Neighborhood-level Crime Deterrence in Mexico City*

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Abstract

Do surveillance cameras deter crime? This paper addresses this question by analyzing the Participatory Budget (PB) Program in Mexico City and crime rates at the neighborhood level. The PB program allows neighborhoods to choose how to allocate a percentage of public spending on projects proposed by its inhabitants. I focus on neighborhoods that choose to implement surveillance cameras. I leverage the PB program structure and employ the variation of its associated neighborhood-level expenditures, and I empirically test whether crime rates in neighborhoods that implement cameras are lower. I initially classify crimes following the FBI's UCR categories; then I define additional relevant crime categories. I find that the effect of surveillance cameras on crime – that is, the *camera deterrence effect* – is not statistically significant at the neighborhood level for most crimes. For other crimes, the estimated coefficient is positive and statistically significant, contrary to what was expected. I check for robustness, and find that when including both the lagged value of the crime rate and quadratic terms of the neighborhood observables in the regression, the *camera deterrence effect* is not statistically significant, with only 'theft from auto' and 'disorderly conduct' positive and statistically significant. Possible hypotheses for this finding are the meager resources assigned to neighborhoods, the lack of active monitoring, or a possibly suboptimal location chosen for the cameras.

Keywords: Crime, neighborhood-level data, surveillance systems, Mexico City.

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1 Introduction

Crime reduction is an priority of every national- and local-government to ensure the quality of life of their population. Two distinct mechanisms are available towards this objective: incapacitation (or incarceration) and deterrence. Incapatiation refers to the reduction in crime due to physical isolation of convicted offenders. Crime deterrence refers to behavioral response of a potential offender, in which a criminal act is discouraged due the threat of punishment (Nagin et al., 2013). I focus on crime deterrence, in particular in one of the most employed instruments: surveillance cameras.[1] The proponents of Closed-Circuit Television (CCTV) systems argue that potential offenders are deterred from committing crimes if they perceive an increase in the probability of getting caught within a police-monitored camera's line-of-view (Ratcliffe, 2016).[2] However, the literature has not found conclusive evidence on the effect of camera surveillance.

This paper seeks to provide evidence on the *camera deterrence effect* by analyzing Mexico City's Participatory Budget (PB) Program and its effect on neighborhood crime rates. The PB program allows neighborhoods to choose how to allocate a percentage of the public spending on projects proposed by its inhabitants. I focus on neighborhoods that implement Closed-Circuit Television (CCTV) systems.

Several papers find a significant crime reduction after surveillance cameras' deployment.[3] However, Winge and Knutsson (2003), Farrington et al. (2007) do not find any evidence for crime reduction. Gerell (2016) analyzes the deterrence effect of the combination of cameras and hot spot policing but finds no significant impact for these combined interventions. Most city-wide CCTV systems are publicly funded, such that local security agencies decide their location.[4] To the best of my knowledge, only Gomez-Cardona et al. (2017) and Munyo and Rossi (2020) study the implementation of CCTV systems in emerging countries, focusing on Medellin (Colombia) and Montevideo (Uruguay) respectively. This paper contributes to the literature by analyzing the effectiveness of a CCTV system in an emerging country. Moreover, rather than focusing on locations decided by the security agencies, I focus on the areas throughout the city chosen for CCTV systems deployment by the neighborhoods' inhabitants.

Potential endogeneity arises because areas with higher crime rates are selected for camera deployment by the funding institutions. Hayes and Downs (2011) and La Vigne and Lowry (2011) adress

[1]For example, estimates of the number of surveillance cameras in the United Kingdom range from 1.85 to 4.2 million (Norris and McCahill, 2006; Gerrard and Thompson, 2011).

[2]An additional channel through which crime deterrence might be in effect is the following: cameras' footage is employed to convict and incarcerate offenders, whose behavioral response might change after the imprisonment period effectively reducing crime afterwards. However, this potential channel is not the focus of this paper.

[3]See King et al. (2008), Welsh and Farrington (2003), Caplan et al. (2011), Hayes and Downs (2011).

[4]Among these papers, King et al. (2008) study the implementation of cameras in San Francisco, California; Caplan et al. (2011) and Piza et al. (2014) study the CCTV system of Newark, New Jersey. Ratcliffe et al. (2009) analyze the city of Philadelphia, Pennsylvania.

this endogeneity concern through a randomized control trial. For quasi-experimental data, several papers take advantage of installation timing to obtain a causal interpretation of the cameras' effect on crime. Both Gomez-Cardona et al. (2017) and Munyo and Rossi (2020) employ a difference-in-differences design finding reductions in crime of around 20-25%. Piza (2018) employs a propensity score matching approach, finding that cameras deter auto theft.[5] Relative to these papers, I employ panel data with four treatment periods. Both Goodman-Bacon (2020) and Callaway and Sant'Anna (2020) provide estimators when there is variation in single-dose treatments' timing with multiple periods. In the case studied here, the PB program data shows that there are units that repeatedly received treatment: 165 neighborhoods voted for cameras twice, while 35 neighborhoods voted three. No paper provides a framework for studying multiple periods with variation in treatment timing and dosage to the best of my knowledge. I contribute to the deterrence effect literature with an identification strategy that allows me to exploit treatment variation, existence of multiple periods, and dosage to estimate if there is a reduction in crime after cameras' deployment. Potential future research within similar environments and data constraints can find useful the identification strategy employed in this paper.

My identification strategy focuses on neighborhoods that choose cameras as the winning project. I leverage the PB program structure and employ the variation between the budget designated by the law (the *'planned expenditure'*, henceforth) and the amount received (the *'actual expenditure'*, henceforth) for all neighborhoods that choose cameras. The identifying assumption argues that, conditional on a neighborhood choosing cameras and its neighborhood-level observables, there is no variation in the *'actual expenditure'* that is systematically correlated with variation in unobserved factors that influence the area's crime rate.[6] To support the identifying assumption, I test for equality of means for the areas that choose cameras by grouping them according to the ratio of *'actual expenditure'* to *'planned expenditure'*. I cannot reject the null hypothesis of equality of means at the 5% significance level, adding credibility to the strategy.

The data collected for this paper contains the following neighborhood level variables: the PB program winning options, voting margins, *'planned expenditure'*, and *'actual expenditure'*. I also employ the Mexican Census data to obtain neighborhood observables. I geocode and allocate crimes to each neighborhood from January 2016 to June 2020. Following the literature, I first employ the FBI's Uniform Crime Reporting classification to categorize the crime data; in particular, I employ the Part I and Part II crime definitions. Then, leveraging the detailed data I construct additional crime categories, that differ from the FBI's definitions, and can be considered premeditated offenses. Employing both the FBI's UCR and the categories I defined, I check for balance in the pretreatment crime rates. Among the FBI UCR's categories, I reject the null hypothesis of equality of means at the 5% significance level for Robbery and Drug abuse violations. For the additional crime categories, I

[5] Piza (2018) finds that auto theft is deterred by surveillance cameras for only two of the 13 matching methods employed.

[6] The identifying assumption in this paper is inspired by Drago et al. (2009), who employ a similar assumption for the Collective Clemency Bill in Italy.

reject the null hypothesis of equality of means for Street robbery, which provides evidence that the identification strategy is valid.

To obtain an estimate of the camera deterrence effect, I employ regression analysis in which the outcome variable is the quarterly crime rate at the neighborhood level. I further control for neighborhood-level observables, delegation and quarter fixed effects, and an indicator variable indicating if the neighborhood choose cameras. The period of study is January 2016 to March 2020.

The coefficient of interest is associated with the number of cameras installed with the PB program *'actual expenditure'* in the regression equation.[7] I find evidence that cameras do not deter crime at the neighborhood level. Employing the basic regression equaiton and the FBI's UCR crime categories, I find positive and statistically significant coefficients for Robbery, Theft from auto, and Disorderly conduct. The positive coefficient can be interpreted in the following way: neighborhood-level crime rates have a positive elasticity with respect to the number of surveillance cameras installed through the PB program. Part I property crimes, which include Theft from auto, also has a positive and statistically significant coefficient. Including the lagged crime rate removes the statistical significance of the cameras' coefficient for Robbery as the dependent variable. Including lagged crime rates also reduce the magnitude of the estimate of the effect of cameras when the outcome variable is the Theft from auto rate and Disorderly conduct. However, even when controlling for nonlinear relations between population and unemployment, the coefficient associated with cameras for these two crimes is analyzed is positive and statistically significant.[8] Street robbery, Car-driver robbery, and Delivery service theft have a positive and statistically significant coefficients for cameras. However, accounting for the persistence of the crime rate through its lagged value causes the cameras' coefficient to be statistically indistinguishable from zero. The implication is that, on average, there is no deterrence effect from the cameras in the neighborhoods that vote to implement them once crime rates persistence is taken into account.

I consider a combination of factors to explain the results of this paper. First, only 628 neighborhoods voted for cameras during the years 2016–2019. Further, areas that voted for cameras received on average 69% of the planned budget, with 134 neighborhoods of them receiving zero actual expenditure. Assuming the price of a camera equal to US$ 4,000, the average number of cameras installed with the actual expenditure is 4.60. An individual camera might deter a potential criminal in a narrow location. However, four cameras as a neighborhood system could be lower than needed to generate a change in the potential criminals' incentives at the neighborhood level. Both camera location and line-of-sight play an essential role in deterring crime (Piza et al., 2014). However, these characteristics are not observable and can contribute to explaining the results, given that both location and line-of-sight might be suboptimal.

[7] I divide the PB program *'actual expenditure'* for neighborhoods that choose cameras by the average price of a camera paid by the Mexico City Government and calculate the actual number of cameras installed through the PB program.

[8] Previous research found that cameras do not significantly deter Theft from auto Caplan et al. (2011). Ratcliffe and Groff (2019) find no impact from CCTV systems, while McLean et al. (2013) find that cameras deter Disorderly conduct.

The rest of the paper is organized as follows: Section 2 presents the background and institutional context for this paper. The dataset and the crimes studied are discussed in Section 3. Section 4 presents the identification strategy and the supporting evidence, while section 5 presents the regression analysis, the robustness checks, and the discussion of the results. Finally, Section 6 briefly concludes.

2 Background and Institutional Context

The Participatory Budget Program. Mexico City's 'Participatory Budget' (PB) program[9] is a yearly policy intervention through which neighborhoods propose projects, within the general guidelines established by the EICM,[10] and vote for them.

For political and administrative purposes, Mexico City is comprised of 16 delegations.[11] This division matters for the implementation of the PB program. Within each delegation, there is a varying number of neighborhoods. Each delegation's government will implement the winning project for all the neighborhoods within its boundaries in the following year. Each delegation shall devote three percent of their annual budget (referred henceforth as 'PB funds') to execute all the winning projects within their boundaries.[12] All neighborhoods or original settlements[13] within a delegation are entitled, ex-ante, to the same amount, as the 'PB funds' are divided equally among them. I will refer to this equally divided funds among a delegation's neighborhoods as the *'planned expenditure'* throughout the paper.

