Police video surveillance and crime: Evidence from a nationwide policy *

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Abstract

Police departments around the world invest heavily on crime prevention technologies. In the US, virtually every local police department has a video-surveillance system in place or access to one. This paper studies a nationwide police video-surveillance policy implemented in Ecuador in 2012. By 2019, it had presence in over 45% of parishes – smallest administrative unit in the country – within all provinces and surveilled over 30% of all urban space. The gradual rollout of the policy across time and space allows us to estimate its short and medium-term effect on crime. We use (i) maps representing urban centers, and unique georeferenced administrative data on the (ii) universe of reported crimes to the police – 447k incidents – and (iii) emergency calls made to the 911 system – 2.2m calls – to construct a panel at the city block-month level. Our spatial design allows us to exploit variation in proximity to installation sites to estimate potential displacement effects. We find that on aggregate cameras decreased crimes by around 12%. However, that aggregate masks two opposing effects: a decrease within surveilled blocks and displacement to unsurveilled blocks. We also find that the effects are concentrated within poor, more populated, and urban settings. Using a back-of-the-envelope calculation our result suggests a drop of around 5.8k less reported crimes in a given year. Our findings indicate that video-surveillance systems can be an effective city-level crime prevention policy especially within contexts where policing is costly and challenging.

JEL Classification: K42, H41, D04
Keywords: Police Surveillance, Crime Deterrence, 911

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1. Introduction

Several governments have invested heavily on police monitored video-surveillance systems. These systems are largely viewed as a catch-all solution and efficient complement to policing. According to a survey done by the Bureau of Justice Statistics, 89% (11k) of surveyed local police departments in the US had a video-surveillance system in place or access to one (Reaves, 2015). Large surveillance coverage is rather common within developed countries, but definitely not unique to them. Recent industry reports argue that there are over 1 billion video-surveillance cameras around the world. This number represents a 30% increase from 2019 numbers (Lin and Purnell, 2019). Much, if not most, of that growth is coming from developing countries. According to that same report, countries like India, Brazil, and Indonesia will overtake high-income countries like the U.K and Japan in terms of market size. Police video-surveillance systems are usually justified as a tool to help prevent crime, however, due to the (i) lack of systematic registry of installations, (ii) difficulty to address endogeneity concerns, and (iv) lack of access to consistent and detailed administrative data they are hard to evaluate.

The focus of our study will be to estimate the hyperlocal effect of surveillance cameras on crime. There are multiple mechanisms through which cameras may affect crime. One is deterrence. Cameras are installed in current structures (bridges, lamp posts, etc) which need to be located in proximity to power sources. This means that they are relatively visible and easy to locate, hence criminals might be less likely to perpetrate a crime in an area that is being surveilled. This could translate to a decrease in crime within surveilled areas, however, it might lead to crime being displaced elsewhere. Hence, the overall effect on crime is not clear. Crime could potentially decrease or there could simply be a new equilibrium at the city or neighborhood level. Potentially, another crime-reducing mechanism is incapacitation and it is likely to take time to become active. Cameras are being actively monitored by police personnel, hence the police has the ability to live track a crime as it evolves which increases the probability of arrest. Additionally, the video recording can be requested and used as evidence in insurance claims, court proceedings, etc. These two aspects combined might increase the capacity of the police to capture criminals, hence decreasing crime through incapacitating potential future offenders.

In this paper we evaluate the introduction of a nationwide system implemented in Ecuador. The installation of surveillance cameras was coordinated through the ECU911 which is equivalent to the 911 in the US. The first camera was installed in January of 2012 and as of August 2019 there were 4,730 operating cameras. They are distributed over 45% of parishes – smallest administrative unit in the country – which represent 88% of the country's population. Parishes have an average population and surface area of 14k inhabitants and 250km^2. In terms of coverage of populated areas, cameras surveil over 30% of all urban areas in the country. Cameras have 360° horizontal view and cover a maximum visual field of up to 300 meters. Finally, the system has the capacity to store recorded content which can be released under civilian request or a judicial order. The installation of cameras happened gradually over time and across space with no spatial or temporal concentration. The exact installation site within crime-prone areas was determined based on a series of exogenous factors: good internet connectivity, existing structure in place and relative proximity to locations of interest such as schools, hospitals, government buildings, etc. According to government officials, around 95% of camera installations have been installed following a detailed technical procedure which highlights one key aspect that we will use for identification: the identified crime-prone areas are not randomly selected across space, however, the exact installation site i.e block within these areas is exogenously determined. Additionally, we will exploit the variation in proximity to the camera to identify treatment effects and potential displacement effects.

In order to study their effect on crime we use three unique and independent georeferenced administrative data sources. The first one represents the universe – 447k incidents – of all reported property crimes to the police between 2014-2019. For each reported crime we know the exact location, time, and date the incident took place. We also know the type of crime – based on the target – and the method – violent vs. non-violent. Given the known issue of under reporting in administrative crime reports we incorporate an alternative measure of crime. We use the universe of emergency calls made to the 911 line where the police was dispatched – 2.2m calls – between 2016-2019. For each call we know its exact location, time, and date. Calls are classified based on the information provided on the call report. Finally, the third one represents the installation site and date for all 4.7k cameras installed between January of 2012 and August of 2019.

The georeferenced nature of our data allows us to construct a unit of analysis representative of a city block: 100x100 meter cell. First, we define the area of analysis for each camera conditional on their context which ensures comparability across space. Second, we split that area into a fixed grid composed of 100x100 meter cells. Third, we assign cells located up to 500 meters to their closest installation site. Fourth, we classify cells into groups – 100 meter bins – based on their relative distance to their assigned camera. Fifth, we assign each crime and 911 call to their respective cell. Sixth, we collapse our data at the cell-month level to construct a panel which covers all space being intervened by the policy. Therefore, we have measures at the cell-month level for crimes and 911 calls. Our identification strategy relies on the (i) spatial and temporal variation in the installation of cameras and (ii) proximity to installation sites.

In order to estimate direct and displacement effects we use a difference-in-difference approach. We find that crimes within directly treated cells i.e. cells which received an installation relative to cells beyond 500m of an installation, decreased by around 33%. The effect decreases in magnitude as we move further away, however, once we move past the 300m threshold we find that the estimated effect becomes positive and significant. We interpret this result as evidence of cameras displacing crime to areas which are not under direct surveillance. This result is robust to different estimators which account for the staggered rollout of the policy. When we aggregate both opposing effects we find that crime decreased by 12% which translates to a drop of 5.8k crimes within a given year. If we focus on 911 calls as a measure of crime, where crime under-reporting is less of an issue, we find a similar pattern: the effect is concentrated within cells closer to an installation. Using an event study approach we find that the effect is long-lasting, increases with time, and eventually tapers off after 8 years. Finally, we find that the effect is heavily concentrated within contexts where policing is more costly and challenging: poorer, more populated, and urban settings. Our findings indicate that video-surveillance systems can be an effective city-level crime prevention policy.

This paper contributes to three main strands of literature. The first one talks about criminal deterrence and the study of two main mechanisms: length and severity of punishment and policing intensity and force (Chalfin and McCrary, 2017). Within the latter mechanism, various studies have found that policing effectively reduce crime (Draca et al., 2011; Di Tella and Schargrodsky, 2004; Machin and Marie, 2011; Levitt, 1997; Klick and Tabarrok, 2005). However, evidence is mixed when focused on video-surveillance systems (Piza et al., 2019). More recently, and perhaps more relevant to our paper, there are a set of studies done within contexts relatively similar to ours: developing country with a high-crime environment. Gómez et al. (2021) evaluate the effect of surveillance cameras in the city of Medellin, Colombia and find that monthly crime reports fell by 19% with no displacement to nearby areas. Munyo and Rossi (2020) study a similar policy in Montevideo, Uruguay with treated street segments and find that crime fell by 20% with no displacement effect. There are other papers, such as Priks (2015) and Priks (2014), which study the introduction of cameras in transportation systems or sporting venues and also find decreases in criminal behavior. In comparison to these recent studies, our setting evaluates a nationwide policy covering over 30% of all urban space. Large baseline differences in crime, population, and socioeconomic levels across parishes allows us to perform several heterogeneity checks and expand the analysis to non-urban settings. Incorporating an alternative measure of crime: 911 calls will help us address the issue of under-reporting in administrative crime data. Finally, our long panel will allow us to evaluate short and medium-term –up to 8 years post-treatment – effects of the policy.

Finally, this paper also speaks, more generally, to a set of empirical papers focused on estimation of displacement effect. In general, displacement is an understudied issue, perhaps in part because it is hard to measure (McCrary, 2010). Displacement is the relocation of crime across several possible dimensions such as time, space, target, tactic or offense, among others (Guerette and Bowers, 2009). Most commonly, the literature has paid attention to spatial (Blattman et al., 2021) or temporal displacement Jacob et al., 2007). The policy implications of displacement are clear since it may undermine the effectiveness of targeted policies. This paper attempts to shed light on this issue as well. The breakdown of this paper is as follows. Section 2 includes a brief description of the analytical framework which informs our analysis. Section 3 explains the ECU911 policy implementation in detail. Section 4.1 goes over the data and empirical strategy. Section 5 presents our main results. Section 6 looks at the heterogeneous effects of the policy. Finally, in section 7 we conclude.

2. Analytical Framework

Economic theory argues that (i) the threat of punishment along with (ii) improvements in the probability of capture can reduce crime by increasing its relative costs (Becker and Stigler, 1974; Becker, 1968). One basic depiction of Becker (1968) framework suggests that an offender compares costs and benefits when deciding to commit a crime. It states that a rational offender will commit a crime if $(1-p)U_{c1} + pU_{c2} > U_{NC}$. Where p represents the probability of capture, U_{c1} represents the utility associated with choosing to commit a crime when not being caught, U_{c2} represents the utility associated with choosing to commit a crime but being caught and punished – it considers a generalized cost function C which encompasses all perceived costs that are related to the risk of receiving a sanction. Finally, U_{NC} represents the utility associated with the alternative of choosing not to commit a crime. In other words, it predicts that an offender commits a crime when expected gains are larger than opportunity costs.

Under this simple model, we can hypothesize the conditions under which surveillance cameras may alter equilibrium crime levels taking into account the endogenous reaction of the police, potential offenders and potential victims. From the police side, video-surveillance can affect their efficiency in terms of reacting to crimes and subsequently apprehending offenders. Cameras are being monitored by agents which gives them the ability to (i) live track a crime as it evolves, or (ii) geolocate the incident based on the address provided by the caller after the incident. The video recording can also be requested and used as evidence in insurance claims, court proceedings, etc. These three characteristics increases the capacity of the police to react which would also lead to a higher probability of apprehension ($\uparrow p$). It is straightforward to see that through this channel i.e. incapacitation, the installation of surveillance cameras would decrease overall crime levels ($\downarrow Crime$).

From the offenders side, cameras are installed in current structures (bridges, lamp posts, etc) which need to be located in proximity to power sources. This means that they are relatively visible and easy to locate, hence criminals might be less likely to perpetuate a crime in an area that is being surveilled since their perceived risk of being captured has changed ($\uparrow p$). This could translate to a decrease in crime within surveilled areas ($\downarrow Crime$), however, it might lead to crime being displaced elsewhere ($\uparrow Crime$). Hence, through this channel i.e. deterrence, the installation of surveillance cameras could have ambiguous effects on crime. Crime could potentially decrease or there could simply be a new equilibrium at the city or neighborhood level. The specific response for this type of reaction is one of the empirical questions we address in this paper. However, these two predictions can be modified when we consider the reaction of potential victims. Surveillance cameras may alter their behavior by providing a sense of security. Potential victims might be more willing to take risks i.e. walk outside at night, leave their house, shop, or car unlocked, etc in the presence of a camera, hence increasing their probability of being victimized ($\uparrow Crime$). Similarly, the simple presence of a camera could lead to an increase in crime reporting from potential victims – not crime itself – since it (i) raises the probability of capture and (ii) makes the service more noticeable. Thus incorporating potential adaptations of victims leaves us with no clear theoretical prediction, in terms of crime levels, since we cannot be certain which potential response will dominate.

