The Crime Reduction Effects of Public CCTV Cameras: A Multi-Method Spatial Approach

Jerry H. Ratcliffe, Travis Taniguchi and Ralph B. Taylor

Public Closed Circuit TeleVision (CCTV) initiatives have been utilized as methods of monitoring public space for over two decades. Evaluations of these efforts to reduce crime have been mixed. Furthermore, there has been a paucity of rigorous evaluations of cameras located in the USA. In this analysis, crime in the viewshed of publicly funded CCTV cameras in Philadelphia, PA, is examined using two evaluation techniques: hierarchical linear modeling and weighted displacement quotients. An analysis that incorporates controls for long-term trends and seasonality finds that the introduction of cameras is associated with a 13% reduction in crime. The evaluation suggests that while there appears to be a general benefit to the cameras, there were as many sites that showed no benefit of camera presence as there were locations with a positive outcome on crime. The policy implications of these findings are discussed.

Keywords CCTV; video surveillance; repeated measures; hierarchical linear modeling; weighted displacement quotients; Philadelphia

Introduction

Closed Circuit Television (CCTV) seeks to reduce crime primarily by increasing the perception among potential offenders that there is an increased risk of

Jerry Ratcliffe is a Professor in the Department of Criminal Justice at Temple University. Recent books have included *Intelligence-Led Policing*, and *Strategic Thinking in Criminal Intelligence* (second edition). Further details are online at jratcliffe.net. Travis Taniguchi is a doctoral candidate in the Department of Criminal Justice at Temple University. His publications can be found in *Justice Quarterly* and *Crime Patterns & Analysis*. Ralph B. Taylor is a Professor in the Department of Criminal Justice at Temple University. Research interests include incivilities, communities and crime, reactions to crime, guns, juries, and DNA policies. Publications are listed online at www.rbtaylor.net/pubs.htm. Correspondence to: Jerry H. Ratcliffe, Department of Criminal Justice, Temple University, 1115 W. Berks Street, Philadelphia, PA 19122, USA. E-mail: jhr@temple.edu



detection and capture (Ratcliffe, 2006). Proponents of CCTV argue that increased surveillance will reduce crime and increase arrests of offenders, while opponents lament the invasion of privacy in public areas and point to research findings that are less than definitive. Irrespective of the theoretical validity of the crime prevention role of CCTV systems, the growth of CCTV schemes across numerous countries (including the USA) has been substantial. The history of CCTV technology is one of rapid evolution from static, low-resolution cameras to high quality technology solutions that can pan, tilt, and zoom at the command (through either wireless interface or fiber optic cable) of remote operators connected to a police radio network. This implementation and technological expansion of CCTV schemes has, until recently, taken place in an environment largely devoid of rigorous evaluation of the effectiveness of CCTV to prevent crime (see Welsh & Farrington, 2007, for a comprehensive review).

The emergence of CCTV has taken place during a period when crime analysis has improved in resolution (both spatial and temporal) enabling academic research and practitioner focus to become more place-specific rather than generalized to the neighborhood level (Mazerolle, Hurley, & Chamlin, 2002), and during a period that has seen the rise of problem-oriented policing (Clarke, 2004; Goldstein, 2003) as an operational strategy that can capitalize on the analytical improvements available. Intelligence-led policing has provided a business model to coordinate crime detection and prevention activities, through which problem-oriented policing can flow in an operational environment (Ratcliffe, 2008). From the earliest wide-scale implementation of CCTV technology in Britain in the 1980s, however, the assessment of CCTV schemes has been significantly hampered on two fronts. Numerous well-meaning evaluations have lacked either an impartial perspective and/or methodological rigor. For example, many have been either conducted by city agencies or technology companies involved in the scheme and whom may be perceived to have vested interests in the evaluation outcomes: or, like the earliest independent evaluation of a CCTV implementation from King's Lynn, UK (Brown, 1995)—where 19 cameras were installed at public car parks across the city—had methodological limitations due to a lack of controls for seasonality or long-term temporal trends. Numerous other studies since King's Lynn have lacked measures of control areas, controls for seasonal variation, or have been absent of any indicators of potential displacement (or diffusion of benefits).

Furthermore, the existing evaluation literature demonstrates considerable variation in not only methodology, but also outcome measures and independent variables. Some studies examine the impact of cameras on crime within a defined distance of CCTV cameras (Harada, Yonezato, Suzuki, Shimada, Era, & Saito, 2004), while others surveyed residents in camera areas for their perceptions of how crime has changed (Squires, 2003). Other studies have interviewed key stakeholders (Hood, 2003) or examined emergency room attendance levels related to assaults (Sivarajasingam, Shepherd, & Matthews, 2003).

Welsh and Farrington's (2007) systematic review identified four essential criteria for inclusion in their study:

- (1) CCTV was the main intervention examined;
- (2) the outcome measure was crime;
- (3) the evaluation had a minimum methodological design that incorporated at least before-and-after measures of crime in experimental and comparable control areas; and
- (4) there was a minimum number of crimes (20) recorded in the experimental area prior to the CCTV implementation.

Even within this basic evaluation criteria framework, Welsh and Farrington (2007) had to exclude numerous studies because they lacked appropriate and comparable control areas. They were able to identify 44 relevant studies, but only 22 that were applicable to city centers and public urban areas. Of these 22 studies, 17 were conducted in the UK, two in Scandinavia, and three from the USA; however, the three from the USA were actually at three locations in Cincinnati, Ohio, and were reported in a single journal article (Mazerolle et al., 2002).¹

Given the scarcity of CCTV evaluations in the USA, the study conducted by Mazerolle et al. (2002) is worth discussing in some depth both because of its innovations and its limitations. This study utilized a multi-method approach to evaluating the CCTV initiative in Cincinnati, Ohio. First, they used an innovative method to measure both pro- and anti-social behavior in the vicinity of the camera locations. The researchers reviewed random samples of video captured by the cameras and coded activity along a number of dimensions including: the quality of image being recorded, the number of people and vehicles at the target site, and a range of pro-social (e.g., pedestrian traffic and people shopping) and anti-social (such as people loitering, dealing drugs, or begging) behaviors. Use of interrupted time series models found a complicated relationship between the implementation of cameras and their crime deterrence effects. The second evaluation method evaluated the change in calls for service (not recorded crime) in the areas surrounding CCTV target sites. Overall, it was concluded that the implementation of CCTV systems produced an initial deterrence effect in the one to two months following implementation. This crime suppressing effect, however, seemed to decline as people adapted to camera placement. While the study conducted by Lorraine Mazerolle and colleagues is methodologically sound and empirically sophisticated, there are a number of limitations that are worth addressing. First, the use of calls for service rather than recorded crime basically means that there has not been a single study of CCTV in America that uses recorded crime as an outcome measure in a manner that satisfies Welsh and Farrington's (2007) systematic review criteria. Second, the authors utilized circular buffers surrounding the camera target areas. These uniform buffers are not sensitive to the actual viewsheds of the cameras. It is possible that these buffers are both over-inclusive and under-inclusive of areas

^{1.} There have also been two US studies that examined CCTV in public housing complexes. These are discussed in Welsh and Farrington (2007).

where cameras may have a crime deterrent effect. Finally, Mazerolle et al (2002) do not consider the possible displacement effects of camera implementation. The current evaluation attempts to rectify these limitations.

