IDENTIFYING THE BEST CONTEXT FOR CCTV CAMERA DEPLOYMENT: AN ANALYSIS OF MICRO-LEVEL FEATURES

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ABSTRACT OF THE DISSERTATION

Identifying the Best Context for CCTV Camera Deployment: An Analysis of Micro-Level Features

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CCTV has become a mainstream crime prevention mechanism around the world. Despite the popularity of the technology, evidence of CCTV's crime prevention capabilities is inconclusive. Little research has attempted to identify factors contributing to this variance. Research designs have been largely one-dimensional in nature with most evaluations exclusively testing CCTV's deterrence capabilities. Data related to the detection and response to crime has been largely ignored. In addition, units of analysis typically focus on aggregate land usage and fail to capture the unique characteristics of each camera's surrounding environment. Collectively, these shortcomings have resulted in a lack of "transferrable lessons" that can help identify the ideal context for CCTV.

This dissertation is comprised of two separate analyses of the CCTV system in Newark, NJ. The first measured the influence of a series of independent variables on the effectiveness of CCTV. Viewsheds of individual camera sites, rather than the CCTV system as a whole, were utilized as units of analysis. The variables were grouped into five categories: environmental features (14), camera design (2), line of sight (4), enforcement activity (4), and pre-intervention crime levels (1). A series of regression models tested the influence of the independent variables on six separate crime categories. The analysis generated three main findings. First, high levels of proactive surveillance activity resulting in police enforcement were significantly related to the reduction of most crime types. Secondly, certain environmental features had a criminogenic effect in CCTV areas, with the concentration of specific environs being significantly related to crime increases. Thirdly, there may be somewhat of a “deterrence threshold” in respect to CCTV, with a certain level of pre-installation crime being necessary for cameras to produce a crime reduction.

These findings influenced the research design of the second analysis, which measured the effect of the overall CCTV system. A Propensity Score Matching technique incorporating pre-intervention crime levels and criminogenic environmental features was utilized to select equivalent control areas. The system-wide analysis found that auto theft was the only crime to have experienced a statistically significant reduction, as well as a diffusion of crime control benefits to the surrounding area. The fact that a large number of cameras in the system produced little-to-no enforcement activity was identified as a contributing factor to the lack of a system-wide reduction of most crime types. The dissertation concludes with a discussion of how police may be able to design CCTV programs in a manner that overcomes traditional barriers to video surveillance, which may maximize their deterrent effect.

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PREFACE: THE RISE OF CCTV

The popularity of Closed Circuit Television (CCTV) has grown exponentially in recent times. The tactic's rise can be traced to Great Britain, where the Home Office's "CCTV Challenge" provided direct funding for over 550 systems between 1994 and 1997 (Painter & Tilley, 1999: p. 2). In total, three quarters of the Home Office budget was allocated to CCTV- related projects from 1996 to 1998 (Armitage, 2002). Such policy decisions dramatically increased the number of CCTV systems in Britain from approximately one hundred in 1990 (Armitage, 2002) to over four million less than two decades later (Farrington, Gill, Waples, & Argomaniz, 2007). This vast expansion established CCTV as Britain's "crime prevention initiative of the century" (Norris & Armstrong, 1999a). Cities throughout the United States have likewise made substantial investments in CCTV. American cities have invested in large CCTV systems, including Baltimore (La Vigne, Lowry, Markman, & Dwyer, 2011a), Chicago (Babwin, 2007; La Vigne et al., 2011a), Cincinnati (Mazerolle, Hurley, & Chamlin, 2002), Newark, NJ (Caplan, Kennedy, & Petrossian, 2011), New Orleans (Usher, 2003), Philadelphia (Ratcliffe, Taniguchi, & Taylor, 2009), Washington D.C. (La Vigne et al., 2011a), and San Francisco (King, Mulligan, & Raphael, 2008), to name a few. Chicago's system is particularly robust. The city maintains a vast network of thousands of cameras deployed by the police department as well as private businesses, and devotes millions annually towards the further integration of CCTV and various information systems (Babwin, 2007).

This vast expansion begs an important question; why do policy makers consider CCTV such a worthwhile investment? A review of research suggests this expansion occurred irrespective of empirical findings. Evidence of CCTV effectiveness is inconclusive (Armitage, 2002; Eck, 2002; Gill & Spriggs, 2005; Phillips, 1999; Ratcliffe, 2006a; Welsh & Farrington, 2002, 2007). Some studies find CCTV to be moderately effective (Armitage, Smythe, & Pease, 1999; Caplan, Kennedy, & Petrossian, 2011; Gill & Spriggs, 2005; La Vigne et al., 2011a; Ratcliffe et al., 2009; Short & Ditton, 1996) with others finding no effect on crime (Brown, 1995; Ditton & Short, 1999; King et al., 2008; Waples & Gill, 2006; La Vigne et al., 2011a). Furthermore, much research suggests CCTV impact to be restricted to property offenses (Phillips, 1999; Welsh & Farrington, 2002) and areas conducive to motor vehicle crime (Gill & Spriggs, 2005; Tilley, 1993; Welsh & Farrington, 2009).

While the literature offers some level of support for CCTV the evidence does not seem to warrant such a substantial worldwide investment. Many have attributed the vast rise to political motivation and public enthusiasm surrounding the technology. Painter and Tilley (1999) argued that CCTV's rise in Britain was due to the "surface plausibility" of the measure and the expected political benefits officials could expect from "being seen to be doing something visible to widespread concerns over crime…" (p. 2). Painter and Tilley also point to monetary motivations behind CCTV deployment: "Cash-strapped local authorities…are quick to take advantage of any funding opportunities offered by central government…One of the major, if unsurprising, lessons from the extensive installation of CCTV in Britain is the leverage that funding can have in shaping approaches to crime prevention" (p. 3). Pease (1999) commented on the popularity of CCTV and how small a role evaluation played in its expansion. "Crime reduction has been bedeviled by the tendency to polarize measures into those which will be helpful in all circumstances and those which will not be helpful in any, a process that the evaluative process has often mirrored and accelerated. In recent years…closed circuit television (CCTV) has sadly fallen into the first category" (p. 48). Pease further lamented the CCTV movement by stating "one is tempted to ask where rigorous standards went into the headlong rush to CCTV deployment" (p. 53). Indeed, less expensive methods of enhancing surveillance may be as effective against crime as CCTV. Welsh and Farrington (2004) compared the effects of formal surveillance in the form of CCTV with natural surveillance in the form of improved street lighting. Thirty-two studies (19 CCTV, 13 street lighting) were included in the meta-analysis, which found the impact CCTV and street lighting to be nearly identical. CCTV achieved a 21% net crime reduction and effect size of 1.27 compared to 22% and 1.28 for street lighting.

Norris and Armstrong (1999a) argued that the rapid adoption and expansion of CCTV has created, amongst the public and practitioners alike, a substantial amount of "technological determinism" which they define as "an unquestioning belief in the power of technology" (p. 9). Norris (2003) attributed the following statement to a government official who championed CCTV as a crime prevention measure. "CCTV catches criminals…The spread of this technology means that more town centers, shopping precincts, business centers and car parks…will become no-go areas for the criminal… CCTV is a wonderful technological supplement to the police…One police officer likened the 20-camera system as having 20 officers on duty, 24-hours a day constantly taking notes" (p. 254). These remarks, while from a single person, reflect the colloquial view of CCTV as an "all seeing" mechanism that successfully combats crime in all circumstances (Fyfe & Bannister, 1996).

Such "technological determinism" has multiple consequences. First, as discussed above, the rise of video surveillance has occurred despite the absence of strong empirical evidence demonstrating the ability of CCTV to prevent crime. Secondly, the deterrent effects of CCTV have been taken for granted leading to little in the sense of exploration beyond "pre" and "post" measurement of crime in target areas. Best-practices for CCTV in policing have been largely understudied or ignored by empirical researchers, and little effort has been devoted to understanding how the benefits of CCTV can be maximized (beyond adding more cameras) within the police function. Gill and Spriggs (2005) considered these shortcomings as a lack of "transferrable lessons" by which effective tactics can be replicated across various sites (p. 3). Furthermore, police have implemented video surveillance strategies absent a concrete understanding of the precise mechanisms by which the tactic can prevent crime. CCTV systems often have a vague mission to "prevent crime," with little consideration being given to a number of pertinent issues, such as how to best deploy cameras, and best practices regarding monitoring, evidence collection, and training (Gill & Spriggs, 2005; Mazerolle et al., 2002). This can lead police to view CCTV as a "stand alone" mechanism instead of integrating the strategy into existing practices and procedures of the agency (La Vigne et al. 2011b).

This dissertation is a modest attempt to produce "transferrable lessons" in respect to CCTV. Previous research has found mixed evidence of CCTV effectiveness, with the technology successfully impacting crime in certain cases and having no discernible effect in others. However, little is known as to why effect has been so variable. While studies have identified broad contexts which are amenable to CCTV effect (Phillips, 1999;

Welsh & Farrington, 2007, 2009) the precise factors influencing crime prevention are currently unknown.

This dissertation is separated into five chapters. Chapter one explores the previous literature and conceptual framework guiding the study. Chapter two describes the data sources, key concepts, and units of analysis for this study. Chapter three presents "Analysis A," a test of the influence numerous micro-level variables have on crime levels in CCTV camera areas of Newark, NJ. Chapter four presents "Analysis B," which incorporates the findings of analysis A in a propensity score matching model to evaluate the system-wide effect of Newark's CCTV system. Chapter five presents the joint policy implications of the analyses and discusses how police may be able to design CCTV strategies in a manner that maximize their crime reduction capacity.

CHAPTER ONE: CONCEPTUAL FRAMEWORK

Evaluations of CCTV

The "Mixed" Effect of CCTV

Reaching a firm consensus on the crime prevention capability of CCTV is difficult. Evidence of effectiveness varies greatly across evaluations. Complicating matters is the fact that early studies suffered from specific methodological flaws. Short and Ditton (1995) identified five types of problems inherent in early studies of CCTV. First, pre and post installation time periods were often too short for adequate testing. Second, studies typically failed to disaggregate crime, thus ignoring increases or reductions of specific crime types in favor of measuring overall crime levels. Third, many evaluations did not utilize control areas, which compromised the internal validity of the research. Fourth, the reporting of results as percentage changes absent the overall number of incidents did not allow for significance testing in many cases. Lastly, many early studies failed to adequately measure displacement or diffusion of benefits.

While research designs have improved over time, the overall body of CCTV research remains methodologically weak. Welsh, Peel, Farrington, Elffers, and Braga (2011) reported that over 55% of research on public surveillance—including CCTV, security guards, place managers, and defensible space—utilized less than a comparable control design, which is widely considered the minimum interpretable design (Cook & Campbell, 1979; Farrington, Gottfredson, Sherman, & Welsh, 2002). This has important ramifications for the study of CCTV. Prominent research reviews have found a significant inverse relationship between research design and study outcome; weaker research designs, as indicated by internal validity, produce stronger effects while stronger research designs produced weaker effects (Weisburd, Lum, & Petrosino, 2001; Welsh et al., 2011). This suggests that many evaluations of public surveillance (including CCTV) may be "biased upward," reporting larger effects due to their weaker designs.

In addition to potentially compromising the validity of individual evaluations, weak methodology may be hindering the further creation of a body of knowledge on CCTV. For example, when updating their original meta-analysis, Welsh and Farrington (2007) were forced to exclude 23 of 45 new studies due to their insufficient research design, particularly the absence of control areas. This means that roughly half of the new research on CCTV was unable to be included in a cumulative test of camera performance. In the United States, this problem is compounded by the fact that CCTV research is quite scarce. It is valid to debate the level to which findings from studies conducted in other countries are generalizable to the U.S. Unfortunately, at the time of publication, Welsh and Farrington (2007) identified only one rigorous evaluation of CCTV in the United States (Mazerolle et al., 2002) with Cameron, Kolodinski, May, and Williams (2008), Caplan, Kennedy, and Petrossian (2011), La Vigne et al. (2011a), and Ratcliffe et al. (2009) appearing since. These five studies obviously represent a proverbial drop in the bucket compared to the overall CCTV usage in the United States.

Successes and Shortcomings

While acknowledging the limitations of CCTV evaluations, certain themes have emerged within the literature. Welsh and Farrington (2002) identified 22 evaluations of CCTV with rigorous research designs for inclusion in their meta-analysis. Of these studies, half found a decrease, five found no effect on crime, and five found an increase.

Welsh and Farrington (2002) concluded CCTV worked best in well-defined settings and was most effective against property crime. Welsh and Farrington's updated meta-analysis (2007) provided particular support for CCTV use in car parks. While CCTV caused a 16% reduction in crime across all 44 studies included in the analysis, the reduction was largely driven by the car park systems. Car park systems produced a 51% decrease in crime with most other settings experiencing small, statistically insignificant crime reductions.

National-level evaluations provide further (albeit statistically modest) support for CCTV in parking areas. Of the thirteen systems analyzed by Gill and Spriggs (2005) only two produced statistically significant crime reductions, as demonstrated by the effect size. However, confidence intervals were completely above 1 only in the case of the car park, discrediting the reduction at a hospital site. A meta-analysis conducted by Farrington, Gill, Waples, and Argomaniz (2007) yielded similar results, with a car park being one of only two sites to achieve statistically significant reductions.

CCTV's effect in car parks in normally attributed to levels of camera coverage and the nature of crime in these settings. Camera coverage is typically high in car parks, making most of the area visible to CCTV (Gill & Spriggs, 2005; Welsh & Farrington, 2007). Furthermore, vehicle crime may more amenable to surveillance than other crimes, such as violence, due to the presumed rationality of this offender population (Welsh & Farrington, 2007). However, the findings are not without caveats. In particular, CCTV deployment in car parks typically occurs alongside other interventions. Poyner (1991), for example, was not able to isolate the effects of CCTV since improved lighting and pruning of trees being implemented during the same time. Sarno (1996) experienced similar difficulties, with crime decreases coinciding with improved lighting and overnight locking of the car parks as well as camera installation. Each of the six evaluations of CCTV in car parks included in CCTV meta analyses (Farrington, Gill, Waples, & Argomaniz, 2007; Welsh & Farrington, 2002, 2007) were combined with other interventions such as improved lighting, fencing, and security personnel. Thus, reductions in car parks may speak more to the effectiveness of a package of interventions focused on a particular crime type (e.g. "car crime') rather than the specific effect of video surveillance (Welsh & Farrington, 2007: p. 46).

Outside of car parks, evidence of CCTV impact is much less persuasive, especially in public places. While the twenty-two city and town center systems analyzed by Welsh and Farrington (2007) produced a small overall reduction it was not statistically significant. Furthermore, only ten of the twenty-two evaluations were considered to have a desirable effect on crime, with twelve producing either an undesirable or null effect. Brown's (1995) evaluation of three British cities provides an illustration of CCTV's varied effect. In Birmingham slight decreases in burglary and theft could not be attributed to CCTV. At the same time, criminal damage, theft from auto, theft from person, and robbery all increased. In New Castle and Lynn, monthly incidents of crime decreased compared to areas not covered by CCTV. However, reductions in vehicle crime and criminal damage faded over time. Other CCTV evaluations have reported similar "deterrence decay" effects. Armitage et al. (1999) demonstrated that while crime in Burnley decreased in police beats receiving CCTV cameras, the effect seemed to diminish as more cameras were put into place. In Crawley, Squires (2000) found that after a 20% crime reduction over the first six months of the program. However, after the program's first year crime reached levels that were 30% higher than when CCTV was first installed.

Additional studies show CCTV impact to be limited in public spaces. In Doncaster city center, burglary, criminal damages, assault, and overall thefts were not impacted by CCTV (Skinns, 1998). Similarly, CCTV had no effect on burglary, shoplifting, violence, and drug offenses in Ilford town center (Squires, 1998). Sivarajasingam and Shepherd (1999) concluded CCTV had little effect on violence in Cardiff and Rhyl. Ditton and Short (1999) analyzed CCTV in the town centers of two of Scottish cities: its most populous city of Glasgow, and in the smaller town of Airdire. The Airdire systems produced a 21% reduction which did not seem to fade over time. However, specific crimes increased substantially, specifically drug and public order offenses. Glasgow failed to show a reduction whatsoever, with overall crime actually increasing 109%. However, the Glasgow effort was an "image building" exercise designed to improve public perception of the city rather than prevent crime and thus should not be used to evaluate CCTV as a crime prevention tool (Eck, 2002: p. 274).

While these studies were all implemented in European cities, American systems have reported similar shortcomings. In their study of San Francisco's CCTV system, King et al. (2008) found that the 19 camera sites, each comprised on multiple cameras, had no significant effect on violent crime, drug offenses, vandalism, or prostitution. The system produced a 23% reduction in property crime. However, the effect was driven entirely by declines in larceny theft, including incidents that occurred indoors (and are likely not likely to be impacted by publicly deployed cameras). Cameron et al. (2008) analyzed CCTV systems in two separate areas of Los Angeles: Hollywood Boulevard's

“Walk of Fame” and the Jordan Downs public housing development, representing two very different environments. Cameron et al. (2008) found that neither system had any effect on violent crime, property crime, or misdemeanor arrests.

Given the nature of CCTV, some have suggested that utilizing reported crime data in evaluations may not be appropriate. Since CCTV operators are uniquely placed to spot offenses, they may be in a position to report crime that had previously gone unseen (Winge & Knutsson, 2003). While this may be lead to an increase in *reported* crime an increase in *actual* crime may not have actually occurred (Ratcliffe, 2006a). However, methodology incorporating data types besides (or in addition to) to reported crime has also produced inconsistent results.

Mazerolle et al. (2002) utilized an innovative, multi-method approach in their study of CCTV in Cincinnati. In addition to measuring calls for service within buffers of CCTV cameras, Mazerolle et al. coded random samples of camera footage for instances of pro-social and anti-social behavior. With both measures, CCTV was shown to have an immediate deterrent effect in the two months following installation. However, the effect seemed to decline after the initial period, with both calls for service and observed anti-social behavior increasing. Gill and Spriggs (2005) conducted public surveys prior to and following CCTV installation in twelve areas throughout the UK. While respondent data in eight schemes suggested a reduction in victimization, in only four schemes was the reduction larger than within the control area. Furthermore, none of these observations were statistically significant. Farrington, Bennett, and Welsh (2007) similarly conducted victimization surveys to measure CCTV effect in Cambridge City Center. Surveys were conducted within the target area as well as a control area. The results suggested that CCTV had no effect on victimization or fear of crime.

Towards Explaining the Varying Effect of CCTV

Two recent studies add further perspective to the “mixed” findings that have come to represent CCTV research. Caplan, Kennedy, and Petrossian (2011) and Ratcliffe et al. (2009) utilized “viewsheds” denoting the actual line-of-sight of cameras as units of analysis. Ratcliffe et al. (2009) found Philadelphia’s CCTV cameras to have generated a 13.3% reduction in overall crime counts, a 16% reduction in disorder crime, and no change in serious crime. While the overall results suggest a positive effect on crime, the authors found just as many individual cameras that had no effect on crime as there were locations which showed a benefit. Caplan, Kennedy, and Petrossian (2011) observed a similar pattern in Newark, NJ. The authors studied CCTV impact on 3 crime types: auto theft, theft from auto, and shootings with a statistically significant reduction being achieved only in respect to auto theft. However, an analysis of the disaggregate camera sites (N=73) found that 58 experienced reduced levels of shootings, with auto theft and theft from auto reducing in 34 and 41 camera locations, respectively. These studies suggest that CCTV effect varies, not just from system-to-system, but between different cameras within the same system. This observation of intra-system variance further highlights the importance of identifying the factors that impact CCTV effect.

Despite the observance of “mixed” CCTV effect in numerous studies, little perspective has been provided to explain this variance. A noteworthy exception is the recent work by the Urban Institute (La Vigne et al., 2011a), which suggests the level to which CCTV is incorporated into law enforcement may be related to effectiveness. This study analyzed seven CCTV systems in three US cities: Baltimore (four systems), Chicago (two systems), and Washington, DC (one system). The systems that proved to be effective against crime were those which were frequently monitored by police and heavily incorporated into the police function. In Baltimore, stakeholders emphasized that the cameras would provide their maximum benefit only when used in a proactive manner. Therefore, the Baltimore Police Department integrated the camera system into the daily routine of proactive street units and designed patrols to add additional coverage to areas officials felt would be susceptible to crime displacement. This resulted in significant crime decreases in three of the four Baltimore systems. In Chicago, officials released surveillance camera “missions,” which identified specific areas to receive enhanced levels of monitoring, on a daily basis. Chicago’s Humboldt Park system experienced a significant decrease in total crime counts as well as robbery and drug related offenses. While the system in Garfield Park did not enjoy as pronounced reductions as Humboldt Park, Garfield Park did experience a reduction of robbery. Washington DC, on the other hand, rarely incorporated active monitoring operations. La Vigne et al. (2011) pointed to this difference in monitoring practices to explain the results, with Baltimore and Chicago experiencing crime reductions in their CCTV areas and Washington DC’s system producing no tangible crime control benefits. Similarly, La Vigne and Lowry’s (2011) analysis of photographic cameras[1] in commuter parking lots found no effect on crime. This finding was attributed to the fact that budget cuts prevented the police from

[1] While this analysis was of photographic cameras, rather than video (CCTV) cameras, the goal of the program was similar to most CCTV programs; deterrence of offenders through the conspicuous presence of recording technology. Therefore, the implications of this study relate to the use of CCTV as well as photographic cameras.

integrating the cameras into patrol or investigative activities, creating a situation where the increased *perception* of risk was not accompanied by a true increase in the likelihood of apprehension.

These projects show the importance of implementing CCTV in a manner that leverages proactive police tactics, rather than as a stand-alone measure. While all CCTV systems aim to deter offenders, the effect of unmonitored and monitored cameras may vary greatly. Indeed, while CCTV is commonly discussed as a singular tactic, the activity of human agents, relative to the monitoring of cameras and the formulation of policy, make the effect of video surveillance largely context specific (Haggerty, Wilson, & Smith, 2011; Mackay, 2006; Norris & McCahill, 2006).

To understand why certain systems underachieve, it is important to identify the manner by which CCTV is expected to prevent crime. Pawson and Tilley (1994) offered nine potential mechanisms by which CCTV can impact crime: catching offenders in the act, generating deterrence, increasing natural surveillance by encouraging more use of the area, effectively deploying personnel, general publicity, specific publicity, allowing criminals less time for crime, encouraging people to be more security conscious, and attracting more cautious (and less vulnerable) people to CCTV areas. Gill and Spriggs (2005) offered a truncated list of five CCTV mechanisms: deterrence, increasing natural surveillance through increased usage of the area, facilitating effective deployment of personnel, encouraging the public to take more precautions, and encouraging the general public and employees to intervene to prevent crime. Many of the mechanisms, however, enjoy little empirical support. This may be partly due to the difficulty in measuring certain phenomenon (e.g. increased usage of public space) or the lack of construct validity of certain mechanisms.

CCTV effectiveness is largely considered to revolve around specific factors. The primary preventive utility is the triggering of a perceptual mechanism within an offender so that they consider the risk of crime commission to outweigh any perceived benefits (Ratcliffe, 2006a: p. 8). Secondly, CCTV can assist in the detection and subsequent arrest of offenders (Ratcliffe, 2006a; Welsh & Farrington, 2007: p. 48). More broadly, as a place-based tactic, CCTV is assumed to provide a presence which fundamentally influences behavior dynamics within a crime prone environment (Mazerolle et al., 2002). Understanding why crime patterns are not universally influenced by CCTV begins with a discussion of how these mechanisms are expected to prevent crime in the first place.

Generating Deterrence

Theoretical perspectives of surveillance are traditionally rooted in Foucault's (1977) model of the panopticon. Foucault's theory on surveillance built upon 19th century philosopher Jeremy Bentham's notion of the panopticon prison, which incorporated a central observation tower from which an unseen observer monitors inmates housed in transparent cells. The panopticon maintained power over inmates by creating a setting in which, at any moment, each individual inmate may be under surveillance. Foucault (1977) extended the panoptic notion to the realm of public surveillance, where the state induced in the populace "a state of consciousness and permanent visibility that assures the automatic functioning of power… He who is subjected to a field of visibility, and knows it, assumes responsibility for the constraints of power" (Foucault, 1977: p. 201-

202). For Foucault, the goal of surveillance was a sense of omnipresence; the potential for observation was equally important as observation itself (Haggerty et al., 2011).

The underlying assumption of the panoptic principle is straightforward; people are less likely to commit crime if they believe they may be seen. What is left implicit is the fact that subjects consciously choose to abstain from crime. From a crime control perspective, this emphasis on decision making aligns with the Rational Choice theory (Cornish & Clarke, 1986). Whereas deterministic theories view crime as an inevitable byproduct of social ills, Rational Choice considers crime as “purposive behavior designed to meet the offender’s commonplace needs” (Clarke, 1997: p. 9-10). Under this perspective, offenders do not indiscriminately engage in crime, but decide whether or not to offend on a case-by-case basis. While these decisions often occur in a state of “bounded rationality” constrained by the limits of time and information (Clarke & Cornish, 1985) the offender nonetheless rationally ponders the situation at hand. The decision making process considers a number of “choice structuring properties” which include the pros, cons, and inherent risk involved the commission of a particular crime. The decision to offend is “the outcome of an appraisal process which…evaluates the relative merits of a range of potential courses of action, comprising all those thought likely in the offender’s view to achieve his or her current objective (for example, for money, sex, or excitement)” (Cornish & Clarke, 1987: p. 935).

Given the highly specific nature and range of offender needs, choice structuring properties typically vary greatly across cases, even amongst those sharing similar crime classifications (e.g. Part 1 Crime) (Clarke, 1997). Failing to account for the unique factors of situational opportunities and the related decision making process can minimize the potential impact of an intervention. A burglar who targets commercial properties, for example, likely takes advantage of different situational factors than a burglar who takes copper piping from desolate housing. An intervention targeting factors which facilitate commercial burglaries is less likely to deter the burglar targeting abandoned properties.

The primary aim of CCTV is considered to be the triggering of a perceptual mechanism in a potential offender "so that an offender believes if he commits a crime, he will be caught" (Ratcliffe 2006a: p. 8). Specifically, CCTV presence must communicate that crime commission carries an increased level of risk in target areas. This is paramount in impacting the choice structuring properties of an offender in a manner that persuades them to abstain. In this respect, CCTV impact is closely related to the offender's ability to recognize the presence of cameras (Eck, 2002; Ratcliffe, 2006a) though the public's ability to recognize CCTV cameras is unclear. Honess and Charman (1992) found that 63% of respondents reported being aware of cameras in the areas where interviews were conducted. However, those interviewed on public streets noticed cameras in only 35% of cases. Gill and Spriggs (2005) noted that public awareness of CCTV increased as the number of cameras per unit increased (though the observation was not statistically significant).

However, the ability of potential offenders to notice or be mindful of surveillance cameras has been considered secondary to the belief that an increased risk of apprehension accompanies the presence of cameras (Gill & Loveday, 2003). In the study of CCTV, such perceptual mechanisms have seemingly been taken for granted. As argued by Mazerolle et al. (2002), "Advocates of CCTV claim that the technology deters criminal activity because people believe that their behavior is being monitored. We would therefore expect that, for some people, the very presence of CCTV is enough to deter criminal or otherwise anti-social activity" (p. 59). However, the actions of offenders suggest that such cognitive processes are not automatic. Coding of nine violent crime incidents captured on CCTV in Newark (Piza, Caplan, and Kennedy, 2010) provides a telling example. Each incident occurred feet from a camera site and was immediately preceded by other criminal infractions, showing the offenders to be unconcerned with the presence of CCTV. While it cannot be definitively stated that the offenders were cognizant of the camera's presence, ground truthing of the crime scenes confirmed the close proximity and conspicuous presence of CCTV, making their recognition by those on the scene probable.

Additional studies have similarly documented offender willingness to operate in sight of CCTV, with offenders in retail environments (Butler, 1994; Gill & Loveday, 2003; Gill & Turbin, 1998) and public places (Ditton & Short, 1998; Gill & Loveday, 2003) expressing that CCTV does little to deter them from offending. During interviews with prisoners, Gill and Loveday (2003) found that most offenders did not consider surveillance cameras as a serious threat. This disregard for CCTV spread across all offender types included in the study: street robbers, burglars, credit card fraudsters, shop thieves, and drug dealers. Interestingly, offenders were more concerned with police presence and the ability of the police to respond to crime observed on camera than the cameras themselves. As Gill and Loveday observed, "offenders appear to believe that the notification of an incident [via CCTV] carries no guarantee that the police are able to respond quickly" (p. 19). The following offender quotes add perspective (Gill & Loveday, 2003: p. 18):

> "For me I think it's about speed—do the robbery and then get out of there. Even if you are seen they have to catch you."
>
> "Unless you are unlucky and they have a team [police] working the street, by the time they [the camera] have found you and called for the police you are long gone."
>
> "It's not like you hang around. You are in and out and away. Just unlucky if they stop you and then they have to find you."

Drug dealers in particular expressed little fear of CCTV. They often stated that the risk posed by CCTV can be easily bypassed. As one prisoner stated, "If I can dip a wallet I can palm gear over just as quick and just as nimble. You won't even have realized that I'd just done business" (Gill & Loveday, 2003: p. 22). Blind spots created by visible obstructions can also provide a safe haven for drug dealers: "They [cameras] cannot see everywhere—they all have blind spots. All you got to do is work out your angles and you're safe" (Gill & Loveday, 2003: p. 22).

The findings of Gill and Loveday (2003) challenge the assumption that the presence of video surveillance cameras automatically generates deterrence. However, while most offenders did not worry about CCTV in planning their offenses, prisoners previously caught or convicted with CCTV footage were significantly more likely to report that surveillance cameras increase the likelihood of apprehension. This demonstrates that deterrence effects may be at least partially related to the successful detection and apprehension of offenders via CCTV.

The findings of Gill and Loveday (2003) have significant implications for the use of CCTV by suggesting that the mere presence of a camera does not generate deterrence unless it is known to be accompanied by a real threat of apprehension. This observation is supported by the literature on deterrence. Previous research reveals an inverse relationship between deterrence and the successful completion of a crime. The commission of a criminal act provides individuals with “direct knowledge about the consequences and implications of that behavior” which becomes “much more salient to future decisions about continuance or desistance” (Clarke & Cornish, 1985: p. 164). Offenders whom escape sanction are less likely to be deterred in future instances (Paternoster, Saltzman, Chiricos, & Veldo, 1982). On a macro-level, this finding suggests that criminals can potentially grow less susceptible to the effects of deterrence. As argued by Paternoster (1987), “[M]ost instances of rule breaking go undetected and…participants in crime eventually lower their initially unrealistically high estimates of the risks involved” (p. 180). The level to which this realization takes hold may vary amongst criminal populations based on their levels of activity. Offenders more prominently involved in crime and delinquency report “lower estimates of the risk of legal sanctions than those who are less experienced” (Paternoster, 1987: p. 180-181). Loughran, Piquero, Fagan, and Mulvey (2012) found that serious adolescent offenders with high levels of offending had much lower estimates of the risk of offending than medium and low-level offenders. Loughran et al. (2012) considered these findings as an example of “differential deterrence, a term meant to recognize the significant amount of heterogeneity that exists across juvenile offenders, both with respect to their decision-making calculus and involvement in criminal activity” (p. 7). Indeed, much research has found deterrence effects to be highly contextual, with certain individuals being more resistant to deterrence efforts than others (Pogarsky, 2002; Tittle, Botchkovar, and Antonaccio, 2011).

In light of the inherent shortcomings of broadly applied deterrence, crime prevention efforts should be tailored towards the situational factors of crime incidents in an attempt to more directly convey increased risk levels to potential offenders. As noted by Brantingham and Brantingham (1993a), "because of the high variability in what is *called* a crime, in the people who *commit* crimes and in the *sites* and *situations* in which criminal events occur, solutions to crime problems will often have to be focused and specialized" (p. 5). This emphasis on the specificity of intervention efforts provides the foundation of Situational Crime Prevention (SCP). The explicit goal of SCP is the elimination of crime opportunities within very specific situations (Clarke, 1997; Cornish & Clarke, 2003). As described by Clarke (1997), "proceeding from an analysis of the circumstances giving rise to specific kinds of crime, it [SCP] introduces discrete managerial and environmental change to reduce the opportunities for those crimes to occur. Thus it is focused on the setting for crime, rather than upon those committing criminal acts" (p. 2).

Given the role of situational factors in crime commission, Cusson (1993) deemed general deterrence tactics to be limited. In particular, Cusson (1993) argued that perceptual deterrence theory is not time-specific enough, being incapable of grasping short-term impact of variations in sanctions, and does not adequately specify the concrete contingencies in which crimes occur. Cusson further argued that legal punishment is but one means of deterrence and acknowledge three principal sources of intimidation: legal sanctions, informal sanctions, and situational measures. Cusson particularly stressed the importance of situational measures, arguing that the manipulation of specific situational variables more directly impacts the "choice structuring properties" of offenders, thereby increasing their assessment of the inherent risks involved.

Previous research supports the notion of "situational deterrence." Burglars, for example, have reported that their target selection revolves around the likelihood of a house being unoccupied and being able to enter to premise without being seen (Clarke & Cornish, 1985). More recently, Copes, Hochstetler, and Cherbonneau (2011) found that carjackers chose victims in a somewhat serendipitous manner by identifying motorists they came across as either likely or unlikely to resist, with the latter group being chosen as targets. The "focused deterrence" approach suggests that tailoring response towards specific crime problems and directly communicating risk levels to specific offenders more effectively controls crime than messages broadly delivered to the general public (Kennedy, 2008).

As a situational crime prevention tactic, CCTV aims to increase the risk of offending by increasing levels of formal surveillance (Clarke, 1997: p. 18). However, CCTV should be deployed in a manner that addresses specific situational aspects of the target offense, rather than in an attempt to increases general levels of deterrence. Utilizing CCTV as a general deterrent may fail to disrupt specific situational opportunities exploited by offenders. Additionally, it is not enough to hope the mere presence of a camera instills sufficient fear in potential offenders.

As noted by Caplan, Kennedy, and Petrossian (2011a), "it is expected…that CCTV monitoring, and the swift and certain punishment that cameras signify, is enough to deter criminal activity in places where cameras are present" (p. 256). However, it may not be enough for cameras to *signify* swift and certain punishment; their deterrence capabilities may be directly influenced by the ability or inability of police to successfully apprehend offenders detected by CCTV. As argued by Cusson (1993), "all offenders can read in the pre-criminal situation the signs that enable them to estimate their risk of being punished sooner or later: inquisitive passerby, a watchman, metal detectors, alarms, closed-circuit television, etc. But if they are to be deterred, punishment must follow" (p. 61-62). The extensive literature on deterrence finds strong evidence that the *certainty* of punishment is much more important than its *severity* in deterring offenders from committing crime (Apel, 2012; Nagin 2010; Nagin & Pogarsky 2001; Piquero & Pogarsky, 2002). Cusson (1993: p. 58) argues that the sequence connecting certainty of punishment and deterrence is three-fold: 1) Punishment applied systematically will result in a high percentage of offenders punished and in a high percentage of potential offenders who know people who were punished. 2) The more offenders who directly or indirectly experience the certainty of punishment, the higher the risk of punishment will be perceived. 3) The greater the perceived risks of punishment, the less crime will be committed.

Research supports this relationship between deterrence and punishment, with the experience of sanction causing "the apprehended offender to revise upward his estimate of apprehension risk and thereby deter him from future crime" (Durlauf & Nagin, 2011: p. 19). This cyclical relationship between deterrence and sanction can be maintained through increased certainty of punishment, even when the sanction is not particularly severe. In arguing this point, Durlauf and Nagin (2011) discussed Hawaii's Project Hope (Hawken & Kleiman, 2009) and a randomized experiment conducted by Weisburd, Einat, and Kowalski (2008). Both projects utilized short term, but highly certain, jail sentences to produce deterrence. While the punishments were relatively minor in both projects (a jail sentence of only a day or two), Weisburd, Einat, and Kowalski (2008) and Hawken and Kleiman (2009) observed a significant reduction in failures of defendants to pay court ordered fines and rates of positive drug tests, missed appointments, and arrests in probationers, respectively.

Given the importance of punishment certainty, human components of CCTV operations (e.g. personnel to view cameras and respond to observed infractions) are of equal importance as the technological aspects. An inappropriately small distribution of resources towards the day-to-day operational aspects of CCTV in favor of the technological aspects can have grave consequences for CCTV systems. As argued by Tilley (1993), "If the mechanism is deterrence via a rise in perceived risk which is not rooted in real risk increase, then many offenders may come to appreciate that they can safely resume their criminal behavior" (p. 5). Pease (1999) further argued that "no public place…will be crime free if offenders have good reason to believe that they will not be recognised, or, if recognised, will not be reported to the police, or, if reported will escape meaningful criminal justice outcomes" (p. 49). The lack of a true risk increase was observed in an evaluation of San Francisco's CCTV system, with a Police officer being quoted as saying "when the type of stuff that they're (offenders) involved in kept happening and they realized they weren't getting arrested, nothing was happening because of those cameras. I do not think (the camera program) works as a deterrent at all….because there's no immediate consequence to the behavior" (King et al., 2008: p. 87). Similar frustrations were expressed by police in a British CCTV operation. "People on the ground are needed to make it a success. It's a shame when you have equipment like this and it stops (being used) because we do not have enough people to mount an operation" (Gill, Rose, Collins, & Hemming, 2006: p. 454).

Detecting and Arresting Offenders

Most CCTV evaluations analyze programs that task operators with monitoring cameras for the purpose of detecting criminal and suspicious behavior (Armitage et al., 1999; Brown, 1995; Caplan, Kennedy, & Petrossian, 2011; Ditton & Short, 1999; Farrington, Gill, Waples, and Argomaniz, 2007; Gill, Spriggs, Allen, Hemming, Jessiman, & Kara, 2005; Norris & Armstrong, 1999a,b; Norris & McCahill, 2006; Ratcliffe et al., 2009; Smith, 2004). Given the emphasis placed on the proactive use of the technology, the common research finding is somewhat surprising; the detection of criminal events by CCTV operators is fairly rare.

The size of many surveillance systems places a heavy burden on camera operators. Norris and Armstrong (1999a) estimated that the twenty cameras in a British surveillance system created over 43 million unique "images" on a daily basis (p. 159), giving operators a significant amount footage to monitor. This issue is compounded when CCTV systems include a large amount of cameras, which appears to be the norm. Farrington, Gill, Waples, and Argomaniz (2007) noted that cameras monitored per operator varied from 25-40 to 173-520 in 14 separate CCTV systems (p. 26). Such high camera-to-operator ratios mean that during most times most cameras are not being actively monitored. This has the predictable result of crime occurring within sight of a camera going undetected. The following quote from a CCTV operator adds perspective:

"I cannot tell you how many things we've missed when we have not been watching the other screens. Break-ins, assaults and car thefts have been going on whilst we've been operating the other cameras." (Smith, 2004: p. 385). Offenders seem to be at least somewhat cognizant of this fact, with Gill and Loveday (2003) quoting an offender as stating "We've got so many cameras man, they cannot all be watched. They have to find you, guess what you're going to do and then do something about it" (p. 19).

Consequent to the aforementioned burdens placed on surveillance operators, studies of control rooms have found CCTV detections of crime to be a fairly rare occurrence. For example, Ditton and Short (1999) found that operator activity led to only one arrest per 967 hours of monitoring in two Scottish city centers. Sarno, Hough, and Bulos (1999) reported that a London CCTV unit provided police with footage of crime incidents a mere eight times over twelve months. Other studies focusing on general surveillance activity, rather than enforcement actions, report similarly low levels. Norris and Armstrong (1999a) quantified operator activity through observing "targeted surveillances," which they defined as an operator observation "that lasted more than one minute on an individual or group of individuals, or where the [video] surveillance was initiated from outside the system, for example, by police or private security…" (p. 161). In 592 hours, Norris and Armstrong (1999) observed 888 separate targeted surveillances, translating to a rate of 1.5 per hour. Norris and McCahill (2006) found similarly low levels of crime detection in four separate English systems with 84 targeted surveillances occurring over 120 hours. Further analysis revealed "proactive" activity to be even lower; 59 of the 84 surveillances occurred in response to requests from outside entities. Only 35% (29 of 84) of targeted surveillances were initiated by operators, meaning truly proactive use of the systems only occurred once every four hours (Norris & McCahill, 2006: p. 108).

Following the detection of a criminal incident, a response is obviously necessary to address the situation at hand. In this respect, the technological innovation of CCTV is (ironically) largely dependent upon traditional law enforcement functions. Specifically, CCTV is highly incorporated into the patrol and response functions of policing. O.W. Wilson's *Police Administration* (1963), widely considered the seminal text during the professional era of law enforcement, cemented "rapid response" as a key strategy in American policing. Despite its early strong hold on law enforcement, rapid response came to be seen as ineffective in the fight against crime. Spelman and Brown (1981) found that 75% of reported crimes were deemed "discovery crimes" in which the victim does not realize he/she's been victimized until well after the event took place. In addition, Spelman and Brown (1981) found that victims took an average of four to 5.5 minutes to notify the police of the crime. Such delays can render the speed of police response inconsequential. The Kansas City Police Department (1977) found that only 3% of all calls for service in their jurisdiction experienced an arrest due to rapid-response. Replications of the study in four additional cities found similar results, while adding that between 80 and 90 percent of serious crimes were reported too slowly for a response-related arrest to have occurred. Furthermore, the authors found that no more than 70 per 1000 (7%) crimes would be cleared by arrest if all delays in police notification were eliminated (Spelman & Brown, 1981). In interpreting these findings, Eck and Spelman (1987) argued that delays in the discovery and reporting of crime renders officer response times inconsequential: "True, a fast response drastically increases the chances an offender would be arrested if the crime were reported quickly; but the chances of an arrest at or near the scene dropped to nearly zero if the citizen delayed reporting as much as 5 or perhaps 10 minutes. And in 90 percent of the crimes reported, citizens were unable or unwilling to report of its commission" (p. 14).

After the event is reported, an additional time lapse commonly occurs before an officer responds. Police Communications systems, especially in large urban areas, experience high call volumes on a daily basis. Immediate dispatch of an officer to all jobs is not a realistic option. It is standard procedure for requests for police service to be addressed in a "differential response" manner, with calls of a higher priority being dispatched before lower priority calls for service. All reported incidents awaiting police response are stored in the "calls pending queue" of the police department's Computer Aided Dispatch (CAD) system. After an incident is closed, the police dispatcher sends an officer to the next call in the calls pending queue (LEITSC, 2008). For many calls, specifically pertaining to low priority incidents, the time spent in the queue is substantial.