3. Policy Implementation

The installation of surveillance cameras was coordinated through the ECU911. The ECU911 is a public institution which centralizes and articulates all emergency response units in the country. It coordinates with national and local police departments, armed forces, fire departments, national transit agency and the ministry of public health. In practice, it plays the same role as the 911 system in the US. Currently, the ECU911 operates 17 regional and 14 municipal operation centers located within all 24 provinces. Formally, it started operations in 2012 and currently there are over 1.5k direct employees, out of which 65% are solely tasked with surveillance operations. The first camera was installed in January of 2012 and as of August of 2019 there were 4,730 cameras in operation. Cameras are distributed over 45% of parishes representing over 88% of the country's population. Conditional on being treated, the average parish received around 10 cameras (Figure 2a).

The installation of cameras happened gradually over time and across space with no regional or temporal concentration. Figure 1 shows the rollout of the policy at the parish level. Over our study period (69 months) there was an average of 53 monthly installations, however, these installations were not heavily concentrated among the most populated parishes (Figure 2b). All cameras allow for 360° horizontal and 290° vertical view. Additionally, they cover a maximum visual field of up to 300 meters [1] This last feature will be important when constructing our treated city-blocks as we will rely on the visual field for each camera. In terms of coverage of populated areas, cameras surveil over 30% of all urban areas in the country. Out of that total, around half comes from the 5 most populated urban centers in the country: Quito, Guayaquil, Cuenca, Santo Domingo and Machala (Figure 2c). Out of the 4,730 cameras, most have night vision and a small sample are equipped with long distance capacity, facial recognition technology and thermal imagery. Finally, the system has the capacity to store recorded content which can be released under civilian request or a judicial order for criminal proceedings.

Camera installation sites are selected through the following three step process. First, GIS technicians within the ECU911 map crime prone areas using historical data. According to the technicians, these areas vary largely in terms of size since it depends on the spatial distribution of calls. Second, these areas are presented to a separate technical team which is in charge of mapping them to existing surveilled areas so as to not overlap cameras. Third, based on the first two steps, a set of crime prone sub-areas which are not currently under surveillance are presented to the last technical team. This team is composed of police officials, members of the public telecommunications company, and senior ECU911 officials. They are in charge of selecting the precise installation sites by taking into account the following information as inputs: the areas suggested by the prior technical teams, the presence of an existing structure (lamp posts, bridges, traffic light, etc) and public entities (schools, hospitals, government buildings, etc), and lastly the availability of reliable internet coverage [2].

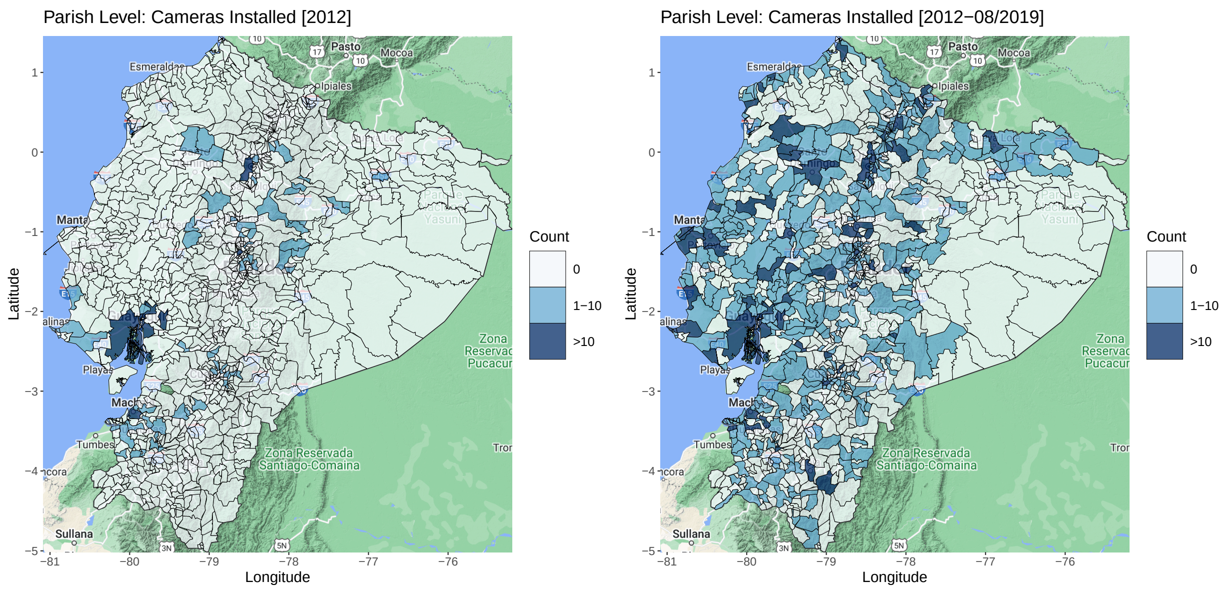
Finally, based on these inputs and at the discretion of the technical team a set of locations are selected and a separate team is sent out to validate them. Once they are validated, the cameras are installed. This process takes place every time there is a batch of new cameras being installed which can be as small as a single camera. According to ECU911 officials, around 95% of camera installations have been installed within the suggested sub-areas and have followed this detailed procedure. This process highlights one key aspect that we will use for identification: the

[1] Figure 11 shows photos of the camera itself, its installation process and operating centers

[2] Many efforts were made to obtain these areas i.e maps in a usable format, as well as the georeferenced inputs used during these meetings, however they were not released under the current confidentiality agreements nor did the ECU911 kept a systematic record of such documents.

identified crime-prone areas are not randomly selected across space, however, the exact installation site i.e block within these areas is exogenously determined. Additionally, we will rely on the variation in rollout across time and space as well as proximity to the camera to identify treatment effects.

Figure 1: Camera Installations at the Parish Level

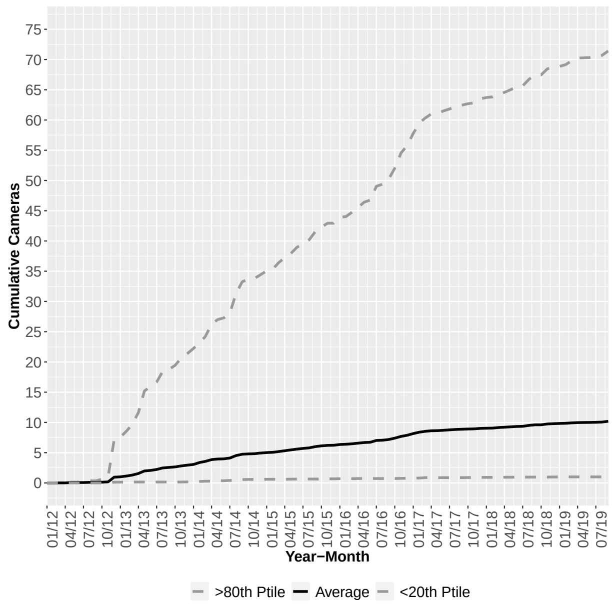


(a) Cameras Installed: 2012

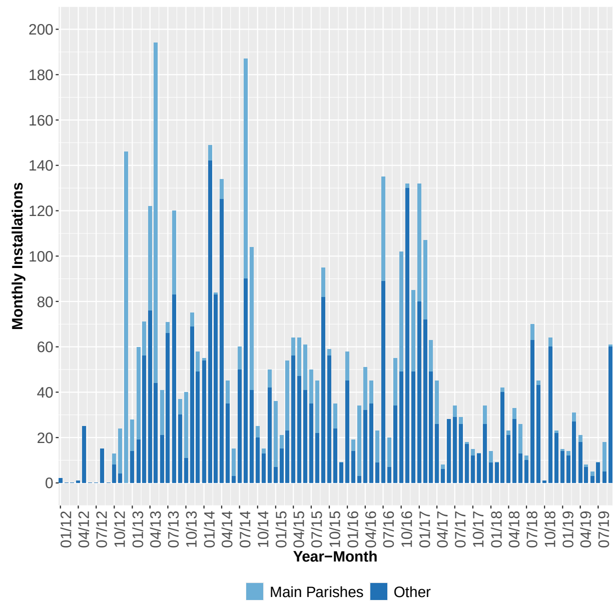
(b) Cameras Installed: 2012-08/2019

Notes: Figure 1 shows policy adoption at the parish level. Parishes are the smallest administrative unit in the country and they have an average population and surface area of 14k inhabitants and 250km^2. The figure on the left shows the spatial distribution of all cameras installed in 2012. The figure on the right shows the spatial distribution of all cameras installed during our study period.

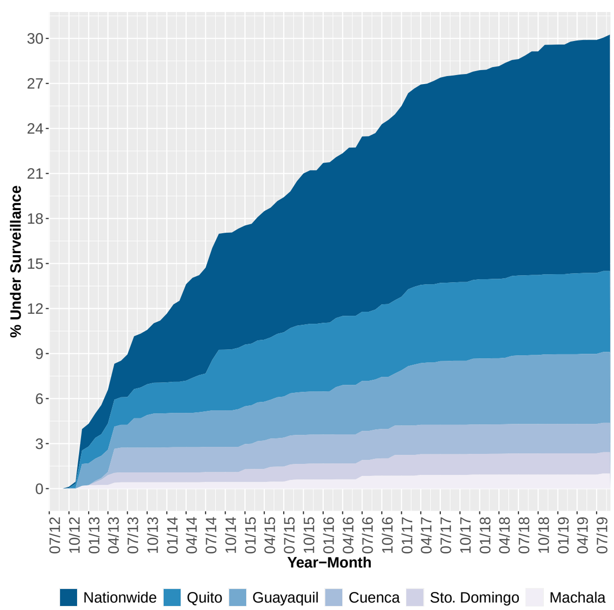
Figure 2: Policy Adoption, Rollout and Coverage



(a) Policy Adoption p/Parish



(b) Monthly Camera Installations



(c) % Urban Area Surveilled

Notes: Figure 2a shows policy adoption for all treated parishes. Parishes are the smallest administrative unit in the country and they have an average population and surface area of 14k inhabitants and 250km^2. The dotted grey lines represent the average cumulative cameras installed within the top and bottom 20th percentiles for each month. The solid black line represents the average. Figure 2b shows the total number of cameras installed per month. The lighter blue color depicts the installations within the most populated parishes: Quito, Guayaquil, Cuenca, Sto. Domingo and Machala. Figure 2c shows the share of urban area under surveillance. The lighter blue colors represent the contribution to the total share for each of the five most populated parishes. The numerator represents the total area under surveillance – using a 300m buffer around installation sites – and the denominator represents the sum of urban areas in the country.

4. Data & Empirical Strategy

In this section we describe the available data and our spatial research design to identify the different effects of police-monitored surveillance cameras on reported crimes and 911 calls.

