A descriptive model of the relationship between Police CCTV systems and crime. Evidence from Mexico City

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<th>Journal:</th>
<th>Police Practice and Research: An International Journal</th>
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<td>Manuscript ID</td>
<td>GPPR-2017-0040.R2</td>
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<tr>
<td>Manuscript Type:</td>
<td>Original Article</td>
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<td>Keywords:</td>
<td>CCTV, policing, spatial analysis, Mexico</td>
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URL: http://mc.manuscriptcentral.com/gprr
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Abstract

We test the relationship of police closed circuit television (CCTV) systems with crime at the census block level. Our descriptive model is based on environmental criminology theory and spatial modeling. We use as case study the Colonia Roma neighborhood in Mexico City which is a neighborhood characterized by high density, mixed uses, and high levels of crime. We found that CCTV correlated only with non-violent crime and, further, that crime was more strongly correlated to other crime opportunity and social disorganization correlates. In the remaining blocks we found no statistical evidence of an association between CCTV and crime. We discuss these results in terms of research methods and policy.
Introduction

Mexico is a country characterized by high rates of crime. In 2014 alone, a total of 33.7 million crimes were committed against 22.8 million victims. In addition, between 2010 and 2014 crime incidence increased by 45.8% and crime prevalence increased by 25.9%.\(^1\) Crime rates vary by location, urban and non-urban, as well as by region and state. Victimization rates are particularly high in Mexico City and the state of Mexico, in the center of the country, with more than 36% of adults reporting having been a victim of any crime in 2014.

Several solutions have been put forward to reduce crime in Mexico. One has been significant government investment in technology and situational crime prevention solutions such as (CCTV) systems. One example is the Federal District or Mexico City local police, which as of today, it has a total of 8,088 CCTV systems (or 1 for every thousand residents) in public places such as government buildings, parks, banking and commercial areas, highway exits, metro stations, and other places with large numbers of people such as pedestrian cross lines.\(^2\) This large-scale use of CCTV by Mexico City police started in 2006 when the newly elected Governor of the city promised that a massive high-tech video surveillance system would be installed in the next few years. Accordingly, the high-tech public security Ciudad Segura program started in 2009. This program is basically a massive CCTV security surveillance network integrated with other high-tech communication features all enhancing police tracking capabilities, traffic control, and

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emergency call handling and dispatching. This CCTV security network is expected to grow to about 20,000 CCTV cameras by the end of 2018.³

This trend of investing heavily in CCTV systems in public places is common in many countries (Welsh and Farrington, 2011). However, questions have been raised regarding the efficacy of this solution relative to high public expenditures or simply by outrightly rejecting its use (Karstedt, 2007)

In spite of the lack of any local studies proving the efficacy of CCTV against crime, it is now an indispensable tool for the Mexico City police (Valenzuela-Aguilera, 2014; Becker and Müller, 2013; Thomson, 2011). Just in the first six months of 2015, official data show CCTV cameras have been used 30,972 times in relation to crime reports, misdemeanors and other contraventions such as traffic violations.⁴ However, intensive use does not mean it is effective against crime. To date there is no evidence coming from Mexico that it is correlated with crime incidence. As it has been said for the case of Spain (Clavell et al, 2012) not even the most basic assumptions about CCTV have yet to be tested in Mexico.

In this article, we test whether there is a relationship between the locations of police CCTV systems and the frequency of crime. We present a case study of Colonia Roma in Mexico City, a neighborhood of more than 40,000 residents located in the central part of the metropolitan area (see Figure 1). We use census block data to compare the frequency of crimes between census

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blocks that have CCTV systems with those without. We use two methods to examine this relationship. One Zero-truncated Poisson regression model and a geographically weighted Poisson regression model.

In sum, this is a descriptive study that with the use strong statistical-theoretical controls and spatial modeling approaches, allows a robust test of the correlation between police CCTV systems with crime. This enables a better understanding of CCTV given the data limitations in the Mexican context.

In the following section, the theoretical and empirical evidence that inform this study is described in detail. After presenting the hypothesis and the study area, and discussing the data and methods used in this study, the results from the statistical analyses are presented. This study concludes by discussing the implications of our findings.

Theoretical and empirical evidence

Crime Pattern and Social Disorganization theories provide explanations of the spatial patterns of crime in relation to CCTV are tested in this study. Previous studies have shown how both theories are compatible (Johnson and Summers, 2015) as they aim to describe the physical and social environment in which crimes occur.

CCTV
There have been a significant number of studies looking at the use of CCTV and the incidence of crime. Many of these studies have taken place in the UK, as a response to the very large numbers of systems deployed, under a variety of circumstances. Of particular value are meta-analyses of CCTV because they highlight the combination of factors involved with detecting cross-sectional or longitudinal patterns (Welsh and Farrington 2004, 2009, 2011). Welsh and Farrington (2009) point out how cultural differences play a role in attitudes toward CCTV by comparing UK, US, Sweden, and Norway. This may be a more significant factor in the public’s willingness to pay for such systems, rather than CCTV’s actual effectiveness as measured by researchers.

TABLE 1 --- HERE

Research on CCTV and crime has grown as an increasing number of cities have implemented these systems on a broad scale. The pervasiveness of CCTV in publicly accessible space has been reported being in the range of 40% (London and Oslo) to 20% (Berlin and Vienna) by Norris, McCahill, and Wood (2004). Studies have also sought to identify particular characteristics that may explain the effectiveness of CCTV such as city centers, suburban areas, and public housing (Ratcliffe et al. 2009; Cerezo 2013). Other factors also include locations like garages and other parking facilities (Tilley 1993; Welsh and Farrington, 2009), CCTV visibility and signage (Farrington et al. 2007; Welsh and Farrington 2002).