In respect to police response, detection of crime through CCTV can provide distinct advantages over the 9-1-1 emergency line. Specifically, discovery time and reporting time are nil when a crime is detected by a camera operator. This is where the differences between CCTV detections and calls-for-service cease. CAD assignments, both CCTV events and 9-1-1 calls for service, are stored in the calls pending queue and dispatched in the aforementioned differential response manner. Although "discovery" and "reporting" times are minimized with CCTV, the "queue" times remain. While there has yet to be a large scale study of the process times associated with CCTV detections, anecdotal evidence suggests that delays in police dispatch negatively affect CCTV operations. Gill and Spriggs (2005) reported an incident where a camera operator generated an assignment in CAD after witnessing an assault. After nearly half an hour, police still had not responded. Such situations can be frustrating for video operators, and can cause some to not bother reporting certain crimes (specifically low-priority crimes) observed on camera. Lomell (2004) reported that CCTV operators in Olso stopped reporting street-level drug transactions due to the police emphasizing the apprehension of drug traffickers rather than the disruption of street-level markets. Norris and McCahill (2006) documented a CCTV operator not reporting a shoplifting incident due to his belief that there was not enough staff on duty for a swift response. Norris and Armstrong (1999a,b) reported several instances where operators did not bother reporting relatively low-prioritized incidents of prostitution and domestic disturbances to the police. Additionally, Piza, Caplan, and Kennedy (2010) reported that more than half of Newark, NJ's camera operators noted large queue times when explaining their decision to not report street-level infractions preceding serious violent crime incidents.

While theoretical perspectives suggest that CCTV generates deterrence, the practical application of the technology oftentimes fails to provide increased levels of certainty and swiftness of punishment. The increased "risk" implied by a camera's presence is not supplemented with a real threat to offenders. The manner by which CCTV is incorporated into the police function does not lend itself to the disruption of incidents that can lead to crime. For example, Sacco and Kennedy (2002) describe crime incidents as being comprised of three stages: precursor, transaction, and aftermath. While CCTV emphasizes deterrence, the standard use of the technology does little to address risk factors present in the precursor stage. It is assumed that the passive presence of cameras is enough to convince potential offenders to abstain from crime, despite the fact that addressing risk factors is likely contingent upon enforcement activity generated by CCTV. Street-violence provides a telling example. Many violent crimes result from "precursor" events, such as the escalation of relatively minor disputes (Braga, Kennedy, Waring, & Piehl, 2001; Griffiths, Yule, & Gartner, 2011; Jacobs, 2000; Ratcliffe & Rengert, 2008). Kennedy and Van Brunschot (2009), argue that the "active rather than passive use of this technology in managing public areas may afford an important new resource in the reduction of risk" (p. 141). While certain individuals may be unwilling to engage in precursor offenses in the presence of surveillance cameras, it is likely that many offenders do not consider CCTV as a real threat and may willingly offend within camera sight (see Gill & Loveday, 2003).

The common strategy of CCTV operations means that the perceived threat of cameras may not often translate into action against offenders. This means that a key factor in deterrence, "the certainty of a disciplinary response to deviancy, is absent" (Norris & Armstrong, 1999b: p.199). Such a "bluff" can have grave consequences for crime prevention efforts. While criminals have been known to overestimate the true extent of policing efforts (Clarke & Weisburd, 1994; Johnson & Payne, 1986), evidence exists that offenders may gradually discover true risk levels and adjust their actions accordingly (Brisgone, 2004; Taylor, Koper, and Woods, 2011). "Deterrence decay" often occurs in respect to police operations due to potential offenders learning "through trial and error that they had overestimated the certainty of getting caught at the beginning of the crackdown" (Sherman, 1990: p. 10). Accurately gauging risk may be especially possible in the case of CCTV, given the limited coverage area of most cameras. Risk appraisal may be even easier when the precise line of sight of cameras is easily determined. For example, Waples and Gill (2006) evaluated a redeployable CCTV intuitive that utilized highly visible “box type cameras” whose line of sight was easily determined. While officials chose these overt cameras to send a message of reassurance to citizens and warning to offenders, the box camera style made it “much easier for offenders to monitor where the cameras were pointing, and consequently, calculate how likely they were to be captured on CCTV…it was relatively easy for offenders to evade being captured by CCTV, simply by moving to another part of the estate. It is quite possible that offenders chose to offend ‘behind the cameras’ back’” (p. 12). The lack of a visible increase in law enforcement actions in response to crime in CCTV areas can further communicate the absence of a true risk increase. If continued criminality within sight of CCTV is not met with an increase in police presence or response, criminals may consider the situation to be “business as usual” and act accordingly.

CCTV and the Influence of Place

The Spatial Concentration of Crime

There is much empirical support for the “crime and place” perspective (Braga & Weisburd, 2010; Eck & Weisburd, 1995). The seminal work of the Chicago School (Burgess, 1928; Park, 1936; Shaw & McKay, 1942) demonstrated the environmental composition of neighborhoods to be more closely associated with high crime rates than resident demographics over three-plus decades in Chicago. They concluded that the physical qualities of these places created opportunities for crime irrespective of the demographic composition of the population.

With time, and technological advancements, scholars examined the concentration of crime in micro-environments, such as street segments, block faces, and addresses, further illustrating the influence of place-level factors on crime (Eck & Weisburd, 1995). In a seminal study, Sherman, Gartin, and Buerger (1989) found that three percent of addresses accounted for over 50% of calls for service in Minneapolis over a one-year period. Similar observations were made in respect to calls reporting predatory crimes, with robberies, rapes, and auto thefts being confined to approximately 2%, 1%, and 3% of addresses, respectively (Sherman et al., 1989). Subsequent evaluations have produced similar findings. Significant clustering has been observed in respect to gun crime (Braga, Papachristos, & Hureau 2010; Ratcliffe & Rengert, 2008; Sherman & Rogan, 1995a; Wells, Wu, & Ye, 2011), robbery (Block, 2008; Braga, Hureau & Papachristos, 2011), burglary (Farrell & Pease, 1993; Forrester, Frenz, O'Connel, and Pease, 1990; Johnson & Bowers, 2004), and drug dealing (Sherman & Rogan, 1995b; Weisburd, Wyckoff, Ready, Eck, Hinkle, and Gajewski, 2006; Weisburd & Green, 1995). Hot Spots also manifest over rather extensive time periods. Weisburd, Bushway, Lum, and Yang (2004) found that in every year over a 14-year period approximately five percent of Seattle's street segments accounted for roughly 50% of the city's reported crime incidents. Amongst these particular street segments, only two percent experienced noticeable increases with steady declines occurring in 14%, demonstrating how micro-places drove Seattle's crime reduction throughout the 1990's. Similar concentration was found when observations were restricted to juvenile crime; just 86 of Seattle's street segments accounted for one-third of crime incidents in which a juvenile was arrested during the 14-year study period (Weisburd, Morris, & Groff, 2009). Replications of the Seattle study, which incorporated street intersections as well as street segments as units of analysis, found firearm assaults (Braga et al., 2010) and robbery (Braga, Hureau, & Papachristos, 2011) to be similarly confined to a small number of places over a 29 year period in Boston. In both studies, steeply rising or declining crime trends were similarly confined to few places.

The concentration of crime is explained by opportunity-based theories of criminology. Routine Activities considers crime as the result of the spatial and temporal convergence of a motivated offender and likely target in the absence of a capable guardian (Cohen & Felson, 1979). This convergence typically occurs as a result of everyday patterns of activity across the life course. For example, the rise of residential burglary between the 1960's and 1970's was explained by a change in the routine activities of American households. Due to the increased numbers of single-headed households and women in the workforce homes were left empty and unguarded more often than had previously been the case (Cohen & Felson, 1979). Micro-level crime patterns are similarly influenced by the activity of both victims and offenders (Brantingham & Tita, 2008; Kennedy & Forde, 1990; Tita & Griffiths, 2005). For example, Wiebe, Anderson, Richmond, Nance, and Branas (2010) found that juvenile gun assault victims in Philadelphia were often victimized during the course of their daily travel patterns. Ratcliffe (2006b) argued that the temporal constraints of daily life contribute to the clustering of crime along an offender’s path of travel. Crime Pattern Theory adds further perspective. Brantingham and Brantingham (1993b) argue that offenders find targets of victimization primarily through their daily travels from home to work to recreation. Crime commonly occurs around these nodes and the paths traveled between them for reasons of convenience; it is easier to commit crime during the course of daily activity than by making a special journey to do so (Clarke & Eck, 2005: step 16). Edges, the boundaries between distinct geographic areas, also play a prominent role in the formation of crime patterns (Brantingham & Brantingham, 1993b). Edges allow offenders to exploit new crime opportunities offered by nearby vicinities without traveling far from their primary area of familiarity. In the case of burglary, Brantingham and Brantingham (1975) suggested that homes on the borders of affluent areas were at the highest risk of victimization since they afforded burglars an opportunity to operate where they were relatively inconspicuous.

Micro-level crime concentrations are additionally shaped by the presence of hot-spot places, particularly crime “generators” and “attractors” (Brantingham & Brantingham, 1995). The term “crime generator” refers to a place “to which large numbers of people are attracted for reasons unrelated to criminal motivation,” while crime attractors “are places affording many criminal opportunities that are well known to offenders” (Clarke & Eck, 2005: step 17). An example of a crime generator is a local shopping mall or transit hub, while drug and prostitution markets are common crime attractors. The criminogenic influence of crime generators and attractors is well established. A recent work by Bernasco and Block (2011) found that each of the 14 types of crime generators and attractors included in their analysis were associated with increased numbers of robberies within census blocks in Chicago.

Certain environs have been recognized as being specifically criminogenic. The link between liquor establishments and crime, particularly violence, is well established (Scott & Diedel, 2006). Block and Block (1995), for example, found taverns and liquor stores in nightlife areas of Chicago to generate a high volume of the city’s alcohol-related violence. Public transit stations and stops commonly have been observed to generate crime, particularly robbery and other street-level violence (Block & Block, 1999; Smith & Clarke, 2000; van Wilsem, 2009). Traditional designs of large scale housing complexes facilitates the commission of crime (Eck & Spelman, 1987; Newman, 1972). Public housing in particular has been considered prone to serious violence and the illicit drug trade (Eck, 1994; U.S. Department of Housing and Urban Development, 2000). Even in the absence of serious, systematic crime problems, residential high rise buildings present opportunities for crime due to the concentration of persons and property in a compact area (Poyner, 2006). Recent research emphasizes the importance of "risky facilities," defined as the small number of establishments producing the majority of crime and disorder problems experienced by the group as a whole (Clarke & Eck, 2007). Eck, Clarke, and Guerette (2007) demonstrated that a small number of facilities accounted for the vast majority of calls for service amongst homogenous establishment sets in four U.S. cities. The layout of street networks has also been seen to contribute to the formation of crime patterns. Since offenders discover crime opportunities during travels between nodes, pathways (e.g. "streets") determine how potential offenders travel amongst these nodes and the frequency with which they will encounter crime opportunities (Beavon, Brantingham, & Brantingham, 1994). Thus, major roadways as well as streets with high levels of permeability (e.g. access points and connections to other roadways) are commonly associated with higher levels of crime (Beavon et al., 1994; Johnson & Bowers, 2010; van Wilsem, 2009).

Place-based Crime Prevention and Units of Analysis

The concentration of crime has particular implications for crime prevention. Given the high level of crime concentration, crime prevention resources “should be similarly concentrated rather than diffused across urban areas” to achieve maximum impact (Braga et al., 2010). This ideal has become well established in law enforcement, with contemporary crime control tactics commonly directing resources towards high crime places (Weisburd, 2008). Reviews of contemporary police practices find geographically focused prevention efforts to have the strongest evidence of effectiveness (Skogan & Frydl, 2004; Weisburd & Eck, 2004). Place-based interventions also offer a more efficient method of policing than offender-based strategies. While places often demonstrate relatively stable crime levels over time, it is well established that individuals experience both short-term and long-term variations in criminal propensity (Agnew, 2011). Weisburd (2008), for example, noted that police in Seattle would have to target four times as many people as places to account for 50 percent of the crime incidents between 1989 and 2002.

CCTV represents a technological approach to "place-based” policing. Analogous to a patrol officer riding the streets in a radio car, CCTV personnel use cameras to visually “patrol” an area in search of crime and disorder. Despite CCTV’s focus on “place” little effort has gone towards understanding the precise relationship between “place” and CCTV effect. The vast majority of CCTV evaluations measure impact on a macro level; systems as a whole are deemed as either effective or ineffective in preventing crime (Armitage, 2002; Cameron et al., 2008; Eck, 2002; Farrington, Gill, Waples, & Argomaniz, 2007; Gill & Spriggs, 2005; La Vigne et al., 2011a; Phillips, 1999; Welsh & Farrington, 2002, 2004, 2007, 2009). A long-standing limitation of such an approach is the ecological fallacy, which refers to "an error in the interpretation of results whereby assumptions about specific cameras are based solely upon aggregate statistics for the group to which those individual cameras belong" (Caplan, Kennedy, and Petrossian, 2011: p. 270). As noted by Johnson, Bowers, Birks, and Pease (2009), "When analyses are performed using data from the less appropriate larger areal units, the temptation may be to assume that patterns observed across an area will apply equally to the mosaic of smaller areas (and individual locations) of which it is composed…" (p. 172). As far back as 1950, Robinson warned against drawing inferences on individual cases based on observations of aggregate level data: "[T]he individual correlation depends on the internal frequencies of the within-areas individual correlations, while the ecological correlation depends upon the marginal frequents of the within-areas individual correlations" (p. 354). Robinson's observations caution that the ecological fallacy can lead to "meaningless conclusions" by improperly substituting ecological correlations for individual correlations (Weisburd, Bernasco, & Bruinsma, 2009: p. 15). In respect to CCTV, such research designs dismiss the possibility that effective camera sites are deployed within ineffective systems, and vice versa.

Units of analysis have similarly failed to accurately reflect "places" in the study of CCTV. Researchers have typically utilized aggregate geographies where cameras were installed, such as "neighborhoods" or "police districts," in tests of CCTV (Brown, 1995; Ditton & Short, 1999; Sivarajasingam, Shepard, & Matthews, 2003; Squires, 2000). Another common approach is the designation of circular buffer areas around cameras (Cameron et al., 2008; La Vigne et al., 2011b; Mazerolle et al., 2002). Both of these approaches do no accurately operationalize CCTV locations. Being that publicly-deployed surveillance cameras have the ability to view limited distances, aggregate areas such as “neighborhoods” likely overestimate CCTV coverage. Furthermore, these aggregate geographies do not accurately reflect patterns of important variables. In this respect, Oberwittler and Wikström (2009) caution readers of the “zonation effect,” which “relates to the difficulty of drawing meaningful boundaries within an area which reflect rather than blur the spatial patterns of important variables” (p. 40). While boundaries of administrative areas such as neighborhoods, census tracts, and block groups are likely drawn to capture patterns of various demographic features, Oberwittler and Wikström (2009) argue smaller units of analysis are less likely to be significantly heterogeneous in their environmental composition. In addition, pre-determined administrative boundaries are ill-fit for social analysis for a simple—yet commonly overlooked—fact: they are not real. While an offender’s travel is restricted by a natural boundary like a river, his activity is restricted to a much lesser degree, if at all, by the boundary of an administrative unit such as a census tract. Peoples’ conceptions of space rarely coincide with such administrative areas. An innovative study conducted in Philadelphia demonstrates this fact. Basta, Richmond, and Wiebe (2010) conducted rapport-building exercises with adolescent gunshot victims and control subjects who each created hand-drawn sketches on street maps of the area they considered their neighborhood, as well as the routes they traveled over the course of one full day. The authors found that the hand-drawn neighborhoods and activity paths for each subject varied greatly in shape and size, and largely deviated from neighborhood boundaries as defined by the census. Basta et al.

(2010) thus argued that utilizing census boundaries was a poor way to operationalize "neighborhoods" in social science studies.

While buffer zones truncate the size of targets areas, they are also inaccurate representations of CCTV coverage. Buffer zones assume a 360 degree, unobstructed line of sight for each camera, which is rarely the case in a real world environment. Identifying areas free of obstruction can be difficult, especially in the urban landscape (Chainey, 2000; Eck, 2002). Street signs, building awnings, and telephone poles are common fixtures that can limit a camera's line of sight. Leaves and bushes can present added hardships for camera operators while providing areas of cover for offenders. Left unkempt, foliage can signal obvious places within a viewshed which are out of a camera's line of sight. In his observational study of a CCTV control room, Smith (2004) quoted a camera operator as saying, "Look at this camera…how the hell are we supposed to see anything from it….there's a great bleedin' tree in the way…it completely blocks our view…The yobs [criminals] know it as well" (p. 387). In a similar sense, Gill et al. (2006) identified "difficulty in establishing a 'line of sight' due to obstructions" as a factor contributing to a CCTV program's ineffectiveness (p. 455). Unfortunately, camera sites are typically selected with little consideration to potential environmental constraints to surveillance (Chainey, 2000; La Vigne et al., 2011b). Furthermore, the level to which obstructions influence CCTV effectiveness has yet to be empirically tested.

The call to identify the places where CCTV best performs has been made in numerous works (Caplan, Kennedy, & Petrossian, 2011; Gill & Spriggs, 2005; Phillips, 1999; Ratcliffe et al., 2009; Ratcliffe, 2006a; Tilley, 1993; Welsh & Farrington, 2002, 2004). A noteworthy contribution is the meta-analysis conducted by Welsh and

Farrington (2009), which attempted to identify "the specific conditions and contexts under which CCTV may have an effect on crime" (p. 719). Forty-four studies were categorized according to one of four main settings: city and town centers, public housing, public transport, and car parks. The cark park systems produced the largest crime reductions. Welsh and Farrington (2009) concluded that CCTV is most effective within car parks, which concurs with findings of previous evaluations (Gill & Spriggs, 2005; Farrington, Gill, Waples, & Argomaniz, 2007; Welsh & Farrington, 2007). However, Welsh and Farrington (2009) cautioned readers against universally dismissing CCTV use in other environments by stating "exactly what the optimal circumstances are for effective use of CCTV schemes is not entirely clear at present, and this needs to be established by future evaluation research" (p. 736).

The confusion revolving around the optimal placement of CCTV cameras may be largely driven by the choice of units of analysis. Grouping all "city center" systems together, for example, ignores micro-level criminogenic features that can differ across sites. It is certainly possible that a particular city center may be rife with such criminogenic features with others being relatively free of them. While grouping "city centers" together suggests homogeneity amongst these areas, the unique distribution of micro-level crime generators and attractors within each area creates spatial units that may differ considerably across a number of important characteristics. Furthermore, the spatial influence of crime attractors or generators may be limited in scope and may not influence an administrative area, such as a block group or census tract, in its entirety. The use of large units of analysis cannot adequately account for such micro-level variance; either micro-units are ignored or are assumed to have uniform impact across the entirety of the unit (Rengert & Lockwood, 2009: p. 117).

The relationship between crime and micro-level features of the environment has been explained through Brantingham and Brantingham's (1981) conceptualization of the "environmental backcloth." As explained by Brantingham and Brantingham (1993a), "the term 'environmental backcloth' is used within environmental criminology to attach a label to the uncountable elements that surround and are part of an individual and that may be influenced by or influence his or her criminal behavior" (p. 6). This dynamic person-environment interaction is what makes certain environs more suitable settings for crime than others. As argued by Brantingham and Brantingham (1993a) "criminologists have begun to accept the idea that a crime must be viewed as an event that occurs at a specific site and in a specific situation…and that the individual who commits the offense is influenced by and influence both the site and the situation" (p. 6). Brantingham and Brantingham (1993a) further articulate the environmental backcloth through the following example: "a house may be an attractive break-in target for an intending thief, but the owners may be clearly home, making the house temporarily unattractive. At a later time, the house may be empty: whether it then becomes victimized will be a function of the continuing attention and desire of the intending thief…What is seen as an attractive and acceptable criminal target varies depending on the expectation of the potential offender in conjunction with the site and situation of the moment" (p. 6).

While the influence of micro-level features on crime rates has been demonstrated in a number of criminological studies (see: Bernasco & Block, 2011; Brantingham & Brantingham, 1995; Caplan, Kennedy, & Miller, 2011; Eck & Weisburd, 1995; Groff, 2007, Kennedy, Caplan, & Piza, 2011) less attention has been given to the influence of the environmental backcloth has on specific crime prevention efforts. Just as certain crimes are conducive to certain environments, specific crime prevention tactics (e.g. CCTV) may be more effective in certain places than others. As argued by Eck (2002), "Though many opportunity blocking tactics appear to work in many places, there is no guarantee they will hold up as they are tried in different types of places. These tactics are being applied where they are most plausible, so success is most likely. As people try them in other less plausible places, there is greater likelihood of failure" (p. 285). While CCTV has been demonstrated to work well in car parks, commonly employed research designs have prevented further investigation into the relationship between camera effectiveness and environmental composition.

Recent CCTV evaluations have made strides towards the understanding of the relation between CCTV effect and the environment. Methodologies incorporated by Caplan, Kennedy, and Petrossian (2011) and Ratcliffe et al. (2009) more accurately capture CCTV "places" than traditional research. Both of these studies utilized viewsheds denoting the actual line-of-sight of cameras as units of analysis. Caplan, Kennedy, and Petrossian (2011) utilized a method which estimated each camera's line-of-sight via aerial imagery of CCTV areas in Newark, NJ. The researchers created 582-foot buffers around each camera location (representing twice the median length of the City's block faces) then used ArcGIS tools to digitize viewshed polygons that accounted for buildings and other barriers to a camera's line of sight. Ratcliffe et al. (2009) took a more hands-on, albeit less replicable, approach in their evaluation of Philadelphia's CCTV system by viewing actual camera feeds at the Police department. In conjunction with Police personnel, the researchers ascertained the system's viewsheds by utilizing the pan, tilt, and zoom functions of each camera to gauge the visible areas.

Ratcliffe et al. (2009) found just as many individual cameras that had no effect on crime as there were locations that showed a benefit, with Caplan, Kennedy, and Petrossian (2011) observing a similar pattern in Newark. These findings avoid common pitfalls related to the ecological fallacy by recognizing each camera site as a unique attempt to reduce crime. These findings also suggest CCTV performance to be related to place-based characteristics that differ between sites. As suggested by Caplan, Kennedy, and Petrossian (2011) "some places are likely to be more crime prone than others—regardless of any police interventions, including CCTV cameras. Therefore, the effect of police-monitored CCTV cameras on crime deterrence could be very minimal in some places while other places yield better results" (p. 266). This suggests that CCTV impact and micro-environmental features can potentially be related in a host of ways. For example, it may be that potential offenders within crime attractors are more deterred by CCTV effects that those within crime generators. However, such observation are merely speculative; research has yet to establish the precise influence such features have on CCTV

Chapter Summary, Research Questions, and Hypotheses

Summary

Research on CCTV has thus far generated little in the sense of "transferrable lessons" (Gill & Spriggs, 2005). Most evaluations find the crime prevention utility of CCTV to be "mixed." However, limitations of common research designs do not allow for exploration of why impact is so variable. Units of analysis often fail to adequately capture the "places" covered by CCTV systems by incorporating aggregate geographies rather than micro-level geographies more appropriate in the study of place-based crime prevention efforts (Weisburd, Bernasco, & Bruinsma, 2009; Weisburd, Morris, & Ready, 2008). Geographically condense units of analysis also more readily reflect the theoretical framework of deterrence, which suggests offender activity space and perceptions of CCTV presence and associated risk to be heightened in the space immediately surrounding the cameras (Caplan, Kennedy, and Petrossian, 2011; Ratcliffe et al., 2009). In addition, most evaluations fail to account for alternate mechanisms by which CCTV can prevent crime. Specifically, while the detection and apprehension of offenders have received much attention in studies of control room operations (Gill et al., 2005; Lomell, 2004; Norris & Armstrong, 1999a,b; Norris & McCahill, 1999; Smith, 2004), the definitive impact of proactive monitoring and response on crime reduction is unknown. Furthermore, the micro-level impact of CCTV has received little attention. With the exception of Caplan, Kennedy, and Petrossian (2011) and Ratcliffe et al. (2009), changes in crime levels are typically measured on a system-wide rather than on an individual-camera level. Finally, the impact of micro-level environmental features on the crime prevention capabilities of surveillance cameras has yet to be analyzed—an irony given that CCTV is a place-based tactic. While previous research observed the influence of aggregate environments (Welsh & Farrington, 2009) micro-level features that comprise the environmental backcloth (Brantingham & Brantingham, 1993a) of CCTV viewsheds have yet to be incorporated in the study of CCTV.

Research Questions and Hypotheses

This project contributes to the CCTV literature through both an analysis of micro-level features that contribute to individual camera effect as well as a macro analysis of the system-wide effect of CCTV in Newark, NJ. Three separate research questions guide this dissertation.

The first research question is “what is the change in observed levels of crime in *each individual camera viewshed* in the one-year period following CCTV camera installation?” Both Caplan, Kennedy, and Petrossian (2011) and Ratcliffe et al. (2009) found the individual camera sites to have generated varying levels of crime reduction. In light of these studies, I hypothesize that the individual camera viewsheds will exhibit variability, with numerous effective and ineffective cameras being identified.

The second research question is “what impact do twenty-five micro-level features have on the observed crime level changes within each individual camera viewshed?” The features are separated into five separate categories: environmental features (14), camera line of sight (four), camera design and quantity (two), enforcement activity (four), and pre-installation crime level (one). I make two separate hypotheses relative to this research question. The first is that enforcement activity generated by the surveillance cameras will be significantly related to decreased crime levels. Since the recent work of the Urban Institute (La Vigne et al., 2011a) showed systems to vary in effectiveness based on the level of proactive monitoring and enforcement, it makes sense that a similar relationship exists intra-system, with viewsheds experiencing high levels of camera-related enforcement more effectively reducing crime than viewsheds with low levels of enforcement. I expect the hypotheses to be proven across all crime types. The second hypothesis is that drug markets will negatively impact camera effect. Research on deterrence has suggested the certainty of punishment to be a key factor in generating deterrence. The successful commission of crime has shown to have a criminogenic effect by causing offenders to lower their previous estimates of the inherent "risk" of crime commission. Simply put, offenders who "get away with it" are more likely to commit crime in the future. If we consider each individual narcotics transaction as a separate crime incident, then crimes likely occur at much higher rates within drug markets than in other crime settings (e.g. a drug dealer engages in more "crime incidents" than a car thief). When the high volume of crime is not met with increased police attention, drug offenders may quickly learn that offending is no more "risky" in the presence of cameras. More directly, previous research has found drug offenders to consider CCTV to be of minimal threat to their operations. Drug dealers have reported bypassing the view of cameras with relative ease while engaging in narcotics transactions (Gill & Loveday, 2003). It is therefore hypothesized that CCTV will not provide the requisite deterrent effect to reduce crime within established drug markets.

The third and final research question is "what is the change in observed levels of crime in *the cumulative viewshed areas* in the one-year period following CCTV camera installation?" After identifying the environmental factors significantly related to camera effectiveness, control areas were selected through a propensity score matching process to ascertain the cumulative effect of Newark's CCTV cameras. While Caplan, Kennedy, and Petrossian (2011) measured the impact of the CCTV system in Newark, the scope of their work is expanded upon in two important ways. First, Caplan, Kennedy and Petrossian included the 73 cameras in place at the time of their study; the current study incorporates a total of 128 cameras. Secondly, Caplan, Kennedy, and Petrossian limited their study to the crime categories of shootings, auto theft, and theft from auto. This study includes a total of six crime types: robbery, auto theft, theft from auto and the aggregate categories of violence (comprised of murder, shootings, and robbery), property crime (comprised of auto theft and theft from auto), and overall crime (comprised of the violence and property crime categories). I hypothesize that none of the included crime categories will experience a statistically significant reduction in the target area as compared to the matched control areas. While I certain viewsheds exhibited high levels of enforcement, the system wide level of enforcement is low (as will be discussed in chapter two). A large number of camera locations had little-to-no enforcement activity, which likely prevented a system-wide deterrent effect from taking hold.

CHAPTER TWO: SCOPE OF THE CURRENT RESEARCH

Research Setting

Newark, NJ

Newark is the largest city in New Jersey, spanning over twenty-six square miles with a population of nearly 280,000 persons: an estimated 11,494 persons per square mile, compared to 1,134 statewide (U.S. Census Bureau, 2011). The riots of 1967 brought national attention to Newark and earned it a reputation as a tumultuous, dangerous urban environment, an image the city grappled with through the ensuing decades (Tuttle, 2009). A 1975 Harper's Magazine article identified Newark as the worst city in America. Newark ranked among the five worst cities in nineteen of the study's twenty-four categories such as per capita violent crime and infant death (Louis, 1975). In 1996, CNN's *Money Magazine* named Newark the most dangerous city in America (Fried, 1996). In 2006, under new leadership, the Newark Police department underwent a major re-organization and change in mission. The Newark Police adopted an Intelligence-Led Policing mantra and re-organized many units within the agency to provide increased coverage during evenings and weekends. Simultaneously, the city made significant investments to upgrade many of their technological capabilities.

Newark has experienced a reduction in crime, particularly gun violence, since these aforementioned changes in strategy and technology upgrades. According to department figures, overall crime decreased 13% from 2006 through 2010 with murders and shootings decreasing 20% and 29% respectively. Despite a recent uptick in violence during 2010 and 2011, shooting and murder numbers remain below 2006 levels (see Figure 1). However, violent crime is still high in Newark. The city's 2010 murder rate of

30.4 per 100,000 residents, for example, was nearly three times the national average (10.24) for cities with populations greater than 250,000 (UCR, 2011). In addition, while murders and shootings have decreased from their 2006 levels, other crimes have increased. As shown in Table 1, the violent crime of robbery has substantially increased, with a 2011 total (2,020) over 50% higher than the 2006 total (1,305). Burglary is the only other crime type that occurred more often in 2011 than 2006.

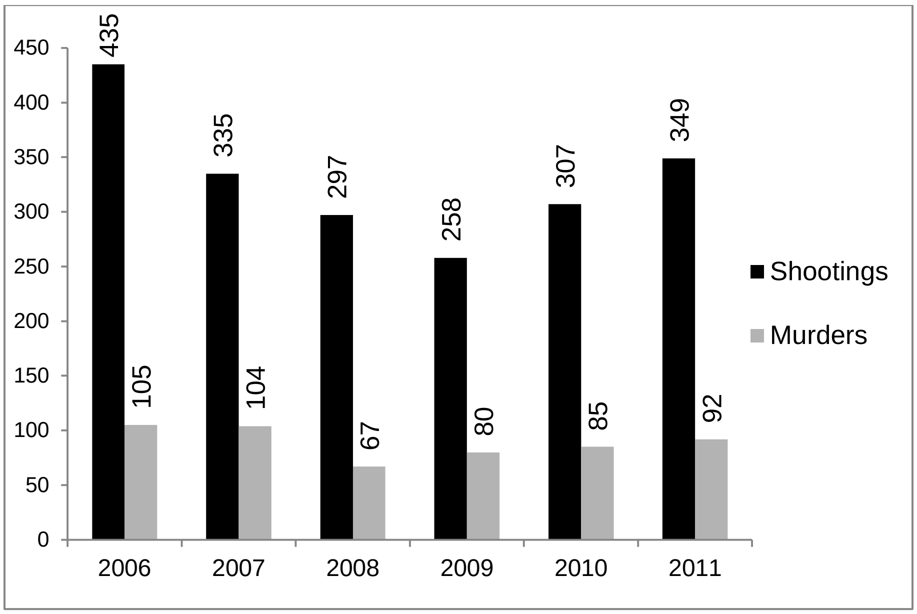

Figure 1: Newark, NJ Yearly Shooting & Murder Totals, 2006-2011.

CRIME	2011	2010	2009	2008	2007	2006
Murder	92	86	80	67	100	107
Rape	52	71	59	58	61	96
Robbery	2,020	1,664	1,414	1,467	1,208	1,305
Agg. Assault	1,136	1,205	1,167	1,253	1,211	1,355
Burglary	2,354	2,004	1,948	1,994	1,753	1,904
Theft	4,095	3,779	3,689	3,956	4,326	4,471
Auto Theft	3,673	3,734	3,208	3,911	4,468	5,154
TOTAL	**13,422**	**12,543**	**11,565**	**12,706**	**13,127**	**14,392**
Shootings	349	306	258	297	335	435
**Incidents of shootings are captured within the other crime categories, namely murder and aggravated assault.*						

Table 1: Newark, NJ part 1 crime and shooting totals, 2006-2011.

Newark made an appropriate setting for this study for numerous reasons. For one, the city showed an immediate commitment to CCTV, with the initial installation of cameras being followed by six additional installation phases over three years. This resulted in cameras being deployed in a wide array of settings, allowing for the testing of CCTV effect in various environmental contexts. Secondly, the manner by which the Newark Police Department staff's its surveillance operation, and the manner by which police respond to detected infractions, seems to mirror the process observed by researchers in other cities (Gill, Spriggs, Allen, Hemming, Jessiman, & Kara, 2005; Norris & Armstrong, 1999a,b; Norris & McCahill, 2006; Ratcliffe et al., 2009; Smith, 2004). Thirdly, the City of Newark, like many U.S. cities, has been faced with radically dwindling resources over the past several years. The city's fiscal crisis led to the termination of 167 police officers (13% of the force) and over 100 civilian employees in November of 2010. The city has tried to maximize the effect of technology in order to compensate for these decreased levels of manpower. These characteristics of Newark's camera deployment, surveillance operation, and the city itself makes it representative of a number of medium- to large–sized American cities, which supports the generalizability of this dissertation's findings.

Newark Police Department, Video Surveillance Program

Newark Officials credit the cumulative strategy of the police for the achieved reductions in murders and shootings while often citing the benefits provided by the video surveillance system (Santiago, 2009). However, the specific role and capabilities of the CCTV system has received little empirical attention outside of the preliminary analysis by Caplan, Kennedy, and Petrossian (2011). One-hundred-forty-six surveillance cameras are located throughout Newark to-date. Live video footage from the cameras is monitored from a centralized control room at the police department's communications center. The control room is staffed by the Newark Police Department's Video Surveillance unit. Two video surveillance operators under the supervision of a police sergeant monitor the cameras during all shifts. The video operators are tasked with monitoring the cameras for the purpose of detecting incidents of crime and disorder. Upon detecting such an incident, operators report the event via the department's Computer Aided Dispatch (CAD) system. Reported incidents (both CCTV events and 9-1-1 calls for service) are stored in CAD's "calls pending queue." These assignments are addressed in a "differential response" manner by the police dispatcher, with higher priority incidents taking precedence over those with lower priority levels. After an incident is closed, the dispatcher sends an officer to the next call in the calls pending queue. This aforementioned process is considered standard operating procedure in police departments across the United States (LEITSC, 2008). In addition to their active monitoring function, operators are tasked with monitoring a police scanner and the CAD screen for calls-for-service taking place within camera viewsheds. When a call-for-service occurs within view of a camera, the operators monitor the situation at hand and inform the police dispatcher of any pertinent information observed on camera (suspect direction of flight, etc.).

Cameras were installed in seven phases from June 2007 through April 2010: 6/8/07 (11 cameras), 3/15/08 (49 cameras), 7/31/08 (51 cameras), 9/14/09 (1 camera), 12/10/09 (23 cameras), 1/7/10 (1 camera), and 4/23/10 (10 cameras). Phases one and two (60 cameras) were funded through an urban renewal grant, which mandated that the cameras be installed within the city's Urban Enterprise Zone. Donations from private corporations made to the Newark Police Foundation, the fund-raising arm of the Newark Police Department, paid for the remaining cameras. The placement of these cameras occurred in consultation with Newark Police Department, the City of Newark Mayor's office, as well as the Newark city council.

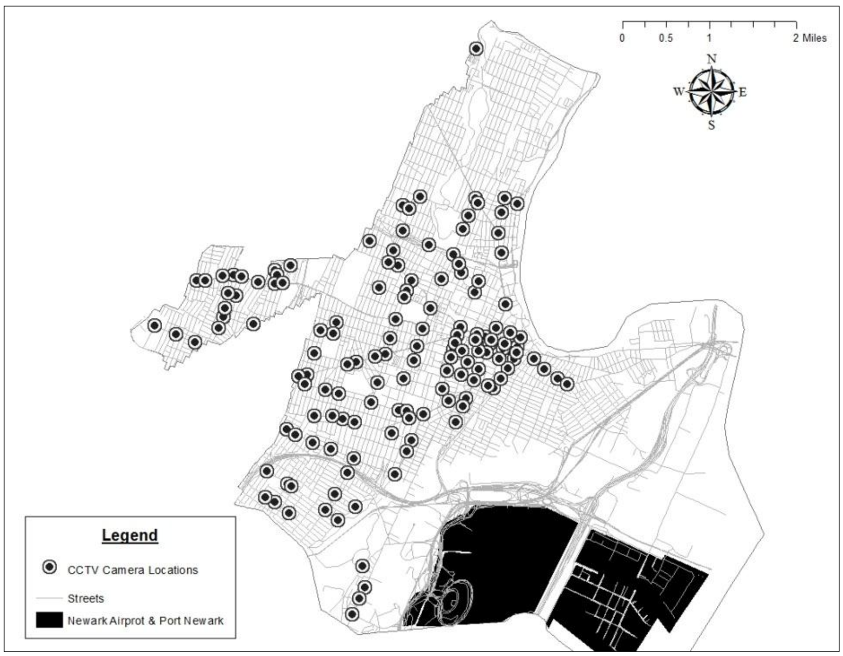

Figure 2: Newark, NJ Surveillance Camera Locations (N=146).

All of the cameras are PTZ units whose "pan," "tilt," and "zoom" functions are directly controlled by the user. When not manually controlled, the cameras view their target areas in panning mode, moving in a left-to-right manner. The cameras differ in respect to mounting style and design. Most are installed on the street-level (N=140) compared to rooftops (N=9) with the design being split between semi-covert "dome" cameras (N=117) and traditionally-designed bullet resistant cameras (N=32). All cameras have the ability to zoom and pan 360 degrees. However, the dome cameras have a tinted hemisphere glass which hides the camera's actual direction while the line-of-sight of bullet resistant cameras is easily determined.

Figures 3 through 5 display the proactive activity of the video surveillance operators. Data were available for a period of 42 months from November 2007 through April 2011. Data were collected by manually referencing every surveillance detection in the Newark Police Department's Computer Aided Dispatch (CAD) system and recording information on the case disposition. The surveillance unit made a total of 1,641 detections (that were reported) during this time period. Figure 3 shows that the discovery of part 1 crime incidents is rare. Violent crime and property crime incidents, respectively, only account for 11.27% and 1.00% of the overall detections. What occurs much more frequently are detections of disorderly behavior and narcotics activity. This observation makes intuitive sense; street-level incidents of disorder and narcotics occur more often than violent and property crime, and are therefore most likely to be observed on camera. Motor vehicle violations accounted for 1.77% of the total with an "other crime" category accounting for 11.58%.

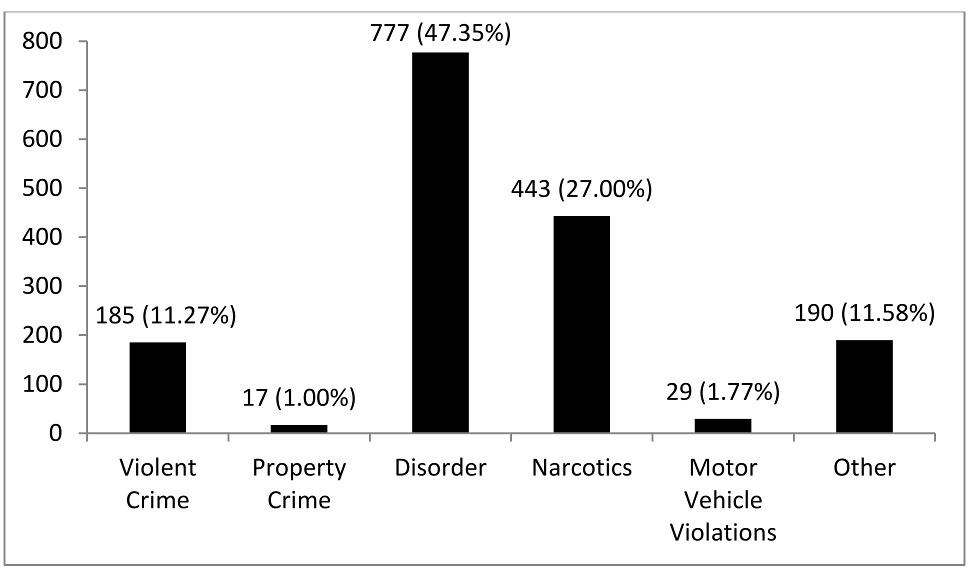

Figure 3: Surveillance Detections by Crime Type, Nov. 2007-Dec. 2010

Figure 4 shows the percentage of detections that were closed by an arrest. Overall, 10.3% of operator detections resulted in an arrest. However, the arrest percentages differ across crime types. Violence, disorder, and motor vehicle violations resulted in arrest in less than 10% of cases, and in the case of motor vehicle violations, less than 1%.[2] The "other" crime category resulted in an arrest in approximately 10% of cases. Property crime and narcotics resulted in arrests over 20% of cases. However, since only 17 (1.17% of total) property crime detections occurred, the high arrest rate should not be considered evidence of CCTV's enhanced ability to apprehend property crime offenders. Narcotics offenses, on the other hand, seem to be effectively addressed by CCTV. When excluding property crime, the narcotics arrest rate of 20.6% is more than twice the size of any other category.

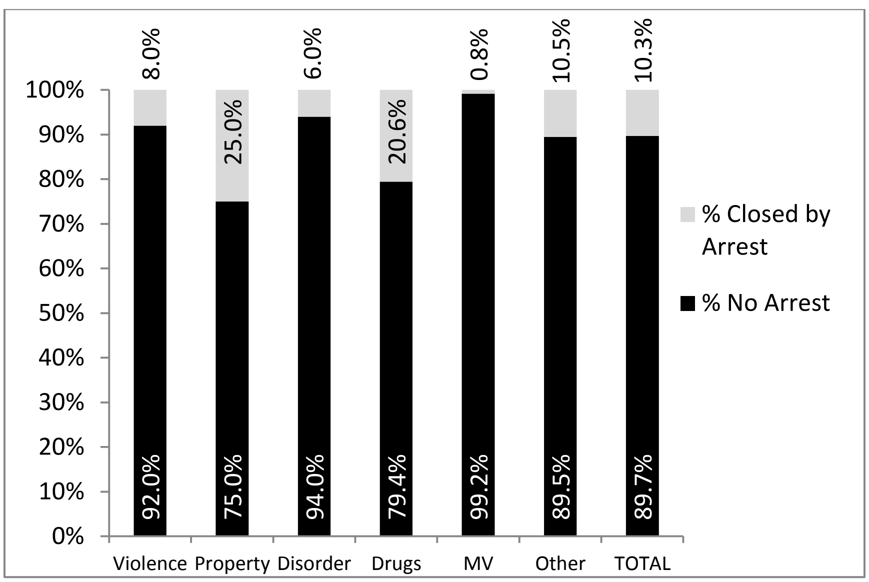

Figure 4: Percentage of Detections closed by arrest, Nov. 2007-Dec. 2010

[2] This is not surprising since most motor vehicle violations do not offer grounds for arrest.

