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Crime Reduction Effects of Open-street CCTVs in Cincinnati

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ABSTRACT

This study aims to address the conditional nature of the effectiveness of open-street CCTV (Closed Circuit Television). Therefore, this study examined the differences in the effects of CCTV between daytime crime and nighttime crime, between weekday crime and weekend crime, and across specific-crime offenses. Also, this study examined crime reduction effects of CCTV depending on CCTV site type (e.g., downtown location, business district, school/university location, or residential area). For the analyses, this study used HLM (hierarchical linear modeling) with 84 repeated measures across 34 camera locations in Cincinnati, OH and Z-tests in order to compare coefficients.

During the first stage of analysis, the findings showed that open-street CCTV did not have crime reduction effects on daytime crime, nighttime crime, weekday crime, weekend crime, robbery, auto theft, and theft from auto, whereas it had significant crime reduction effects on assault and burglary. During the second stage of analysis, location type was considered, and results showed that the crime reduction effects of open-street CCTVs during weekends varied depending on implementation sites. The reduction effects were greater in residential areas in comparison to the effects in business districts and downtown areas. The crime reduction effects of open-street CCTVs for robbery also varied depending on implementation site type. The reduction effects were greater in residential areas in comparison to business districts.

The final stage of analysis examined diffusion of benefits versus displacement effects. The findings supported the hypothesis that diffusion of benefits effects were greater than displacement effects. Specifically, WDQ analyses showed that when CCTV had crime reduction effects in target areas, diffusion of benefits rather than displacement occurred for daytime crime, nighttime crime, weekday crime, weekend crime, assault, robbery, and

burglary.

Although the findings of this study supported only some hypotheses (many were unsupported), they still produced important information for future research. That is, the effectiveness of open-street CCTVs may be conditional based on the timing of crime, the type of crime, and characteristics of implementation.

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CHAPTER I

INTRODUCTION

This study aims to address the conditional nature of the effectiveness of Closed Circuit Television (CCTV) for crime prevention in Cincinnati, Ohio. CCTV was originally developed to prevent crime in private places but has been rapidly spreading throughout the world to prevent crime in public places. The United Kingdom (U.K.) has implemented CCTVs in public places since the 1990s (Cerezo, 2013). Approximately 500,000 CCTVs have been implemented in public places in London, and thus far, it is estimated that over 4,200,000 CCTVs have been implemented in public places throughout the U.K. (Norris & McCahill, 2006). Since 1995, France has also implemented CCTVs in public places within approximately 300 cities (Hempel & Töpfer, 2009). In the United States (U.S.), CCTV installation in public places was not active in the past due to privacy concerns, but it has spread in recent years to meet the demands for policing and public safety (La Vigne, Lowry, Markman, & Dwyer, 2011). In Australia, CCTV installation in public places has been rapidly spreading since 199l (Dean Wilson & Sutton, 2003). Furthermore, the installation of CCTVs in public places has been pervasive in Asia and Africa. For example, with the active support of local governments, CCTVs have been implemented in public places in South Korea since 2002 (Cho, 2009) and South Africa has been installing CCTVs in public places in several major cities since the mid-2000s (Anton du & Louw, 2005). From these facts, it appears as though implementation of CCTVs is advocated on an international level as a mechanism for ensuring public safety.

The spread-rate of CCTVs in public places is probably due to the various advantages of CCTVs. First, CCTVs increase the likelihood of arresting criminals, help police investigation, and provide information to the police by observing the behaviors of known criminals (La Vigne et al., 2011; Ratcliffe, 2006). Second, CCTVs in public places increase the feeling of safety among people who comply with the law (La Vigne et al., 2011; Ratcliffe, 2006). Third, the installation of CCTVs in public places can support the aid of emergency patients who have received injuries. For instance, an emergency response may be more efficient and effective if video footage is available of the incident. Furthermore, the video footage provides information for police officers to effectively manage demonstration and traffic jams (Ratcliffe, 2006). Finally, CCTVs in public places can provide crime reduction effects in areas *near* the CCTV locations, as well as the CCTV locations themselves because criminals do not know the actual distance that the CCTVs view (Ratcliffe, 2006). For example, a motivated offender who wants to commit burglary in a site that is beyond the view of CCTVs may be deterred after he/she finds the existence of CCTVs in public places near a site, that is, in reality, out of view of the CCTVs. The various strengths make CCTVs more attractive for public safety and more pervasive in public places.

Overview of Open-street CCTV Studies

Researchers refer to CCTVs in public places using a variety of terms. For example, Dean Wilson and Sutton (2003) call CCTVs in public places "open-street CCTVs," while La Vigne et al. (2011) refer to them "public surveillance cameras." Ratcliffe, Taniguchi, and Taylor (2009) refer to them as "public CCTV cameras" and Caplan, Kennedy, and Petrossian (2011) call them "police-monitored CCTVs." This study will use the term "open-street CCTVs" when referring to public CCTVs and will define them as the CCTVs that are implemented to mainly prevent crime in public places and managed by the police or local governments.

Many studies have been conducted on the effects of open-street CCTVs with their rapid spread. Some research examines the effects of open-street CCTVs on fear of crime (e.g., Gill, Bryan, & Allen, 2007). Other studies examines the influence of open-street CCTV on investigation and prosecution (e.g., King, Mulligan, & Raphael, 2008). Also, there are studies on the costs and effects of open-street CCTVs (e.g., La Vigne et al., 2011). Recently, Piza and his colleagues have conducted several studies on processes related to police use of CCTV. For example, they conducted research on micro-level implementation factors influencing crimes in CCTV areas, including camera design and line of sight (Piza, Caplan, & Kennedy, 2014a) as well as the effects of process times on crime prevention through CCTV monitoring (Piza, Caplan, & Kennedy, 2014b). They also conducted relationship between CCTV and certainty of punishment (Piza, Caplan, & Kennedy, 2014c) and the effectiveness of integration of CCTV monitoring and proactive police activity (Piza, Capalan, Kennedy, & Gilchrist, 2014). However, most extant studies test the crime reduction effects of open-street CCTVs (e.g., Caplan et al, 2011; Gill, Allen, Jessiman, & Bryan, 2005; Gill & Sprigg, 2005; La Vigne et al., 2011; Ratcliffe et al., 2009; Welsh & Farrington, 2009).

Studies on the crime reduction effects of open-street CCTVs have focused mainly on three distinct topics. First, some studies examined whether open-street CCTVs reduce overall crime (e.g., La Vigne et al., 2011; Park, Oh, Paek, 2012; Ratcliffe et al., 2009). Second, some studies have examined crime reduction effects of open-street CCTVs across different crime types (e.g., Caplan et al., 2011; Cerezo, 2013; La Vigne et al., 2011; Phillips, 1999; Ratcliffe et al., 2009). Finally, some studies have examined whether the crime reduction effects of open-street CCTVs depend on the characteristics of installation locations (e.g., Farrington, Gill, Waples, & Argomaniz, 2007; Gill & Sprigg, 2005; Welsh & Farrington, 2009).

The quality of studies on crime reduction effects of open-street CCTVs has improved over time in several important ways. First, the studies have improved their internal validity. Early research used simple pretest-posttest designs that compared the number of crime incidents before versus after the CCTV installation (e.g., Chatterton & Frenz, 1994; Goodwin, 2002). Then, researchers began to use quasi-experimental design to address the serious threats to internal validity faced by pretest-posttest designs (e.g., La Vigne et al., 2011; Mazerolle, Hurley, & Chamlin, 2002). They examined the change of the number of crime incidents in control areas as well as the areas of CCTV installation and compared the two changes. However, the quasi-experimental designs had a weakness. That is, the design could not control seasonal effect and crime trends that are important threats to internal validity in studies on crime reduction effects of open-street CCTVs. Recently, Ratcliffe et al. (2009) used Hierarchical Linear Modeling (HLM) to advance more fully the rigor of the research. In their research, they tested crime reduction effects of open-street CCTVs after controlling for seasonal effect and crime trends at each open-street CCTV location.

Second, unlike the initial studies, more recent studies have examined indirect effects such as displacement and diffusion of benefits in addition to the direct crime reduction effects of open-street CCTVs (e.g., Caplan et al., 2011; La Vigne et al., 2011; Ratcliffe et al., 2009). Examining processes of displacement and diffusion of benefits provides a clearer indication of open-street CCTVs' net crime reduction effects. For example, even if CCTV installation were associated with crime reduction in areas within reach of the cameras, it would be problematic to say that open-street CCTVs have crime reduction effects if offenders simply moved to areas away from the open-street CCTV locations and committed crimes in these new areas.