4.1. Data

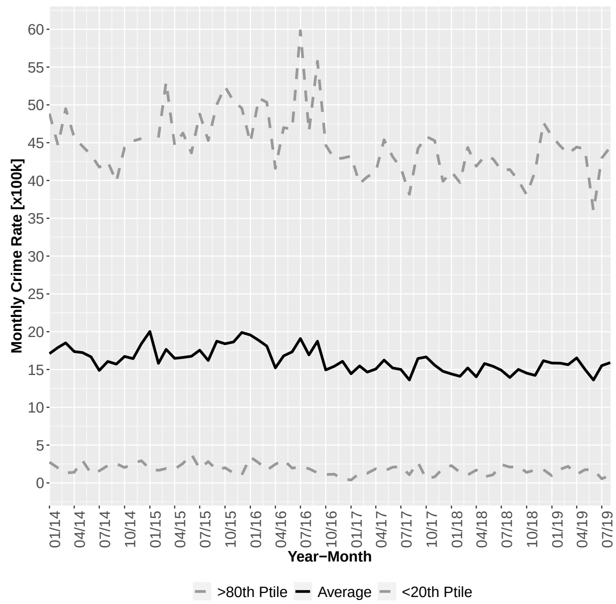
Our analysis uses three unique georeferenced data sources. The first one represents the universe of all 447k crimes reported to the national police and public prosecutor's office between January 2014 and August 2019. In 2010 the national police established the Information Analysis Center (CAI) which over time evolved to what is now the Criminal Data Analysis Department (DAID). This unit automatically receives detailed incident reports from the national police and public prosecutor's office. After an internal validation protocol, the DAID verifies aggregate numbers with the civil registration office, institute for statistics and census (INEC) and the national transit agency (ANT). As of 2017, it had over 30 offices with presence in all 24 provinces of the country. Within each office there is a technical team composed of a supervisor and statistical, reporting and GIS analysts (Melo and López (2018)). The main input for their operations is the information generated by police reports, which are immediately uploaded to an internal online system. Each incident is georeferenced based on its exact address or point of reference and is also classified into different types based on the target – residence, people, business & vehicles – of the crime as well as the method – violent vs. non-violent. Figures 3a and 3b show the evolution of the crime rate at the parish level and monthly crimes by target. The rigorousness of the validation protocols, the georreferencing system and the national coverage of the DAID make us confident that the data is accurate and comparable across time and space.

The second one represents the universe of all 2.2m emergency calls to the ECU911 which led to a police unit dispatch between January of 2016 and August of 2019. Every emergency call made to the 911 line gets assigned to its closest regional or municipal center. However, when a call comes from a mobile phone – over 65% of calls come from mobile phones– this georeferencing is not exact since it is based on the triangulation of telecommunication antennas. The dispatcher manages the call by asking the reason for the call and the exact location of the caller. When no precise location is given, the dispatcher asks for the closest point of reference. This exact location is then assigned to the call report. The reason for the call and the exact location is used to dispatch the relevant unit (police, firefighters, ambulance, etc). Once the emergency is handled the dispatcher goes back online. Finally, at the end of their work shift dispatchers revise and validate all the information within each of their handled calls. The report for each call is then uploaded to an internal system. The available data represents the universe of these reports where a police unit was dispatched, the georeferenced address or point of reference, along with the reason for the call. Given that a single incident can lead to several calls a unique incident identifier is created by agents. This allows us to collapse the universe of calls reports to the incident level.

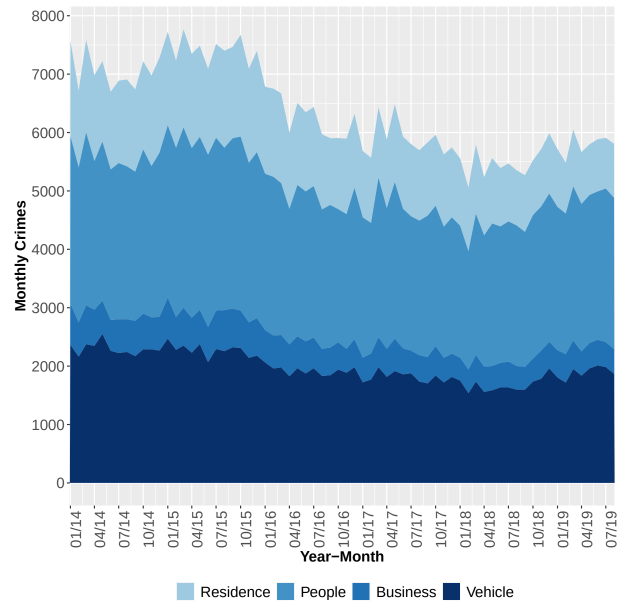
Finally, we further group calls to homogenize them and make them comparable with property crime reports. We group calls for (i) private property alarms and (ii) home robberies into 'Residence'. We group calls for (i) vehicle alarms, (ii) vehicle theft, or (iii) theft of properties inside a vehicle into 'Vehicle'. We group calls for (i) street theft or (ii) robbery where the victim is a person into 'People'. We group calls for (i) robberies against banks, (ii) local shops, (iii) factories, etc into 'Business'. We group (i) other or (ii) unclassified robberies into 'Other'. Figure 3c shows monthly 911 calls where a police unit was dispatched by our grouped categories. The ECU911 achieved national representatives by the end of 2012 which makes us confident that the data is comparable across time and space. Figure 4 shows the average monthly crime and 911 call rates at the parish level for the first and last year of available data. Importantly, We observe variation across time and space for both of our outcome measures.

The third one represents the universe of all 4,730 cameras installed by the ECU911 since they started operations in January 2012 until August 2019. In addition to the technical characteristics of each camera they also report the exact site and date of installation of all cameras in operation. This information was provided by the data analysis department of the ECU911. We remove from the original sample all cameras which had missing coordinates or duplicated installations. One important aspect to point out is that both institutions, the DAID and ECU911, are independent of each other. Finally, in order to ensure comparability across space and to distinguish between urban and rural areas we use the GHS Urban Centre Database (Florczyk et al., 2019). This database gives us the location, extension, and shape of all urban centers within Ecuador.

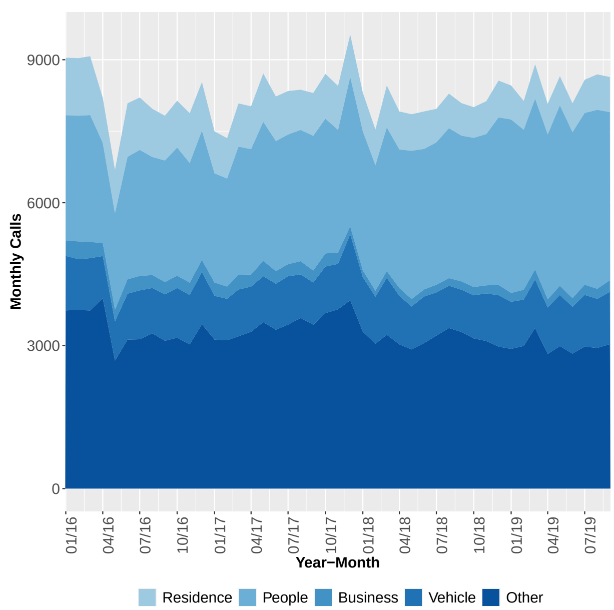
Figure 3: Crime Rate and Total Crime [2014-08/2019]



(a) Parish Level: Monthly Average Crime Rate



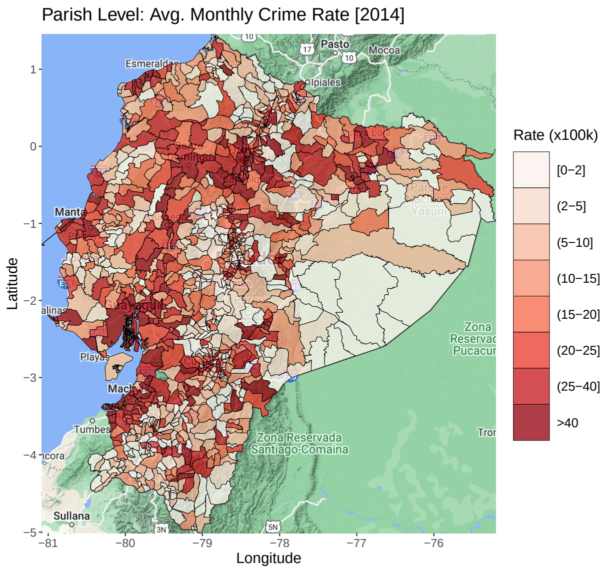
(b) National Level: Monthly Crimes



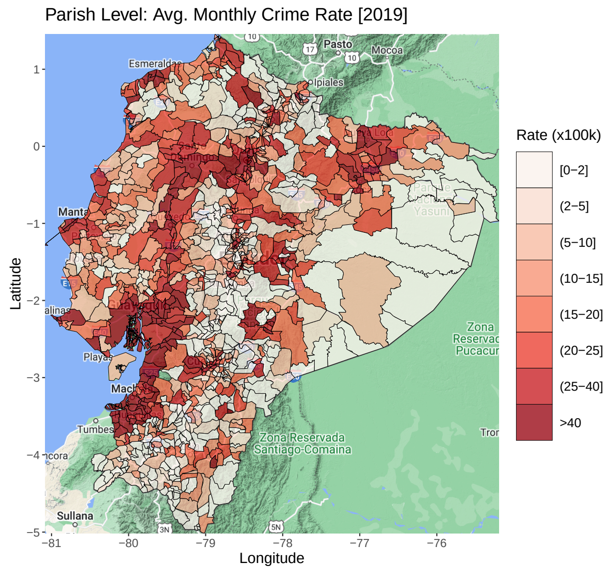
(c) National Level: Monthly 911 Calls

Notes: Figure 3a shows the average monthly crime rate among all 1,024 parishes. Parishes are the smallest administrative unit in the country and they have an average population and surface area of 14k inhabitants and 250km^2. The dotted grey lines represent the average crime rate within the top and bottom 20th percentiles for each month. The solid black line represents the average. We use the population for each parish from the 2010 census. Figure 3b shows the monthly reported crimes by target. Figure 6d shows the monthly 911 calls where a police unit was dispatched.

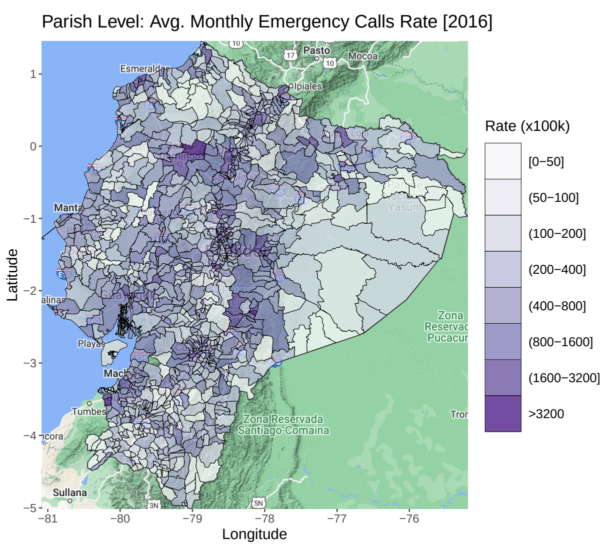
Figure 4: Parish Level: Crime & Emergency Call Rates [2014 & 2019]