However, given the nature of most CCTV detections, “arrests” may not be the most accurate measure of case closure. A detection of an aggressive panhandler, for example, may be grounds for a quality of life summons rather than an arrest. In addition, case outcomes are typically shaped by officer discretion, where a police officer deems an incident undeserving of arrest (even if there are legal grounds for arrest) and thus decide to issue a less punitive sanction (Bittner, 1990). Figure 5 shows the clearance rates when alternative sanctions[3] are considered along with arrests. Under this metric, overall detections have a clearance rate of 33.9%. While property crime’s clearance rate remained unchanged, clearance rates for all of the crime categories at least doubled. The changes were most drastic in the case of motor vehicle violations and disorder, which had the two lowest arrest rates. When all sanctions are included, motor vehicle violations and disorder have two of the three highest clearance rates, increasing from 0.8% to 44.2% and 6% to 32.3%, respectively. Narcotics activity again had the highest clearance rate of 44.5%. As was the case with property crime’s arrest rate, caution should be taken with motor vehicle’s high clearance rate because of its low level of occurrence (29 incidents). Disorder and narcotics, on the other hand, are the two largest detection categories. The fact that they so often result in enforcement is telling.

[3] These include motor vehicle summonses, quality-of-lie summonses, field interrogations, and record checks.

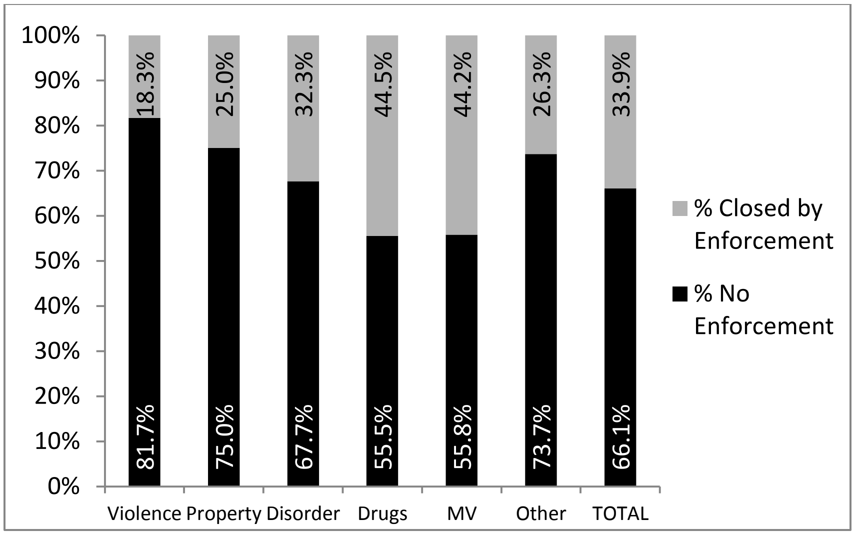

Figure 5: Percentage of detections closed by any enforcement action, Nov. 2007-Dec. 2010.

Unfortunately, the effect of these high clearance rates may be minimized by the somewhat infrequent occurrence of proactive surveillance activity. Figure 6 and Figure 7 display the number of detections and enforcement actions occurring within each viewshed during the one-year study period, respectively. As can be seen, both detections and enforcement activity are confined to a small number of viewsheds. On average, the 117 viewsheds included in this analysis generated 6.30 detections and 1.91 enforcement actions each. However, the mode for both of these activities is 0 (see Table 2).

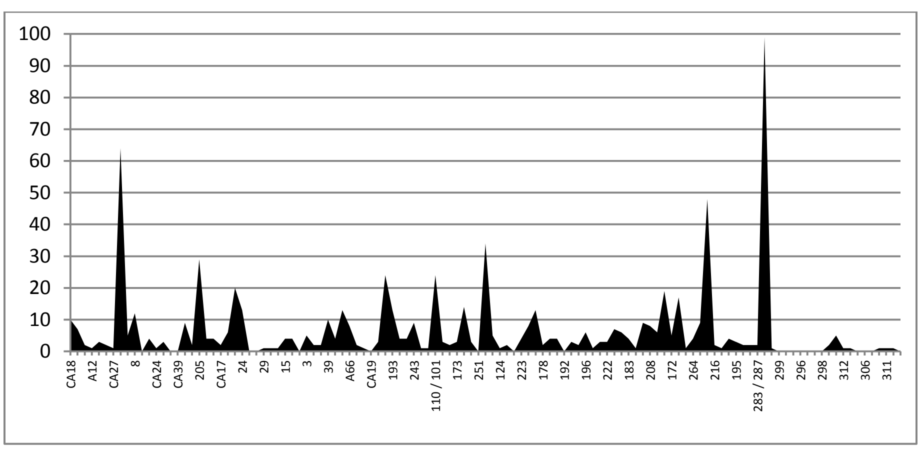

Figure 6: Camera detections per viewshed

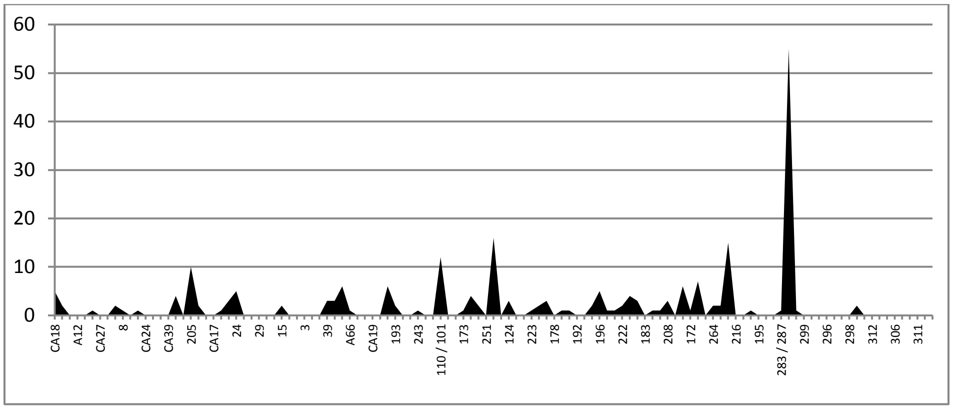

Figure 7: Camera enforcement actions per viewshed

CCTV ACTIVITY	AVERAGE	S.D.	MIN.	MAX.	MODE
Detections	6.30	12.49	0	99	0
Enforcement	1.91	5.65	0	55	0

Table 2: CCTV activity overview

Figure 8 and Figure 9 further illustrate this point. These figures display the frequency distribution of detection and enforcement totals, respectively. For both of these measures, the distributions are drastically skewed left, showing low levels to be the common occurrence. Twenty-one viewsheds (17.9%) generated no detections in the one-year period following their installation. In total, 86 (73.5%) viewsheds generated five or less detections over the one-year period.

Enforcement activity generated by the cameras occurred even more infrequently. Sixty five viewsheds, which represented over half of the total included in the analysis (55.5%), did not generate a single enforcement action. One hundred eight cameras (92.3%) generated five or less enforcement actions.

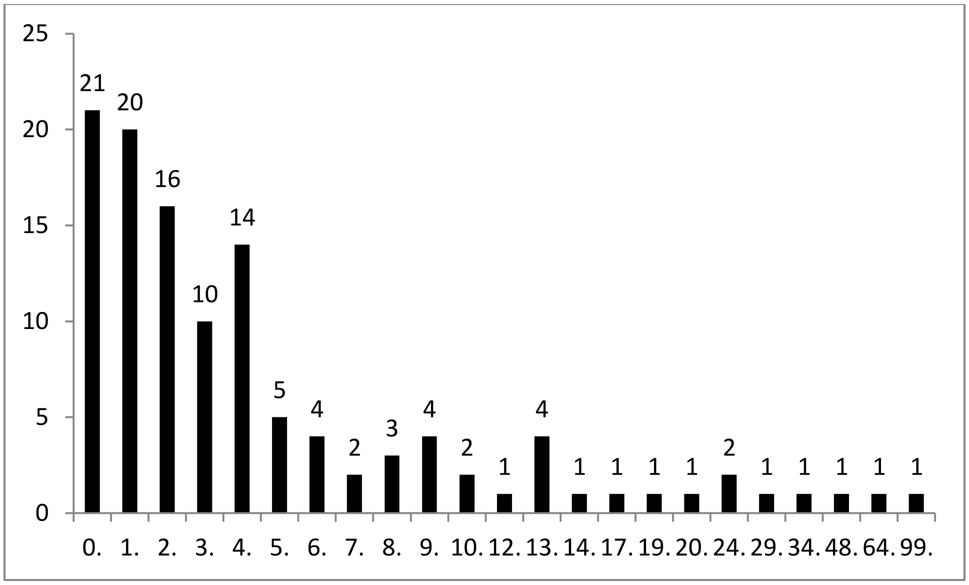

Figure 8: Detection Frequency

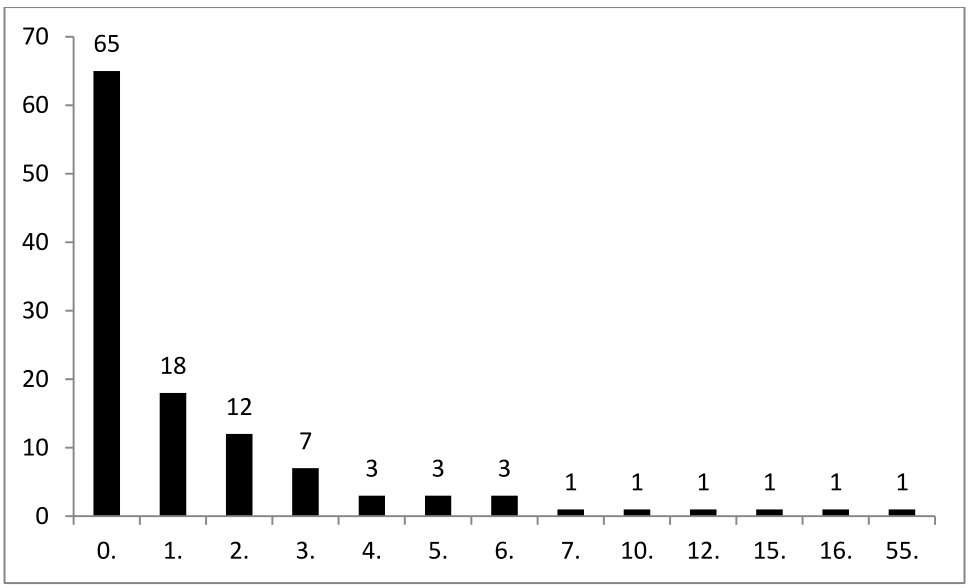

Figure 9: Enforcement Frequency

Geography of the Study Area

Figure 10 displays the study area for this project, which excludes the portion of Newark comprising police sector 317. This area is largely comprised of Newark Liberty Airport and the (shipping) Port of Newark, which fall within the jurisdiction of the New York/New Jersey Port Authority Police, and are not covered by the Newark Police

Department. In addition, as illustrated in Figure 10, outside of the airport and port, the area is almost entirely comprised of highways and vacant land. The activity in this area is nearly entirely comprised of long-distance motor vehicle traffic with little-to-no pedestrian activity. As a result, crime rarely occurs in this area. The Newark Police Department, in fact, does not normally deploy a patrol car to cover the portion of sector 317 that falls within its jurisdiction. Due to these reasons, coupled with the fact that no CCTV cameras were installed in this area, this area was excluded from the final study area. The study area totals 15.86 mi^2 as measured within a GIS.[4]

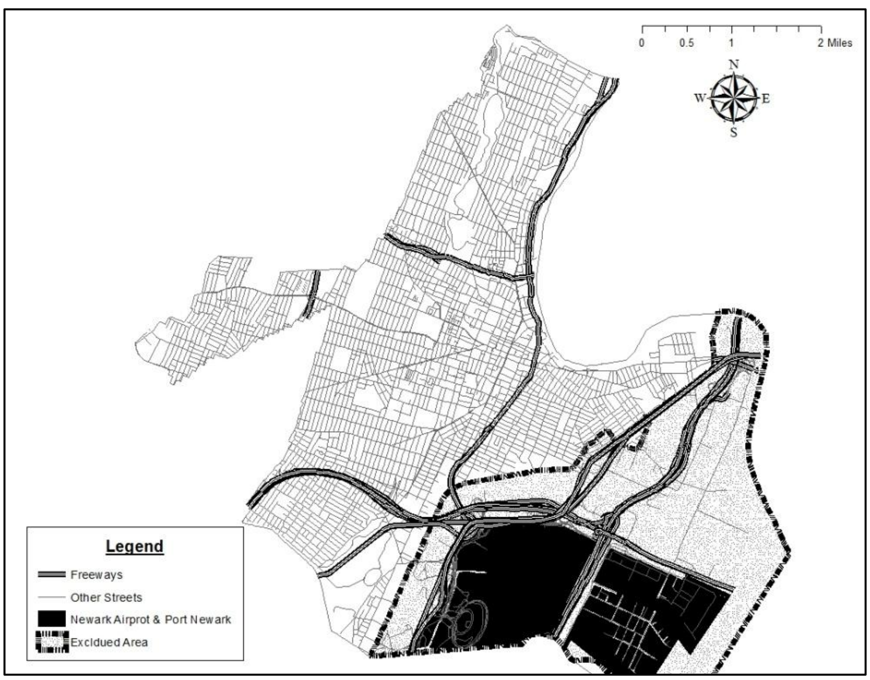

Figure 10: Map of the final study area.

The Current Study

This project expands upon the preliminary analysis of Newark's CCTV system conducted by Caplan, Kennedy, and Petrossian (2011) in numerous ways. This study

[4] The entire geography of Newark totals 25.99 mi^2 as measured within a GIS.

includes 128 total cameras whereas only 73 cameras were installed at the time of Caplan, Kennedy, and Petrossian's data collection. This study also includes more crime categories. This study analyzes a total of six crime types: robbery, auto theft, theft from auto and the aggregate crime categories of violence (comprised of murder, shootings, and robbery), property crime (comprised of auto theft and theft from auto), and overall crime (comprised of the violence and property crime categories). Furthermore, this study also expands upon the viewshed methodology. While previous studies have digitized continuous geography visible to CCTV, this study also identified specific areas within each viewshed obstructed from sight. Finally, this study explores the factors that influence individual camera effectiveness, a call made by Caplan, Kennedy, and Petrossian (2011). The factors identified as significant were also incorporated in a propensity score matching technique to test the aggregate effect of Newark's CCTV cameras.

Data Sources and Operationalization of Key Concepts

Crime and Arrests

Data for this project generated from numerous information systems of the Newark Police Department. The data sources include the CCTV cameras, Geographic Information Systems (GIS) files, and NPD Video Surveillance Unit (VSU) reports and records. The Newark Police Department geocodes crime incident data on a daily basis. These daily files are separated by crime type and merged with "year-to-date" crime layers which contain all incidents occurring during the calendar year. To maintain the accuracy of the data, each week crime incidents for the previous 28 days (the department's "Compstat" period) replace the cases from the same time period within the year-to-date layers. This process occurs in order to capture changes in crime classification, ensuring that each incident is contained within the appropriate layer. For example, follow-up investigations may lead police to re-classify a crime by either upgrading the incident (e.g. a theft is re-classified a robbery) or downgrading the incident (e.g. a shooting is discovered to be self-inflicted and is no longer considered an aggravated assault). While most crimes are correctly classified at the time of reporting, this process provides an added mechanism which maximizes data integrity.

Arrest data are similarly geocoded and updated on a weekly basis by the Newark PD. In addition to the aforementioned process undertaken with the crime data, a separate step occurs due to the manner by which the Newark PD’s arrest database stores information. For each arrest an entry appears for each individual charge related to the incident. For example, if a suspect is arrested and charged with robbery, possession of a weapon, and an outstanding warrant, the incident appears in the database three separate times. While this accurately reflects the nature of the arrest incidents, it complicates the mapping process by creating numerous points where only one incident took place. Therefore, after the overall charges are geocoded, an ArcGIS model exports all unique incidents into a separate layer that captures the *arrests* as opposed to *charges*; each incident appears only once. The arrests were incorporated in this analysis as a metric of officer activity within CCTV areas.

Environmental Features

In addition to the crime and arrest information, GIS files of various land use and establishment types were utilized in this study: bars, liquor stores, corner stores, take out eateries and fast food restaurants, sit-down restaurants, "at-risk" housing[5], other residential high rise buildings, schools, gas station, retail shops and department stores, public transit stops, parking lots,[6] drug markets, and major roadways. A number of these files were obtained directly from the Newark Police Department[7], who maintain the data layers. Facility types not captured within Newark Police GIS files[8] were obtained from InfoGroup, a leading provider of residential and commercial information for reference, research, and marketing purposes. InfoGroup continuously compiles data from hundreds of data sources including 4300+ US Yellow and White Page directories, hundreds of county level public sources, real estate data, press releases, news feeds, and postal processing (Infogroup, 2010).

Researchers extracted the "major roadways" layer from the layer of overall street segments in Newark. The City of Newark utilizes the classification schema put forth by the Association of State Highway and Transportation Officials (2004). All street segments classified as major roads by the Newark Division of Transportation (2,675 of Newark's 10,920 street segments) were exported into a new "major roads" layer. The

[5] This layer includes public housing and all privately owned subsidized housing with 10 or more units.
[6] This layer includes all city parcels classified as a parking lot, whether a stand-alone facility (such as a commercial parking garage) or a lot used primarily by patrons of a separate facility (such as a parking lot outside of an office building).
[7] Bars, liquor stores, schools, transit stops, "at-risk" housing, other residential high-rise buildings, and parking lots.
[8] Take-out eateries, sit-down restaurants, gas stations, corner stores, and retail shops.

data was further cleaned so that freeway street segments only included the on-off ramps. As noted by Rengert, Ratcliffe, and Chakravorty (2005), freeways in their entirety have little relation to street-level crime patterns since they are physically separate from the neighborhoods they lie adjacent to. In describing patterns of drug transactions, Rengert et al. (2005) argued "Since drug sales involve a transaction between at least two stationary individuals, it is highly unlikely that a dealer would undertake sales on the highway itself….Moreover, areas that are directly adjacent to highways may appear to be possible transaction zones on two-dimensional maps, but even the most casual observer of speeding automobiles knows that such zones are physically unapproachable, and therefore unsuitable for any transaction" (p. 74-75). While this argument was presented in the context of drug dealing, it is equally relevant to the type of street crime that is the focus of this analysis. The on/off ramps serve as access features and determine the movement of automobiles from between the freeway and neighborhood roads. The on/off ramps are thus the only "freeway" street segments included in the major roads layer.

GIS layers denoting drug markets were created during a separate study of crime and drug activity in Newark (Braga, Grossman, & Piza, 2011). The methodology was informed by previous research that has utilized qualitative police intelligence to identify criminogenic geographies (Braga, McDevitt, & Pierce, 2006; Dalton, 2003; Kennedy, Braga, & Piehl, 1998; McGarrel & Chermak, 2003; McGloin, 2005). A series of focus groups lasting between 3 and 4 hours each were held with officers with non-administrative, investigative assignments from various units of the Newark Police Department. The goal of the focus groups was the identification of precise geographies containing prevalent open-air narcotics markets and experiencing high-levels of narcotics-related violence. Active criminal enterprises operating within each area were also identified through this exercise. During each focus group, researches focused on a particular police precinct, asking officers to identify these areas by drawing on a large map. Officers provided criminal intelligence regarding the nature and scope of the drug activity, related violence, and active offenders to support their answers. Considerable agreement was observed amongst the participants.[9]

Each of the aforementioned data layers was included in the analysis due to their capacity to generate crime, as evidenced by previous empirical research as well as their specific importance in CCTV evaluations and/or Newark's situational crime context. The illicit drug trade has long been associated with incidents of serious violence (Harocopos & Hough, 2005; Lum, 2008), particularly since individuals involved in this lifestyle have no legal means for settling disputes (Blumstein, 1995). Liquor establishments and their immediate surroundings are common settings of crimes (Block & Block, 1999; Scott & Dedel, 2006). In addition, as an activity nodes of large numbers of youth (Brantingham & Brantingham, 1993a; Felson, 2002) schools have shown to generate crime (Roncek,

[9] Drug markets have typically been identified through quantitative methods, namely the mapping of drug arrest locations in previous research (Rengert et al., 2005; Weisburd & Green, 1995; Weisburd et al., 2006). However, criminological research has long suggested that arrest data suffer from both underreporting and enforcement bias (Black, 1970) which can lead to misleading results. In the case of Newark, mapping drug arrests may have more directly measured police activity than drug market presence. As previously discussed, the Newark police department employs street-level narcotics enforcement as the primary tactic against violent crime. Narcotics enforcement typically occurs in a systematic manner, with the command staff specifying specific areas to receive heightened levels of police presence and proactive enforcement. These operations result in heighted levels of arrest. For example, the Newark Police Department enacted Operation Impact in the summer of 2008, mandating that a team of 12 foot-patrol officers patrol a concise target area on a nightly basis. This operation led to 3,185 enforcement actions, including 634 arrests, over the course of one year within this single area (Piza & O'Hara, 2012). As another example, in 2010, the department launched a similar operation at the Garden spires housing complex. In preparation for the operation, the department conducted a series of drug raids resulting in the arrest of 149 people over a single weekend (Whitlow, 2010) with sustained enforcement activity continuing on a nightly basis. Such intensive place based narcotics operations occur regularly throughout the city. Since the common result of directed police initiatives is a drastic increase in arrests (Sherman, 1990), I decided to instead operationalize drug markets based on the intelligence gathered from the focus-groups.

2000; Roncek & Faggiani, 1985). Sit down restaurants and retail stores bring together large amounts of individuals unknown to one another, which can facilitate the commission of crime from a rational choice/environmental Criminology perspective (Brantingham & Brantingham 1995; Cohen & Felson, 1979; Felson 2002). Parking lots have shown to be particularly conducive to the effect of CCTV (Tilley 1993; Welsh & Farrington 2009). Public housing has long been associated with heightened levels of serious crime (Eck, 1994; U.S. Department of Housing and Urban Development, 2000). Privately owned complexes with similar characteristics as public housing can also generate crime problems (Poyner, 2006). In Newark, privately owned complexes are seen as particularly problematic, with large-scale private complexes playing a prominent role in the city's illicit drug trade in Newark (Piza & O'Hara, 2012; Zanin, Shane, & Clarke, 2004). Even complexes dissimilar from public housing (e.g. "condominiums") can present opportunities for crime due to the concentration of persons and property in a compact area (Poyner, 2006). Gas stations are frequent targets of "drive-up" robberies in Newark while take out eateries have been seen to generate violence due to the large amounts of foot traffic, late hours of operation, and general lack of guardianship (Kennedy et al., 2011). Corner stores are considered common anchor points of gangs and illicit narcotics dealers. Similarly, major roads (Beavon et al., 1994; Johnson & Bowers, 2010) and transit stops (Loukaitou, 1999; Smith & Clarke, 2000; van Wilsem, 2009) can influence crime patterns by facilitating the movement of both potential offenders and victims throughout the landscape. While a number of the above features can be categorized together based on certain similarities (e.g. "bars" and "liquor stores" are both establishment types with liquor licenses while "take-out eateries" and "sit-down restaurants" are both food-service establishments) disaggregating these micro-features minimizes potential threats to content validity that can surface through considering different areas as if they were the same (Stucky & Ottensmann, 2009).

Camera Enforcement

Various data sources containing information on the detection and response to crime via CCTV were also consulted. The first were the video surveillance unit weekly activity reports. At the conclusion of every shift, operators are required to submit a log listing all incidents occurring within CCTV areas, whether they are detected by CCTV or reported via 9-1-1. On a weekly basis, operator logs are merged into a Weekly Video Surveillance Unit (VSU) activity report, which captures the following data for each incident: event number, date of incident, time of incident, location of incident, type of incident, the camera used to view the location, whether it was a CCTV detection or not, and whether an arrest occurred. Since an arrest is not the only way that a crime could be closed by an enforcement action (e.g. a summons could be issued or a field interrogation could have taken place), additional disposition information was collected for each incident from the Newark PD's Computer Aided Dispatch (CAD) system. Each incident contained within the VSU reports that did not result in arrest was cross-referenced in the Newark Police Department's Computer Aided Dispatch (CAD) system. The case disposition, which denotes the specific action taken by the responding officer, was recorded for each incident. Upon completion of the CAD data collection, all of the weekly reports were merged into a single database and the number of detections and enforcement actions was tallied for each individual camera.

In addition to the live detection of crime, the CCTV cameras are utilized for evidentiary and investigative purposes by the Newark Police. Newark Detectives often request copies of footage to aid in investigations through the potential identification of suspects or witnesses involved in a criminal incident. To keep track of requests for and the releasing of footage, the video surveillance unit maintains an evidence log book. This book lists each instance where a DVD of camera footage is requested by an investigator and the camera from which the footage was extracted. The log book was queried in order to identify the number of investigatory disks created for each camera.

Units of Analysis: Camera Viewsheds

I visited the CCTV control room in order to create viewsheds for each camera in the system. The "panning mode" of each CCTV camera was viewed and digitized within a GIS to denote each camera's viewshed.[10] While CCTV cameras are able to view extended distances, their deterrent effects are likely constricted by space. CCTV is most likely to prevent crime when an offender believes cameras may be monitoring their activity and perceives this attention to put them at increased risk of apprehension. However, as articulated by Ratcliffe et al. (2009), "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—

[10] When manually controlled by a user, each camera has the ability to see much more than what is visible in panning mode. However, the panning mode was digitized as the viewshed for two reasons. One, given the large camera to operator ratio all of the cameras are in "panning mode" more often than they are actively controlled by an operator. Secondly, constructing the viewshed based on a camera's possible view would lead to areas significant distances away from the camera being designated as "CCTV areas." This would lead to an over-estimation of CCTV's potential deterrent effects, mirroring the problem encountered when aggregate geographies serve as units of analysis.

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” (p. 751).

In light of these complications, Ratcliffe et al. (2009) constructed viewsheds to reflect the extent of camera vision. While Ratcliffe et al. presented this as an alternative to the “offender perception” approach, the concepts certainly overlap. Deterrence can only be realistically expected where a potential offender’s conception of “space” and a CCTV camera’s line-of-sight coincide. In this sense, a camera’s surrounding environment comprises a “spatial node” cogitatively identified by pedestrians as a singular “place” (Lynch, 1960). It is within such an area an offender would most likely perceive a heightened level of risk. Given the limited visual extent of cameras, the area immediately visible to CCTV is probably the geography in which offender perception of camera presence is at its peak.

This study approached viewshed creation in a similar manner as Ratcliffe et al. (2009). A detailed GIS base map (with layers displaying streets, parcels, building footprints and aerial imagery) was incorporated to ensure that the digitized viewsheds accurately account for the physical geography. Viewshed boundaries were operationalized as the furthest area which was brought into immediate focus during the camera’s panning mode. For example, when a camera zooms into an intersection, buildings at the end of the next block may be somewhat visible. However, being that they are not the main focus of the camera’s view, the buildings would be excluded and the intersection would be considered the boundary of the viewshed.[11] In addition, the research design took precaution to not overlook the insight of Newark’s CCTV operators.

[11] Target areas have been established through visual means in other studies as well. For example, in their randomized hot spots policing experiment, Sherman & Weisburd (1995) designated target areas as “as far as the eye could see from sidewalk corners” in each direction (p. 633).

Since Newark PD's surveillance unit proactively monitors the cameras on a daily basis, CCTV personnel should possess a reliable sense of what areas are truly "covered" by CCTV's deterrent effects. Ratcliffe et al. (2009) utilized a similar approach by consulting with Philadelphia police officers to determine viewshed boundaries. In order to gain such perspective, at the conclusion of each visit to the control room, I met with the commander of the Video Surveillance Unit to review each viewshed created during that particular visit, using live camera feeds as reference. The commander was asked to ascertain whether the viewshed accurately captures the areas where the department anticipated offenders would be deterred by the cameras. There was a high level of agreement between the commander and myself, with viewshed boundaries being adjusted in only a few rare occasions.

This study's methodology further improves upon previous research by denoting areas within viewsheds that are obstructed from view. While previous studies have estimated the overall coverage areas of CCTV, such procedures do not allow for the identification of ground level objects, such as street signs, traffic poles, or tree leaves, that commonly impede upon a camera's (and camera operator's) visibility. For example, while a street segment may be viewable, certain addresses can be blocked from sight. An overgrown bush may block a specific corner of an intersection or a building awning may block one side of a street (see Figure 11). Viewsheds created for this study took into account such obstructions. Obstructed areas were categorized into two groups: 1) areas obstructed by immovable objects (such as traffic signs, buildings, and telephone poles), and 2) areas obstructed by foliage (mainly leaves from trees and bushes). These obstructions were digitized and combined with the visible geography to construct the overall viewshed. An example viewshed, with the denoted visible areas and areas of obstruction, is shown in Figure 12.

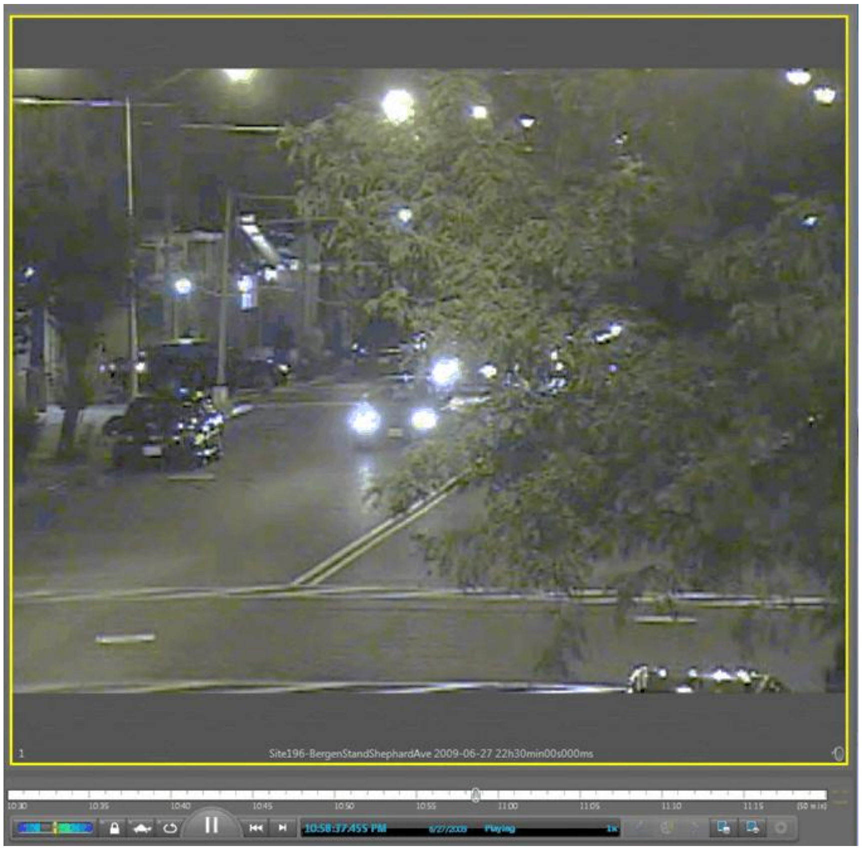

Figure 11: Leaves from a tree obstructing the view of a camera.

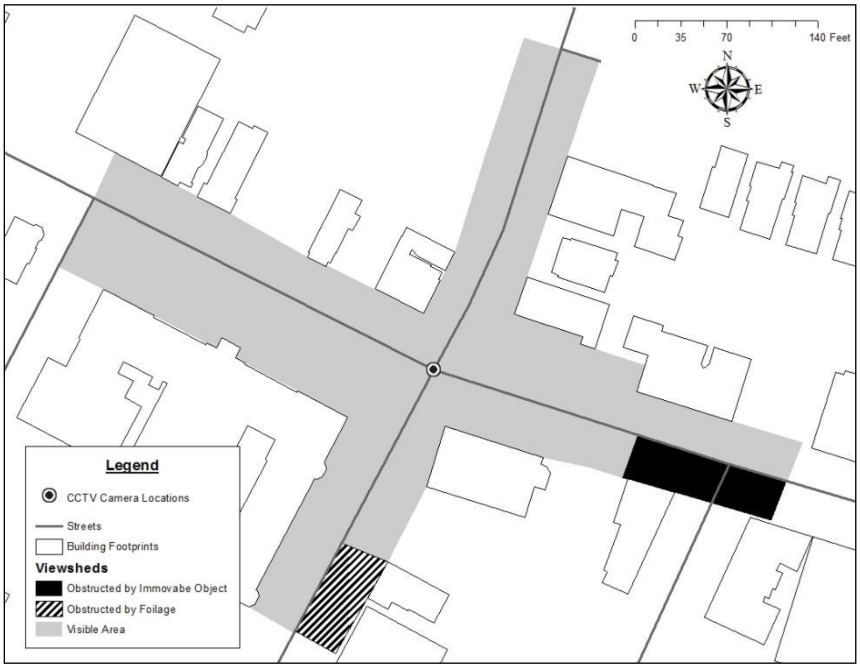

Figure 12: Example viewshed with denoted areas of obstruction.

This process resulted in the creation of viewsheds for 141 of the system's 146 cameras. Five cameras had been out of service for close to a year and were thus unable to be viewed. After careful consideration, it was decided to exclude 13 additional viewsheds from the analysis. The first eleven cameras were installed at an undetermined time. The Newark Police Department advertises the installation date of these cameras as 6/8/2007. However, this date actually reflects the formation of the Video Surveillance unit, as mandated by a written departmental order. According to the Newark Police official who oversaw the camera deployment, the actual installation of these cameras occurred during a "test phase" spanning several months in 2006 with intermittent monitoring of the cameras beginning as early as February 2007. The lack of precise information regarding the time of installation, coupled with the fact that the presence of the cameras occurred well before their integration into the department's function, led to exclusion of these cameras. In addition, due to technical difficulties, two cameras physically installed on

7/31/08 and 12/10/09, respectively, were unable to transmit footage to the control room for over a year. It was decided that including these cameras in the analysis would be inappropriate since the cameras' presence and ability to alert police to criminal activity occurred at vastly different times. Finally, similar to Ratcliffe et al. (2009), cameras with overlapping viewsheds were considered as single sites to prevent individual crime incidents that fell within more than one viewshed from being counted multiple times. In total, 18 viewsheds that overlapped with at least one other viewshed were combined into seven cases. After these aforementioned adjustments, the analysis included 117 separate viewsheds. The final viewsheds included in the analysis had four separate installation dates: 6/8/07 (44 viewsheds), 7/31/08 (50 viewsheds), 12/10/09 (13 viewsheds), and 4/23/10 (10 viewsheds).

In addition, an accompanying catchment area was created for each viewshed for the purpose of measuring the presence of any displacement of diffusion of benefits effects. In order to create appropriately-sized catchment areas (Weisburd & Green, 1995) displacement zones started as 291 foot buffers around viewsheds, to reflect the median block size in Newark. The buffers were adjusted to take into account local geography and road patterns surrounding each viewshed (see Figure 13). While this approach creates

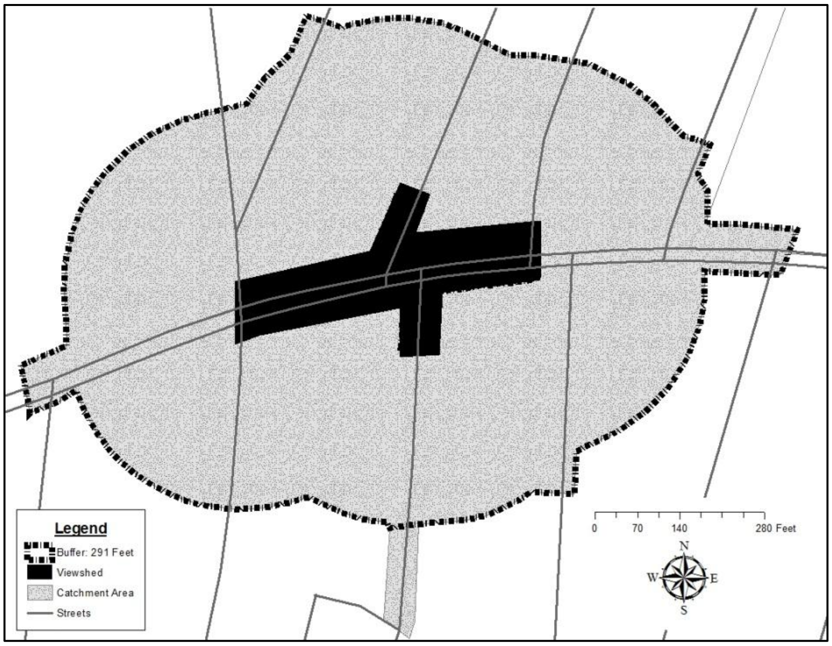

Figure 13: Example catchment area with respective viewshed and 291 foot buffer.

zones of slightly varying sizes, it reflects the variability of street networks around cameras. As explained by Ratcliffe et al. (2009), "…the use of actual camera viewsheds can mean that a...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 create a buffer that is a more realistic approximation of the likely displacement area" (p. 752). With this in mind, when a buffer was half a block or less from the nearest intersection, the catchment area was extended to the intersection. Otherwise, the catchment area constricted at the point of the buffer.

Chapter Summary

This chapter discussed the key concepts and data that provide the foundation of this dissertation. Various data sources were utilized, including the Newark Police Department's Geographic Information system, the Newark Police Department's CAD system, Newark Police Department Video Surveillance records, facility and business data from third party vendors, and the surveillance cameras themselves. The surveillance cameras were utilized in the creation of viewsheds that denote the precise line of sight of each individual camera. The viewsheds serve as the units of analysis for the two separate analyses comprising this dissertation. The first, conveniently (and uncreatively) named Analysis A, tests the effect of various features on the effectiveness of individual camera sites. Chapter three presents the precise methodology and findings of Analysis A.

CHAPTER THREE: ANALYSIS A. THE IMPACT OF MICRO-LEVEL FEATURES ON CAMERA EFFECT

Introduction

The literature on CCTV can generally be summarized as "mixed." There is consensus on CCTV being effective against automobile crimes in parking lots. However, all documented cases of CCTV in parking lots were instituted along with other measures. This makes it difficult (if not impossible) to disentangle the effect of CCTV from the cumulative interventions. In addition, while public CCTV systems are seen as less effective as their parking lot counterparts, recent research has reported instances where public CCTV systems have had a level of success against crime (Caplan, Kennedy, and Petrossian, 2011; La Vigne, 2011a; Mazerolle et al., 2002; Ratcliffe et al., 2009).

Despite these inconsistent findings there has been little research investigating why effectiveness has been so variable. Some noteworthy exceptions, however, have recently emerged. La Vigne et al. (2011a) conducted a study of CCTV systems is Baltimore, Chicago, and Washington D.C. They found that the effectiveness of the systems varied based on their level of integration with police practices. Namely, cameras that were monitored in real time by police personnel experienced crime reductions while unmonitored passive systems did not have a positive effect. These findings are supported by King et al.'s (2008) analysis of San Francisco's passive system, which did not have an effect on any of the crime types included in the analysis (homicide, violent crime, part 1 property offenses, drug offenses, prostitution, and vandalism). The recent works of Caplan, Kennedy, and Petrossian (2011) and Ratcliffe et al. (2009) suggests an avenue of further inquiry. Both of these studies found *intra*-system variation, with effective and ineffective camera sites being present within the same system. Both of these studies seem to suggests that La Vigne et al.'s (2011a) attempt to identify the source of variably in regards to camera effect could be focused on disaggregate camera sites as well as across aggregate systems.

Analysis A continues along the trajectory suggested by Caplan, Kennedy, and Petrossian (2011) and Ratcliffe et al. (2009). A success measure was calculated for each camera viewshed in Newark's system. A series of regression models tests how this success measure is influenced by twenty-five variables related to various micro-level, empirically suggested features.

Methodology

Dependent Variable: Camera Effect on Crime

CCTV camera effectiveness was determined by measuring crime level changes within their respective viewsheds. Crime incidents were selected for inclusion according to their likely susceptibility to CCTV. While most CCTV evaluations give little consideration to the locations where crime incidents occur, the impact of CCTV is limited to incidents that can potentially be viewed on camera. Crimes occurring out of public view, such as a domestic assault in a residence or a theft inside a department store, should not be included in a test of CCTV effectiveness (Cameron et al., 2008; Caplan, Kennedy, & Petrossian 2011; Ratcliffe et al. 2009).

In an attempt to maximize the construct validity of the findings, this analysis was initially designed to only include crimes occurring outdoors. Newark Police GIS files from 2008-2010 include a variable denoting whether the crime occurred indoors or outdoors, facilitating the identification of such incidents. However, the analysis necessitated the use of crime incidents from as far back as 2007 in order to account for the pre-installation period of cameras installed on 3/15/08. Unfortunately, the Newark Police Department's pre-2008 GIS files do not include the "indoor/outdoor" variable. Therefore, it was decided to include crime *types* that predominantly occur outdoors instead of crime *incidents* that did occur outdoors. Crime incidents from 2008 through 2010 were queried based on location of occurrence (indoors or outdoors). As displayed in Figure 14, murder, robbery, non-fatal shootings, auto theft, and theft from auto occurred outdoors over 80% of the time, with no other crimes occurring outdoors in more than 63.9% of cases, and were thus selected for inclusion.

