—is still unclear.

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

II. Data

To investigate the effect of police monitoring on crime we use two sources of data. First, we use a database that includes information on the exact date of installation of all surveillance cameras installed in Montevideo between March 2013 and December 2014. This operation was
part of *Ciudad Segura* (“safe city”), a program that consists in the installation of surveillance cameras in the main financial and commercial areas of Montevideo in order to reduce crime through an efficient police response. Figure 1 summarizes the geographical distribution of surveillance cameras in Montevideo. A surveillance center with one hundred employees has been strategically mounted to monitor the cameras twenty four hours a day. We consider the latitude and longitude of all the streets of the city to divide Montevideo in 10,868 areas or street segments. We define a treated street segment as the area under strict police monitoring (see Figure 2). There are 282 street segments in Montevideo with surveillance cameras. In each of these treated street segments there could be more than one camera in order to ensure a visual recognition of any potential offender.

Second, we use daily data on crime provided by the Police Department of Montevideo. This dataset comprises the universe of criminal incidents reported at Montevideo (1.5 million of inhabitants), between January 1st 2012 and December 31st 2014 (273,700 reported felonies). The database is geo-located, i.e. each criminal incident recorded includes information on the exact location through its coordinates (latitude and longitude).

Reported crime is classified by the police department in more than 130 different types of crime. Only six crime categories, however, account for 92 percent of total crime (see Figure 3). 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 of total crime in Montevideo in the period 2012-2014.

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

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6 The share of these categories in total crime is quite stable though time: 92 percent in 2012, 92 percent in 2013, and 91 percent in 2014.
an intentional physical attack or threat against another person, and excludes 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 to gain or maintain power and control over another 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.

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. Damages and murders are somewhere in between, with some of them occurring indoors and others outdoors. We follow the authorities’ classification and we construct three variables: Outdoor crime (thefts and robberies), Indoor crime (assaults and domestic violence), and Other crime (damages, murders, and all other remaining crime).

Summary statistics are reported in Table 1.

III. Empirical strategy and results

Empirical strategy

To identify the effect of police monitored cameras on crime we exploit the variability in the introduction of the cameras over time and space. Formally, we want to estimate the following difference-in-differences equation,

\[ Y_{it} = \beta T_{it} + \alpha_i + \mu_t + \epsilon_{it} \]  (1)

where \( Y_{it} \) is crime in street segment \( i \) and day \( t \), \( T_{it} \) is a dummy variable that takes the value one for treated street segments (those where is a surveillance camera at time \( t \)) and zero for control street
segments, $\alpha_i$ is a street-segment fixed effect, $\mu_t$ is a day fixed effect, and $e_{it}$ is the usual error term. In this equation the parameter of interest is $\beta$.

To construct the control group we follow three strategies: (i) the control group includes all untreated street segments in the city of Montevideo; (ii) restrict the sample to those jurisdictions with at least one treated street segment at some point during the sample period (5 jurisdictions out of the 24 jurisdictions in the city). In this sample, the control group includes all untreated street segments in these 5 jurisdictions; (iii) restrict the sample to eventually treated street segments. In this sample, the control group includes those street segments that are untreated at time $t$ but that are going to be eventually treated at some point in the future (always during the sample period). Identification comes from the fact that eventually treated street segment are treated at different moments in the sample period.

Difference-in-differences estimate assumes that the change in crime in control street segments is an unbiased estimate of the counterfactual. While we cannot directly test this assumption, we can test 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 been continued being parallel in the post-treatment period in the absence of the treatment. Column (1) in Table 2 reports estimates of pre-treatment trends in total crime for the entire city of Montevideo, using data collapsed at the monthly level. We cannot reject the hypothesis of parallel crime trends in the pre-treatment period, thus validating the difference-in-differences assumption.\(^7\) As shown in column (2) in Table 2, the common trend assumption holds when we restrict the sample to jurisdiction with at least one treated street segment.