To fix ideas, consider the following example for the PB program in 2016. First, the EIMC sets general project categories and calls for projects in the first quarter of 2016. After a vetting and discussion process of the proposed projects, the neighborhoods vote for the approved projects in the third quarter of 2016, and the EIMC validates the results. During the last quarter of 2016, the Legislative Assembly receives the winning projects and allocates the PB program funds in the delegations' 2017 budget appropriations through the Expenditures Law.[14]

The Finance Secretariate of Mexico City publishes financial statements for all expenditures in the

[9]The PB program is an initiative established by the 2010 reform of the Citizen Participation Law (CPL, henceforth). The Electoral Institute of Mexico City (henceforth EIMC) has been in charge of its organization since its introduction.

[10]The general categories for the projects are set by the IECM and are the following: a) Services and construction (e.g., speed bumps, sidewalks, among others); b) Urban equipment (e.g., garbage trucks); c) Urban infrastructure (e.g., passersby brigdges, traffic lights); d) Urban infrastructure related to sports, culture and arts; and e) Security-related options.

[11]Delegations are equivalent to boroughs.

[12]The 2014 reform of the Citizen Participation Law (CPL) established this percentage.

[13]The Citizen Participation Law recognizes original settlements based on cultural or social identity or ethnicity, self-regulated organizational structures, and recognition of its inhabitants' geographical area as a single settlement. Further, the EICM delimits its area for counsel election purposes.

[14]The Expenditures Law for Mexico City allocates funds for the Mexico City Government, delegations, and all other Mexico City institutions.

city, including the PB program. These financial statements include the amount of money designated to every project (the 'planned expenditure'), i.e., the PB program's budget established in the delegation's appropriations. I can also check whether this amount suffered any change and the final amount spent on every project (I will refer to the final amount spent on every project as the *'actual expenditure'*). According to the data, the projects are performed in the last quarter of the year. An important aspect is that to implement the winning project, the resources are not given to the neighborhood's inhabitants; rather, the delegation uses the resources to execute or implement the winning project. However, financial records show that the *'planned expenditure'* is not equal to the *'actual expenditure.'* The difference between *'planned expenditure'* and *'actual expenditure'* in neighborhoods that choose for cameras guides the paper's identification strategy.

Public CCTV systems in Mexico City City-wide public-funded CCTV systems are traditionally the focus of the analysis in the literature. Mexico City has a city-wide public-funded CCTV system, and although this city-wide surveillance system is not the focus of this paper, it is important to take it into account given the complementarities between it and the cameras installed through the PB program. Throughout the paper I will refer interchangeably to the public CCTV system as government cameras or city-wide CCTV system.

In Mexico City, the government funded the public CCTV system's installation through the 'Proyecto Bicentenario Ciudad Segura' in two stages. Between 2009 and 2012, the first stage included the installation of one city-wide center for control, command, communication, computation, and quality ('C5 Centre'), five regional centers for command and control ('C2 Centres'), 8,088 cameras for the streets and three thousand cameras for the subway. Also, 192 of these initial eight thousand cameras had the capability of recognizing the license plates. Furthermore, 35 shooting sensors were installed in zones the government deemed most efficient. The Mexico City government hired and certified 1,800 operators for the system operation, plus it hired 100 employees for maintenance and 60 more as strategic personnel.

In the second stage of the project, between 2014 and 2016, seven thousand additional were deployed, with panic buttons and loudspeakers attached to the cameras' poles to strengthen the existing capability. A further third stage began in the last quarter of 2019. The Mexico City Government announced 15,000 new cameras in 333 priority neighborhoods and the renewal of those deemed inoperative or obsolete. However, the timing of installation is unavailable. Thus, I do not include them in the analysis.

3 Data

The Mexico City's government 'Open Data Initiative' publishes both crime data and the location of the cameras installed by the central government. Fiscal data is obtained directly from the Legislative Assembly of Mexico City and the Finance Secretariat of Mexico City. All the information regarding the projects, voting margins, and results regarding the Participatory Budget Program comes from the Electoral Institute of Mexico City. Finally, I obtain census tract data and firms' data from the National Institute of Statistics and Geography of Mexico (INEGI).

Crime data is only currently available from 2016. The current Covid-19 situation can create confounding effects regarding the cameras' deterrence effect and the crime rate due to the lockdown conditions. Thus, the period studied goes from the first quarter of 2016 to the first quarter of 2020. An advantage, discussed below, of the Mexico City crime data is the crime description's granularity, allowing me to investigate certain crimes not previously studied in the existing literature.

I coded a geolocation process to assign the neighborhood where the crimes were committed. I employed the same procedure to match the government cameras with neighborhoods. Firms' location data is available from the National Statistical Directory of Economic Units (DENUE). This directory is updated twice a year by INEGI; firms are classified by sector of activity employing the North America Industry Classification Standard (NAICS). Firms are aggregated through their 2-digit NAICS code.[15] The DENUE data contains latitude and longitude values that allow me to geolocate the firms by neighborhood with the same code used for geolocating the government cameras and the crime rates.

Population and related neighborhood-level observables are obtained through aggregating at the neighborhood level the data from the Mexican Census[16]. The neighborhood observable characteristics in this paper are: *a)* total population, *b)* the percentage of population aged 15 and older, *c)* the percentage of unemployed population, *d)* the percentage of population with access to health and social security, and *e)* the percentage of male-headed households.[17]

After the geolocation and aggregation procedures, the novel dataset employed in this paper contains the following variables at the neighborhood level:

1. Crime rate.
2. Winning projects, voting margins, 'planned', and 'actual' expenditure of the PB program.

[15] The sectors in which firms are aggregated are 11-Agriculture, Forestry, Fishing and Hunting, 21-Mining, 22-Utilities, 23-Construction, 31-33-Manufacturing, 43-Wholesale trade, 44-45-Retail trade, 48-49 Transportation and Warehousing, 51-Information, 52-Finance and Insurance, 53-Real Estate Rental and Leasing, 54-Professional, Scientific, and Technical Services, 55-Management of Companies and Enterprises, 56-Administrative and Support and Waste Management and Remediation Services, 61-Educational Services, 62-Health Care and Social Assistance, 71-Arts, Entertainment, and Recreation, 72-Accommodation and Food Services, 81-Other Services (except Public Administration), 92-Public Administration.

[16] The process employed is a spatial join in the Software ArcMap.

[17] Average neighborhood income is an important observable possibly correlated with crime. However, due to the geo-statistical decisions by INEGI, income data at the neighborhood level is not available.

3. The stock of government-cameras.

4. The number of firms, classified using the North America Industry Classification Standard (NAICS) two-digit codes.

5. Total population, the percentage of population aged 15 and older, the percentage of unemployed population, the percentage of population with access to health and social security, and the percentage of male-headed households.

The neighborhood-level crime rate is calculated as follows: for any crime type, the total count is divided by the neighborhood population and multiplied by 100,000. Thus, the crime rate is at the neighborhood level per hundred thousand individuals. 'Planned' and 'actual' expenditure are transformed into US Dollars employing the average exchange rate for the corresponding year. Given that I focus on neighborhoods where cameras' deployment is the winning project, I further transform these dollar values into 'planned' and 'actually' installed cameras dividing by US$4,000.[18]

Crimes studied Surveillance cameras will deter potential offenders if they perceive an increased probability of getting caught within a police-monitored camera's line-of-view Ratcliffe (2016). Thus, it is reasonable to consider that cameras might only deter outdoor crimes. The existing literature has analyzed different crime categories when assessing the cameras' deterrence effect. I employ the FBI's Uniform Crime Reporting (UCR) Classification[19] as an initial categorization guideline.[20] The UCR Program divides offenses into two groups: Part I and Part II crimes. The following are Part I crimes: Criminal homicide, Forcible rape, Aggravated assault, Robbery, Burglary, Larceny-theft (except motor vehicle theft), Motor vehicle theft, and Arson.[21]

King et al. (2008) analyze violent crime, homicides, Part I property offenses (Robbery, Burglary, Larceny-theft -except Motor vehicle theft-, and Motor vehicle theft), drug offenses, prostitution, and vandalism. Caplan et al. (2011) focus on shootings, auto theft, and theft from auto. Piza (2018) employs auto theft and theft from automobiles, and creates an aggregate violent crime measure by combining murder, non-fatal shootings, and robbery. Gomez-Cardona et al. (2017) analyze property crimes, including all kinds of thefts, plus violent crimes (homicide and assault cases). McLean et al. (2013) also employ the FBI's Uniform Crime Reporting Classification, with the following categorization: a) Violent offenses, including murder and nonnegligent manslaughter, Robbery, forcible rape, and aggravated assault; b) property offenses are Burglary, Larceny-theft, Motor vehicle theft, and

[18]The value of US$4,000 is not random. According to fiscal data, that is the average price paid per camera in the first two stages of Mexico City's government-funded CCTV system deployment.

[19]The definitions of these crimes are available at: `https://www2.fbi.gov/ucr/cius_04/appendices/appendix_02.html`

[20]See the following for papers that employ the FBI's UCR program categorization: King et al. (2008); Piza (2018); Caplan et al. (2011); McLean et al. (2013); Ratcliffe et al. (2009); Ratcliffe and Groff (2019)

[21]Throughout the paper, when I refer to crime categories I capitalize the first letter; when I refer to types of crime I use only lowercase letters

arson. Additionally, McLean et al. (2013) analyze the sum of Part I and selected Part II offenses (Vandalism, Simple assault, and Drug offenses) and call them 'Total crime.' Furthermore, McLean et al. (2013) study disorderly conduct as the outcome variable, including in this category 'annoying' persons or groups, fights, drug sales, and parking complaints.

To relate with the previous literature, I will first analyze Part I crimes, except Arson, individually and aggregate them into two categories: Part I Violent Crimes (Criminal homicide, Forcible rape, Aggravated assault), and Part I Property Crimes (Robbery, Burglary, Larceny-theft -except Motor vehicle theft-, and Motor vehicle theft). I also study individually both passersby theft and theft from automobiles (from the UCR's Larceny-theft category).

Additionally, I will examine the following selected UCR's Part II offenses, considered predominantly committed outdoors: Vandalism, Disorderly Conduct, and Drug Abuse Violations McLean et al. (2013).[22] I do not aggregate all crimes into a total crime category as in McLean et al. (2013). Given that Part II Crimes can be considered not premeditated, thus not affected by any deterrence mechanism, I choose to keep the categories separated to avoid any possible confounding mechanisms through aggregation.