Finally, as the research on CCTV effects has mounted, researchers have more recently begun to conduct meta-analyses that aggregate the results of existing open-street

CCTV studies (e.g., Farrington et al., 2007; Welsh & Farrington, 2009). Meta-analyses show general crime reduction effects of open-street CCTVs that individual studies could perhaps not produce. In other words, whereas individual studies show crime reduction effects of open-street CCTVs in some settings but not in others, meta-analyses are able to show a general crime reduction effects of open-street CCTVs. Also, meta-analyses have produced important information on crime reduction effects of open-street CCTVs. For example, individual studies rarely showed crime reduction effects of open-street CCTVs depending on the characteristics of the locations but meta-analyses showed the information well (e.g, Farrington et al., 2007; Welsh & Farrington, 2009).

Limitations of Past Studies

As indicated above, past studies have greatly helped improve knowledge about crime reduction effects of open-street CCTVs. The studies have provided information about the places where open-street CCTVs has reduced crime and about the types of crimes open-street CCTVs has impacted. Further, some studies have shown the crime reduction effects of open-street CCTVs net at any displacement and diffusion of benefits.

However, there are still important gaps in our knowledge about the effects of open-street CCTVs. First, past studies have not shown daytime versus nighttime crime reduction effects of open-street CCTVs. However, this distinction is important. For example, crime reduction effects of open-street CCTVs may be significant during daytime hours, whereas they may not be significant at night. Such findings would imply that additional interventions (e.g. lighting) should be considered to reduce crimes at nighttime in open-street CCTV locations. Also, the findings may indicate that people passing through open-street CCTV locations should pay heed to their safety from crimes at nighttime more so than during daytime.

Second, past studies have not examined weekday versus weekend crime reduction effects of open-street CCTVs. However, this issue is also important. For example, crime reduction effects of open-street CCTVs may be significant during weekdays, whereas they may not be significant during weekends. Such findings may indicate that additional interventions (e.g. additional police patrol) should be considered to further reduce crimes during weekends in open-street CCTV locations. Alternatively, such findings might suggest that the most cost-effective use of open-street CCTVs would be to install them in locations where many crimes occur during weekdays rather than weekends.

Third, a limitation of past studies is that there is little research on the crime-specific effects of open-street CCTVs. Most past studies that have examined crime reductions across crime types utilize broad categories of crimes (e.g., violent crime and property crime) instead of specific offenses (e.g., robbery and burglary). For example, many studies have tested crime reduction effects of open-street CCTVs for violent crime versus property crime (Phillips, 1999; Sivarajasingam & Shepherd, 1999; Welsh & Farrington, 2004a). Others have examined crime reduction effects of open-street CCTVs for serious crime and disorder crime (Ratcliffe et al., 2009). However, open-street CCTVs do not necessarily have the same crime reduction effects across specific offenses within these broad categories. For example, although both auto theft and thefts from auto belong to property crime, crime reduction effects of open-street CCTVs are conceivably different between the two specific types of crimes (Caplan et al., 2011). Thus, the crime reduction effects of open-street CCTVs for specific types of crimes need to be examined in order to improve knowledge and more efficiently prevent crime.

Fourth, more information is needed about the crime reduction effects of open-street CCTVs, depending on installation locations. Although several past studies show characteristics of installation location can moderate CCTVs effect on overall crime, we have very little information about how location characteristics moderate differentially the effects on daytime versus nighttime crime, weekday versus weekend crime, and across specific offenses. For example, Welsh and Farrington (2009) examined overall crime reduction effects of open-street CCTVs depending on CCTV locations (e.g., city enters and public housing), but they did not examine how these location characteristics moderated CCTVs' effects across specific offense categories. However, the influence of the characteristics of open-street CCTV locations on crime reduction effects of open-street CCTVs can be different depending on specific types of crimes. Thus, for more efficient use of cameras, it is important to consider how location properties interact with daytime/nighttime distinctions, weekday/weekend distinctions, and offense type in moderating the crime reduction effects of open-street CCTVs.

Fifth, more information is needed about displacement/diffusion of benefits following the implementation of open-street CCTVs. Although various studies have examined the displacement and diffusion of benefits caused by the implementation of open-street CCTVs, there is no research on comparing the displacement/diffusion of benefits of daytime versus nighttime or weekday versus weekend crime. In addition, although there are past studies examining displacement and diffusion of benefits regarding specific types of crime, the number of past studies is relatively small. For example, there is only one study on displacement/diffusion of benefits in auto theft following the implementation of open-street CCTVs (Caplan et al, 20ll).

Finally, although past studies have developed rigorous research methods to get more valid results over time, they still have not considered synergistic effects that may emerge in the locations where open-street CCTVs are overlapping. For example, Caplan et al. (2011)

assume that crime reduction effects of open-street CCTVs are the same between overlapping areas and non-overlapping areas. However, crime reduction effects of open-street CCTVs may be bigger in overlapping areas than non-overlapping areas due to synergistic effects. Thus, without considering the potential differences between locations that involve overlapping camera space and those that do not, a study may produce overestimation of crime reduction effects of open-street CCTVs.

Overview of the Present Study

Again, this study aims to examine the crime reduction effects of open-street CCTV in Cincinnati, Ohio. The Southwestern Ohio city of Cincinnati is 77.94 square miles and has 296,943 residents (U.S. Census Bureau, 2010). Cincinnati implemented a phased-installation of open-street CCTVs to prevent crime between November, 2009 and May, 2011. The installation sites included the downtown area (eight cameras), other business districts (twelve cameras), university/high school settings (seven cameras), and residential areas (seven cameras).

This study of the effectiveness of the CCTV implementation in Cincinnati attempts to overcome the limitations of past CCTV studies and improve knowledge about the potential conditional nature of the crime reduction effects offered by open-street CCTVs. First, this study compares the daytime versus nighttime crime reduction effects of open-street CCTVs. Second, this study compares the crime reduction effects of open-street CCTVs during weekdays and weekends. Third, this study tests crime reduction effects of open-street CCTVs for specific types of crimes such as robbery, assault, burglary, and theft. Fourth, this study tests how daytime versus nighttime, weekday versus weekend, and offense-specific crime reduction effects of open-street CCTVs are influenced by CCTV location type – in particular, in terms of whether the CCTV is located downtown, another business district, near a school/university or in a residential area. Finally, this study methodologically improves research on crime reduction effects of open-street CCTVs by considering synergistic effects that may emerge in locations where crime reduction effects of open-street CCTVs are overlapping and suggests the solution to the problem. The improvement in methodology may help measure crime reduction effects of open-street CCTVs more precisely and be a guide for the solution to the same problem occurring in future studies.

These issues are addressed using open-street CCTV location data and crime incident data from Cincinnati Police Department (CPD). Geographic Information Science (GIS) techniques are used to designate target areas, buffer areas, and control areas. For the analysis, Hierarchical Linear Modeling (HLM), Z-stat, and Weighted Displacement Quotient (WDQ) will be used. More specifically, HLM and Z-stat analyses will be used to show daytime, nighttime, weekday, and weekend crime reduction effects of open street CCTVs. Such analyses will also be used to demonstrate the crime reduction effects of open-street CCTVs depending on specific types of crimes and the characteristics of installation locations. WDQ analyses will be used in order to show displacement or diffusion of benefits in accordance with the installation of open-street CCTVs.

The study will unfold over the course of four remaining chapters. In Chapter II, I will review the theory that underlies the use of open-street CCTVs, and I will present the results of past studies on the crime reduction effects of open-street CCTVs. Also, at the conclusion of Chapter Two, hypotheses for the present study will be presented. In Chapter III, I will explain the data, measures, and analytic methods in detail. In Chapter IV, I will report the findings of my analyses. Finally, in Chapter V, I will draw conclusions from the findings and discuss their policy implications.

CHAPTER II

RESEARCH FRAMEWORK

Theoretical Background

Opportunity theories provide explanations for the expected crime reduction effects of CCTV. Opportunity theories elucidate that criminal opportunity in a given situation, not the innate criminality of a criminal, is the cause of crime. Thus, opportunity theories state that by obstructing criminal opportunity in a situational fashion, instead of changing the criminal's traits, crime reduction is possible. Opportunity theories include the rational choice perspective, routine activity theory, offender search theory, and environmental design theory. Although the various kinds of opportunity theories are different in their foci, all of them explain criminal opportunity structure in a compatible and overlapping manner.

Rational Choice Perspective

The rational choice perspective was mainly developed by Ronald Clarke and Derek Cornish (e.g., Clarke & Cornish, 1985). It was observed that an offender makes a decision to commit a crime and presumably makes rational choices at each stage of its commission. Clarke and Cornish (1985) divided the decision-making process of crime into the involvement stage and the criminal event stage to personify the argument. According to them, the involvement is a stage in which an offender makes a decision on whether he would commit a crime. In contrast, the criminal event is a stage in which an offender makes a decision on how he commits a specific crime. Criminal event decisions are related to target characteristics, time, and place characteristics.