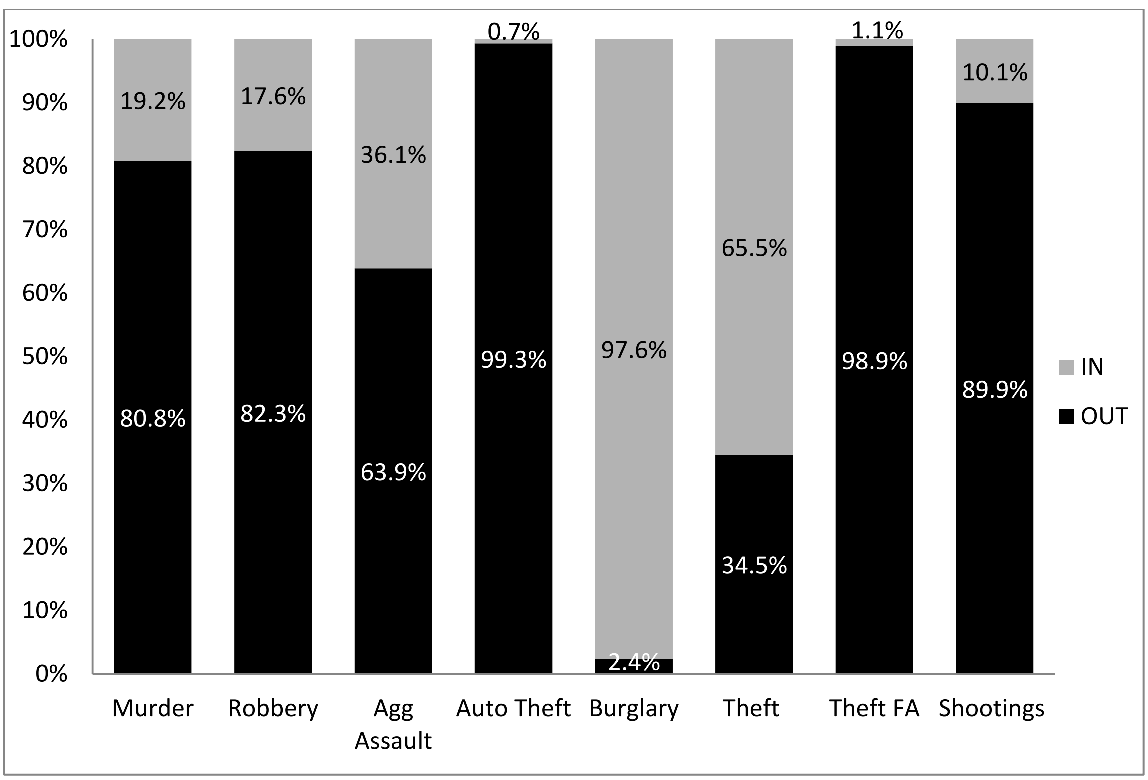

Figure 14: Percentage of crime incidents occurring indoors/outdoors, 2008-2010.

The crime data were classified into six different crime categories for the analysis. All of the crime types (robbery, murder, shootings, auto theft, and theft from auto) were combined to create an "Overall Crime" category. Robbery, murders, and shootings were combined to create a "Violent Crime" category. Auto theft and theft from auto were combined to create a "Property Crime" category. Finally, "Robbery," Auto Theft," and "Theft From Auto" were included on their own as crime categories in the analysis. Murder and shootings were not included as crime categories for the analysis due to their sparse occurrence, compared to the other crime categories (see Table 3).

CRIME CATEGORY	2007	2008	2009	2010	2011	YEARLY AVERAGE
Murder	100	67	80	92	92	86.20
Shootings	335	297	258	306	349	309.00
Robbery	1,208	1,467	1,414	1,664	2,020	1,554.60
VIOLENT CRIME	**1,643**	**1,831**	**1,752**	**2,062**	**2,461**	**1,949.80**
Auto Theft	4,468	3,911	3,208	3,734	3,673	3,798.80
Theft From Auto	2,654	2,480	2,125	2,212	2,596	2,413.40
PROPERTY CRIME	**7,122**	**6,391**	**5,333**	**5,946**	**6,269**	**6,212.20**
OVERALL CRIME	**8,765**	**8,222**	**7,085**	**8,008**	**8,730**	**8,162.00**

Table 3: Crime category yearly counts and five-year average, 2007-2011.

The prevalence of the six crime categories was measured as a Location Quotient (LQ). An LQ measures the prevalence of crime in a particular area (e.g. viewshed) compared to its prevalence over an aggregate area (e.g. Newark). The LQ adds perspective to observed crime in the viewshed by accounting for aggregate crime levels. While traditional crime rates measure crime relative to the number of units at risk (commonly the total number of residents), the LQ controls for the crime distribution across the larger comparison area as well as the size of the unit of analysis. This is especially important in the current study due to the varying sizes of the viewsheds. Prior studies have utilized LQs to explore a range of public safety issues (Brantingham &

Brantingham 1998; Carcach & Muscat 2002; McCord & Ratcliffe, 2007; Rengert et al., 2005), including CCTV (Caplan, Kennedy, & Petrossian, 2011).

LQ's were calculated for each viewshed according to the following formula:

$$LQ=(x_i/t_i)/(X/T)$$

where x_i represents the number of crimes in viewshed i; t_i represents the total area of viewshed i; and X and T represent the city-wide numbers of crimes of type x and area, respectively (Caplan, Kennedy, & Petrossian., 2011). LQ values below one suggest the area to have less crime than is more generally found across the aggregate geography with LQ values greater than one suggesting a relative crime concentration. As a level of measurement, LQ are ratio values, making different LQ values proportional to one another. As explained by Brantingham and Brantingham (1998) an area with an LQ of 1.4 is 40% higher than the aggregate trend while a value of 0.7 would suggest the area to be 30% below the aggregate trend (p. 271).

Each viewshed received two separate LQs: one for the one-year pre-installation period and one for the one-year post-installation period. Each viewshed's "pre" LQ was subtracted from the "post" LQ, creating a "Difference in Location Quotients" (DLQ) change score variable. Viewsheds with changes towards the negative were deemed to have experienced crime reductions while positive changes suggests crime did not improve following camera installation. DLQ values were calculated for each of the six crime categories.

All viewsheds with negative DLQ values (suggesting a crime reduction) were included in a subsequent analysis of displacement.[12] Similar to the main analysis, “pre” and “post” LQ values were calculated for the catchment areas surrounding each viewshed with LQ changes towards the negative suggesting a crime reduction and positive values suggesting an increase.

Independent Variables

Twenty five independent variables were included in the test of camera effectiveness. The variables are grouped into five categories: environmental features (14), camera design and quantity (two), line of sight (four), enforcement activity (four), and pre-intervention crime levels (one). The variables were measured through separate processes, which are discussed below.

Environmental Features

The fourteen environmental feature variables capture the prevalence of specific environmental features surrounding camera locations. The specific layers are bars, liquor stores, corner stores, take out eateries and fast food restaurants, sit-down restaurants, “at-risk” housing, other residential high rise buildings, schools, gas station, retail establishments, transit stops, parking lots, drug markets, and major roads.[13] An important

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[12] Since displacement and diffusion of benefits are outcomes of successful prevention efforts, it makes little sense to look for evidence of such in the absence of achieved crime reductions (Clarke & Eck, 2005: Step 51).

[13] Previous research has suggested that overtly alerting pedestrians to the cameras’ presence, either through flashing lights or signage, may help to generate deterrence by making potential offenders aware that they are being monitored. However, Newark did not install flashing lights on their cameras. The city did install 11 signs announcing the presence of the surveillance system. However, none of them actually fell within a camera viewshed. The signs were installed at the entrances and exits of select highways in the city as a way

consideration is the proximity at which these features impact crime within viewsheds. As previously discussed, viewsheds accurately denote areas monitored by CCTV; the measurement of crime levels within these boundaries is a valid metric of CCTV effect. However, it is impractical to consider features falling in the surrounding area of a camera but outside of a viewshed (e.g. a bar across the street or a housing complex immediately around the corner) to be unrelated to observed crime levels. These nearby locations may influence potential offender and victim travel and behavior patterns in and around camera location, and should not be overlooked.

Early studies of geography explored the relationship between micro features and their surrounding environmental space (Ittelson, 1973). Within this discipline, small scale "objects" (including people) are seen as interconnected features influenced by the surrounding environment (Freundschuh & Egenhofer, 1997). Criminology makes similar observations in the form of "behavior settings" which are physical and social environments which host specific activities and interactions (Felson, 1995; Taylor, 1997; Taylor & Harrell, 1996) and "environmental backcloths" which are the micro-level features which comprise a specific area (Brantingham & Brantingham, 1993a). These locales have significant influence on crime opportunities and more readily explain crime patterns than aggregate geographies (Weisburd, Bernasco, & Bruinsma, 2009).

The prevalence of the environmental variables was measured within the immediate surrounding area of CCTV cameras. Particular consideration was paid to street segments (or "block faces") since such features have been seen to function as venues for regularly occurring patterns of social activity (Hunter & Baumer, 1982; Taylor,

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of advertising the CCTV system to motorists driving to/from Newark. Therefore, "signage" was not included as an independent variable in this analysis.

Gottfredson, & Brower, 1984; Whyte, 1943). Operationalizing the surrounding area of each camera location was a two-step process. First, the camera's maximum visibility (the number of feet from the camera to the furthest extent of its viewshed) was measured via the "measurement tool" in ArcGIS. A buffer of this distance was then generated around the camera (see Figure 15). ArcGIS's "clip" function was utilized to truncate the features of the underlying street files based upon the outline of the buffer. The resulting layer was the precise portion of street segments falling within the camera's surrounding environment (denoted by the buffer). This process was repeated for each viewshed included in the analysis.

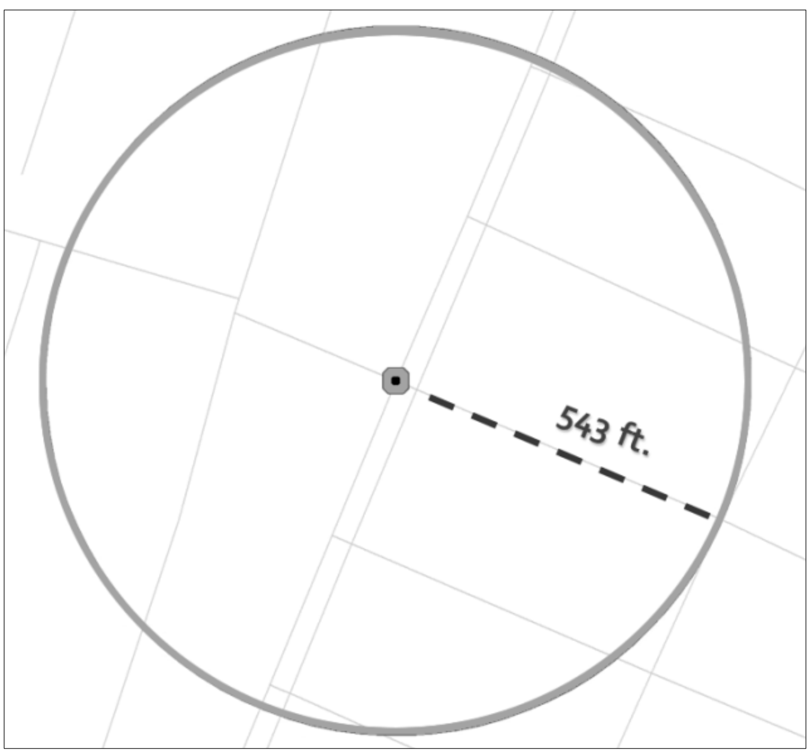

Figure 15: Example camera with a maximum visible distance and resulting buffer of 543 feet.

The prevalence of each feature was measured through a Location Quotient (LQ) controlling for the size of the camera environment as well as the distribution of the feature across the entirety of Newark. The process differed slightly by the data type. LQ's for the point features (bars, liquor stores, corner stores, take out eateries and fast food restaurants, sit-down restaurants, schools, gas stations, and retail establishments) controlled for the overall length of street segments. For example, 313 bars are present in Newark while the streets in the city measure a total of 641.39 miles, as measured within a GIS. In the example shown by Figure 16, three bars fall within a street network totaling 5,000 feet in length. The resulting location quotient is 6.49: (3/5,000 ft)/(313/641.39 mi).[14]

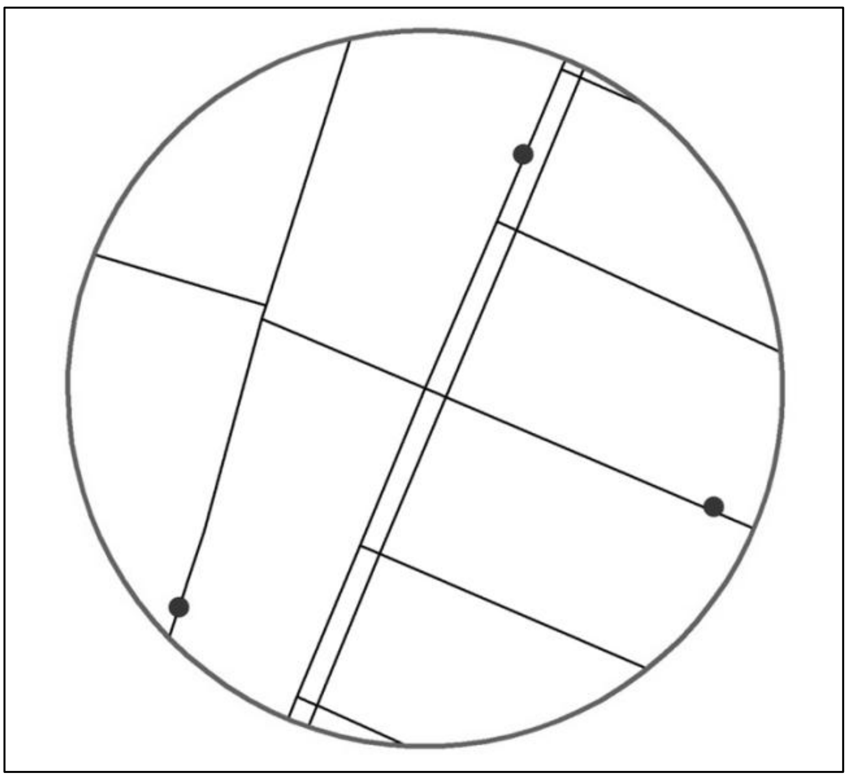

Figure 16: Clip process for point environmental features

A slightly different process was undertaken for the polygonal and linear features. LQ's for the polygonal features (at-risk housing complexes, residential high rises, parking lots, and drug markets) controlled for the area of the polygons, buffer, and

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[14] Within the LQ formula, the city street length of 641.39 miles is converted into 3,386,581.47 feet.

overall city. In the case of at-risk housing, the features total 0.64 square miles with the overall land mass of Newark being approximately 26 square miles, as measured within a GIS. Therefore, as exemplified in Figure 17, if a housing complex totaling 10,000 square feet was within a 40,000 square foot camera buffer, the LQ would be 0.24: (10,000 ft²/40,000 ft²)/(0.64 mi²/15.84 mi²).[15] In the case of the Major Roads layer, the lone linear feature, the LQ controlled for the length of the major roads and Newark's overall street network (see Figure 18). Therefore, if 900 feet of major roads fell within a buffer with 1800 feet of overall streets, the LQ would be 1.34 (900 ft/ 1800 ft)/(233.76 mi/641.39 mi).[16]

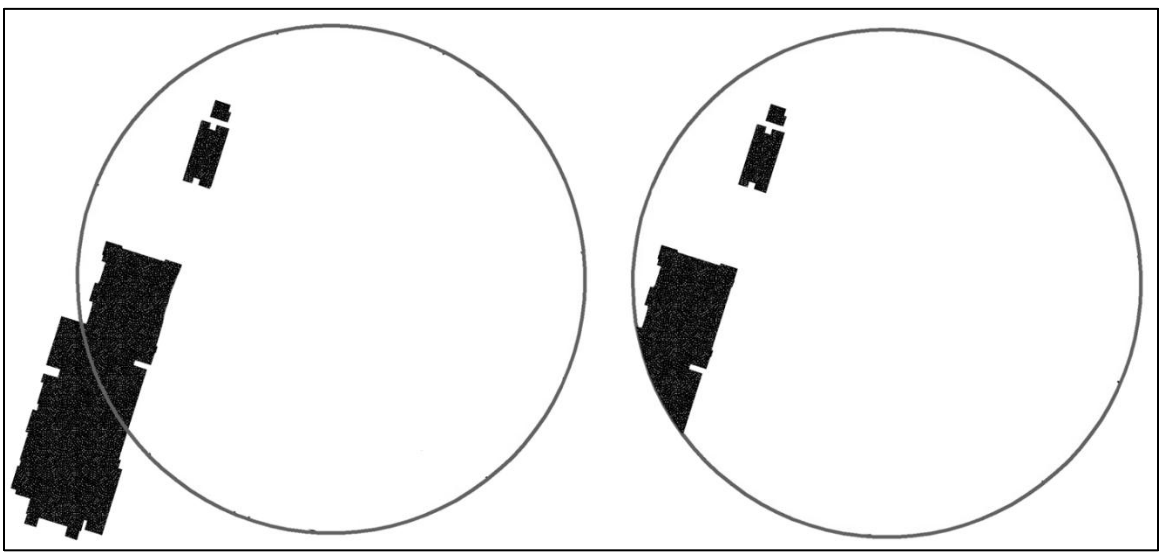

Figure 17: Clip process for polygon environmental features

[15] Within this formula, the overall square mileage of at-risk housing is converted to 17,976,593.56 square feet and the square mileage of Newark's land area is converted to 441,853,035.57 724,779,325.66 square feet.

[16] Within this formula, the overall square mileage of the major roads is converted to 1,234,264.49 feet and the city street length of 641.39 miles is converted into 3,386,581.47 feet.

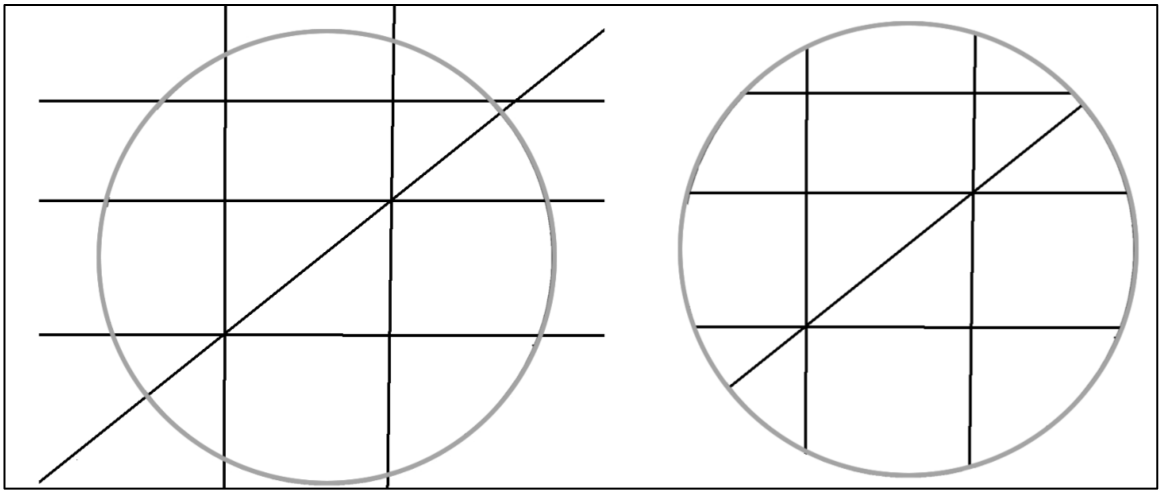

Figure 18: Clip process for linear environmental features

Line of Sight

Previous research suggests CCTV coverage and dosage to be related to camera effectiveness (Farrington, Gill, Waples, & Argomainz, 2007; Gill & Spriggs 2005). In this sense, four variables related to the coverage of cameras are included. The first is the overall square footage of the viewshed. Three additional variables measure visible obstructions within viewsheds. These variables are the percentage of the overall viewshed that is blocked by foliage, the percentage of the viewshed that is obstructed by immovable objects, and the total percentage of the viewshed that is in some way obstructed (either by foliage or an immovable object). While the link between obstructions and CCTV impact has yet to be empirically tested, anecdotal evidence exists that suggests it can impede upon the proactive monitoring process (Smith, 2004; Gill et al., 2005).[17]

[17] At the outset of the research, I planned on including a camera's night vision quality as a line-of-sight variable. However, the process of assessing night-time image quality proved to be difficult and highly subjective. For example, while most of the cameras display color images at night, some are black and white. While this seemingly provides a metric by which to assess a camera's night time quality, other factors may impact the nighttime visibility of a camera. For example, extremely bright lights (e.g. car headlights or street lamps) can sometimes restrict the visibility of a camera, especially when shining

Camera Design and quantity

Two variables capture the design and quantity of cameras within each viewshed. The first (named "overlap") identifies the number of individual cameras comprising the viewshed. To review, several camera locations have viewsheds that overlap with others. These overlapping viewsheds were merged into singular viewsheds in order to prevent single crime incidents from being counted multiple times. The result of this process was the 128 cameras included in the analysis being represented by 117 viewsheds. The camera design variable is a dummy variable identifying each camera as either a circular "dome" camera or not. For viewsheds comprised of a single camera, "1" classifies the camera as a "dome" and "0" specifies the camera as a traditionally designed bullet-resistant camera. For viewsheds with more than 1 camera, the average of the dichotomous values is calculated. For example, if a viewshed is comprised of three dome cameras, the resulting "dome" variable is 1 ([1+1+1]/3=1). However, if the viewshed was comprised of two dome cameras and one bullet resistant camera the variable value is 0.66 ([1+1+0]/3=0.66).

Enforcement Actions

The final four variables measure the enforcement actions conducted in CCTV areas. The first variable determines how much each camera is used as an investigatory

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directly at a camera. Conversely, the absence of adequate lighting can make specific areas invisible to color cameras. Therefore, a color camera may actually have a worse quality of night vision than a black and white camera in certain instances. Complicating matters further is the fact that the cameras pan in a 360 degree manner. It may be that certain angles have inadequate lighting, other angles have overly bright lighting, and still others offer decent visibility. Given the totality of these circumstances, I decided that including a "night vision" variable would have potentially led to misleading results.

tool by the NPD. Newark Detectives often request copies of footage to aid in investigations through the potential identification of suspects or witnesses involved in a criminal incident. The total footage requests were calculated for each camera through the manual inspection of the evidence logs. The following two variables measure the proactive use of CCTV: 1) the number of criminal incidents detected by each camera, and 2) enforcement activity (such as an arrest, summons, or field interrogation) in response to said detections. The final variable accounts for the potential impact of arrests unrelated to the surveillance system. [18] GIS arrest files were queried to identify incidents taking place within camera viewsheds. Arrests made by investigators for past crimes are excluded. This is because an arrest made by an investigator may have little relation to the environment in which it occurred. If an investigation finds a specific person to be responsible for a crime, it is likely that they would be arrested at a location besides where the crime took place (e.g. their home address). Therefore, the "unrelated arrests" variable only included arrest made by non-investigative officers. GIS files were queried by "officer command" to only include the relevant incidents (e.g. "2nd Precinct Patrol" or "Safe City Task Force"). The number of arrests in response to CCTV activity was subtracted from the overall arrest number to calculate those unrelated to CCTV.

Pre-Intervention Crime Levels

The last control variable captures the viewshed's pre-intervention crime level. The crime prevention utility of CCTV may be restricted when too few crime incidents occur during the "pre" period for certain viewsheds. In the extreme case, a viewshed that

[18] While total "enforcement actions" are measured in respect to the CCTV operation, observations of unrelated police activity are restricted to arrests. This is due to city-wide enforcement data being unavailable for all other enforcement actions (e.g. "summonses") prior to 2009.

experienced zero crime incidents in the pre-installation phase cannot "reduce" crime. Previous crime prevention efforts have noted that a specific threshold may exist in respect to crime levels in order for a reduction to be reasonably expected (Ratcliffe et al., 2011). To measure the effect existing crime levels have on program effect, viewsheds were sorted by pre-intervention crime LQ so that x_i is the smallest value and x_n is the largest. Each viewshed then had a percentile calculated to denote its spot in the distribution via the following formula:

$$p_i=100*(i-0.5/n)$$

where i is the case's place in the distribution and n is the total number of cases. The resulting percentile is the approximate percentage of cases that have values smaller than the case at hand. A viewsheds with a pre-intervention crime level in the 80th percentile has higher crime levels than 80% of the overall viewsheds, for example.

Summary of Variable Distribution

This section described the dependent and independent variables for Analysis A. Table 4 provides a statistical summary of each variable. As suggested by the means and standard deviations, a fair amount of variance exists within each variable. The analysis measures the level to which the variance across the independent variables impacts the variance within the dependent variables (e.g. camera effectiveness). The next section discusses the statistical approach of the analysis in detail.

	Mean	SD	Min	Max
DEPENDENT VARIABLES				
DLQ Overall Crime	-0.09	2.67	-9.53	7.63
DLQ Violent Crime	-0.19	6.57	-22.14	15.77
DLQ Robbery	-0.34	7.10	-23.12	15.58
DLQ Property Crime	-0.33	2.71	-10.39	6.05
DLQ Auto Theft	-0.22	2.98	-12.11	8.26
DLQ Theft From Auto	-0.51	4.87	-20.94	14.90
INDEPENDENT VARIABLES				
Environmental Features				
Bars LQ	1.42	2.28	0.00	10.18
Corner Stores LQ	2.41	3.40	0.00	14.60
Gas Stations LQ	1.89	6.31	0.00	39.14
Liquor Stores LQ	2.86	5.41	0.00	25.72
Department Stores and Retail Shops LQ	4.27	11.60	0.00	73.21
Schools LQ	1.68	3.34	0.00	16.81
Sit Down LQ	2.06	3.04	0.00	11.32
Take Out LQ	2.46	3.54	0.00	22.58
Transit Stops LQ	2.22	1.67	0.00	7.08
Housing LQ	5.25	10.98	0.00	60.81
Apartment Complexes LQ	5.63	8.78	0.00	46.88
Parking Lots LQ	7.00	11.90	0.00	63.36
Drug Markets LQ	7.65	11.56	0.00	59.69
Major Roads LQ	1.50	0.62	0.00	2.86
Line of Sight				
Viewshed Area (sq. ft.)	131,485.60	97,904.48	46,309.71	683,805.30
% Obstructed by Immovable Objects	6.45	7.16	0.00	28.45
% Obstructed by Foliage	15.81	47.71	0.00	514.84
Overall % Obstructed	17.91	11.50	0.00	55.63
Camera Design and Quantity				
Overlap	1.09	0.41	1.00	4.00
Dome	0.84	0.37	0.00	1.00
Enforcement Actions				
Footage Requests	3.49	8.41	0.00	89.00
Detections	6.30	12.54	0.00	99.00
Camera Enforcement	1.91	5.67	0.00	55.00
Unrelated Arrests	50.45	88.28	0.00	865.00

Table 4: Statistical summary of dependent and independent variables.

Statistical Approach

For both the main analysis and the displacement analysis, DLQ values were utilized as dependent variables in Ordinary Least Squares (OLS) regression models. OLS regression models rest on particular assumptions, namely a normally distributed dependent variable (Maxfield & Babbie, 2001: p. 404). As a first step, histograms of DLQ values for each crime type were created. As displayed in Figure 19, distributions for all DLQs approximate bell curves, suggesting them to be normally distributed.

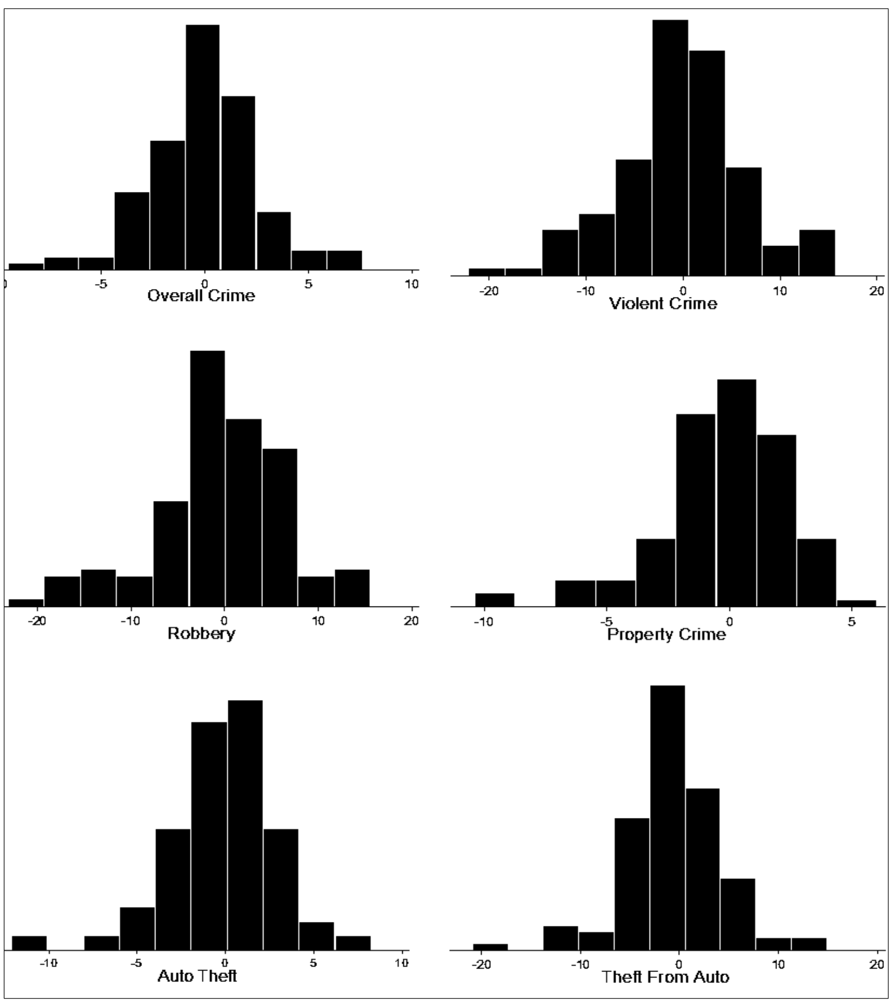

Figure 19: DLQ histograms.

To further test the normalcy of the distribution, a Kolmogorov-Smirnov (K-S) goodness of fit test was conducted on the dependent variables. The K-S test is used to identify whether a sample differs from a standard normal distribution (Chakravart, Laha, & Roy, 1967: p. 392-394). As shown in Table 5, DLQs for all crime categories exhibited statistically insignificant p-values which fail to reject the null hypothesis that the DLQ does not differ from a normal distribution. The work now turns to a description of the independent variables that will be utilized in the analysis.

CRIME CATEGORY	D	P-VALUE	CORRECTED P-VALUE
Overall Crime			
DLQ	0.0777	0.243	
Cumulative	-0.0756	0.263	
Combined K-S	0.0777	0.480	**0.434**
Violent Crime			
DLQ	0.0594	0.438	
Cumulative	-0.0712	0.306	
Combined K-S	0.0712	0.594	**0.549**
Property Crime			
DLQ	0.0501	0.556	
Cumulative	-0.1137	0.049	
Combined K-S	0.1137	0.097	**0.079**
Robbery			
DLQ	0.061	0.419	
Cumulative	-0.0918	0.139	
Combined K-S	0.0918	0.278	**0.241**
Auto Theft			
DLQ	0.0742	0.275	
Cumulative	-0.0607	0.422	
Combined K-S	0.0742	0.539	**0.493**
Theft From Auto			
DLQ	0.0636	0.388	
Cumulative	-0.0963	0.114	
Combined K-S	0.0963	0.228	**0.194**

Table 5: Kolmogorov-Smirnov tests on DLQ variables.

Findings

Table 6 summarizes the dependent variables. Consistent with previous research (Caplan, Kennedy, & Petrossian, 2011; Ratcliffe et al., 2009) Newark's CCTV system is comprised of both effective and ineffective camera sites. For each crime category the frequency of viewsheds with negative DLQ values (suggestive of a crime decreases) and positive DLQ values (suggestive of a crime increase) is nearly even. The largest difference in frequency is for theft from auto, for which 56.88% of viewsheds had negative DLQ values and 43.12% had positive. For every other crime category, percentage differences were less than eight percentages points with numerous categories being nearly evenly distributed between positive and negative.

CRIME CATEGORY	NEG. DLQ	Neg. %	POS. DLQ	Pos. %	NO CHANGE DLQ	% NO CHANGE
Overall Crime	55	47.01%	62	52.99%	0	0.00%
Violent Crime	58	51.33%	55	48.67%	4	3.42%
Property Crime	62	53.91%	53	46.09%	2	1.71%
Robbery	56	50.45%	55	49.55%	6	5.13%
Auto Theft	56	49.12%	58	50.88%	3	2.56%
Theft From Auto	62	56.88%	47	43.12%	8	6.84%

Table 6: Number of viewsheds with negative and positive DLQ values.

To measure the causal effects of the varied levels of camera effect, the research design employed three separate regression models. The first model, model A, includes all of the viewsheds. Model B incorporates only those viewsheds that experienced at least one crime incident in the pre-installation period. Since viewsheds absent pre-installation crime can only experience a change in one direction (a crime increase), excluding the no-crime viewsheds adds perspective. Model C measures the impact of the independent variables on DLQ values in the catchment area of all viewsheds that experienced a reduction in crime level.

Model A Findings: All Viewsheds

Table 7 displays the model A findings for the aggregate crime categories of Overall Crime, Violent Crime, and Property Crime. To review, the dependent variable of each model was the "Difference in Location Quotient (DLQ)," a change score computed by subtracting the pre- installation LQ from the post-installation LQ. In each model, various environmental features were statistically significant. Furthermore, each of the significant features exhibited positive β values suggesting their presence to be related to post-installation crime increases. The significant environmental features differed by crime category. Drug markets (0.05) and liquor stores (0.21) were statistically significant in the overall crime and violent crime models, respectively. For property crime, both retail stores (0.06) and schools (0.14) were statistically significant. Only violent crime was influenced by any of the line of sight variables; foliage obstruction (-0.04) was associated with lower crime levels in the post-installation period. This finding is somewhat surprising, since previous research has suggested that visual obstruction may impede on an operator's ability to actively monitor cameras (Gill et al., 2005; Smith, 2004). Neither of the two camera design and quantity variables was statistically significant.

Interesting findings were observed in respect to the enforcement activity variables. For both overall crime and violent crime, detections and camera enforcement were statistically significant, but in opposite directions. For overall crime, the detections variable was positive (0.07) and camera enforcement was negative (-0.27).

Variables	Overall Crime (N=117)			Violent Crime (N=117)			Property Crime (N=117)		
	β	Std. Err.	t	β	Std. Err.	t	β	Std. Err.	t
Constant	0.72	1.22	0.59	4.56	2.65	1.72	1.16	1.17	0.99
Environmental Features									
Bars	-0.18	0.12	-1.52	-0.20	0.27	-0.74	-0.13	0.11	-1.17
Corner Stores	0.10	0.08	1.20	0.15	0.18	0.86	0.09	0.08	1.17
Gas Stations	-0.04	0.04	-0.96	-0.02	0.08	-0.20	-0.04	0.03	-1.10
Liquor Stores	0.03	0.05	0.67	**0.21***	0.10	2.09	-0.02	0.04	-0.37
Retail Stores	0.03	0.03	0.98	-0.11	0.06	-1.76	**0.06***	0.03	2.32
Schools	0.11	0.07	1.48	0.09	0.16	0.56	**0.14***	0.07	2.10
Sit Down Restaurants	-0.02	0.10	-0.16	-0.02	0.22	-0.09	-0.04	0.09	-0.40
Take Out Eateries	0.04	0.09	0.45	0.29	0.19	1.57	-0.03	0.08	-0.37
Transit Stops	0.02	0.19	0.11	0.14	0.41	0.34	-0.12	0.17	-0.71
Housing	-0.02	0.02	-0.65	-0.05	0.05	-0.93	-0.01	0.02	-0.28
Apartment Complexes	0.00	0.03	-0.04	-0.05	0.06	-0.92	0.01	0.02	0.43
Parking Lots	0.00	0.02	0.15	-0.02	0.05	-0.44	-0.01	0.02	-0.49
Drug Markets	**0.05***	0.02	2.01	0.06	0.05	1.13	0.03	0.02	1.59
Major Roads	0.58	0.45	1.28	0.40	0.99	0.40	0.57	0.42	1.35
Line of Sight									
Viewshed Area	0.00	0.00	0.44	0.00	0.00	0.61	0.00	0.00	0.91
% Overall Obstruct	0.00	0.02	0.13	0.05	0.05	0.94	-0.01	0.02	-0.38
% Immovable Obstruct	0.02	0.04	0.46	-0.09	0.08	-1.11	0.03	0.04	0.93
% Foliage Obstruct	-0.01	0.01	-1.36	**-0.04****	0.01	-3.45	0.00	0.00	-0.43
Camera Design and Quantity									
Overlap	-1.14	1.14	-1.00	-3.64	2.51	-1.45	-0.87	1.07	-0.82
Dome	1.15	0.67	1.72	2.50	1.48	1.69	0.78	0.63	1.25
Enforcement Activity									
Footage Requests	0.08	0.06	1.21	0.27	0.14	1.90	0.03	0.06	0.45
Detections	**0.07***	0.03	1.98	**0.15***	0.08	1.96	0.05	0.03	1.56
Camera Enforcement	**-0.27***	0.11	-2.37	**-0.70****	0.25	-2.79	-0.19	0.11	-1.84
Unrelated Arrests	0.00	0.00	0.10	0.00	0.01	0.63	0.00	0.00	-0.27
Pre-Installation Crime Levels									
Percentile	**-0.05****	0.01	-5.70	**-0.12****	0.02	-6.50	**-0.06****	0.01	-7.10
*p<.05; **p<.01 R-squared (Adjusted)	.41 (.25)			.53 (.40)			.50 (.37)		

Table 7: Model A Results for Overall Crime Violent Crime, and Property Crime

Violent crime experienced similar outcomes, with a coefficient of 0.15 for detections and -0.70 for camera enforcement. This shows that operators reporting crime incidents and police officers effectively addressing the said incidents are unique phenomena with different effects on crime. None of the enforcement activity variables were significant for property crime. The percentile variable was negative and statistically significant for all of the three aggregate crime categories.

Table 8 displays the findings of the models for the desegregate crime categories of robbery, auto theft, and theft from auto. As was the case with the aggregate crime categories, each of the disaggregate crime categories were negatively impacted (e.g. associated with crime increases) by different environmental features. Liquor stores (0.24) were statistically significant in respect to robbery, schools (0.22) and drug markets (0.05) were statistically significant for auto theft, and corner stores (0.30) and retail stores (0.13) were statistically significant for theft from auto. With an observed p value of 0.06, major roads was nearly significant (1.39) for theft from auto.

Robbery was the only crime influenced by the line of sight variables with foliage obstructions (-0.04) being associated with lower crime levels in the post-installation period. This mirrors the findings for the violent crime category. Neither auto theft nor theft from auto was influenced by any of the line of sight variables. Auto theft was the only disaggregate category influenced by the camera design and quantity variables. The overlap variable, which captures the number of cameras that comprise the viewsheds, had a statistically significant coefficient of -2.28. This shows the concentration of cameras to have a substantial impact on auto theft. Interestingly, “dome” cameras were associated with auto theft increases, with a significant coefficient of 1.36. Similar to the cumulative crime categories, the percentile variable was significant and negative across all crime types.

Variables	Robbery (N=117)			Auto Theft (N=117)			Theft From Auto (N=117)		
	B	Std. Err.	t	*B*	Std. Err.	t	*B*	Std. Err.	t
Constant	**5.98***	2.84	2.11	2.24	1.26	1.78	0.69	1.97	0.35
Environmental Features									
Bars	-0.30	0.28	-1.07	-0.03	0.12	-0.26	-0.29	0.20	-1.44
Corner Stores	0.13	0.19	0.68	-0.10	0.08	-1.21	**0.30***	0.13	2.21
Gas Stations	-0.05	0.09	-0.60	0.01	0.04	0.15	-0.10	0.06	-1.59
Liquor Stores	**0.24***	0.11	2.26	0.04	0.04	0.88	-0.10	0.07	-1.38
Retail Stores	-0.06	0.07	-0.87	0.00	0.03	-0.05	**0.13****	0.05	2.72
Schools	0.18	0.17	1.05	**0.22****	0.07	2.94	-0.01	0.12	-0.12
Sit Down Restaurants	0.01	0.23	0.04	0.03	0.10	0.32	-0.11	0.16	-0.70
Take Out Eateries	0.15	0.20	0.75	0.08	0.08	0.90	-0.11	0.14	-0.77
Transit Stops	0.06	0.43	0.15	-0.04	0.19	-0.21	-0.13	0.30	-0.42
Housing	-0.03	0.05	-0.63	0.01	0.02	0.54	-0.02	0.04	-0.62
Apartment Complexes	-0.01	0.06	-0.14	0.01	0.03	0.38	0.01	0.04	0.35
Parking Lots	0.00	0.05	-0.07	-0.01	0.02	-0.41	0.00	0.04	0.01
Drug Markets	0.04	0.05	0.73	**0.05***	0.02	2.35	-0.02	0.04	-0.43
Major Roads	0.43	1.06	0.40	-0.08	0.45	-0.18	1.39	0.73	1.89
Line of Sight									
Viewshed Area	0.00	0.00	0.82	0.00	0.00	1.56	0.00	0.00	-0.05
% Overall Obstruct	0.01	0.06	0.16	-0.01	0.02	-0.23	-0.01	0.04	-0.15
% Immovable Obstruct	-0.10	0.09	-1.14	0.07	0.04	1.80	-0.06	0.06	-0.99
% Foliage Obstruct	**-0.04****	0.01	-3.16	-0.01	0.01	-1.17	0.01	0.01	0.72
Camera Design and Quantity									
Overlap	-3.46	2.68	-1.29	**-2.28***	1.14	-2.00	1.38	1.85	0.74
Dome	1.56	1.58	0.99	**1.36***	0.67	2.04	0.41	1.09	0.37
Enforcement Activity									
Footage Requests	0.17	0.15	1.11	0.12	0.06	1.84	-0.09	0.10	-0.90
Detections	**0.17***	0.08	2.14	0.00	0.03	0.06	**0.12***	0.06	2.13
Camera Enforcement	**-0.61***	0.26	-2.30	-0.12	0.11	-1.05	-0.30	0.18	-1.62
Unrelated Arrests	0.00	0.01	-0.39	0.00	0.00	-0.75	0.00	0.00	0.15
Pre-Installation Crime Levels									
Percentile	**-0.13****	0.02	-6.80	**-0.06****	0.01	-7.46	**-0.08****	0.01	-7.00
*p<.05; **p<.01 R-squared (Adjusted)	.54 (.41)			.53 (.40)			.53 (.40)		

Table 8: Model A Results for Robbery, Auto Theft, and Theft From Auto.

Model B Findings: Viewsheds experiencing at least 1 crime during the pre-installation period.

Model B included only those viewsheds that experienced at least 1 crime incident during the pre-installation period. Table 9 displays the results for the aggregate crime categories. Results for overall crime and violent crime were similar to model A in respect to the environmental features. Drug markets (0.05) and liquor stores (0.24) were significantly associated with crime level increases for overall crime and violent crime, respectively. A total of three environmental features were significant in the property crime model: retail stores (0.07), schools (0.16), and major roads (0.90). Only retail stores and schools were statistically significant in model A. In respect to the line of sight variables, model B replicated the findings of the previous model with the percentage of the viewshed obstructed by foliage being associated with lower violent crime levels. Similarly, neither of the camera design and quantity variables was statistically significant.

In respect to the enforcement variables, camera enforcement was associated with lower post installation crime levels for overall crime (-0.27), violent crime (-0.68), and property crime (-0.24), whereas it was statistically significant for only overall crime and violent crime in model A. The detections variable was statistically significant only in the case of overall crime (0.07). Percentile was negative and statistically significant for each of the aggregate crime categories.