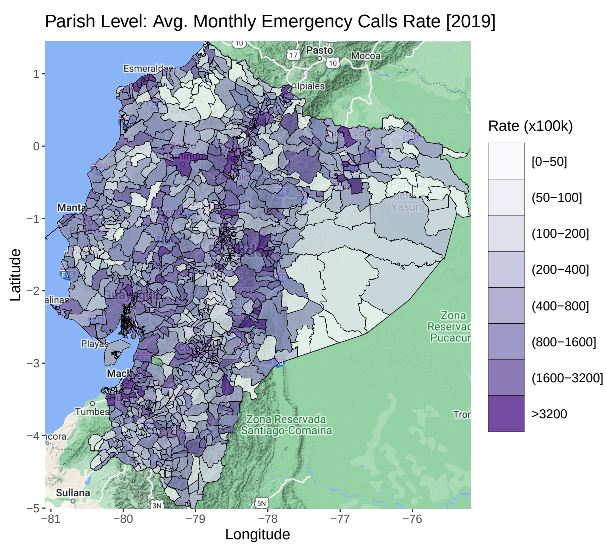
(a) Crime Rate: 2014



(b) Crime Rate: 2019



(c) 911 Calls Rate: 2016



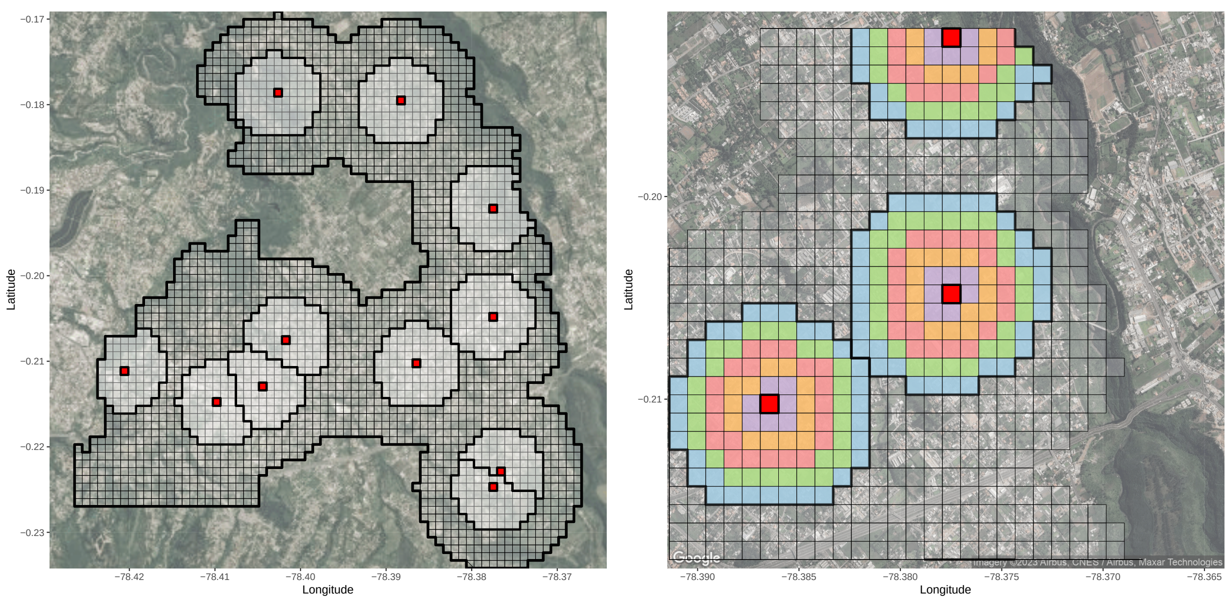
(d) 911 Calls Rate: 2019

Notes: Figure 4 shows the average monthly crime and 911 call rate for the first (2014 & 2016) and last (2019) years for both data sources. We use the population for each parish from the 2010 census. Parishes are the smallest administrative unit in the country and they have an average population and surface area of 14k inhabitants and 250km^2.

4.2. *Empirical Strategy*

Our main identification strategy relies on exploiting (i) the large spatial and temporal variation in the introduction of the policy and (ii) distance to cameras. In order to do that we construct a balanced panel at the cell-month level for January 2014 to August of 2019. First, we define the area of analysis for each camera conditional on their context. For urban cameras – those located within urban centers – we restrict to the urban boundary of each parish. For rural cameras – those outside urban centers – we restrict to all area within 1km of its installation site. We do this for all cameras in our sample. This procedure ensures comparability across space. Second, we split our total area of analysis into a fixed grid composed of 100x100 meter cells. Third, we assign cells located up to 500 meters to their closest camera. Fourth, we classify cells into seven groups i.e bins based on their relative distance to their assigned camera: direct (cell with a camera installation), 0-100m (excluding direct cell), 100-200m, 200-300m, 300-400m, 400-500m, and beyond 500m. Fifth, using the exact location for reported crimes and emergency calls we assign each of them to their respective cell. Finally, we collapse our data at the cell-month level to construct a balanced panel covering a period of 69 months and, virtually, all space being intervened by the policy. Therefore, we have measures at the cell-month level representing the (i) total number of reported property crimes and the (ii) total number of 911 calls where a police unit was dispatched. Figure 5 uses a specific parish – Tumbaco – as an example to depict the spatial process followed to create our panel. Figure 6 shows the georeferenced nature of our outcome measures and the assignment process. From this figure we can see that reported crimes and 911 calls are concentrated within the same cells and areas. This is consistent with the rest of the country.

Figure 5: Grid Design & Cells Classification – Ex: Tumbaco

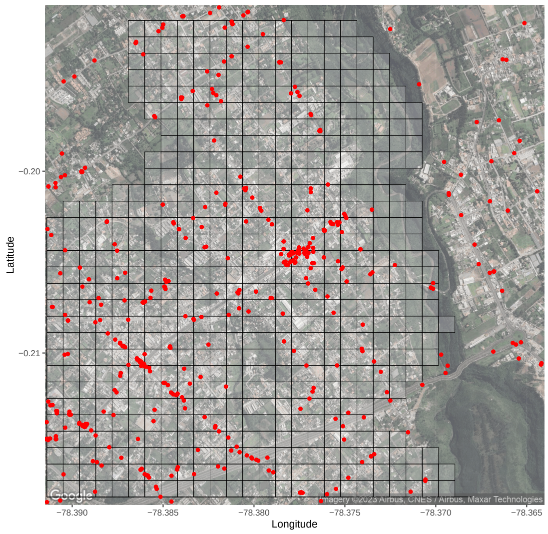


(a) Grid Design

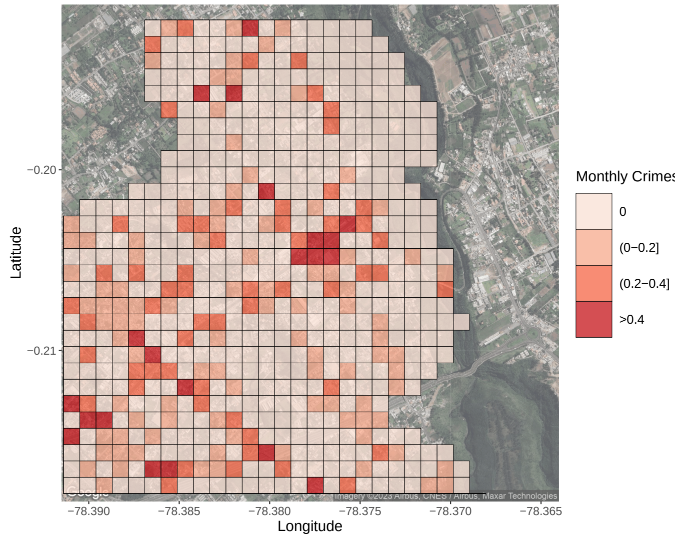
(b) Cell Classification – Ex: Downtown Tumbaco

Notes: Figure 5a shows the fixed grid composed of 100x100 meter cells for the parish of Tumbaco. Parishes are the smallest administrative unit in the country and they have an average population and surface area of 14k inhabitants and 250km^2. The red cells represent installation sites and the surrounding lighter colored cells represent all cells within 500 meters of an installation site. Figure 5b depicts the classification of cells based on the relative distance i.e 100m bins from the installation site: direct (red), 0-100m (purple), 100-200m (orange), 200-300m (pink), 300-400m (green), 400-500 (blue), and control (transparent).

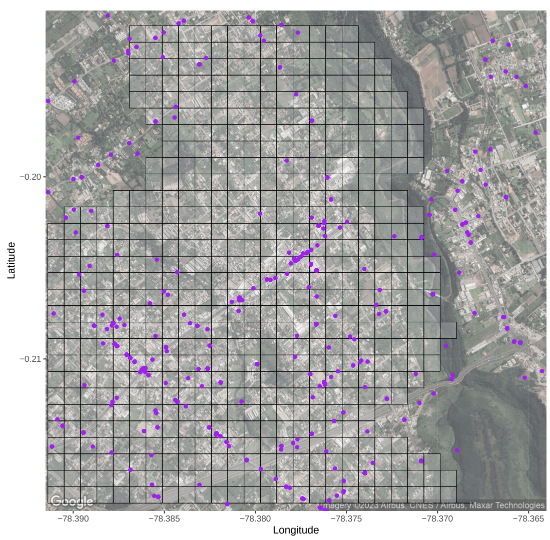
Figure 6: Crimes & Emergency Calls Assignment – Ex: Downtown Tumbaco



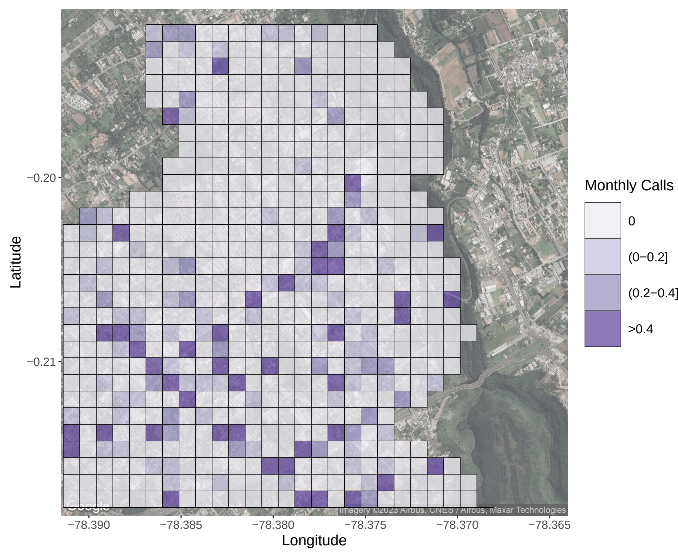
(a) Reported Crimes



(b) Avg. Monthly Reported Crimes



(c) Emergency Calls



(d) Avg. Monthly Emergency Calls

Notes: Figure 6 represents the transformation from the original georeferenced data to the total count of monthly crimes and emergency calls per cell. Figures 6a and 6c depict the distribution of reported crimes and emergency calls for the downtown area of Tumbaco. Figures 6b and 6d depict the average monthly crimes and emergency calls made during our study period for that same area.

First, we will focus on identifying the causal effect of the policy on (i) crimes and (ii) emergency calls. The combination of the two outcomes gives us a clearer picture on the overall effect and allows us to circumvent the known issue of under-reporting in crime data. As mentioned above, the exact installation site within selected crime-prone areas was determined based on a series of exogenous factors: good internet connectivity, existing structure in place and relative proximity to locations of interest such as schools, hospitals, government buildings, etc. The main identification assumption is that, had there been no camera installation, our outcomes of interest would be, on average, statistically equal between treated cells – cells within 300 meters of a camera – and control cells – cells further than 500 meters. The average range of vision for all cameras i.e 300 meters allows us to determine the area that was being surveilled. Additionally, we include cells within 300-500m to capture potential displacement effects. In our main specification the average treatment effect is estimated as the difference in the post-treatment means of the outcome variables between treated and control cells. Formally, we estimate the following linear regression model by Ordinary Least Squares (OLS) using information at the cell (c) level:

$$Y_{c,t} = \sum_{d} 1[d = c] \times \beta_d D_{c,t} + \alpha_c + \mu_t + \epsilon_{c,t} \tag{1}$$

Where $Y_{c,t}$ are our outcomes of interest within cell c at time t i.e year-month. Each β_d captures the observed variation in crime within cells falling in each our distance bins (d): direct, 0-100m, 100-200m, 200-300m, 300-400m, and 400-500m. The interaction with the treatment indicator $D_{c,t}$ allows us to identify the set of β_d coefficients relative to each other. For simplicity, we estimate a regression using OLS in which we include treatment dummies for cells within each distance bin. We include cell (α_c) and time (μ_t) fixed effects. Finally, $\epsilon_{b,t}$ is the error term. This specification captures the average treatment effect of cameras at the hyperlocal level. Instead of relying on the range of vision for each camera this specification allows us to more flexibly estimate treatment effects based on relative distance to treatment. Additionally, it will let us identify potential displacement effects to cells which are not under surveillance. Results from estimating equation 1 are presented in tables 1 and 2 and shown graphically in figure 7. [3]. We complement these results with an event study approach which will help us disentangle short and medium-term effects. Lastly, it will also help us better understand dynamics around camera installations. Formally, we estimate the following regression by OLS using information at the cell (c) level:

$$y_{c,t} = \sum_{d} \sum_{-k}^{k} 1[d = c, k = t] \times \beta_{d,k} D_{c,t} + \alpha_c + \mu_t + \epsilon_{c,t} \tag{2}$$

Where each $\beta_{d,k}$ captures the observed variation in crime, relative to k months before or after a camera installation within cells in each of our distance bins d. The interaction with the treatment indicator $D_{c,t}$ allows us to identify the set of $\beta_{d,k}$ coefficients only relative to an installation in cell c belonging to bin d during month t. For simplicity, we group all months into years with the exception of our baseline coefficient which becomes the month prior to an installation. Additionally, we group months up to 8 years – 84 months – after an installation and up to 5 years – 60 months – before an installation. Finally, we include the same set of fixed effects as in our main specification. Results from estimating equation 2 are presented in figure 9.

5. Main Results

The results from our main specification suggests that cameras are effective at deterring crime within their surveilled area. According to estimates from table 1, there was a decrease of 0.0305 reported crimes within directly

[3] As robustness, in table 3 we use logged crime instead of total crime as well as estimate a linear probability model. Given the staggered design of our policy, we also use alternative estimators, specifically Callaway and Sant'Anna (2021) and Sun and Abraham (2021). Both results are shown in table 4.

treated cells i.e. cells which received an installation relative to cells beyond 500m of an installation. This decrease represents a 33% drop relative to pre-treatment crime levels. These results suggest that the effect on crime is heavily concentrated on cells in close proximity to cameras. Specifically, we find a large effect within the first 100 meters, however, the effect decreases in magnitude as we move further away up to 300 meters. This pattern is suggestive of cameras deterring criminals from offending within surveilled areas. Interestingly enough, the effect is closer to null within the 200-300m bin. We interpret this as validation of the distance threshold we will use to aggregate effects. However, once we move past the 300m threshold we find that the estimated effect becomes positive and significant. This pattern can be seen visually in figure 7a which simply plots the coefficients and their respective effect size by distance bin. We interpret this result as evidence of cameras displacing crime to areas which are not under direct surveillance. [4] Finally, we find that our findings are consistent across crimes with different targets: residences, people, businesses, and vehicles.

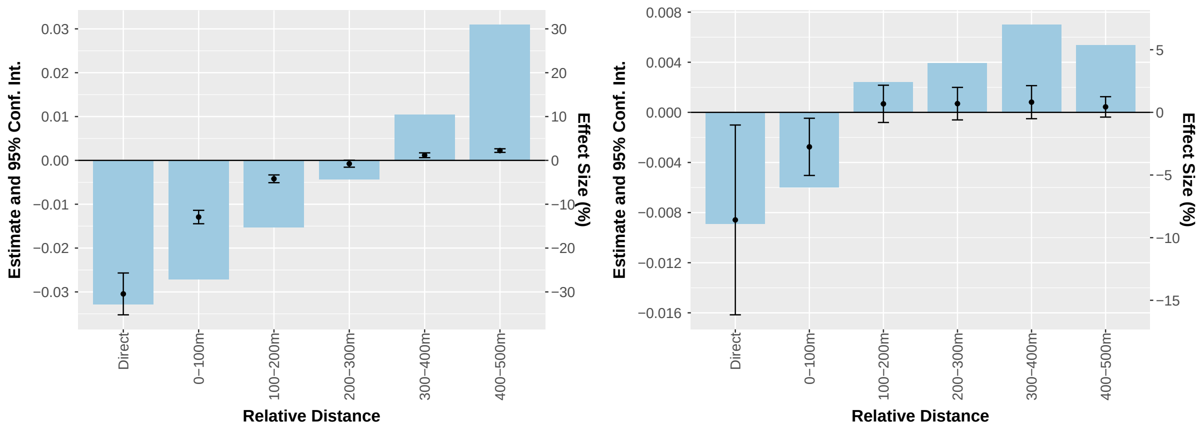
[4] We estimate a simplified version of equation 1 in which we group bins within 0-300m and 300-500m. The results are shown in table 5.

Table 1: Estimated Effect of Cameras on Property Crime by Relative Distance

Target:	Total	Residence	People	Business	Vehicle
	(1)	(2)	(3)	(4)	(5)
Direct	-0.0305***	-0.0056***	-0.0108***	-0.0040***	-0.0100***
	(0.0024)	(0.0007)	(0.0015)	(0.0006)	(0.0012)
0-100m	-0.0129***	-0.0033***	-0.0039***	-0.0011***	-0.0046***
	(0.0008)	(0.0002)	(0.0005)	(0.0002)	(0.0003)
100-200m	-0.0042***	-0.0012***	-0.0012***	-0.0004***	-0.0014***
	(0.0005)	(0.0002)	(0.0003)	(0.0001)	(0.0002)
200-300m	-0.0008*	-0.0003**	-0.0002	-0.0001	-0.0001
	(0.0004)	(0.0001)	(0.0002)	(0.0001)	(0.0002)
300-400m	0.0012***	0.0001	0.0005***	0.0002***	0.0003***
	(0.0003)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
400-500m	0.0022***	0.0005***	0.0008***	0.0002***	0.0008***
	(0.0002)	(0.0001)	(0.0001)	(0.0000)	(0.0001)
Effect size:					
Direct	-32.85% [0.0927]	-43.7% [0.0129]	-24.88% [0.0435]	-41.57% [0.0096]	-37.46% [0.0267]
0-100m	-27.15% [0.0476]	-39.59% [0.0084]	-19.24% [0.0204]	-26.25% [0.0042]	-31.29% [0.0146]
100-200m	-15.21% [0.0276]	-21.24% [0.0056]	-10.76% [0.0114]	-19.48% [0.0021]	-16.36% [0.0084]
200-300m	-4.31% [0.0175]	-9.13% [0.0038]	-3.42% [0.0072]	-7.54% [0.0012]	-1.31% [0.0053]
300-400m	10.49% [0.0112]	5.4% [0.0026]	11.69% [0.0045]	24.26% [0.0007]	9.95% [0.0034]
400-500m	31.05% [0.0072]	25.89% [0.0018]	28.92% [0.0029]	33.01% [0.0005]	36.45% [0.0021]
Fit statistics:					
Nbr. Parishes	460	460	460	460	460
Nbr. Cams	4,204	4,204	4,204	4,204	4,204
Nbr. Cells	418,021	418,021	418,021	418,021	418,021
Observations	28,843,449	28,843,449	28,843,449	28,843,449	28,843,449
R^2	0.17709	0.03258	0.14891	0.04061	0.08159
Fixed-effects					
Year-Month	Yes	Yes	Yes	Yes	Yes
Cell	Yes	Yes	Yes	Yes	Yes

Notes: This table represents estimates of separate regressions for each type of crime. We split treated cells – 0-300m – into 100 meter bins: direct (cell with a camera installation), 0-100m (excluding direct cell), 100-200m, and 200-300m. Additionally, we include cells within 300-400m and 400-500m. Control cells are defined as those beyond 500 meters of an installation. The effect size is estimated relative to the pre-treatment mean – reported in brackets – for each type of crime within each bin. We include installations prior to 2014 as always treated cells. Finally, we cluster standard errors – reported in parenthesis – at the cell level and include cell and year-month fixed effects. Significance codes: ***: 0.01, **: 0.05, *: 0.1

Figure 7: Estimated Effect of Cameras on Property Crimes and 911 Calls by Relative Distance



(a) Reported Crimes

(b) 911 Calls

Notes: This figure plots the estimated coefficients and effect sizes reported in tables 1 and 2. We split treated cells – 0-300m – into 100 meter bins: direct (cell with a camera installation), 0-100m (excluding direct cell), 100-200m, and 200-300m. Additionally, we include cells within 300-400m and 400-500m. Control cells are defined as those beyond 500 meters of an installation. The coefficients and confidence intervals estimated for each distance bins corresponds to the primary y-axis. The effect size is estimated relative to the pre-treatment mean – reported in brackets in tables 1 and 2. The light blue bars are the estimated effect size for each distance bins and corresponds to the secondary y-axis. We include installations prior to 2014 as always treated cells in figure 7a. We include installations prior to 2016 as always treated cells in figure 7b. Finally, we cluster standard errors at the cell level and include cell and year-month fixed effects.

When we focus on table 2 looking at 911 calls a similar pattern emerges. We find that there was a decrease of 0.0086 calls related to property crimes within directly treated cells. This decrease represents a 9% drop relative to pre-treatment levels. We estimate the same equation on 911 calls related to violent events, such as assault, police support, and public order, and find a similar pattern. Results are shown in table 9. The effect also appears to decrease in magnitude as we move further away from the installation site. This pattern can be seen visually in figure 7b which simply plots the coefficients and their respective effect size by distance bin. However, this pattern is less clear than on reported crimes. This, we believe, has to do with the nature of the data itself. Unlike crime reports, the location of 911 calls do not necessarily reflect the exact location of the incident. When we disaggregate by target we find a similar – with the exception of property crimes against people – pattern. We believe that has to do with cameras simply increasing calls when the victim is a person but not necessarily crimes. These sort of calls are more sensitive to the saliency of a camera since they usually happen contemporaneously to the crime, unlike those related to a residence, business, or vehicle [5]. This first result suggests that offenders, and perhaps potential victims, do in fact adjust their behavior based on their updated perceived risk of capture.

[5]We plan to test this hypothesis explicitly by checking if the share of calls relative to crimes increases following an installation. This would explain the increase for property crimes against people.

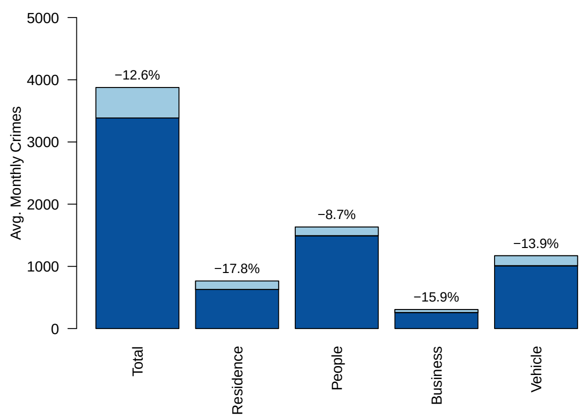
Table 2: Estimated Effect of Cameras on 911 Emergency Calls by Relative Distance