According to Clarke and Cornish (1985), criminal involvement is divided into three sub-stages: initial involvement, continuance, and desistance. Clarke and Cornish (1985) posited that an offender's decision making process and the influential factors that affect decisions making were different across the three involvement stages.

Initial involvement is the primary involvement sub-stage. According to Clarke and Cornish (1985), an individual's initial decision to commit a crime is influenced by his/her background factors (e.g., temperature, broken home, education), previous experience, and learning in initial involvement. However, some kinds of events such as easy opportunity, urgent need for cash, and peer pressure also influence an individual's decision-making to commit a crime.

Continuance is the secondary involvement sub-stage. Continuing criminal involvement will advance an offender's professionalism regarding crime. His/her criminal skills improve, thereby decreasing perceived risks and increasing perceived benefits. Additionally, his/her lifestyle and values change as his criminal activities continue. In the stage of continuance, an offender, for instance, begins to justify his/her criminal activities. An offender also increasingly finds peers similar to him/her in the new social environment his ongoing criminal activities carve for him. The emerging professionalism and the lifestyles, values, and peer groups are major factors affecting decisions to stay involved in crime.

The third involvement sub-stage is desistance. Recent criminal experience or exterior experience such as marriage or imprisonment influence desistance from committing a crime. A burglar, for instance, may consider discontinuing his/her burglary when he/she is nearly killed by the owner of the house. Moreover, a burglar imprisoned for his/her crime will cease to commit it any longer.

After an individual makes a decision to commit a crime, the process of decision-making in a criminal event takes on several sub-stages as well. For example, in case of burglary, a burglar makes a decision, first, regarding an area where he will commit a burglary. He/she may select a middle-class suburb because it is easily accessible, has little patrol and little security equipment. Next, the burglar decides on a specific house where he/she will commit the crime. He/she may try to choose a house with small risk and much benefit from his/her burglary. A large and expensive but remote house may be his target for his purpose. Further into the criminal event, the burglary needs to decide how to enter the targeted house, how to search the target, how to convert stolen goods to cash, and so on (Clarke & Cornish, 1985). Overall, at both all involvement and event sub-stages, the rational choice perspective presumes that decisions are made by considering costs (e.g., effort, risk) versus benefits of alternative lines of action, though there is a clear assumption that the information upon which such decisions are made may be substantially bounded (Clarke & Cornish, 1985). Additionally, and important for the purpose of this dissertation, decision are crime-specific, with the factors that affect offender perceptions of effort, risk, and reward potentially varying across crime types.

Routine Activity Theory

Lawrence E. Cohen and Marcus Felson (Cohen & Felson, 1979) first articulated routine activity theory. They tried to comprehend the surge in crime in the U.S. after World War II despite the fact that American society had become more affluent. In order to account for this paradox, they posited that increasing crime was due to change in the criminal opportunity structure in American society following World War II. They developed routine activity theory to explain the situation more fully.

At the core of their theory, Cohen and Felson (1979) maintained that crime requires three situational conditions. Those are 1) a motivated offender, 2) a suitable target, and 3) absence of capable guardianship. They stated that these three elements should coincide at the same time and in the same place for a crime to occur.

Cohen and Felson (1979) elucidated that these three requirements – especially the presence of suitable targets and the absence of capable guardianship – were more abundant in the U.S. post World War II. This time period also saw more women having careers, thus increasing the number of double-income households. These changes increased the level of household consumption and rendered many houses vulnerable without adult guardianship during the day. In short, following the Second World War, changes in educational and work activities (especially among women) created a much richer American society resulting in people more capable of buying durables (e.g., TVs and VCRs) and enjoying their leisure time outside. These changes after World War II made new opportunities for criminals; the change of people's routine activities gave more opportunity for motivated offenders to meet suitable targets with absence of capable guardianship at same time and space.

In their theory, Cohen and Felson (1979) focused on crime events instead of criminals in order to explain the cause of crime. They argued that the increase of crime rate in American society after World War II is not due to the increase of motivated offenders but due to the increase of suitable targets and absence of capable guardianship. Their explanation means that the crime rate can be increased in a society without considering criminal motivation that traditional criminological theories stressed.

Offender Search Theory

Brantingham and Brantingham developed offender search theory to explain where crime mainly happens – or, the patterns of crime, including hot spot formation (Brantingham & Brantingham, 1981a, 1981b, 1993, 1995, 1999). They introduced the important concepts to explain their theory. The concepts include nodes, paths, edges, environmental backcloth, crime generators, and crime attractors. According to them, a node refers to a hub of daily activity such as a school, home, workplace, or restaurant. A path refers to a road or transit artery that connects nodes. An edge refers to the periphery of a space such as a node or path. Edges represent transitions from one space to another and thus divide spaces into natural regions of homogeneity. Environmental backcloth refers to informal social characteristics and environmental defense characteristics of a place.

Brantingham and Brantingham (1981a, 1981b, 1993, 1995) presumed that crime occurs when an individual who is prepared to commit a crime meets a target that gives sufficient opportunity. According to them, an offender tries to find a target at nodes and paths that he knows well because they are familiar, target-rich spaces. If an offender meets a target at such places, a crime can occur. Edges of nodes and paths are also opportunistic because convergence of the offender and a suitable target is still likely yet due to heterogeneity of users, guardianship is diminished at edges. Brantingham and Brantingham also stressed the importance of environmental backcloth. They assumed that the social and physical features of the broader environmental backcloth also affects opportunities at places, thus, playing an important role in non-randomness of crime.

In addition to the concepts of nodes, paths, edges, and backcloth, Brantingham and Brangtingham (1999, 2003) also provided the concepts of “crime generators” and “crime attractors” in order to understand the spatial distribution of crime. According to them, crime generators are specific places, often major nodes, where many people gather for reasons other than crime. Crime generators include shopping malls, housing complexes, and amusement parks. Crime generators produce crime by gathering people or other targets in a specific space-time context. In contrast, crime attractors refer to places that are well-known for producing criminal opportunity such as drug market. Thus, crime attractors lure people who have strong criminal motivation.

Environmental Design Theory

One of the first and most famous environmental design theories is defensible space theory, introduced by Oscar Newman, an architect (1972/1973). Defensible space theory was influenced by "The Life and Death of Great American Cities" written by Jane Jacobs in 1961. In the book, Jacobs criticized that modern urban planners tried to evict neighbors living in complex land-use areas. She argued that the efforts would make a lonely and unnatural urban place.

Under the influence of Jacobs, Newman became interested in changing the complex land-use areas into a lower-crime area instead of evicting residents living in the areas (Newman, 1972/1973). Newman investigated Pruitt-Igoe, a public housing complex in St. Louis that was suffering from crimes. He compared the public housing complex with other communities near the place. For example, he compared Pruitt-Igoe with a community consisting of low-rise housing, with most houses in-line on both sides of the street. The social class of the area was similar to Pruitt-Igoe but unlike Pruitt-Igoe, the area had little crime.

Through this comparison, Newman (1972/1973) theorized on how the characteristics of Pruitt-Igoe brought about crime and disorder. He put for the idea that the design of the building and the density of many buildings made it difficult for the residents to control the environment. He claimed that, due to design, residents in Pruitt-Igoe could not distinguish between residents and outsiders. They also did not have a sense of ownership or responsibility for much of the complex, as it was virtually all public space.

Newman organized his thoughts about how community design can strengthen space control by residents and suggested four principles for environmental design to prevent crime (Newman, 1972/1973). The first principle is territoriality. Territoriality refers to the demarcation of space for specific purposes, providing a sense of propriety. The second principle is surveillance. Surveillance refers to the extent that residents and their representatives can monitor the community. The third principle is image. Image refers to environmental design that makes a community unique, well-maintained, and not alone. The final principle is milieu. Milieu refers to aspects of environmental design that give a feeling of being located in the vicinity of safe area. Newman suggested that spaces that had strong territoriality, surveillance, image, and milieu were more defensible.

The mechanisms by which the four principles of environmental design to prevent crime are twofold. First, the environmental – including aspects of territoriality, surveillance, image, and milieu – can cause residents to participate more in their community and increase the sense of ownership over their space, resulting in greater informal social control and lower crime and disorder. Second, the physical changes in the environmental can simply lower the extent to which an offender can access a suitable target, making an offender's commission of crime much more difficult. For example, if sight line from resident's windows are altered, offenders may be reluctant to commit a crime in the community.

Newman's theory has been revised and extended. Contemporary environmental design theory (e.g., crime prevention through environmental design, broken window theory) still emphasizes some of the original concepts that Newman talked about. But such design theory also downplays aspects of the built environment such as building height and includes access control, target hardening, and activity support as additional important tactics for preventing crime. As such, contemporary design theory is thought to more practically contribute to crime prevention than Newman's defensible space theory. For example, various studies have shown that target hardening greatly reduces crime. Household that employ more safety precautions experience fewer burglaries (e.g., Miethe & McDowall, 1993; Wilcox, Madensen, Tillyer, 2007), and convenience stores that have implemented additional clerks and CCTV systems show significant reductions in robbery (Casteel & Peek_Asa, 2000).