I also study the following crime categories(definitions): Manslaughter, Assault, Street robbery, Business customer robbery, Car driver robbery, Delivery service theft, Motor vehicle robbery, Motor vehicle and machinery theft, Business robbery, Secure business robbery, Vehicle break-in, Auto-parts theft, and (Home) Burglary. I choose to depart from the FBI's UCR program categories because of three reasons:

1. The granularity in crimes' definition from the data collected for this paper.
2. The aggregate nature of some of the FBI's UCR categories.
3. The (types of) crimes the population of Mexico City are mostly subjected to, according to results from the 2019 National Survey on Victimization and Perception of Public Safety (ENVIPE).

It is important to state the differences between the FBI's UCR crimes categories and the categories I additionally employ. Criminal homicide in the UCR definition includes manslaughter but does not include attempts to kill or assaults to kill. In the Manslaughter category that I employ, I consider attempts and assaults to kill because premeditated crimes as these do consider the CCTV systems around the locations chosen to commit the crime. Thus, my Manslaugher category (or definition) is more general than the FBI.

[22] In a similar situation, Piza et al. (2014) recognize that their data does not allow them to differentiate where the crimes occurred indoors or outdoors. Thus, they incorporated types of crime that predominantly occur outdoors: aggravated assault, auto theft, burglary, murder, robbery, shootings, theft, and theft from auto.

The UCR's category 'Robbery' is defined as the "*taking or attempted taking of anything of value from the care, custody, or control of a person or persons by force or threat of force or violence and/or by putting the victim in fear*" (FBI, 2019). Following this definition, I included business robberies, street robberies, bank branch robberies, and any other crime committed with violence that entails removing anything of value from another person(s) when I constructed the data for the UCR's 'Robbery' category. However, due to the available data, I decide to further study these types of crime separately as the possible deterrence mechanism might vary by type of crime. For example, any bank branch is deemed a secure business because it has private security and a CCTV system of its own. For any potential criminal considering a bank branch robbery, the potential deterrence effect of a camera located in the street might not be strong enough compared to any potential criminal considering a street robbery. The intuition for this statement follows the fact that the potential offender might perceive a higher probability of getting captured because of the bank's security systems, rather than by the street surveillance cameras. Thus, I categorize separately different types of robberies: Street robbery, Business customer robbery, Car driver robbery, Motor vehicle and machinery robbery, Business robbery, and Secure business robbery. The 'Street robbery' category includes the following type of crimes: passersby robbery, public transportation robberies (not subway), ATM users' robberies, and robberies in parks and ,arkets.

Given the detailed data, I observe thefts of machinery with internal combustion engines.[23] I add these thefts to the UCR's category 'Motor vehicle theft' to form a more comprehensive category: 'Motor vehicle and machinery robbery.' I also split the UCR's category 'Theft from auto' into two categories: Vehicle break-in and Auto parts theft. I do so on the following basis: given that committing a vehicle break-in can be potentially faster than removing certain auto parts, and that CCTV systems' operators are unable to pay attention to all cameras, any potential offender might deem easier to break into a car through a smashed window rather than removing any part or accessories, even with the potential car alarm threat.

Finally, the FBI's UCR Burglary category includes both dwellings and commercial structures. I consider that the neighborhoods have incentives to choose cameras to protect their community rather than to protect the businesses not owned by the areas' inhabitants. Thus, I leverage the granularity of the data in this paper and define the category 'Home burglary' to consider only burglaries to homes.

4 Identification

My analysis focuses on neighborhoods that choose cameras. Tables 1 and 2 present selected characteristics and descriptive statistics to contextualize areas that voted for cameras. In total, cameras were the winning option 867 times, with 628 unique areas (Table 1). Some neighborhoods repeat-

[23]For example, Cement Mixers thefts are contained in this category.

edly choose cameras; for example, 165 areas choose cameras twice (Table 1). Also, the number of government cameras varies across neighborhoods, with a neighborhood-level average of 8.4 cameras (Table 2).

Table 1: Selected variables for neighborhoods that voted for cameras in the PB program

	Value
Cameras as the winning option	867
Unique neighborhoods that voted for cameras	628
Voted for cameras once	428
Voted for cameras twice	165
Voted for cameras three times or more	35
Positive 'actual' expenditure	717
Zero 'actual' expenditure	148
Average number of cameras installed with PB 'actual' expenditure	4.6

Notes: The sum of the neighborhoods who have positive 'actual' expenditure and those who got zero 'actual' expenditure is not equal to the total number of times cameras was the winning option because two neighborhoods have missing data. The sample employed here contains only the data for the years 2016-2019.

Neighborhoods receive levels of 'actual' expenditure that are different to the 'planned' expenditure (i.e. the amount that areas are entitled to receive by law). In 148 out of the 867 times, the neighborhoods receive zero 'actual' expenditure (Table 1). On average, areas that choose cameras receive 69% of the 'planned' budget, with a standard deviation of 38.6%. On average, the 'actual' expenditure that neighborhoods receive, and assuming a price of US$4,000 per camera,[24] allows the installation of 4 cameras within their boundaries (Table 1). As discussed in Section 2, the Citizen Participation Law establishes that every neighborhood, within a delegation, must receive the same funding. The process in which the delegation government decides the final expenditure to allocate for an area[25] is not clear or documented in any government publication. This difference motivates the identification strategy.

[24]US$4,000 is the average price that the Mexico City government paid for a pole-mounted camera during the first and second stages of the city-wide surveillance system installation.

[25]That is, what I refer to as the 'actual' expenditure

Table 2: Cameras installed by the Mexico City government.
Descriptive statistics

	Full sample	Voted for cameras
Total number of government cameras	13576	4671
First Quartile	3	3
Median	6	6
Third Quartile	12	12
Mean	8.69	8.40

In traditional settings that study city-wide CCTV systems deployments, potential endogeneity arises due to policy-makers selecting areas with higher crime rates for surveillance systems. In this paper, the potential endogeneity between crime rates and the neighborhood self-selection potentially cause identification of the cameras' deterrence effect impossible. To identify the effect of surveillance cameras on crime and obtain a consistent estimate of it, the observation of varying amounts of expenditure by neighborhood informs my identification strategy. I argue that conditional on areas choosing cameras as the winning option, the delegation in which they are, and the neighborhood observables, there is no variation in the 'actual' expenditure it receives that is systematically correlated with variation in unobserved factors that affect the area's crime rate.[26]

The intuition behind the identification assumption can be explained as follows: conditional on cameras being the winning option and neighborhood observables, the 'actual' expenditure is as good as random. To support this assumption, I calculate a difference in means tests for the observables (Table 3) and the pre-treatment crime rates (Table 4 and 5) for neighborhoods that choose cameras. This is analogous to testing the balance in the observables. The balance tests are constructed through the following steps: first, I calculate the ratio of 'actual' expenditure to 'planned' expenditure for every neighborhood that voted for cameras, and I call this the expenditure ratio. I sort the expenditure ratio and calculate its median. Second, I run a regression for each neighborhood covariate against a full set of delegation dummies and calculate the residuals. Third, I separate the neighborhood sample into two groups: those with an expenditure ratio above the median and those with an expenditure ratio below the median. Finally, with these two subgroups, I test for equality of means by employing the residuals of each covariate's regressions. This procedure allows me to evaluate variation across neighborhoods within Delegations.

Achieving appropriate covariate balance among these groups is important for supporting the identifying assumption, and thus for causal interpretation. Table 3 shows that the neighborhood covariates

[26]The identification strategy employed here is similar to the conditional independence assumption employed before by Drago et al. (2009).

are indeed balanced across the subgroups. Since I am employing the regression residuals to check for balance as described above, column (1) of Table 3 shows that the mean for all areas that voted for cameras is approximately equal to zero. Due to the test's construction, Column (2) shows the average, across all Delegations, of the within-Delegation neighborhoods' differences for all covariates for areas receiving a ratio below the median. Column (3) is similarly defined to column (2) but for areas with an expenditure ratio above the median. Column 4 presents the difference and, column 5 presents the t-statistic. In parenthesis, I present the standard errors for columns (1) to (4) and the p-value for column (5).

Table 3: Neighborhood characteristics balance test - Equality of means.[1]

	Mean				
		Ratio	Ratio		
	Whole Sample	below the Median	above the Median	Difference	t-statistic
	(1)	(2)	(3)	(4)	(5)
Population	-.0000158	-40.62072	42.83462	-83.45534	-0.2807
	(148.528)	(206.8562)	(213.6248)	(297.3635)	(0.7790)
Population aged 15 and older	1.00e-08	.037926	-.0398133	.0777394	0.2325
	(.1677111)	(.2530533)	(.2184883)	(.3343249)	(0.8162)
Unemployed population	-2.49e-09	-.0101918	.010699	-.0208907	-0.2008
	(.0519077)	(.0709305)	(.076085)	(.1040195)	(0.8409)
Population with access to social security	5.08e-08	.027989	-.0293817	.0573707	0.1256
	(.2282438)	(.3211762)	(.3247353)	(.4567353)	(0.9001)
Male-headed households	2.91e-08	.0713638	-.074915	.1462788	0.4567
	(.1601442)	(.2268597)	(.2261346)	(.3203157)	(0.6480)
Government cameras	-3.79e-07	-1.033603	1.085037	-2.11864	-0.2581
	(4.13509)	(6.676262)	(4.774856)	(8.208028)	(0.7964)
Planned expenditure	-3.27e-08	.2929574	-.3090003	.6019577	0.6285
	(.4885509)	(.8997466)	(.3282825)	(.9577648)	(0.5299)
Actual expenditure	1.13e-08	-1.299813	1.370993	-2.670806	-4.4757
	(.3045008)	(.4905664)	(.3397707)	(.5967408)	(0.0000)

Notes: Population aged 15 and older, and the population aged 15 and older with complete basic education are proportions to the neighborhood population. The unemployed population is a proportion of theeconomically active population. Male-headed households is normalized by the number households in the neighborhood. Government cameras are equal to the neighborhood number of government cameras divided by the neighborhood population and multiplied by 100,000. Planned expenditure is the 'planned expenditure' for the neighborhood divided by the neighborhood population and multiplied by 100,000; 'actual expenditure' is defined similarly. I run a regression of these neighborhood covariates against a full set of indicator variables for delegations. The residuals of these regressions are employed in the balance tests. For those neighborhoods which voted for cameras I construct the ratio of actual expenditure to planned expenditure. I then sort the neighborhoods by these values and divide them into two groups: those which are above the ratio and below the ratio, and perform the balance tests.

I choose to employ within-Delegation variation considering the diversity of Mexico City neighborhoods and the available data.[27] I fail to reject the null hypothesis of equality of means for all co-

[27]Comparing neighborhoods across Delegations does not allow me to obtain balance. The hypothesis for unbalanced covariates when comparing neighborhoods across Delegations is that certain Delegation idiosyncratic characteristics generate the unbalance results for the neighborhoods that choose cameras.

variates but the 'actual' expenditure, which was expected. Column (5) of Table (3) demonstrates no significant neighborhood characteristic associated with a higher expenditure ratio. The evidence suggests I can credibly assume that conditional on choosing cameras and the observable neighborhood characteristics, the actual expenditure is as good as a random.

It is equally important to check the balance in the pretreatment crime rates because of the identifying assumption: there is no variation in the actual expenditure a neighborhood receives that is systematically correlated with variation in unobservables that affect the area's crime rate. Thus, we would expect no statistically significant difference in pretreatment average crime rates for neighborhoods receiving funds above and below the median ratio. Table 4 presents the balance tests for the crime rates employing the FBI's UCR classification in the pretreatment period. Overall, pretreatment crime rates are balanced across the two subgroups, lending credibility to our identifying assumption. For individual crime categories, I can only reject the null hypothesis of equality of means for Robbery and Drug abuse violations. The rejection of the null for Robbery guides the rejection of the null for Part I Violent Crimes. One could argue that the rejection of the null hypothesis for Robbery implies that neighborhoods with a higher Robbery rate are assigned a higher amount of 'actual expenditure'. To check this, I run a regression with the ratio of 'actual' expenditure to 'planned' expenditure as the outcome variable against all the neighborhood covariates and the values of the Robbery rate in the pretreatment period as controls. I find that FBI's UCR Robbery rate in the pretreatment periods are jointly statistically significant with an F-statistic of 4.47 (p-value = 0.0040). This suggests that the Delegation might allocate expenditure among neighborhoods based on their Robbery rate.

For the additional crimes studied, I employ the same procedure and test for balance for the pretreatment crime rate in Table 5. I fail to reject the null hypothesis of equality of means in all but Street robbery for these crime categories. These results provide credibility for our identifying assumption that, conditional on choosing cameras and the neighborhood covariates, the actual expenditure is as good as random because there is no significant evidence that the level of any crime rate matters for allocating expenditure. However, for Street robberies, I reject the null hypothesis, which is consistent with the UCR Robbery category's rejection. I also employ a test of joint significance for the pretreatment crime rates for the Street robbery category. I cannot reject the null hypothesis of the parameters being jointly zero with an F-statistic of 1.07 (p-value = 0.3595). Considering all the different crime types, the balance tests for the pretreatment crime rates strengthen the validity of the identifying assumption.

Table 4: Pretreatment FBI index crimes' rates - equality of means.[1]

	Mean				
	Whole Sample (1)	Ratio below the Median (2)	Ratio above the Median (3)	Difference (4)	t-statistic (5)
Criminal homicide	2.92e-08	-.2196024	.2327642	-.4523666	-0.9920
	(.2307162)	(.3808246)	(.2508807)	(.4560357)	(0.3213)
Rape	-7.10e-08	-.0348618	.0369511	-.0718129	-0.0604
	(.6042938)	(1.060156)	(.536137)	(1.188013)	(0.9518)
Robbery	2.16e-07	-5.523857	5.854926	-11.37878	-2.3021
	(2.588323)	(4.109844)	(3.050478)	(5.118226)	(0.0214)
Aggravated assault	-5.88e-08	-.3696015	.3917532	-.7613546	-0.7199
	(.536019)	(.904104)	(.5487115)	(1.057586)	(0.4717)
Part I Violent crimes	3.23e-07	-6.147921	6.516394	-12.66431	-2.1617
	(2.962786)	(4.822888)	(3.326126)	(5.858614)	(0.0307)
Larceny-theft	2.49e-07	-4.578182	4.852573	-9.430755	-1.0281
	(4.651725)	(7.885247)	(4.686565)	(9.172841)	(0.3040)
Passersby theft	3.64e-09	-.5162083	.5471469	-1.063355	-1.3311
	(.4061478)	(.706431)	(.372957)	(.7988379)	(0.1833)
Theft from auto	-1.11e-07	-.8943682	.9479713	-1.842339	-0.4985
	(1.86763)	(3.048216)	(2.089612)	(3.695687)	(0.6182)
Burglary (breaking or entering)	5.75e-09	-5.391799	5.714953	-11.10675	-0.4911
	(11.60193)	(22.02572)	(5.129281)	(22.61508)	(0.6234)
Motor vehicle theft	1.65e-07	-.5110742	.5417054	-1.05278	-0.4739
	(1.124396)	(1.869715)	(1.199535)	(2.221423)	(0.6356)
Part I Property crime	9.22e-07	-10.48105	11.10923	-21.59029	-0.7417
	(14.89729)	(27.66018)	(9.073973)	(29.11052)	(0.4584)
Vandalism	1.08e-07	.5963025	-.6320412	1.228344	0.6727
	(.9270759)	(1.593562)	(.8915294)	(1.825997)	(0.5012)
Disorderly conduct	1.20e-09	.1810021	-.1918503	.3728524	1.0305
	(.1856315)	(.3519678)	(.0839161)	(.3618332)	(0.3030)
Drug abuse violations	5.04e-08	-1.934168	2.050092	-3.98426	-1.4478
	(1.456392)	(2.595572)	(1.179984)	(2.851203)	(0.0000)
Part II Crimes	2.91e-07	-1.156864	1.2262	-2.383064	-0.6770
	(1.790911)	(3.146544)	(1.57786)	(3.5199977)	(0.4985)

Notes: The pretreatment period is the first, second and third quarter of every year. For this balance tests, I first calculate the quarterly crime rate, per type, in the neighborhood as follows: total number of crimes multiplied by 100, 000 and divided by population. I then run a regression of the crime rate against a full set of indicator variables for the delegation. The residuals of these regressions are employed in the balance tests. For those neighborhoods which voted for cameras I construct the ratio of actual expenditure to planned expenditure. I then sort the neighborhoods by these values and divide them into two groups: those which are above the ratio and below the ratio.

Table 5: Pretreatment crime rates - equality of means.[1]

	Mean				
	Whole Sample (1)	Ratio below the Median (2)	Ratio above the Median (3)	Difference (4)	t-statistic (5)
Manslaughter[a]	6.00e-08	-.6015601	.6376143	-1.239174	-1.8147
	(.3446725)	(.5499441)	(.4048139)	(.682871)	(0.0697)
Assault[b]	7.69e-08	-.1749815	.185469	-.3604505	-0.2050
	(.8914451)	(1.507296)	(.906025)	(1.758642)	(0.8376)
Street robbery[c]	-6.80e-09	-5.911624	6.265933	-12.17756	-2.1573
	(2.866227)	(4.884769)	(2.829129)	(5.644904)	(0.0311)
Business customer robbery	5.29e-09	.0017621	-.0018677	.0036297	0.0220
	(.0846217)	(.1577297)	(.0494687)	(.1653052)	(0.9825)
Car driver robbery	2.94e-08	-.3963271	.4200807	-.8164078	-0.6808
	(.6004359)	(.864282)	(.831227)	(1.199134)	(0.4960)
Delivery service theft	-1.69e-08	.0517333	-.0548339	.1065672	0.3144
	(.170984)	(.2731488)	(.200694)	(.3389518)	(0.7532)
Motor vehicle robbery	-6.82e-08	-.9087999	.9632681	-1.872068	-1.0817
	(.8654657)	(1.217577)	(1.229896)	(1.730647)	(0.2795)
Motor vehicle and machinery Theft[d]	1.57e-08	-.1105463	.1171719	-.2277182	-0.3912
	(.2894446)	(.3690509)	(.4501176)	(.5820691)	(0.6957)
Business robbery	6.00e-09	-.4665426	.4945046	-.9610472	-0.5985
	(.8148971)	(1.394986)	(.7951573)	(1.605696)	(0.5496)
Secure business robbery	-1.64e-09	.0239465	-.0253817	.0493283	1.0985
	(.0225855)	(.0345918)	(.0286361)	(.0449068)	(0.2721)
Vehicle break-in	-6.73e-08	-1.351863	1.432885	-2.784748	-1.6309
	(.85884899)	(1.311774)	(1.093037)	(1.707478)	(0.1030)
Auto parts theft	6.23e-08	.3223229	-.3416409	.6639638	0.4173
	(.8068751)	(1.370375)	(.8085258)	(1.591113)	(0.6765)
(Home) Burglary	-5.44e-08	.1111004	-.1177593	.2288597	0.1754
	(.6544345)	(.9646827)	(.8789442)	(1.30505)	(0.8608)

Notes: The pretreatment period is the first, second and third quarter of every year. For these balance tests, I first calculate the quarterly crime rate, per type, in the neighborhood as follows: total number of crimes multiplied by 100, 000 and divided by population. I then run a regression of the crime rate against a full set of indicator variables for the delegation. The residuals of these regressions are employed in the balance tests. For those neighborhoods which voted for cameras I construct the ratio of actual expenditure to planned expenditure. I then sort the neighborhoods by these values and divide them into two groups: those which are above the ratio and below the ratio. a) Manslaughter differs from Criminal Homicide because I include include Attempted Manslaughters and Assaults to kill in this category. b) The category "Assault" includes Simple Assaults plus Aggravated Assaults. c) Street Robbery considers Passersby Robberies, Public Transportation Robberies (not subway), ATM users' robberies, and Robberies in Parks and Markets. d) Motor Vehicle and Machinery Theft include theft of vehicles employed for construction, and Auto Theft.

5 Regression Analysis

Denote by $y_{i,t}$ the neighborhood i crime rate, in quarter t, with $ae_{i,t}$ the *'actual expenditure'* allocated to neighborhood i which voted for cameras[28], $1[Cameras_{i,t}]$ an indicator variable for choosing cameras, $x_{i,t}$ the neighborhood i covariates discussed in the Data section plus the total number of cameras in that neighborhood,[29] λ_j and λ_t are delegation and quarter fixed effects respectively. The basic regression model is:

$$y_{i,t} = \alpha + \beta_0 \cdot ae_{i,t} + \beta_1 \cdot 1[Cameras_{i,t}] + x'_{i,t}\gamma + \lambda_t + \lambda_j + \varepsilon_{i,t} \tag{1}$$

Equation (1) shows the importance of the identifying assumption to obtain a consistent estimate of the effect of the *'actual expenditure'*. The identifying assumption is that, conditional on neighborhoods choosing cameras and its characteristics, the *'actual expenditure'* is as good as random. In other words, the identifying assumption requires that, conditional on neighborhoods' choice of cameras, the delegation to which they belong, and its observable characteristics,there is no variation in the *'actual expenditure'* that is systematically correlated with variation in unobservables that affect the neighborhood crime rate. The evidence presented in the previous section allows us to support this hypothesis. The identifying assumption is:

$$E[y_{i,t}|1[Cameras_{i,t}] = 1, x_{i,t}, \lambda_j] = E[y_{i,t}|1[Cameras_{i,t}] = 1, x_{i,t}, \lambda_j, ae_{i,t}] \tag{2}$$

Employing the neighborhood i *'actual expenditure'* per 100,000 in the estimation would make the interpretation of its associated coefficient in terms of dollars per 100,000 in cameras. A more readily policy interpretation would be the elasticity of the crime rate to the number of cameras per capita. I divide the neighborhood i's *'actual expenditure'* by US$4,000, which is the average price paid for a single camera by the Mexico City Government in the first two stages of the city-wide CCTV system installation (see 'Public CCTV systems in Mexico City' in the Data section). Denote by $ac_{i,t}$ the number of cameras installed with the neighborhood i's *'actual expenditure'* per 100,000 individuals.[30] A natural measure to consider is the elasticity of the crime rate to the number of cameras. In a log-log specification, the coefficient associated with the logarithm of cameras can be interpreted as an elasticity. The data available for Mexico City has a non-trivial number of zeroes for different crimes and neighborhoods. Since the logarithm of 0 is undefined, adding a positive constant to employ those observations can lead to bias Pape and Bellego (2019). To address the observations with a zero value

[28] The *'actual expenditure'* is zero for neighborhoods which have a winning option different than cameras.

[29] To obtain this variable I do the following procedure: 1) for all neighborhoods that voted for cameras previously during 2011 to 2015, I divide the *'actual expenditure'* by $4,000 which is the average price paid by the Mexico City government for a camera in the city-wide funded program (see the Institutional Background section). I then add the number of central government cameras plus the calculated number of PB cameras installed during 2011 to 2015. Thus, I have the total number of cameras a neighborhood has at the beginning of 2016

[30] That is: $ac_{i,t} = ae_{i,t} * 100,000/(pop_{i,t} * 4000)$, where $pop_{i,t}$ is the neighborhood i's population.

and the outliers in the neighborhoods' covariates distribution, I apply the inverse hyperbolic sine transformation Bellemare and Wichman (2020). This function is similar to a logarithmic transformation, and it allows retaining zero-valued observations. Further, Bellemare and Wichman (2020) provide specific derivations on calculating elasticities when one employs the inverse hyperbolic sine transformation.[31]

I apply the inverse hyperbolic sine transformation to the neighborhood i crime rate, the number of cameras bought with the *'actual expenditure'* allocated to that neighborhood, the neighborhood i covariates, and the total number of cameras in the neighborhood. The main regression equation employed in this paper is:

$$\tilde{y}_{i,t} = \alpha + \beta_0 \cdot \tilde{ac}_{i,t} + \beta_1 \cdot 1[Cameras_{i,t}] + x'_{i,t}\gamma + \lambda_t + \lambda_j + \varepsilon_{i,t} \tag{3}$$

where $\tilde{y}_{i,t}$ is the neighborhood i crime rate per 100,000 individuals transformed with the inverse hyperbolic sine function, $\tilde{ac}_{i,t}$ is the number of cameras bought by the *'actual expenditure'* per 100,000 individuals, the vector x_i is a vector of covariates, each transformed with the inverse hyperbolic sine function, and $\tilde{tc}_{i,t}$ is the transformed number of total cameras in neighborhood i. The variables λ_j and λ_t are delegation and quarter fixed effects respectively. The vector of neighborhood observables, $\tilde{x}_{i,t}$ includes the following covariates transformed with the inverse hyperbolic sine function: population, the fraction of the neighborhood population aged 15 and older, the fraction of the unemployed population, the fraction of the population with access to health and social security, the fraction of male-headed households in the neighborhood. These variables are constant through the period at the value observed in the 2010 Mexican Census. The vector $\tilde{x}_{i,t}$ also contains the number of firms in neighborhood i by two-digit NAICS code transformed by the inverse hyperbolic sine function. For example, if there are three firms dedicated to wholesale trade in a neighborhood, the associated column will have a value of archsinh(3). Due to economic conditions, the number of firms in a neighborhood can vary year by year; the DENUE is updated twice a year to account for entry and exit. Further, $\tilde{x}_{i,t}$ also contains the total number of cameras in that neighborhood.[32] The reason to transform the covariates employing the inverse hyperbolic sine function is to account for potential outliers.

[31]The inverse hyperbolic sine transformation is defined as follows. Let $\tilde{z}$ denote any random variable z which has been transformed using the inverse hyperbolic sine transformation (Bellemare and Wichman, 2020), such that $\tilde{z} = archsinh(z) = ln\left(z + \sqrt{z^2+1}\right)$

[32]To obtain this variable I do the following procedure: 1) for all neighborhoods that voted for cameras previously during 2011 to 2015, I divide the *'actual expenditure'* by $4,000 which is the average price paid by the Mexico City government for a camera in the city-wide funded program (see the Institutional Background section). I then add the number of central government cameras plus the calculated number of PB cameras installed during 2011 to 2015. Finally, I apply the inverse sine hyperbolic function to this total number of cameras a neighborhood has at the beginning of 2016

With the transformed variables, the parameter associated with the number of cameras, β_0, can be employed to calculate the elasticity as follows:

$$\hat{\xi}_{y,c} = \hat{\beta} \cdot \frac{\sqrt{y^2+1}}{y} \cdot \frac{ac}{\sqrt{(ac)^2+1}} \tag{4}$$

where y and ac represent the crime rates and the number of cameras installed by the PB program per 100,000 individuals.[33]

5.1 Results

I will first present the crimes following the FBI's UCR categorization and discuss them in the following order: Part I violent crimes, Part I property crimes, and Part II crimes. Within each subcategory, I discuss the results individually. Then I will discuss the results for the additional crime categories studied. In all tables, I present first the implied elasticity, calculated using Equation (4)[34], and then the estimated regression coefficient for cameras actually installed, β_0, using Equation (3).

FBI's UCR crimes Tables 6 presents the elasticities, calculated with Equation (4), and the estimation results for Part I violent crimes. Due to their nature, premeditated crimes are sensitive to any potential change in the environment and are the type of crimes for which deterrence would be expected. Thus, it would be expected that cameras, as a deterrence tool, would have a negative and significant effect. However, I find that the PB cameras per 100,000 individuals have no significant deterrence effect on any Part I violent crimes. On the one hand, both Criminal homicide and Aggravated assault (columns 1 and 4 of table 6) have the expected negative sign for the coefficient, but they are not statistically significant. On the other hand, Rape and Robbery (columns 2 and 3 of table 6) have a positive estimated elasticity. The estimated elasticity of '*actual expenditure*' in cameras per 100,000 individuals to the robbery rate is statistically significant. In column 5 of Table 6, Part I violent crimes is the sum of Criminal homicide, Rape, Robbery, and Aggravated assault. I find no significant effect of the '*actual expenditure*' in cameras per 100,000 individuals for Part I violent crimes. A hypothesis to explain that the rates of Criminal homicide, Rape, Aggravated assault and Part I violent crimes are perfectly inelastic to the deployment of PB cameras, is the low average number of cameras installed. Since these crimes are premeditated, potential offenders can modify their conduct to work around the sparse nature of the neighborhood system (only 4.6 PB cameras installed on average). It is possible that the Robbery rate is highly correlated across periods for the neighborhoods, and the implied elasticity is biased due to this fact. I test this hypothesis in the robustness

[33] Since $lim_{ac\to\infty} \frac{ac}{\sqrt{ac^2+1}} = 1$ and $lim_{y\to\infty} \frac{\sqrt{y^2+1}}{y} = 1$, for large values of ac and y, $\hat{\xi}_{y,ac} \approx \hat{\beta}$.

[34] Due to the outcome variable having zeros, Bellemare and Wichman (2020) recommend evaluating at the sample means of the outcome variable and the independent variable. Thus, when calculating the elasticities I employ $\bar{y}$ and $\bar{c}$.

section by controlling for the persistence in the Robbery rate.

Regarding Part I property crimes in Table 7, I do not find evidence for cameras' deterrence effect. The crimes in this category can also be considered mostly premeditated, and it would be expected that cameras would deter them to some degree. Motor vehicle theft's elasticity to the number of PB cameras has a negative sign, consistent with a theoretical relation between premeditated crimes and deterrence tools. However, it is not statistically significant. Larceny-theft, Passersby theft, Theft from auto, and Burglary have a positive elasticity with respect to cameras bought by the *'actual expenditure'*, with only Theft from auto having a statistically significant coefficient.

Table 6: Part I violent crimes - Estimated elasticity of installed cameras per 100, 000 individuals.

	Criminal homicide	Rape	Robbery	Aggravated assault	Part I violent crimes
Elasticity	-0.00622	0.000487	0.0164*	-0.00443	0.00953
	(0.00527)	(0.00632)	(0.00776)	(0.00580)	(0.00748)
Estimated coefficient	-0.00598	0.000483	0.0165*	-0.00435	0.00954
	(0.00507)	(0.00627)	(0.00777)	(0.00569)	(0.00748)
Observations	26276	26276	26276	26276	26276
Quarter and delegation fixed effects	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Part I property crimes - Estimated elasticity of installed cameras per 100, 000 individuals.

	Larceny-theft	Passersby theft	Theft from auto
Elasticity	0.0115	0.0000944	0.0246**
	(0.00704)	(0.00498)	(0.00810)
Estimated coefficient	0.0115	0.0000916	0.0246**
	(0.00705)	(0.00483)	(0.00811)

	Burglary	Motor vehicle theft	Part I property crimes
Elasticity	0.00873	-0.00260	0.0145*
	(0.00842)	(0.00761)	(0.00679)
Estimated coefficient	0.00874	-0.00260	0.0145*
	(0.00843)	(0.00761)	(0.00679)
Observations	26276	26276	26276
Quarter and delegation fixed effects	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Property crimes are also premeditated crimes, and the potential criminals' incentives can respond to changes in the environment. The fact that there is no evidence for a deterrence effect for Part I property crimes can be the outcome of additional unobserved characteristics of the location, some of which may be correlated with crime in general. For example, the location of the installed cameras, which is absent from the analysis due to data constraints, can be inappropriate such that there is no deterrence effect from those. Part I property crimes in the lower part, right corner of Table 7, is the sum of Larceny-theft, Passersby theft, Theft from auto, Burglary, and Motor vehicle theft. I find

Table 8: Part II crimes - Estimated elasticity of installed cameras per 100, 000 individuals.

	Vandalism	Disorderly conduct	Drug abuse violations	Part II crimes
Elasticity	0.00808	0.0123***	-0.000976	0.0149
	(0.00817)	(0.00368)	(0.00738)	(0.00869)
Estimated coefficient	0.00808	0.00818***	-0.000975	0.0149
	(0.00817)	(0.00244)	(0.00738)	(0.00869)
Observations	26276	26276	26276	26276

Standard errors in parentheses

$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

a statistically significant positive elasticity of cameras installed per 100, 000 individuals for Part I property crimes. I test the hypothesis of omitted variable bias in the robustness section by adding a term for the lagged crime rate, which account for the persistence of the crime rate.

Finally, Table 8 presents the results for the FBI's UCR Part II crimes. Part II crimes are not planned, and as such, it is expected that there will not be a statistically significant cameras' deterrence effect. Only for Disorderly conduct do I find a positive and significant elasticity (column 2 of Table 8). A possible hypothesis for this result is that there might exist a nonlinear effect of certain neighborhood characteristics correlated with the number of crime reports for Disorderly conduct. I investigate this hypothesis in the robustness section below with quadratic terms on population and unemployment. As expected, the estimated coefficient for Vandalism (column 1 of Table 8), and its implied elasticity, are not statistically significant. Drug abuse violations has a negative sign but is not statistically significant (column 3 of Table 8). Finally, Part II crimes (column 4 of Table 8) is the sum of Vandalism, Disorderly conduct, and Drug abuse violations, and has a positive, statistically not significant coefficient. This is expected because these crime types, usually not associated with rational behavior and planning, are less subject to incentives' modification.

Additional crimes Leveraging the granularity in the crime data available, I further investigate different crimes. These are crimes that can be considered premeditated, which allows the possibility of a deterrence mechanism that modifies potential criminals' incentives. Tables 9 to 11 present the estimation results for these crimes. I cannot find any evidence to support the hypothesis of cameras' crime deterrence mechanism among the crime types studied here. Focusing on Table 9, I find that Manslaughter and Assault (columns 1 and 2) have the expected negative sign but are not statistically significant. Unobserved neighborhood idiosyncratic factors may cause that cameras deter potential criminals in certain neighborhoods only, while other areas are not affected. Relative to the FBI UCR's classification, Manslaughter and Assault's coefficients are smaller (in absolute value) than the one for Criminal homicide and Aggravated assault, due to more crime types included in the Manslaughter and Assault categories. The smaller magnitude in the coefficient provides evidence against possible confounding effects when aggregating crimes. Similar to Robbery in the UCR classification, the estimated elasticity for Street robbery is positive and statistically significant. The positive and statistically significant elasticity of cameras to Delivery service theft rate (column 5 of Table 9) can be explained due to the city-wide increase in the availability and the nature of such services in the study period. The activity requires leaving the delivery vehicle unattended. Given that such services' pay rate is a function of the number of deliveries, it is likely that the vehicles are parked in places not visible to cameras or the drivers do not check that the vehicles are closed appropriately. These factors could incentivize a potential criminal to commit this crime.

Table 9: Estimated elasticity of installed cameras per 100, 000 individuals on crime

	Manslaughter	Assault	Street robbery	Car driver robbery	Delivery service theft
Elasticity	-0.00491	-0.00124	0.0205**	0.0146*	0.00994*
	(0.00587)	(0.00734)	(0.00777)	(0.00692)	(0.00414)
Estimated coefficient	-0.00434	-0.00119	0.0203**	0.0143*	0.00765*
	(0.00576)	(0.00733)	(0.00778)	(0.00691)	(0.00317)
Observations	26276	26276	26276	26276	26276
Quarter and delegation fixed effects	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Estimated elasticity of installed cameras per 100, 000 individuals on crime

	Carjacking	Motor vehicle theft	Theft from auto	Auto parts theft
Elasticity	-0.0115	-0.00218	0.00514	0.00719
	(0.00795)	(0.00529)	(0.00748)	(0.00713)
Estimated coefficient	-0.0110	-0.00195	0.00480	0.00680
	(0.00795)	(0.00513)	(0.00748)	(0.00713)
Observations	26276	26276	26276	26276
Quarter and delegation fixed effects	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Estimated elasticity of installed cameras per 100, 000 individuals on crime

	Business customer robbery	Business robbery	Secure business robbery	Burglary
Elasticity	-0.00350	0.00100	0.0165	0.00529
	(0.00543)	(0.00673)	(0.00880)	(0.00747)
Estimated coefficient	-0.00104	-0.000101	0.00195	0.00546
	(0.00166)	(0.00671)	(0.00105)	(0.00747)
Observations	26276	26276	26276	26276
Quarter and delegation fixed effects	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table 10, I present the estimation results for several vehicle-related crimes and their implied elasticity. I find no evidence of cameras' deterrence effect in any crime. While Carjacking and Motor vehicle theft have the expected sign, they are not statistically significant. Carjacking involves violence and Motor vehicle theft does not, but both crimes can be potentially discourageable due to the possibility of spotting a stolen car by the camera operators. The variation of the PB *'actual expenditure'* in cameras translates into variation in the number of cameras installed by neighborhood. A working hypothesis could be that only certain neighborhoods had enough cameras installed in highly visible areas and focused on parking lots, while other neighborhoods concentrated in locations with high pedestrian activity. Both Theft from auto and Auto parts theft have a positive sign (contrary to what is expected), but not statistically significant. The hypothesis behind this result could be that after cameras are installed, certain car owners are less careful about whether they locked their cars appropriately or they did not check to be within sight of the installed cameras. Thus, this creates conflicting incentives for the potential criminals: while some may be deterred, others see increased possibilities for the crime.

Finally, in Table 11, I present the estimated coefficients and implied elasticities of the following crime types: Business customer robbery, Business robbery, Secure business robbery, and Burglary. Ex-ante, the coefficients for Business customer robbery, Business robbery, and Secure business robbery should be statistically indistinguishable from 0. The reason behind such expectation is that businesses tend to have more security tools, such as private CCTV, alarms, and private security. For Business customer robbery (column 1), the estimated coefficient has the expected negative sign, although it is not statistically significant. The selection of the cameras' sight varies per neighborhood, this will imply that only certain cameras are directed towards businesses with clients, for which the deterrence effect works. The cameras in the remaining neighborhoods may not be directed at businesses with customers. This hypothesis could rationalize why the data does not show a statistically significant deterrence effect. For Business robbery and Secure business robbery (columns 2 and 3 of Table 11), I find a positive but not statistically significant elasticity, consistent with no further deterrence from the PB cameras in addition to the businesses' deterrence tools. The program's nature is that neighborhoods vote for projects that increase their inhabitants' welfare; this would result in a safer environment. Thus, I expected a negative and statistically significant for (Home) Burglary. However, I find a positive, not statistically significant coefficient.

5.2 Robustness

In this subsection, I check for robustness on the estimated elasticity of cameras by modifying the main specification in the following ways:

a) I add quadratic terms for population and unemployment to check if there exists nonlinearity between these characteristics and the crime rate and how this affects the elasticity of the *'actual expenditure'* on cameras.

b) In this subtype, the crime rate lagged value is added as a control variable to account for the crime rate's persistence.

c) This subtype of regressions adds both the quadratic terms and the lagged value for the crime rate.

d) Finally, in this subtype, I add quadratic terms for population and unemployment, lagged crime rates, and indicator variables for past decisions on security-related options. The inclusion of the previous security-related options accounts for complementarities among these projects.

From the FBI's UCR categories, I focus on Robbery, Theft from auto, Part I property crimes, and Disorderly conduct. I focus on Street robbery, Car driver robbery, and Delivery service theft for the additional crimes. I center my attention on these crimes because of the statistical significance of the estimated coefficient (and thus of the implied elasticity), plus the fact that after including the different terms for robustness, there is no change in the magnitude or significance for the rest of the crimes. I replicate the implied elasticity of the main specification for reference in the first row for all tables.

Table 12: Estimated elasticity of installed cameras per 100, 000 individuals on crime

	Robbery	Theft from auto	Part I property crimes	Disorderly conduct
Elasticity (Main specification)	0.0164*	0.0246**	0.0145*	0.0123***
	(0.00776)	(0.00810)	(0.00679)	(0.00368)
Elasticity (Quadratic terms included)	0.0170*	0.0249**	0.0150**	0.0124***
	(0.00775)	(0.00810)	(0.00678)	(0.00368)
Elasticity (Lagged crime rates included)	0.00699	0.0190*	0.00610	0.0108**
	(0.00745)	(0.00807)	(0.00644)	(0.00376)
Elasticity (Quadratic terms and lagged crime rates)	0.00716	0.0191*	(0.00626)	0.0108**
	(0.00745)	(0.00807)	(0.00644)	(0.00376)
Elasticity (Quadratic terms, lagged crime rates, and past security choices)	0.00786	0.0192*	0.00702	0.0109**
	(0.00746)	(0.00808)	(0.00645)	(0.00377)
Observations	26276	26276	26276	26276

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The inclusion of these additional terms provides mixed results depending on the type of crime. For Robbery (column 1 of Table 12), taking into account the persistence of the crime rate in such areas and the nonlinear relation between the crime rate and the neighborhood population, the implied elasticity is statistically indistinguishable from zero. This means the Robbery rate is perfectly inelastic to changes in the number of cameras per 100, 000 individuals in the neighborhood. To rationalize why there is no effect of cameras to the Robbery rate, I consider that there may exist unobservable factors, or observable factors not captured in the covariates aside from population, in neighborhoods that chose cameras that drive the persistence of the crime rate and render ineffective cameras' deployment. For example, a constant high influx of persons to the neighborhoods, say workers, plus available escape routes more than compensate the increased probability of getting caught after cameras are installed. This hypothesis considers why an area is chosen by potential offenders to commit a crime. And since crime rates are correlated in areas across periods, the installation of additional cameras through the PB program does not modify the incentives of the potential offenders.

When Theft from auto (column 2 of Table 12) is studied, the coefficient for cameras is positive and statistically throughout all the robustness checks. Caplan et al. (2011) find that cameras do not significantly deter Theft from auto. A potential cause for this result combines two factors: the number of vehicles in Mexico City increased by 67% in the period between 2006-2016, and the sparsity of both the neighborhood's CCTV system and the city-wide system. Although cars that are reported stolen are more easily detectable by the operators as opposed to smaller objects that can be hidden, it is possible that the sparse CCTV systems complicates monitoring the stolen car, which effectively nullifies any potential deterrence. For Part I property crimes, once I account for both the nonlinear relationship between the neighborhood's crime rate and its population, and the persistence of these crime types, the implied elasticity of Part I property crimes rate to the number of cameras installed per 100,000 is statistically indistinguishable from zero. Controlling for these characteristics shows that cameras do not deter these crime types at the neighborhood level.

An interesting result is Disorderly conduct. Previous results from the literature are not definitive. Ratcliffe and Groff (2019) find no impact from CCTV systems, while McLean et al. (2013) find that cameras deter Disorderly conduct. The implied elasticity of Disorderly conduct rate to the number of cameras bought with the *'actual expenditure'* per 100,000 individuals is positive and statistically significant. It is possible that the PB cameras were placed in streets where unobservable neighborhood factors generate a higher concentration of persons. Consider for example highly visited street markets. There are incentives for potential offenders to commit crimes like robbery or theft due to the large number of potential victims. Oftentimes, problems also arise due to traffic or parking spots, generating possible conflicts between persons. Even if the potential thieves reallocate due to the cameras, the unobservable factors generating a higher and persistent Disorderly conduct rate in that area remain .