Variables	Overall Crime (N=116)			Violent Crime (N=94)			Property Crime (N=112)		
	B	Std. Err.	t	*B*	Std. Err.	t	*B*	Std. Err.	t
Constant	0.72	1.22	0.59	**7.66***	3.47	2.21	1.11	1.20	0.92
Environmental Features									
Bars	-0.18	0.12	-1.52	-0.33	0.31	-1.08	-0.04	0.12	-0.35
Corner Stores	0.10	0.08	1.20	0.06	0.21	0.26	0.12	0.08	1.52
Gas Stations	-0.04	0.04	-0.96	-0.03	0.09	-0.28	-0.05	0.03	-1.47
Liquor Stores	0.03	0.05	0.67	**0.24***	0.11	2.23	0.00	0.04	0.11
Retail Stores	0.03	0.03	0.98	-0.14	0.07	-1.95	**0.07***	0.03	2.34
Schools	0.11	0.07	1.48	-0.02	0.21	-0.09	**0.16***	0.07	2.36
Sit Down Restaurants	-0.02	0.10	-0.16	0.09	0.25	0.36	-0.09	0.10	-0.90
Take Out Eateries	0.04	0.09	0.45	0.32	0.22	1.43	0.00	0.08	0.03
Transit Stops	0.02	0.19	0.11	0.23	0.52	0.45	-0.27	0.18	-1.48
Housing	-0.02	0.02	-0.65	-0.10	0.06	-1.55	0.00	0.02	-0.20
Apartment Complexes	0.00	0.03	-0.04	-0.11	0.06	-1.64	0.01	0.03	0.25
Parking Lots	0.00	0.02	0.15	0.04	0.07	0.57	-0.02	0.02	-1.15
Drug Markets	**0.05***	0.02	2.01	0.06	0.06	1.02	0.03	0.02	1.44
Major Roads	0.58	0.45	1.28	-0.25	1.15	-0.22	**0.90***	0.46	1.97
Line of Sight									
Viewshed Area	0.00	0.00	0.44	0.00	0.00	0.17	0.00	0.00	0.92
% Overall Obstruct	0.00	0.02	0.13	0.03	0.06	0.54	0.00	0.02	0.06
% Immovable Obstruct	0.02	0.04	0.46	-0.07	0.10	-0.69	0.05	0.04	1.30
% Foliage Obstruct	-0.01	0.01	-1.36	**-0.04****	0.01	-3.11	0.00	0.00	-0.33
Camera Design and Quantity									
Overlap	-1.14	1.14	-1.00	-3.00	2.84	-1.05	-1.19	1.08	-1.10
Dome	1.15	0.67	1.72	1.94	1.84	1.06	0.94	0.64	1.47
Enforcement Activity									
Footage Requests	0.08	0.06	1.21	0.30	0.16	1.94	0.05	0.07	0.70
Detections	**0.07***	0.03	1.98	0.11	0.08	1.37	0.05	0.03	1.65
Camera Enforcement	**-0.27***	0.11	-2.37	**-0.68***	0.27	-2.51	**-0.24***	0.11	-2.12
Unrelated Arrests	0.00	0.00	0.10	0.00	0.01	0.64	0.00	0.00	-0.44
Pre-Installation Crime Levels									
Percentile	**-0.05****	0.01	-5.70	**-0.14****	0.04	-3.93	**-0.06****	0.01	-7.12
*p<.05; **p<.01 R-squared (Adjusted)	.41 (.25)			.52 (.35)			0.52 (.38)		

Table 9: Model B Results for Overall Crime Violent Crime, and Property Crime.

Table 10 displays the model B results for the disaggregate crime categories. All of the statistically significant environmental features exhibited positive coefficients suggestive of a crime increase. For robbery, the liquor stores variable was the only statistically significant environmental feature, mirroring the findings of model A. The influential environmental features for auto theft and theft from auto differed when the no-crime viewsheds were excluded. For auto theft, schools (0.23), drug markets (0.05), and major roads (0.09) were statistically significant. Major roads was not statistically significant in Model A. For theft from auto, corner stores (0.40) and major roads (2.42) were statically significant. This differed from the model A results, in which only corner stores and retail stores were statistically significant for theft from auto.

Robbery and auto theft were both influenced by the line of sight variables. The foliage obstruction variable displayed a negative coefficient (-0.03) for robbery, suggestive of a crime decrease. For auto theft, the immovable object obstruction variable displayed a statistically significant coefficient of 0.09, showing immovable visible obstructions to have led to increased crime levels.

Auto theft was the only disaggregate category influenced by the camera design and quantity variables. The overlap variable's coefficient was -2.58 in the auto theft model. The dome variable, while significant in model A, was not statistically significant for auto theft. As was the cases in all of the previous models, the percentile variable was negative and statistically significant for all crime types.

Variables	Robbery (N=89)			Auto Theft (N=104)			Theft From Auto (N=89)		
	B	Std. Err.	t	*B*	Std. Err.	t	*B*	Std. Err.	t
Constant	**13.13****	4.14	3.17	2.38	1.37	1.74	1.51	2.80	0.54
Environmental Features									
Bars	-0.45	0.33	-1.38	0.09	0.13	0.66	0.03	0.27	0.11
Corner Stores	-0.05	0.23	-0.23	-0.09	0.09	-1.00	**0.40***	0.19	2.14
Gas Stations	-0.04	0.09	-0.41	0.01	0.04	0.19	-0.15	0.10	-1.52
Liquor Stores	**0.24***	0.12	2.06	0.05	0.05	1.02	-0.05	0.10	-0.50
Retail Stores	-0.08	0.07	-1.02	0.03	0.03	0.86	0.07	0.07	1.14
Schools	0.01	0.22	0.04	**0.23****	0.07	3.05	-0.04	0.18	-0.22
Sit Down Restaurants	0.26	0.26	1.00	-0.03	0.11	-0.32	-0.34	0.22	-1.59
Take Out Eateries	0.10	0.24	0.42	0.07	0.09	0.80	0.07	0.17	0.39
Transit Stops	0.55	0.57	0.96	-0.21	0.20	-1.07	-0.20	0.39	-0.52
Housing	-0.09	0.07	-1.43	0.02	0.02	0.78	-0.01	0.05	-0.21
Apartment Complexes	-0.11	0.07	-1.65	0.01	0.03	0.40	-0.01	0.05	-0.11
Parking Lots	0.10	0.07	1.37	-0.02	0.02	-0.98	-0.03	0.04	-0.69
Drug Markets	0.05	0.06	0.81	**0.05***	0.02	2.13	-0.02	0.05	-0.32
Major Roads	-0.22	1.25	-0.18	**0.09***	0.50	0.18	**2.42***	1.01	2.40
Line of Sight									
Viewshed Area	0.00	0.00	-0.28	0.00	0.00	1.41	0.00	0.00	0.01
% Overall Obstruct	0.04	0.07	0.49	0.00	0.03	-0.06	0.02	0.05	0.40
% Immovable Obstruct	-0.12	0.11	-1.13	**0.09***	0.04	2.15	-0.10	0.07	-1.38
% Foliage Obstruct	**-0.03****	0.01	-2.62	0.00	0.01	-0.94	0.00	0.01	0.40
Camera Design and Quantity									
Overlap	-2.45	3.02	-0.81	**-2.58***	1.15	-2.25	0.80	2.11	0.38
Dome	0.77	1.96	0.39	1.11	0.71	1.57	0.41	1.44	0.28
Enforcement Activity									
Footage Requests	0.20	0.16	1.21	**0.28****	0.11	2.63	-0.09	0.14	-0.64
Detections	0.12	0.09	1.36	-0.02	0.04	-0.47	0.13	0.14	0.99
Camera Enforcement	**-0.55***	0.28	-1.95	-0.04	0.14	-0.28	-0.28	0.37	-0.77
Unrelated Arrests	0.00	0.01	-0.61	0.00	0.00	-1.02	0.00	0.01	-0.41
Pre-Installation Crime Levels									
Percentile	**-0.21****	0.04	-4.74	**-0.06****	0.01	-6.05	**-0.11****	0.02	-4.93
*p<.05; **p<.01									
R-squared (Adjusted)	.56 (.39)			.56 (.42)			.51 (.32)		

Table 10: Model B results for Robbery, Auto Theft, and Theft From Auto

Model C Findings: Catchment Areas

Model C includes the catchment areas of all viewsheds with negative DLQ values, suggestive of a crime reduction. To prevent single incidents from being counted multiple times, overlapping catchment areas were considered as single sites (see Table 11). The environmental features were measured within the catchment area. “Bars,” for example, refers to the amount of bars (measured through a location quotient) in the catchment area NOT the viewshed. The reaming variable categories (line of sight, camera design and quantity, enforcement activity, and pre-installation crime levels) are obviously camera specific and refer to the actual viewshed. Similar to the viewsheds, merged catchments differed slightly in how the “dome” variable was measured (see p. 83-84).

CRIME CATEGORY	VIEWSHEDS	CATCHMENT AREAS
Overall Crime	56	41
Violent Crime	62	32
Property Crime	65	44
Robbery	59	33
Auto Theft	61	41
Theft From Auto	66	41

Table 11: Number of viewsheds with negative DLQ values and resulting catchment areas.

Table 12 and Table 13 show the results of model C for the aggregate crime categories and disaggregate crime categories, respectively. Much fewer variables are statistically significant in model C compared to the viewshed models. In respect to the aggregate crime categories, take out eateries (-0.19) was significant for overall crime. This suggests the presence of take-out eateries to be related to overall crime decreases in the catchment area, a diffusion of benefits effect. For both violent crime and property crime, none of the independent variables were significant.

Variables	All Crime (N= 41)			Violent Crime (N= 32)			Property Crime (N= 44)		
	B	Std. Err.	t	*B*	Std. Err.	t	*B*	Std. Err.	t
Constant	1.00	0.72	1.40	0.29	1.74	0.17	0.30	1.37	0.22
Environmental Features									
Bars	-0.11	0.11	-0.93	-0.10	0.48	-0.22	0.07	0.21	0.34
Corner Stores	0.13	0.09	1.55	-0.48	0.29	-1.69	0.13	0.20	0.67
Gas Stations	0.00	0.08	0.05	-0.03	0.17	-0.20	-0.06	0.14	-0.42
Liquor Stores	-0.08	0.05	-1.52	-0.12	0.15	-0.80	-0.12	0.13	-0.89
Retail Stores	-0.05	0.04	-1.38	-0.44	0.20	-2.22	0.02	0.07	0.24
Schools	-0.15	0.08	-1.89	-0.44	0.24	-1.84	0.00	0.13	0.01
Sit Down Restaurants	0.20	0.13	1.57	0.41	0.41	1.01	-0.27	0.21	-1.26
Take Out Eateries	**-0.19***	0.09	-2.17	0.34	0.23	1.47	-0.13	0.15	-0.84
Transit Stops	-0.15	0.17	-0.89	0.42	0.47	0.89	0.02	0.36	0.05
Housing	-0.09	0.07	-1.20	0.28	0.37	0.75	-0.02	0.17	-0.12
Apartment Complexes	0.06	0.07	0.85	0.10	0.24	0.43	0.01	0.17	0.07
Parking Lots	0.10	0.08	1.33	-0.12	0.22	-0.57	-0.03	0.13	-0.24
Drug Markets	0.04	0.08	0.46	0.28	0.17	1.59	-0.15	0.15	-0.97
Major Roads	-0.07	0.44	-0.17	0.97	1.60	0.61	-0.39	0.74	-0.52
Line of Sight									
% Overall Obstruct	0.01	0.02	0.39	-0.05	0.06	-0.70	0.00	0.05	0.02
% Immovable Obstruct	(omitted due to collinarity)			(omitted due to collinarity)			(omitted due to collinarity)		
% Foliage Obstruct	0.00	0.02	0.04	-0.01	0.08	-0.17	0.02	0.04	0.44
Camera Design and Quantity									
Overlap	-0.53	0.32	-1.65	0.12	0.54	0.22	-0.28	0.65	-0.43
Dome	-0.34	0.34	-0.99	1.11	1.25	0.88	0.67	0.74	0.91
Enforcement Activity									
Footage Requests	0.02	0.03	0.49	-0.02	0.04	-0.43	0.11	0.12	0.95
Detections	0.01	0.04	0.35	-0.14	0.10	-1.37	0.16	0.11	1.45
Camera Enforcement	-0.03	0.12	-0.24	0.31	0.25	1.25	-0.40	0.32	-1.27
Unrelated Arrests	0.00	0.00	-0.60	0.00	0.01	-0.22	0.00	0.00	-0.71
Pre-Installation Crime Levels									
Percentile	-0.01	0.00	-1.68	-0.01	0.01	-0.94	0.00	0.01	-0.20
***p<.05; **p<.01** R-squared (Adjusted)	.56 (-.11)			.87 (.44)			.51 (-0.10)		

Table 12: Model C results for Overall Crime Violent Crime, and Property Crime.

Variables	Robbery (N= 33)			Auto Theft (N= 41)			Theft From Auto (N= 41)		
	B	Std. Err.	t	B	Std. Err.	t	B	Std. Err.	t
Constant	**-3.4***	1.06	-3.21	1.39	0.85	1.63	**4.01****	1.12	3.60
Environmental Features									
Bars	0.28	0.23	1.22	-0.23	0.13	-1.77	**-0.66***	0.19	-3.47
Corner Stores	-0.07	0.10	-0.66	0.14	0.08	1.79	0.11	0.14	0.79
Gas Stations	0.07	0.07	0.93	-0.13	0.09	-1.44	0.07	0.08	0.98
Liquor Stores	-0.21	0.13	-1.60	-0.09	0.05	-1.89	-0.14	0.13	-1.06
Retail Stores	**-0.50****	0.14	-3.64	**-0.10***	0.04	-2.28	0.00	0.06	-0.06
Schools	-0.08	0.20	-0.40	-0.08	0.07	-1.19	-0.14	0.13	-1.03
Sit Down Restaurants	0.03	0.23	0.14	0.04	0.09	0.41	**0.72****	0.20	3.56
Take Out Eateries	0.26	0.20	1.26	-0.17	0.08	-2.01	-0.07	0.16	-0.43
Transit Stops	0.24	0.30	0.79	0.22	0.18	1.21	-0.54	0.27	-2.00
Housing	-0.06	0.18	-0.35	-0.04	0.08	-0.50	**0.31***	0.14	2.12
Apartment Complexes	**0.28***	0.10	2.71	0.02	0.07	0.30	-0.10	0.15	-0.65
Parking Lots	-0.36	0.18	-2.02	0.12	0.09	1.34	0.15	0.13	1.13
Drug Markets	0.16	0.09	1.69	0.01	0.09	0.15	-0.13	0.12	-1.01
Major Roads	**2.95****	0.68	4.33	0.47	0.45	1.06	**-1.70***	0.81	-2.10
Line of Sight									
% Overall Obstruct	**-0.07****	0.02	-3.71	-0.05	0.03	-1.81	-0.03	0.04	-0.83
% Immovable Obstruct	**0.13***	0.05	2.77	(omitted due to collinarity)			(omitted due to collinarity)		
% Foliage Obstruct	0.00	0.00	2.32	0.03	0.02	1.40	0.02	0.03	0.70
Camera Design and Quantity									
Overlap	-0.56	0.29	-1.89	0.65	0.44	1.46	**-0.94***	0.33	-2.87
Dome	1.48	0.73	2.01	**-1.06***	0.51	-2.08	0.08	0.64	0.12
Enforcement Activity									
Footage Requests	-0.09	0.05	-1.61	-0.21	0.10	-2.07	**0.13***	0.05	2.67
Detections	-0.03	0.06	-0.45	0.01	0.02	0.84	0.07	0.06	1.14
Camera Enforcement	0.01	0.19	0.05	-0.03	0.05	-0.49	-0.06	0.16	-0.38
Unrelated Arrests	0.01	0.00	1.64	0.00	0.00	1.69	0.00	0.00	0.83
Pre-Installation Crime Levels									
Percentile	-0.01	0.01	-0.76	**-0.01***	0.00	-3.47	0.00	0.01	-0.68
***p<.05; **p<.01**									
R-squared (Adjusted)	.96 (.78)			.78 (.44)			.78 (.44)		

Table 13: Model C results for Robbery, Auto Theft, and Theft From Auto.

More variables achieved statistical significance in respect to the disaggregate crime categories. For robbery, retail stores exhibited a negative β -0.50 while apartment complexes (0.28) and major roads (2.95) were positive. For auto theft, retail stores were associated with lower auto theft levels (-0.10). Three environmental features were statistically significant in the theft from auto model. Sit down restaurants (0.72) and housing (0.31) were associated with crime increases (displacement) while major roads (-1.70) were associated with decreases (diffusion of benefits).

Robbery was the only crime category impacted by the line of sight variables. The overall obstruction variable was negative (-0.07). However, the immoveable obstruction variable had a positive coefficient (0.13). This suggests that cameras with higher levels of immovable obstructions were more likely to have increased robbery levels in their catchment areas, despite the fact that overall obstructions variable was associated with decreased crime levels.

The camera design and quantity variables were statistically significant for auto theft and theft from auto. Dome cameras were associated with decreases in auto theft levels (-1.06) and the “overlap” variable was associated with decreases in theft from auto (-0.94). Footage requests were significant for theft from auto (0.13), the only case where an enforcement variable was significant in model C. Auto theft was the only crime category for which the percentile variable (-0.01) was statistically significant.

Discussion of Results

The most consistent finding in the micro-level analysis was that the percentile variable was negatively correlated with changes in crime levels. Different interpretations can be drawn from this observation. For many, the significance of the percentile variable gives evidence of a regression to the mean effect; “individuals with high pretest scores will tend to move down on the posttest, while individuals with low pretest scores will tend to move up" (Allison, 1990: p. 95). However, an alternate explanation may be that a certain amount of pre-intervention crime may be necessary in order for CCTV to reasonably be expected to produce a crime reduction. While CCTV is typically seen as a crime reduction tool, reducing *fear* of crime may be the primary goal behind camera deployment in certain instances (Cordner, 2010: p. 51). In such cases, cameras may be placed in areas where crime levels are low but police want to ensure that visitors to the area believe they are secure. In Newark, several CCTV cameras were installed in conjunction with the opening of the Prudential Center sports arena. A number of cameras were placed in the immediate surrounding area of the arena as well as on McCarter Highway, a main thoroughfare adjacent to the arena. Since these areas experienced very low levels of crime, a crime reduction was unlikely (if not impossible) following the installation of cameras. The recent work of Shah and Braithwaite (2012) found a similar effect in Chicago, with cameras in high-crime areas having a significant effect on crime with cameras in other areas producing little benefit. This suggests the existence of a "deterrence threshold" with place-based interventions, where a certain amount of pre-intervention crime is necessary for a significant reduction to be reasonably expected. The recent Philadelphia Foot-Patrol experiment (Ratcliffe, Taniguchi, Groff, & Wood, 2011) further illustrates this point. A total of 60 hot spots were chosen as target areas. When all target areas were considered, the foot patrols were shown to not have produced a significant crime reduction. However, when observations were restricted to areas with crime counts in the 60^{th} percentile and higher, the researchers observed a statistically significant crime reduction.

Less consistency was observed outside of the percentile variable. The statistically significant variables varied by crime type, suggesting the ideal context for camera location to vary across crime types. This supports the notion that CCTV should be implemented within a problem-oriented policing framework (Mazerolle et al., 2002) that accounts for pertinent factors relative to the specific crime type at hand. This was especially the case in respect to the environmental features. Each crime category had at least one statistically significant environmental feature. Each of the significant environments exhibited positive β values indicative of crime increases. Thus, the environmental features tell more about where to *not* install cameras rather than were *to* install them. However, which, and how many, environmental features achieved significance varied by crime type.

The relationship between the environmental features and specific crime categories can be explained by factors highlighted in the empirical literature. Drug markets were associated with higher levels of overall crime, which is supported by previous research finding open-air drug markets to generate a number of ancillary public safety concerns (Harocopos & Hough, 2005). Violent crime, as well as the disaggregate category of robbery, increased with the presence of liquor stores (Bernasco & Block, 2011). For property crime, the concentration of retail stores, schools, and major roads were associated with crime level increases. Schools have previously been associated with increased crime levels (Roncek, 2000; Roncek & Faggiani, 1985), while research on the criminogenic influence of major roads often utilizes property crime to illustrate their point (Beavon et al., 1994; Johnson & Bowers, 2010). Major roads were also significant in the auto theft model, along with schools and drug markets.

The environmental features were also influential within the catchment areas. Again, the significant environmental variables differed by crime type. Catchment areas with high levels of major roads and apartment complexes experienced increased levels of robbery. Conversely, catchment areas with retail stores experienced lower levels of robbery, as well as auto theft. Theft from auto increased in catchment areas with high levels of sit down restaurants and at-risk housing complexes while decreasing in catchment areas with high levels of bars and major roads. The displacement findings tend to support previous research finding the presence of nearby crime attractors and generators to heighten the likelihood of displacement (Brantingham & Brantingham, 2003). Robbery, for example, likely increased in areas with apartment complexes and major roads because there were likely appropriate targets in these areas. Apartment complexes offer a high number of people in a dense location (Stucky & Ottensmann, 2009) while major roads are typically used as travel paths between nodes by many people (Brantingham & Brantingham, 1993a,b). Conversely, retail stores do not offer street-robbers adequate opportunities for robbery, which likely explain the diffusion of benefits in areas with high level of retail stores. Similarly, theft from auto increased in catchment areas with high levels of sit down restaurants and at-risk housing; areas where a large number of cars are likely parked for extended periods of time. Bars, on the other hand, led to a diffusion of benefits perhaps because the same volume of parked cars is not present at these locations. The influence of major roads on theft from auto was counterintuitive, however. Despite being significantly associated with theft from auto increases within viewsheds, major roads were associated with diffusion of benefits in displacement zones.

These findings raise an important question regarding CCTV within certain environmental contexts. Particularly, why does CCTV have a criminogenic effect when deployed nearby certain environmental features? This finding is certainly counterintuitive, and somewhat puzzling. While one would expect that crime would not be impacted by CCTV in certain environments, the fact that CCTV may have led to crime *increases* within these environments was unexpected. Previous research has argued that CCTV can have unintended consequences, which may directly or indirectly lead to crime increases. The most common observation is that CCTV operators may observe crime that may have otherwise gone unobserved (an unreported), which can cause increase in reported crime whether or not actual crime levels changed (Winge & Knutsson, 2003). However, since Newark's CCTV detections are mostly comprised of disorderly behavior and narcotics transactions, with part 1 crime detections being a rarity (see Table 2 in Chapter 2), this explanation does not seem to apply in this case. Other researchers have noted that CCTV can increase crime through more indirect means. For example, Gill and Turbin (1998) argued that CCTV could decrease the vigilance of officials (e.g. police) and third parties, which may produce additional opportunities for crime. They also argued that CCTV may reduce natural surveillance as fewer people use the area because they dislike the idea of being watched. It is unclear which of these mechanisms, if any, contributed to crime increases in response to CCTV cameras in Newark. The necessary data to explore these hypotheses is, unfortunately, unavailable to me. However, this is certainly an important aspect of CCTV in Newark worthy of future research.

Results pertaining to the line of sight variables were somewhat surprising. Obstructions were related to crime increases in two cases. Immovable obstructions were related to increases in auto theft within viewsheds and increases in robbery within catchment areas. Obstructions caused by foliage, however, where associated with crime decreases in two instances: violent crime and robbery in viewsheds. There may be two possible explanations for this observation. Since foliage obviously is not a permanent fixture in the northeastern United States, it may not pose a year-round impediment to the cameras. While foliage blocked portions of certain viewsheds during spring and summer months, when the viewshed creation occurred, they may be less of a problem during colder months. Secondly, places obstructed by foliage may be harder for potential offenders to identify than areas obstructed by immovable objects. A brick wall directly to the right of a camera, for example, obviously prevents the camera (and camera operator) from observing anything behind the brick wall. A bush or leaves from a tree, on the other hand, may not be as definitive. While the leaves may appear adjacent to the camera, it may be more difficult for those on the street to gauge whether the foliage is blocking the view of the camera in its entirety. Also, since the amount of foliage fluctuates with weather, it may not be obvious exactly when foliage is significantly obstructing the view of a camera.

The number of cameras that comprise a viewsheds (the "overlap" variable) was significant in two cases. The first was auto theft in viewshed areas (-2.58). This findings echoes the discussion of Caplan, Kennedy, and Petrossian (2011), who argued that CCTV prevented auto theft because offenders may have realized that a stolen car could be readily recognized across a series of different camera viewsheds. The network of cameras "would create a longer period of time (or risk) in which the offender could be noticed and apprehended while getting away from the scene of his/her crime" (p. 270). This analysis supports this notion on a micro-level by suggesting a high density of cameras may enact a similar thought process in potential auto offenders. In addition, dome cameras were associated with a diffusion of benefits effect in respect to auto theft. A noted benefit of dome cameras is their tinted hemisphere glass that prevents individuals on the street from knowing if they are currently being monitored (Ratcliffe, 2006a). Dome cameras may have led auto theft offenders to consider the cameras as a threat outside of the immediate area, perhaps due to not knowing precisely where the camera's influence ceased to exist. Indeed, previous research has suggested that diffusion of benefits is generated due to offenders believing, due to the limited information at their disposal, that an intervention is much more far reaching than it actually is (Clarke & Weisburd, 1994; Johnson & Payne, 1986).

Overlapping cameras were also associated with a diffusion of benefits in respect to theft from auto. While theft from auto is not likely a crime that requires as much time as auto theft, a high concentration of cameras may have had a similar effect on potential theft from auto offenders. In respect to theft from auto, Caplan, Kennedy, and Petrossian (2011) argued that CCTV may not have an effect because "small items such as GPS units, money, or cell phones are relatively easy to hide after theft from autos and, thus, make the offender less conspicuous very shortly after committing the crime. If the offender were to walk along the street through another camera's viewshed, the stolen items could not be seen in a bag or pocket and would not trigger suspicion by police" (p. 270). However, since theft from auto offenders are assumed to be on foot, they may be particularly likely to notice the high concentration of cameras. Similar to auto theft offenders, theft from auto offenders may believe that these cameras also pose a risk in the catchment area.

Findings relative to camera enforcement support the recent work of the Urban Institute (La Vigne et al., 2011a; La Vigne & Lowry, 2011), which suggests CCTV effect depends largely on the level to which they are integrated into the police function. In particular, these works found the proactive motoring of cameras and effective police response to observed infractions to be the keys to successful CCTV systems. In this respect, "camera enforcement" was associated with decreased levels of overall crime, violent crime, property crime, and robbery. The implications of this finding are obvious; police agencies should work to maximize the amount of crime incidents that are detected and subsequently closed by a police action. Unfortunately, the typical manner by which CCTV is deployed by police does not lend itself to high levels of crime detection nor enforcement. A number of barriers are present in the surveillance function, which can prevent operators from proactively monitoring cameras and police officers from effectively addressing incidents viewed on CCTV. A discussion of how police can possibly address these barriers is included in the "Policy Implications and Conclusion" chapter.

Chapter Summary

I formulated three distinct hypotheses relative to analysis A. The first, camera effectiveness will vary across viewsheds, was supported by the findings. For each crime category, the standard deviation of the DLQ was much greater than the mean, suggesting that effectiveness varied greatly from case-to-case. In addition, across all crime categories, the number of viewsheds with negative DLQ values was nearly equal to the number of viewsheds with positive DLQ values. This suggests that the number of effective camera sites was similar to the number of ineffective camera sites. The second hypothesis was that the number of enforcement actions generated by the camera would be related to crime decreases. This hypothesis was also supported by the findings. Camera enforcement was statistically significant and negative for each of the aggregate crime categories: overall crime, violent crime, and property crime. The disaggregate category of robbery was also negatively correlated with camera enforcement. While camera enforcement was not statistically significant in the auto theft and theft from auto models, the fact that property crime (which was comprised of auto theft and theft from auto) was related to camera enforcement suggests that auto theft and theft from auto were at least partially influenced by camera enforcement.

CHAPTER FOUR: ANALYSIS B. THE SYSTEM-WIDE EFFECT OF THE CCTV CAMERAS

Introduction

The reach of public CCTV cameras is limited in scope. Line-of-sight extends a finite distance and is commonly obstructed by street-level objects, such as poles, buildings, and tree leaves. Units of analysis do not typically account for this reality, with aggregate geographies (i.e. "neighborhoods" or "police districts") or circular buffers around camera sites typically being utilized. Such issues also exist in respect to control areas, which have typically been operationalized in a similar manner.

Analysis B contributes to the CCTV literature by incorporating micro-level units of analysis and control areas that are more appropriate for place-based evaluations than larger geographies (Oberwittler & Wikström, 2009; Weisburd, Morris, & Ready, 2008). The viewsheds incorporated in Analysis A are again utilized as units of analysis. In addition, "pseudo" viewsheds comparable in size and environmental composition as the units of analysis were created and utilized as control areas. A total of 961 pseudo viewsheds were created, with final control areas being selected through a propensity score matching technique (Rosenbaum & Rubin, 1983, 1985). Through the use of near-equivalent control areas similar to treatment areas in respect to size, crime levels, and pertinent environmental features, the research design achieved a level four (out of five) on the Maryland Scientific Methods Scale (Farrington et al., 2002).

Methodology

Prospective Control Areas

The research design had the particular goal of creating control areas that were nearly equivalent to the treatment areas on three criteria: size, pre-intervention crime levels, and environmental features shown to be related to camera effectiveness (as identified in Analysis A). In an effort to create control areas similar in size to the treatment areas, I decided to approximate "viewsheds" in non-CCTV areas of Newark. Since all system cameras were placed at street intersections, the first step was the creation of a GIS file of all intersections throughout Newark. A series of GIS functions contained in "ArcToolbox" were run to generate points at every location where two or more streets intersected. This resulted in a point layer denoting all intersections in the Newark, NJ study area (N=2,141)[19]. All intersections falling with an existing camera viewshed or catchment area were excluded,[20] leaving a total of 961 intersections to serve as "pseudo" camera locations in the control viewshed creation (see Figure 20).

The creation of prospective control viewsheds followed the method of viewshed creation incorporated by Caplan, Kennedy, and Petrossian (2011). Caplan, Kennedy, and Petrossian first created 582 foot buffer zones, approximately twice the average block length in Newark, around each camera location. Using imagery from Google maps and ArcGIS editing tools, they drew viewsheds within each buffer zone, excluding areas blocked by permanent fixtures, such as buildings.

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[19] The intersections file was cleaned by removing "false positives." The GIS function placed points where street segments intersected with one another. However, in certain cases, such as a highway overpass that travels over a several streets, the segments may not actually intersect in the real world. Such cases were identified and deleted from the file.
[20] Including the viewsheds and respective catchment areas of cameras that were excluded from the study.

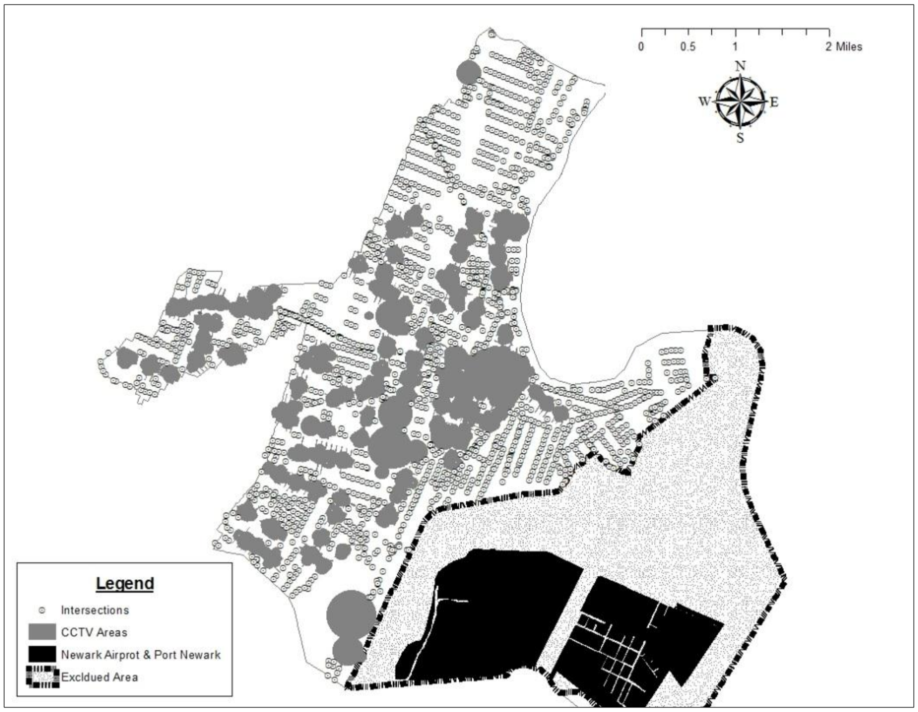


Figure 20: Intersections in Non-CCTV Areas of Newark

The current study utilized 423 foot buffers around intersections, to reflect the average maximum visible extent of the 128 cameras included in the analysis. Viewsheds were then drawn around each intersection, excluding areas of obstruction as identified through the aerial imagery (see Figure 21). This process approximated the line of sight of a hypothetical camera installed at the intersection. After viewsheds were constructed, each of the 14 environmental features incorporated in the micro–level analysis were measured through the same process outlined in chapter three. Location quotients controlling for the overall size of the control viewsheds, control buffers, and city-wide geography were calculated for each feature. This process was repeated for each of the 961 intersections outside of CCTV areas.

After measuring the prevalence of the environmental features, the necessary crime data were measured in each prospective control area. One year "pre" and "post" installation crime totals were measured for each of the six crime categories included in the analysis: overall crime, violent crime, property crime, robbery, auto theft, and theft from auto. In order to control for the different sizes of the prospective control areas, crime levels were measured as Location Quotients via the same formula utilized in chapter three:

$$LQ=(x_i/t_i)/(X/T)$$

where x_i represents the number of crimes in viewshed i; t_i represents the total area of viewshed i; and X and T represent the city-wide numbers of crimes of type X and area, respectively (Caplan, Kennedy, & Petrossian, 2011). Since cameras were installed in four different phases (3/15/2008, 7/31/2008, 12/10/2009, and 4/23/2010) crime totals were measured for the one-year the "pre" and "post" periods of each installation phase.

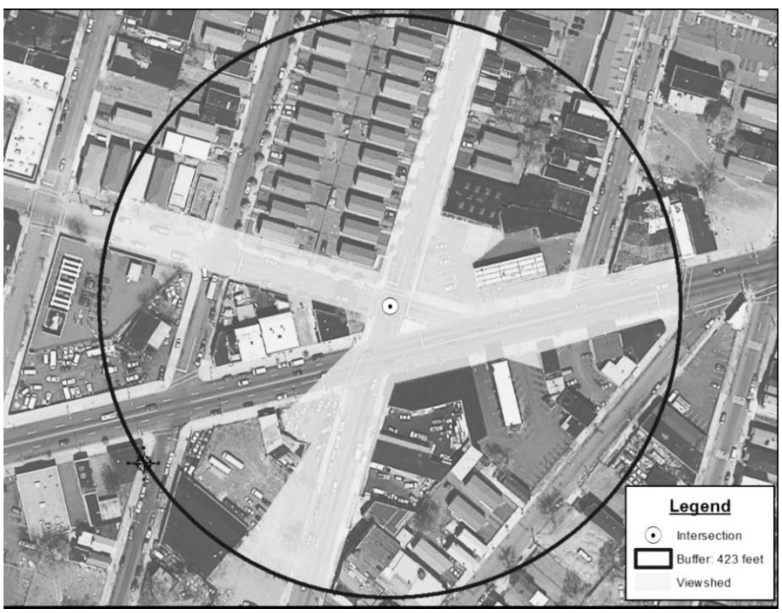


Figure 21: Sample control viewshed and 423 foot buffer.

Resulting from this process, the 961 prospective control areas were assigned the following attributes: a measure of the point environmental features falling within their buffer (count and location quotient), a measure of the polygonal environmental features falling within their buffer (total square footage and location quotient), a measure of the linear environmental features falling within their buffer (total length and location quotient), and "pre/post" measures of the six crime categories for each of the four installation phases (location quotients and difference in location quotients [DLQ]).

Matching Treatment Viewsheds with Control Viewsheds

To ensure that treatment viewsheds were compared with equivalent controls, the final control areas were selected through a propensity matching process. Developed by Rosenbaum and Rubin (1983, 1985), propensity score matching (PSM) provides a method to overcome selection bias commonly found in non-experimental studies. Randomization eliminates selection bias, a key reason why randomized experimental designs are widely considered the "gold standard" of research methodology (Farrington et al., 2002). However, randomly assigning cases to receive treatment is not often feasible in social science research. In the absence of randomization, matching techniques are often utilized, whereby researchers attempt to identify for each treatment case at least one comparison that shares similarities on characteristics relevant to the treatment in question (Apel & Sweeten, 2010: p. 543).

With traditional matching techniques, researchers are challenged by the difficulty in finding an appropriate match from the control group for a given treatment case when multiple matching variables are present (Guo & Fraser, 2010: p. 132). PSM allows for comparison across a number of characteristics by collapsing various covariate values into a single "propensity score." The matching of treatments and controls based upon the propensity score ensures the two groups are balanced on the relevant covariates, thus approximating the conditions of a controlled experiment. Propensity score matching has a rich history in Criminology (see Apel & Sweeten, 2010 for numerous examples), including a recent place-based policing evaluation (Braga, Hureau, & Papachristos, 2012).

Propensity score creation and matching were conducted through the PSMATCH2 program in the Stata 12.0 software package (Leuven & Sianesti, 2003). While a number of matching techniques are available with PSM, I decided to utilize nearest neighbor matching, in which each treatment is matched to the control case whose propensity score is nearest. Matching was done with the “without replacement” option. Once a control case was matched with a treated case it was removed from the candidate for matching, meaning it could not serve as the comparison for multiple treatment cases (Apel & Sweeten, 2010: p. 551).

The particular covariates utilized in the PSM model differed by crime type. While some scholars have advocated a “kitchen sink” approach that utilizes all available variables in a data set, others have warned that using more variables can lead to poor matches by inflating the range of propensity scores (Smith & Todd, 2005). It is therefore considered good practice to only include carefully chosen covariates that are truly related to the outcome in question (Guo & Fraser, 2010: p. 138-139). Thus, different models were configured for each crime category in order to select control areas according to the characteristics shown to be the most influential on the crime in question. Models for each crime category include 2 sets of covariates: 1) the pre-intervention crime Location Quotient and 2) Location Quotients for all of the environmental features found to be statistically significant in Analysis A. Since cameras were installed in four separate phases, PSM models were conducted four separate times. The model for Overall Crime, for example, was first conducted for the 44 "phase 1" viewsheds, then the 50 "phase 2" viewsheds, etc. This process was necessary to account for the fact that the "pre" and "post" periods were different for each set of viewsheds. Since some installation phases had relatively small numbers of viewsheds (see Table 14), the bootstrapping method was incorporated in the PSM model in order to overcome potential sampling error that may result from small samples (Lechner, 2002; Ozer & Engel, 2012).[21]

INSTALLATION PHASE	CAMERAS	VIEWSHEDS
1	44	44
2	51	50
3	23	13
4	10	10

Table 14: Total cameras and viewsheds per installation phase.

Statistical Approach

The overall program effect is reported as an odds ratio. As described by Welsh and Farrington (2009), the odds ratio (OR) indicates the "proportional change in crime in the control area compared with the experimental area" (p. 135). The OR is calculated via the following formula:

$$\mathrm{OR}=(a*d)/(b*c)$$

with *a, b, c*, and *d* designated as follows:[22]

[21] Ozer and Engel (2012) illustrated the importance of utilizing the bootstrapping method with small samples. Ozer and Engel conducted an analysis of the Gang Resistance Education and Training (GREAT) survey data utilized by Gibson, Miller, Jennings, Swatt, and Grover (2009). Gibson et al. utilized propensity score matching in their analysis and found no significant differences in reported instances of violent victimization between gang members and non-gang members, which challenged conventional wisdom. However, when re-analyzing the data using bootstrapping (as well as other methodological improvements) Ozer and Engel reported that gang members did in fact report higher levels of violent victimization than non-gang members.

[22] Adapted from Welsh and Farrington (2009: p. 135).

	Pre-Intervention Crime Count	During-Intervention Crime Count
Target Area	*a*	*b*
Control Area	*c*	*d*

The obtained value represents the strength and direction of the program impact. An OR greater than 1 indicates a desirable effect on crime in the target area relative to the control while an OR below 1 indicates an undesirable effect. An OR of 1.3, for example, shows that crime increased 30% in the control area relative to the target area.[23] The statistical significance of each OR was measured through its variance (VOR) and associated 95% confidence interval, which were calculated using the Effect Size Calculator developed by David B. Wilson, available on the Campbell Collaboration website.[24]

The Odds Ratio holds particular appeal for the study at hand. For one, OR values are intuitive and easily communicated to a wide variety of audiences. This is an important consideration given the numerous calls to more closely integrate academic research and practice (Braga, 2010; Clear, 2010; Weisburd & Neyround, 2011). Secondly, recent studies have incorporated the odds ratio in their statistical design, providing a precedent for this method. For example, Piza and O'Hara (2012) and Ratcliffe et al. (2011) reported the effect of foot-patrol interventions in Newark and Philadelphia, respectively, as odds ratios. More related to the research at hand, the CCTV meta-analyses of Gill and Spriggs

[23] The inverse of the OR displays the crime difference within the target area. An OR of 1.3 implies that target area crime reduced 23% relative to the control since the inverted value of the OR (1/1.3) is 0.77 (Welsh & Farrington, 2009: p. 135).

[24] http://www.campbellcollaboration.org/resources/effect_size_input.php

(2005), Farrington, Gill, Waples, and Argomaniz (2007), and Welsh and Farrington (2002, 2007, 2009) reported system effects as odds ratios, showing the approach to be standard in the study of video surveillance.

Each crime category found to have experienced a statistically significant crime reduction was included in a separate test of spatial displacement. A Weighted Displacement Quotient (WDQ)[25] was calculated for each such observation using the Weighted Displacement Quotient Calculator developed by Ratcliffe and Breen (2008). The WDQ is a statistic that compares changes in the target area to those in the control and buffer zones (Bowers & Johnson, 2003) with negative values showing evidence of displacement and positive values implying a diffusion of crime control benefits.

Findings

Propensity Score Matching

The system wide analysis began with the selection of control areas from the 961 pseudo viewsheds. A propensity score matching technique was incorporated in the selection of control areas to ensure they were near-equivalent to the target areas. Covariates for the propensity score model were selected based on the findings of model B in Analysis A. All of the propensity score models include a location quotient of the pre-installation crime level and location quotients for all environmental features[26] identified as statistically significant in model B. Covariates differed by crime type. The number of

[25] The formula is as follows: WDQ=([Da/Ca]-[Db/Cb])/([Ra/Ca]-[Rb/Cb]) where D, R, and C represent the displacement, response, and control areas, respectively, and "b" and "a" indicating the period before and after the intervention, respectively.
[26] Drug markets were operationalized through a dichotomous variable denoting the presence (1) or absence (0) of a drug market rather than a location quotient. This was due to the fact that the propensity score routine was unable to identify sensible matches when drug markets were operationalized via a location quotient.

covariates ranged from two (overall crime, violent crime, robbery) to four (property crime). The particular covariates for each model are specified below.