Situational Crime Prevention

The various opportunity theories explained above are overlapping. First, every opportunity theory assumes that offenders make rational choices, as outlined by the rational choice perspective. For example, according to routine activity theory, offenders consider guardianship of targets when they commit crime. According to offender search theory, offenders consider environmental backcloth of target area when they commit crime. According to crime prevention through environmental design (CPTED), offenders consider things such as the natural surveillance of a target area when they commit crime. Second, every perspective or theory discussed above assumes that the crime prevention is possible by blocking the criminal opportunity via situational crime prevention, including CPTED.

Situational crime prevention was developed by Ronald V. Clarke (Clarke, 1980, 1997). Clarke (1997) had interest in opportunity theories focusing on environmental factors such as the rational choice perspective, routine activity theory, offender search theory, and environmental design theory rather than traditional theories focusing on removing an offender's criminal motivation. In line with these opportunity theories, Clarke (1980, 1997) posited that change in situational opportunity structures can prevent crimes. Thus, the manipulation of immediate and specific situations can decrease an individual's criminal temptation.

Five principles have been developed to guide Clarke's arguments about prevention (Cornish & Clarke, 2003; Wortley, 2001). The first principle is that situational measures can increase an offender's effort to commit a crime. The second principle is that situational measures can be taken to increase risks for an offender to be revealed before, during, and after commission of crime. The third principle is that situational measures can remove the benefits of crime. The fourth principle is that situational measures are able to remove an offender's excuses for commission of crime. Finally, the fifth principle is that situational measures can remove provocations that lead to crime.

Opportunity Theory, Situational Crime Prevention, and CCTV

CCTV is a form of situational crime prevention that is thus supported by opportunity theories of crime. Scholars explain, more specifically, the various mechanisms by which CCTV prevents crime (Farrington et al., 2007, p. 22; Welsh & Farrington, 2003, p. 111). First, CCTV may deter potential offenders' decisions to engage in criminal activities by increasing the possibility of being captured on tape and, in turn, captured by police. Second, places where CCTV has been installed may be used by more people due to greater perceived safety, thus, increasing risk to offenders in the form of enhanced bystander surveillance. Third, CCTV helps effective and efficient stationing of police officers and security guards, thus, increasing risk to offenders in that regard as well. Fourth, CCTV may lead the general public to exercise more caution so as not to have carelessness captured by CCTV. The greater caution on the part of the general public can heighten the effort required by offenders and it can diminish rewards and provocations offered to offenders.

Review of Past Studies

Findings from past research on the crime reduction effects of open-street CCTVs can be summarized using several categories. First, some past studies have examined whether open-street CCTVs influence overall crime. Second, some past research has studied how the crime reduction effects of open-street CCTVs vary depending on crime types. Third, another set of past studies have examined whether the crime reduction effects of open-street CCTVs vary depending on the characteristics of implementation sites. Finally, several past studies have tested whether implementation of open-street CCTVs bring about displacement and diffusion of benefits. Often, a single study has multiple objectives and thus fits into several of these different categories.

Overall Crime Reduction Effects

Table 2. 1 summarizes past studies that have examined the effects of CCTVs on overall crime reduction. In general, much research reports that open-street CCTVs have an overall crime-reduction effects (Cho, 2009; Griffiths, 2003; Ratcliffe et al., 2009; Short & Ditton, 1996; Welsh & Farrington, 2003; Yim & Hong, 2008). For example, Ratcliffe et al. (2009) examined the effects of open-street CCTVs implemented at 12 locations in Philadelphia and found that overall crime at the locations had decreased by approximately 13% after the implementation of the CCTVs. Also, Welsh and Farrington (2003) meta-analysis of 22 studies found an overall crime-reduction effects of open-street CCTVs. However, some studies reported null effects of open-street CCTVs on overall crime. For example, Cerezo (2013) found that overall crime did not significantly decrease after the implementation of 17 open-street CCTVs in Malaga, Spain.

Some studies of the effects of CCTVs on overall crime show mixed results. That is, several studies found different effects of open-street CCTVs depending on implementation sites. For example, La Vigne et al. (2011) examined the effects of open-street CCTVs implemented in Baltimore, Chicago, and Washington D.C. and found differences across places. In Baltimore, overall crime declined at most implementation places. However, in Chicago overall crime reduction effects emerged in just half of implementation places. Also, implementation of open-street CCTVs in Washington D.C. did not lead to a reduction in overall crime.

We should note several points when we interpret the results from the past studies. First, although several studies reported mixed or non-significant effects of CCTVs on overall crime, we cannot assume from such findings that open-street CCTVs have no (or very little) impact on overall crime. The results may be due to poor implementation as opposed to the true lack of effectiveness of CCTVs. For example, CCTVs might have been implemented using an inappropriate density of cameras, inadequate signage indicating the implementation of open-street CCTVs, or without appropriate publicity. The viewpoint is supported by La Vigne et al.'s research (2011) that showed mixed results regarding the effects of open-street CCTVs on overall crime. In their research, open-street CCTVs significantly reduced crime in Baltimore, where there was a high density of open-street CCTVs; yet, it was little or no significant reduction in crime in Chicago and Washington D.C., where there was a low density of open-street CCTVs.

When the past studies on the effectiveness of CCTVs are considered cross-culturally, there is no clear difference in the crime reduction effects of open-street CCTVs, depending on country. Many U.K. studies (Griffiths, 2003; Short & Ditton, 1996; Welsh & Farrington, 2003), U.S. studies (Ratcliffe et al., 2009; Welsh & Farrington, 2003), and several Korean studies (Cho, 2009; Yim & Hong, 2008) have shown that open-street CCTVs have overall crime-reduction effects.

Table 2. 1. Overall Crime Reduction Effects of Open-street CCTVs

Study	Location	Data	Method	Findings
Cerezo (2013)	Spain (Malaga)	Crime incident data (one year before and after implementation) , citizen survey, shopkeeper survey	Quasi-experimental design, comparing percentage	N.S.
La Vigne *et al*. (2011)	US (Baltimore, Chicago, Washington D.C.)	Crime incident data (two or three years)	Quasi-experimental design, time series, difference-in-differences analyses, WDQ	Mixed
Cho (2009)	South Korea (Seoul Borough of Gangnamgu)	Crime incident data (four months before and after implementation)	Quasi-experimentation design, comparing percentage	Sig.
Ratcliffe *et al.* (2009)	US (Philadelphia)	Crime incident data (32 months)	Quasi-experimental design, hierarchical linear modeling, WDQ	Sig.
Yim & Hong (2008)	South Korea (Seoul)	Crime incident data (one year)	Quasi-experimental design, regression	Sig.
Gill & Hemming (2004)	UK (London Borough of Lewisham))	Crime incident data (one year before and after implementation), police attitudes survey	Quasi-experimental design, Mann-Whitney U	Mixed
Griffiths, M. (2003)	UK (Gillingham)	Crime incident data (one year before and five years after implementation)	Quasi-experimental design, comparing number of crime incidents	Sig.
Welsh & Farrington (2003)	UK, US	22 evaluations	Meta-analysis, effect size (odds ratio)	Sig.
Mazerolle et al. (2002)	US (Cincinnati)	Recorded videotapes, police calls-for-service data (23-24 months before and 4-6 months after implementation)	Quasi-experimental design, time-series, comparing percentage	Mixed
Short & Ditton (1996)	UK (Airdrie)	Crime incident data (24 months before and after implementation)	Pre-post design, time-series, comparing percentage	Sig.

N.S. − Non-significant reduction; Sig − Significant reduction; Mixed – Mixed results (i.e., effect varied across areas)

Crime-Specific Crime Reduction Effects

Crime-specific analysis of the effects of CCTV has been conducted using a variety of outcome measures. For ease in comparing, studies with similar crime-specific outcome measures are grouped accordingly in Tables 2. 2 through 2. 9. First, as shown in Table 2. 2, a number of studies study “property crime.” Some such studies report crime reduction effects of open-street CCTVs on overall property crime (King et al., 2008; Phillips, 1999; Welsh & Farrington, 2004b). Other studies show that open-street CCTVs reduced “property crimes” as measured by burglary and theft (Cho, 2009; Choi & Kim, 2007; Kim, 2008; C. Park & Choi, 2009; Yim & Hong, 2008). Another group of studies supports “burglary and robbery” reduction effects of open-street CCTVs (Cerezo, 2013; H. H. Park et al., 2012), and one study shows that CCTVs reduced burglary, theft, and robbery (Cheong & Hwang, 2012). Overall, regardless of how “property crime” is operationalized, most of the studies provide support for the idea of CCTV reducing property crimes.