\(^7\) The common trend assumption holds for all dependent variables used later in Table 3. All results mentioned but not shown are available from the authors upon request.
For the sample of the eventually treated areas it is not possible to test for differences in pre-treatment trends using the usual procedures since all street segments in this sample are untreated by February 2013 and treated by December 2014. However, in these cases it is possible to test the parallel trend assumption in a different way by estimating Equation (1) lagging all installation dates and restricting the sample to the pre-installation period (January 2012-February 2013). We tried with different structures of lags, and in Table 2 we report results lagging all installation dates one and six month (similar conclusions are obtained by using other lag structures). As observed in columns (3) and (4), there are no significant differences between “treatment” and “control” areas in the months previous to the installation of the cameras, a result that validates the common trend assumption. These results are also placebo tests that provide re-assurance that any differences found using the actual installation dates is not random.

In addition, 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 further validating the difference-in-differences approach (particularly in the eventually-treated sample).8

Main estimates

Table 3 reports estimates of Equation (1) for Total crime, Outdoor crime, Theft, and Robbery, using all street segments in the city of Montevideo. The coefficient on Police monitoring in column (1) is negative and statistically significant at the 1 percent level, indicating that the installation of surveillance cameras reduces total crime in monitored areas of the city relative to un-monitored areas of the city. The result is not only statistically significant but also economically

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8 The period 2012-2014 was very active in terms of new policies implemented in the Police Department. The government (Minister 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 all of 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 they should be captured by the time dummies.
relevant: the incorporation of police-monitored surveillance cameras reduces crime in 85 percent in monitored areas relative to un-monitored areas. As reported in column (2), when we use Outdoor crime as the dependent variable the coefficient remains significant and with a similar value to the one reported in column (1). Columns (3) and (4) report results for Theft and Robbery and, in the two cases, the coefficient on Police monitoring is negative and statistically significant at the 1 percent level.

Table 4 reports estimates of Equation (1) for Total crime, Outdoor crime, Theft, and Robbery, restricting the sample to those jurisdictions where there is at least one treated street segment at some point during the sample period (5 jurisdictions out of the 24 jurisdictions in the city). Again, in all cases the coefficient on Police monitoring is negative and statistically significant at the 1 percent level, indicating that the installation of surveillance cameras reduces crime.

Table 5 reports estimates of Equation (1) for Total crime, Outdoor crime, Theft, and Robbery, restricting the sample to eventually treated areas of the city. Again, in all cases the coefficient on Police monitoring is negative and statistically significant at the 1 percent level, and the value of the estimated coefficients is similar to the ones reported in Table 3 and Table 4, thus providing further evidence that the installation of surveillance cameras has an important effect in reducing crime in monitored areas relative to un-monitored areas.

As a robustness check, we collapsed the data at the month level. Table 6 reports estimates using collapsed data. As observed in columns (1) to (4), the coefficient on Police monitoring is negative and significant at the 1 percent level. In addition, the values of the coefficients are similar to the ones reported using daily data. 

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9 Results are similar when we use the alternative samples.
Table 7 reports placebo regressions using indoor-type crimes as dependent variable. For these types of crimes surveillance cameras should not have an impact, or at least they should have a much smaller impact. Column (1) shows that there is no impact of surveillance cameras on Indoor crime. In addition, as reported in columns (2) and (3) of Table 7, the result holds for each of the components of Indoor crime, thus further validating the causal interpretation of our main estimates.

In Table 8 we restricted the sample to the pre-treatment period (14 months, from January 2012 to February 2013), assigning a fake treatment to those street segments that were eventually treated. We use a fake treatment dummy that takes a value of 1 after July 2012 (the mid-point in the pre-treatment period). We reproduce the main results previously reported in Table 3 using the fake treatment and, as expected, all the coefficients associated to the fake treatment dummy are small and not significantly different from zero. This finding provides additional support to the validity of the identification strategy.

Overall, our estimates indicate that the presence of surveillance cameras in certain areas of the city is associated to an important decrease in crime in those areas relative to other areas of the city without surveillance cameras.