The lack of evaluation research seems a significant omission on the part of the research community given the growing enthusiasm across America for CCTV. While there are no national estimates on the extent of CCTV across America, newspaper accounts suggest that CCTV cameras are being implemented at a significant rate. For example, San Francisco has spent close to \$1m on 74 cameras at 25 locations, and a further 25 cameras are planned (Bulwa, 2008); and Washington, DC plans a \$4.5 million expansion of its surveillance system (Klein, 2008). This rapid and unprecedented expansion of video surveillance technology is not just limited to the major urban areas (Welsh & Farrington, 2007). Reductions in technology cost and a perception that CCTV is a cost-effective crime prevention tool, have driven investment in video surveillance in municipal areas across America.

For all this enthusiasm for video surveillance, there has been a lack of high quality, independent evaluation studies (Eck, 1997). Using Hierarchical Linear Modeling (HLM) and Weighed Displacement Quotient (WDQ) methodologies, we explore serious crime, disorder crime, and an all-crime measure combining serious crime and disorder, with a multi-method spatio-temporal evaluation of 18 pilot CCTV cameras across 10 sites in Philadelphia, PA.

Data

Camera types, locations, and implementation details

The Philadelphia pilot project employed two different camera types. Eight pan, tilt, zoom (PTZ) cameras were installed between July 2006 and October 2006. These cameras have the capacity to tilt up and down, pan around the surrounding area, and zoom. Examination of the zoom capacity by the researchers indicated that the camera allows the police officer to read a car license plate more than a block away, and observe street activity up to three blocks distance, if the view is unobstructed. The video feed is routed directly to police headquarters where a police officer monitors all PTZ cameras in real time. The images are also recorded digitally, with a hard drive storage capacity sufficient to store images for 12 days.

The remaining 10 cameras did not allow for live monitoring. The Portable Overt Digital Surveillance System (PODSS) cameras, as implemented in Philadelphia, provide a moveable, self-contained digital camera and recording system that is housed in a bullet-resistant unit with flashing strobe lights to draw the attention of the public and potential offenders. The cameras are visually quite different from the PTZ cameras, being housed in a much larger and more visible unit. As implemented in Philadelphia, these cameras are not monitored at police headquarters; however, nearby patrol officers with the correct

equipment in two-officer cars can theoretically view the feed from cameras over a wireless link (though the senior officer in charge of implementation did not believe this took place on any regular basis). The system is also able to record up to five days of street activity on a digital hard drive. When a crime is suspected to have occurred within the view of the camera, a police officer meets street engineering personnel from the city and the digital video record hard drive is retrieved from the unit with the aid of a crane. Discussions with police officers suggested that the whole process can take up to two hours.

Although there are a total of 18 cameras at 12 locations, some cameras are located so close to other cameras (within a block's distance) that the decision

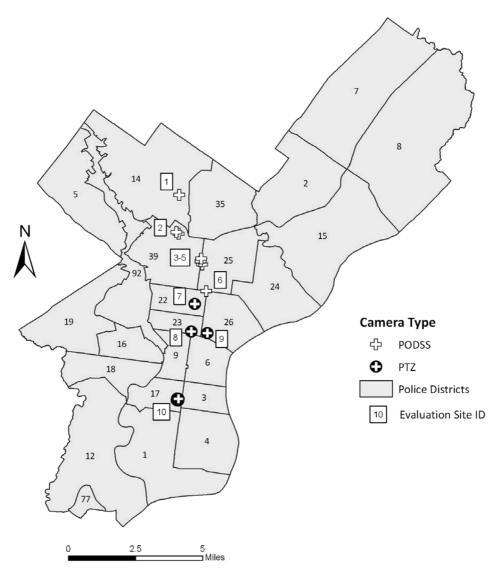


Figure 1 Pilot project camera locations in Philadelphia, PA.

was made to evaluate spatial sites rather than individual cameras. The situation is further complicated by cameras three to five which are not located at a single site but are close enough that any potential displacement would likely be to overlapping areas. Therefore, we collapsed sites three to five into a single location leaving eight different evaluation areas, labeled 1, 2, 3-5, 6, 7, 8, 9, 10 on Figure 1. The choice of camera was dictated by the locational demands of the area, and was made by Philadelphia Police Department (PPD) officers prior to our involvement in the project.

Offender perception or camera viewshed?

It can be argued (e.g., Ratcliffe, 2006) that from a rational choice perspective (Clarke & Felson, 1993; Cornish & Clarke, 1986; Jeffery & Zahm, 1993) comes the supposition that cameras may work to prevent crime if two criteria are met: the offender is aware that the camera may be monitoring their activity, and the offender perceives that the risk of capture by police may outweigh the benefits of the crime they are considering. As crime prevention is therefore a feature of offender perception, it may be that irrespective of whether cameras may only be able to see a certain amount of public space, offenders perceive that the cameras can observe their activity to a greater or lesser range. The choice from an evaluation standpoint is therefore to define target evaluation areas based on possible offender perception of camera range, or on the actual area that the camera can view.

The difficulty with offender perceptions is that they are not measurable without extensive and expensive interviewing. Furthermore, the resultant offender perception will most likely vary from person to person. In other words, while the range of a CCTV camera—as perceived by a criminal—is in the eye of the beholder, finding and interviewing suitable beholders is beyond the budget of most studies, and the results are likely to be quite variable.

The second option is to define the boundaries of a likely impact area by the extent of actual camera vision. The advantages of this approach include being able to: work with camera operators to establish the viewshed of cameras; incorporate the natural constraints on viewsheds (such as trees or buildings); include areas that camera operators are likely to initiative action within; and build spatial map units that reflect a single areal unit for the camera. In the analysis conducted here, this approach is taken; namely, to map the actual area that cameras can view. Furthermore, in the event of a misspecification of the surveillance zone, the weighted displacement quotient (WDQ) analysis is able to incorporate a measure for diffusion or displacement.

For the PTZ cameras, we visited the CCTV viewing station at PPD headquarters. The researchers worked with PPD officers to map the individual viewsheds of the cameras by panning and zooming the cameras and discussing active viewing areas with the officers. In combination with street maps, we were able to establish the workable range of each camera. This approach is sensitive to the

geography of the camera location and was therefore deemed preferable to the selection of an arbitrary buffer distance that counts crime up to a fixed distance in all directions from the camera, a technique employed by Harada and colleagues (2004). Because, as previously stated, the authors were unable to view the video feed from PODSS cameras (it is not a live feed in Philadelphia), the target area was designated as simply the junction (street intersection) where the camera was located, a choice supported by PPD officers that had viewed footage from fixed cameras.

Two areas were designated around each camera site. The first area was designated the target area—the area where the cameras are expected to have a positive effect. Buffer areas were also generated around camera locations. These areas were designed to be likely places in the surrounding neighborhood of the cameras where crime activity could potentially be displaced. The buffer area is also a zone where potential diffusion of benefits (Clarke & Weisburd, 1994) could occur. This can happen when the cameras exert a benefit to surrounding areas beyond their target area, and may occur because offenders move out of the general area of the camera, or offenders at unviewed areas curtail their activity because they think the camera can still see them. Displacement areas began as simple 500 ft buffers surrounding the target areas. 500 ft was chosen as a rounded median estimation of the length of one city block. These 500 ft buffers were then adjusted to account for local geography and road patterns surrounding each location. This means that at some locations the displacement buffer was slightly less than 500 ft while in others it was greater. While it may seem intuitively better to have uniform displacement areas, doing so ignores the substantial variability in the geography surrounding camera implementation areas. For example, the use of actual camera viewsheds can mean that a 500 ft buffer stretches to just short of a neighboring intersection. In circumstances like this, the addition of an extra 20 ft is sufficient to include the street intersection (and thus the crime at that location) and create a buffer that is a more realistic approximation of the likely displacement area. The method utilized here, while requiring more effort and a greater understanding of local geographic conditions, produces more realistic target and displacement areas. Figure 2 illustrates the unique shape of PTZ buffers compared to the more traditional buffer approach that was utilized for the PODSS cameras.

Finally, as a control on general trends in the surrounding areas beyond the target and buffer area, the surrounding police district(s) beyond the displacement areas became designated as a control area. As such, the control areas are comparable across both socio-economic and organizational parameters. First, the control areas represented territory that was within the region of the target (experimental) area, so remained within the generalized socio-economic structure of the block of neighborhoods that make up the police district. By being within the same police district as the cameras, the control areas were also susceptible to the same organizational forces that affected the camera areas. Researchers using control areas that are in entirely different police districts run the risk that the districts without cameras may conduct a different style of

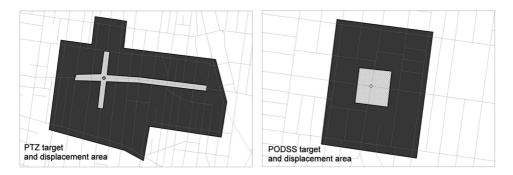


Figure 2 Example of PTZ and PODSS camera target and displacement area. The camera location is shown as a small cross in the center of each image, while the lighter (hash-marked) area near the center is the designated target area. Potential buffer areas (to assess displacement or diffusion of benefits) are shown as dark grey. Individual lines indicate a road network.

policing or introduce their own crime fighting initiatives that could confound the study. Using control areas that are in the same district as the cameras means that both target and control areas are policed in generally the same manner, resulting in greater comparability of area for the study.

Where a camera target or buffer area intersected more than one police district, we used the remainder (all areas not included with target and buffer areas) of the intersecting police districts combined. Table 1 provides details of how these control areas were constructed, along with the number of months the cameras had been operational at the site at the time of evaluation, the specific dates of the pre-/post-camera implementation evaluation period, the camera type, the number of cameras deployed at that location, and the police district. As can be seen from the last column of the table, the definition of control areas was confounded by camera sites being relatively close to each other, and sometimes on the boundary between police districts.

Crime data

Crime data from January 2005 through August 2007 (32 months) was sourced from the PPD's Crime Analysis and Mapping Unit. This dataset contained information about crime type, date, and the x-y coordinates of the crime location, as geocoded by the PPD to a successful geocoding hit rate in excess of 97%; a satisfactory level in excess of minimum geocoding levels estimated through simulation processes (Ratcliffe, 2004).

This evaluation limits crimes examined in the study to those that could be expected to be influenced by CCTV cameras. Therefore, only crimes that generally occur on the street were included in the analysis. In other words, theft from a vehicle is included while theft by shoplifting (because it would happen inside a store away from the view of the camera) is not. The crimes are aggregated into

: parameters
quotient
displacement quot
weighted (
Specification of v
e 1

)		-			
Site	Months camera operational	Pre- implementation dates	Post- implementation dates	Camera type	No. of cameras	Location (police district)	Control area composition
_	6	Jan 2005-Nov 2006	Dec 2006-Aug 2007	PODSS	-	41	14th police district crime totals, minus target and displacement areas for camera at site 1
2	6	Jan 2005-Nov 2006	Dec 2006-Aug 2007	PODSS	2	39	39th police district crime totals, minus target and displacement areas for cameras at site 2
3-5	10	Jan 2005-Oct 2006	Nov 2006-Aug 2007	PODSS	4	25	25th and 39th police district crime totals, minus target and displacement areas for cameras at sites 2-5
9	10	Jan 2005-Oct 2006	Nov 2006-Aug 2007	PODSS	-	25	22nd, 25th and 26th police district crime totals, minus target and displacement areas for cameras at sites 3, 4, 5, 6, 7, and 9
_	7	Jan 2005-Sep 2006	Oct 2006-Aug 2007	PTZ	2	22	22nd police district crime totals, minus target and displacement areas for cameras at site 2
∞	1	Jan 2005-Sep 2006	Oct 2006-Aug 2007	PTZ	2	23	6th, 9th and 23rd police district crime totals, minus target and displacement areas for cameras at site 8
6	4	Jan 2005-Jun 2006	July 2006-Aug 2007	PTZ	2	26	26th police district crime totals, minus target and displacement areas for camera at site 9
10	7	Jan 2005-Sep 2006	Oct 2006-Aug 2007	PTZ	4	17	17th police district crime totals, minus target and displacement areas for camera at site 10

three categories; serious crime (UCR Part 1 street offenses), disorder crime (UCR Part 2 street offenses), and all crime (the sum of the unweighted serious and disorder crime categories). The full list of crimes included in the analysis can be found in Appendix A.

Analysis

Two methods were utilized to investigate the impact of camera implementation upon localized crime. HLM allows for rigorous statistical evaluation of camera implementation while controlling for factors such as seasonality and ongoing trends. The use of HLM in this analysis, however, is limited because it is not possible to investigate specific cameras or specific locations. In order to further investigate the effects of specific cameras we utilize WDQ as described by Bowers and Johnson (2003). We discuss the HLM model first.