Table 2. 2. Crime Reduction Effects of Open-street CCTVs on Property Crime

Study	**Location**	**Data**	**Method**	**Findings**
Cerezo (2013)	Spain (Malaga)	Crime incident data (one year before and after implementation), citizen survey, shopkeeper survey	Quasi-experimental design, comparing percentage	Burglary & robbery: Sig
Cheong & Hwang (2012)	South Korea (Cheonan, Asan)	Crime incident data (one year)	Multivariate analysis	Burglary, theft, & robbery: Sig.
Park et al. (2012)	South Korea (Guangmeong)	Crime incident data (five months before and after implementation)	Quasi-experimental design, WDQ	Burglary & robbery: Sig.

La Vigne *et al*. (2011)	US (Baltimore, Chicago, Washington D.C.)	Crime incident data (two or three years)	Quasi-experimental design, time series, difference-in-differences analyses, WDQ	Property crime: Mixed
Cho (2009)	South Korea (Seoul Borough of Gangnamgu)	Crime incident data (four months before and after implementation)	Quasi-experimental design, comparing percentage	Burglary & theft: Sig.
Park & Choi (2009)	South Korea (Seoul Borough of Gangnamgu)	Crime incident data (six years)	Quasi-experimental design, chi-square test, relative effect size	Burglary & theft: Sig.
Kim (2008)	South Korea (Borough of Gangnamgu)	Crime incident (one year before and after implementation)	Quasi-experimental design, WDQ	Burglary & theft: Sig.
King et al. (2008)	US (San Francisco)	Crime incident data (209 days before and 264 days after implementation)	Quasi-experimental design, difference-in-difference analyses	Property crime: Sig.
Yim & Hong (2008)	South Korea (Seoul)	Crime incident data (one year)	Quasi-experimental design, multivariate analysis	Burglary & theft: Sig.
Choi & Kim (2007)	South Korea (Seoul Borough of Gangnam)	Crime incident data (five years)	Quasi-experimental design, time-series	Burglary & theft: Sig.
Welsh & Farrington (2004b)	UK, US	19 evaluations	Meta-analysis, effect size (odds ratio)	Property crime: Sig. .
Phillips (1999)	UK	27 evaluations	Meta-analysis	Property crime: Sig.

Sig − Significant reduction; Mixed – Mixed results (i.e., effect varied across areas)

Table 2. 3 shows studies that examined broad categories of "violent crime." These studies measured multiple types of violence as dependent variables, though the specific crime that comprised "violence" varied across studies. Most of these studies produced null crime reduction effects of open-street CCTVs (Cheong & Hwang, 2012; Griffiths, 2003; King et al., 2008; H. H. Park et al., 2012; Sivarajasingam & Shepherd, 1999; Welsh & Farrington, 2003, 2004a, 2004b, 2009). Only one study showed even mixed results (La Vigne et al., 2011).

Table 2. 3. Crime Reduction Effects of Open-street CCTVs on Violent Crime

Study	**Location**	**Data**	**Method**	**Findings**
Cheong & Hwang (2012)	South Korea (Cheonan, Asan)	Crime incident data (one year)	Multivariate analysis	N.S.
Park et al. (2012)	South Korea (Guangmeong)	Crime incident data (five months before and after implementation)	Quasi-experimental design, WDQ	N.S.
La Vigne *et al*. (2011)	US (Baltimore, Chicago, Washington D.C.)	Crime incident data (two or three years)	Quasi-experimental design, time series, difference-in-differences analyses, WDQ	Mixed
Welsh & Farrington (2009)	UK, US, Canada, Sweden, Norway	44 evaluations	Meta-analysis, OR effect size	N.S.
King et al. (2008)	US (San Francisco)	Crime incident data (209 days before and 264 days after implementation)	Quasi-experimental design, difference-in-difference analyses	N.S.
Welsh & Farrington (2004a)	UK, US	22 evaluations	Meta-analysis, effect size (odds ratio)	N.S.
Welsh & Farrington (2004b)	UK, US	19 evaluations	Meta-analysis, effect size (odds ratio)	N.S.

Griffiths (2003)	UK (Gillingham)	Crime incident data (one year before and five years after implementation)	Quasi-experimental design, comparing number of crime incidents	N.S.
Welsh & Farrington (2003)	UK, US, Canada	22 evaluations	Meta-analysis, effect size (odds ratio)	N.S.
Goodwin (2002)	UK (Devonport)	Crime incident data and calls-for-service data (24 months before and after implementation), community survey	Pre-post design, comparing number of crime incidents and calls-for-services	Assault/Robbery: N.S.
Sivarajasingam & Shepherd (1999)	UK (Cardiff, Swansea, Rhyl)	A&E department and local police assault data, British Crime Survey, police crime statistics	Comparison between before and after CCTV installation	N.S.

N.S. − Non-significant reduction; Mixed – Mixed results (i.e., effect varied across areas)

Table 2. 4, below, summarizes two studies on crime reduction effects of open-street CCTVs on burglary. Overall, the results regarding studies of burglary are mixed. One study found that open-street CCTVs reduced burglary (Goodwin, 2002). However, the other study did not support such effects (M. Gill & Hemming, 2004).

Table 2. 4. Crime Reduction Effects of Open-street CCTVs on Burglary

Study	**Location**	**Data**	**Method**	**Findings**
Gill & Hemming (2004)	UK (London Borough of Lewisham)	Crime incident data (one year before and after implementation), police attitudes survey	Quasi-experimental design, Mann-Whitney U	N.S.
Goodwin (2002)	UK (Devonport)	Crime incident data and calls-for-service data (24 months before and after implementation), community survey	Pre-post design, comparing number of crime incidents and calls-for-services	Sig.

N.S. − Non-significant reduction; Sig − Significant reduction

Table 2. 5 shows studies that examined the crime reduction effects of open-street CCTV on robbery. Overall, the results are mixed. Similar to studies of burglary, some studies showed that open-street CCTVs reduced robbery (Cho, 2009; Choi & Kim, 2007; C. Park & Choi, 2009), while others report null effects on robbery (M. Gill & Hemming, 2004; Yim & Hong, 2008).

Table 2. 5. Crime Reduction Effects of Open-street CCTVs on Robbery

Study	Location	Data	Method	Findings
Cho (2009)	South Korea (Seoul Borough of Gangnamgu)	Crime incident data (four months before and after implementation)	Quasi-experimental design, comparing percentage	Sig.
Park & Choi (2009)	South Korea (Seoul Borough of Gangnamgu)	Crime incident data (six years)	Quasi-experimental design, chi-square test, relative effect size	Sig.
Yim & Hong (2008)	South Korea (Seoul)	Crime incident data (one year)	Quasi-experimental design, multivariate analysis	N.S.
Choi & Kim (2007)	South Korea (Seoul Borough of Gangnam)	Crime incident data (five years)	Quasi-experimental design, time-series	Sig.
Gill & Hemming (2004)	UK (London Borough of Lewisham)	Crime incident data (one year before and after implementation), police attitudes survey	Quasi-experimental design, Mann-Whitney U	N.S.

N.S. − Non-significant reduction; Sig − Significant reduction

Table 2. 6 provides a review of studies of open-street CCTVs' effect on auto theft. In this table, "vehicle crime" refers to a combined measure of auto theft and theft from auto (Welsh & Farrington, 2009). As shown in the table, all study supported the preventive effects of CCTV on auto theft and vehicle crime (Caplan et al., 2011; Farrington et al., 2007; Griffiths, 2003; Short & Ditton, 1996; Welsh & Farrington, 2003, 2004a, 2009).

Table 2. 6. Crime Reduction Effects of Open-street CCTVs on Auto Theft

Study	Location	Data	Method	Findings
Caplan et al. (2011)	US (Newark)	Crime incident data (13 months before and after implementation)	Quasi-experimental design ANOVA analysis, LQ (location quotient) test	Auto theft: Sig.
Welsh & Farrington (2009)	UK, US, Canada, Sweden, Norway	44 evaluations	Meta-analysis, OR effect size	Vehicle crime: Sig.
Farrington et al. (2007)	UK	14 evaluations	Meta-analysis, relative effective sizes	Vehicle crimes: Sig.
Welsh & Farrington (2004a)	UK, US	22 evaluations	Meta-analysis, effect size (odds ratio)	Vehicle crime: Sig.
Griffiths (2003)	UK (Gillingham)	Crime incident data (one year before and five years after implementation)	Quasi-experimental design, comparing number of crime incidents	Vehicle crime: Sig.
Welsh & Farrington (2003)	UK, US, Canada	22 evaluations	Meta-analysis, effect size (odds ratio)	Vehicle crime: Sig.
Short & Ditton (1996)	UK (Airdrie)	Crime incident data (24 months before after implementation)	Pre-post design, time-series, comparing percentage	Crimes of dishonesty (e.g., theft of motor vehicle): Sig.