Some meta-analyses and experimental studies have found a crime deterrent effect of police monitored CCTV, but only if accompanied by other strategies such as proactive police activity (Piza et al. 2015) or street lighting (Farrington et al. 2007). CCTV has been found to be effective
against some crimes like vehicle theft (Caplan et al. 2011; Farrington et al. 2007) but much less effective on others like drug crimes. Evidence suggests that the effect is conditional on the number of cameras and their location (Farrington et al. 2007). Likewise, CCTV efficacy seems to be a function of the type of public space, with more worth in train stations and parking lots, but less in city centers and residential areas (Farrington et al. 2007). These studies provide no evidence of displacement or diffusion of benefits to neighboring places (Caplan et al. 2011, Farrington et al. 2007).

Other studies have sought to consider both spatial and temporal changes that would suggest that crime is displaced by introducing CCTV however the evidence is not conclusive (Farrington et al. 2004; Caplan et al 2011; Park et al 2012; Cerezo, 2013). Small changes have been detected in some cases, but it is likely that locational characteristics of public spaces do not remain static over time, thus making displacement analyses difficult (Waples et al. 2009). One spatiotemporal analysis based on Philadelphia, aiming to control for long-term trends and seasonality effects, found CCTV to have significantly reduced crime in general for the city, but having differential effects on specific locations –as many locations showed no benefit of camera presence and even some other locations correlated positively with crime (Ratcliffe et al. 2009).

In a similar vein, we contribute to this line of research by introducing other spatial controls and techniques to deal with potential problems of proximity and locational effects. We contribute to the literature by providing the case of a Mexico City neighborhood characterized by high density, intensive use of CCTV, and high levels of crime. We also demonstrate the need of controlling for environmental criminology correlates when evaluating the efficacy of CCTV to prevent crime.
Crime pattern theory

Theories of crime can be divided into those that seek to explain the development of offenders and those that seek to explain the development of a crime event (Eck and Weisburd, 1995). Most research has focused on the first type of theories whereas research focusing on why criminal events occur where and when they occur is less frequent. Why some places and targets are more attractive to offenders is the subject matter of Crime pattern theory. Brantingham and Brantingham’s (1993) basic theoretical argument is that some places have higher levels of crime because they offer more criminal opportunities due to the characteristics of the activities associated with them.

Crime pattern theory is a meta-theory that combines rational choice and routine activity theory to help explain this geography of crime opportunity. On the one hand, rational choice theory explains why some places and targets within those places are preferred over others. The basic premise is that offenders will tend to minimize risks and maximize profits. The use of CCTV surveillance is based on rational choice theory. It is expected that offenders will be less likely to commit a crime if they know they are being watched and have a greater risk of being apprehended (La Vigne et al. 2011). The risk of being apprehended is positively correlated with increases in the effort to commit the crime, decreasing rewards from crime commission, and reducing provocations that overall give rise to criminal opportunities (La Vigne et al. 2011). In other words, places and targets with CCTV surveillance should be less attractive for crime
because there is assumed to be a higher level of safety with a greater chance of a perpetrator being caught.

Routine activity theory explains the occurrence of a crime due to the spatio-temporal convergence of three elements: A motivated offender, an suitable target, and the lack of capable guardianship. The CCTV security camera is a proxy for guardianship. The basic premise of routine activity theory is that the changes in routine-activities associated with the increase in small households and two-income families, has increased the opportunity for property crimes mostly. Naturally, the density of offenders, attractive targets, and ineffective guardianship is not randomly distributed across space. Some places offer more crime opportunities than others. Likewise, one main difference between crime pattern theory and routine activity theory is that the former will focus on the behaviors of offenders in selecting the target for crime, whereas the latter will explain the crime event from the perspective of the victim’s behavior. These theories allow on to focus on offenders or victims, but they do not focus exclusively on them. Both are concerned with the convergence of offenders and victims.\(^5\)

Crimes occurring ihappen due to the interaction of victims and offenders. Brantingham and Brantingham (2008) argue that the urban form creates areas that serve as “crime generators” and “crime attractors” (p. 88). “Crime generators” are places created by high flows of people. On the other hand, “crime attractors” are places created when potential victims (i.e. targets) coincide with individuals who have a willingness to commit a crime (Brantingham and Brantingham, 2008).

\(^5\) This was pointed out by one of the reviewers.
Likewise, offenders will tend to search for targets in main avenues that connect them, with the exception of safe zones (e.g. blocks with CCTV) that offenders either avoid or simply go through without intent to commit a crime there. Consequently we expect that areas with bars and restaurants, hotels, main avenues and bank branches all serve as crime generators and crime attractors. Likewise, public transport is massive in Mexico City, therefore we also expect that offenders will tend to operate in or around metro stations. These locations create opportunities for offenders to seek out victims. This explains the clustering of crime in these places. Crime hotspots are geographical areas where numerous offenders overlap with suitable opportunities for crime (Johnson and Summers, 2015).

Social Disorganization and Neighborhood Cohesion Theory

It is indeed the case that most crimes are committed by teenage and early adult males in neighborhoods with higher levels of social disadvantage and lower levels of formal and informal controls (Sampson 2011; Sampson and Groves, 1989). This has been shown to be the case of Ciudad Juarez and the Mexico City metropolitan area in Mexico (Vilalta and Muggah, 2014, 2016).

The main premise of social disorganization theory is that unstable communities lack the capacity and the opportunity to control deviant behaviors. More precisely, the capacity of neighborhood residents to prevent collective problems and crime is assumed to originate from social cohesion that promotes social control (Sampson and Groves, 1989; Bursik and Grasmick, 1993; Sampson
et al. 1997; Steenbeek and Hipp, 2011). Social control in the neighborhood is exercised through a variety of means such as gossiping about inappropriate behaviors, withdrawing social support or esteem, directly criticizing or admonishing inappropriate behavior, yelling or retaliating, and negotiation of grievances (Warner, 2007).

In its original formulation, social disorganization predicted that the spatial variation in crime rates within cities would depend on levels of ethnic heterogeneity, poverty, and rapid population growth Shaw and McKay (1942). The basic idea was that the combination of previous factors hold back social bonding. This results in a low capacity for communities to regulate themselves and to monitor the behavior of its members. Modern formulations of social disorganization theory have incorporated other factors. Sampson and Wilson (1995) postulated a theory of crime, race, and inequality on social disorganization premises. This theory is based on the idea that modern structural factors (i.e. deindustrialization, migration, and socioeconomic segregation) deeply influence urban culture and increase crime and antisocial behaviors. This happens due to changes in structural factors which result in the spatial concentration of the disadvantaged. This process of inequality weakens the social and cultural fabric of communities, undermining the quality and quantity of social bonding.

This theory was further refined a few years later with the idea of collective efficacy and neighborhood social cohesion (Sampson, 2011; Sampson et al. 1997). Collective efficacy is understood as the degree of social cohesion among residents of a community that would be willing to intervene on behalf of the common good. It is argued that greater levels of collective efficacy will lead to lower levels of crime and violence. In other words, this theory predicts that
informal social controls of violence and antisocial behaviors will reduce crime incidence. In this sense then, neighborhoods with low levels of collective efficacy are characterized by low levels of civic participation, sparse local friendship networks and unsupervised teenage peer groups. The policy implication is that collective efficacy is at the core of crime prevention.

Along the lines of social disorganization theory, there is evidence of other related and important spatial patterns of concentrated disadvantage and criminal behaviors, such as the tendency of criminals to live geographically close to their victims (Vilalta, 2010; Van Dijk 1990), the endemic character of crime hotspots (Eck and Weisburd 1995), high crime rates in residential areas with high percentages of rented dwellings (Bottoms and Wiles 1986), and in large housing projects (Block and Block 1995), and also the finding that the probability of becoming a criminal is greater if the individual grows in a high crime area of the city (Krivo and Peterson 1996). The causal mechanism of the latter finding is that the higher the density of crime in a community, the greater the probability of finding accomplices, because a wide and closer communication network between them (Reiss 1986).

Based on these theories, our argument is that CCTV may prevent crime but only if it can counter crime opportunities and social disorganization pressures towards crime. In a sense, we explicitly assume that situational prevention measures such as CCTV do not operate in a spatial and social isolation.

The challenge here is how to provide the right method to discern the relationship of CCTV with crime when risk factors such as available crime opportunities and social disorganization are not
evenly distributed across space within neighborhoods. If CCTV and crime are not associated controlling for spatial and social factors, then the evidence in favor of CCTV as a crime prevention tool will be weak at best and perhaps even based on false positives or anecdotal evidence. We test this relationship by using an original dataset of crime events recorded at the city block level in a neighborhood of Mexico City.

Study area

The study area covers the *Colonia Roma* neighborhood (Figure 2) in Mexico City. This neighborhood is divided into two areas: *Roma Norte* and *Roma Sur*. The total population in the neighborhood was 44,352 inhabitants in 2010. The gender distribution of residents is 52.5% female and 47.3% male. The adult population in the neighborhood is 79.2% and 19.2% of the adult resident population has some college education which in both case are a higher figures than the rest of Mexico City.\(^6\)

The total area is about 3.5 km\(^2\) thus this is a high density neighborhood (12.6 thousand per square kilometer).\(^7\) It is a very old and highly developed neighborhood. It was developed as a residential area at the beginnings of the 20\(^{th}\) century for the upper and upper middle classes of the *Porfirista* era. As such, it has a good number of Parisian boulevards, tree-lined sidewalks and several splendid manors, which in many cases have today been either subdivided into modern townhouses or converted into commercial land uses. It is currently one of the neighborhoods in

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\(^6\) Source: *Censo de Poblacion y Vivienda*, 2010. INEGI.

\(^7\) Equivalent to 1.4 square miles and 31.6 thousand inhabitants per mi\(^2\)
the city with the highest concentration of young adults, bars, restaurants, and neighborhood
amenities.

FIGURE 1 --- HERE

The Roma neighborhood is an important business and services center within Mexico City. It
includes more than 30 hotels, 40 banks, and nearly one thousand bars and restaurants in just 1.4
square miles. It also contains the highest concentration of metro stations (N = 5) in the city after
colonia Centro in the historical downtown (N = 6). Overall, it is a well established and highly
dense neighborhood.