Hierarchical Linear Modeling

HLM is a type of statistical analysis that recognizes nested data structures (Raudenbush & Bryk, 2002; Snijders & Bosker, 1999). This also applies to repeated observations across individuals or locations (Laird & Ware, 1982). The current analysis examines time nested within camera locations. The particular analysis completed has a number of practical benefits. First, it includes a variable that statistically controls for seasonal effects on crime. Seasonal effects could be particularly important for the street crimes under analysis here, because people spend more time outside when the weather is warmer. Secondly, the analysis controls for preexisting temporal trends at each camera location. Failing to control for these pre-camera implementation trends could result in under or overestimating the cameras' effects on crime patterns. Examples of such pre-camera implementation trends include the possibility of regeneration taking place near a camera location potentially resulting in a generally declining crime trend—an additional effect beyond simple seasonal variation.

Specific HLM variables are as follows. The *length of month* variable represents the number of days per month, given that it is reasonable to expect that longer months will have higher crime counts. The *temporal trend* variable represents the sequential position of the month in the data series in the level-1 HLM equation. This variable captures the linear trend of crime around the cameras over time at each location. This variable can be positive if crime is generally increasing, negative if crime is decreasing or zero if the crime trend is showing no change over time. The ongoing effects of changes over time are tailored for each location in that each camera location is allowed to have its own unique linear crime trend over time.

A seasonal effect variable controls for seasonality through the use of a value to represent the monthly average of the average daily temperature. These

figures were obtained from the historical archives provided by Weather Underground (available at www.wunderground.com/history). The *camera* variable represents the effects of camera implementation (0 = non-camera month; 1 = camera implemented). Because of the other variables included, this variable represents camera implementation while controlling for length of the month, pre-existing crime trends, and seasonal effects.

At level-1, the units are repeated measurements (monthly observations from January 2005 through August 2007) on the dependent (crime count) and independent (camera implementation, length of month, pre-existing crime trends, and seasonal effects) variables. These level-1 repeated measures are nested within the level-2 units (cameras). In this analysis, three dependent variables are utilized; serious crimes, disorder crimes, and all crime (the sum of both serious offenses and disorder crimes).

These separate dependent variables were modeled using the same specifications for the independent variables. All three dependent variables are non-normally distributed. For this reason, the HLM models are specified as a Poisson distribution with over-dispersion.² Thus, all models follow the specification:

Crime Count_{it} =
$$\beta_{0i}$$
 + β_{1i} (Length of month) + β_{2i} (Temporal trend)
+ β_{3i} (Seasonal effect) + β_{4i} (Camera) + r_{it}

Where $\operatorname{Crime} \operatorname{Count}_{it}$ is the number of crimes occurring within the camera buffer area for camera i at time t; β_{0i} is the mean crime count in camera i in April 2006 (the mid-point of the study period) when length of month and seasonal effects are set to their mean for camera i; β_{1i} is the slope coefficient for length of month for camera i; β_{2i} is the slope for the linear temporal trends at camera i; β_{3i} is the slope coefficient for the impact of seasonal trends at camera i; β_{4i} is the slope coefficient for the dummy variable representing camera implementation at camera location i; and r_{it} is the residual or unexplained variance.

The level-2 model was specified as:

$$\begin{split} \beta_{0i} &= \gamma_{00} + u_{0i} \\ \beta_{1i} &= \gamma_{10} \\ \beta_{2i} &= \gamma_{20} + u_{2i} \\ \beta_{3i} &= \gamma_{30} \\ \beta_{4i} &= \gamma_{40} \end{split}$$

where γ_{00} is the average intercept (mean crime count) in April 2006 across all cameras; γ_{10} represents the fixed slope of the length of the month; γ_{20} repre-

^{2.} All three dependent variables demonstrate over-dispersion with a standard deviation greater than the mean: serious crime m = 3.86, sd = 4.48; disorder crime m = 15.60, sd = 18.22; all crime m = 19.46, sd = 21.51.

sents the varying slope of ongoing temporal trends; γ_{30} represents the fixed slope of seasonal effects; γ_{40} represents the fixed slope of camera implementation; and u_{0i} and u_{2i} are the residuals or unexplained between camera variance in the intercept and temporal trend slope coefficients, respectively.

Weighted Displacement Quotient (WDQ)

Bowers and Johnson's (2003) WDQ is employed to determine if differences between the target and buffer areas are a result of displacement from the target area or a diffusion of benefits from the use of CCTV surveillance in the target area. The determination of a WDQ first requires the researcher to determine three operational areas; the target area where the crime reduction strategy has been deployed (in this case, CCTV camera viewsheds), a buffer area that is estimated to be the most likely location that crime would be displaced to, and a control area that acts as a check on general crime trends that are affecting the region in general. The equation for the WDQ is as follows:

$$WDQ = (Bt_1 / Ct_1 - Bt_0 / Ct_0) / (At_1 / Ct_1 - At_0 / Ct_0),$$

where A is the count of crime events in the target area, B is the count of crime events in the buffer area, C is the count of crime events in the control area, t_1 is the time since the camera(s) have been active, and t_0 is the preintervention time period (in this case, an equivalent number of months immediately prior to the installation of the cameras). The examination of the difference between the buffer and control areas from the pre-intervention to the intervention period provides the measure of displacement or diffusion into the buffer area, while the differences between the target and control area ratios at both times provide the measure of success for the intervention. The equation above is therefore comprised of both a buffer displacement measure $(Bt_1/Ct_1 - Bt_0/Ct_0)$ and a success measure $(At_1/Ct_1 - At_0/Ct_0)$.

If the success measure is a positive value, this indicates that the camera implementation was *not* successful in reducing crime when compared to the control area. In this situation—indicating the camera implementation was unsuccessful in reducing crime—then neither the displacement measure nor the WDQ values are calculated. Only if the success measure indicates a reduction in crime in the target area is a displacement measure calculated. If the displacement measure is a positive number, this indicates that when the cameras were implemented, crime went up in the buffer area to a greater extent than in the control area. This is suggestive of a displacement effect. A negative displacement value suggests a diffusion of benefits from the target area to the buffer area.

Finally, these two values are combined to form the WDQ value. According to Bowers and Johnson (2003), WDQ values greater than 1 indicate crime reductions in the target area and substantial diffusion of benefits to the surrounding

buffer. WDQ values between 0 and 1 indicate diffusion of benefits that are less than the direct crime reduction effect found in the target area. WDQ values between 0 and -1 indicate slight displacement from the target area into the buffer area. WDQ values near -1 indicate displacement effects that offset the reduction effects seen in the target area. A value near -1 indicates no net benefit for the program. WDQ values less than -1 indicate displacement effects much greater than the crime reduction effects in the target area.