Sig – Significant reduction

Table 2. 7 shows studies on crime reduction effects of open-street CCTVs on theft from auto. Similar to Table 2. 6, in Table 2. 7, "vehicle crime" refers to a measure that combines both auto theft and theft from auto (Welsh & Farrington, 2009). Studies on crime reduction effects of open-street CCTVs on only theft from auto found null effects (Caplan et al., 2011; Goodwin, 2002). However, also reported in Table 2. 6, all studies on crime

reduction effects of open-street CCTVs on vehicle crime (i.e., auto theft and theft from auto) showed significant effects (Farrington et al., 2007; Griffiths, 2003; Welsh & Farrington, 2003, 2004a, 2009). Hence, overall, these results imply that open-street CCTV may have significant crime reduction effects on auto theft but not on theft from auto.

Table 2. 7. Crime Reduction Effects of Open-street CCTVs on Theft from Auto

Study	Location	Data	Method	Findings
Caplan et al. (2011)	US (Newark)	Crime incident data (13 months before and after implementation)	Quasi-experimental design ANOVA analysis, LQ (location quotient) test	Thefts from auto: N.S.
Welsh & Farrington (2009)	UK, US, Canada, Sweden, Norway	44 evaluations	Meta-analysis, OR effect size	Vehicle crime: Sig.
Farrington et al. (2007)	UK	14 evaluations	Meta-analysis, relative effective sizes	Vehicle crimes: Sig.
Welsh & Farrington (2004a)	UK, US	22 evaluations	Meta-analysis, effect size (odds ratio)	Vehicle crime: Sig.
Griffiths (2003)	UK (Gillingham)	Crime incident data (one year before and five years after implementation)	Quasi-experimental design, comparing number of crime incidents	Vehicle crime: Sig.
Welsh & Farrington (2003)	UK, US, Canada	22 evaluations	Meta-analysis, effect size (odds ratio)	Vehicle crime: Sig.
Goodwin (2002)	UK (Devonport)	Crime incident data and calls-for-service data (24 months before and after implementation), community survey	Pre-post design, comparing number of crime incidents and calls-for-services	Motor vehicle burglary: N.S.

N.S. − Non-significant reduction; Sig − Significant reduction

Table 2. 8 shows studies on crime reduction effects of open-street CCTVs on assault. Overall, the results are mixed. As shown in the table, some studies found significant crime reduction effects of open-street CCTVs (Cho, 2009; Gill & Hemming, 2004). However, other studies showed null effects (Choi & Kim, 2007; Goodwin, 2002; Yim & Hong, 2008).

Table 2. 8. Crime Reduction Effects of Open-street CCTVs on Assault

Study	Location	Data	Method	Findings
Cho (2009)	South Korea (Seoul Borough of Gangnamgu)	Crime incident data (four months before and after implementation)	Quasi-experimental design, comparing percentage	Assault: Sig.
Yim & Hong (2008)	South Korea (Seoul)	Crime incident data (one year)	Quasi-experimental design, multivariate analysis	Assault: N.S.
Choi & Kim (2007)	South Korea (Seoul Borough of Gangnam)	Crime incident data (five years)	Quasi-experimental design, time-series	Assault: N.S.
Gill & Hemming (2004)	UK (London Borough of Lewisham)	Crime incident data (one year before and after implementation), police attitudes survey	Quasi-experimental design, Mann-Whitney U	Assault: Sig.
Goodwin (2002)	UK (Devonport)	Crime incident data and calls-for-service data (24 months before and after implementation), community survey	Pre-post design, comparing number of crime incidents and calls-for-services	Assault/Robbery: N.S.

N.S. − Non-significant reduction; Sig − Significant reduction

Table 2. 9 shows crime reduction effects of open-street CCTV on other types of

crime. These are all categories or types of crime that are not as commonly examined, and are not among the dependent variables examined in this dissertation. Thus, they are combined into a final "other types" residual categories of crime-specific studies. As shown in the table, some research shows that open-street CCTVs reduce shootings (Caplan et al., 2011), whereas other research shows no effects on homicide (Choi & Kim, 2007; Yim & Hong, 2008) and injuries[1] (Cerezo, 2013). Past research also shows mixed results regarding the rape-reduction effects of open-street CCTVs. In reference to rape, Yim and Hong (2008) supported the crime reduction effects of open-street CCTVs, but Cho (2009) and Choi and Kim (2007) did not find such effects. Ratcliffe et al. (2009), found no effect of CCTV on "serious crime" but a significant effect on disorder crime (Mazerolle et al., 2002; Ratcliffe et al., 2009). Other researchers demonstrated that open-street CCTVs reduced "crimes of dishonesty" (Short & Ditton, 1996). In contrast, open-street CCTVs did not reduce drug offenses, prostitution, and vandalism in other studies (King et al., 2008; Short & Ditton, 1996).

Table 2. 9. Crime Reduction Effects of Open-street CCTVs on Other Types of Crime

Study	Location	Data	Method	Findings
Cerezo (2013)	Spain (Malaga)	Crime incident data (one year before and after implementation), citizen survey, shopkeeper survey	Quasi-experimental design, comparing percentage	Injuries: N.S.
Caplan et al. (2011)	US (Newark)	Crime incident data (13 months before and after implementation)	Quasi-experimental design ANOVA analysis, LQ (location quotient) test	Shootings: Sig.

[1] Cerezo (2013) investigated crime reduction effects of open-street CCTVs on vandalism, injuries, threats, burglary, car theft, theft/robbery, and others in her study. The injuries might be the result of aggravated assaults.

Cho (2009)	South Korea (Seoul Borough of Gangnamgu)	Crime incident data (four months before and after implementation)	Quasi-experimental design, comparing percentage	Rape: N.S. Homicide: Mixed
Ratcliffe *et al.* (2009)	US (Philadelphia)	Crime incident data (32 months)	Quasi-experimental design, hierarchical linear modeling, WDQ	Disorder crime: Sig. Serious crime: N.S.
King et al. (2008)	US (San Francisco)	Crime incident data (209 days before and 264 days after implementation)	Quasi-experimental design, difference-in-difference analyses	Drug offenses, prostitution, and vandalism: N.S.
Yim & Hong (2008)	South Korea (Seoul)	Crime incident data (one year)	Quasi-experimental design, multivariate analysis	Rape: Sig. Homicide: N.S.
Choi & Kim (2007)	South Korea (Seoul Borough of Gangnam)	Crime incident data (five years)	Quasi-experimental design, time-series	Rape: N.S. Homicide: N.S
Farrington et al. (2007)	UK	14 evaluations	Meta-analysis, relative effective sizes	Other types of crimes: N.S.
Gill & Hemming (2004)	UK (London Borough of Lewisham)	Crime incident data (one year before and after implementation) , police attitudes survey	Quasi-experimental design, Mann-Whitney U	Criminal damage: Sig.
Griffiths (2003)	UK (Gillingham)	Crime incident data (one year before and five years after implementation)	Quasi-experimental design, comparing number of crime incidents	Shoplifting: Sig.
Goodwin (2002)	UK (Devonport)	Crime incident data and calls-for-service data (24 months	Pre-post design, comparing number of	Injury to property: N.S.

		before and after implementation), community survey	crime incidents and calls-for-services	
Mazerolle et al. (2002)	US (Cincinnati)	Recorded videotapes, police calls-for-service data (23-24 months before and 4-6 months after implementation)	Quasi-experimental design, time-series, comparing percentage	Disorder: Sig.
Phillips (1999)	UK	27 evaluations	Meta-analysis	Personal crime: Mixed Public order: Mixed
Short & Ditton (1996)	UK (Airdrie)	Crime incident data (24 months before after implementation)	Pre-post design, time-series, comparing percentage	Fire-raising & vandalism: Sig. Drug: N.S.

N.S. − Non-significant reduction; Sig − Significant reduction; Mixed – Mixed results (i.e., effect varied across areas)

As with studies that address the effectiveness of CCTVs on overall crime, it is notable that research on CCTVs' effectiveness for specific crime types has taken place in many different geographic contexts, with consistent results appearing across contexts. For example, we can point to studies across Table 2. 2 through 2. 9 showing that CCTVs reduce general property crime in South Korea (Cheong & Hwang, 2012; H. H. Park et al., 2012), Spain (Cerezo, 2013) as well as the U.K. and the U.S. (Caplan et al., 2011; King et al., 2008; Welsh & Farrington, 2009). In contrast, studies have indicated that open-street CCTVs did not reduce violent crime in South Korea (Cheong & Hwang, 2012; H. H. Park et al., 2012) and Spain (Cerezo, 2013) as well as the U.K. and the U.S. (King et al., 2008; Welsh & Farrington, 2004a, 2004b, 2009).