Target:	Total (1)	Residence (2)	People (3)	Business (4)	Vehicle (5)	Other (6)
Direct	-0.0086**	-0.0025**	0.0043**	-0.0021***	-0.0033***	-0.0050**
	(0.0039)	(0.0010)	(0.0022)	(0.0006)	(0.0011)	(0.0022)
0-100m	-0.0028**	-0.0013***	0.0016***	-0.0004**	0.0001	-0.0028***
	(0.0012)	(0.0003)	(0.0006)	(0.0002)	(0.0003)	(0.0007)
100-200m	0.0007	-0.0006***	0.0016***	-0.0001	0.0004	-0.0006
	(0.0008)	(0.0002)	(0.0004)	(0.0001)	(0.0002)	(0.0005)
200-300m	0.0007	-0.0003	0.0011***	0.0000	-0.0001	0.0000
	(0.0007)	(0.0002)	(0.0003)	(0.0001)	(0.0002)	(0.0004)
300-400m	0.0008	0.0001	0.0003	0.0000	0.0001	0.0002
	(0.0007)	(0.0001)	(0.0003)	(0.0001)	(0.0001)	(0.0003)
400-500m	0.0004	0.0002*	0.0001	0.0001	0.0001	-0.0001
	(0.0004)	(0.0001)	(0.0002)	(0.0000)	(0.0001)	(0.0003)
Effect size:						
Direct	-8.9% [0.0965]	-33.42% [0.0075]	12.12% [0.0357]	-51.58% [0.0041]	-27.67% [0.0119]	-13.4% [0.0373]
0-100m	-5.98% [0.0460]	-27.33% [0.0046]	10.6% [0.0152]	-23.69% [0.0018]	2.75% [0.0048]	-14.35% [0.0196]
100-200m	2.43% [0.0280]	-18.32% [0.0031]	17.42% [0.0090]	-12.52% [0.0008]	12.08% [0.0030]	-4.81% [0.0121]
200-300m	3.93% [0.0177]	-12.03% [0.0022]	19.9% [0.0054]	2.19% [0.0005]	-4.95% [0.0020]	-0.35% [0.0076]
300-400m	6.97% [0.0117]	9.59% [0.0014]	7.69% [0.0036]	11.4% [0.0003]	10.21% [0.0013]	4.65% [0.0051]
400-500m	5.34% [0.0082]	20.57% [0.0010]	4.76% [0.0022]	31.94% [0.0002]	17.8% [0.0008]	-2.04% [0.0039]
Fit statistics						
Nbr. Parishes	460	460	460	460	460	460
Nbr. Cams	4,204	4,204	4,204	4,204	4,204	4,204
Nbr. Cells	418,021	418,021	418,021	418,021	418,021	418,021
Observations	18,810,945	18,810,945	18,810,945	18,810,945	18,810,945	18,810,945
R^2	0.46002	0.15660	0.33174	0.04854	0.11871	0.24413
Fixed-effects						
Year-Month	Yes	Yes	Yes	Yes	Yes	Yes
Cell	Yes	Yes	Yes	Yes	Yes	Yes

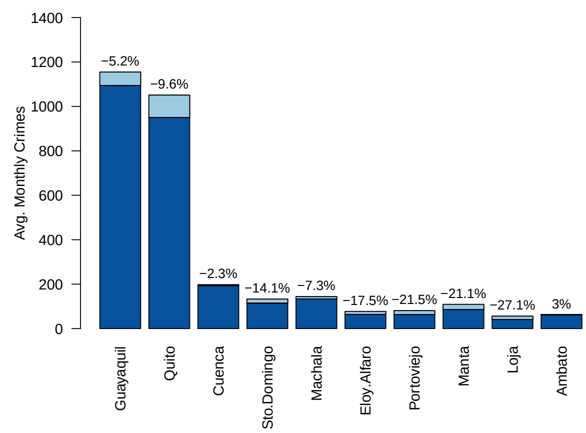
Notes: This table represents estimates of separate regressions for 911 calls by type in which the police was dispatched. We split treated cells – 0-300m – into 100 meter bins: direct (cell with a camera installation), 0-100m (excluding direct cell), 100-200m, and 200-300m. Additionally, we include cells within 300-400m and 400-500m. Control cells are defined as those beyond 500 meters of an installation. The effect size is estimated relative to the pre-treatment mean – reported in brackets – for each type of call category within each bin. We include installations prior to 2016 as always treated cells. Finally, we cluster standard errors – reported in parenthesis – at the cell level and include cell and year-month fixed effects. Significance codes: ***: 0.01, **: 0.05, *: 0.1

Since we are interested in evaluating the overall or net effect of the policy we have to take into account both direct and displacement effects. We attempt to translate these results into aggregate values by estimating the following three-step back-of-the-envelope calculation. First, we estimate the effect size relative to the pre-treatment mean for each crime type and distance bin. For example, as reported on table 1 the effect size on total crime within directly treated cells was of 32.85%. Second, we calculate the pre-treatment average monthly crimes for each distance bin. To do that we count the number of cells that fall under each bin. Then, we multiply that total by the pre-treatment mean. For example, nationwide there were 4,204 directly treated cells with a pre-treatment monthly average of 0.0927 crimes. This translates to a monthly average of 390 reported crimes to the police. Therefore, by combining both steps – 32.85% × 390 – we estimate that there was a decrease of 128 monthly – 1.5k annual – reported crimes to the police within directly treated cells. We replicate this procedure for each distance bin and aggregate them. The sum of monthly pre-treatment averages within all cells 0-500m of an installation was 3,877 crimes. The aggregate drop was of 490 monthly – 5.9k annual – reported crimes. This number translates to a drop of 12.6%. Figure 8a shows the nationwide total as well as the breakdown per crime target. This analysis suggests that the aggregate effect remains negative in spite of crime being displaced to nearby blocks. Similarly, we can aggregate the effect at the parish level. We follow the same procedure except that we estimate separate regressions i.e. equation 1 for each parish. Within the two largest parishes in the country – where 27% of the population is concentrated – the drop was of 160 less crimes which represents 33% of the nationwide total. Figure 8b shows the breakdown per parish. This process is analogous to estimating a version of equation 1 with a single treatment dummy: 0-500m. If we estimate that regression the estimated effect size is also of 12.6% (shown on table 6).

Figure 8: Aggregate Effects by Crime Type & Parish: 0-500m



(a) Effects by Crime Type



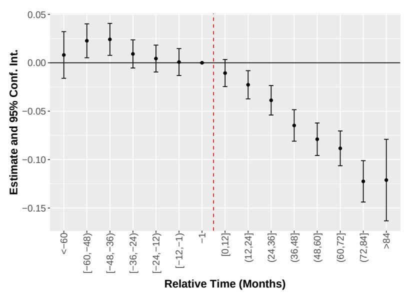
(b) Effects by Parish

Notes: Figure 8b shows the aggregate effects at the parish level. The bars represent the average monthly crimes reported in all cells within 500 meters of an installation for the ten most populated parishes in the country. Parishes are the smallest administrative unit in the country and they have an average population and surface area of 14k inhabitants and 250km^2. The aggregate effect in crime is represented by the light blue portion. The effect in percent terms is reported on top. To estimate these values we: 1) estimate a separate equation 1 for each parish, 2) estimate the effect size relative to the pre-treatment mean, 3) estimate the average monthly crimes for the surveilled area by counting the number of cells within 300m of an installation and multiplying by its pre-treatment mean, and 3) multiplying both values to get the aggregate effect per parish. Figure 8a shows the aggregate effects by the crime target.

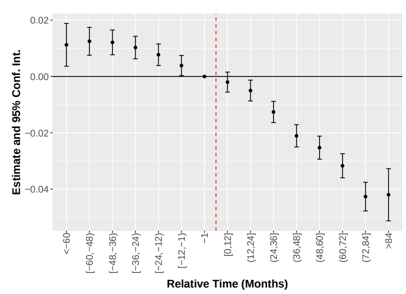
Given the gradual rollout of the policy we can investigate how the effect varies over time. This allows us to study the short and medium-term effects of the policy. We believe this is relevant given that criminals and potential victims might learn and react differently over time to being surveilled. Figure 9 plots the estimation of equation 2 for total property crimes. These results show that the effect is long lasting and persists even 8 years after. Similarly, we find that the effect increases over time until eventually tapering off. Finally, we find that the effect follows the same pattern as in table 1. Namely that the effect is concentrated within cells closer to cameras and there is evidence of displacement as we move further away. Within the first post-treatment year crimes fell by around 0.011 monthly crimes – 11% drop relative to pre-treatment levels. That reduction increases to 0.122 crimes - 130% drop -on year seven and eventually levels off. The opposite pattern emerges within cells 400-500m of an installation. Within the first post-treatment year, crimes increased by around 0.001 monthly crimes – 17% increase relative to pre-treatment levels.

That effect rises to 0.005 crimes - 70% increase - eight years after installations. This same pattern is consistent across crime types and highlights the importance of understanding dynamics around installations. We interpret this result as evidence of the persistent effect of cameras on crime.

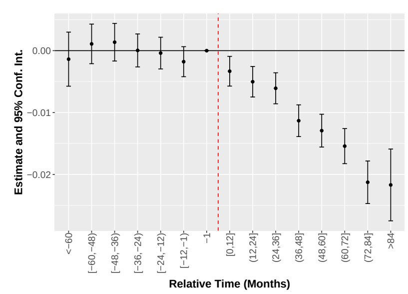
Figure 9: Event Study Estimates on Total Crime by Relative Distance: 0-500m