Aggregate effects

Now we explore whether the introduction of surveillance cameras in certain areas of the city has any effect on aggregate crime. This is a first-order question in terms of policy implications of the intervention. To try to answer this question we follow two strategies. In the first strategy we restrict the sample to those observations (i.e., street-segment/day) without police monitoring, and we regress Total crime, Outdoor crime, Theft, and Robbery on the total number of cameras in the city.

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10 It is possible to argue that even for indoor crimes surveillance cameras can deter criminal behavior by providing potential evidence against aggressors.
11 We try with other fake periods, with similar results.
city (and a linear time trend). Under the hypothesis of displacement, crime should increase in those areas without cameras as the total number of cameras in the city also increases.

Table 9 reports the results of this exercise. In all cases, the coefficient on the total number of cameras (Total cameras) is positive and significant, in line with the hypothesis of displacement.

In the second strategy we collapse the data at the month level, so that we end up with a time series of crime for the entire city of Montevideo. Under the hypothesis that the installation of surveillance cameras has an impact on aggregate crime, we should observe a change in the trend of crime following the installation date of the cameras (the first ones were installed in March 2013). Formally, we want to estimate the following equation:

\[ Y_t = \eta \text{Time} + \sigma \text{Police Monitoring} + \rho \text{Time} \times \text{Police Monitoring}_t + \epsilon_t \]  

(2)

The parameter of interest are the coefficients on Police Monitoring, \( \sigma \), and on the interaction term, \( \rho \). Under the null hypotheses \( H_0: \rho = \sigma = 0 \), the level and the time trend in crime in the post-installation period are not different from the level and the time trend in crime in the pre-installation period, thus suggesting that there is no effect of the installation of surveillance cameras on crime.

Table 10 reports the results of estimates of Equation (2) for Total crime, Outdoor crime, Theft, and Robbery and in all cases we cannot reject the hypothesis that the coefficients on Police Monitoring and on the interaction term between the time trend and Police monitoring are equal to zero (in this model, Police monitoring is defined as the total number of cameras in the city). Overall, the findings suggest that there is no change in the level and in the trend of crime after the installation of the cameras. The finding that there is no effect on aggregate crime indicates that the reduction in crime in police monitored areas of the city is compensated by an increase in crime in
other areas of the city. Thus, the reduction in crime in monitored areas of the city is displaced to un-monitored areas of the city.

IV. Conclusions and discussion

This paper sheds new light on the aggregate effects of police monitoring on aggregate crime. First, we report evidence that the installation of police-monitored surveillance cameras significantly reduces street crime in monitored street segments relative to un-monitored street segments. Second, we move to understanding aggregate effect and we find there is no effect of monitoring certain areas of the city on aggregate crime.

The facts that surveillance cameras have a significant impact in reducing crime in monitored areas relative to un-monitored areas and that there is no impact of surveillance cameras on aggregate crime suggests that previous crime in eventually monitored areas is displaced towards other areas of the city.

Our findings have important policy implications: they suggest that surveillance cameras in certain areas of the city are not enough to reduce crime. Surveillance cameras, however, could be an adequate instrument to keep certain areas of the city with low crime.
References


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Notes: Outdoor crime includes thefts and robberies; Indoor crime includes assaults and domestic violence; Other crime includes damages, murders, and all other remaining crime.
Table 2. Pre-treatment trends

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Notes: Standard errors clustered at the street segment level are shown in parentheses. All regressions include street-segments dummies. Column (1) uses data from the whole city of Montevideo (10,868 street segments). In column (2) the sample is restricted to those jurisdictions with at least one surveillance camera (1,437 street segments). In columns (3) and (4) the sample is restricted to eventually treated street segments. *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.
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Notes: Standard errors clustered at the street segment level are shown in parentheses. All regressions include street-segment dummies (10,868 street segments) and day dummies (1,096 days). *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.
Table 4. Sample restricted to jurisdictions with at least one surveillance camera

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<td>1,576,048</td>
<td>1,576,048</td>
</tr>
</tbody>
</table>