We should note several points when we review past studies on crime reduction effects of open-street CCTVs across various crime types. First, the categorization of robbery has differed among past studies. Much research has categorized robbery as property crime (Cerezo, 2013; Cheong & Hwang, 2012; H. H. Park et al., 2012), but some studies have included it in categories of violent crime (Goodwin, 2002). For example, Cerezo (2013) treated robbery as property crime by pooling robbery and burglary, whereas Goodwin (2002) treated robbery as violent crime by pooling robbery and assault. The issue is likely caused by the fact that robbery has characteristics of both property crime and violent crime, but it necessitates that we interpret the results of past research examining the effectiveness of CCTV on crime categories with caution. This issue also suggests value in research on the effects of CCTV in relation to specific offenses instead of broad categories. Although many studies on crime reduction effects of open-street CCTVs exist, the majority to date focused on broad categories instead of specific offenses (e.g., King et al., 2008; Ratcliffe et al., 2009; Welsh & Farrington, 2009). More studies need to focus on specific offenses in order to understand more deeply the crime reduction effects of open-street CCTVs.

Additionally, as mentioned before in relation to studies of the effectiveness of CCTVs in reducing overall crime, results from studies on specific crime types need to be interpreted carefully due to variation in implementation quality. Null results may stem from appropriate small density of open-street CCTVs or inadequate signage or publicity surrounding their implementation.

Crime Reduction Effects and Implementation Site Type

Past studies shows that crime reduction effects of open-street CCTVs are different depending on implementation site type. Overall, this body of research reveals that open-street CCTVs has reduced crime at some sites but not at others. For example, open-street CCTVs has demonstrated significant crime reduction effects in car parks but not in city centers, public housings, and residential areas (Farrington et al., 2007; Welsh & Farrington, 2003, 2004b, 2009). To show such location-specific effects more clearly, Table 2. 10 shows studies on crime reduction effects of open-street CCTVs, first, in city centers. As shown in the table, all studies found null effects (Farrington et al., 2007; Welsh & Farrington, 2003, 2004b, 2009). The results may mean that crime reduction effects of open-street CCTVs are weak in city center.

Table 2. 10. Crime Reduction Effects of Open-street CCTVs in City Center

Study	Location	Data	Method	Findings
Welsh & Farrington (2009)	UK, US, Canada, Sweden, Norway	44 evaluations	Meta-analysis, OR effect size	City & town center: N.S.
Farrington et al. (2007)	UK	14 evaluations	Meta-analysis, relative effective size	City center: N.S.
Welsh & Farrington (2004b)	UK, US	19 evaluations	Meta-analysis, effect size (odds ratio)	City center: N.S.
Welsh & Farrington (2003)	UK, US, Canada	22 evaluations	Meta-analysis, effect size (odds ratio)	City center or Public housing: N.S.

N.S. − Non-significant reduction

Next, Table 2. 11 shows studies on crime reduction effects of open-street CCTVs in public housing. As shown in the table, all studies found null effects (Welsh & Farrington, 2003, 2004b, 2009). The results may mean that crime reduction effects of open-street CCTVs are weak in public housing.

Table 2. 11. Crime Reduction Effects of Open-street CCTVs in Public Housing

Study	Location	Data	Method	Findings
Welsh & Farrington (2009)	UK, US, Canada, Sweden, Norway	44 evaluations	Meta-analysis, OR effect size	Public housing: N.S.
Welsh & Farrington (2004b)	UK, US	19 evaluations	Meta-analysis, effect size (odds ratio)	Public housing: N.S.
Welsh & Farrington (2003)	UK, US, Canada	22 evaluations	Meta-analysis, effect size (odds ratio)	City center or Public housing: N.S.

N.S. − Non-significant reduction

Table 2. 12 shows studies on crime reduction effects of open-street CCTVs in car parks. As shown in the table, all studies found significant effects (Farrington et al., 2007; Welsh & Farrington, 2003, 2004a, 2004b, 2009). The results suggests that crime reduction effects of open-street CCTVs are much stronger in car parks in comparison to city centers and public housing.

Table 2. 12. Crime Reduction Effects of Open-street CCTVs in Car Park

Study	Location	Data	Method	Findings
Welsh & Farrington (2009)	UK, US, Canada, Sweden, Norway	44 evaluations	Meta-analysis, OR effect size	Sig.
Farrington et al. (2007)	UK	14 evaluations	Meta-analysis, relative effective size	Sig.
Welsh & Farrington (2004a)	UK, US	22 evaluations	Meta-analysis, effect size (odds ratio)	Sig.
Welsh & Farrington (2004b)	UK, US	19 evaluations	Meta-analysis, effect size (odds ratio)	Sig.
Welsh & Farrington (2003)	UK, US, Canada	22 evaluations	Meta-analysis, effect size (odds ratio)	Sig.

Sig − Significant reduction

Next, Table 2. 13 shows studies on crime reduction effects of open-street CCTVs in public transportation facilities. As shown in the table, one study found mixed effects (Welsh & Farrington, 2004a). However, other studies reported no evidence of effects of open-street CCTVs (Welsh & Farrington, 2003, 2004b, 2009).

Table 2. 13. Crime Reduction Effects of Open-street CCTVs in Public Transportation

Study	Location	Data	Method	Findings
Welsh & Farrington (2009)	UK, US, Canada, Sweden, Norway	44 evaluations	Meta-analysis, OR effect size	N.S.
Welsh & Farrington (2004a)	UK, US	22 evaluations	Meta-analysis, effect size (odds ratio)	Mixed
Welsh & Farrington (2004b)	UK, US	19 evaluations	Meta-analysis, effect size (odds ratio)	N.S.
Welsh & Farrington (2003)	UK, US, Canada	22 evaluations	Meta-analysis, effect size (odds ratio)	N.S.

N.S. − Non-significant reduction; Mixed – Mixed results (i.e., effect varied across areas)

Finally, Table 2. 14 shows studies on crime reduction effects of open-street CCTVs in several other less commonly-studied locations (i.e., residential area, city hospital). As shown in the table, Farrington et al. (2007) reported that open-street CCTVs had null effects in residential areas and city hospitals. This suggests that crime reduction effects of open-street CCTVs may be weak in those areas, though further evidence is clearly needed.

Table 2. 14. Crime Reduction Effects of Open-street CCTVs in Other Sites

Study	Location	Data	Method	Findings
Farrington et al. (2007)	UK	14 evaluations	Meta-analysis, relative effective size	Residential area: N.S. City hospital: N.S.

N.S. − Non-significant reduction

We should note some important points in relation to past studies that examine the crime reduction effects of open-street CCTVs across site type. First, meta-analyses were used for most of these studies. Because meta-analyses generalize results from various settings, it is hard to disentangle the effects of differences across site types and difference across research settings. Thus, research examining the crime reduction effects of open-street CCTVs according to implementation site-type may be best done in one research setting.

Elements Influencing Crime Reduction Effects of Open-street CCTVs

Piza and his colleagues had more interest in processes surrounding the potential crime reduction effects of open-street CCTVs rather than straightforward evaluation of the crime reduction effects of open-street CCTVs themselves (Piza et al., 2014, 2014a, 2014b, 2014c). They conducted their studies on open-street CCTVs implemented in Newark, NJ. First, they examined whether reports through monitoring open-street CCTVs can prevent crimes by analyzing nine case studies. (Piza et al., 2014b). The findings showed that if the police intervene in situations with probable cause or reasonable suspicion through monitoring open-street CCTVs, serious crimes like shooting can be prevented. Second, Piza and his colleagues examined whether detections through open-street CCTVs affect the certainty of punishments by using crime data from Newark Police Department (2014c). The findings showed that reports through monitoring open-street CCTVs lead to greater enforcement than reports through calls-for-service.

Third, Piza and his colleagues examined whether integration of proactive open-street CCTV monitoring and proactive police activity reduced crimes in a randomized block design (2014). They divided open-street CCTVs into treatment group and control groups. An additional camera operator monitored only treatment group CCTVs. Further, two additional patrol cars were utilized in treatment areas, focusing on reports through the CCTVs. The findings showed that the integration of proactive CCTV monitoring and proactive police activity can reduce more crime than the integration of "normal" CCTV monitoring and "normal" police activity. Finally, Piza and his colleagues examined the factors influencing crime change at open-street CCTV sites by using data from Newark Police Department (2014a). They used the change of crime rates between pre- and post-CCTV implementation as dependent variables (e.g., ΔLQ overall crime, ΔLQ violent crime). They also used environmental variables (e.g., bars, liquor stores, and schools), line of sight (e.g., % immovable obstruct, % foliage obstruct), enforcement actions (e.g., detections, camera enforcement), and camera design (e.g., dome) as independent variables. The findings showed that environmental features influenced crime changes differently depending on crime types. For example, obstruction of open-street CCTV surveillance by immovable object increased auto theft but decreased violent crime, theft from auto, and robbery. Also, enforcement significantly decreased overall crime, violent crime, and theft from auto.