Table 13: Estimated elasticity of installed cameras per 100, 000 individuals on crime

	Street robbery	Car driver robbery	Delivery service theft
Elasticity (Main specification)	0.0205**	0.0146*	0.00994*
	(0.00777)	(0.00692)	(0.00414)
Elasticity (Quadratic terms included)	0.0210**	0.0150*	0.0101*
	(0.00776)	(0.00692)	(0.00414)
Elasticity (Lagged crime rates included)	0.0111	0.0118	0.00872*
	(0.00750)	(0.00696)	(0.00430)
Elasticity (Quadratic terms and lagged crime rates)	0.0112	0.0119	0.00874
	(0.00749)	(0.00696)	(0.00430)
Elasticity (Quadratic terms, lagged crime rates, and past security choices)	0.0123	0.0121	0.00924
	(0.00751)	(0.00697)	(0.00431)
Observations	26276	26276	26276

Standard errors in parentheses
$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

Regarding the additional crimes studied, only Street robbery, Car driver robbery, and Delivery service theft have a positive statistically significant implied elasticity in the main regression. Thus, I check for the robustness of their implied elasticity to a different set of control variables.[35]

As one of the crimes included in the FBI's UCR Robbery category, Street robbery has a similar dynamic. It is important to recall here that Street robbery considers Passersby robberies, Public transportation robberies (not subway), ATM users' robberies, and Robberies in parks and markets. Accounting for

[35] After including the different terms for robustness, there is no change in the magnitude or significance for the rest of the additional crimes.

the persistence of the Street robbery rate in neighborhood i, shows that the Street robbery rate is inelastic to the number of cameras installed through the PB per 100,000 individuals. Factors not captured in the regression's covariates or unobserved idiosyncratic neighborhood characteristics make the neighborhood a desirable location for potential criminals. Also, the average number of cameras installed by the PB program (4.6 cameras) could be relatively low to modify the potential criminals' incentives. It is possible to explain Car driver robbery similarly to Street robbery, which potentially suggests strong substitutability between the two types of crimes.

Finally, controlling for both persistence of the Delivery service theft rate and nonlinear relationships with population and unemployment, I find that cameras do not deter this type of crime. It is possible that due to the characteristics of the possible goods stolen from any Delivery service, criminals can hide more easily without any increased perceived probability of getting caught. Further, cameras are effectively only through monitoring, so there may be insufficient operators. It is also possible that cameras were installed in suboptimal places to deter this crime types.

5.3 Discussion

The robustness exercise shows the possibility that the persistence of the crime rate in the neighborhoods plays an important role. For the UCR categories 'Robbery' and 'Part I property crimes,' when I include the lagged crime rate, I cannot reject the null hypothesis of not being statistically significant for the coefficient associated with the actual number of cameras installed. I find a similar result for the additional categories of 'Street robbery' and 'Car driver robbery.' The case of 'Delivery service theft' is interesting as well. When I control for quadratic terms in population and unemployment plus the lagged value of the crime rate, the coefficient of interest is statistically indistinguishable from zero.

For the UCR categories of 'Theft from auto' and 'Disorderly conduct,' I find that even when adding more controls, the coefficient of interest (or its elasticity) is positive and statistically significant. These suggest the possibility of an unobserved time-invariant neighborhood characteristic causing our estimates to be inconsistent.

It is essential to consider which assumption will lead to identify the parameter of interest correctly. The challenge is to choose between fixed effects and lagged dependent variable models. If one is willing to assume a conditional independence assumption as in (5), it is possible to obtain a consistent estimate of the causal effect of the *'actual expenditure'* in the presence of lagged dependent variables. However, the conditions for consistent estimation of β_0 under this assumption are much more demanding than those required with fixed effects or lagged dependent variables alone.

$$E[y_{i,t}|1[Cameras_{i,t}] = 1, x_{i,t}, y_{i,t-1}, \lambda_j] = E[y_{i,t}|1[Cameras_{i,t}] = 1, x_{i,t}, \lambda_j, y_{i,t-1}, ae_{i,t}] \tag{5}$$

If we consider that a time invariant neighborhood effect is the source of the endogeneity, it may be possible to use first differences to eliminate the neighborhood fixed effect. Consider the following equation:

$$y_{i,t} = \alpha + \beta_0 \cdot ae_{i,t} + \beta_1 \cdot 1[Cameras_{i,t}] + x'_{i,t}\gamma + \lambda_t + \lambda_j + \mu \cdot y_{i,t-1} + \varepsilon_{i,t} \tag{6}$$

And now taking the first difference:

$$\Delta y_{it} = \beta_0 \Delta ae_{i,t} + \Delta x'_{i,t}\gamma + \Delta\lambda_t + \mu \cdot \Delta y_{i,t-1} + \Delta\varepsilon_{i,t} \tag{7}$$

However, the differenced residual, $\Delta\varepsilon_{i,t-1}$ is necessarily correlated with the lagged dependent variable $\Delta y_{i,t-1}$ because both are a function of $\varepsilon_{i,t-1}$. OLS will not consistently estimate the parameters (Nickell, 1981). Dynamic panel models (Arellano and Bond, 1991; Blundell and Bond, 1998) can help in consistently estimating beta. Nonetheless, Blundell and Bond (1998) identification relies on a stationarity condition, and any violiation of it may induce estimation bias. If the epsilon is serially correlated, there may be no consistent estimator. If one is willing to use a version of the conditional independence assumption as in (8) plus the relevant stationarity condition as in Blundell and Bond (1998), then it might be possible to consistently estimate β_0.

$$E[y_{i,t}|x_{i,t}, y_{i,t-1}, \lambda_j] = E[y_{i,t}|x_{i,t}, \lambda_j, y_{i,t-1}, ae_{i,t}] \tag{8}$$

There are several potential explanations regarding the lack of evidence for the Participatory Budget cameras' deterrence effect. First, the amount of resources allocated to neighborhoods is insufficient. On average, neighborhoods get 69% of the *'planned expenditure.'* These resources reflect the low average number of cameras installed: 4.6. Installing only four cameras may prove insufficient as a neighborhood-level system to deter crime.

Previous research employs single-camera locations or clusters of cameras for a single location. Further, the location of both crimes and cameras is observable, which enables the researchers to construct measures around the cameras' location. In this paper, the data does not allow me to pin down PB cameras' street location, rather than the neighborhood in which they are installed. This paper presents evidence that the PB cameras as a neighborhood-level system do not deter crime. However, PB cameras may deter crime at their individual locations. Having the PB cameras' location would provide evidence to test this hypothesis. Furthermore, the exact location of the cameras installed through the PB program could allow me to observe whether they are installed in crime hot-spots through the neighborhood.

Considering the micro-level factors around the cameras is also important (Piza et al., 2014). Data on the type of camera, location, viewshed, and maintenance is unavailable. I have implicitly assumed no depreciation in both the PB cameras and the government cameras throughout the paper. However, data on daily status – active cameras, maintenance requests – can provide additional variation that is unaccounted for in this paper.

Finally, the number of operators monitoring the cameras' viewshed is paramount. According to the Mexico City government, the number of operators hired for the monitoring centers is 1,800. The number of government cameras amounts to 13,576 street cameras. The number of cameras installed by the PB program is equal to 3984, using an average unit price of US$4,000. Assuming no increase in the number of operators, and three eight-hour shifts, with an equal amount of operators each, every operator would have to monitor 29 cameras. Potential offenders, taking into account this information, would not be effectively deterred from committing any crime.

6 Conclusion

In this paper, I investigate the deterrence effect of CCTV systems on the neighborhood-level crime rate. I leverage the structure of the Participatory Budget program in Mexico City, which allows neighborhoods to annually propose and vote on projects to be implemented within their boundaries. I focus specifically on neighborhoods that choose cameras as the winning project during the years between 2016 and 2019.

Using crime reports from Mexico City, I construct a neighborhood-level crime rate for different types of crimes. It is possible that areas with higher crime rates self-select for cameras' deployment, threatening the identification of the deterrence effect. To overcome the potential endogeneity, I exploit the difference between the 'planned expenditure' and the 'actual expenditure' of the PB project for neighborhoods that voted for cameras. The identifying assumption employed in this paper states that conditional on neighborhood choosing cameras and its observable characteristics, the actual expenditure a neighborhood receives is as good as random. This assumption allows me to identify of the cameras' expenditure effect on the neighborhood's crime rate.

The point estimates in this paper do not support the existence of a CCTV systems deterrence effect. I check for robustness of the results, finding that the neighborhood crime rate is perfectly inelastic to the number of cameras installed by the PB program per 100,000 inhabitants. Among potential explanations discussed, I highlight the relatively low average amount received by the neighborhoods, the lack of data on the location and micro-factors surrounding the cameras, and the possible sparse monitoring due to insufficient personnel. Future empirical work should include these factors, and potentially study the combination of hot-spot policing and active surveillance cameras monitoring in Mexico City as in Gerell (2016).

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Appendix A - Main specification regressions

In this appendix, I present the estimation results using the main specification for the FBI's UCR crimes and the additional crimes. This regressions are employed to calculate the elasticities presented in Tables 6 to 8 in the main text for the FBI's UCR crimes and in Tables 9 to 11 for the additional crimes.