Notes: Standard errors clustered at the street segment level are shown in parentheses. All regressions include street-segment dummies (1,437 street segments) and day dummies (1,096 days). There are 24 jurisdictions in Montevideo. Jurisdictions with at least one surveillance camera are jurisdictions 1, 2, 3, 6, and 15. *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.
Table 5. Sample restricted to eventually treated areas

<table>
<thead>
<tr>
<th></th>
<th>(1) Total crime</th>
<th>(2) Outdoor crime</th>
<th>(3) Theft</th>
<th>(4) Robbery</th>
</tr>
</thead>
<tbody>
<tr>
<td>Police monitoring</td>
<td>-0.0145***</td>
<td>-0.0110***</td>
<td>-0.0086***</td>
<td>-0.0024***</td>
</tr>
<tr>
<td></td>
<td>(0.0034)</td>
<td>(0.0027)</td>
<td>(0.0025)</td>
<td>(0.0006)</td>
</tr>
<tr>
<td>Observations</td>
<td>309,072</td>
<td>309,072</td>
<td>309,072</td>
<td>309,072</td>
</tr>
</tbody>
</table>

Notes: Standard errors clustered at the street segment level are shown in parentheses. All regressions include street-segment dummies (282 street segments) and day dummies (1,096 days). *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.
Table 6. Robustness checks: data collapsed at monthly level

<table>
<thead>
<tr>
<th></th>
<th>(1) Total crime</th>
<th>(2) Outdoor crime</th>
<th>(3) Theft</th>
<th>(4) Robbery</th>
</tr>
</thead>
<tbody>
<tr>
<td>Police monitoring</td>
<td>-0.5223***</td>
<td>-0.4116***</td>
<td>-0.3422***</td>
<td>-0.0693***</td>
</tr>
<tr>
<td></td>
<td>(0.0589)</td>
<td>(0.0441)</td>
<td>(0.0409)</td>
<td>(0.0093)</td>
</tr>
<tr>
<td>Observations</td>
<td>391,248</td>
<td>391,248</td>
<td>391,248</td>
<td>391,248</td>
</tr>
</tbody>
</table>

Notes: Standard errors clustered at the street segment level are shown in parentheses. All regressions include street-segment dummies (10,868 street segments) and month dummies (36 months). *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.
Table 7. False experiments: indoor crime

<table>
<thead>
<tr>
<th></th>
<th>Indoor crime</th>
<th>Domestic violence</th>
<th>Assault</th>
</tr>
</thead>
<tbody>
<tr>
<td>Police monitoring</td>
<td>-0.0001</td>
<td>-0.0001</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>(0.0004)</td>
<td>(0.0002)</td>
<td>(0.0004)</td>
</tr>
<tr>
<td>Observations</td>
<td>11,936,536</td>
<td>11,936,536</td>
<td>11,936,536</td>
</tr>
</tbody>
</table>

Notes: Standard errors clustered at the street segment level are shown in parentheses. All regressions include street-segment dummies (10,868 street segments) and day dummies (1,096 days). *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.
Table 8. False experiments: fake treatment

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total crime</td>
<td>Outdoor crime</td>
<td>Theft</td>
<td>Robbery</td>
</tr>
<tr>
<td>Fake treatment</td>
<td>-0.0014</td>
<td>-0.0016</td>
<td>-0.0012</td>
<td>-0.0004</td>
</tr>
<tr>
<td>(=1 after July 2012)</td>
<td>(0.0020)</td>
<td>(0.0014)</td>
<td>(0.0012)</td>
<td>(0.0004)</td>
</tr>
<tr>
<td>Observations</td>
<td>4,628,675</td>
<td>4,628,675</td>
<td>4,628,675</td>
<td>4,628,675</td>
</tr>
</tbody>
</table>

Notes: Standard errors clustered at the street segment level are shown in parentheses. All regressions include street-segment dummies (10,868 street segments) and day dummies (1,424 days). The sample is restricted to the pre-treatment period (January 2012 to February 2013). *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.
<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) Total crime</th>
<th>(2) Outdoor crime</th>
<th>(3) Theft</th>
<th>(4) Robbery</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total cameras</td>
<td>0.0000***</td>
<td>0.0000***</td>
<td>0.0000***</td>
<td>0.0000***</td>
</tr>
<tr>
<td></td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>Observations</td>
<td>11,862,776</td>
<td>11,862,776</td>
<td>11,862,776</td>
<td>11,862,776</td>
</tr>
</tbody>
</table>

Notes: Standard errors clustered at the street segment level are shown in parentheses. All regressions include street-segment dummies (10,868 street segments) and a linear time trend. The sample is restricted to street segments without cameras. *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.
### Table 10. Aggregate effects

<table>
<thead>
<tr>
<th></th>
<th>(1) Total crime</th>
<th>(2) Outdoor crime</th>
<th>(3) Theft</th>
<th>(4) Robbery</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Time</strong></td>
<td>-10.8682</td>
<td>-19.8103***</td>
<td>-23.1074***</td>
<td>3.2970</td>
</tr>
<tr>
<td></td>
<td>(10.0017)</td>
<td>(6.8907)</td>
<td>(5.5740)</td>
<td>(3.8326)</td>
</tr>
<tr>
<td><strong>Police Monitoring</strong></td>
<td>-0.0212</td>
<td>0.0616</td>
<td>-0.0164</td>
<td>0.0780</td>
</tr>
<tr>
<td></td>
<td>(0.1876)</td>
<td>(0.1186)</td>
<td>(0.0765)</td>
<td>(0.0552)</td>
</tr>
<tr>
<td><strong>Time * Police Monitoring</strong></td>
<td>0.0012</td>
<td>-0.0007</td>
<td>0.0012</td>
<td>-0.0019</td>
</tr>
<tr>
<td></td>
<td>(0.0052)</td>
<td>(0.0031)</td>
<td>(0.0019)</td>
<td>(0.0014)</td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>6,826***</td>
<td>4,904***</td>
<td>3,986***</td>
<td>918***</td>
</tr>
<tr>
<td></td>
<td>(145.05)</td>
<td>(77.93)</td>
<td>(72.21)</td>
<td>(55.74)</td>
</tr>
</tbody>
</table>

- Observations: 36  36  36  36

Notes: Newey–West heteroskedasticity- and autocorrelation-consistent standard errors using 3 lags are in parentheses. Police monitoring is the total number of cameras. *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.
Figure 1. Areas with surveillance cameras

Note: The numbers refer to police jurisdictions.
Figure 2. Surveillance areas
Figure 3. Types of crime
Table A1. Further results: Other crime

<table>
<thead>
<tr>
<th></th>
<th>(1) Other crime</th>
<th>(2) Murder</th>
<th>(3) Damage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Police monitoring</td>
<td>-0.0037***</td>
<td>-0.0000</td>
<td>-0.0014***</td>
</tr>
<tr>
<td></td>
<td>(0.0012)</td>
<td>(0.0000)</td>
<td>(0.0003)</td>
</tr>
<tr>
<td>Observations</td>
<td>11,936,536</td>
<td>11,936,536</td>
<td>11,936,536</td>
</tr>
</tbody>
</table>

Notes: Standard errors clustered at the street segment level are shown in parentheses. *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.
<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total crime</td>
<td>Total crime</td>
<td>Total crime</td>
<td>Total crime</td>
<td>Total crime</td>
</tr>
<tr>
<td>Police monitoring</td>
<td>-0.0115*** (0.0043)</td>
<td>-0.0157* (0.0080)</td>
<td>-0.0205*** (0.0050)</td>
<td>-0.0039* (0.0023)</td>
<td>-0.0131*** (0.0045)</td>
</tr>
<tr>
<td>Observations</td>
<td>204,952</td>
<td>200,568</td>
<td>250,984</td>
<td>465,800</td>
<td>453,744</td>
</tr>
</tbody>
</table>

Notes: Standard errors clustered at the street segment level are shown in parentheses. There are 24 jurisdictions in Montevideo. Jurisdictions with at least one surveillance camera are jurisdictions 1, 2, 3, 6, and 15 (reported in columns 1 to 5 respectively). *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.