CCTV Effects, Displacement and Diffusion of Benefits

Displacement and diffusion of benefits can happen due to the implementation of open-street CCTVs. Among the five kinds of displacement (i.e., temporal, spatial, target, method, and crime type), a number of past studies have examined whether spatial displacement occurs due to the implementation of open-street CCTVs (Caplan et al., 2011; Cerezo, 2013; Cho, 2009; Choi & Kim, 2007; Farrington et al., 2007; M. Gill & Hemming, 2004; La Vigne et al., 2011; H. H. Park et al., 2012; Short & Ditton, 1996). Only one study examined all five types of displacement in response to the implementation of open-street CCTVs (Lee, 2008). Various studies examine diffusion of benefits caused by the implementation of open-street CCTVs (Caplan et al., 2011; Cho, 2009; Choi & Kim, 2007;

Farrington et al., 2007; Kim, 2008; Lee, 2008; C. Park & Choi, 2009; H. H. Park et al., 2012).

Past studies on CCTV, displacement, and diffusion of benefits can be summarized into several points. First, overall, studies report little displacement after the implementation of open-street CCTVs. Although some studies find evidence of displacement (Choi & Kim, 2007; H. H. Park et al., 2012), more studies deny that displacement is caused by the implementation of open-street CCTVs (Caplan et al., 2011; Cho, 2009; Farrington et al., 2007; M. Gill & Hemming, 2004; Short & Ditton, 1996).

Second, whether spatial displacement occurred upon implementation of open-street CCTVs may depend on the crime type measured. For example, one study showed that the implementation of open-street CCTVs caused displacement of property crime but it did not cause displacement of personal crime (Cerezo, 2013).

Third, the one study that has examined all five kinds of displacement potentially caused by the implementation of open-street CCTVs found that evidence of target and method displacement were stronger than evidence of spatial and temporal displacement (Lee, 2008). Crime type displacement did not emerge at all in this study (Lee, 2008).

Fourth, most studies examining the issue found that the implementation of open-street CCTVs created a spatial diffusion of benefits (Cho, 2009; Choi & Kim, 2007; Kim, 2008; H. H. Park et al., 2012).

Fifth, like displacement whether spatial diffusion of benefits occurred upon implementation of open-street CCTVs may depend on the crime type measured. For example, the implementation of open-street CCTVs created diffusion of benefits regarding the crime types of auto theft (Caplan et al., 2011), robbery(Cho, 2009), and burglary and theft (Cho, 2009; Kim, 2008), but few diffusion effects were noted for shootings (Caplan et al., 2011).

Sixth, studies examining *both* displacement and diffusion show that, although displacement may happen after the implementation of open-street CCTVs, diffusion of benefits is stronger than the displacement. For example, a recent study found that the implementation of open-street CCTVs led to displacement of burglary and robbery, but the diffusion of benefits was stronger than the displacement (H. H. Park et al., 2012).

Finally, studies suggest that the diffusion of benefits caused by the implementation of open-street CCTVs is stronger in the short term than in the long term. For example, Park & Choi (2009) indicated that the diffusion of benefits of open-street CCTVs was stronger during the three months shortly after news reporting the implementation of open-street CCTVs than during three to six months after the news report.

The Present Study

As reviewed above, various studies on crime reduction effects of open-street CCTVs were conducted in the past. Nevertheless, there is still important knowledge we do not know about the crime reduction effects of open-street CCTVs. In sum, as noted in Chapter 1, the current literature has the following notable gaps: 1) there is no research on daytime versus nighttime crime reduction effects of open-street CCTVs; 2) there is no research on weekday versus weekend crime reduction effects of open-street CCTVs; 3) there is little research on the crime-specific effects of open-street CCTVs; 4) there is very little information about how location characteristics moderate the crime reduction effects of open-street CCTVs on specific offenses and no information about how location type moderates the CCTV effect differentially for daytime versus nighttime crime and weekday versus weekend crime; 5) there is a need for more research on displacement and diffusion of benefits depending on crime type, and there is no research comparing displacement and diffusion of benefits during daytime versus nighttime, and weekdays versus weekends following open-street CCTV implementation; and 6) there is no research examining the preventive effects of CCTV while also considering synergistic effects that may emerge in the locations where open-street CCTVs are overlapping. This study's hypotheses, stated below, are intended to fill these gaps and provide a more nuanced understanding of the crime reduction effectiveness of open-street CCTVs.

Research Hypotheses:

Hypothesis 1: Crime reduction effects of open-street CCTVs will be greater during the daytime than the nighttime.

Hypothesis 1-1: Crime reduction effects of open-street CCTVs during the daytime will vary depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The reduction effects will be greatest in residential areas and lowest in downtown districts.

Hypothesis 1-2: Crime reduction effects of open-street CCTVs at nighttime will vary depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The reduction effects will be greatest in residential areas and lowest in downtown districts.

Hypothesis 2: Crime reduction effects of open-street CCTVs will be greater during weekdays than during the weekends.

Hypothesis 2-1: Crime reduction effects of open-street CCTVs during weekdays will vary depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The reduction effects will be greatest in residential areas and lowest in downtown districts.

Hypothesis 2-2: Crime reduction effects of open-street CCTVs during weekends will vary depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The reduction effects will be greatest in residential areas and lowest in downtown districts.

Hypothesis 3: Crime reduction effects of open-street CCTVs are different between crime types (i.e., assault, robbery, burglary, auto theft, theft from auto). The reduction effects of robbery, burglary, auto theft, theft from auto will be greater than the reduction effects of assault.

Hypothesis 3-1: Crime reduction effects of open-street CCTVs for *assault* will vary depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The reduction effects will be greatest in residential areas and lowest in downtown districts.

Hypothesis 3-2: Crime reduction effects of open-street CCTVs for *robbery* will vary depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The reduction effects will be greatest in residential areas and lowest in downtown districts.

Hypothesis 3-3: Crime reduction effects of open-street CCTVs for *burglary* will vary depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The reduction effects will be greatest in residential areas and lowest in downtown districts.

Hypothesis 3-4: Crime reduction effects of open-street CCTVs for *auto theft* will vary depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The reduction effects will be greatest in residential areas and lowest in downtown districts.

Hypothesis 3-5: Crime reduction effects of open-street CCTVs for *theft from auto* will vary depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The reduction effects will be greatest in residential areas and lowest in downtown districts.

Hypothesis 4: Open-street CCTV implementation brings about diffusion of benefits effects rather than displacement effects. This effect is expected to be seen regardless of daytime/nighttime, weekday/weekend, and crime types.

Theory-Hypotheses Linkages

Drawing upon the opportunity perspectives described earlier in this chapter, these hypotheses are supported theoretically as follows. Hypothesis 1 is derived from the proposition that open-street CCTVs can better monitor the implementation area and be better recognized by offenders during the day than at night. Offenders may be more likely to think that the possibility of being arrested will increase if they commit crimes near open-street CCTV implementation sites during the day due to the brightness offered by daytime. In addition, since daylight allows potential offenders to more easily recognize the existence of open-street CCTVs, offenders may be more deterred by the open-street CCTVs during the day than the night.

Specifically, these explanations can be connected with opportunity theories as follows. According to rational choice perspective, offenders may be more reluctant to commit crime at open-street CCTV implementation sites during the day than at night because they perceive great risk. As mentioned above, perceived risk from the crime is greater during the day than at night at the places (Coupe & Blake, 2006). Similarly, according to routine activity theory, open-street CCTV may produce more crime reduction effects during the day than at night because it works to provide stronger guardianship particularly during the day in comparison to nighttime. Drawing upon similar ideas, yet using concepts from environmental design theory, open-street CCTV may produce more crime reduction effects during the day than at night because it enhances surveillance during the day more so than at night.

Hypothesis 2 can be derived from Felson & Boba's (2009) discussions of the flows of recreational activity, especially in city centers. Major entertainment and cultural events are often concentrated on weekends, when they can draw large crowds. Such patterns of activity create especially high levels of opportunity during the weekend (many people, many cars, etc.). The ease of access to an abundance of targets during weekends could potentially outweigh the risk associated with CCTV among offenders who consider the costs versus benefits of crime events. In contrast, weekdays tend to host fewer activities/events that produce such opportunistic crowds. Hence, the risk associated with CCTV stands a greater chance of outweighing the perceived rewards of crime during weekdays.

Hypothesis 3 is derived from the proposition that crime reduction effects of open-street CCTVs may be different depending on the characteristics of the crimes. For example, offenders who commit expressive crimes, such as assault, may not consider the existence of the open-street CCTVs compared to those who commit more instrumental crimes such as robbery, burglary, auto theft, theft from auto. