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A Longitudinal Quasi-Experimental Study of Violence and Disorder Impacts of Urban CCTV Camera Clusters

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Abstract
Methodological challenges have hampered a number of previous studies into the crime reduction effectiveness of closed-circuit television (CCTV) surveillance systems. These have included the use of arbitrary fixed distances to represent estimated camera deterrence areas and a lack of control for camera sites with overlapping surveillance areas. The current article overcomes the first of these challenges by using camera view areas individually constructed by researchers viewing and manipulating cameras to determine precise camera viewsheds. The second challenge is addressed by grouping cameras into clusters of combined viewshed areas. The longitudinal crime and disorder reduction effectiveness of these clusters of overlapping CCTV cameras is tested in Philadelphia, PA. Multilevel mixed-effects models with time-varying covariates and measures from a noncomparable control area are applied to 10 years of crime data (2003–2012) within the viewsheds of 86 CCTV cameras grouped into 13 clusters. Models applied across violent street felonies and disorder incidents find no significant impact associated with the introduction of CCTV surveillance. Potential reasons for this are discussed.

Keywords
ecology and crime/spatial analysis, crime/delinquency theory, crime prevention, law enforcement/security, property crime, other

The use of closed-circuit television (CCTV) video surveillance systems for crime prevention in public places has grown rapidly in recent years (Lim & Wilcox, 2017). In the United States, Washington, DC, New York, Baltimore, and Chicago have collectively spent more than US$40 million (Klein, 2008; LaVigne, Lowry, Markman, & Dwyer, 2011). By mid-2012, Philadelphia, PA (the site of the current study) had already spent more than US$17 million (City

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of Philadelphia, 2012). CCTV systems have the potential to aid crime investigations, identify offenders, streamline police response, increase punishment certainty, and reduce the public fear of crime (Ashby, 2017; LaVigne et al., 2011; Piza, Caplan, & Kennedy, 2014; Ratcliffe, 2006). When police have been proactively tasked based on activity observed by CCTV cameras, significant reductions in violence and social disorder have been observed (Piza, Caplan, Kennedy, & Gilchrist, 2015).

Studies of urban public CCTV systems are increasing, though at the time of Welsh and Farrington's (2007) systematic review, they identified only 22 from 44 studies that were applicable to city centers and urban public areas, and their conclusions were dominated by the results from public car parks. The earliest independent evaluation of a CCTV implementation dates from King's Lynn, UK (Brown, 1995), where 19 cameras were installed at public car parks across the city; however like many studies that followed, this evaluation suffered methodological issues such as a lack of controls for low numbers of initial crimes and for long-term temporal trends. Overall, the existing CCTV evaluation literature displays considerable variation in not only methodology but also outcome measures and independent variables. Some studies examined the impact of cameras on crime within a defined distance of CCTV cameras (Harada et al., 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 after the introduction of a CCTV surveillance system (Sivarajasingam, Shepherd, & Matthews, 2003). To date, few researchers have addressed the challenge represented by camera viewshed overlap that has theoretical and—more importantly—analytical implications (Lim & Wilcox, 2017, is a recent exception). Cameras in close proximity to each other with overlapping viewsheds may not necessarily work independent of each other; instead their effect may be enhanced by the presence of multiple cameras magnifying the deterrence signal to potential offenders.

This article reports the results of a quasi-experimental, longitudinal study of the violence and disorder impact of 13 clusters of CCTV cameras (86 cameras in total) in the city of Philadelphia, PA. After a brief overview of the theoretical rationales for CCTV implementation, the article describes the methods, camera design, study setting, and the analytic approach. We report the results for two crime types and summarize the findings before discussing them and offering implications.

Theory

CCTV cameras may reduce crime in a number of ways. Drawing on a rational choice and situational crime prevention framework (Clarke & Felson, 1993; Cornish & Clarke, 1986), the prevention mechanism most commonly argued is deterrence through a potential offender becoming aware of a camera and deciding that the risk of their identity being captured outweighs the benefits of the imminent offense (LaVigne et al., 2011; Piza et al., 2015; Ratcliffe, 2006). Within a situational framework, CCTV camera schemes fall under the general approach of increasing the risks of committing crime and represent a "formal surveillance" technique that enhances or replaces the role of security staff or the police (Clarke & Eck, 2005; Welsh & Farrington, 2008).

In one study, police actively monitored the CCTV with the explicit intention of anticipating trouble in a popular bar area of the town of Malmő, Sweden. When the camera monitor observed an incipient disturbance, officers were dispatched to the scene to de-escalate situations or prevent ongoing fights escalating (Gerell, 2016). Within the situational crime prevention framework, this combination of technology and organizational response would seek to reduce provocations. However, most researchers hypothesize the primary mechanism is offender awareness of camera location and that awareness will generate a change in the perception of risk and subsequently a reduction in offending (Piza et al., 2015).

The rational choice perspective considers potential criminality from the offender perspective and recognizes that this decision mechanism is separated into choices regarding initial involvement in criminal activity and target selection around the specific criminal event (Cornish & Clarke, 1987). In other words, at the point where CCTV may be effective, criminals decide to offend on a case-by-case basis (Piza et al., 2014) that is crime-specific and potentially "bounded" (Clarke & Cornish, 1985) by constraints on decision-making. There is evidence that some offenders were aware of the CCTV cameras yet committed crime within view of the cameras due to impaired judgment caused by drugs or alcohol (Short & Ditton, 1998). Thus, under certain situationally specific circumstances, surveillance cameras are unable to prevent crime even when ideally situated to do so.

Visible CCTV cameras might also reduce crime by deterring potential offenders or changing the risk of detection. CCTV cameras are hypothesized to generate a *general deterrence* mechanism that increases the perceived risk of capture among the potential offender population should crime be committed. Hypothetically, there may also be *specific deterrence* that occurs when camera schemes result in the arrest of offenders who are subsequently dissuaded from future offending—assuming they are aware that they were detained because of the cameras. As a mechanism of formal surveillance, Welsh and Farrington (2009) stress the importance of the video surveillance system being widely publicized. This is particularly relevant for general deterrence (rather than specific deterrence). CCTV cameras are therefore argued to be more effective when they are overtly positioned and visible and accompanied with informative signs and flashing lights to advertise their presence (LaVigne et al., 2011). Offenders may overestimate the capacity of the camera scheme and a "diffusion of benefits" (Clarke & Weisburd, 1994; Guerette & Bowers, 2009) may spread to areas beyond the effective visible range of the camera. Although often evaluated alongside other measures (Brands, Aalst, & Schwanen, 2015), CCTV cameras might also increase the detection rate, improve the police response by allowing camera operators to coordinate the appropriate reaction to an incident, encourage victims to take more security precautions, increase usage of public places, and encourage community pride and informal social control (Ashby, 2017; Gerell, 2016; LaVigne et al., 2011; Piza et al., 2015). CCTV may therefore be about changing the perception of the public and social space under surveillance rather than a specific mechanism of physical crime prevention (Zurawski, 2010).

A backfire effect is also possible, in that CCTV cameras could inadvertently increase crime. Farrington and Walsh (2007) hypothesize that potential victims may observe the presence of cameras and relax their vigilance due to a potentially false sense of security, encouraging more risky behaviors. The cameras may also increase crime reporting by the police and the public (which may only increase *reported* crime rather than actual crime) or cause spatial crime displacement to other areas beyond the purview of the cameras.

All of the crime deterrence theoretically associated with CCTV systems relies on a close relationship between an offender's perception that they are visible from a camera, how that changes their risk-reward calculus, and any associated change in offending behavior. How different researchers have addressed the issue of camera visibility is one of the aspects discussed in the next section.

Previous Work

Most of the initial research on the effectiveness of public surveillance systems originates from Europe. Gill and Spriggs (2005) found that of the 13 studied areas, six showed measurable crime reduction, though only two achieved levels of crime reduction that were statistically significant. They surmised that CCTV was less effective at combating impulsive crimes (such as alcohol-related offenses) compared to premeditated offences (such as vehicle theft), writing that the "most obvious conclusion to be drawn . . . is that CCTV is an ineffective tool if the aim is to reduce overall crime rates and make people feel safer" (Gill & Spriggs, 2005, p. 61). Welsh and Farrington (2008) completed a meta-analysis of studies that had CCTV as the main intervention and, at a minimum, involved an evaluation design comprising before-and-after measures of crime in experimental and control areas. The study had to involve at least one experimental area and one control area. They identified 22 studies that occurred in cities and town centers, while others occurred in public housing schemes, transportation systems, and car parks. Various outcome measures were employed, ranging from crime (Sarno, Hough, & Bulos, 1999) to hospital admissions (Sivarajasingam et al., 2003). The authors conclude that in cities and town centers,

> CCTV has a modest but significant desirable effect on crime, is most effective in reducing crime in car parks, is most effective when targeted at vehicle crimes (largely a function of the successful car park schemes), and is more effective in reducing crime in the U.K. than in other countries. (Welsh & Farrington, 2008, pp. 18, 19)

One of the first U.S. studies examining the crime (rather than calls for service) reduction effect of cameras examined 18 pilot CCTV cameras across 10 sites in Philadelphia (Ratcliffe, Taniguchi, & Taylor, 2009). Given the theoretical importance of camera visibility in crime prevention, camera viewsheds (GIS polygons representing the exact street locations that could be viewed by each camera) were drawn in consultation with Philadelphia Police Department (PPD) officers responsible for monitoring the cameras. The authors manipulated each pan, tilt, and zoom (PTZ) camera to determine exactly how far down each street the cameras could see. Using hierarchical linear modeling and time-varying covariates to control for seasonality and temporal trend, the research team found the cameras were associated with a 13% drop in crime. Buffer areas were then created that extended approximately 500 ft. from the viewsheds (a little more than one city block), though adjusted depending on local geography and street network. A weighted displacement quotient analysis revealed some cameras were associated with a diffusion of benefits, while others experienced a slight displacement into the buffer areas, and crime reduction at one site was completely offset by displacement into the buffer area.

The largest U.S. study to date examined the crime reduction effects of CCTV in Baltimore, MD; Chicago, IL; and Washington, DC (LaVigne et al., 2011). The research design had numerous strengths, in part because the researchers used pre–postmeasures and matched comparison areas that were identified based on a variety of place characteristics. As Alexandrie (2017) points out, the use of control areas can overcome some of the problems of endogenous camera installation practices where CCTV systems are instigated in response to rising crime, unobserved causes of which are likely to be correlated with camera installation.