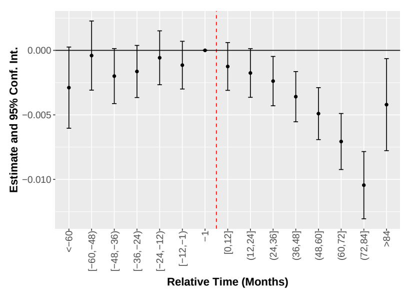
(a) Direct



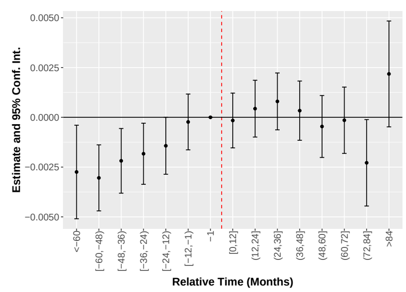
(b) 0-100m



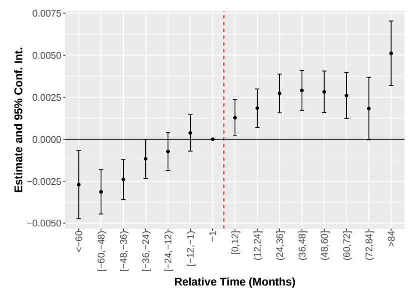
(c) 100-200m



(d) 200-300m



(e) 300-400m



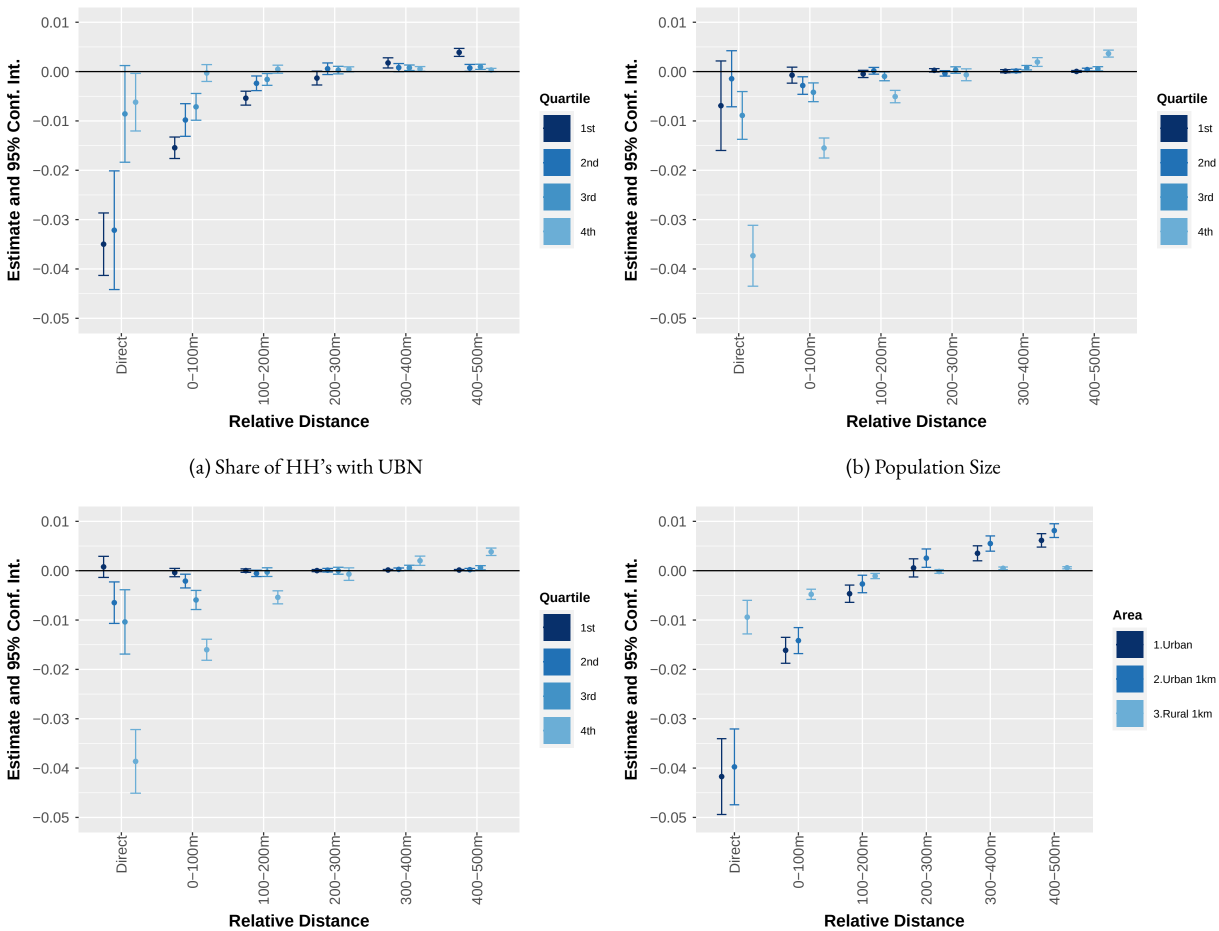
(f) 400-500m

Notes: This figure represents event study results from estimating equation 2 for total property crime. We split treated cells – 0-300m – into 100 meter bins: direct (cell with a camera installation), 0-100m (excluding direct cell), 100-200m, and 200-300m. Additionally, we include cells within 300-400m and 400-500m. Control cells are defined as those beyond 500 meters of an installation. We include installations prior to 2014 as always treated cells. Finally, we cluster standard errors at the cell level and include cell and year-month fixed effects.

6. Heterogeneity by parish characteristics

The nationwide coverage of the policy allows us to explore heterogeneous effects of cameras across space. One can hypothesize that the returns, in terms of decrease in crime, might differ across several dimensions. We do this analysis at the parish level using measures of poverty and population from the 2010 census. Specifically, we split all 460 treated parishes into quartiles based on their: (i) share of households with unmet basic needs (UBN), (ii) population size, (iii) cell-level pre-treatment crime level. Then, we estimate equation 1 separately on each quartile separately. Figures 10a, 10b and 10c plots the estimated coefficient. Finally, we classify cameras as urban and rural using the urban center maps from the GHS. Additionally, we impose a 1km filter for urban cameras which further restricts control cells to those within 1km. We then estimate equation 1 separately for each subset of cameras. Figure 10d plots the estimated coefficients.

Figure 10: Effects on Total Crime by Parish Characteristics



(a) Share of HH's with UBN

(b) Population Size

(c) Baseline Crime Rate

(d) Urban vs. Rural Cameras

Notes: This figure plots coefficients from estimating equation 1 separately on a subset of parishes. Parishes are the smallest administrative unit in the country and they have an average population and surface area of 14k inhabitants and 250km^2. Figure 10a splits all 460 treated parishes into quartiles based on the share of HH's with unmet basic needs (UBN) according to the 2010 census. Figure 10b splits parishes based on population size. Figure 10c splits parishes based on their pre-treatment crime rate. Figure 10d splits cameras based on whether they were installed within urban or rural settings. Urban cameras are defined as those that fall within urban centers according to the GHS maps. Rural cameras are those that fall outside. We split treated cells – 0-300m – into 100 meter bins: direct (cell with a camera installation), 0-100m (excluding direct cell), 100-200m, and 200-300m. Additionally, we include cells within 300-400m and 400-500m. Control cells are defined as those beyond 500 meters of an installation. The 1km filter in figure 10d restricts cells to those within 1km of an installation. We include installations prior to 2014 as always treated cells. Finally, we cluster standard errors at the cell level and include cell and year-month fixed effects.

First, we find that both effects: direct and displacement are heavily concentrated within poorer parishes. Specifically, both effects are only statistically significant within the 2 poorest quartiles. Similarly, we find that more populated parishes are driving the effect. Both of these findings might have to do with police response capacity as well as offenders operating within poorer neighborhoods being more sensitive to this policy. We also find that the effect is stronger for urban cameras. Regardless of the restriction of control cells the effect of urban cameras on reported crimes is four times as large as that of cameras within rural settings. Obviously since we are regressing on levels these patterns are driven by crime being higher within poor, more populated, urban parishes, however, it is informative since it shows where these cameras have higher returns. Finally, we also show that the effects observed in table 1 are entirely driven by parishes with a high baseline crime level. From a policy perspective this implies that surveillance cameras can be an effective crime control policy, especially within contexts where policing might be particularly hard or challenging: poor, populous, urban, and high-crime neighborhoods.

7. Conclusion

Police monitored video-surveillance systems are viewed as a catch-all solution and efficient complement to policing. Around the world they have increased in popularity, especially within developing countries. However, due to the (i) lack of systematic registry of installations, (ii) difficulty to address endogeneity concerns, and (iv) lack of access to consistent and detailed administrative data they are hard to evaluate. In this paper we focus on the introduction of a nationwide policy – 4.7k surveillance cameras – implemented in Ecuador which by the end of our study period covered over 30% of all urban space. The installation of cameras happened gradually over time and across space with no spatial or temporal concentration. Additionally, the exact installation site within crime-prone areas was determined based on a series of exogenous factors: good internet connectivity, existing structure in place and relative proximity to locations of interest such as schools, hospitals, government buildings, etc. This highlights one key aspects that we use for identification: the identified crime-prone areas are not randomly selected, however, the exact installation site i.e block within these areas is exogenously determined.

Using unique georeferenced administrative data sources representing (i) crime reports and (ii) 911 calls we construct a panel at the city block-month level. Using a difference-in-difference approach we find that crimes within directly treated cells decreased by around 33%. This effect decreases in magnitude as we move further away and once we move past the 300m threshold we find that the effect becomes positive and significant. We interpret this result as evidence of cameras displacing crime to areas which are not under direct surveillance. Aggregating both opposing effects gives us a net decreased of 12% which translates to a drop of 5.8k crimes within a given year. If we focus on 911 calls, where crime under-reporting is less of an issue, we find a similar pattern: the effect is concentrated within cells closer to an installation. We also find that the effect is persistent and long-lasting as well as concentrated within contexts where policing is more costly and challenging: poorer, more populated, and urban settings. These findings suggest that video-surveillance systems can be an effective city-level crime prevention policy.

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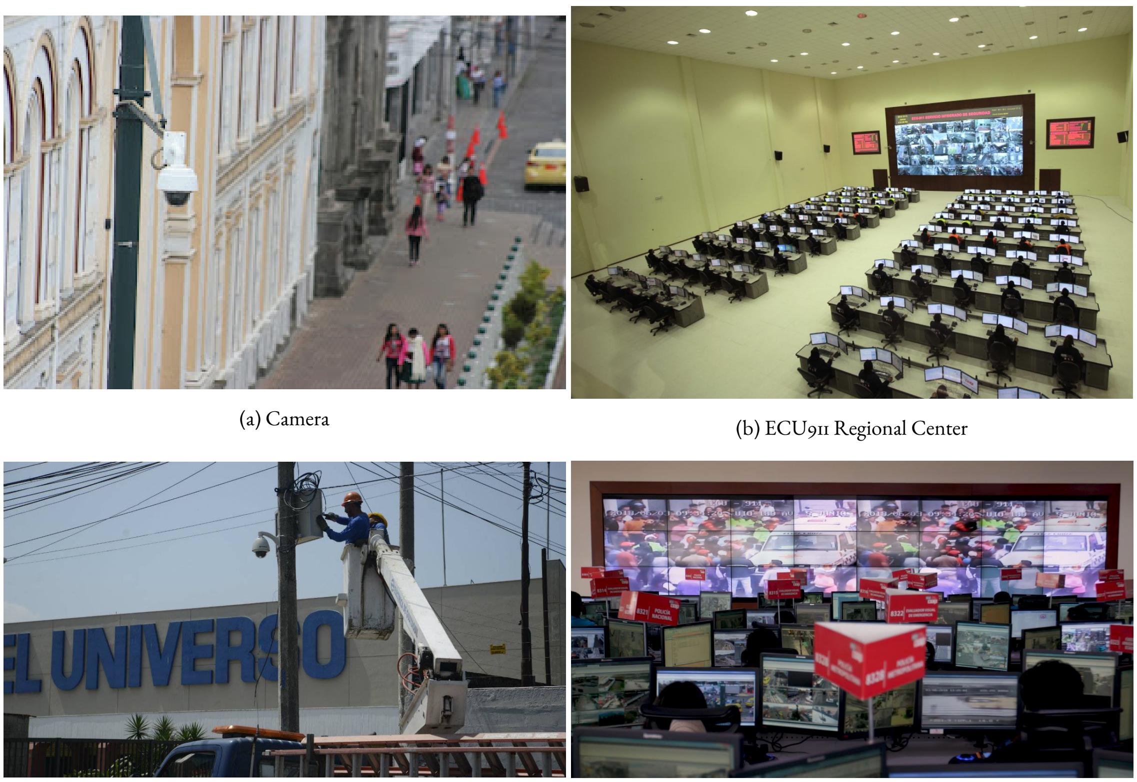
9. Appendix

Figure 11: ECU911 Cameras & Regional Centers



(a) Camera

(b) ECU911 Regional Center

(c) Camera Installation

(d) ECU911 Municipal Center

Notes: This figure shows photos of cameras, their installation process, and example of regional and municipal operating centers. Cameras allow for 360° horizontal and 290° vertical view. Additionally, they cover a maximum visual field of up to 300 meters. ECU911 operates 17 regional and 14 municipal operation centers located within all 24 provinces. Currently there are over 1.5k direct employees, out of which 65% are solely tasked with surveillance operations.