Estimated coefficients for Part I violent crimes

	Manslaughter	Rape	Robbery	Aggravated assault	Part I violent crimes
Cameras installed per 100, 000 individuals	-0.00598	0.000483	0.0165*	-0.00435	0.00954
	(0.00507)	(0.00627)	(0.00777)	(0.00569)	(0.00748)
Indicator for cameras as winning option	-0.0449	0.0765*	0.0597	0.0746**	0.0594
	(0.0255)	(0.0316)	(0.0391)	(0.0286)	(0.0377)
Population	0.233***	0.404***	0.497***	0.329***	0.460***
	(0.0108)	(0.0134)	(0.0165)	(0.0121)	(0.0159)
Population aged 15 and older	-0.176	0.563**	2.712***	-0.0197	2.079***
	(0.168)	(0.208)	(0.258)	(0.189)	(0.248)
Population aged 15 and older with complete basic education	0.131***	-0.0892**	-0.146***	-0.00320	-0.0230
	(0.0280)	(0.0346)	(0.0429)	(0.0314)	(0.0413)
Unemployed population	-0.0457*	-0.0687**	-0.176***	-0.0204	-0.160***
	(0.0196)	(0.0242)	(0.0300)	(0.0220)	(0.0289)
Population with access to social security	-0.428***	-0.735***	-1.463***	-0.818***	-1.249***
	(0.0878)	(0.108)	(0.134)	(0.0984)	(0.129)
Male-headed households	0.201	-0.326*	-1.647***	-0.662***	-1.369***
	(0.122)	(0.150)	(0.186)	(0.136)	(0.179)
Government cameras	0.0702***	0.113***	0.321***	0.0897***	0.322***
	(0.00542)	(0.00670)	(0.00830)	(0.00608)	(0.00800)
Constant	-0.766	-3.398*	-15.86***	3.838**	-16.08***
	(1.148)	(1.419)	(1.758)	(1.287)	(1.693)
Observations	26276	26276	26276	26276	26276
Delegation and quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Establishments by two-digit NAICS codes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Estimated coefficients for Part I property crimes

	Larceny-theft	Passersby theft	Theft from auto
Cameras installed per 100, 000 individuals	0.0115	0.0000916	0.0246**
	(0.00705)	(0.00483)	(0.00811)
Indicator for cameras as winning option	0.00300	0.00651	0.00261
	(0.0355)	(0.0243)	(0.0408)
Population	0.407***	0.173***	0.568***
	(0.0150)	(0.0103)	(0.0173)
Population aged 15 and older	3.543***	1.387***	3.807***
	(0.234)	(0.160)	(0.269)
Population aged 15 and older with complete basic education	-0.875***	-0.156***	-1.007***
	(0.0389)	(0.0267)	(0.0447)
Unemployed population	-0.0999***	-0.102***	-0.0654*
	(0.0273)	(0.0187)	(0.0313)
Population with access to social security	-0.832***	-0.960***	-1.039***
	(0.122)	(0.0836)	(0.140)
Male-headed households	-1.955***	-0.567***	-2.663***
	(0.169)	(0.116)	(0.194)
Government cameras	0.311***	0.0790***	0.254***
	(0.00753)	(0.00516)	(0.00866)
Constant	-17.93***	-1.812	-12.75***
	(1.596)	(1.093)	(1.835)
Observations	26276	26276	26276
Delegation and quarter fixed effects	Yes	Yes	Yes
Establishments by two-digit NAICS codes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Estimated coefficients for Part I property crimes

	Burglary	Motor vehicle theft	Part I property crimes
Cameras installed per 100, 000 individuals	0.00874	-0.00260	0.0145*
	(0.00843)	(0.00761)	(0.00679)
Indicator for cameras as winning option	0.0810	0.0379	0.0429
	(0.0424)	(0.0383)	(0.0342)
Population	0.655***	0.687***	0.337***
	(0.0180)	(0.0162)	(0.0145)
Population aged 15 and older	4.276***	4.477***	3.669***
	(0.280)	(0.253)	(0.226)
Population aged 15 and older with complete basic education	-1.265***	-0.704***	-0.922***
	(0.0465)	(0.0420)	(0.0375)
Unemployed population	-0.138***	-0.0789**	-0.0975***
	(0.0326)	(0.0294)	(0.0263)
Population with access to social security	-2.042***	-1.646***	-1.082***
	(0.146)	(0.132)	(0.118)
Male-headed households	-0.179	-1.069***	-1.355***
	(0.202)	(0.182)	(0.163)
Government cameras	0.263***	0.206***	0.312***
	(0.00901)	(0.00813)	(0.00726)
Constant	-24.97***	-19.94***	-19.53***
	(1.908)	(1.723)	(1.537)
Observations	26276	26276	26276
Delegation and quarter fixed effects	Yes	Yes	Yes
Establishments by two-digit NAICS codes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Estimated coefficients for Part II crimes

	Vandalism	Disorderly conduct	Drug abuse violations	Part II crimes
Cameras installed per 100, 000 individuals	0.00808	0.00818***	-0.000975	0.0149
	(0.00817)	(0.00244)	(0.00738)	(0.00869)
Indicator for cameras as winning option	0.0157	-0.0120	0.113**	0.0715
	(0.0411)	(0.0123)	(0.0372)	(0.0438)
Population	0.665***	0.0352***	0.494***	0.778***
	(0.0174)	(0.00520)	(0.0157)	(0.0185)
Population aged 15 and older	2.192***	0.358***	-0.00766	1.571***
	(0.271)	(0.0810)	(0.245)	(0.289)
Population aged 15 and older with complete basic education	-0.243***	-0.0401**	0.275***	-0.00153
	(0.0451)	(0.0135)	(0.0407)	(0.0480)
Unemployed population	-0.0611	-0.0112	0.00939	-0.0295
	(0.0316)	(0.00943)	(0.0285)	(0.0336)
Population with access to social security	-1.244***	-0.377***	-1.075***	-1.475***
	(0.141)	(0.0422)	(0.128)	(0.150)
Male-headed households	-0.627**	-0.0492	-1.198***	-1.377***
	(0.196)	(0.0585)	(0.177)	(0.208)
Government cameras	0.136***	0.0172***	0.125***	0.203***
	(0.00873)	(0.00261)	(0.00789)	(0.00929)
Constant	-10.31***	-0.278	3.222	-6.415**
	(1.849)	(0.552)	(1.670)	(1.967)
Observations	26276	26276	26276	26276
Delegation and quarter fixed effects	Yes	Yes	Yes	Yes
Establishments by two-digit NAICS codes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Estimated coefficients for the additional crime categories.

	Manslaughter	Assault	Street robbery	Car driver robbery	Delivery service theft
Cameras installed per 100, 000 individuals	-0.00434	-0.00119	0.0203**	0.0143*	0.00765*
	(0.00576)	(0.00733)	(0.00778)	(0.00691)	(0.00317)
Indicator for cameras as winning option	0.0414	0.0635	0.0576	0.0304	0.00498
	(0.0290)	(0.0369)	(0.0391)	(0.0348)	(0.0159)
Population	0.336***	0.545***	0.469***	0.417***	0.0755***
	(0.0128)	(0.0163)	(0.0173)	(0.0154)	(0.00705)
Population aged 15 and older	0.0185	0.427	2.573***	0.856***	0.498***
	(0.191)	(0.243)	(0.258)	(0.229)	(0.105)
Population aged 15 and older with complete basic education	0.228***	-0.138***	-0.235***	0.160***	-0.0774***
	(0.0319)	(0.0405)	(0.0430)	(0.0382)	(0.0175)
Unemployed population	-0.110**	-0.0402	-0.0842	-0.0977*	-0.0418
	(0.0412)	(0.0524)	(0.0556)	(0.0494)	(0.0226)
Population with access to social security	-0.587***	-1.191***	-1.343***	-0.833***	-0.490***
	(0.0997)	(0.127)	(0.135)	(0.119)	(0.0548)
Male-headed households	-0.137	-0.814***	-1.990***	-1.094***	-0.113
	(0.138)	(0.176)	(0.187)	(0.166)	(0.0761)
Government cameras	0.0868***	0.167***	0.299***	0.141***	0.0329***
	(0.00616)	(0.00783)	(0.00831)	(0.00738)	(0.00339)
4-2017	0.190***	0.389***	0.713***	0.196**	0.0996***
	(0.0502)	(0.0638)	(0.0677)	(0.0601)	(0.0276)
Constant	14.80*	0.969	-17.72*	-9.359	1.469
	(6.054)	(7.696)	(8.168)	(7.252)	(3.326)
Observations	26276	26276	26276	26276	26276
Delegation and quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Establishments by two-digit NAICS codes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Estimated coefficients for the additional crime categories.

	Carjacking	Motor vehicle theft	Theft from auto	Auto parts theft
Cameras installed per 100, 000 individuals	-0.0110	-0.00195	0.00480	0.00680
	(0.00795)	(0.00513)	(0.00748)	(0.00713)
Indicator for cameras as winning option	0.0302	-0.0550*	-0.0790*	0.0356
	(0.0400)	(0.0258)	(0.0377)	(0.0359)
Population	0.654***	0.227***	0.381***	0.506***
	(0.0177)	(0.0114)	(0.0167)	(0.0159)
Population aged 15 and older	3.936***	0.346*	2.145***	3.735***
	(0.264)	(0.170)	(0.249)	(0.237)
Population aged 15 and older with complete basic education	-0.372***	-0.353***	-0.882***	-0.649***
	(0.0440)	(0.0284)	(0.0414)	(0.0394)
Unemployed population	-0.155**	-0.106**	-0.0537	0.104*
	(0.0568)	(0.0367)	(0.0535)	(0.0510)
Population with access to social security	-1.681***	-0.514***	-0.876***	-0.944***
	(0.137)	(0.0887)	(0.129)	(0.123)
Male-headed households	-0.169	-0.275*	-0.910***	-2.804***
	(0.191)	(0.123)	(0.180)	(0.171)
Government cameras	0.157***	0.0585***	0.203***	0.135***
	(0.00850)	(0.00548)	(0.00800)	(0.00762)
Constant	-6.301	4.962	-22.28**	-20.15**
	(8.348)	(5.386)	(7.860)	(7.485)
Observations	26276	26276	26276	26276
Delegation and quarter fixed effects	Yes	Yes	Yes	Yes
Establishments by two-digit NAICS codes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Estimated coefficients for the additional crime categories.

	Business customer robbery	Business robbery	Secure business robbery	Burglary
Cameras installed per 100, 000 individuals	-0.00104	-0.000101	0.00195	0.00546
	(0.00166)	(0.00671)	(0.00105)	(0.00747)
Indicator for cameras as winning option	0.00204	0.0156	-0.00668	0.104**
	(0.00836)	(0.0338)	(0.00529)	(0.0376)
Population	0.0243***	0.363***	0.00151	0.744***
	(0.00370)	(0.0149)	(0.00234)	(0.0166)
Population aged 15 and older	0.232***	3.215***	0.0631	4.328***
	(0.0552)	(0.223)	(0.0349)	(0.248)
Population aged 15 and older with complete basic education	-0.0531***	-0.340***	-0.0106	-0.781***
	(0.00919)	(0.0371)	(0.00582)	(0.0413)
Unemployed population	-0.0179	0.111*	0.00362	-0.167**
	(0.0119)	(0.0480)	(0.00751)	(0.0534)
Population with access to social security	-0.136***	-1.495***	-0.0505**	-1.807***
	(0.0287)	(0.116)	(0.0182)	(0.129)
Male-headed households	-0.0501	-0.554***	-0.0106	0.333
	(0.0399)	(0.161)	(0.0252)	(0.179)
Government cameras	0.00311	0.144***	0.00575***	0.107***
	(0.00178)	(0.00717)	(0.00112)	(0.00798)
Constant	0.547	-48.64***	-0.569	-18.28*
	(1.745)	(7.046)	(1.104)	(7.843)
Observations	26276	26276	26276	26276
Delegation and quarter fixed effects	Yes	Yes	Yes	Yes
Establishments by two-digit NAICS codes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$