The LaVigne et al. study used fixed spatial buffers to establish target areas of 200 ft. from the cameras. The authors do not explain why they chose to employ a uniform 200 ft. distance in their study, though in their defense there is little established research to determine offender perception of CCTV effectiveness. In the downtown Baltimore area, both property and violent crimes declined by large percentages in the months following camera implementation. In Chicago, the analysis indicated that crime was reduced in some areas while not in others. Cameras alone did not appear to have an impact on crime in the District of Columbia. Consistent with previous studies as well as a recent study from Schenectady, NY (McLean, Worden, & Kim, 2013), the LaVigne et al. research indicated that CCTV cameras are not universally effective.

A more recent study focused on whether the deterrent effects of CCTV cameras differ by types of crime (Caplan, Kennedy, & Petrossian, 2011). They examined shootings, auto theft, and theft from autos 13 months before and after the installation of CCTV cameras in 2008 in Newark, NJ. As with the Ratcliffe, Taniguchi, and Taylor (2009) study, the researchers created digital viewsheds manually supplemented with information from Google Earth to account for permanent obstructions to the camera's view. Their study detected a significant reduction in auto theft, although they also concluded that it is essential to contextualize the places where CCTV cameras deter crime better than at other locations. More recent work in the same city has explored the benefits of more active monitoring and engagement with a more proactive policing response, and this approach suggests some potential benefits for crime reduction (Piza et al., 2015).

Gaps and Limitations of the Evidence Base

Given the amount of money spent on CCTV, it is surprising that researchers have only in the last decade or so conducted empirically sound, crime-focused evaluations of public street CCTV cameras in the United States. Much of the existing literature from overseas may not have relevance to the U.S. environment, given the different crime dynamic between British and U.S. urban centers. Only a couple of the existing studies tailor the analysis to the individual viewsheds of the cameras, the rest employ a fixed distance around cameras—a distance that varies by study and does not consider if cameras can see (and be seen) from farther away.

Second, some researchers recognize that camera viewsheds or estimated viewing areas can overlap, but it is rare for an analysis to acknowledge or incorporate this consideration. Crime events that fall into overlapping viewsheds create a statistical problem. Unless explicitly controlled, regression techniques require independent observations where the frequency of events in one unit is not influenced by another. By assigning an event (or fraction of an event) to more than one measurement unit, the assumption of independence is violated. Camera viewsheds are therefore preferable to fixed distance measures, but the issue of event independence has to be managed.

Finally, existing evaluations often lack controls for factors such as long-term drift or seasonality or employing limited historical data on which to estimate precamera trends. Failing to incorporate temporal controls for trends such as regression to the mean might spuriously indicate deterrence effects where none exist (Stutzer & Zehnder, 2013). This also includes accounting for the likely autocorrelation of crime frequencies across repeated temporal periods during longitudinal studies (Box, Jenkins, Reinsel, & Ljung, 2015).

The Present Study

The current study in Philadelphia, PA, aims to overcome some of these research limitations with an examination that employs camera viewsheds rather than fixed buffers. When the camera system was expanded, it became abundantly clear that the city was installing cameras in targeted groups aimed to address violence and disorder. This clustered installation approach limited the opportunity to evaluate the impact of individual devices. We therefore identified clusters of cameras that were proximate to each other but spatially distinct from neighboring clusters. This not only addresses the statistical issue of independence but also has a conceptual benefit. If offender perception is important to deterrence, they may miss the presence of a single camera. The value in multiple cameras may not just be in increasing visible area under surveillance but also being able to provide visual reinforcement of the general presence of CCTV assets in the area.

Because the cameras were focused in high crime areas of the city, there was no opportunity to find equivalent control areas based on the most important characteristics—in this case violence and disorder. We evaluate two possibilities for addressing that challenge. One possibility is to follow the approach of Ratcliffe et al. (2009) and include time-varying covariates to model temperature (known to correlate with violent crime; Sorg & Taylor, 2011) and control for long-term trends and other temporal characteristics. Another possibility is to use violence and disorder counts from non-CCTV camera areas as a proxy for regional effects in areas absent the cameras. This approach has the advantage of incorporating within the variance some of the weather and long-term trend but also including unmeasured variance due to additional unobserved behaviors. These could include organizational changes, such as policing approach. We compare both approaches below.

We conducted the study in Philadelphia, PA. Covering 135 square miles, the City of Philadelphia is the sixth largest in the United States and the largest city in the State of Pennsylvania, home to over 12% of the state's population. When the current study concluded, it was the 21st most violence-plagued city in the United States with 563 reported violent offenses per 100,000 residents (Federal Bureau of Investigation, 2013, table 4). The camera system was implemented across the city after a citywide referendum and subsequent change to the City Home Charter (City of Philadelphia, 2012). Each camera was installed in a violent crime area (as determined by the city) with signs indicating the area is under surveillance. Although the cameras themselves were small and relatively unobtrusive, they had a blue flashing light that was active and visible throughout the day and night. The research question that framed the study is; did the introduction of CCTV cameras significantly reduce violence and disorder in the city's camera cluster areas?