- Overall Crime: pre-installation crime level (LQ) and drug markets.
- Violent Crime: pre-installation crime level (LQ) and liquor stores.
- Property Crime: pre-installation crime level (LQ)), major roads, retail stores, and schools.
- Robbery: pre-installation crime level (LQ) and liquor stores.
- Auto Theft: pre-installation crime level (LQ), drug markets, and schools.
- Theft From Auto: pre-installation crime level (LQ), corner stores, and major roads.

Tables 15 through 20 show the results of independent samples t-tests comparing the treatment and control groups on the relative covariates. For each crime type, p values are well above the 95% confidence interval, showing that the propensity score model achieved in creating balance between the treatment and control group.

Overall Crime	Obs	Mean	S.E.	S.D.	95% CI	
CRIME LQ						
Control	117	4.07864	0.3025	3.2721	3.479493	4.677789
Treatment	117	3.99539	0.26813	2.9003	3.464322	4.526455
t (p<)	0.20 (0.84)					
CRIME INCIDENTS						
Control	117	7.53846	0.55144	5.9648	6.446262	8.630661
Treatment	117	8.44444	0.62331	6.7421	7.209905	9.678984
t (p<)	-1.09 (0.28)					
Drug Markets YN						
Control	117	0.58974	0.04567	0.494	0.4992885	0.6801986
Treatment	117	0.5812	0.04581	0.4955	0.4904688	0.6719243
t (p<)	0.13 (0.90)					

Table 15: Treatment and control area covariate balance after propensity score matching, overall crime.

VIOLENT CRIME	Obs	Mean	S.E.	S.D.	95% CI	
CRIME LQ						
Control	117	6.03464	0.5924	6.4078	4.861312	7.207958
Treatment	117	6.68009	0.58776	6.3576	5.515949	7.844223
t (p<)	-0.77 (0.44)					
CRIME INCIDENTS						
Control	117	2.05983	0.18778	2.0312	1.687901	2.431757
Treatment	117	2.50427	0.23021	2.4901	2.048321	2.960226
t (p<)	-1.50 (0.14)					
p	0.136					
LIQUOR STORES LQ						
Control	117	3.60643	0.5208	5.6333	2.574921	4.63794
Treatment	117	2.86271	0.49994	5.4077	1.872519	3.852899
t (p<)	1.03 (0.30)					

Table 16: Treatment and control area covariate balance after propensity score matching, violent crime.

PROPERTY CRIME	Obs	Mean	S.E.	S.D.	95% CI	
CRIME LQ						
Control	117	4.15947	0.39458	4.268	3.377966	4.940977
Treatment	117	3.39698	0.29467	3.1873	2.813354	3.980601
t (p<)	1.55 (0.12)					
CRIME INCIDENTS						
Control	117	5.90598	0.45502	4.9218	5.004762	6.807203
Treatment	117	5.94017	0.57136	6.1802	4.808524	7.071818
t (p<)	-0.05 (0.96)					
MAJOR ROADS LQ						
Control	117	1.51934	0.06188	0.6693	1.396786	1.641895
Treatment	117	1.49757	0.05717	0.6183	1.384345	1.610791
t (p<)	0.26 (0.80)					
RETAIL LQ						
Control	117	2.61702	0.78355	8.4754	1.065104	4.168943
Treatment	117	4.2655	1.07281	11.604	2.140673	6.390326
t (p<)	-1.24 (0.22)					
SCHOOLS LQ						
Control	117	1.83865	0.28695	3.1038	1.270312	2.406985
Treatment	117	1.6838	0.30834	3.3352	1.073089	2.294516
t (p<)	0.37 (0.71)					

Table 17: Treatment and control area covariate balance after propensity score matching, property crime.

ROBBERY	Obs	Mean	S.E.	S.D.	95% CI	
CRIME LQ						
Control	117	6.45843	0.56052	6.0629	5.34825	7.568604
Treatment	117	6.8848	0.63689	6.8891	5.623354	8.146253
t (p<)	-0.50 (0.62)					
CRIME INCIDENTS						
Control	117	1.82906	0.16209	1.7533	1.508019	2.1501
Treatment	117	2.08547	0.2122	2.2953	1.665176	2.505764
t (p<)	-0.96 (0.34)					
LIQUOR STORES LQ						
Control	117	3.27895	0.51433	5.5634	2.260243	4.297652
Treatment	117	2.86271	0.49994	5.4077	1.872519	3.852899
t (p<)	0.58 (0.56)					

Table 18: Treatment and control area covariate balance after propensity score matching, robbery.

AUTO THEFT	Obs	Mean	S.E.	S.D.	95% CI	
CRIME LQ						
Control	117	3.1852	0.27475	2.9719	2.641018	3.729375
Treatment	117	3.23263	0.29242	3.163	2.653466	3.811798
t (p<)	-0.12 (0.91)					
CRIME INCIDENTS						
Control	117	3.00855	0.23429	2.5342	2.544506	3.472588
Treatment	117	3.24786	0.27865	3.0141	2.695961	3.799765
t (p<)	-0.66 (0.51)					
DRUG MARKETS YN						
Control	117	0.61538	0.04517	0.4886	0.5259182	0.704851
Treatment	117	0.5812	0.04581	0.4955	0.4904688	0.6719243
t (p<)	0.53 (0.60)					
SCHOOLS LQ						
Control	117	1.70247	0.3217	3.4797	1.065312	2.339635
Treatment	117	1.6838	0.30834	3.3352	1.073089	2.294516
t (p<)	0.04 (0.97)					

Table 19: Treatment and control area covariate balance after propensity score matching, auto theft.

THEFT FROM AUTO	Obs	Mean	S.E.	S.D.	95% CI	
CRIME LQ						
Control	117	3.94092	0.51193	5.5374	2.926982	4.954864
Treatment	117	3.65556	0.42377	4.5838	2.816223	4.494889
t (p<)	0.43 (0.67)					
CRIME INCIDENTS						
Control	117	2.61539	0.29382	3.1782	2.033432	3.197337
Treatment	117	2.69231	0.37366	4.0417	1.952232	3.432384
t (p<)	-0.16 (0.87)					
CORNER STORES LQ						
Control	117	2.16193	0.30176	3.264	1.564264	2.7596
Treatment	117	2.41475	0.31421	3.3987	1.792426	3.037076
t (p<)	-0.58 (0.56)					
MAJOR ROADS LQ						
Control	117	1.4968	0.05805	0.6279	1.381822	1.611771
Treatment	117	1.49757	0.05717	0.6183	1.384345	1.610791
t (p<)	-0.01 (0.99)					

Table 20: Treatment and control area covariate balance after propensity score matching, theft from auto.

Effect on Crime in Viewsheds

Table 21 shows the result of the statistical analyses. The table contains the "pre" and "post" crime totals for the target and control areas, the obtained odds ratio (OR), OR variance as well as the 95% confidence interval. As displayed in Table 21, four of the six crime categories experienced a reduction of incidents in the target area from the pre to the post period: overall crime, property crime, auto theft, and theft from auto. However, only auto theft's OR of 1.42 was statistically significant, showing that crime reduced in the target area 30% relative to the control areas. Surprisingly, odds ratios for violent crime and theft from auto were statistically significant and below 1, suggesting that crime increased in the target area over 29% compared to the control area.

CRIME TYPE	TARGET PRE	TARGE T POST	CONTROL PRE	CONTROL POST	ODDS RATIO	OR Log.	VARIANCE of OR Logged	95% C.I.	
Overall Crime	988	903	882	796	0.99	-0.01	0.00	0.87	1.13
Violent Crime	293	342	241	217	0.77*	-0.26	0.02	0.61	0.98
Property Crime	695	561	701	569	1.01	0.01	0.01	0.86	1.18
Robbery	244	294	214	203	0.79	-0.24	0.02	0.61	1.02
Auto Theft	380	325	352	427	1.42*	0.35	0.01	1.16	1.74
Theft From Auto	315	236	306	177	0.77*	-0.26	0.02	0.60	0.99
*p<0.05									

Table 21: Odd Ratios for all viewsheds

Considering the findings of Analysis A, I calculated an additional set of OR values, excluding all viewsheds that experienced zero incidents during the pre-intervention period. As previously discussed, cameras installed in very low crime areas have limited crime reduction capacity. Indeed, it is impossible for a camera installed in an area with no crime during the pre-period to produce a crime reduction: crime can only remain stable or increase in these areas.

Table 22 displays the odds ratios excluding all viewsheds that did not experience at least one incident in the one-year period prior to camera installation. Auto theft was once again the only crime category to achieve a statistically significant reduction. Auto theft's OR of 1.45 suggests a reduction of approximately 31% in the target area compared to the control area. ORs for violent crime and theft from auto, while still below 1, were no longer statistically significant.

CRIME TYPE	TARGET PRE	TARGET POST	CONTROL PRE	CONTROL POST	ODDS RATIO	OR log.	VARIANCE OF OR logged	95% C.I.	
Overall Crime	988	899	882	795	0.99	-0.01	0.00	0.87	1.13
Violent Crime	293	304	235	200	0.82	-0.20	0.02	0.64	1.05
Property Crime	695	555	673	557	1.04	0.04	0.01	0.88	1.21
Robbery	244	252	211	188	0.86	-0.15	0.02	0.66	1.12
Auto Theft	380	304	352	408	1.45*	0.37	0.01	1.18	1.78
Theft From Auto	315	199	233	131	0.89	-0.12	0.02	0.67	1.18
*p<0.05									

Table 22: Odds Ratios excluding all no-crime viewsheds.

At this time, it is worth discussing the theft from auto findings. Theft from auto experienced the largest decrease of incidents within the target area. The theft from auto reduction even outpaced auto theft (79 incidents vs. 55 incidents: a difference of 44 incidents), the only crime to have archived a statistically significant reduction. The difference is even greater when considering the findings from Table 22; theft from auto reduced by 116 incidents while auto theft reduced by 76, a difference of 40 incidents. However, theft from auto also reduced at a great rate in the control area. While the target area experienced a reduction of 116 incidents from the pre to the post period the control area decreases by 129 incidents. While the control area reduction decreases to 102 incidents when the no-crime viewsheds are excluded, no other crime type experienced such a pronounced reduction in the control area as theft from auto.

Table 23 displays the results of ANOVA tests on the average crime reductions by crime category for the target and control areas. Across the 117 target areas, theft from auto reduced an average of 0.68 incidents, the third highest amount amongst the six crime categories. Across the control areas, on the other hand, theft from auto reduced an average of 1.10 incidents which was the second highest reduction amongst the six crime types. This begs an obvious question; exactly what led to the sharp reduction of theft from auto in the control area? This question will be further explored in this chapter's discussion section.

TARGET AREAS			
Crime	**Mean**	**Std. Dev.**	**Freq.**
Overall Crime	-0.73	5.65	117
Violent Crime	0.42	2.83	117
Property Crime	-1.15	4.99	117
Robbery	0.43	2.52	117
Auto Theft	-0.47	2.67	117
Theft From Auto	-0.68	3.60	117
Total	-0.36	3.93	702
Source	**SS**	**df**	**MS**
Between	244.40	5	48.88
Within	10589.69	696	15.22
Total	**10834.10**	**701**	**15.46**
F	3.21		
p	0.01		

CONTROL AREAS			
Crime	**Mean**	**Std. Dev.**	**Freq.**
Overall Crime	-0.74	4.88	117
Violent Crime	-0.21	2.28	117
Property Crime	-1.13	3.85	117
Robbery	-0.09	2.18	117
Auto Theft	0.64	2.63	117
Theft From Auto	-1.10	2.83	117
Total	-0.44	3.30	702
Source	**SS**	**df**	**MS**
Between	274.14	5	54.83
Within	7374.60	696	10.60
Total	**7648.74**	**701**	**10.91**
F	5.17		
p	0.00		

Table 23: ANOVA results for average crime reduction by crime type.

Displacement and Diffusion of Benefits

Since it was the only crime type to experience a statistically significant reduction, auto theft was the only crime type included in the test of displacement/diffusion of benefits. Table 24 shows the results of the weighted displacement quotient analysis. As displayed in the "catchment area" columns, auto theft decreased in the catchment area as well as the target area, suggesting a diffusion of crime control benefits. This is confirmed by the Weighted Displacement Quotient of 3.56, a value that suggests diffusion of

AUTO THEFT	**TARGET AREA**		**CONTROL AREA**		**CATCHMENT AREA**		**WDQ**
	Pre	**Post**	**Pre**	**Post**	**Pre**	**Post**	
All Viewsheds	380	325	352	427	1227	1004	3.56
Viewsheds with at least 1 auto theft in the "pre" period	380	304	352	408	1162	946	3.41

Table 24: Weighted displacement quotients (WDQ) for auto theft

benefits to the catchment area to have been even greater than the direct program effects experienced in the target area (Ratcliffe & Breen, 2008). When only viewsheds with at least 1 crime in the "pre" period are considered, the WDQ drops slightly to 3.41. However, the interpretation of the WDQ remains the same; the diffusion of benefits was even greater than the direct program effects. The WDQ, along with the odds ratio for the target area, obviously show the CCTV cameras to have effectively reduced incidents of auto theft.

Discussion of Results

Overall, the findings of the macro-level analysis concur with previous CCTV research. CCTV cameras have most effectively reduced incidents of vehicle crime (Welsh & Farrington, 2007, 2009). Influence on other crime types, namely violence, has been minimal. In this study, auto theft was the only one of the six crime categories to have experienced a statistically significant crime reduction. In addition, the cameras led to a very robust diffusion of benefits effect, with auto theft reductions in the displacement zone outpacing the reduction within actual CCTV viewsheds. In addition, although not statistically significant, theft from auto experienced a reduction of 25% within the target area. The reduction grows to almost 37% when observations are limited to viewsheds that experienced at least one theft from auto in the year preceding camera installation. The theft from auto reduction failed to reach statistical significance due to a sizable decrease also occurring within the control viewsheds.

This observation regarding theft from auto raises a number of important questions. Essentially, why did the control areas, which did not have public CCTV cameras, experience similar theft from auto reductions as areas where CCTV cameras were installed? Table 25 displays the control sites that experienced theft from auto reductions that were equal to or greater than two positive standard deviations from the mean. This table shows the drastic reduction; many control locations experienced a near 100% decline in theft from auto.

CONTROL SITE	MATCHED TREATMENT	PRE-INCIDENTS	POST-INCIDENTS	DIFF.	% CHANGE	LAND USAGE
C_197	55	18	6	-12	-66.67%	Shopping Center
C_1078	A66	9	0	-9	-100.00%	Warehouses/Garages
C_69	15	12	4	-8	-66.67%	Hotel
C_1058	108	7	1	-6	-85.71%	Residential Area (behind school)
C_368	169	6	0	-6	-100.00%	Government Building (DMV)
C_833	175	10	4	-6	-60.00%	School
C_389	303	7	1	-6	-85.71%	Residential Area (Apartment Complex)
C_1101	221	9	4	-5	-55.56%	Residential Area (Apartment Complex)
C_376	238	11	6	-5	-45.45%	School
C_342	263	6	1	-5	-83.33%	Commercial Corridor
C_363	199	5	0	-5	-100.00%	Warehouses/Garages

Table 25: Control sites with theft from auto changes equal to or more + 2 standard deviations from the mean.

The final column of Table 25 shows the primary land usage of the area (see Figure 22 and Figure 23 for street-level photographs of these locations, obtained from Google maps). The areas seem to share commonalities relative to their environment; most of the control sites are comprised of private entities, such as schools, government buildings, and privately owned businesses such as hotels or warehouses. Each of these locations is likely under some level of guardianship by entities other than the police. Even the three residential areas, control sites C_1058, C_389, and C_1101, are directly adjacent to a school or large apartment complex. Similar to the other locations, non-law enforcement entities likely play prominent roles in maintain these areas.

Such non-law enforcement guardians are typically referred to as “place mangers” in the literature. Place mangers likely have an invested interest in maintaining public safety within areas under their control. Research has consistently shown place mangers to have great influence in discouraging crime through providing guardianship over targets and motoring places under their control (Eck, 1994; Felson, 1995). Also, given the concise geography under their watch, place mangers may be readily able to efficiently guard against crime through employing specific private security measures (Clarke, 1997; Farrell, Tseloni, Mailley, & Tilley, 2011; Van Dijk, 2006). It may be that the presence of place mangers, security measures they enacted, or some combination of the two was as effective at preventing theft from auto as the presence of CCTV cameras.

The previous discussion was, of course, hypothetical. While the discussed control areas were of the type that typically employs place managers, it is impossible to know whether place mangers were the precise reason for the sharp decline in theft from auto at these locations. However, whatever led to the decline, it was not public CCTV cameras.

Control Site C_197: Shopping Center

Control Site C_1078: Warehouses/Garages

Control Site C_69: Hotel

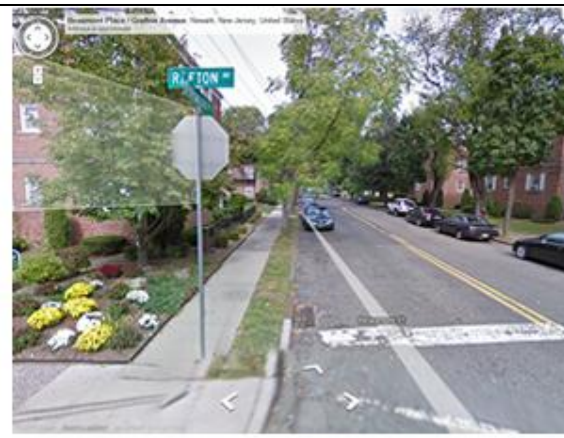
Control Site C_1058: Residential Area (behind School)

Control Site C_368: Govenrment Building (DMV)

Control Site C_833: School

Figure 22: Google map street view pictures of control areas that experienced large theft from auto reductions.

Control Site C_389: Residential Area (Apartment Complex)



Control Site C_1101: Residential Area (Apartment Complex)

Control Site C_376: School

Control Site C_342 Commercial Corridor

Control Site C_363: Warehouses/Garages

Figure 23: Google map street view pictures of control areas that experienced large theft from auto reductions (continued)

Given the price tag associated with CCTV, it may be prudent for officials to weigh whether the expense is worth the benefits. In Newark, for example, each camera site costs nearly $10,000 when accounting for equipment and paying vendors to perform the installation and necessary network configuration (personal communication, Peter Lutz, Management Information Systems Director, Newark Police Department). La Vigne et al. (2011b: p. 2-3) point out that start-up costs are only a small part of the CCTV expenses, with continuous funds needed to replace broken cameras, readjust misaligned antennae to maintain the wireless network communication, and staff the operation. In an example of the high recurring costs of CCTV, Ratcliffe and Groff (2011) reported that the city of Philadelphia paid $200,000 a month in maintenance costs for its system.

Is CCTV worth the costs? Evidence exists that cheaper alternatives may be as effective as CCTV. Welsh and Farrington (2004) noted that natural surveillance, in the form of improved street lighting, produced similar crime reduction gains as CCTV. Agencies can also choose to fund on-the-ground projects with an established record of success, such as hot spots policing (Braga, 2005, 2008), problem oriented policing (Weisburd, Telep, Hinkle, and Eck, 2010), or focused deterrence strategies (Braga & Weisburd, 2011), in lieu of investing in CCTV.

However, such options are irrelevant to those already heavily invested in CCTV. For these agencies, the more appropriate question seems to be “how can existing CCTV systems be made more effective?” Taking into account the findings of Analysis A, the answer may be to maximize the amount of proactive detections and subsequent enforcement actions of video surveillance units. Viewsheds with higher levels of camera enforcement experienced reductions in robbery, violent crime, property crime, and overall crime. Interestingly, the only two categories for which camera enforcement was not significant (auto theft and, to a lesser degree, theft from auto) were the only crimes to experience system-wide reductions. This finding concurs with previous research, which has suggested CCTV's deterrent effect to be somewhat limited to motor vehicle crime (Phillips, 1999; Farrington, Gill, Waples, & Argomaniz, 2007; Gill & Spriggs, 2005; Tilley, 1993; Welsh & Farrington, 2007, 2009).

The implications of these findings touch upon the relation between deterrence and the certainty of punishment. Many have argued that advocates of CCTV consider its deterrent effects as automatic; the presence of a camera alone is sufficient to deter potential offenders (Norris & Armstrong, 1999a,b; Norris, 2003). However, these findings suggest auto theft to be the only crime category that can be deterred through camera presence alone. If the goal is the prevention of other crime types (or crime as a whole) the presence of cameras may need to be accompanied with an increased certainty of punishment for offenders. Unfortunately, as discussed earlier, CCTV detections of crime and subsequent enforcement activity does not occur often in Newark, a finding that has also manifested in numerous previous evaluations.

Chapter Summary

Chapter four presented the findings of Analysis B, which measured the system-wide effect of Newark's CCTV cameras. I hypothesized that none of the crime categories would experience a statistically significant crime reduction. Auto theft, however, reduced over 30% relative to the control group. In addition, auto theft experienced a significant diffusion of benefits within the catchment area.

The hypothesis was based in part on the fact that camera detections and enforcement were concentrated amongst a few cameras in the system. Since most viewsheds did not experience significant levels of enforcement, a system-wide reduction was not expected. This relationship seems to exist for the other crime categories, particularly overall crime, violent crime, property crime, and robbery. Theft from auto experienced a decrease in the target area, however, the control area experienced an even greater reduction. In the case of theft from auto, the lack of enforcement was not as pertinent as the fact that at the control sites other activity besides CCTV more effectively prevented theft from auto. I postulated that place mangers and the security measures they enact may have driven the reduction in the control area, but the precise reason for the crime drop is unknown.

CHAPTER FIVE: POLICY IMPLICATIONS AND CONCLUSION

Introduction

Findings from this dissertation have practical implications for the use of Video Surveillance by law enforcement. The joint findings of the analyses point to two phenomena: 1) CCTV effects are restricted in certain environments and 2) enforcement activity generated by the cameras is related to crime reduction in viewsheds. This final chapter discusses how law enforcement agencies may be able to design CCTV operations in a manner that best leverages these implications. The issues discussed in this chapter can inform both agencies currently considering installing CCTV cameras as well as those already invested in the technology.

Policy Implications

Ideal Environments for CCTV Cameras

Research suggests CCTV deployment should be preceded by an in-depth analysis of the spatial distribution and nature of crime patterns (Ratcliffe 2006a; Welsh & Farrington, 2002). A police agency wishing to combat violent crime, for example, is best served by first identifying specific places experiencing disproportionate levels of violence. Secondly, the specific incidents should be analyzed to identify whether or not the crime activity is susceptible to CCTV. For example, a street corner experiencing a large amount of street-level robberies is a more appropriate camera location than the outside of a mall in which strong arm robberies occur indoors.

Findings of this study suggest that police should also account for the composition of the environment when installing cameras. Consider the example of theft from auto.

The system-wide analysis found that while incidents of theft from auto reduced within viewshed areas, comparable decreases in the control area rendered the reduction insignificant. In addition, the micro-level analysis identified corner stores and major roads as major impediments to crime reduction via CCTV. Therefore, police should place future cameras in areas that do not contain high amount of corner stores and are not near major roads, if the goal of the CCTV system includes reducing theft from auto.

Police can utilize easily applied analytical tools and methods to identify the best places for CCTV. In particular, the Risk Terrain Modeling (RTM) technique can aid in the selection of camera locations. At its core, RTM is a crime forecasting approach which standardizes underlying criminogenic factors into a single “risk layer” predictive of future events (Caplan, Kennedy, & Miller, 2010). Operationally, each separate feature is connected to a common geography in the form of a density raster map comprised of equally sized cells. Within each layer, cells are re-classified and coded with a “risk” value based on their density values. These “risk” values range from 0 (density value below the mean) to 3 (density value +2 SD). Finally, the separate layers are combined within a single “risk” layer via the ArcGIS raster calculator tool, which sums the risk values of cells in the different layers (Caplan & Kennedy 2010: p. 29-33). The interpretation of RTM risk layers is straight forward; the higher a cell’s risk value, the higher the concentration of the composite criminogenic features.

In the event Newark decided to install additional CCTV cameras, or redeploy underachieving cameras to different areas, such an analysis could help identify the most appropriate locations. The necessary steps will vary slightly based upon the specific crime type. To illustrate this point, I will conduct an exploratory analysis using 2011 robbery and theft from auto data.

As a first step, density maps are created for each of the crime types.[27] Density values are reclassified so that each cell in the raster grid received a score between 0 and 3, based on the following criteria: 0 for values below the mean, 1 for values between the mean and +1 standard deviation above the mean, 2 for values between +1 and +2 standard deviations above the mean, and 3 for values above +2 standard deviations above the mean. Areas with scores of 3 have the highest crime concentration and would seem to be appropriate sites for future cameras. Figure 24 and Figure 25 show density maps for robbery and theft from auto, respectively.

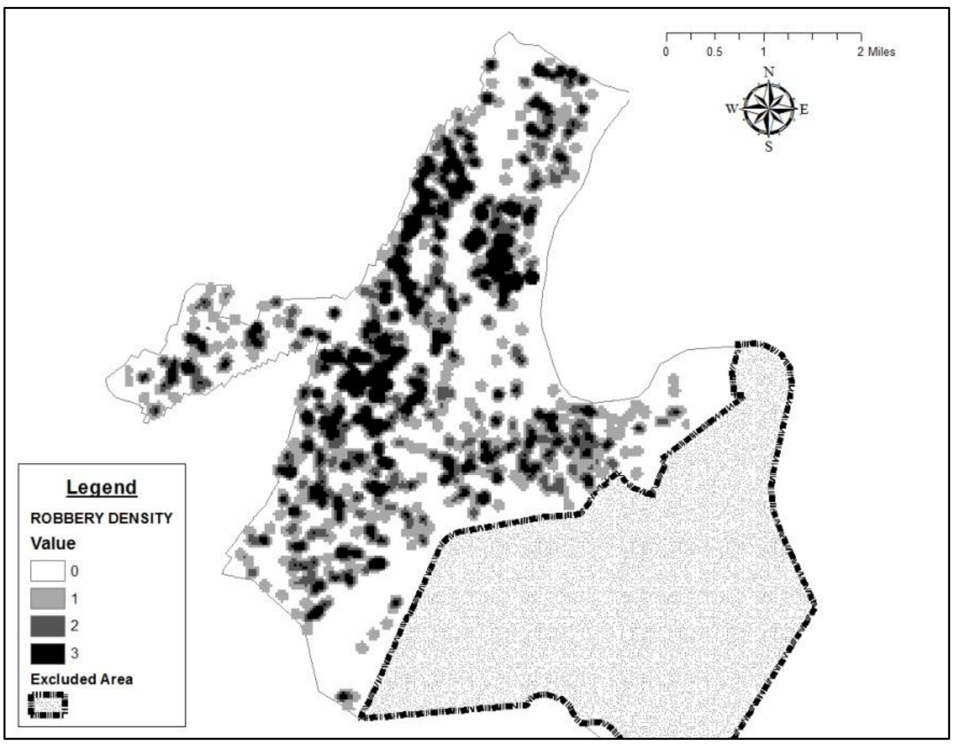


Figure 24: 2011 robbery density map

[27] The cell size was set to 145 feet which is approximately half the length of the average block in Newark, as measured within a GIS. The search radius was set to 500 feet.

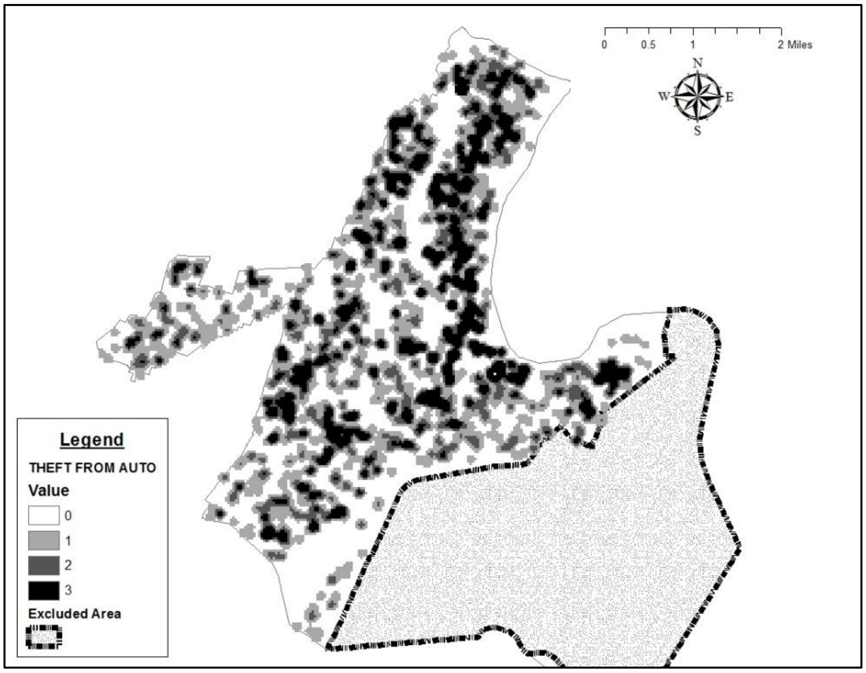


Figure 25: 2011 theft from auto density map

The second step of the analysis identifies the concentration of environmental features identified as related to camera effectiveness in Analysis A. For robbery, liquor stores were shown to be associated with crime increases while corner stores and major roads were shown to have similar influence on theft from auto. The previous geoprocessing steps are then repeated for these environmental features to accurate reflect where their "spatial influence" (Caplan, 2011) may diminish camera effect. For robbery, a density map of liquor stores is created (see Figure 26). A slightly different process occurs for theft from auto, since two separate environmental features (corner stores and major roads) achieved statistical significance. Two density maps (Figure 27 and Figure 28) are created, one for corner stores and another for major roads.[28] To measure the joint influence of the corner stores and major roads, their respective raster layers are summed

[28] Risk Terrain Modeling is user driven, and, thus based on the users' observations. Since Analysis A tested the influence of the level to which environmental features were present (as measured through a location quotient), I chose to operationalize the spatial influence of major roads through measuring the

using the “raster calculator” function in ArcMap. The raster calculator performs mathematical functions on cell values from different layers. In this analysis, density values for corner stores are summed with the major road value to create a composite value. For example, if a particular cell has a value of “2” for corner stores and a value of “3” for major roads, then the cumulative value is “5.” Since the corner store and major roads layers have cell values ranging from 0 to 3, cell values for the composite layer range from 0 to 6. The cumulative raster layer is then re-coded in order to provide consistency with the crime layer, whose cell values range from 0 to 3. In the composite layer, cells with values of 5 or 6 are recoded as 3, values of 3 or 4 are recoded as 2, values of 1 or 2 are recoded as 1 and values of 0 are left as is. Figure 29 displays the composite density map for corner stores and major roads.

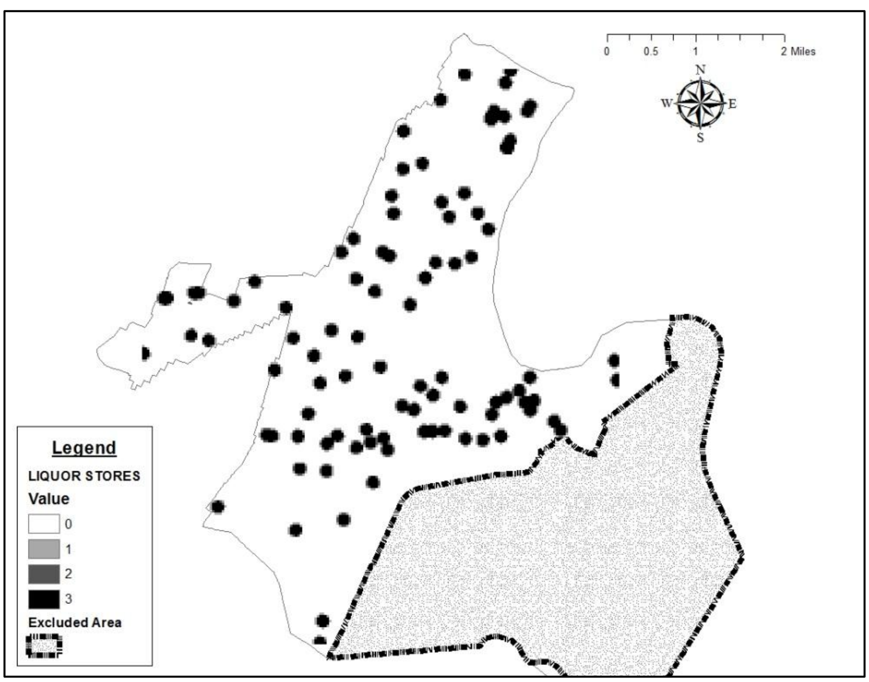


Figure 26: Liquor stores density map

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concentration of features. However, the spatial influence could have also been operationalized as the presence or absence of a major road or a certain distance (e.g. “1 block”) from a major road. Such decisions should be made in accordance with empirical evidence (Caplan & Kennedy, 2010).

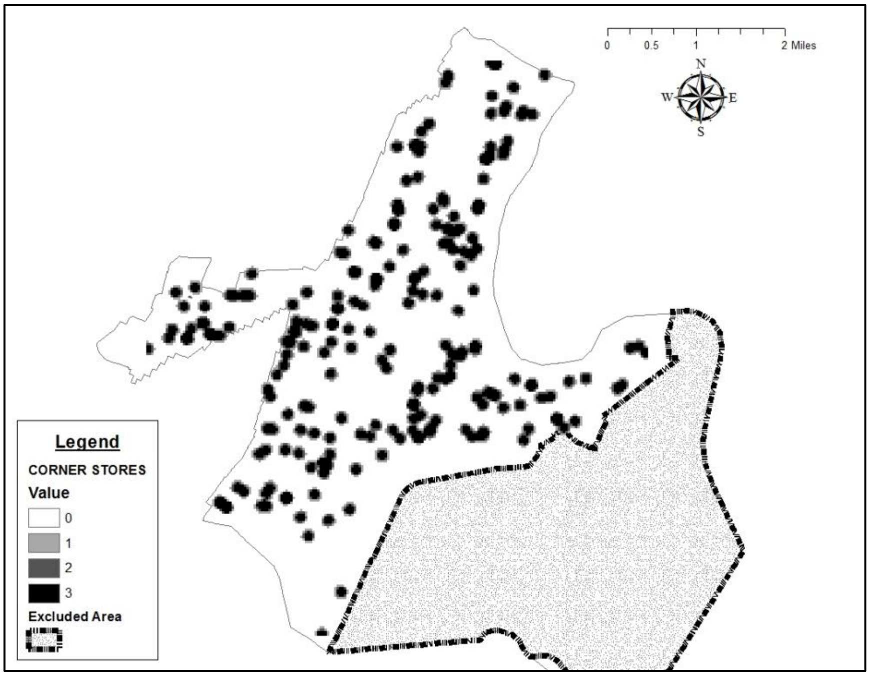

Figure 27: Corner stores density map

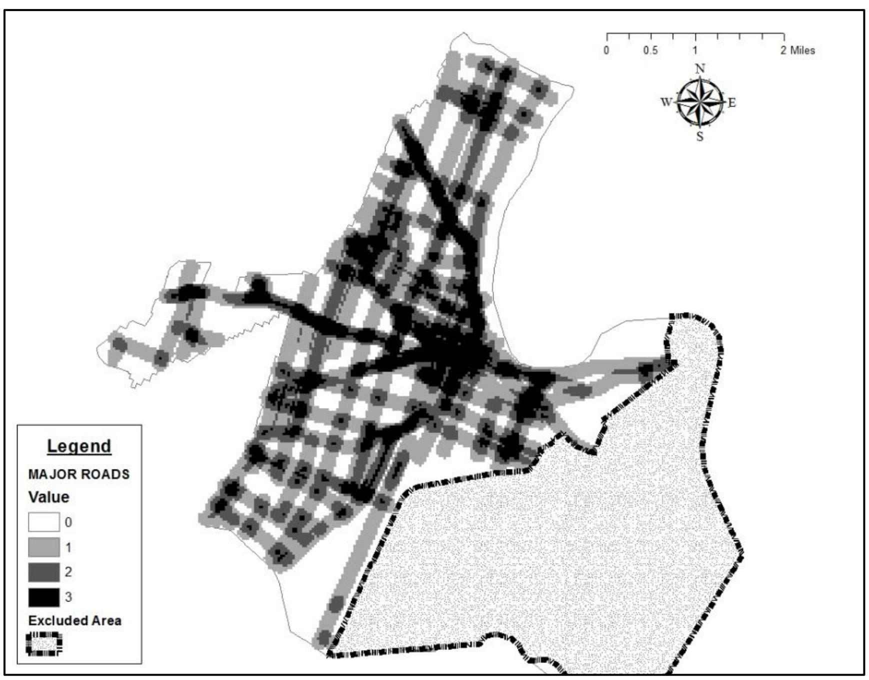

Figure 28: Major Roads Density map

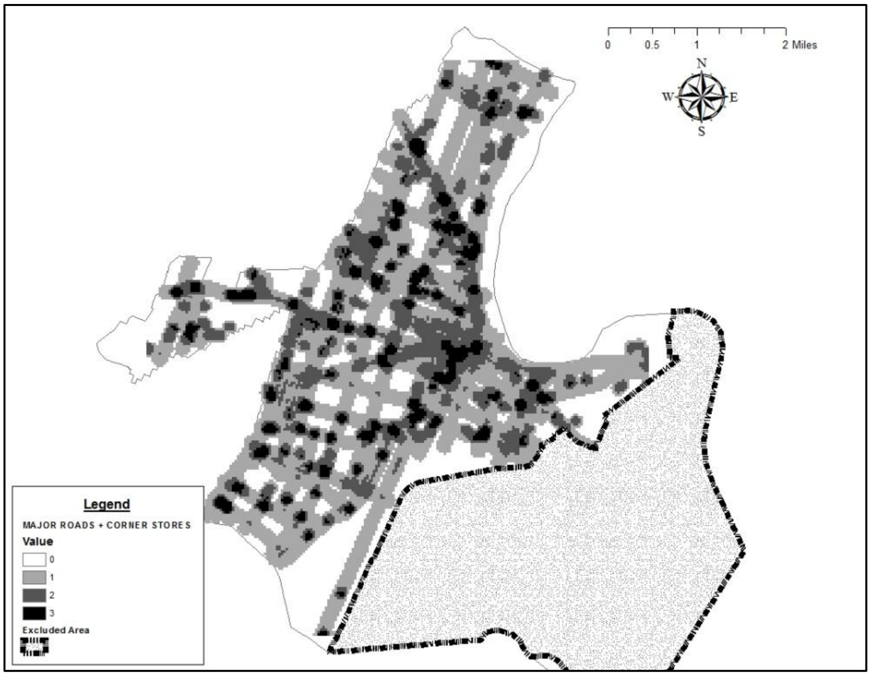

Figure 29: Composite major roads and corner stores density map

The result of these two steps is the creation of two layers: 1) a density map of crime with cell values ranging from 0 to 3 (with 3 suggesting the need for CCTV cameras) and 2) a density map of criminogenic features with cell values also ranging from 0 to 3 (with 3 suggesting that CCTV would not be effective there). The raster calculator is again used to subtract the criminogenic feature layer from the crime layer. The resulting layer contains a final measure of CCTV appropriateness. For example, if a cell with a crime value of 3 is subtracted by a cell with a criminogenic value of 3, the resulting value (0) suggests that CCTV would not be effective in the particular area. Conversely, if a cell with a crime value of 3 is subtracted by a criminogenic value of 0, the resulting value (3) suggests that the location is an appropriate site for CCTV. Figure 30 and Figure 31 show areas of Newark where CCTV may be effective in combating robbery and theft from auto, respectively. These areas suffer from high levels of crime and are void of environmental feature that may reduce the deterrent effects of CCTV.

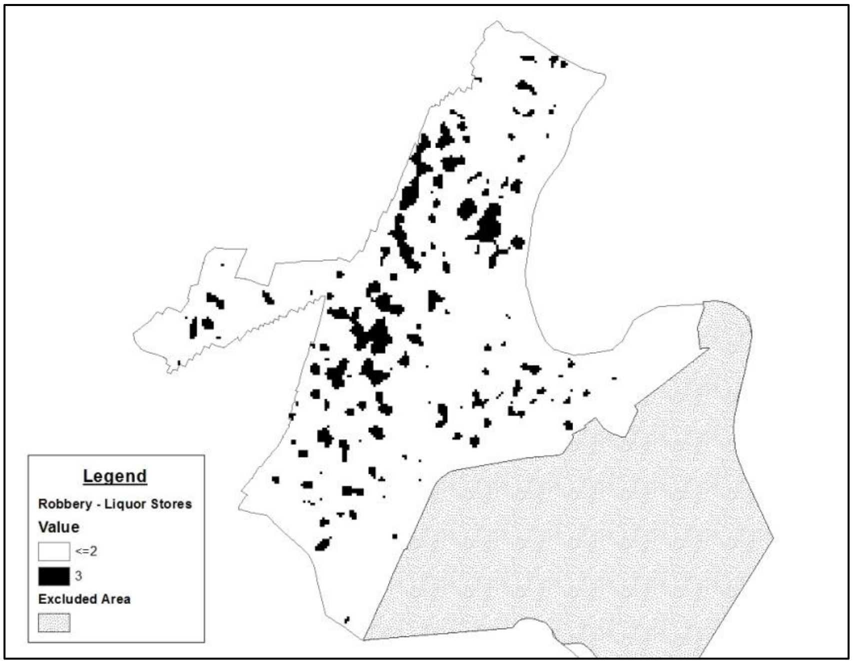

Figure 30: Prospective Robbery camera locations (Robbery Density map - Liquor Stores Density Map)

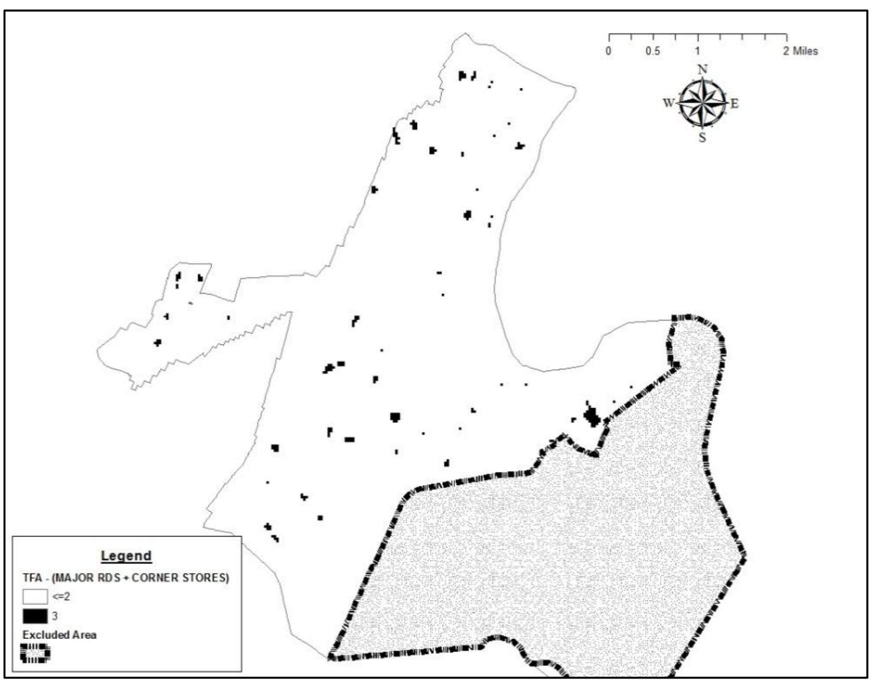

Figure 31: Prospective Theft From Auto camera locations (Theft From Auto Density Map - Composite Major Roads & Corner Store Density Map)

While this analytical framework can be applied by agencies with pre-existing surveillance systems, it can also be incorporated during the beginning stages of CCTV deployment. While correlates of success for particular cameras cannot be generated until the cameras have been operational for a period of time, police can rely on empirical research to identify locations whose environment composition and behavior settings may be susceptible to the deterrent effects of CCTV. Correlates of success could be identified for existing cameras after a pre-determined period (e.g. 6 months, 1 year). This information could then be incorporated into an analysis in order to choose future camera locations. Such an approach is preferable to the expansion of CCTV systems absent an understanding of where cameras truly work best.