Results

The following section will present the results from both the HLM analysis and the WDQ analysis grouped by crime type: serious crime, disorder crime, and all crimes. Each crime type was analyzed using both HLM and WDQ.

Serious crime

Results from the initial ANOVA 3 analysis found that there are, on average, 2.67 serious crimes per month per location with significant variation between locations (p < 0.001). The temporal trend variable showed that there were, on average, no significant linear crime trends during the time period under analysis here. Across all camera locations, crime was neither rising nor falling during the time period (as reflected by the temporal trends variable). The results also found no evidence of significant seasonal trends. The HLM analysis of serious crimes found that camera implementation had no significant impact upon the amount of crime in the target area. Serious crime decreased slightly after camera implementation, by about 5%, but this drop was not statistically significant. Overall, the inclusion of days per month, temporal trends, seasonal effects, and camera implementation explained about 3.4% of the variance in serious crime count. Table 2 presents the results from the HLM analysis using serious crime as the dependent variable.

Table 3 shows each camera site, followed by the percentage change (post-camera implementation compared to an equivalent period pre-implementation) in crime level in the target area, the buffer area and the control area for that site. If these values are positive numbers, then this indicates that crime increased in the area during the time when the camera was functioning at that location, compared to an equivalent number of months before the introduction of the cameras. For serious crimes, four camera locations (sites 3-5, 6, 9, and 10) demonstrated reductions in crime in the target area when compared to the control area. For these locations displacement measures and WDQ values were calculated. The WDQ values indicated that sites 3-5, 6, and 10 showed crime reduction in the target area and a diffusion of benefits into the surrounding

^{3.} ANOVA analyses were conducted with no predictor variables entered into the HLM equation.

			_		. 1
Table 2	HI M	recults	tor	SELIUIS	crime

Fixed Effects	Coefficient (S.E.)	Event rate ratio	Confidence interval
Number of days per	0.064 (0.034)	1.066	0.997-1.140
Temporal trend	0.002	1.002	0.989-1.015
Seasonality	0.003	1.003	1.000-1.007
Camera	-0.050 (0.104)	0.951	0.774-1.169
Random effect Between camera (level-2)	Variance component	Chi-square	Df
Mean crime count	0.859**	1855.120	9
Temporal trend	0.007*	17.394	9
Within-camera (level-1)			
Residual variation	0.889		
Total variance explained	3.357%		

^{*}p < 0.05, **p < 0.001.

buffer area. Site 9 shows crime reduction in the target area and more modest crime reduction in the surrounding buffer area. Table 3 presents the results of the WDQ analysis for serious crime.

Disorder crime

Results from the ANOVA analysis finds that there are, on average, 8.34 disorder crimes per month per location with significant variation between locations (p < 0.001). Table 4 provides the results of the HLM analysis when investigating the impact of cameras upon disorder crimes. As expected the length of month was a significant predictor of higher crime counts. The temporal trend variable showed that the number of disorder crimes increased slightly during the study period, on average, across all locations. The expected count of disorder crimes increased, on average, about 1.3% every month across the evaluation sites. The significance of the seasonality variable indicates that there are more disorder crimes in warmer months. The coefficient for the camera variable indicates that camera implementation significantly reduced disorder crime in the target area. After camera implementation, the average expected disorder crime count for the target areas was 16% lower, after controlling for all other variables. Overall, the inclusion of days per month, temporal trends, seasonal effects, and camera implementation explained about 10.4% of the variance in disorder crime count.

¹Dependent variable specified as Poisson distribution with over-dispersion. Number of days per month, seasonality, and camera implementation dummy were specified as fixed slopes. The temporal trend variable was specified as varying slope.

Table 3 Weighted displacement quotient (WDQ) for serious crimes¹

WDQ Interpretation of WDQ	Did not reduce crime in the target area	Did not reduce crime in the target area	Camera reduced crime, and there was strong diffusion of benefits	Camera reduced crime, and there was strong diffusion of benefits	Did not reduce crime in the target area	Did not reduce crime in the target area	Camera reduced crime, and there was some diffusion of benefits	Camera reduced crime, and there was strong diffusion of benefits
WDQ			1.852	2.914			0.350	1.832
Displacement measure			-0.003	-0.001			-0.002	-0.010
Success Displacer measure measure	0.00004	0.00040	-0.00163	-0.00021	0.00279	0.00398	-0.00583	-0.00540
Control	-0.8	8.9	-2.4	-10.9	1.3	-0.3	9.4	5.4
Buffer	17.0	9.9	-20.5	-15.0	7.7	7.1	5.4	-9.2
Target	0.0	14.3	-28.9	-18.2	11.1	14.6	-15.0	-21.4
Camera Type	PODSS	PODSS	PODSS	PODSS	PTZ	PTZ	PTZ	PTZ
Site	_	2	3-5	9	7	∞	6	10

¹Target, buffer, and control categories are expressed as percent change between the number of crimes pre- and post-camera implementation. Displacement measure and WDQ are not calculated if the success measure does not indicate crime reduction in the target area.

Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval
Number of days per month	0.052* (0.023)	1.054	1.007-1.103
Temporal trend	0.013* (0.006)	1.013	1.001-1.026
Seasonality	0.006** (0.070)	1.006	1.004-1.009
Camera	-0.174* (0.001)	0.840	0.733-0.963
Random effect	Variance component	Chi-square	Df
Between camera (level-2)			
Mean crime count	1.578**	6357.731	9
Temporal trend	0.000**	68.442	9
Within-camera (level-1)			
Residual variation	0.1627		
Total variance explained	10.421%		

Table 4 HLM results for disorder crime¹

WDQs were calculated using disorder crimes as the outcome variable. Sites 3-5, 8, 9, and 10 had success measures indicating a reduction in crime after the implementation of the cameras; therefore, displacement measures were calculated for these locations. For these four sites, only one had a negative displacement measure. Overall, sites 1, 2, 6, and 7 had no reduction in crime after implementation of the cameras. Sites 3-5 and 10 had reductions in the target area but these reductions were offset by displacement into the surrounding areas. Site 8 had a reduction in crime in the target area but slight increases in the buffer area, though there was an overall reduction in crime. Only camera 9 demonstrated a crime reduction in the target area with a diffusion of benefit into the buffer area. Table 5 presents the findings from the WDQ analysis for disorder crimes.

All Crime

The final analysis combined serious crime with disorder events. This had the effect of weighting each incident equally, and is reported here as a measure of the value of CCTV cameras for all incidents, irrespective of seriousness. Table 6 provides the results of the HLM analysis when utilizing all (both serious and disorder) crime. Results from the ANOVA analysis find that there are, on average, 11.35 crimes per month per location with significant variation between locations (p < 0.001). The temporal trend variable was not significant; there was no change in trend during the study period. The length of month variable was significant with each additional day being related to a 5% increase in the expected count per camera. Crime counts were also significantly higher during months with higher temperatures. The implementation of cameras significantly

p < 0.05, **p < 0.001.

¹Dependent variable specified as Poisson distribution with over-dispersion. Number of days per month, seasonality, and camera implementation dummy were specified as fixed slopes. The temporal trend variable was specified as varying slope.

Table 5 Weighted displacement quotient (WDQ) for disorder crimes¹

WDQ Interpretation of WDQ	Did not reduce crime in the target area	Did not reduce crime in the target area	-3.454 Camera reduced crime, but displacement negated gains	Did not reduce crime in the target area	Did not reduce crime in the target area	-0.209 Camera reduced crime, but there was slight displacement (net gain)	0.479 Camera reduced crime, and there was some diffusion of benefits	-2.267 Camera reduced crime, but displacement negated gains
Success Displacement neasure measure			0.001			0.001	-0.005	0.009
Success Control measure	0.0023	0.0017	-0.0002	0.0003	0.0008	-0.0072	-0.0107	-0.0040
Control	-9.8	-6.7	3.8	-16.7	-4.1	5.4	-6.7	8.1
Buffer	-20.2	-8.8	9.4	-26.5	0.0	10.9	-21.9	21.0
Target	19.2	11.8	1.1	-3.0	0.9	-16.4	-35.9	-2.7
Camera type	PODSS	PODSS	PODSS	PODSS	PTZ	PTZ	PTZ	PTZ
Site	_	7	3-5	9	7	∞	6	10

¹Target, buffer, and control categories are expressed as percent change between the number of crimes pre- and post-camera implementation. Displacement measure and WDQ are not calculated if the success measure does not indicate crime reduction in the target area.

Table 6	ΗΙМ	results	for	all	crime ¹

Fixed effects	Coefficient (S.E.)	Event rate ratio	Confidence interval
Number of days per month	0.055* (0.020)	1.056	1.014-1.099
Temporal trend	0.010 (0.005)	1.010	0.999-1.020
Seasonality	0.006** (0.001)	1.006	1.003-1.008
Camera	-0.142* (0.061)	0.867	0.768-0.979
Random effect	Variance component	Chi-square	Df
Between camera (level-2)			
Mean crime count	1.292**	6843.160	9
Temporal trend	0.000**	49.689	9
Within-camera (level-1)			
Residual variation	1.590		
Total variance explained	12.855%		

^{*}p< 0.05, **p < 0.001.

reduced the number of crime events within the target areas. The months following the implementation of the cameras saw a statistically significant 13.3% reduction in expected crime counts after controlling for the other factors (p < 0.05). Overall, the inclusion of days per month, temporal trends, seasonal effects, and camera implementation explained about 12.9% of the variance in the crime count.

WDQ values were calculated for all crimes. Camera locations 3-5, 8, 9, and 10 demonstrated crime reductions in the target area after implementation of the cameras. Sites 3-5 and 9 saw some diffusion of benefits into the surrounding buffer area. Site 8 saw a slight displacement of crime into the buffer area, though the crime reduction in the target area was enough to offset the effects of displacement. Finally, at site 10, the reduction of crime in the target area was offset by the displacement of crime into the surrounding buffer area. Table 7 reports the results from the WDQ analysis on all crimes.

Discussion

Overall, results from the HLM analysis suggest that the introduction of the cameras was associated with a 13% reduction in all crime in the target areas surrounding CCTV implementation sites. The reduction was statistically significant, after controlling for general temporal trends at each camera site, seasonality, and the number of days in each month. This reduction was largely

¹Dependent variable specified as Poisson distribution with over-dispersion. Number of days per month, seasonality, and camera implementation dummy were specified as fixed slopes. The temporal trend variable was specified as varying slope.

Table 7 Weighted displacement quotient (WDQ) for all crimes¹

	•			-	•			
Site	Camera Type	Target Bu	Buffer	Control	Success Control measure	Success Displacement measure measure	WDQ	WDQ Interpretation of WDQ
_	PODSS		-12.3	6.9–	0.0015			Did not reduce crime in the target area
7	PODSS	12.2	-5.4	-3.8	0.0013			Did not reduce crime in the target area
3-5	PODSS	-10.6	0.0	2.2	-0.0006	-0.0003	0.508	Camera reduced crime, and there was some diffusion of benefits
9	PODSS	-6.8	-24.3	-15.6	0.0002			Did not reduce crime in the target area
7	PTZ	4.7	-2.3	-2.9	0.0014			Did not reduce crime in the target area
∞	PTZ	-9.1	9.6	3.7	-0.0040	0.0017	-0.433	-0.433 Camera reduced crime, but there was some displacement (net gain)
6	PTZ	-34.0	-17.0	-4.9	-0.0102	-0.0043	0.424	0.424 Camera reduced crime, and there was some diffusion of benefits
10	PTZ	-5.4	14.2	7.5	-0.0042	0.0047	-1.114	-1.114 Camera reduced crime, but displacement negated gains

¹Target, buffer, and control categories are expressed as percent change between the number of crimes pre- and post-camera implementation. Displacement measure and WDQ are not calculated if the success measure does not indicate crime reduction in the target area.

due to a decline in disorder offenses, as the frequency of serious crimes around each camera location was generally too low to detect a measurable impact in serious crime alone.

This does not mean that serious crime was not impacted. It is worth noting that one would normally expect seasonality and the length of month to be significant in an analysis of serious street crime. Because the coefficients for these variables were not statistically significant, this suggests that a possible cause for this lack-of-finding is that in each month there were insufficient crimes in the target area for the technique to detect a statistically significant change. For example, serious crime in the target area for site 1 was two per month prior to and after camera installation. The values for the target area of site 2 were even lower. With this in mind, the lack of statistical significance in the serious crime category could probably be better interpreted as resulting from a lack of reported serious crime generally, rather than a failure of the CCTV initiative. In the same vein, Mazerolle et al. (2002) could not attempt an evaluation of violent crimes around CCTV locations because of the low base rate in the target areas.

A further cause of the low number of serious offenses within the purview of each camera may be the manner in which the dependent variable was constructed. First, rather than including a broad measure of all serious crime (e.g., Squires, 2003), only those serious offenses that the CCTV cameras were expected to influence were included in the dependent variable count. Secondly, rather than setting an arbitrary buffer distance out from each camera location, individual viewsheds were examined for the PTZ cameras. Had we taken the approach of Sarno, Hough, and Bulos (1999) and established a fixed buffer of 200 meters (just over 650 feet), we would most likely have included a number of offenses that occurred out of the view of a camera.

The introduction of CCTV was associated with considerably different impacts on crime at each site. At half of the sites, crime did not reduce in the target area. At four sites, serious crime was reduced and there was evidence of a diffusion of positive benefits to surrounding streets. At some sites, crime was reduced in the target area but there was apparent displacement to surrounding streets. Therefore the 13% reduction in overall crime was comprised of very different behaviors at CCTV evaluation sites.

The results of the WDQ are further complicated by the differences seen across camera type. Both PTZ cameras and PODSS cameras have examples of successful crime reduction in their target areas. From a policy perspective choosing between PTZ cameras and PODSS cameras can be important. These cameras differ on both their usefulness to police investigations and their initial installation and ongoing maintenance cost. However, from an outcome perspective, it may be that the actual camera mechanism may be less important than the choice of location. This might help to explain why both camera types appeared to have successes and failures. It may have been the location selected for camera implementation, not the camera type, that ultimately determined the crime suppression effects. Of course, this is merely raised as a hypothetical explanation given the limited number of cameras and sites under examination in

this study. It is certainly a finding from the study that merits further investigation with a larger study.

Inevitably in a study of this nature there are some limitations. Data were generously provided by the police department of the City of Philadelphia, and were provided already geocoded and with most address-specific information removed (beyond the location coordinates). As such, ground-truthing the accuracy of the geocoding process employed by the city was not possible. Our extensive previous experience with PPD data, as well as personal contact with the GIS Mapping Unit, lead us to have confidence in the accuracy and precision of their geocoding processes such that we could attempt this study, however, it should be noted that we did not perform the geocoding ourselves.

Perhaps the biggest limitation of the HLM analysis is its inability to disaggregate the effectiveness of each camera type. An attempt to control for the type of camera at each location is met with difficulty primarily because there are so few cameras to analyze. Disaggregating the analysis by the type of camera leaves too few cases for a robust statistical analysis. This line of inquiry, however, is a worthy area of further investigation. From a practical perspective, PTZ cameras and PODSS cameras have substantial differences in both initial and ongoing monitoring cost. Therefore, in order to better understand the effects of different cameras at different locations, a WDQ analysis was utilized.

Unlike the HLM analysis, WDQ is not able to incorporate sensitivity to seasonality patterns or to control for subtle trends in changing crime patterns over time. It compensates for this by incorporating a control area measurement, used to adjust the result for differences in an area not related to the target or displacement zones of the cameras. In other words, the control area provides an indication of what was happening in unaffected areas, and is a broad indication of trends over the same period of time as the CCTV intervention. WDQ does, however, provide the opportunity to measure a general indication of the success of each evaluation site, something not possible with the HLM analysis.

Policy-makers looking to this study to provide a definitive answer are likely to be a little disappointed in the ambiguity of the results. The reduction in overall crime of 13% is welcome, though the WDQ results that suggest some camera sites were unsuccessful in reducing crime at their locations casts a cloud over any suggestion of there being a benefit to blanket citywide CCTV coverage. The finding does fit into the broad pattern of results typified by the multi-site study by Gill and Spriggs (2005), the meta-analysis of Welsh and Farrington (2007, p. 46) who found a 'small but significant desirable effect on crime,' and the review by Ratcliffe (2006, p. 19) that found 'achieving statistically significant reductions in crime can be difficult.'

Evaluating the effectiveness of CCTV is often confounded by the conduct of other crime prevention initiatives at the same time, making it difficult to tease out the benefit of the cameras alone; however, some reviews have noted the benefit of bundling CCTV with other crime prevention programs as a package of measures. This may help to overcome the public perception that CCTV is a 'silver bullet' that will reduce crime in the absence of any other socio-economic

or opportunity-related changes to the local environment. Farrington, Gill, Waples, & Argomaniz (2007) concluded that CCTV could reduce crime in car parks, but was generally ineffective in residential areas or city centers; they also suggested that the benefits of CCTV may increase when implemented alongside improved lighting.

Camera success as an investigative tool (an additional factor beyond crime reduction worth considering, according to Gill & Spriggs, 2005) is potentially tied to factors such as operator familiarity with the area under examination, the likely offenders in an area, the nature of businesses and individuals in a camera location, and the type of crime common to the camera area. Further potential factors can also include the ability of local police to have sufficient resources to respond quickly to any incident viewed on the camera, as well as the nature of the local geography at a camera location; even the quickest police work can be hampered by easy and accessible escape routes for offenders. Future studies of camera effectiveness might care to consider these factors as controls on camera efficiency in the crime prevention arena.

Finally, we did not examine the issue of public perceptions of safety. It may be that CCTV is politically palatable if public surveys and interviews indicated improvements in perception of safety and quality of life within the range of CCTV even in the face of a lack of crime reduction benefits. The evidence from the British studies is not optimistic (see Gill & Spriggs, 2005); however, it should be considered an avenue for further work in the evaluation of CCTV in the USA.

Conclusion

This evaluation finds that when serious and disorder offenses were considered together crime was reduced by 13% after the implementation of the CCTV cameras while controlling for length of month, seasonal effects, and the unique temporal trends at each camera. WDQs were then utilized in an attempt to disaggregate this finding by location and camera type. While there was evidence that camera implementation had positive effects, the fact that crime did not reduce in the surveillance areas of half the sites examined cannot be ignored. Given the low volume of serious crime at each site (as measured on a monthly basis), it may be prudent to prioritize future CCTV sites based on an objective measure of the volume of crime at each intersection. Furthermore, given that the PTZ cameras are able to view activity at more than one street intersection, selection of future sites would be improved by attempting to find clusters of street intersections and blocks that have crime problems rather than single corners. If multiple locations can be viewed effectively from a single camera, this may be a more cost beneficial use of CCTV technology. Finally, the paucity of CCTV evaluations is a hindrance in advancing our understanding of any crime prevention benefits of surveillance technology, a gap in the research literature that criminologists should seek to remedy as soon as possible. Research or not, cities are moving ahead with CCTV systems, and if criminologists are to remain relevant in this crime prevention expansion, more experimental or high quality quasi-experimental research is necessary.

Acknowledgments

The researchers would like to thank Commissioner Charles Ramsey and Deputy Commissioner Jack Gaittens, Philadelphia Police Department, for supporting this project and provision of the necessary data. The views expressed herein are those of the authors and do not necessarily reflect the views or opinions of Temple University, the City of Philadelphia, or the Philadelphia Police Department.

References

- Bowers, K. J., & Johnson, S. D. (2003). Measuring the geographical displacement and diffusion of benefit effects of crime prevention activity. *Journal of Quantitative Criminology*, 19(3), 275-301.
- Brown, B. (1995). *CCTV in town centres: Three case studies* (Crime Detection and Prevention Series, Paper 68). London: Home Office.
- Bulwa, D. (2008, February 7). New criminal justice chief wants cops monitoring cameras. *The San Francisco Chronicle*, p. B-3.
- Clarke, R. V. (2004). Technology, criminology and crime science. *European Journal on Criminal Policy and Research*, 10(1), 55-63.
- Clarke, R. V., & Felson, M. (1993). Introduction: Criminology, routine activity, and rational choice. In R. V. Clarke & M. Felson (Eds.), *Routine activity and rational choice* (Vol. 5, pp. 259-294). New Brunswick, NJ: Transaction.
- Clarke, R. V., & Weisburd, D. (1994). Diffusion of crime control benefits. In R. V. Clarke (Ed.), *Crime prevention studies* (Vol. 2, pp. 165-183). Monsey, NY: Criminal Justice Press.
- Cornish, D., & Clarke, R. (1986). *The reasoning criminal: Rational choice perspectives on offending.* New York: Springer-Verlag.
- Eck, J. (1997). Preventing crime at places. In L. W. Sherman, D. Gottfredson, D. MacKenzie, J. Eck, P. Reuter, & S. Bushway (Eds.), *Preventing crime: What works, what doesn't, what's promising.* Washington DC: National Institute of Justice.
- Farrington, D. P., Gill, M., Waples, S. J., & Argomaniz, J. (2007). The effects of closed-circuit television on crime: Meta-analysis of an English national quasi-experimental multi-site evaluation. *Journal of Experimental Criminology*, 3(1), 21-38.
- Gill, M., & Spriggs, A. (2005). Assessing the impact of CCTV. London: Research, Development and Statistics Directorate [Home Office]).
- Goldstein, H. (2003). On further developing problem-oriented policing: The most critical need, the major impediments, and a proposal. In J. Knutsson (Ed.), *Problem-oriented policing: From innovation to mainstream* (pp. 13-47). Monsey, NY: Criminal Justice Press
- Harada, Y., Yonezato, S., Suzuki, M., Shimada, T., Era, S., & Saito, T. (2004, November 17-20,). *Examining crime prevention effects of CCTV in Japan*. Paper presented at the American Society of Criminology Annual Meeting, Nashville, Tennessee.
- Hood, J. (2003). Closed circuit television systems: A failure in risk communication? *Journal of Risk Research*, 6(3), 233-251.

- Jeffery, C. R., & Zahm, D. L. (1993). Crime prevention through environmental design, opportunity theory, and rational choice models. In R. V. Clarke & M. Felson (Eds.), *Routine activity and rational choice* (Vol. 5, pp. 323-350). New Brunswick, NJ: Transaction.
- Klein, A. (2008, February 21). Cameras have cut violence, study says: Skeptics suspect crime 'displacement.' *Washington Post*, p. 4.
- Laird, N. M., & Ware, J. H. (1982). Random-effects models for longitudinal data. *Biometrics*, 38(4), 963-974.
- Mazerolle, L., Hurley, D. C., & Chamlin, M. (2002). Social behavior in public space: An analysis of behavioral adaptations to CCTV. Security Journal, 15(1), 59-75.
- Ratcliffe, J. H. (2004). Geocoding crime and a first estimate of an acceptable minimum hit rate. *International Journal of Geographical Information Science*, *18*(1), 61-73.
- Ratcliffe, J. H. (2006). *Video surveillance of public places* (Problem-oriented guides for police, Response guides series no. 4). Washington DC: Center for Problem Oriented Policing.
- Ratcliffe, J. H. (2008). Intelligence-led policing. Cullompton, Devon: Willan.
- Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods*. Thousand Oaks, CA: Sage.
- Sarno, C., Hough, M., & Bulos, M. (1999). *Developing a picture of CCTV in Southwark town centres: Final report*. London: Criminal Policy Research Unit, South Bank University.
- Sivarajasingam, V., Shepherd, J. P., & Matthews, K. (2003). Effect of urban closed circuit television on assault injury and violence detection. *Injury Prevention*, 9(4), 312-316.
- Snijders, T., & Bosker, R. (1999). Multilevel analysis: An introduction to basic and advanced multilevel modeling. Thousand Oaks, CA: Sage.
- Squires, P. (2003). An independent evaluation of the installation of CCTV cameras for crime prevention in the Whitehawk estate, Brighton. Brighton: Health and Social Policy Research Centre.
- Welsh, B. C., & Farrington, D. P. (2007). *Closed-circuit television surveillance and crime prevention*. Stockholm: Swedish National Council for Crime Prevention.

Appendix A

This table lists the offenses examined in this study and their UCR codes. The categories are either 'serious' (indicating a crime from the FBI UCR Part 1 list) or 'disorder' from the (FBI UCR Part 2 list). Both categories are added together to create the 'all crime' category.

UCR code	Crime description	Category
111-116	Homicide	Serious
211, 231	Rape: stranger	Serious
300-305	Robbery: on the highway	Serious
306-308	Robbery: purse snatch (force or injury)	Serious
388-399	Robbery: of vehicle	Serious

UCR code	Crime description	Category
411-416, 421-426, 471-476	Aggravated assault	Serious
510-517, 520-521, 530-537, 540-541, 591-592	Burglary: residential (including attempts)	Serious
550-567, 570-587, 593-594	Burglary: non-residential (including attempts)	Serious
610, 620, 630	Theft: pocket picking	Serious
611, 621, 631	Theft: purse snatching	Serious
614, 618, 624, 628, 634, 638, 640, 641, 642, 643, 649	Theft: from vehicle	Serious
720, 722, 724, 726, 728	Vehicle theft (including attempts)	Serious
710, 721, 723, 727, 730, 741, 743, 725	Recovery of stolen vehicle	Serious
801, 802, 813	Simple assault	Disorder
807, 817	Resisting arrest	Disorder
1402, 1403, 1404, 1405	Vandalism: public	Disorder
1406, 1407, 1408, 1409	Vandalism: private	Disorder
1420, 1421, 1422, 1423	Graffiti	Disorder
1501-1507, 1516-1518	Violation of the uniform firearms act (VUFA): adult	Disorder
1519	Prohibited offensive weapon: adult	Disorder
1531-1534, 1541-1544	Violation of the uniform firearms act (VUFA): juvenile	Disorder
1535, 1545	Prohibited offensive weapon: juvenile	Disorder
1601	Pandering	Disorder
1602	Solicitation	Disorder
1708	Public indecency	Disorder
1710	Statutory sexual assault	Disorder
1711	Open lewdness	Disorder
1713	Aggravated indecent assault	Disorder
1716	Luring	Disorder
1801-1807	Drug sales	Disorder
1811-1817	Drug mfg., delivery, or possession with intent to deliver	Disorder
1821-1827	Drug possession	Disorder
1907	Gambling on highway	Disorder
2404	Disorderly conduct	Disorder
2501, 2502	Loitering	Disorder
3302	Minor disturbance	Disorder
3306	Disorderly crowd	Disorder