Table 3: Estimated Effect of Cameras on Property Crime: Alternative Outcomes

Target:	Total (1)	Residence (2)	People (3)	Business (4)	Vehicle (5)
Logged(+0.1)					
0-300m	-0.0120***	-0.0037***	-0.0038***	-0.0014***	-0.0046***
	(0.0005)	(0.0002)	(0.0004)	(0.0001)	(0.0003)
300-500m	0.0030***	0.0007***	0.0013***	0.0004***	0.0012***
	(0.0004)	(0.0002)	(0.0002)	(0.0001)	(0.0002)
Binary					
0-300m	-0.0047***	-0.0015***	-0.0015***	-0.0006***	-0.0019***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
300-500m	0.0011***	0.0003***	0.0005***	0.0001***	0.0005***
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)
Fit statistics					
Nbr. Parishes	460	460	460	460	460
Nbr. Cams	4,204	4,204	4,204	4,204	4,204
Nbr. Cells	418,021	418,021	418,021	418,021	418,021
Observations	28,843,449	28,843,449	28,843,449	28,843,449	28,843,449
Fixed-effects					
Year-Month	Yes	Yes	Yes	Yes	Yes
Cell	Yes	Yes	Yes	Yes	Yes

Notes: This table represents estimates of separate regressions for each type of crime. The top panel shows results for logged(+0.01) outcomes. The bottom panel shows results for binary outcomes. We split all cells within 500m of an installation into two groups: 0-300m and 300-500m. Control cells are defined as those beyond 500 meters of an installation. We include installations prior to 2014 as always treated cells. Finally, we cluster standard errors – reported in parenthesis – at the cell level and include cell and year-month fixed effects. Significance codes: ***: 0.01, **: 0.05, *: 0.1

Table 4: Alternative Estimators for the Effect of Cameras on Property Crime

Target:	Total (1)	Residence (2)	People (3)	Business (4)	Vehicle (5)
Callaway & Sant'Anna	-0.0089*** (0.0009)	-0.0019*** (0.0004)	-0.0028*** (0.0006)	-0.0007*** (0.0003)	-0.0035*** (0.0005)
Effect size:	28.22% [0.0315]	31.99% [0.0059]	20.89% [0.0134]	27.35% [0.0026]	36.76% [0.0095]
Sun & Abraham	-0.0091*** (0.0009)	-0.0019*** (0.0004)	-0.0028*** (0.0006)	-0.0007*** (0.0003)	-0.0036*** (0.0005)
Effect size:	28.82% [0.0315]	32.8% [0.0059]	21.23% [0.0134]	28.17% [0.0026]	37.54% [0.0095]
Fit statistics					
Nbr. Parishes	460	460	460	460	460
Nbr. Cams	2,992	2,992	2,992	2,992	2,992
Nbr. Cells	310,629	310,629	310,629	310,629	310,629
Observations	21,433,401	21,433,401	21,433,401	21,433,401	21,433,401
Fixed-effects					
Year-Month	Yes	Yes	Yes	Yes	Yes
Cell	Yes	Yes	Yes	Yes	Yes

Notes: This table represents estimates of separate regressions for each type of crime using two different alternative estimators: Callaway and Sant'Anna (2021) & Sun and Abraham (2021). Treated cells are those within 0-300m of an installation. Control cells are those beyond 500m of an installation. We remove cells within 300-500m. The effect size is estimated relative to the pre-treatment mean – reported in brackets – for each type of crime within each bin. Finally, we cluster standard errors – reported in parenthesis – at the cell level and include cell and year-month fixed effects. Significance codes: ***: 0.01, **: 0.05, *: 0.1

Table 5: Estimated Effect of Cameras on Property Crime by Relative Distance

Target:	Total	Residence	People	Business	Vehicle
	(1)	(2)	(3)	(4)	(5)
0-300m	-0.0062***	-0.0016***	-0.0019***	-0.0006***	-0.0021***
	(0.0003)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
300-500m	0.0017***	0.0003***	0.0007***	0.0002***	0.0006***
	(0.0002)	(0.0001)	(0.0001)	(0.0000)	(0.0001)
Effect size:					
0-300m	-19.75% [0.0315]	-27.09% [0.0059]	-14.54% [0.0134]	-23.79% [0.0026]	-21.64% [0.0095]
300-500m	18.63% [0.0092]	13.91% [0.0022]	18.51% [0.0037]	27.9% [0.0006]	20.57% [0.0027]
Fit statistics					
Nbr. Parishes	460	460	460	460	460
Nbr. Cams	4,204	4,204	4,204	4,204	4,204
Nbr. Cells	418,021	418,021	418,021	418,021	418,021
Observations	28,843,449	28,843,449	28,843,449	28,843,449	28,843,449
R^2	0.17701	0.03256	0.14888	0.04059	0.08156
Fixed-effects					
Year-Month	Yes	Yes	Yes	Yes	Yes
Cell	Yes	Yes	Yes	Yes	Yes

Notes: This table represents estimates of separate regressions for each type of crime. We split all cells within 500m of an installation into two groups: 0-300m and 300-500m. Control cells are defined as those beyond 500 meters of an installation. The effect size is estimated relative to the pre-treatment mean – reported in brackets – for each type of crime within each bin. We include installations prior to 2014 as always treated cells. Finally, we cluster standard errors – reported in parenthesis – at the cell level and include cell and year-month fixed effects. Significance codes: ***: 0.01, **: 0.05, *: 0.1

Table 6: Estimated General Equilibrium Effect of Cameras on Property Crime

Target:	Total (1)	Residence (2)	People (3)	Business (4)	Vehicle (5)
0-500m	-0.0027***	-0.0008***	-0.0008***	-0.0003***	-0.0009***
	(0.0002)	(0.0001)	(0.0001)	(0.0000)	(0.0001)
Effect size:					
0-500m	-12.66% [0.0215]	-17.64% [0.0043]	-8.65% [0.0091]	-16% [0.0017]	-13.91% [0.0065]
Fit statistics					
Nbr. Parishes	460	460	460	460	460
Nbr. Cams	4,204	4,204	4,204	4,204	4,204
Nbr. Cells	418,021	418,021	418,021	418,021	418,021
Observations	28,843,449	28,843,449	28,843,449	28,843,449	28,843,449
R^2	0.17697	0.03254	0.14887	0.04059	0.08154
Fixed-effects					
Year-Month	Yes	Yes	Yes	Yes	Yes
Cell	Yes	Yes	Yes	Yes	Yes

Notes: This table represents estimates of separate regressions for each type of crime. We group all cells within 500m of an installation. Control cells are defined as those beyond 500 meters of an installation. The effect size is estimated relative to the pre-treatment mean – reported in brackets – for each type of crime within each bin. We include installations prior to 2014 as always treated cells. Finally, we cluster standard errors – reported in parenthesis – at the cell level and include cell and year-month fixed effects. Significance codes: ***: 0.01, **: 0.05, *: 0.1

Table 7: Estimated Effect of Cameras on Property Crime by Target and Method

Target:	Residence		People		Business		Vehicle	
Method:	Violent	Non-Violent	Violent	Non-Violent	Violent	Non-Violent	Violent	Non-Violent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0-300m	-0.0002***	-0.0014***	-0.0016***	-0.0003***	-0.0002***	-0.0004***	-0.0004***	-0.0016***
	(0.0000)	(0.0001)	(0.0002)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)
300-500m	0.0000*	0.0003***	0.0006***	0.0001***	0.0001***	0.0001***	0.0000	0.0005***
	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Effect size:								
0-300m	-24% [0.0010]	-28% [0.0049]	-14% [0.0115]	-18% [0.0019]	-21% [0.0010]	-25% [0.0016]	-26% [0.0016]	-20% [0.0080]
300-500m	12% [0.0004]	14% [0.0019]	18% [0.0032]	29% [0.0004]	43% [0.0002]	28% [0.0003]	2% [0.0006]	25% [0.0022]
Fit statistics								
Nbr. Parishes	460	460	460	460	460	460	460	460
Nbr. Cams	4,204	4,204	4,204	4,204	4,204	4,204	4,204	4,204
Nbr. Cells	418,021	418,021	418,021	418,021	418,021	418,021	418,021	418,021
Observations	28,843,449	28,843,449	28,843,449	28,843,449	28,843,449	28,843,449	28,843,449	28,843,449
R^2	0.01862	0.02944	0.12044	0.07032	0.02784	0.03235	0.03155	0.07839
Fixed-effects								
Year-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table represents estimates of separate regressions for each type of crime-method combination. We split all cells within 500m of an installation into two groups: 0-300m and 300-500m. Control cells are defined as those beyond 500 meters of an installation. The effect size is estimated relative to the pre-treatment mean – reported in brackets – for each type of crime within each bin. We include installations prior to 2014 as always treated cells. Finally, we cluster standard errors – reported in parenthesis – at the cell level and include cell and year-month fixed effects. Significance codes: ***: 0.01, **: 0.05, *: 0.1

Table 8: Estimated Effect of Cameras on Total Property Crime by Camera Concentration

Restriction:	None (1)	3 Months (2)	6 Months (3)	1 Years (4)	2 Years (5)	Never (6)
0-300m	-0.0062***	-0.0047***	-0.0042***	-0.0033***	-0.0024***	-0.0010***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)
300-500m	0.0017***	0.0009***	0.0010***	0.0009***	0.0008***	0.0006***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Effect size:						
0-300m	-19.75% [0.0315]	-18.35% [0.0254]	-17.17% [0.0243]	-14.85% [0.0223]	-12.07% [0.0202]	-7.71% [0.0136]
300-500m	18.63% [0.0092]	11.52% [0.0081]	13.22% [0.0078]	12.53% [0.0075]	10.76% [0.0072]	10.72% [0.0057]
Fit statistics						
Nbr. Parishes	460	416	413	409	391	369
Nbr. Cams	4,204	2,127	1,939	1,732	1,402	984
Nbr. Cells	418,021	290,226	278,321	266,476	243,740	210,253
Observations	28,843,449	20,025,594	19,204,149	18,386,844	16,818,060	14,507,457
R^2	0.17701	0.16084	0.16155	0.15536	0.15468	0.14636
Fixed-effects						
Year-Month	Yes	Yes	Yes	Yes	Yes	Yes
Cell	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table represents estimates of separate regressions for total property crime. We filter cameras based on whether they had other camera installed within 500m and up to: 3 months, 6 months, etc before or after. We split all cells within 500m of an installation into two groups: 0-300m and 300-500m. Control cells are defined as those beyond 500 meters of an installation. The effect size is estimated relative to the pre-treatment mean – reported in brackets – for each type of crime within each bin. We include installations prior to 2014 as always treated cells. Finally, we cluster standard errors – reported in parenthesis – at the cell level and include cell and year-month fixed effects. Significance codes: ***: 0.01, **: 0.05, *: 0.1

Table 9: Estimated Effect of Cameras on 911 Emergency Calls by Relative Distance

Type:	Violent	Support	Public Order
	(1)	(2)	(3)
Direct	-0.0096	0.0002	-0.1997***
	(0.0072)	(0.0030)	(0.0251)
0-100m	0.0008	-0.0024**	-0.1030***
	(0.0021)	(0.0011)	(0.0058)
100-200m	0.0055***	0.0006	-0.0542***
	(0.0014)	(0.0004)	(0.0045)
200-300m	0.0031***	0.0008***	-0.0266***
	(0.0011)	(0.0002)	(0.0051)
300-400m	0.0022**	0.0011***	-0.0021
	(0.0010)	(0.0002)	(0.0032)
400-500m	0.0014	0.0006***	0.0151***
	(0.0009)	(0.0002)	(0.0025)
Effect Size			
Direct	-5.43% [0.1762]	1.55% [0.0134]	-58.26% [0.3427]
0-100m	0.94% [0.0866]	-32.78% [0.0074]	-60% [0.1717]
100-200m	9.76% [0.0564]	25.63% [0.0024]	-48.15% [0.1125]
200-300m	8.16% [0.0381]	61.79% [0.0013]	-34.49% [0.0770]
300-400m	8.52% [0.0253]	164.19% [0.0007]	-4.06% [0.0519]
400-500m	7.75% [0.0181]	87.04% [0.0007]	43.22% [0.0350]
Fit statistics			
Nbr. Parishes	460	460	460
Nbr. Cams	4,204	4,204	4,204
Nbr. Cells	418,021	418,021	418,021
Observations	18,810,945	18,810,945	18,810,945
R^2	0.57561	0.21864	0.34841
Fixed-effects			
Year-Month	Yes	Yes	Yes
Cell	Yes	Yes	Yes

Notes: This table represents estimates of separate regressions for 911 calls by type in which the police was dispatched. We split treated cells – 0-300m – into 100 meter bins: direct (cell with a camera installation), 0-100m (excluding direct cell), 100-200m, and 200-300m. Additionally, we include cells within 300-400m and 400-500m. Control cells are defined as those beyond 500 meters of an installation. The effect size is estimated relative to the pre-treatment mean – reported in brackets – for each type of call category within each bin. We include installations prior to 2016 as always treated cells. Finally, we cluster standard errors – reported in parenthesis – at the cell level and include cell and year-month fixed effects. Significance codes: ***: 0.01, **: 0.05, *: 0.1