Data and methods

Crime incidence data are spatial as crime occurs and are recorded at the place level. We chose to
aggregate the data to the census block level as the unit of analysis for this study (“block” is
Manzana in Spanish) as is defined by the National Institute of Statistics and Geography (INEGI)
of Mexico. Each census block is an area that may contain housing units, buildings and empty lots
with different uses and densities. These types of areas or polygons may be found in urban and
rural areas where their limits are streets, property limits, streams, and so on. Manzanas or census
blocks, are used as spatial sampling frameworks for conducting national censuses and surveys.
An advantage of using census blocks as the unit of analysis is that it allows for the analysis
within neighborhoods and they are typically the same every decennial census so that next spatial
analyses can be performed over time.
The Federal District side of the Mexico City metropolitan area contains a total of 56 thousand census blocks. The study area is one considerably large neighborhood containing a total of 308 blocks (or 0.6% of the total).

Dependent variables

The dependent variables were the counts of the number of criminal investigations for non-violent crimes and violent crimes initiated by the Mexico City’s Attorney’s Office (PGJDF) in 2013.\(^8\) The distinction between non-violent and violent crimes is the same the PGJDF does for statistical purposes. The PGJDF considers the following as violent crimes: intentional homicide, rape, kidnapping, car theft and carjacking, robbery, assault, and injuries caused by a firearm. Non-violent crimes are all other crimes.\(^9\)

These data were geocoded by place of occurrence according to where the victim reported the location of the crime. For the criminal investigation to initiate, among other things, the victim is given a map of blocks of the neighborhood where they must pinpoint where the crime occurred. These locations are later given geographic coordinates by the PGJDF for mapping purposes. Criminal investigations count data (i.e. point data) were assigned to its nearest census block (i.e. polygon data) to the closest neighboring block.

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\(^8\) In Spanish: Procuraduría General de Justicia del Distrito Federal (PGJDF)

Even though the underreporting of crimes to the police is quite common, there are no other sources of crime data. We have no evidence to suggest that our data are biased within neighborhoods, or that this problem invalidates the findings of the analysis. Previous studies (Baumer, 2002) have found differences in the reporting of some crimes between neighborhoods in American cities depending upon the level of disadvantage in the neighborhood, but we have no grounds to make the same argument at the neighborhood scale.

Independent variables

The predictor variable was the number of CCTV cameras property of the Mexico’s City police department in the neighborhood during 2013. The source for these data was also the Mexico City’s Attorney’s Office (PGJDF). CCTV systems count data (i.e. point data) were also joined to its nearest neighboring block (i.e. polygon data) as were the crime data.

Theoretical correlates

Variables used in the analyses include measures of Crime Pattern Theory and Social Disorganization theory. Crime Pattern Theory was represented by the following seven variables: the number of parking lots, banks, hotels, bars and restaurants, metro stations, parks, city blocks in main avenues, hospitals, and percentage of vacant housing units. These variables indicate offender-victim spatial convergence and crime target availability within the neighborhood. The data source for the number of banks, hotels and bars and restaurants was the National Statistical
Directory of Economic Units (DENUE) from INEGI in 2013.\textsuperscript{10} We used Google maps to determine the location of metro stations, parks, and main avenues. All variables were operationalized as binary, where values of 1 indicate that a census block contains or is adjacent to a metro station, to a main avenue, or whether it contains a park. Data source for the percent of occupied housing units was the 2010 decennial Census from INEGI.

Social disorganization theory was represented by two variables: proportions of male unemployed residents (% of male residents without employment and actively looking for a job) and female headed households with children (% female headed households with children). The first variable represents economic disadvantage and the second variable represents family disruption risk as presumably single mothers have to work for a living and this reduces the time available for the supervision of minors. The data source for variables was the 2010 decennial Census from INEGI.

Analytical strategy

Zero-inflated Poisson regression (ZIPR) with robust standard errors and Geographically Weighted Poisson Regression (GWPR) with geographically varying coefficients models were used in the analysis given the spatial nature of the unit of analysis and that the dependent variables were count variables with a sizeable proportion of zeros.

ZIPR is ideal to account for an excess of zeros in a count distribution, however it cannot detect spatial heterogeneity as relationships are assumed to be spatially stationary (i.e. space

\textsuperscript{10} In Spanish: Directorio Estadístico Nacional de Unidades Económicas (DENUE).
independent). However, if spatial heterogeneity is present, data will not adequately fit the ZIPR model (Vilalta, 2013). More specifically, local relationships will cancel each other out in the calculation of the global estimates.

The GWPR model extends the geographically static ZIPR model by allowing parameters to vary across space. The location of a census block in this study was defined as its geographic centroid. In comparison to ZIP regression, GWPR provides a probabilistic model for each location as the goal of GWR is local estimation. This can be done as it incorporates spatial nonstationarity by using local parameters in opposition to global parameters, that is, GWR analysis allows parameters to vary over space (Fotheringham et al., 2002).

GWPR was run in several steps. First, as spatial kernels need to be used to define spatial neighbors and their weights, weights were calculated with a negative exponential continuous function of the square distance among geographic centroids. We allowed the Kernel function to be adaptive in the number of neighbors, that is, to increase its bandwidth (i.e. area of influence) when census blocks were sparser and decrease it when they were concentrated (Charlton & Fotheringham, 2009). As such, optimal adaptive numbers of neighbors were applied to each regression and the weight of each location was computed using the specified kernel.

In addition to the regression analyses, other traditional and spatial bivariate tests were also performed. In specific, the global univariate Moran’s I statistic was used to test if the dependent variables (i.e. number of non-violent and violent crimes in each census block) were spatially
autocorrelated. The local Moran’s I statistic was used to detect census block hotspots and coldspots of crime.

Results

In 2013, a total of 583 crimes occurred in the study area. Violent crime showed a random pattern, while non-violent crime and the total number of crimes had a clear pattern of spatial clustering (see table 2). In particular, non-violent crime (i.e. shoplifting, theft, and vehicle theft without use of force) was highly spatially dependent. Crime in general was spatially clustered in the south and east sides of the neighborhood, where unemployment and female headed households with children are more prevalent. As expected, as the radius for the neighbor matrix increases (i.e. more blocks are added to the calculation of autocorrelation coefficients) the strength of the spatial dependency tends to decrease or remains stable. However, as previously mentioned, violent crimes (i.e. homicide, assault, robbery, carjacking, kidnapping and sexual crimes) were not spatially dependent, suggesting that the likelihood of violent crime victimization is the about the same regardless of spatial location within the neighborhood.

TABLE 2 --- HERE

However, local Moran’s I coefficients allowed for the identification of specifically dangerous (i.e. hostpots) and not dangerous census blocks (i.e. coldspots). This is a fundamental finding as residents and visitors can be right in being fearful of specific locations within the neighborhood. Each type of crime (violent and non-violent) has its own hotspot geography (see Figure 2). Even
though the global Moran analysis suggested that violent crime victimization may occur in any block of the neighborhood as a general pattern, local Moran analysis shows that in some blocks violent crime victimization was actually more likely than in others. As previously mentioned, most hotspots were located in the south side of the neighborhood, precisely where unemployment and female headed households with children are more common. In contrast, coldspots were more common in the northwest side of the neighborhood.

FIGURE 2 --- HERE

With regards to the hypothesis of a relationship between CCTV and crime, we have no evidence of a bivariate correlation between the number of crimes and the number of CCTV cameras per census block (see Table 3). Blocks with CCTV systems had similar number of crime counts than blocks without CCTV systems.

TABLE 3 --- HERE

A total of twelve environmental criminology correlates were included in our regression model. The statistical summary is shown in Table 4. As shown in the table, an average of 2 crimes were committed in every block (N = 308) during 2013, ranging from at least 1 crime to a maximum of 10. The total number of CCTV systems existing in the same year was 93 in total, distributed among 81 census blocks, ranging from 0 to a maximum of 3. Likewise, there are nearly 1,000 bars and restaurants, as well as many hotels, parking lots, hospitals and banks. A total of 193 (62.6%) of census blocks are located on main avenues. Thus, it is clear that many blocks in the
neighborhood are in some way vulnerable to crime and that there are plenty of crime targets available to choose from.

TABLE 4 --- HERE

As shown in figure 4, the level of disadvantage, measured as the percentage of unemployed, ranging from 0% to almost 27%, is relatively high and highly concentrated in some census blocks. Likewise, family cohesion, as measured by the percentage of female headed households with children is also high and highly variable among census blocks.

In spite of a significant number of police CCTV systems in the neighborhood, there are many spots unmonitored by the police as 70% of the blocks have no CCTV system installed. They also seem to be dispersed across the neighborhood (see Figure 3). This is reasonable given the neighborhood has a high density of visitors everyday, mixed land uses, and business activities.

FIGURE 3 --- HERE

The results of the three Zero-inflated Poisson regressions (ZIPR) with robust standard errors are presented in Table 5 below. Incidence rate ratios (IRR) are presented and can be interpreted as the change in the likelihood of crime counts associated with a 1 unit change in each correlate. The number of CCTV systems is not statistically correlated with any of our dependent variables. Instead, the number of crimes in 2013 was associated with a set of crime pattern and social disorganization correlates. The number of non-violent crimes (i.e. theft, car theft, fraud, drug crimes) was positively associated with metro stations and male unemployment and negatively
associated with Bars and Restaurants and hospital locations. Metro stations emerged as the
strongest correlate of crime in _colonia_ Roma. City blocks with or around metro stations
increased the likelihood of a non-violent crime event (e.g. petty theft, damage to property, non-
intended injuries etc.) by 372% after controlling for other crime attractors or social factors. The
number of violent crimes was negatively associated with parking lots and banks. The likelihood
of violent victimization (e.g. intentional homicide, robbery, carjacking or rape) decreases by 25%
in parking lots and by 20% in street blocks where a bank is located. Finally, blocks with banks,
hotels and bars and restaurants offered a lower likelihood of victimization for all crimes, while
the percent of male unemployment increased the likelihood of victimization in general,
presumably since the former have more guardianship services provided by business owners.

TABLE 5 --- HERE

As it was said in the methods section, one limitation with the previous modeling approach is that
it assumes that all census blocks are located in the same place as if they were stacked on top of
each other. Thus, given the spatial patterns noted above, additional spatial modeling was
conducted to further test the hypothetical connection between CCTV systems and crime. The
results of the GWPR model are shown in Table 6. As GWPR produces a local coefficient for
every spatial unit, the mean of the coefficients are shown. Overall, the AICc statistic indicates
that the Poisson GWR model was a statistically significant improvement to the ZIPR model for
violent and non-violent crimes.

TABLE 6 --- HERE
The results of the GWPR model provided further insight into the spatial structure of crime in our area of study. Even though the Poisson global model (ZIPR) did not detect a (global) statistically significant relationship between the number of CCTV systems and the number of crimes in the neighborhood, the GWPR model was able to detect local (i.e. census block level) negative and statistically significant relationships between the number of CCTV systems and non-violent crimes. No local relationships were detected between the number of CCTV systems and the number of violent crimes or the total number of violent crimes.

The mapping of the local t-values reveals which census blocks have statistically significant estimates. The maps of the local t-values for our independent variable are presented in Figure 4. The number of CCTV systems are strongly and negatively associated with non-violent crimes across all blocks in the neighborhood, but particularly more in the central side of the neighborhood. What this indicates is that for 2013, ceteris paribus, police CCTV systems were located in census blocks where less non-violent crimes actually occurred. Likewise, that this relationship is spatially variable, that is, in some blocks the relationship is stronger than in others. As for other crimes, no spatial relationship could be detected.

FIGURE 4 --- HERE
This is not evidence of a causal relationship between CCTV systems and crime as it cannot be argued such an impact based on a descriptive correlational model that does not take into account any experimental effects. Instead, this is solely evidence of a spatial mismatch between CCTV and non-violent crime events.

Discussion

CCTV systems are being used by police agencies in many countries around the world (Ariel et al. 2014; Welsh and Farrington, 2011). In Mexico City, the police use of CCTV is relatively recent. Usage increased significantly 2006 when the newly elected governor then promised that high-tech would be at the forefront of his public security policy. His promise was fulfilled. Just in the first six months of 2015, a total of 8 thousand CCTV cameras have recorded 30,972 crimes, misdemeanors, and other administrative offenses citywide.\(^{11}\) One problem is that massive use of CCTV does not prove it effective against crime. Intensive use of CCTV might mean that police is heavily dependent on it.

In this article, we tested if there was a correlation between the count of crimes and the number of police CCTV systems in a high-density high-crime neighborhood in Mexico City in 2013. Based on strategic police data, two types of blocks (N = 308) were identified within the neighborhood: blocks without any CCTV cameras and those with one, two or three cameras. Based on police crime data too, crimes were divided into two types: Violent and Non-Violent crimes. The


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correlation between the two variables was tested controlling for a set of social disorganization and crime pattern theories variables.

Using the census block as unit of analysis and a geographically weighted regression approach, we obtained results that showed a negative correlation between the number of CCTV police cameras and the number of non-violent crimes in each block. This suggests that a lower number of non-violent crimes occurred where more CCTV cameras were installed. However, we found no correlation between violent crimes or the total number of crimes with the number of CCTV police cameras. Likewise, we found no correlation between the number of CCTV police systems and the number of crimes in adjacent blocks, meaning there is an absence of evidence of a spillover effect as well.

GWR results supported our premise that incorporating spatial heterogeneity is important for the modelling of crime patterns. The justification for using this modelling approach was that both the dependent and independent variables showed to have non-random spatial patterns as indicated by the global and local spatial autocorrelation tests. The assumption of spatial homogeneity in the data was discarded soon after. The significant heterogeneous distribution of the local relationships between CCTV and non-violent crimes suggest the possibility of CCTV having some role in preventing some types of crimes (e.g. petty theft, damage to property, fraud, manslaughter, theft of car parts, non-intended injuries, sexual harassment, etc.). However, CCTV still was not the strongest correlate of non-violent crime in this neighborhood.
In terms of Social Disorganization and Crime Pattern Theory, the results of incorporating spatial heterogeneity helped to detect a number of locally varying relationships between metro stations, banks, and parking lots with the total number of crimes. Also, male unemployment significantly increased violent crime in a number of blocks. Finally, non-violent crimes were strongly associated with main avenue blocks and negatively associated with the number of banks. All these correlates were significantly stronger than the number of CCTV systems. As such, crime in this neighborhood seems to have a variety of social and crime pattern risk factors which may be overturned with the use of social crime prevention solutions rather than situational crime prevention solutions. All in all, global results mask the importance of local results in the context of crime.¹²

The results presented in this study are based on a case study, data, and spatial modeling approach which are not typical to the crime prevention literature. Very few studies test the relationship between CCTV and crime with the use of spatial methods and criminological theory altogether. Still our approach and methods are not tied exclusively to the use of CCTV systems or to the case study itself. It can safely be assumed that the results are not a function of our particular approach or limited to one particular neighborhood in one particular Latin American city. This approach can be replicated to other neighborhoods with a similar crime distribution and social composition. In this sense, other studies at the neighborhood level would give further insight into the true relationship between CCTV and crime. This would result in a better understanding of these crime prevention tools.

¹² This was a good insight from one of the reviewers regarding the interpretation of the results.
References


URL: http://mc.manuscriptcentral.com/gprr


URL: http://mc.manuscriptcentral.com/gppr


URL: http://mc.manuscriptcentral.com/gppr


A descriptive model of the relationship between Police CCTV systems and crime. Evidence from Mexico City

### TABLES

Table 1. Previous studies on CCTV and crime

<table>
<thead>
<tr>
<th>Author/year</th>
<th>Location</th>
<th>Relationship</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>Piza et al. 2014</td>
<td>Newark, NJ</td>
<td>+</td>
<td>If used altogether with policing</td>
</tr>
<tr>
<td>Reid and Andresen, 2014</td>
<td>Surrey, BC</td>
<td>None</td>
<td>No evidence of effect on vehicle theft</td>
</tr>
<tr>
<td>McLean et al. 2013</td>
<td>Schenectady, NY</td>
<td>+</td>
<td>Only in places where cameras are easily visible</td>
</tr>
<tr>
<td>Cerezo, 2013</td>
<td>Malaga, Spain</td>
<td>+</td>
<td>Only for crimes against property and assaults. There is a displacement effect of crime to areas without cameras</td>
</tr>
<tr>
<td>Park et al. 2012</td>
<td>Gwang Myeong, South Korea</td>
<td>+</td>
<td>Only for street theft and robbery crimes. No crime displacement effects</td>
</tr>
<tr>
<td>Caplan et al. 2011</td>
<td>Newark, NJ</td>
<td>+</td>
<td>Only for vehicle theft. No crime displacement effects. Some locations are more effective than others.</td>
</tr>
<tr>
<td>Ratcliffe et al. 2009</td>
<td>Philadelphia, PA</td>
<td>+</td>
<td>Only in some areas of the city</td>
</tr>
<tr>
<td>Welsh and Farrington, 2009</td>
<td>Meta-analysis (93)</td>
<td>+</td>
<td>Greater efficacy on parking lots and transit areas. Minor efficacy on residential areas.</td>
</tr>
<tr>
<td>Farrington et al. 2007</td>
<td>14 locations in UK</td>
<td>+</td>
<td>If good lighting is available and only in transit areas and only against vehicle theft. The number of cameras matter. No crime displacement effects.</td>
</tr>
<tr>
<td>Welsh and Farrington, 2004</td>
<td>Meta-analysis (83)</td>
<td>+</td>
<td>CCTV and street lighting are both more effective in reducing property crimes than violent crimes. Both were more effective in UK than in US</td>
</tr>
</tbody>
</table>

Source: Authors own.
<table>
<thead>
<tr>
<th></th>
<th>131 meters</th>
<th>200 meters</th>
<th>300 meters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non violent crimes</td>
<td>0.283***</td>
<td>0.226***</td>
<td>0.224***</td>
</tr>
<tr>
<td>Violent crimes</td>
<td>-0.031</td>
<td>-0.001</td>
<td>-0.017</td>
</tr>
<tr>
<td>All crimes</td>
<td>0.146***</td>
<td>0.140***</td>
<td>0.142***</td>
</tr>
</tbody>
</table>

*p < 0.10, **p < 0.05, ***p < 0.01. Euclidian distances between centroids in meters. Threshold distance: 131 meters.
Table 3 Cramer’s V correlation coefficients

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Number of CCTV</td>
<td>-</td>
<td>0.108</td>
<td>0.130</td>
<td>0.113</td>
</tr>
<tr>
<td>2. Non violent crimes</td>
<td>0.108</td>
<td>-</td>
<td>0.123</td>
<td>0.643***</td>
</tr>
<tr>
<td>3. Violent crimes</td>
<td>0.130</td>
<td>0.123</td>
<td>-</td>
<td>0.485***</td>
</tr>
<tr>
<td>4. All crimes</td>
<td>0.113</td>
<td>0.643***</td>
<td>0.485***</td>
<td>-</td>
</tr>
</tbody>
</table>

*p < 0.10, **p < 0.05, ***p < 0.01. N = 308
Table 4 Statistical summary of variables for Poisson regression models

<table>
<thead>
<tr>
<th>Variable</th>
<th>Count</th>
<th>Mean</th>
<th>Median</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-violent crimes</td>
<td>305</td>
<td>1.0</td>
<td>0</td>
<td>9</td>
</tr>
<tr>
<td>Violent crimes</td>
<td>278</td>
<td>0.9</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>All crimes</td>
<td>583</td>
<td>1.9</td>
<td>1</td>
<td>10</td>
</tr>
<tr>
<td>CCTV</td>
<td>93</td>
<td>0.3</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>Parking lots</td>
<td>109</td>
<td>0.4</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>Banks</td>
<td>45</td>
<td>0.1</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>Hotels</td>
<td>33</td>
<td>0.1</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>Bars and Restaurants</td>
<td>914</td>
<td>3.0</td>
<td>2</td>
<td>37</td>
</tr>
<tr>
<td>Metro station**</td>
<td>23</td>
<td>0.1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Parks*</td>
<td>6</td>
<td>0.02</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Main avenue*</td>
<td>193</td>
<td>0.6</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Hospital*</td>
<td>10</td>
<td>0.3</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Female HH w/ children (%)</td>
<td>-</td>
<td>1.3%</td>
<td>0.0%</td>
<td>12.0%</td>
</tr>
<tr>
<td>Vacant housing units (%)</td>
<td>-</td>
<td>4.5%</td>
<td>2.0%</td>
<td>34.2%</td>
</tr>
<tr>
<td>Male unemployment (%)</td>
<td>-</td>
<td>2.7%</td>
<td>0.0%</td>
<td>26.7%</td>
</tr>
</tbody>
</table>

*Number of blocks with these amenities or characteristics,
*Number of blocks with or around these metro stations,
N = 308
Table 5 Results of Zero-inflated Poisson regression (ZIPR)

<table>
<thead>
<tr>
<th></th>
<th>All crimes</th>
<th>Violent crimes</th>
<th>Non-violent crimes</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCTV</td>
<td>1.065</td>
<td>1.177</td>
<td>1.096</td>
</tr>
<tr>
<td>Parking lots</td>
<td>0.784</td>
<td>0.746*</td>
<td>0.838</td>
</tr>
<tr>
<td>Banks</td>
<td>0.709**</td>
<td>0.797*</td>
<td>0.529</td>
</tr>
<tr>
<td>Hotels</td>
<td>0.775*</td>
<td>1.003</td>
<td>0.687</td>
</tr>
<tr>
<td>Bars and restaurants</td>
<td>0.948**</td>
<td>1.002</td>
<td>0.888*</td>
</tr>
<tr>
<td>Metro stations</td>
<td>1.741</td>
<td>0.787</td>
<td>4.723***</td>
</tr>
<tr>
<td>Main avenue</td>
<td>1.258</td>
<td>1.157</td>
<td>1.203</td>
</tr>
<tr>
<td>Hospitals</td>
<td>0.670</td>
<td>1.210</td>
<td>0.124**</td>
</tr>
<tr>
<td>Female HH w/Children</td>
<td>0.978</td>
<td>0.990</td>
<td>0.965</td>
</tr>
<tr>
<td>Vacant housing units</td>
<td>0.986</td>
<td>0.980</td>
<td>1.005</td>
</tr>
<tr>
<td>Male unemployment</td>
<td>1.045***</td>
<td>0.994</td>
<td>1.108***</td>
</tr>
</tbody>
</table>

** Wald chi-square: 38.86***  9.180  52.2***
** AICc: 90.28  344.94  10,371.78
** Non zero obs.: 83  68  42
** Log pseudo likelihood: -181.173  -128.97  -124.67

Notes: Incidence rate ratios (IRR) are presented. Robust standard errors were utilized where statistical significance is identified as *p < 0.10, **p < 0.05, ***p < 0.01. The variable Parks was omitted due to collinearity.
Table 6 Results of Geographically Weighted Poisson Regression (GWPR)

<table>
<thead>
<tr>
<th></th>
<th>All crimes</th>
<th>Violent crimes</th>
<th>Non-violent crimes</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCTV</td>
<td>0.709</td>
<td>1.007</td>
<td>0.434</td>
</tr>
<tr>
<td>Parking lots</td>
<td>1.358</td>
<td>0.924</td>
<td>0.422</td>
</tr>
<tr>
<td>Banks</td>
<td>1.606</td>
<td>0.988</td>
<td>0.280</td>
</tr>
<tr>
<td>Hotels</td>
<td>0.976</td>
<td>1.029</td>
<td>0.809</td>
</tr>
<tr>
<td>Bars and restaurants</td>
<td>0.970</td>
<td>0.979</td>
<td>1.010</td>
</tr>
<tr>
<td>Metro stations</td>
<td>4.771</td>
<td>1.014</td>
<td>0.587</td>
</tr>
<tr>
<td>Main avenue</td>
<td>0.376</td>
<td>0.920</td>
<td>4.015</td>
</tr>
<tr>
<td>Hospitals</td>
<td>0.997</td>
<td>0.985</td>
<td>0.727</td>
</tr>
<tr>
<td>Female HH w/Children</td>
<td>0.985</td>
<td>1.009</td>
<td>1.022</td>
</tr>
<tr>
<td>Vacant housing units</td>
<td>0.959</td>
<td>1.016</td>
<td>0.947</td>
</tr>
<tr>
<td>Male unemployment</td>
<td>0.484</td>
<td>1.515</td>
<td>0.820</td>
</tr>
<tr>
<td><strong>Bandwidth</strong></td>
<td><strong>308</strong></td>
<td><strong>99</strong></td>
<td><strong>64</strong></td>
</tr>
<tr>
<td><strong>AICc</strong></td>
<td><strong>91.77</strong></td>
<td><strong>328.03</strong></td>
<td><strong>8094.14</strong></td>
</tr>
</tbody>
</table>

Notes: Incidence rate ratios (IRR) of the GWR mean coefficients are presented. GWR mean coefficients calculated with the use of Adaptive Gaussian kernels. The variable Parks was omitted due to collinearity in previous models.
FIGURES

Figure 1 Colonia Roma, 2015

Source: Own based on GIS Community
Figure 2 Colonia Roma: Spatial hotspots and coldspots of crime, 2013

<table>
<thead>
<tr>
<th>All crimes</th>
<th>Violent crimes</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="http://mc.manuscriptcentral.com/gppr" alt="Map of All crimes" /></td>
<td><img src="http://mc.manuscriptcentral.com/gppr" alt="Map of Violent crimes" /></td>
</tr>
<tr>
<td><img src="http://mc.manuscriptcentral.com/gppr" alt="Legend for All crimes" /></td>
<td><img src="http://mc.manuscriptcentral.com/gppr" alt="Legend for Violent crimes" /></td>
</tr>
</tbody>
</table>

Source: Own based on Police data. Threshold distance: 131 meters.
Figure 3 Colonia Roma: Spatial distribution of police CCTV cameras in operation, 2013

Source: Own based on Police data
Figure 4 Local t values for the number of police CCTV cameras as a predictor of crime

All crimes

<table>
<thead>
<tr>
<th>Equal Intervals: AllCCTV</th>
</tr>
</thead>
<tbody>
<tr>
<td>[-0.63, -0.573] (119)</td>
</tr>
<tr>
<td>[-0.573, -0.517] (82)</td>
</tr>
<tr>
<td>[-0.517, -0.46] (157)</td>
</tr>
</tbody>
</table>

Violent crimes

<table>
<thead>
<tr>
<th>Equal Intervals: VicCCTV</th>
</tr>
</thead>
<tbody>
<tr>
<td>[-0.91, -0.857] (122)</td>
</tr>
<tr>
<td>[-0.857, -0.804] (84)</td>
</tr>
<tr>
<td>[-0.804, -0.75] (97)</td>
</tr>
</tbody>
</table>

Non violent crimes

<table>
<thead>
<tr>
<th>Equal Intervals: NvicCCTV</th>
</tr>
</thead>
<tbody>
<tr>
<td>[-0.55, -0.38] (144)</td>
</tr>
<tr>
<td>[-0.38, -0.21] (74)</td>
</tr>
<tr>
<td>[-0.21, -0.04] (90)</td>
</tr>
</tbody>
</table>

Source: Own based on GWPR results