Method

We used a quasi-experimental repeated measure design, involving counts of crime events in 13 spatial units over 120 temporal periods. The spatial unit was the combined viewshed areas for clusters of CCTV cameras in close proximity. Viewsheds have been used a number of times in previous CCTV studies (Caplan, Kennedy, & Petrossian, 2011; Piza et al., 2014, 2015; Ratcliffe et al., 2009). Camera viewsheds were determined by a researcher manipulating individual camera controls. The entire visible range of the cameras was determined by panning a complete 360°. The researcher also zoomed down each street to determine at what distance it was still possible to read a street identification sign. The researcher noted camera viewshed boundaries on paper maps at police headquarters and then digitized them as a GIS polygon later. The resultant viewsheds reflected the varying distances visibility extended down each side of a street. The process by which cameras were located was never formalized by the city, though cameras were overwhelmingly placed in the highest crime areas. This resulted in a haphazard distribution with some cameras being isolated, but many installed in clusters of cameras within a street of each other and easily viewable from one to another. The impact of these camera clusters can be seen in Figure 1, where the overlapping viewsheds of a number of cameras can be seen in an example cluster.

Using clusters of camera viewshed rather than individual viewsheds had several advantages. Multiple cameras in an area increase the likelihood that potential offenders will be aware of being in an area under surveillance. In other words, while an offender might not see one camera or dismiss it as a unique device, multiple cameras are likely to reinforce the sense of surveillance necessary for effective crime prevention (LaVigne et al., 2011). Second, there were times when cameras would temporarily go out of commission for a variety of reasons (e.g., weather damage, technical difficulties, or malicious destruction). While this was usually for a short period of time, we assumed that the loss of surveillance capacity of an inoperable camera would be minimized if it affected a camera that was part of a cluster. Third, the small viewsheds of the individual cameras also placed a statistical constraint on the analysis due to high numbers of zero crime counts when crime in individual camera viewsheds was examined on a monthly basis. Finally, using camera cluster, viewsheds avoids the issue of lack of independent observations that occurs when the response for one unit is conditional on another, as mentioned earlier. With the move to clusters, we examine crime frequencies in 13 camera cluster areas on a monthly basis over 120 months from January 2003 to December 2012.

Data

We use two measures of crime for this study. Because the cameras were predominantly installed to address public disorder and violence, we examine two crime types, *violent street felonies* (*VSF*), a

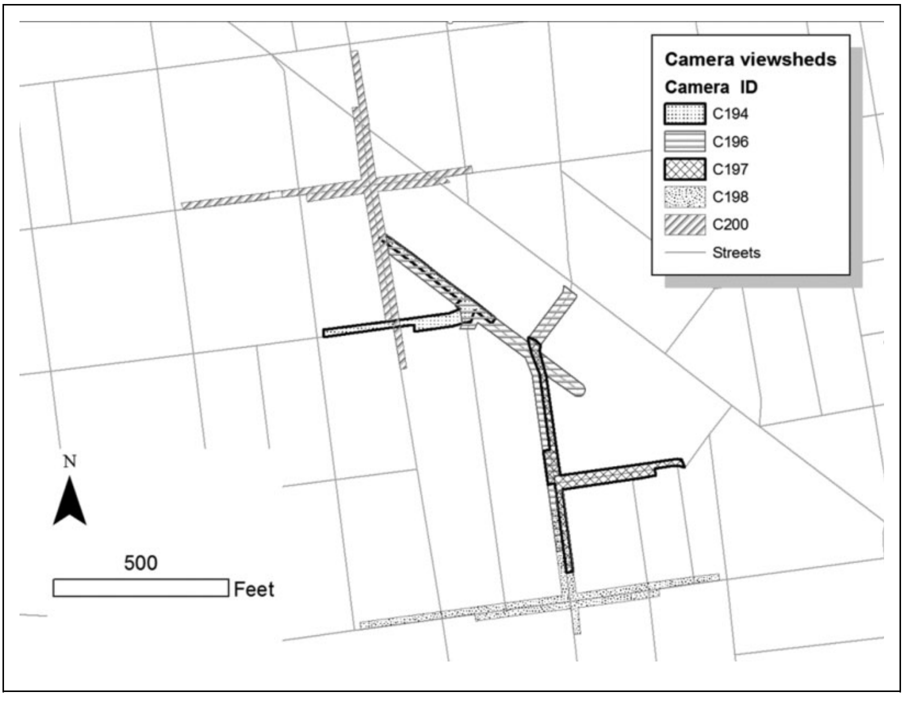

Figure 1. Overlapping camera viewsheds.

category covering all reported homicides, robberies, and aggravated assaults, and *disorder*, a category addressing varying forms of lower level disorder, including misdemeanor assault, vandalism and criminal mischief, liquor law violations, disorderly conduct, vagrancy, minor disturbances, and disorderly crowds. The PPD provided crime information for the 10 years from January 1, 2003 to December 31, 2012. The file contained the date, offense type, and location coordinates for each crime. A lengthy time series prior to an intervention is important for establishing a baseline that has sufficient observations to identify any long-term trends of seasonality, with one estimate suggesting 50 observations are necessary (Box et al., 2015). Crime locations are geocoded by the PPD's automated crime mapping system, monitored by the PPD mapping unit. Their regularly evolving geocoding process was able to map the crimes described below to a successful geocoding hit rate in excess of 97%, a satisfactory level in excess of a minimum geocoding standard of 85% (Ratcliffe, 2004).

Philadelphia installed a pilot group of eight PTZ cameras between July 2006 and October 2006. These cameras have the capacity to tilt up-and-down, pan around the surrounding area, and zoom, and they allow an observer to read a car license plate more than a block away, and observe street activity up to a three block distance, if the view is unobstructed. These actively monitored cameras had a patrol function (i.e., when the cameras were not being actively manipulated by a viewer, they would "patrol" a predetermined area). This patrol function would automatically cancel as soon as a camera operator began to actively move the camera. Cameras recorded digital images 24 hr a day, 7 days a week, with a hard drive storage capacity sufficient to store footage for 12 days.