Increasing Enforcement Activity

The second takeaway from this dissertation is that camera enforcement has a positive impact on a camera's ability to generate deterrence. Unfortunately, the level of enforcement was low within most camera viewsheds. An obvious implication is that levels of enforcement should be increased so that a system-wide deterrent effect could be realized. However, it is important to first ask why enforcement levels are so low to begin with. Only then can a course of action be proposed to increase enforcement.

The Newark surveillance unit is faced with numerous obstacles to their proactive enforcement duties. The surveillance unit is staffed by no more than two operators under the supervision of one sergeant, who is responsible for administrative functions of the unit and does not typically monitor cameras. Given the current size of the system (149 cameras) each operator is responsible for watching approximately 74 cameras at a time. Also, the growth of the system did not occur gradually. Cameras were installed over a total of seven phases, each causing a substantial increase in the total number of cameras.

The installation phases are as follows: Phase 1: 6/8/07 (11 cameras installed), Phase 2: 3/15/08 (49 cameras installed, system size increased to 60), Phase 3: 7/31/08 (51 cameras installed, system size increased to 111), Phase 4: 9/14/09 (1 camera installed, system size increased to 112), Phase 5: 12/10/09 (23 cameras installed, system size increased to 135), Phase 6: 1/7/10 (1 camera installed, system size increased to 136), and Phase 7: 4/23/10 (10 cameras installed, system size increased to 146). This could be overwhelming to operators, who were forced to familiarize themselves with a large amount of new locations in a short period of time. This rapid increase in the camera to operator ratio likely forces the operators to spread their attention more thinly across numerous sites, and likely prevents them from spending significant time monitoring any given location.

In addition, other duties are expected of the operators, particularly creating DVDs of footage and monitoring the department's gunshot detection system. Footage is needed for evidentiary purposes each time an arrest occurs in which the CCTV cameras provided probable cause. Furthermore, detectives often request extended hours of footage when a crime is reported in the vicinity of a camera for the purpose of searching for visible clues. While CD/DVD creation and duplication seems simple, research suggests that such tasks are somewhat difficult in certain instances. For example, King et al. (2008) reported that it took two hours to burn one hour of footage in San Francisco. Similarly, Gill et al. (2005) reported that the management of footage for evidentiary purposes comprised up to 35% of an operator's shift. In August of 2009, Newark installed gunshot detection sensors in a seven-square mile area of the city. Each time a gunshot detection occurs, video operators listen to various recordings of the gun shots to determine the validity of the shots fired call and then notify the on-duty dispatcher whether an officer should be dispatched to the scene. This process can take several minutes to complete, and takes the operator away from monitoring the cameras. Indeed, previous research has noted that tasks unrelated to surveillance can limit the proactive monitoring activity of an operator (Leman-Langlois, 2002). In addition, the Newark Police Department's CCTV operation, as well as the agency as a whole, was negatively impacted by police layoffs occurring in November 2010. While the layoffs did not occur until November 2010, department functions were impacted before the official layoff date. The city's financial deficit was well known at the beginning of the yeas; Newark Police officials considered layoffs of some magnitude as inevitable. Therefore, starting early in 2010, personnel in "non-essential" assignments were often temporarily reassigned to core assignments in an attempt to minimize overtime expenditures. In the case of the surveillance unit, camera operators would occasionally be reassigned as 9-1-1 call takers, which would obviously leave the surveillance function at less than full capacity.[29]

The aforementioned barriers to the surveillance function led to a steady decline in surveillance activity. Figure 32 and Figure 33 show the weekly number of video detections and resulting enforcement, respectively, from the last week of October 2007 through the final week of December 2010. The graphs clearly show a sharp downward trend for both detections and enforcement. During the early stages of the surveillance program, over 40 detections and 20 enforcement actions occurred per week. Spikes in activity are evident in the months around February 2009 and February 2010. However, by mid-2010, detections and enforcement both became a rare occurrence.

[29] Similar measures were taken in respect to patrol, with officers detailed to specialized foot-patrol posts being reassigned to motorized patrol, which have city-mandated minimum levels, in order to avoid overtime expenditures (Piza & O'Hara, 2012).

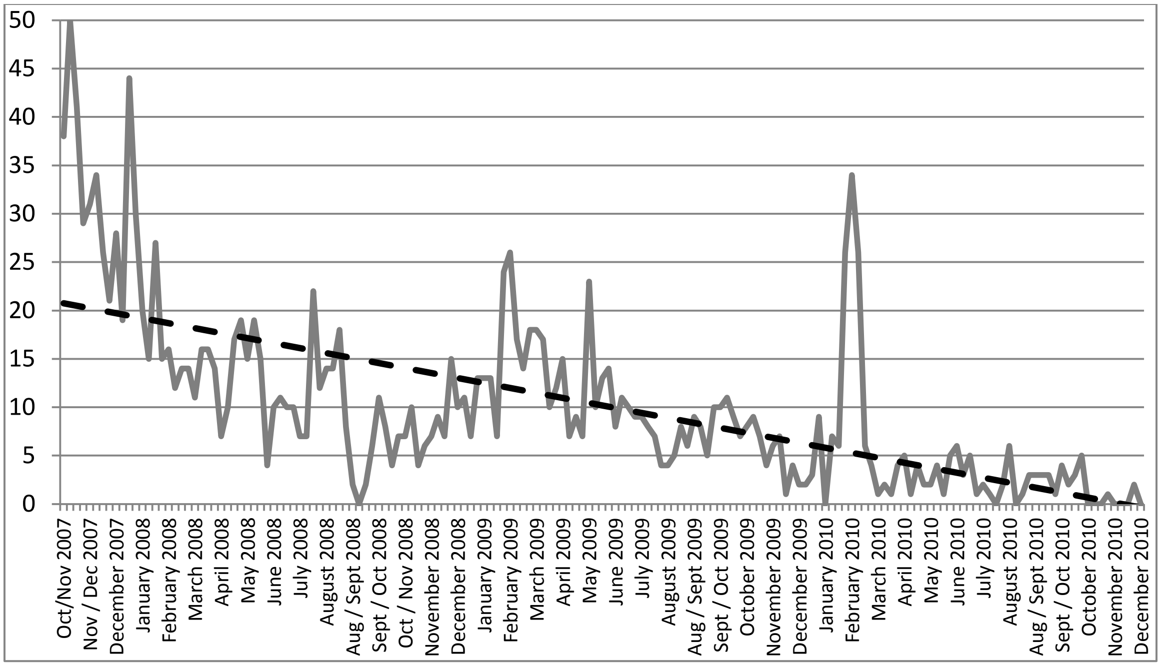

Figure 32: Weekly Detections

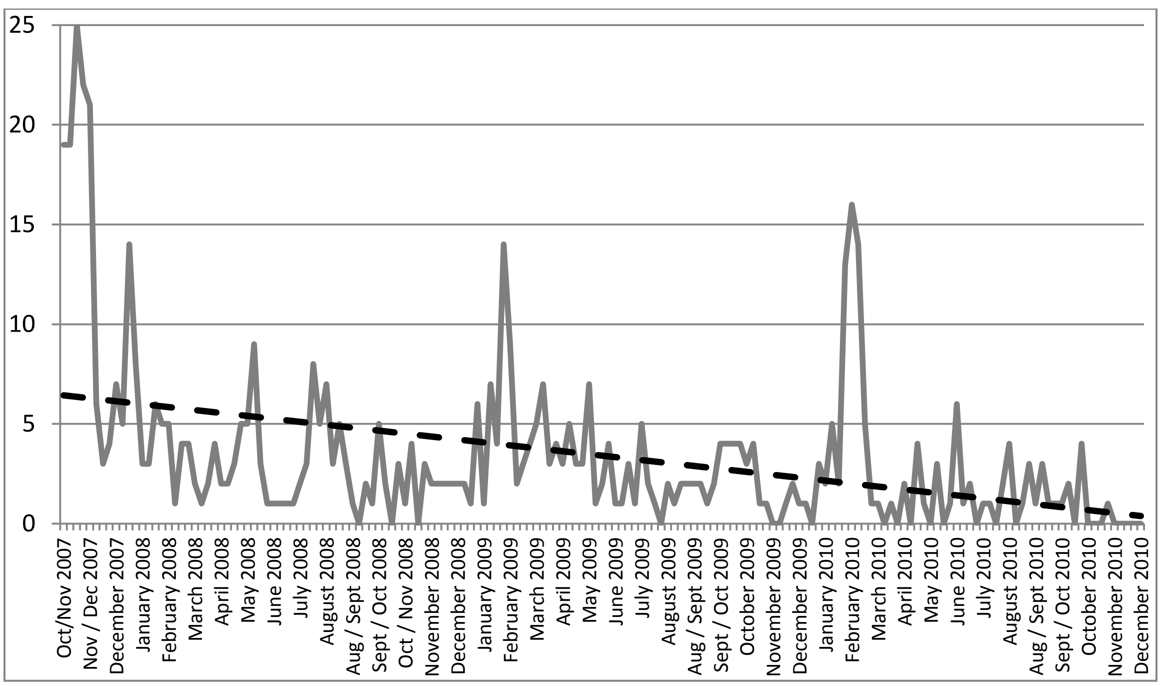

Figure 33: Weekly Enforcement Actions

In an effort to more clearly identify the factors that contributed to this reduction, the results of a series of count models are presented in Table 26 and Table 27. Seven-day periods (e.g. “weeks”) spanning from Sunday through Saturday were the units of analysis. The number of individual weeks totaled 165. The independent variables represented potential “surveillance barriers” operating in Newark: the installation phase of the camera program (an ordinal variable form 1 to 5); the four-week average of the footage requests made to the surveillance unit during the month;[30] a dichotomous variable identifying whether the gun shot detection system was installed yet (1) or not (0); a dichotomous variable identifying if the week was after the November 2010 layoffs (1) or not (0); and a dichotomous variable identifying if the week was in the year 2010 (1) or not (0). Two additional covariates were included as controls for features of weather that may influence street-level activity and, consequently, the amount of surveillance activity. Specifically, we would expect higher amounts of street-level activity to occur during warmer weather and when there is no precipitation (e.g. rain or snow). Therefore, the average daily high-temperature for each week (“Temperature”) and the days with either rain or snow (“Precipitation”) were calculated for each week. This data was compiled from the history pages of the “Weather Underground” website.[31]

Table 26 and table 27 display the findings of the negative binomial and Poisson regression models for the weekly number of detections and enforcement actions, respectively.[32] The negative binomial and Poisson models exhibited a high level of

[30] Data on the number of footage requests were only available for monthly periods. In order to incorporate this data with weeks as units of analysis, the four-week average of each monthly count was taken. For example, if 20 footage requests occurred during a calendar month the weekly average was denoted as 5 (20/4=5). In respect to weeks spanning more than 1 month (e.g. a week that begins the last week of January and ends the first week of February) the requests for the two months was summed together and then divided by 8. For example, if 20 requests were received in January and 15 in February, the weekly average for the week spanning January and February would be 4.5 ([20+15]/8=4.5).

[31] www.wunderground.com/history

[32] Negative binomial and Poisson regression models are typically considered as competing models. Poisson models work under the assumption that the conditional mean and variance of the distribution is equal. Since this assumption is rarely met in in criminology, researchers often advocate the use of negative binomial

agreement. For detections, both models found camera phase, footage requests, after gun shot detection, after layoffs, and temperature to be statistically significant. Footage requests was positive, showing them to be related to increased numbers of detections. The findings regarding footage requests being associated with higher levels of detections should be taken with a grain of salt. Since a disc of footage is created every time an enforcement action results from a CCTV detection, the correlation between footage requests and detections may be somewhat artificial. While measuring the outside requests for footage separately from the disks burned as a result of operator activity may have been helpful, the data was not disaggregated in such a manner. The camera phase variable was negative for both models, showing that with each installation of a new wave of cameras weekly detections reduced by over 60%. The after layoffs variable showed that the widespread officer terminations was associated with an over 200% reduction is weekly detections . Both models found the installation of the gunshot detection system to be associated with an over 30% reduction of weekly detections. This suggests that the hands-on nature of the gunshot detection system, in which operators manually review and validate all detected gunshots, may take personnel away from monitoring the CCTV cameras. This is contrary to the view that the integration of surveillance and gunshot detection technology may improve the functionality of CCTV (La Vigne et al., 2011). The Poisson model suggested that the Year 2010 variable was associated with an increase in weekly detections, despite the fact that ensuing layoffs caused a sharp decrease.

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models, which specifically correct for over dispersion in the data (MacDonald & Lattimore, 2010; Osgood, 2000). However, Berk and MacDonald (2008) demonstrated through sophisticated simulation models that negative binomial regression only improves upon the shortcomings of Poisson models when all of the relevant predictors of the dependent variables are accounted for in the model. This assumption, like that of equal means and variances, is also rare in criminology. Given the debate surrounding count models, I decided to report the results of both negative binomial and Poisson models.

However, the year 2010 variable was insignificant in the negative binomial model. In each model, temperature was significantly related to the amount of weekly detections, but not in the expected direction. Results for both the negative binomial and Poisson model show that for every 1 degree increase in the temperature, weekly detections decreased by 1% (-0.01). While one may expect more detections to occur in warmer weather (e.g. when more people are outside) previous research has shown how ground level obstructions such as leaves from trees and bushes (which are more prominent in warm weather) often impede upon an operator's ability to monitor CCTV areas (Gill et al., 2006; Smith, 2004). Such a situation may have also presented hardships to CCTV operators in Newark. Footage requests was the only significant variable with a positive β value (0.05), suggestive of a positive correlation with detections.

Less variables achieved statistical significance in the enforcement models. Camera Phase, year 2010, and temperature were statistically significant in each model. Camera phase was associated with a decrease in weekly enforcement. Both models found year 2010, and temperature to be associated with increased numbers of enforcement activity. The Poisson model additionally found footage request to be associated with higher levels of enforcement.

Variables	Negative Binomial				Poisson			
	B	Std. Err.	z	*p*	*B*	Std. Err.	z	*p*
Camera Phase	-0.64	0.10	-6.44	0.00	-0.61	0.06	-10.76	0.00
Footage Requests	0.05	0.02	2.59	0.01	0.05	0.01	3.82	0.00
After Gun Shot Detection	-0.34	0.17	-2.08	0.04	-0.33	0.10	-3.19	0.00
After Layoffs	-2.00	0.76	-2.64	0.01	-2.04	0.71	-2.86	0.00
Year 2010	0.31	0.21	1.48	0.14	0.31	0.13	2.45	0.01
Temp	-0.01	0.00	-3.88	0.00	-0.01	0.00	-6.04	0.00
Precipitation	0.01	0.03	0.21	0.83	0.00	0.02	-0.06	0.96

Table 26: Results of count regression models testing the effect of camera amount, additional duties, and the police layoffs on the weekly number of detections.

Variables	Negative Binomial				Poisson			
	B	Std. Err.	z	*p*	*B*	Std. Err.	z	*p*
Camera Phase	-0.63	0.15	-4.32	0.00	-0.69	0.09	-7.41	0.00
Footage Requests	0.04	0.03	1.33	0.18	0.05	0.02	2.47	0.01
After Gun Shot Detection	-0.30	0.26	-1.13	0.26	-0.28	0.19	-1.52	0.13
After Layoffs	-20.27	8556.83	0.00	1.00	-15.23	710.28	-0.02	0.98
Year 2010	0.88	0.32	2.79	0.01	0.97	0.21	4.54	0.00
Temp	-0.01	0.00	-2.82	0.01	-0.01	0.00	-3.79	0.00
Precipitation	-0.03	0.05	-0.66	0.51	-0.05	0.03	-1.61	0.11

Table 27: Results of count regression models testing the effect of camera amount, additional duties, and the police layoffs on the weekly number of enforcement actions.

The "year 2010" findings were somewhat surprising, with that variable being associated with an 88% increase in the weekly enforcement levels (0.88). The variable was insignificant in the detections models, meaning that year 2010 impacted the result of camera detections (e.g. "enforcement") without impacting the level of detections themselves. Furthermore, year 2010 was conceptualized as the period when the police department was shifting resources in preparation for the impending police layoffs; it was thus unexpected for the "year 2010" and "after layoffs" variables to be correlated with enforcement in opposite directions. Newark Police officials provided a potential explanation for this seemingly counterintuitive observation. A main concern of the Newark Police Department was maintaining adequate levels of officers on the street following the layoffs. Therefore, a number of officers in administrative posts were re-assigned to patrol duties throughout 2010 in order to prepare them to take over for the street officers who were slated for termination. While this was done in anticipation of the layoffs, the immediate effect was an increased number of officers patrolling the streets of Newark; the "replacements" were on the street along with the officers currently assigned to patrol (who would later be terminated). Newark police officials suggested that this increase in street-level personnel may have enhanced the department's ability to respond to CCTV detections, leading to higher levels of enforcement actions.

The results of the count models suggest that the increasing camera-to-operator ratio and low staffing levels hindered the proactive monitoring function of the surveillance unit. Interviews with surveillance operators highlighted another potential source of low detection rates. A number of operators suggested that patrol officers are normally not dispatched to CCTV detections for extended periods of time due to many of the incidents detected by CCTV (e.g. disorder and narcotics activity) having intermediate (as opposed to "high") priority codes. Such incidents do not receive immediate police response since officers have to address high priority calls (such as violent crimes) before being dispatched to lower priority assignments. This often leads to infractions observed by CCTV operators going unreported. When asked why they did not report their detections in certain instances, operator comments revealed aspects of police dispatch—specifically large queue times—discouraged them from reporting many of the intervention opportunities. In respect to an incident where suspected drug dealers and customers met behind a building to seemingly conduct a drug transaction, an operator said, "since we couldn't see it directly, if we did put it into CAD it would be a low priority because we'd have to put it in as unverified (narcotics activity)." In another incident, the operator observed a group of individuals rolling and subsequently smoking what appeared to be a marijuana-filled cigar. After stating that she often views these same individuals engaging in similar behavior, the operator was asked why she didn't report the incident, to which she responded, "Because by the time the radio car gets there they'll be long gone."

Operator beliefs are supported by a particular incident. In this incident, the disorderly behavior of a woman was reported by an operator at 9:45 PM. Twenty-one minutes after the disorderly behavior incident, a shooting occurred at the same location. An officer had yet to be dispatched in response to the disorderly person offense. As reported by the operator, a string of higher priority incidents prevented police from responding to the disorderly behavior incident: "[On the night in question] we already had a shooting prior [to the incident in question]. All the units in this precinct were tied up either [responding to] that job or other [incidents with higher priority codes]. That's why it sat for [nearly] 22 minutes…we had a lot of higher priority jobs going on."

The actions and concerns of the Newark surveillance operators mirror findings of previous research. Numerous studies have shown that not all infractions detected by CCTV operators result in the deployment of a police officer. Gill et al. (2005), for example, found that operators across 13 control rooms only informed police of 24% of the offenses they observed. Similarly, Norris and Armstrong (1999b) found that only 44 of 900 targeted surveillances (5%) resulted in police deployment. While detections are typically viewed exclusively as a measure of operator performance, characteristics of police deployment and response can directly influence an operator's decision to report observed infractions (Norris & Armstrong, 1999b: p. 173-174).

Given the results of the count models and the operator comments, the issues surrounding camera detection and enforcement seem to be two-fold. Firstly, two on-duty operators are unable to adequately monitor the entire system. Secondly, due to the differential response policy of police dispatch, operators do not believe that police officers are able to arrive quick enough to address the situation at hand in every instance.

It seems that both of these issues would need resolution for camera enforcement to be maximized.

A seemingly obvious solution would be to staff the surveillance unit with more operators. Despite the likely benefits this would generate—in respect to increased detections and enforcement—the current fiscal situation of the Newark Police Department likely prevents the assignment of additional personnel to the surveillance unit. However, alternate options may exist for the Newark Police Department to increase the proactive activity of the surveillance unit. For one, police could abandon differential response in CCTV-detected incidents by dispatching an officer immediately upon observation of criminal or suspicious behavior. However, this policy would likely be a tough sell to citizens living outside of CCTV areas who are not likely to consider their emergencies as less important just because they were not captured on video. Immediate response in CCTV areas would also place additional burden on patrol units working in other areas of the city by making these units responsible for responding to a larger number of high-priority incidents.

A more viable solution would be to incorporate the video surveillance function into current proactive operations of the department. In this respect, the Newark Police Department commonly deploys “suppression” units for the purpose of identifying and addressing criminogenic conditions which may generate violence. These units have no or reduced responsibilities for responding to calls-for-service. They are instead tasked with enacting proactive enforcement actions within high-crime areas. Since most camera detections are of narcotics or disorderly behavior, suppression units could be integrated into the surveillance operation, so that they are notified when a camera captures an incident of concern. In addition, a few police officers from a given unit could be assigned to monitor surveillance cameras in support of the operations of the unit as a whole. For example, a main strategy of the Newark Police Department is “Command Field Day,” where officers assigned to administrative posts (e.g. “Human Resources” or “Legal Affairs”) are deployed to motorized and foot-patrol in various high-crime areas throughout the city at least one day per week. The officers are not assigned to any police precinct, but rather remain under the command of their (administrative) unit’s supervisor and are given responsibility for specific areas. For example, both the Human Resources and Legal Affairs units may be deployed to the “Clinton Hill” neighborhood on a certain day. In this scenario, the officers with supervisory ranks (e.g. Sergeants, Lieutenants, and Captains) oversee the deployment of the units’ police officers. It may be worthwhile to assign one of the officers to the surveillance unit for the purpose of monitoring any cameras that fall within the target area. By focusing on a small number of cameras within a concise geography, the officers may be able to detect incidents of concern that may have gone unnoticed by the regular surveillance operators (who are responsible for monitoring a much larger amount of cameras). The “Command Field Day” units could be directly notified and deployed to these incidents.

Incorporating the surveillance cameras into the proactive patrol functions of the Newark Police Department may heighten the effectiveness of the field units. Camera operators may be able to capture incidents at a level of detail not possible otherwise. For example, during a visit to the camera control room, I once heard the following radio-exchange between a lieutenant of the Narcotics Division (who was monitoring cameras) and undercover field officers: “The guys I saw selling on [street name] yesterday are now on [street name #2]. They just served [sold drugs to] a guy in a white Lexus. The kid who made the actual transaction is wearing a turquoise t-shirt. The other 2 dealers are on [street name #3]: [one is wearing a] red shirt, hat and a beard; the other one has a white t-shirt and thinner beard. There are 2 other guys in the area. I haven't seen them make any sales yet, but they keep walking to the back of the building; I think that's where the stash [of drugs] is." As the quote illustrates, footage obtained via CCTV provided field officers with insight into a number of factors—such as the stash location and the presence of additional suspects—which may have been difficult for officers to observe on their own. Norris and Armstrong (1999a) discuss such advantages provided by CCTV: "Because the 'presence' of [CCTV] operatives is remote and unobtrusive, there is less likelihood that people will orient their behavior in the knowledge that they are being watched, and, by virtue of the elevated position and telescopic capacity of the camera, operators have a greater range of vision than the street-level police officer" (p. 159). In light of these observations, the merging of the Newark Police Department's CCTV and proactive patrol operations may pay dividends.

Conclusion

Maximizing the effect of CCTV has particular importance in current times. The recent economic downturn has created an environment in which police resources are extremely limited, and in many cases dwindling. This is certainly the case in New Jersey, where police layoffs have occurred in a number of municipalities throughout the state. Given this decrease in manpower, maximizing the impact of technology is paramount.

Citizens have traditionally held high expectations for law enforcement technology, particularly surveillance cameras. Passionate endorsement of CCTV by the media has led many in the public to consider the technology as infallible (Norris & Armstrong, 1999b: p. 67-69).Compounding this problem is the presence of the "CSI Effect," where citizens hold exaggerated expectations of the technology due to common portrayals in fictional crime dramas (La Vigne et al., 2011a). In recent years two high-profile killings have occurred within direct sight of CCTV cameras in Newark, generating a feeling of disbelief amongst many in the community. In reporting of the aftermath of the shooting death of an off-duty Newark police officer in a take-out eatery, reporter Mark Di Ionno (2011) wrote the following: "And there are Newark police security cameras [at the scene of the murder]. One, in fact, is at the corner of Clinton Place and Lyons Avenue, and as it rotates, it pans the chicken joint. It's hard to miss. And that may say more about the state of lawlessness than anything." In another incident, after the brutal slaying of four college students in an elementary schoolyard, it was discovered that the security cameras on the scene were not working on the night of the murders. Neighborhood residents were irate, with many arguing that the crime could have been prevented had the cameras been working (Ermino, 2007).

A simple truth about video surveillance gets lost amongst the grief and outrage; cameras in-and-of themselves cannot stop a crime. As stated by Ratcliffe (2006a), "A CCTV system is not a physical barrier. It does not limit access to certain areas, make an object harder to steal, or a person more difficult to assault and rob" (p. 8). A camera can only deter potential offenders, either through its presence or the promise of swift action in response to a crime. In both of the aforementioned cases, the fact that the suspects were so indifferent to the cameras highlights CCTV's limited capacity to produce deterrence. While the hope is that offenders will not engage in crime in the presence of cameras, the reality is that many, especially serious violent offenders, are more than willing to take the risk. The precise reasons why these offenders committed such brazen acts in view of cameras may never be known. It may be that the cameras were not noticed. It may be that the views of the cameras were easily bypassed. It may be that certain environmental features make these places most suitable for crime, regardless of the presence of CCTV. In the case of the schoolyard slaying, it may be that the killers somehow knew that the camera was not recording (though this is unlikely). However, it may also be that by frequenting the area the offenders were aware of the true "risk" posed by the cameras. While the initial installation of a camera may *signify* an increased risk to offenders, the threat may quickly ring hollow. If over time, potential offenders notice that the camera is not accompanied by increased police response or presence, they may believe that they are at no more risk of punishment. Given the staffing limitations of Newark's CCTV operation, and the fact that most cameras did not detect a single criminal incident after a year in operation, offenders may be correct to believe that offending within CCTV-covered areas may be no more risky than offending in other public areas.

Law enforcement has undergone significant transformation over recent decades. All strategic innovations in policing emerged in response to shortcomings inherent in traditional methods of law enforcement (Clarke, 1997; Eck & Spelman, 1987; Goldstein, 1979, 1990; Kelling & Coles, 1996; Kennedy, 1998; Sherman & Weisburd, 1995; Skogan & Frydl, 2004; Weisburd & Braga, 2006; Weisburd & Eck, 2004). These strategic innovations were designed in a manner that overcame hurdles inherent in law enforcement, and were (and still are, in some cases) considered radical departures from the traditional police function. Video surveillance, unfortunately, has not been instituted with the same level of creativity as these other police innovations. While CCTV represents a technological innovation in crime prevention, its practical application has been rather unimaginative and one-dimensional. CCTV is primarily expected to deter offenders through its conspicuous presence. Despite evidence of CCTV effectiveness being inconclusive, at best, there has been little exploration into alternate mechanisms by which CCTV can generate reductions in crime and no documented attempts to improve upon the effectiveness of existing CCTV systems, outside of merely installing more cameras.

This dissertation was a modest attempt to move the field forward by exploring how video surveillance effect could be maximized. While the research focused on the city of Newark, the policy implications can inform police agencies in other areas. In addition, the research methods are replicable. More exploration of the context in which CCTV effect is maximized would certainly be beneficial. Such a body of knowledge could produce practical benefits by influencing law enforcement practice and policy relative to video surveillance. In current economic times, it is especially important that CCTV at least come close to providing the benefits practitioners anticipated. As noted by Norris and Armstrong (1999b), “for those who promote CCTV as the panacea to the crime and disorder on our city streets…there is a common assumption: CCTV actually produces the effects claimed for it. They see CCTV surveillance as not only omnipresent but omnipotent” (p. 9). While an impartial review of the empirical evidence should shatter the notion of CCTV as a “panacea,” video surveillance has to potential to effectively address issues of public safety within certain contexts. Proponents of CCTV have long suggested that the tactic is up to the task. Within the current fiscal climate, municipalities utilizing CCTV cannot afford otherwise.

REFERENCES

Agnew, R. (2011). Crime and time: The temporal patterning of causal variables. *Theoretical Criminology, 15 (2):* 115-140.

Allison, P. (1990). Change scores as dependent variables in regression analysis. *Sociological Methodology, 20:* 93-114.

Apel, R. (2012). Sanctions, Perceptions, and Crime: Implications for criminal deterrence. *Journal of Quantitative Criminology.* Published online before print: 18 February 2012.

Apel, R. and Sweeten, G. (2010). Propensity score matching in criminology and criminal justice. In Piquero A. and Weisburd, D. (eds.) *Handbook of Quantitative Criminology.* Springer: NY, NY.

Armitage, R., Smythe, G., Pease, K. (1999). Burnley CCTV evaluation. In Tilley, N. and Painter, K. (eds.) *Surveillance of Public Space: CCTV, Street Lighting and Crime Prevention.* Crime Prevention Studies Vol. 10. Criminal Justice Press: Monsey, NY.

Armitage, R. (2002). *To CCTV or not? A review of current research into the effectiveness of CCTV systems in reducing crime*. London: National Association for the Care and Resettlement of Offenders

Association of State Highway and Transportation Officials. (2004). *A policy on geometric design of highways and streets, 5th edition.* Washington, DC.

Babwin, D. (2007). *Chicago video surveillance gets smarter.* USA Today. Originally published September 27, 2007. Retrieved online at: http://www.usatoday.com/tech/products/2007-09-27-4171345706_x.htm

Barr, R. and Pease, K. (1990). Crime placement, displacement and deflection. In Tonry, M. and Morris, N. (eds.), *Crime and Justice: A Review of Research, Vol. 12*: 277-218. University of Chicago Press: Chicago, IL

Basta, L., Richmond, T., and Wiebe, D. (2010). Neighborhoods, daily activities, and measuring risks experienced in urban environments. *Social Science & Medicine, 71*: 1943-1950.

Beavon, D., Brantingham, P.L., and Brantingham, P.J. (1994). The influence of street networks on the patterning of property offenses. In Clarke, R. (ed.) *Crime Prevention Studies, Vol.2.* Criminal Justice Press: Monsey, NY.

Bernasco, W. and Block, R. (2011). Robberies in Chicago: A block-level analysis of the influence of crime generators, crime attractors, and offender anchor points. *Journal of Research in Crime and Delinquency, 48(1):* 33-57.

Berk, R. and MacDonald, J. (2008). Overdispersion and poisson regression. *Journal of Quantitative Criminology, 24*: 269-284.

Bittner, E. (1990). *Aspects of police work.* Northeastern Press: Boston, MA.

Black, D. (1970). The production of crime rates. *American Sociological Review, 35:* 733-748.

Block, R. (2008). *Street Robbery in Chicago 1991-2005: Overall decline, location persistence, and hot spots.* Presentation at the American Society of Criminology Annual Meeting. St Louis, MO.

Block, R. and Block, C. (1999). The Bronx and Chicago: Street robbery in the environs of rapid transit stations. In Goldsmith, V., McGuire, Pl, Mollenkopf, and Ross, T. (eds.). *Analyzing Crime Patterns: Frontiers of Practice.* Sage: Thousand Oaks, CA.

Block, R. and Block, C. (1995) Space, place, and crime: hotspot areas and hot places of liquor related crime. In: Eck, J. and Weisburd, D. (eds.). *Crime and Place. Crime Prevention Studies, Vol. 4:* 145-184. Criminal Justice Press: Monsey, NY.

Bowers, K. & Johnson, S. (2003). Measuring the Geographical Displacement and Diffusion of Benefit Effects of Crime Prevention Activity. *Journal of Quantitative Criminology, 19*: 275-301.

Braga, A. (2010). Setting a higher standard for the evaluation of problem-oriented policing initiatives. *Criminology & Public Policy, 9 (1)*: 173-182.

Braga, A. (2008). *Crime prevention research review No.2: Police enforcement strategies to prevent crime in hot spot areas.* Washington, D.C.: U.S. Department of Justice Office of Community Oriented Policing Services.

Braga, A. (2005). Hot spots policing and crime prevention: A systematic review of randomized controlled trials. *Journal of Experimental Criminology, 1(3)*: 317-342.

Braga, A. and Weisburd, D. (2011). The effects of focused deterrence strategies on crime: A systematic review and meta-analysis of the empirical evidence. *Journal of Research in Crime and Delinquency.* Published online 13 September 2011.

Braga, A. and Weisburd, D. (2010). *Policing problem places: Crime hot spots and effective prevention.* New York, NY: Oxford University Press.

Braga, A., Hureau, D. and Papachristos, A. (2012). An ex post facto evaluation framework for place-based police interventions. *Evaluation Review.* Published online 11 January 2012.

Braga, A., Hureau, D. and Papachristos, A. (2011). The relevance of micro places to citywide robbery trends: A longitudinal analysis of robbery incidents at street corners and block faces in Boston. *Journal of Research in Crime and Delinquency, 48(1):* 7-32.

Braga, A., Papachristos, A. and Hureau, D. (2010). The concentration and stability of gun violence at micro places in Boston, 1980-2008. *Journal of Quantitative Criminology, 26*: 33-53.

Braga, A., Grossman, L., and Piza, E. (2011). *Understanding serious violence in Newark, New Jersey*. Unpublished working paper. Newark, NJ: Rutgers University, School of Criminal Justice.

Braga, A., McDevitt, J., and Pierce, G. (2006). Understanding and preventing gang violence: Problem analysis and response development in Lowell, Massachusetts. *Police Quarterly, 9 (1):* 20-46.

Braga, A., Kennedy, D., Waring, E., and Piehl, A. (2001). Problem-oriented policing, deterrence, and youth violence: An evaluation of Boston's operation ceasefire. *Journal of Research in Crime & Delinquency, 38 (3):* 195-225.

Brantingham, P.J. and P.L. Brantingham (2003) Anticipating the Displacement of Crime Using the Principles of Environmental Criminology. In Smith, M. and Cornish, D. (eds.) *Theory for Practice in Situational Crime Prevention. Crime Prevention Studies, Vol. 16:* 119-148. Lynne Rienner Publishers: Boulder, CO.

Brantingham, P.J. and Brantingham, P.L. (1995). Criminality of place: crime generators and crime attractors. *European Journal on Criminal Policy and Research, (3), 3*: 1-26.

Brantingham, P. J., & Brantingham, P. L. (1981). *Environmental Criminology*. Sage: Beverly Hills, CA.

Brantingham, P.J. and Brantingham, P.L. (1975). The spatial patterning of Burglary. *Howard Journal of Penology and Crime Prevention, 14:* 11-24.

Brantingham, P.L. and Brantingham, P.J. (1998). Mapping crime for analytic purposes: Location quotients, counts and rates. In. Weisburd, D. and McEwen, T. (eds.) *Crime Mapping and Crime Prevention. Crime Prevention Studies, Vol. 8:* 263-288.

Brantingham, P.L. and Brantingham, P.J. (1993a). Environment, routine, and situation: toward a pattern theory of crime. In. Clarke, R. and Felson, M. (eds.) *Routine activity and rational choice, advances in criminological theory, Vol. 5:* 259-294. Transaction Publishers: New Brunswick, NJ.

Brantingham, P.L. and Brantingham, P.J. (1993b). Nodes, paths and edges: Consideration on the complexity of crime and the physical environment. *Journal of Environmental Psychology, 13*: 32-28.

Brantingham, P.J. and Tita, G. (2008). Offender Mobility and Crime Pattern Formation from First Principles. In Liu, L. and Eck, J. (eds.) *Artificial Crime Analysis Systems: Using Computer Simulations and Geographic Information Systems,* Idea Press: Hershey, PA.

Brisgone, R. (2004). Report of qualitative analysis of displacement in a prostitution site. In Weisburd, D., Wyckoff, L., Ready, J., Eck, J., Hinkle, J., and Gajewski, F. (eds.) *Does crime just move around the corner? A study of displacement and diffusion in Jersey City, NJ:* 178-218. Report submitted to National institute of Justice. Grant no. 97-IJ-CX-0055. Washington, DC: US Department of Justice.

Brown, B. (1995). *CCTV in Town Centres: Three Case Studies.* Crime Detection and Prevention Series, Paper 68. London: Home Office.

Burgess, E. (1928). The growth of the city. In Park, R., Burgess, E., and McKenzie, R. *The City,* Chicago: university of Chicago Press.

Butler, G. (1994). Shoplifters' views on security: Lessons for crime prevention. In Gill, M. (ed.) *Crime at Work: Studies in Security and Crime Prevention.* London: Perpetuity Press.

Cameron, A., Kolodinski, E., May, H., and Williams, N. (2008). *Measuring the effects of video surveillance on crime in Los Angeles.* Report prepared for the California Research Bureau. USC School of Policy, Planning, and Development.

Caplan, J. (2011). Mapping the spatial influence of crime correlates: A comparison of operationalization schemes and implications for crime analysis and criminal justice practice. *Cityscape, 13*(3), 57-83.

Caplan, J., Kennedy, L., and Petrossian, G. (2011). Police-monitored cameras in Newark, NJ: A quasi-experimental test of crime deterrence. *Journal of Experimental Criminology, 7(3)*: 255-274.

Caplan, J., Kennedy, L., and Miller, J. (2011). Risk terrain modeling: Brokering criminological theory and GIS methods for crime forecasting. *Justice Quarterly, 25 (2)*: 360-381.

Caplan, J. and Kennedy, L. (2010). *Risk Terrain Modeling Manual.* Newark, NJ: Rutgers Center on Public Security.

Carcach, C. and Muscat, G. (2002). Location quotients and their use in the study of area crime careers and regional crime structures. *Crime Prevention and Community Safety: An International Journal, 4 (1):* 27-46.

Chainey, S. (2000). Optimizing closed-circuit television use. In La Vigne, N. and Wartell, J. (eds.) *Crime Mapping Case Studies: Successes in the field. Vol. 2.* Police Executive Research Forum: Washington, D.C.

Chakravart, I., Laha, R., and Roy, J. (1967). *Handbook of methods of applied statistics, Volume 1.* John Wiley and Sons.

Clarke, R. (1997). Introduction. In Clarke, R. (ed.) *Situational Crime Prevention, successful case studies, second edition.* Criminal Justice Press: Monsey NY.

Clarke, R. and Cornish, D. (1985). Modeling offenders' decisions: A framework for research and policy. In Tonry, M. and Norris, M. (ends). *Crime and Justice: An Annual Review of Research, Vol. 6.* Chicago: University of Chicago Press.

Clarke, R. and Eck, J. (2007). *Understanding risky facilities.* Problem-Oriented Guides for Police. Problem-Solving Tools Series. No. 6.

Clarke, R. and Eck, J. (2005). *Crime Analysis for Problem Solvers in 60 Small Steps.* U.S. Department of Justice Office of Community Oriented Policing Services. Washington, D.C.

Clarke, R. and Weisburd, D. (1994). Diffusion of crime control benefits. In Clarke, R. (ed.) *Crime Prevention Studies. Vol. 2:* 165-183. Criminal Justice Press: Monsey, NY.

Clear, T. (2010). Policy and evidence: The challenge to the American Society of Criminology. Presidential address to the American Society of Criminology. *Criminology, 48 (1):* 1-25.

Cohen, L. and Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review, 44:* 588-605.

Cook, T. and Campbell, D. (1979). *Quasi-experimentation: Design and analysis issues for field settings.* Rand McNally: Chicago, IL.

Copes, H., Hochstetler, and Cherbonneau, M. (2011). Getting the upper hand: Scripts for managing victim resistance in carjackings. *Journal of Research in Crime and Delinquency.* Published online before print 3 May 2011.

Cordner, G. (2010). *Reducing fear of crime: Strategies for police.* U.S. Department of Justice. Office of Community Oriented Policing Services.

Cornish, D. and Clarke, R. (2003). Opportunities, precipitators and criminal decisions: A reply to Wortley's critique of situational crime prevention. In Smith, M. and Cornish, D. (eds.) *Theory for Practice in Situational Crime Prevention. Crime Prevention Studies, Vol. 16.* Lynne Rienner Publishers: Boulder, CO.

Cornish, D. and Clarke, R. (1987). Understanding crime displacement: An application of rational choice theory. *Criminology, 25(4):* 933-947.

Cornish, D. and Clarke, R. (1986). *The reasoning criminal: Rational choice perspectives on offending.* New York: Springer-Verlag.

Cusson, M. (1993). Situational deterrence: Fear during the criminal event. In Clarke, R. (ed.), *Crime Prevention Studies, Vol. 1:* 55-68. Criminal Justice Press: Monsey, NY.

Dalton, E. (2003). *Lessons in preventing homicide.* Project Safe Neighborhoods Report. Lansing, MI. School of Criminal Justice, Michigan State University.

Di Ionno (2011). *Cleaned crime scene can't wash away fear after fatal shooting of Newark police officer.* The Newark Star Ledger. Originally published May 28, 2011. Retrieved online at: http://blog.nj.com/njv_mark_diionno/2011/05/diionno_crime_scene_is_cleaned.html

Ditton, J. and Short, E. (1999). Yes it works. No it doesn't: Comparing the effects of open-street CCTV in two adjacent Scottish town centres. In Tilley, N. and Painter, K. (eds.) *Surveillance of Public Space: CCTV, Street Lighting and Crime Prevention. Crime Prevention Studies, 10.* Criminal Justice Press: Monsey, NY.

Ditton, J. and Short, E. (1998). When open street CCTV appears to reduce crime: Does it just get displaced elsewhere? *CCTV Today, 5(2)*: 13-16.

Durlauf, S. and Nagin, D. (2011). Imprisonment and crime: Can both be reduced? *Criminology and Public Policy, 10 (1)*: 13-54.

Eck, J. (2002). Preventing crime at places. In Sherman, L. Farrington, D. Welsh, B. and Mackenzie, D. (eds.), *Evidence-Based Crime Prevention:*241-294. Routledge: NY, NY.

Eck, J. (1994). *Drug markets and drug places: A case-controlled study of spatial structure of illicit dealing*. Unpublished Ph.D. Dissertation: University of Maryland, College Park.

Eck, J., Clarke, R. and Guerette, R. (2007). Ricky facilities: Crime concentration in homogeneous sets of establishments and facilities. In Farrel, G., Bowers, K., Johnson, S., and Townsley, M. (eds.). *Imagination for Crime Prevention. Essays in Honour of Ken Pease. Crime Prevention Studies*, 21: 225-264. Criminal Justice Press: Monsey, NY.

Eck, J. and Weisburd, D. (eds.) (1995). *Crime and place. Crime prevention studies Volume 4.* Criminal Justice Press: Monsey, NY and Police Executive Research Forum: Washington, DC.

Eck, J. and Spelman, W. (1987). *Problem solving: Problem-oriented policing in Newport News.* National Institute of Justice.

Ermino, V. (2007). *As police search for suspects, an angry Newark seeks justice.* The Newark Star Ledger. Originally published August 8, 2007. Retrieved online at: http://blog.nj.com/ledgerarchives/2007/08/as_police_search_for_suspects.html

Farrington, D., Gill, M., Waples, S. and 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:* 21-28.

Farrington, D., Bennett, T., and Welsh, B. (2007). The Cambridge evaluation of the effects of CCTV on crime. In Farrel, D., Bowers, K., Johnson, S. and Towsley, M. (eds.) *Imagination for Crime Preventions. Essays in Honour of Ken Pease. Crime Prevention Studies, Vol. 21.* Criminal Justice Press: Monsey, NY.

Farrington, D., Gottfredson, D., Sherman, L. and Welsh, B. (2002). The Maryland scientific methods scale. In Sherman, L., Farrington, D., Welsh, B. and Mackenzie, D. (eds.) *Evidence-Based Crime Prevention. Revised Edition.* Routledge: NY.

Farrell, G., Tseloni, A., Mailley, J. and Tilley, N. (2011). The crime drop and the security hypothesis. *Journal of Research in Crime and Delinquency, 48 (2):* 147-175.

Farrell, G. and Pease, K. (1993). *Once bitten, twice bitten: repeat victimisation and its implications for crime prevention.* Home Office Crime Prevention Unit paper 46. Home Office: London, UK.

Felson, M. (2002). *Crime and Everyday Life. 3rd Edition.* Sage Publications: Thousand Oaks, London, New Delhi.

Felson, M. (1995). Those who discourage crime. In Eck, J. and Weisburd, D. (eds.), *Crime and Place: Crime Prevention Studies. Vol. 4.* Washington, D.C.: Police Executive Research Forum.

Forrester, D., Frenz, S., O'Connel, M., and Pease, K. (1990). *The Kirkholt Burglary Prevention Project.* Home Office Crime Prevention Unit paper 13. Home Office: London, UK.

Foucault, M. (1977). *Discipline and punish: The birth of the prison.* Translated by Sheirdan, A. Vintage: New York.

Freundschuh, S. and Egenhofer, M. (1997). Human conceptions of spaces: Implications for GIS. *Transactions in GIS, 2(4):* 361-375.

Fried, C. (1996). America's safest city: Amherst, NY; The most dangerous: Newark, NJ CNN Money Magazine. November.

Fyfe, N. and Bannister, J. (1996). The eyes on the street: Closed circuit television surveillance in public spaces. *Area, 28(1)*: 37-46.

Gibson, C., Miller, M., Jennings, W., Swatt, M., and Grover, A. (2009). Using propensity score matching to understand the relationship between gang membership and violent victimization: A research note. *Justice Quarterly, 26 (4):* 625-643.

Gill, M., Rose, A., Collins, K., and Hemming, M. (2006). Redeployable CCTV and drug-related crime: A case of implementation failure. *Drugs: education, prevention and policy,* 13(5): 451-460

Gill, M. and Spriggs, A (2005). *Assessing the impact of CCTV.* London: Home Office Research Study No. 292.

Gill, M., Spriggs, A,; Allen, J.; Hemming, M, Jessiman, P. and Kara, D. (2005). *Control room operation: Findings form control room observations.* London: Home Office

Gill, M., and Loveday, K (2003). What do offenders think about CCTV? *Crime Prevention and Community Safety: An International Journal, 5(3):*17-25.

Gill, M. and Turbin, V. (1998). CCTV and shop theft: Towards a realistic evaluation. In. Norris, C., Moran, J. and Armstrong, G. (eds.) *Surveillance, Closed Circuit Television, and Social Control.* Ashgate

Goldstein, H. (1990). *Problem-oriented policing.* Temple University: Philadelphia.

Goldstein, H. (1979). Improving policing: A problem-oriented approach. *Crime and Delinquency,* 25: 236-258.

Griffiths, E., Yule, C., and Gartner, R. (2011). Fighting over trivial things: Explaining the issue of contention in violent altercations. *Criminology, 49 (1):*61-94.

Groff, E. (2007). Situating simulation to model human spatio-temporal interactions: An example using crime events. *Transactions in GIS*, 11(4), 507-530.

Guo, S. and Fraser, M. (2010). *Propensity score analysis: Statistical methods and applications.* Advanced Quantitative Techniques in the Social Sciences Series, Vol. 12. Sage Publications.

Haggerty, K., Wilson, D., and Smith, G. (2011). Theorizing surveillance in crime control. *Theoretical Criminology, 15(3)*: 231-237.

Harocopos, A. and Hough, M. (2005) *Drug dealing in open air markets.* Problem-Oriented Guides for Police. Problem-Specific Guides Series: No. 31. U.S. Department of Justice. Office of Community Oriented Policing Services. Washington, D.C.

Hawken, A. and Kleiman, M. (2009). *Managing drug-involved probationers with swift and certain sanctions: Evaluating Hawaii's HOPE.* NCJ 229023. Washington, DC: National Institute of Justice.

Honess, T. and Charman, E. (1992). *Closed Circuit Television in Public Places: its Acceptability and Perceived Effectiveness.* Police Research Group: Crime Prevention Unit Series, Number 35. London: Home Office.

Hunter, A. and Baumer, T. (1982). Street traffic, social integration, and fear of crime. *Sociological Inquiry, 52:* 122-131.

Infogroup. (2010). *Enhanced business and residential data: The importance of coverage, accuracy and recency for GIS data sets.* Infogroup: Government Division.

Ittelson, W. (1973). Environment perception and contemporary perceptual theory. In. Ittelson, W. (ed.) *Environment and Cognition:* 1-19. New York: Seminar.

Jacobs , B ., Topalli, V. and W right, R . (2000). Managing retaliation: Drug robbery and informal sanction threats . *Criminology, 38:* 171-198.

Johnson, S. and Bowers, K. (2010). Permeability and burglary risk: Are cul-de-sacs safer? *Journal of Quantitative Criminology, 26*: 89-111.

Johnson, S.; Bowers, K.; Birks, D.; and Pease, K. (2009). Predictive mapping of crime by ProMap: Accuracy, units of analysis, and the environmental backcloth. In Weisburd, D., Bernasco, W. and Bruinsma, G. (eds.), *Putting Crime in its Place: Units of Analysis in Geographic Criminology.* New York: Springer.

Johnson, S. and Bowers, K. (2004). The burglary as clue to the future. *European Journal of Criminology, 44(1):* 237-255.

Johnson, E. and Payne, J. (1986). The decision to commit a crime: An information-processing analysis. In Cornish, D. and Clarke, R. (eds.) T*he reasoning criminal: Rational choice perspectives on offending:* 170-185. Springer-Verlag: New York.

Kansas City, Missouri, Police Department (1977). *Response time analysis: Volume II-Part I crime analysis.* United States Department of Justice, Office of Justice Programs, National Institute of Justice: Washington, D.C.

Kelling, G. and Coles, C. (1996). *Fixing broken windows: Restoring order and reducing crime in our communities.* Touchstone: NY, NY.

Kennedy, D. (2008). *Deterrence and crime prevention: Reconsidering the prospect of sanction.* Routledge Press: London.

Kennedy, D. (1998). Pulling levers: Getting deterrence right. *National Institute of Justice Journal,* July 2-8.

Kennedy, D., Braga, A. and Piehl, A. (1998). The (un)known universe: Mapping gangs and gang violence in Boston. In Weisburd, D. and McEwen, T. (eds.) *Crime Mapping and Crime Prevention. Crime Prevention Studies, Vol. 8.* Lynne Rienner Publishers.

Kennedy, L. and Forde, D. (1990). Routine activities and crime: An analysis of victimization in Canada. *Criminology, 28 (1):* 137-152.

Kennedy, L., Caplan, J., and Piza, E. (2011). Risk clusters, hotspots, and spatial intelligence: Risk terrain modeling as an algorithm for police resource allocation strategies. *Journal of Quantitative Criminology, 27(3)*: 339-362.

Kennedy, L. and Van Brunschot, E. (2009). *The risk in crime.* Roman & Littlefield Publishers: Lanham, Boulder, New York, Toronto, Plymouth, UK.

King, J., Mulligan, D, and Raphael, S. (2008). *CITRIS Report: The San Francisco community safety camera program. An evaluation of the effectiveness of San Francisco's community safety cameras. Research in the Interest of Society*. Center for Information Technology Research in the Interest of Society, University of California, Berkeley.

La Vigne, N., Lowry, S., Markman, J., Dwyer, Al. (2011a). *Evaluating the use of public surveillance cameras for crime control and prevention.* US Department of Justice, Office of Community Oriented Policing Services. Urban Institute, Justice Policy Center: Washington, DC.

La Vigne, N., Lowry, S., Markman, J., Dwyer, Al. (2011b). *Using public surveillance systems for crime control and preventions: A practical guide for law enforcement and their municipal partners.* US Department of Justice, Office of Community

Oriented Policing Services. Urban Institute, Justice Policy Center: Washington, DC.

La Vigne, N., and Lowry, S. (2011). *Evaluation of camera use to prevent crime in commuter parking lots: A randomized controlled trial.* Urban Institute, Justice Policy Center: Washington, DC.

Law Enforcement Information Technology Standards Council [LEITSC]. (2008). *Standard functional specifications for law enforcement computer aided dispatch (CAD) systems.* U.S. Department of Justice, Office of Justice Programs, Bureau of Justice Assistance, and the National Institute of Justice.

Lechner, M. (2002). Some practical issues in the evaluation of heterogeneous labor market programmes by matching methods. *Journal of the Royal Statistical Society, a (165):* 59-82.

Leman-Langlois, S. (2002). The myopic panopticon: The social consequences of policing through the lens. *Policing and Society, 13 (1):* 43-58.

Leuven, E. and Sianesti, B. (2003). PSMATCH2: State module to perform full mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing. Retrieved online at: http://ideas.repec.org/c/boc/bocode/s432001.html.

Lomell, H. (2004). Targeting the unwanted: Video surveillance and categorical exclusion in Oslo, Norway. *Surveillance& Society, 2:* p. 346-360.

Loughran, T., Piquero, A., Fagan, J., and Mulvery, E. (2012). Differential deterrence: Studying heterogeneity and changes in perceptual deterrence among serious youthful offenders. *Crime & Delinquency, 58 (1):* 3-27.

Louis, A. (1975). The worst American city. *Harper's, January 1975*: 67-71.

Loukaitou, S. (1999). Hotspots of bus crime: The importance of environmental attributes. *Journal of the American Planning Association, 65 (4):* 395-411.

Lynch, K. (1960). *Image of the city.* Cambridge, MA: MIT Press.

MacDonald, J. and Lattimore, P. (2010). Count models in criminology. In Piquero A. and Weisburd, D. (eds.) *Handbook of Quantitative Criminology.* Springer.

Mackay, D. (2006). The changing nature of public-space CCTV. *Security Journal, 19:* 128-142.

Maxfield, M. and Babbie, E. (2001). *Research methods for criminal justice and criminology. Third edition.* Wadsworth/Thompson Learning: Belmont, CA.

Mazerolle, L., Hurley, D., & Chamlin, M. (2002). Social behavior in public space: An analysis of behavioral adaptations to CCTV. *Security Journal, 15 (3):* 59-75.

McCord, E. and Ratcliffe, J. (2007). A micro-analysis of the demographic and criminogenic environment of drug markets in Philadelphia. *Australian & New Zealand Journal of Criminology, 40 (1):* 43-63.

McGarrell, E. and Chermak, S. (2003). *Strategic approaches to reducing firearms violence: Final report on the Indianapolis violence reduction partnership.* Final report submitted to the US National Institute of Justice. East Lansing, MI: School of Criminal Justice, Michigan State University.

McGloin, J. (2005). Policy and intervention considerations of a network analysis of street gangs, *Criminology & Public Policy, 4 (3):* 601-630.

Nagin, D. (2010). Imprisonment and crime control: Building evidence-based policy. In Rosenfeld, R., Quinet, K., and Garcia, C. (eds.), *Contemporary Issues in Criminological Theory and Research: The Role of Social Institutions (Papers from the American Society of Criminology 2010 Conference)*. Belmont, CA: Wadsworth.

Nagin, D. and Pogarsky, G. (2001). Integrating celerity, impulsivity, and extralegal sanction threats into a model of general deterrence: Theory and evidence. *Criminology, 39 (4)*: 865-891.

Newman, O. (1972). *Defensible Space: Crime prevention through urban design*. New York: Macmillan.

Norris, C. (2003). From personal to digital: CCTV, the panopticon, and the technological mediation of suspicion and social control. In Lyon, D. *(ed.) Surveillance as Social Sorting: Privacy, Risk and Digital Discrimination.* Routledge: London and New York.

Norris, C. and Armstrong, G. (1999a). CCTV and the social structuring of surveillance. In Tilley, N. and K. Painter (1999) *Surveillance of Public Space: CCTV, Street Lighting and Crime Prevention.* Crime Prevention Studies Vol. 10. Criminal Justice Press: Monsey, NY.

Norris, C. and Armstrong, G. (1999b). *The maximum surveillance society. The rise of CCTV*. Berg: Oxford.

Norris, C. and McCahill, M. (2006). CCTV: Beyond penal modernism? *British Journal of Criminology, 46*: 97-118.

Oberwittler, D. and Wikström, P. (2009). Why smaller is better: Advancing the study of the role of behavioral contexts in crime causation. In Weisburd, D., Bernasco, W. and Bruinsma, G. (eds.), *Putting Crime in its Place: Units of Analysis in Geographic Criminology,* New York: Springer.

Osgood, W. (2000). Poisson-based regression analysis of aggregate crime rates. *Journal of Quantitative Criminology,* 16: 21-43.

Ozer, M. and Engel, R. (2012). Revisiting the use of propensity score matching to understand the relationship between gang membership and violent victimization: A cautionary note. *Justice Quarterly, 29 (1):* 105-124.

Painter, K. and Tilley, N. (1999). Seeing and being seen to prevent crime. In. Tilley, N. and Painter, K. (eds.) *Surveillance of Public Space: CCTV, Street Lighting and Crime Prevention. Crime Prevention Studies Vol. 10.* Criminal Justice Press: Monsey, NY.

Park, R. (1936). Human ecology. *American Journal of Sociology, 42*: 158.

Paternoster, R. (1987). The deterrent effect of the perceived certainty and severity of punishment: A review on the evidence and issues. *Justice Quarterly, 4 (2)*: 173-217.

Paternoster, R., Saltzman, L., Chiricos, T., and Veldo, G. (1982). Perceived risk and deterrence: Methodological artifacts in perceptual deterrence research. *Journal of Criminal Law and Criminology, 73*: 1238-1258.

Pawson, R. and Tilley, N. (1994). What works in evaluation research? *British Journal of Criminology* 34(3): 291-306.

Pease, K. (1999). A review of street lighting evaluations: Crime reduction effects. In. Tilley, N. and Painter, K. (eds.) *Surveillance of Public Space: CCTV, Street Lighting and Crime Prevention. Crime Prevention Studies Vol. 10.* Criminal Justice Press: Monsey, NY.

Phillips, C. (1999). A review of CCTV evaluations: Crime reduction effects and attitudes towards its use. In Tilley, N. and Painter, K. (eds.) *Surveillance of Public Space: CCTV, Street Lighting and Crime Prevention. Crime Prevention Studies Vol. 10.* Criminal Justice Press: Monsey, NY.

Piquero, A. and Pogarsky, G. (2002). Beyond Stafford and Warr's reconceptualizing of deterrence: Personal and vicarious experiences, impulsivity, and offending behavior. *Journal of Research in Crime and Delinquency, 39:* 153-186.

Piza, E., Caplan, J. and Kennedy, L. (2010). *Discovering opportunities for early police intervention. An analysis of shooting incidents captured on CCTV in Newark, NJ*

Presentation at the American Society of Criminology Annual Meeting. San Francisco, CA.

Piza, E. and O'Hara, B. (2012). Saturation foot-patrol in a high-violence area: A quasi-experimental evaluation. *Justice Quarterly.* Published online before print 12 March 2012.

Pogarsky, G. (2002). Identifying "deterrable" offenders: Implications for research on deterrence. *Justice Quarterly, 19:* 431-452.

Poyner, B. (2006). *Crime-free housing in the 21st century.* Jill Dando Institute of Crime Science, University College of London. Brook house Publishing: London.

Poyner, B. (1991). Situational crime prevention in two parking facilities. *Security Journal, 2:* 96-101.

Ratcliffe, J. (2006a). *Video Surveillance of Public Places.* Problem-Oriented Guides for Police. Response Guide Series. Guide No. 4. U.S. Department of Justice Office of Community Oriented Policing Services. Center for Problem-Oriented Policing.

Ratcliffe, J. (2006b). A temporal constraint theory to explain opportunity-based spatial offending patterns. *Journal of Research in Crime and Delinquency, 43(3):* 261-191.

Ratcliffe, J. and Groff, E. (2011). *Preliminary findings from the Philadelphia CCTV study.* Presentation at the American Society of Criminology Annual Meeting. Washington DC.

Ratcliffe, J, Taniguchi, T, Groff, E and Wood, J. (2011). The Philadelphia foot patrol experiment: A randomized controlled trial of police patrol effectiveness in violent crime hotspots. *Criminology, 49(3):* 795-831.

Ratcliffe, J., Taniguchi, T., and Taylor, R. (2009). The crime reduction effects of public CCTV cameras: A multi-method spatial approach. *Justice Quarterly, 26 (4)*:746-770.

Ratcliffe, J. and Breen, C. (2008). Spatial evaluation of police tactics in context (SEPTIC) spreadsheet, version 3 (spring 2010). Downloaded from www.jratcliffe.net.

Ratcliffe, J. and Rengert, G. (2008). Near repeat patterns in Philadelphia shootings. *Security Journal, 21 (1-2)*: 58-76.

Rengert, G. and Lockwood, B. (2009). Geographical units of analysis and the analysis of crime. In Weisburd, D., Bernasco, W. and Bruinsma, G. (eds.), *Putting Crime in its Place: Units of Analysis in Geographic Criminology*, New York: Springer.

Rengert, G., Ratcliffe, J. and Chakravorty (2005) *Policing Illegal Drug Markets: Geographic Approaches to Crime Reduction.* Criminal Justice Press: Monsey, NY.

Robinson, W. (1950). Ecological correlations and the behavior of individuals. *American Sociological Review, 15*: 351-357.

Roncek, D. (2000). Schools and crime. In V. Goldsmith, V., McGuire, P., Mollenkopf, J. and Ross, A. (eds.), *Analyzing crime patterns: Frontiers of practice* (pp. 153-165). Thousand Oaks, CA: Sage Publications.

Roncek, D. and Faggiani, D. (1985). High schools and crime. *Sociological Quarterly, 26:* 491-505.

Rosenbaum, P. and Rubin, D. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *American Statistician, 39 (1):* 33-38.

Rosenbaum, P. and Rubin, D. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70 (1):* 41-55.

Sacco, V. and Kennedy, L. (2002). *The criminal event: Perspectives in space and time.* Wadsworth.

Santiago, K. (2009). *Surveillance cameras at Newark public housing credited with reducing crime.* The Newark Star Ledger. Originally published September 13, 2009. Retrieved online at: http://www.nj.com/news/index.ssf/2009/09/surveillance_cameras_at_newark.html

Sarno, C. (1996). The impact of closed circuit television on crime in Sutton town centre. In Bulos, M. and Grant, D. (eds.) *Towards a safer Sutton? CCTV one year on.* London, UK: London Borough of Sutton.

Sarno, C., Hough, M., and Bulos, M. (1999). *Developing a picture of cctv in Southwark Towne Centres: Final Report.* London: Criminal Policy Research Unit, South Bank University.

Scott, M. and Dedel, K. (2006). *Assaults in and around bars. 2nd edition.* Problem-Oriented Guides for Police. Problem-specific Guides Series. Guide No. 4. U.S. Department of Justice, Office of Community Oriented Policing Services, Center for Problem-Oriented Policing: Washington, D.C.

Shaw, C. and Mckay, H. (1942). *Juvenile delinquency in urban areas.* Chicago: university of Chicago Press.

Shah, S. and Braithwaite, J. (2012). Spread too thin: Analyzing the effectiveness of the Chicago camera network on crime. *Police Practice and Research.* Published online before print 4 April 2012.

Sherman, L. (1990). Police crackdowns: Initial and residual deterrence. In Tonry, M. and Morris, N. (eds.), *Crime and Justice: A Review of Research, Vol. 12:* 1-48. University of Chicago Press: Chicago.

Sherman, L., Gartin, P., and & Buerger, M. (1989). Hot spots of predatory crime: Routine activities and the criminology of place. *Criminology, 27(1):* 27-55.

Sherman, L. and Rogan, D. (1995a). Effects of gun seizures on gun violence: 'Hot Spots' patrol in Kansas City. *Justice Quarterly, 12*: 673-694.

Sherman, L. and Rogan, D. (1995b). Deterrent effects of police raids on crack houses: A randomized controlled experiment. *Justice Quarterly*, *12*: 755-782.

Sherman, L. and Weisburd, D. (1995). General deterrent effects of police patrol in crime hot spots: A randomized controlled trial. *Justice Quarterly, 12:* 625-648.

Short E. and Ditton, J. (1996) *Does closed circuit television prevent crime? An evaluation of the use of CCTV surveillance cameras in Airdire towne centre.* Edinburgh: Scottish Officer Central Research Unit.

Short, E. and Ditton, J. (1995). Does CCTV affect crime? *CCTV Today, 2(2):*10-12.

Sivarajasingam, V., Shepherd, J., and Matthews, K. (2003). Effect of urban closed circuit television on assault injury and violence detection. *Injury Prevention, 9,* 312-316.

Sivarajasingam, V. and Shepherd, J, (1999). Effect of closed circuit television on urban violence. *Journal of Accident and Emergency Medicine, 26:*225-257.

Skinns, D. (1998). Crime reduction, diffusion, and displacement: Evaluating the effectiveness of CCTV. In Norris, C., Morgan, J. and Armstrong, G. (eds.) *Surveillance, Closed Circuit Television, and Social Control.* Aldershot, UK: Ashgate.

Skogan, W. and Frydl, K. (2004). *Fairness and effectiveness in policing: the evidence.* Committee to Review Research on Police Policy and Practices. Committee on Law and Justice, Division of Behavioral and Social Sciences and Education. Washington, DC: The National Academies Press.

Smith, J. and Todd, P. (2005). Does matching overcome LaLonde's critique of non-experimental estimators? *Journal of Econometrics, 125:* 305-353.

Smith, G. (2004). Behind the scenes: examining constructions of deviance and informal practices among CCTV control room operators in the UK. *Surveillance & Society*, 2 (2/3): 376-395.

Smith, M. and Clarke, R. (2000). Crime and public transport. *Crime and Justice, 27*: 169-233.

Spelman, W. and Brown, D. (1981). *Calling the police: citizen reporting of serious crime.* Police Executive Research Forum: Washington, D.C.

Squires, P. (2000). *CCTV and crime reduction in Crawley.* Brighton, UK: Health and Social Police Research Center.

Squires, P. (1998). *An evaluation of the Ilford Town Centre CCTV system.* Brighton, UK: Health and Social Policy Research Centre.

Stucky, T. and Ottensmann, J. (2009). Land use and violent crime. *Criminology, 47(4):* 1223-1264.

Taylor, B., Koper, C., and Woods, D. (2011). A randomized controlled trial of different policing strategies at hot spots of violent crime. *Journal of Experimental Criminology, 7(2):* 149-181.

Taylor, R. (1997). Social order and disorder of street-blocks and neighborhood: Ecology, microecology and the systemic model of social disorganization. *Journal of Research in Crime and Delinquency 24*, 113-155.

Taylor, R. & Harrell, A. (1996). *Physical Environment and Crime.* Washington, D.C.: National Institute of Justice.

Taylor, R., Gottfredson, S., and Brower, S. (1984). Block crime and fear: defensible space, local social ties, and territorial functioning. *Journal of Research in Crime and Delinquency, 21:* 303-331.

Tilley, N. (1993). *Understanding car parks, crime and cctv.* Crime Prevention Unit Series Paper 42 Home Office: London, UK.

Tita, G. and Griffiths, E. (2005). Traveling To Violence: The case for a mobility-based spatial typology of homicide. *Journal of Research in Crime & Delinquency*, 42: 275-308.

Tittle, C., Botchkovar, E., and Antonaccio, O. (2011). Criminal contemplation, national context, and deterrence. *Journal of Quantitative Criminology, 27:* 225-249.

Tuttle, B. (2009). *How Newark became Newark*. Piscataway: Rutgers University Press.

Uniform Crime Report [UCR]. (2011). Crime in the United States 2009: Preliminary Annual Uniform Crime Report, U.S. Department of Justice, Federal Bureau of Investigation Washington, DC.

Usher, N. (2003). Video surveillance comes to big easy. *San Diego Union-Tribune.* Originally published August 24, 2003.

U.S. Census Bureau (2011). QuickFacts from US Census Bureau. Retrieved on March 12, 2011 from http://quickfacts.census.gov.

U.S. Department of Housing and Development. (2000). *In the crossfire: The impact of gun violence on public housing communities*. U.S. Department of Housing and Development: Washington, DC.

Van Dijk, J. (1006). What goes up, comes down: Explaining the falling crime rates. *Criminology in Europe, Newsletter of the European Society of Criminology, 5 (3):* 17-18.

van Wilsem, J. (2009). Urban streets as micro contexts to commit violence. In Weisburd, D., Bernasco, W. and Bruinsma, G. (eds.), *Putting Crime in its Place: Units of Analysis in Geographic Criminology.* New York: Springer.

Waples, S. and Gill, M. (2006). The effectiveness of redeployable CCTV. *Crime Prevention and Community Safety, 8*: 1-16.

Weisburd, D. (2008). *Place-based policing.* Ideas in Policing Series. Washington, DC: Police Foundation.

Weisburd, D., Telep, C; Hinkle, J., and Eck, J. (2010). Is problem-oriented policing effective in reducing crime and disorder? Findings from a Campbell systematic review. *Criminology and Public Policy, 9(1):* 139-172.

Weisburd, D., Bernasco, W., & Bruinsma, G. (2009). Units of analysis in geographic criminology: Historical development, critical Issues, and open questions. In Weisburd, D., Bernasco, W. and Bruinsma, G. (eds.), *Putting Crime in its Place: Units of Analysis in Geographic Criminology*, New York: Springer.

Weisburd, D., Morris, N., and Groff, E. (2009). Hot spots of juvenile crime: A longitudinal study of arrest incidents at street segments in Seattle, Washington. *Journal of Quantitative Criminology, 25(4):* 443-467.

Weisburd, D., Einat, T., and Kowalski, M. (2008). The miracle of the cells: An experimental study of interventions to increase payment of court-ordered financial obligations. *Criminology and Public Policy,* 7: 9-36.

Weisburd, D., Morris, N., and Ready, J. (2008). Risk-focused policing at places: An experimental evaluation. *Justice Quarterly, 25(1)*: 163-200.

Weisburd, D., Wyckoff, L., Ready, J., Eck, J., Hinkle, J. and Gajewski, F. (2006). Does crime just move around the corner? A controlled study of spatial displacement and diffusion of crime control benefits. *Criminology, 44(3),* 549-592.

Weisburd, D., Bushway, S., Lum, C. and Yang, S. (2004). Trajectories of crime at places: A longitudinal study of street segments in the city of Seattle. *Criminology, 42(2)*: 283-321.

Weisburd, D., Lum, C., and Petrosino, A. (2001). Does research design affect study outcomes in criminal justice? *The Annals of the American Academy of Social and Political Sciences*, 578: 50-70.

Weisburd, D. and Braga, A. (eds.) (2006). *Police innovation: Contrasting perspectives*. Cambridge, UK: Cambridge University Press.

Weisburd, D. and Eck, J. (2004). What can police do to reduce crime, disorder, and fear? *Annals of the American Academy of Political and Social Science,* 593: 42-65.

Weisburd, D. and Green, L. (1994). Defining the street-level drug market. In Mackenzie, D. and Uchida, C. (eds.) *Drugs and Crime: Evaluating Public Policy Initiatives.* P. 61-76.

Weisburd, D. and Green, L. (1995) Policing drug hot spots: The Jersey City drug market analysis experiment. *Justice Quarterly, 12: 711-736.*

Weisburd, D. and Neyroud, P. (2011). Police science: Toward a new paradigm. *New Perspectives in Policing. Executive Session on Policing and Public Safety.* Harvard Kennedy School, Program in Criminal Justice. National Institute of Justice.

Wells, W., Wu, L. & Ye, X. (2011). Patterns of near-repeat gun assaults in Houston. *Journal of Research in Crime and Delinquency.* Published online 12 May 2011.

Welsh, B. and Farrington, D. (2009). Public area CCTV and crime prevention: An updated systematic review and meta-analysis. *Justice Quarterly, 26 (4):* 716-745.

Welsh, B. and Farrington, D. (2007). *Closed-circuit television surveillance and crime prevention: A systematic review.* Stockholm, Sweden: National Council for Crime Prevention.

Welsh, B. and Farrington, D. (2004). Surveillance for crime prevention in public space: Results and policy choices in Britain and America. *Criminology and Public Policy, 3(3), 497-526.*

Welsh, B. and Farrington, D. (2002). *Crime prevention effects of closed circuit television: A systematic review.* London: Home Office (Research Study No. 25).

Welsh, B., Peel, M., Farrington, D., Elffers, H. and Braga, A. (2011). Research design influence on study outcomes in crime and justice: A partial replication with public area surveillance. *Journal of Experimental Criminology, 7(2):* 183-198.

Whitlow, J. (2010). Newark's garden spires: Attacking, at last, a hotbed of drug trade in the city. The Newark Star Ledger. Originally published March 19th. Retrieved online from: http://blog.nj.com/njv_joan_whitlow/2010/03/newarks_garden_spires_attackin.html.

Whyte, W. (1943). *Street corner society: The social structure of an Italian slum.* Chicago: University of Chicago Press.

Wiebe, D., Anderson, E., Richmond, T., Nance, M., and Branas, C. (2010). N*eighborhood violence and safe routes to school.* Presentation at the American Society of Criminology Annual Meeting. San Francisco, CA.

Wilson, O. W. (1963). *Police Administration.* New York: McGraw-Hill.

Winge S., and Knutsson, J. (2003). An evaluation of the CCTV scheme at Oslo central railway station. *Crime Prevention and Community Safety: An International Journal, 5 (3)*: 49-59.

Zanin, N., Shane, J., and Clarke, R. (2004). *Reducing Drug Dealing in Private Apartment Complexes in Newark, New Jersey.* A Final Report to the U.S. Department of Justice, Office of Community Oriented Policing Services on the Field Applications of the Problem-Oriented Guides for Police Project.

Eric L. Piza: Curriculum Vitae

EDUCATION

May 2012 — **Rutgers University School of Criminal Justice:** Newark, NJ
*PhD in Criminal Justice
*Dissertation Topic: *Identifying the Best Context for CCTV Camera Deployment: An Analysis of Micro-Level Features*

May 2004 — **Rutgers University:** Newark, NJ
*MA in Criminal Justice

Jan. 2004 — **Rutgers University:** Newark, NJ
*BS in Criminal Justice
*AS in Psychology

PROFESSIONAL EMPLOYMENT

Mar. 2012-Present — **Rutgers School of Criminal Justice/Rutgers Center on Public Security**
*Research Assistant Professor/Research Director of Crime Science

Feb. 2007-Mar. 2012 — **Newark Police Department**
*Geographic Information Systems Specialist

Sept. 2003-Feb. 2007 — **Police Institute at Rutgers-Newark**
*Research Program Coordinator

Nov. 2000-Sept. 2003 — **Police Institute at Rutgers-Newark**
*GIS Analyst

TEACHING EXPERIENCE

2010-Present — **International Association of Crime Analysts**
***Training Instructor**
-Classes taught: Crime Mapping and Analysis, Problem Analysis

2005-2009 — **Rutgers University, School of Criminal Justice**
***Part Time Lecturer**
-Classes taught: Contemporary Problems in Policing, Data Analysis, Police and the Community, Police Problem Solving

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GRANT AND FUNDING SUPPORT

December 2011 — **Rutgers School of Criminal Justice Dean's Research Award ($2,499.00)**
***Principal Investigator**
-Title: Drug Market Norms and Behaviors: A Qualitative Analysis of Street-Level Narcotics Transactions

October 2010 — **National Institute of Justice, Research on Policing ($189, 968.77)**
***Co-Principal Investigator (Newark Police Department)**
-Title: Detection of crime, resource deployment, and predictors of success: A multi-level analysis of CCTV in Newark, NJ
-Co-Principal Investigators: Joel M. Caplan, PhD, Rutgers University; Leslie W. Kennedy, PhD, Rutgers University

May 2010 — **Association of Doctoral Programs in Criminology & Criminal Justice Research Support Award ($3,000)**
-Title: Identifying the Best Context for CCTV Camera Deployment: An

JOURNAL ARTICLES (REFEREED)

*__Piza, E.__ and O'Hara, B. (2012). Saturation Foot Patrol in a High-Violence Area: A Quasi-Experimental Evaluation. *Justice Quarterly.* Published online before print 12 March 2012.

*Kennedy, L., Caplan, J. & **Piza, E.** (2011). Risk Clusters, Hotspots, and Spatial Intelligence: Risk Terrain Modeling as an Algorithm for Police Resource Allocation Strategies. *Journal of Quantitative Criminology, 27(3):* 339-362.

MANUSCRIPTS UNDER REVIEW

*__Piza, E.,__ Caplan, J. and Kennedy, L. (Under Review). Is the punishment more certain? An analysis of CCTV detections and enforcement.

*Caplan, J., Kennedy, L., and **Piza, E.** (Revise and Resubmit). Violent crime forecasting with event dependent and contextual crime analysis techniques.

*Moreto, W., **Piza, E.,** and Caplan, J. (Under Review). A plague on both your houses? Risks, repeats, and reconsiderations of urban residential burglary.

INVITED BOOK CHAPTERS

***Piza, E.**, Kennedy, L. and Caplan, J. (2011). Police Resource Allocation. In Caplan, J. and Kennedy, L. (Eds.) *Risk Terrain Modeling Compendium.* Newark, NJ: Rutgers Center on Public Security

*Caplan, J., Kennedy, L. and **Piza, E.** (2011). Joint Utility of Hotspot, Near Repeat, and Risk Terrain Modeling Techniques for Crime Analysis. In Caplan, J. and Kennedy, L. (Eds.) *Risk Terrain Modeling Compendium.* Newark, NJ: Rutgers Center on Public Security

CONFERENCE AND PROFESSIONAL PRESENTATIONS

*Is the Punishment More Certain? Assessing Police Response to Criminal Incidents Detected by CCTV
Co-Authors: Joel M. Caplan, PhD, Rutgers University; Leslie W. Kennedy, PhD, Rutgers University
Academy of Criminal Justice Sciences Annual Meeting: March 2012, New York, NY

*Identifying Best Places for CCTV Camera Placements: An Analysis of Micro-Level Environmental Features
Co-Authors: Joel M. Caplan, PhD, Rutgers University; Leslie W. Kennedy, PhD, Rutgers University
American Society of Criminology Annual Meeting: November 2011, Washington, D.C.

*Risk Clusters, Hotspots, and Spatial Intelligence: Risk Terrain Modeling as an Algorithm for Police Resource Allocation Strategies
Co-Authors: Joel M. Caplan, PhD, Rutgers University; Leslie W. Kennedy, PhD, Rutgers University
National Institute of Justice Crime Mapping and Research Conference: October 2011, Miami, FL

*An Evaluation of a Foot-Patrol Saturation Initiative in Newark, NJ
Academy of Criminal Justice Sciences Annual Meeting: March 2011, Toronto, ON, Canada

*Selecting Target Areas for Police Interventions through a Weighted Analysis of Violence in Newark, NJ
Co-Author: Sgt. Brian O'Hara, M.A., Newark Police Department
ESRI Mid-Atlantic User Group Conference: December 2010, Philadelphia, PA

*Discovering Opportunities for Early Police Intervention. An Analysis of Shooting Incidents Captured on CCTV in Newark, NJ
Co-Authors: Joel M. Caplan, PhD, Rutgers University; Leslie W. Kennedy, PhD, Rutgers University

American Society of Criminology Annual Meeting: November 2010, San Francisco, CA

INVITED LECTURES AND SPEAKING ENGAGEMENTS

ACJS Conference Roundtable. Sustainable Justice: New York, NY
3/12/12
Moderator: Marissa P. Levy, The Richard Stockton College of New Jersey

Toronto Police Service: Online Presentation
11/2/11
Presentation: Operationalizing and Assessing the Spatial Influence of Environmental Features on Crime
Co-Presenter: Joel M. Caplan, Rutgers University
Attendees included newly hired crime analysts and the command staff of the Toronto Police Service.

Ontario Crime Analyst Network: Online Presentation
8/15/11
Presentation: Analyzing Crime Risk to Guide Crime Prevention
Co-Presenter: Joel M. Caplan, Rutgers University
Attendees included crime analysts from police departments across the Ontario, Canada region.

Essex County Prosecutor's Office Career Development Program
7/25/11
Presentation: The practical application of Crime Mapping by the Newark Police Department
Attendees included personnel from the Essex County Prosecutor's Office Division of Community Affairs and the Rutgers University Center for Community-Based Learning as well as approximately 50 honor-roll students from various Essex County High Schools.

ACJS Conference Roundtable. The Role of Crime Analysis Techniques in the U.S. and Canada: Toronto, ON, Canada
3/4/11
Moderator: Marissa P. Levy, The Richard Stockton College of New Jersey
Co-Discussants: D. Kim Rossmo, Texas State University; Manny San Pedro, Toronto Police Service; Christopher M. Sedelmair, University of New Haven

Rutgers School of Criminal Justice: Office of the Chancellor's Annual Junior Day
4/14/10
Careers in Law Enforcement Session
Presentation: Providing the "Intelligence" for Intelligence-led Policing. The crime analyst's role in Law Enforcement
Attendees included approximately 40 11th grade students from various high schools in the City of Newark

University of Scranton: Scranton, PA
12/2/09
Presentation: GIS in Law Enforcement. Problem Solving Analysis of the Newark PD
Attendees included Scranton Chief of Police David Elliott, Scranton Police Command Staff, personnel from the Pennsylvania Attorney General's Office, and Scranton University criminal justice faculty and students.

Passaic County College: Paterson, NJ
3/12/09
Presentation: Beyond the Meeting. The Daily Application of CompStat's Crime Reduction Principles
Attendees included the Passaic County student body as well as personnel from Paterson Police Department and Passaic County Sheriff's Office.

NJ State Police Regional Operations Intelligence Center: Hamilton, NJ
4/21/06
Presentation: Target Area Selection and Weekly Evaluation. GIS Analysis for Operation CeaseFire
Attendees included then Deputy Superintendent Christopher Andreachak and Regional Operations Intelligence Center personnel.

PROFESSIONAL COMMITTEES

Data Steering Committee for an NIJ funded study of Prisoner Cycling and its Effect on Crime
3/10-Present
Principal Investigator: Todd Clear, PhD, Rutgers School of Criminal Justice
A collection of stakeholders from each municipality included in the study brought together to discuss how to best collect, analyze, and interpret necessary crime data for this project.

NJ State Parole Board Mapping Committee
1/09-12/11
Coordinating Agency: NJ State Parole Board, District Office 9
A collaboration between the NJ State Parole board and the Newark Police Department which aims to digitize addresses of prisoners re-entering into the Greater Newark area within a GIS system.

Federal Bureau of Investigation Drug Arrest Analysis
12/09-12/11
Coordinating Agency: Federal Bureau of Investigation, Newark Office
A partnership between the FBI and Newark PD which analyzes drug arrests occurring within Newark for the purpose of informing FBI investigative efforts.

Safer Cities Partnership
11/00-1/09
Coordinating Agency: Police Institute
A committee comprised of criminal justice, community, social service, and religious organizations for the purpose of devising strategies to curtail violence in NJ communities and address public safety problems facing vulnerable populations. Safer Cities strategies include Operation CeaseFire, the Juvenile Justice Reentry Initiative, and the At-Risk caseload.

Newark, NJ Clinton Hill Weed and Seed Steering Committee:
12/05-8/07
Coordinating Agency: Clinton Hill Weed and Seed Committee
A committee comprised of law enforcement and community agencies for the purpose of devising strategies to curtail crime and institute community programs in the Clinton Hill neighborhood of Newark, NJ

Irvington, NJ Anti-Burglary Project
5/06-7/07
Coordinating Agency: Irvington PD
A partnership between Irvington Police Department and the Rutgers Police Institute which analyzed the occurrence of burglary in Irvington for the purpose of devising law enforcement strategies to address the crime**.**

NJ State Police Office of CeaseFire Operations Crime Mapping Committee
7/06-3/07
Coordinating Agency: NJ State Police
A committee of NJ State Police officials and external GIS analysts brought together for the purpose of discussing, designing, and implementing a state-wide, user-based GIS system for Operation CeaseFire.

Newark, NJ Office of the Mayor's Prisoner Reentry Steering Committee
8/06-3/07

Coordinating Agency: University of Medicine and Dentistry of New Jersey
A group brought together by Newark Mayor Cory Booker and the University of Medicine and Dentistry of NJ for the purpose of better understanding the issues facing individuals returning to the Newark area post-incarceration and designing a new system by which the city would address the needs of this population.