Philadelphia installed additional cameras over the next 5 years. By the end of 2011, there were 192 PTZ cameras in the city; however, an examination of camera viewsheds in the summer of 2011 estimated that only 115 were functioning to an acceptable enough level for inclusion in this study. We defined clusters based on whether camera viewsheds overlapped one another, or a camera was positioned within 1,200 ft. of another camera's viewshed (a distance of about three city blocks). The

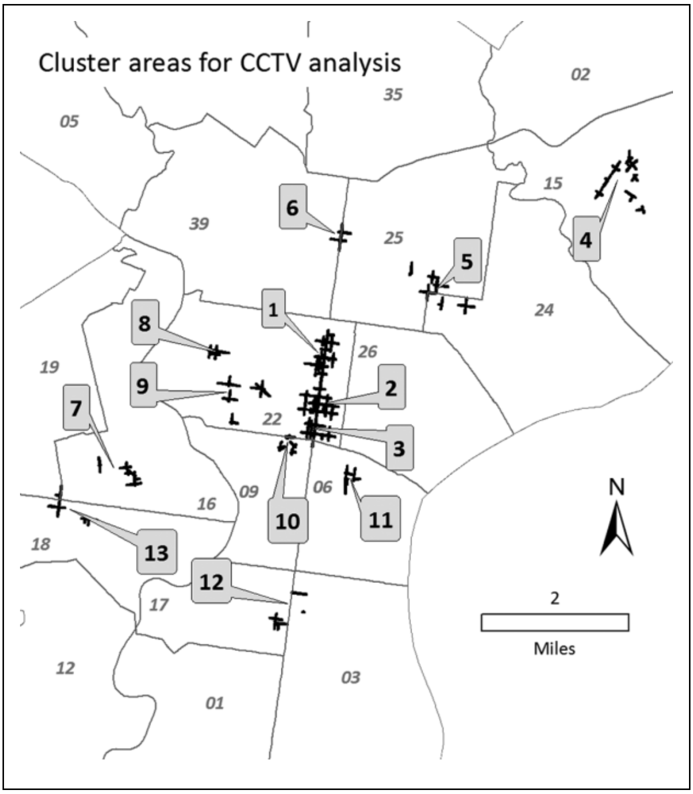

Figure 2. Map showing closed-circuit television viewsheds clustered into 13 groups, over Philadelphia police districts.

camera viewsheds were determined by researchers examining the camera views on screen at police headquarters and verified through field inspection of whether cameras were visible within the viewshed. A threshold distance of 1,200 ft. enabled the inclusion of more cameras in this cluster study, while not including obviously isolated cameras that were not part of the general geographic and socioeconomic area of the main cluster. This created 13 clusters which involved 86 of the 115 cameras available in the city when the study began in the summer of 2011 (Figure 2).

Table 1 shows the number of cameras in each cluster as well as the implementation timing of the cameras. In most cases, the majority of cameras in a cluster began functioning within a few weeks of each other, with an occasional additional camera coming later.

Because the cameras tended to be installed in clusters, the entire cluster was usually activated within a few weeks. We have therefore simplified the intervention to aid with interpretation of the model. A dichotomous dummy variable (*cameras*) reflects the month that the first cameras in a cluster came online.

Given the seasonality that can often exist with crime data, a temperature variable (*temperature*) captured the seasonal component in the time series. It was based on mean monthly temperature for the Center City area of Philadelphia (retrieved from www.weatherunderground.com for zip code 19102). A centered linear variable (*linear*) was included to model for any long-term temporal trends in the city. Over the course of the study period, crime was generally decreasing across much of the United States. And because crime frequencies are counted on a monthly basis, another variable controlled for the length of the month in days (*number of days*).

Table 1. Camera Cluster Descriptions.

Cluster	Number of Cameras	Implementation	Viewshed Area (Sq. Ft.)
1	14	September 2008–November 2008	538,418
2	14	July 2008–November 2008	634,530
3	9	November 2008–December 2008	341,249
4	8	September 2008–December 2008	347,031
5	7	March 2008–June 2009	335,639
6	2	April 2009–April 2009	128,180
7	6	March 2010–March 2010	208,530
8	3	June 2008–June 2008	133,247
9	5	July 2009–April 2010	249,791
10	5	June 2008–July 2009	144,989
11	5	June 2008–July 2009	137,473
12	4	December 2008–July 2009	136,242
13	4	November 2007–February 2008	207,793
Total	86		

Temperature, *linear*, and *number of days* are observed covariates that are capturing what's happening in the city. As stated earlier, an alternative to these time-varying covariates is to incorporate some form of *control* measure. Here, we use violence and disorder crime counts from the remainder of the city from any area more than half a mile from any camera. Although not equivalent on the concentration of violence or disorder with the targeted camera areas, this (noncomparable) control area is able to reflect not only the real—and possibly nonlinear—long-term, macro trend in the region but also incorporate effects of temperature. This (*control*) variable also has the advantage of capturing the variance for unobserved variables relevant to violence and disorder.

Analytical Strategy

This study focuses on changes in 120 monthly crime frequencies within 13 camera viewsheds in Philadelphia, PA, using multilevel random-effects models. The dependent variable is repeated measurements representing monthly observations from January 2003 to December 2012 of crime count in each camera cluster. The intervention is modeled with a dichotomous variable for each camera cluster (*cameras*), and at level one, we also have repeated measures of the following independent variables; a centered linear variable to model long-term trend over time (*linear*), monthly average temperature to model seasonal effects (*temperature*), the length of the month in days (*days in month*), and the crime frequency in the control area (*control*). With the exception of the intervention, all independent variables are grand mean centered. These Level 1 measures are nested within Level 2 units (the camera clusters).[1]

For both violence and disorder, we follow the same modeling strategy. An initial model (Model 1) only includes the intervention parameter. A second model (2) adds the nonequivalent control series (*control*). A single covariate model includes the same covariates as the earlier study by Ratcliffe et al. (2009) by individually adding the *linear* (Model 3), *temperature* (Model 4), or *days in month* (Model 5) variables. A full model (6) includes both the control and covariate variables. The models follow this specification:

$$Y_{tj} = \beta_0 + \beta_1 X_{1tj} + \mu_j + \varepsilon_{tj} \tag{1}$$

$$Y_{tj} = \beta_0 + \beta_1 X_{1tj} + \beta_2 X_{2tj} + \mu_j + \varepsilon_{tj} \tag{2}$$

$$Y_{tj} = \beta_0 + \beta_1 X_{1tj} + \beta_2 X_{2tj} + \beta_3 X_{3tj} + \mu_j + \varepsilon_{tj} \tag{3}$$

$$Y_{tj} = \beta_0 + \beta_1 X_{1tj} + \beta_2 X_{2tj} + \beta_4 X_{4tj} + \mu_j + \varepsilon_{tj} \quad (4)$$

$$Y_{tj} = \beta_0 + \beta_1 X_{1tj} + \beta_2 X_{2tj} + \beta_5 X_{5tj} + \mu_j + \varepsilon_{tj} \quad (5)$$

$$Y_{tj} = \beta_0 + \beta_1 X_{1tj} + \beta_2 X_{2ij} + \beta_3 X_{3tj} + \beta_4 X_{4tj} + \beta_5 X_{5tj} + \mu_j + \varepsilon_{tj} \quad (6)$$

where Y_{tj} is the expected crime count for month t in camera cluster j, β_0 is the overall mean of the dependent variable across all camera clusters, β_1 is the slope coefficient for the dummy variable representing the implementation of cameras (X_1) at time t, β_2 is the coefficient for the observed monthly crime count in the control area (X_2) at time t, β_3 is the slope coefficient for the linear temporal trend (X_3) at time t, β_4 is the population slope coefficient for the impact of seasonal trends (X_4) at time t, β_5 is the slope coefficient for the impact of how many days are in each month (X_5) at time t, μ_j represents the random intercept for cluster j, and e_{tj} is the residual or unexplained variance.

Models were fitted in Stata Version 15.0 as linear mixed-effects formulations. Because most time-series data have long been known to be temporally autocorrelated (Box & Jenkins, 1976; Chatfield, 1989), our approach controls for this by allowing the analysis to assume that within-group residuals are serially correlated from one observation to the next. Various autoregressive (*ar*) residual structures were applied and BIC used to determine the optimal structure. Furthermore, as we are examining two partially correlated dependent variables ($r = 0.805$), the commonly accepted significance value of $p < .05$ is often corrected using a Bonferroni (or similar) correction. We adopt this convention here and adjust the significance level to $p < .025$. Finally, to address the issue of the limited number of clusters available at the second level of the models, we employ a small-sample inference correction for fixed effects. Methods to control for small cluster frequencies in mixed-effects models are relatively established (Kenward & Roger, 1997) though only appearing in commercial statistical packages recently. Recent work by McNeish and Stapleton (2016, p. 505) has established that with as low as 12-level two units, a restricted maximum likelihood estimation approach "vastly reduces the estimation bias in intercept variance."

We compare the various models with their respective Bayesian information criterion (BIC) values. BIC allows us to select more optimal models that have different dimensions (Raftery, 1995; Schwarz, 1978). Because it gauges model-to-data goodness of fit by including a more robust penalty for greater levels of model complexity, it is preferable over Akaike information criterion for identifying lower dimensional models (Acquah, 2010; Schwarz, 1978).

Results

VSF

Each of the models (1–6) was run, and their respective BIC values were recorded, as shown in Table 2. For VSF, the optimal model included cameras plus control (Model 2). Addition of the time-varying covariates did not improve model optimization.

Three of the multilevel models for VSF are shown in Table 3 (the results for less optimal Models 3–5 are omitted for conciseness). Absent any other predictors, activating a CCTV camera cluster generated a statistically significant expected mean reduction of 0.36 VSF per month. Adding the control area crime count improved the model fit, with increases in VSF being associated with a slight increase in crime in the CCTV intervention areas. It also rendered the *cameras* intervention variable nonsignificant ($p = .028$). Adding any one or all of the time-varying covariates of *temperature*, *days in month*, and *linear* trend did not result in better model fit. For all models, there was evidence of residual autocorrelation, with a correlation between successive error terms of between 4% and 6% (.042–.057).

Table 2. Bayesian Information Criterion Values for Various Models.

Model	VSF	Disorder
1. Cameras only	5,949.4	11,406.8
2. Cameras plus control	5,929.4[a]	11,229.0
3. Cameras plus control plus linear	5,936.6	11,214.6[a]
4. Cameras plus control plus temperature	5,933.3	11,236.3
5. Cameras plus control plus days in month	5,936.5	11,235.9
6. Full model	5,947.4	11,227.1

Note. VSF = violent street felonies.
[a]Indicates most parsimonious model by Bayesian information criterion.

Table 3. Multi-level model results for Violent Street Felonies.

Fixed and Random Effects	Model 1	Model 2[a]	Model 6
Fixed effects		Coefficient (*SE*)	
Cameras	−0.359 (.087)*	−0.198 (.090)	−0.321 (.168)
Control		0.006 (.001)*	0.003 (.002)
Linear			0.001 (.002)
Temperature			0.007 (.004)
Days in month			0.036 (.052)
Intercept	1.855 (.381)*	2.269 (.381)*	2.320 (.386)*
Random effects		Estimate (*SE*)	
Intercept	1.855 (.737)	1.851 (.735)	1.855 (.737)
Autoregressive residual (ρ)	0.057 (.026)	0.042 (.026)	0.0412 (.026)
Bayesian information criterion	5,949.4	5,929.4	5,947.4

Note. Temperature, days in month, linear, and control all grand mean centered.
[a]Indicates optimal model based on Bayesian information criterion.
*p < .025.

Disorder

Again, each of the models (1–6) was run for disorder, and their respective BIC values were recorded, as shown in Table 2. This time the optimal model included the *cameras* variable plus *control* plus the *linear* time-varying covariate (Model 3). Adding further covariates did not improve model optimization.

Four of the multilevel models for disorder are shown in Table 4 (the results for Models 4 and 5 are omitted for conciseness). Absent any other predictors, activating a CCTV camera cluster has no statistically significant effect; however, adding the control area crime count improved the model fit, with increases in disorder in the control area being associated with a slight increase in crime in the CCTV intervention areas. At the same time, the intervention variable indicated a significant increase in disorder in CCTV areas. Adding the *linear* time-varying covariate improved model fit and rendered the *cameras* intervention parameter insignificant statistically. Adding further time-varying covariates did not result in better model fit. For all models, there was evidence of substantial residual autocorrelation across two prior months (*ar*2), with a correlation between successive error terms of about 37–42% and 21–26%, respectively (.037–.042 and .215–.241).

Discussion

The cameras intervention did not affect the level of VSF at the significance level selected. This finding is in line with other research into violence (Gerell, 2016; Welsh & Farrington, 2009), though

Table 4. Multi-level model results for Disorder.

Fixed and Random Effects	Model 1	Model 2	Model 3[a]	Model 6
Fixed effects		Coefficient (*SE*)		
Cameras	−0.795 (1.168)	3.846 (1.162)*	−2.421 (1.666)	−2.049 (1.690)
Control		0.006 (0.001)*	0.007 (0.001)*	0.007 (0.001)*
Linear			0.122 (0.025)*	−0.055 (0.038)
Temperature				−0.011 (0.254)
Days in month				0.133 (0.026)*
Intercept	30.55 (7.08)*	28.88 (4.22)*	31.47 (4.28)*	31.31 (4.28)*
Random effects		Estimate (*SE*)		
Intercept	225.78 (90.57)	224.17 (89.79)	228.08 (90.97)	227.85 (90.89)
Autoregressive residual (ρ)	0.425 (.0025)	0.391 (0.025)	0.372 (0.025)	0.372 (.025)
	0.215 (0.026)	0.259 (0.025)	0.239 (0.025)	0.241 (0.025)
Bayesian information criterion	11,406.9	11,229.0	11,214.6	11,227.1

Note. Temperature, days in month, linear, and control all grand mean centered.
[a]Indicates optimal model based on Bayesian information criterion.*$p < .025$.

it contradicts the work of LaVigne and colleagues (2011) who did identify reductions in violent crime in cities of a comparable size. For disorder, the intervention variable is only significant in a less optimal model. While originally not significant, this change is likely due to the *cameras* intervention variable being significantly associated with one or more omitted variables in addition to any effect it possessed. The addition of the linear component (the parsimonious model) likely reduced any partial effects within the *cameras* measure to reveal a more true indication of the variable, which in this case is a nonsignificant relationship with the disorder outcome.

It is difficult to ascertain whether the dissimilarities with the more comparable work are due to differences in setting, camera system operational parameters, effectiveness of the police response, or to "research degrees of freedom" (Simmons, Nelson, & Simonsohn, 2011)—where discretionary choices by researchers with regard to analytical models, choice of variables (not only dependent and predictive but also exposure), and statistical choices regarding corrections for lagged impacts or experimentwise error rates impact study outcomes. Research degrees of freedom has been identified as a potential problem in the field of psychology (Masicampo & Lalande, 2012) and has been recently raised as an issue in criminology (Buck, 2014). With 13 clusters, we recognize that we are at the limit of modelability; however, as McNeish and Stapleton (2016, p. 510) point out, there are a number of similar approaches that can produce parameter estimates from appropriate modes with fewer than 10 clusters, "although the analysis will almost certainly be underpowered to some degree for any effects that are not large in magnitude."

Furthermore, because we had no control over the camera locations and because the city placed them in the most violent areas, it was not possible to identify control areas that were comparable on the dependent variables. To compensate for this we selected a robust multilevel model approach, robust in that it allowed the use of camera viewsheds as well as allowed camera clusters to have their own intercepts. While noncomparable on crime rate, the control variable captured organizational and regional affects, which were in turn combined with the time-varying covariates. This meant that the hurdle for achieving a statistically significant reduction was substantial, even before we added a correction for the experimentwise error rate problem.

The city did not implement a cluster of cameras and make them live at one time. Given that clusters were chosen because of their proximity to other cameras and possibility of overlap, we chose to consider a cluster "live" for analytical purposes in the month when the first camera in the cluster because operational. This decision will have had little impact given the short time frame for implementation of all cameras in most clusters, but in some cases, the cluster became live over a period approaching a year, and this might have an impact on the analysis of that cluster. In those clusters, the "clock" started before the treatment did and this made it less likely we would have found a crime reduction.

The CCTV cameras in Philadelphia are not dissimilar to cameras in other places. They are technologically sophisticated, have reasonable vision at night, and can PTZ. What is more relevant is how they are employed. Over the course of the study, the operationalization of the cameras and how they were viewed changed. Initially, the first batch of cameras was viewed by a single detective (on light duties) at police headquarters. When the number of cameras increased, this function was transferred to a video monitoring unit, though more often than not, the suite of over 100 cameras was viewed by one person during the day and rarely at night. This routine was occasionally interrupted by a request for video footage from a detective investigating a case. After the study finished, the camera images began being sent to the Philadelphia Police Real Time Crime Center, where a team of between 2 and 5 people monitor the cameras (while conducting other duties) 24 hr a day, 7 days a week. Thus, the lack of active monitoring during the study period might have reduced their effectiveness.

Our study examined the crime reduction capacity of the cameras from the preventative perspective of the camera presence alone, while incorporating any residual benefits from successful offender identification from the occasional video footage requests from detectives. We were not able to assess the impact of increased surveillance monitoring as the move to the Real Time Crime Center occurred after the completion of the study. As such, it may be the case that active monitoring by a team of people integrated into the operations of the police department could illicit greater productivity from the cameras. But for this study, it is clear that there was no significant return on investment from CCTV systems that are not actively and thoroughly monitored by the police department. If there is additional value in more active monitoring, that would have to be established by a later study.

Theory suggests that cameras might reduce the likelihood of criminal behavior through both general and specific deterrence by increasing the perceived likelihood of detection or experiencing arrest because of cameras. However, there has been little research examining how cameras are perceived by people on the street. We have no evidence whether the perception of citizens is related to the type of monitoring practiced in a jurisdiction (active or passive). Additionally, we've had no studies to examine the extent to which police inform arrestees that they were caught by a camera. Nor have studies examined the diffusion of benefit that might accrue when an arrested offender tells their friends, family, and extended social network of their experience. This is a critical gap in the extant knowledge of the mechanisms underlying the hypothetical connection between the presence of cameras and less crime.

Another potentially productive avenue for future research concerns the decay function associated with the installation of CCTV.[2] Similar to the findings from investigations of the optimum length of time an officer should spend in a hotspot, it may be that there is a clear pattern of treatment decay after a camera installation (Koper, 1995; Sorg, Wood, Groff, & Ratcliffe, 2017). We leave this investigation to future research. From a policy and practice standpoint, our findings have several implications. First, more investment in monitoring may create a greater return on the investment. Second, creating an automatic notification process would make video footage more accessible. Under such a system, each crime event would be automatically checked and if it fell within a camera viewshed, the detective assigned would be notified. This would make the camera information part of the record in the crime incident data. By making this process automatic, it would be easier for detectives to use video footage, which in turn might improve the detection rate and have a crime reduction impact through specific deterrence.

Third, there may be value in the use of audio detection systems tied to CCTV cameras. This type of technology is largely untested from a scientific perspective, and existing evaluations of audio detection systems are questionable given they often originate from the companies that sell the systems. Finding a way to easily and routinely integrate the cameras with an audio detection system might add sufficient value to a limited number of CCTV cameras in areas with numerous shootings.

Overall however, this study adds to the mounting evidence that passive monitored systems are largely ineffective at significantly reducing violent crime and disorder. Without a more substantial investment in people who can both actively monitor high crime areas and convey that information to officers on the ground who can intervene in a timely manner (Piza et al., 2014, 2015), CCTV will remain an ongoing millstone around the financial neck of cities. The costs of CCTV systems are substantial, running into the millions of dollars for implementation with additional and perpetual maintenance and supervision costs. If these systems can generate no reduction in disorder or VSF, their value must be drawn into question. We cannot definitively say if more active use would improve crime reduction—though there is some evidence that this is likely (Piza et al., 2014, 2015)—but it is clear that it would certainly increase the costs. It may be that active monitoring *and* increased responses from patrol police may generate significant crime reduction benefits, but few police departments have additional capacity in these areas. If cities purchase CCTV systems with the hope that their purchase and installation alone will be beneficial, the evidence to the contrary continues to mount.

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Notes

1. The intraclass correlation indicated that random effects at the cluster level comprise approximately 42.1% of the total residual variance. A likelihood ratio test of the data devoid of independent variables confirmed the nested structure of the data $\bar{\chi}^2 = 794.63$, $p < .0005$.
2. The authors thank one of the anonymous reviewers for this suggestion.

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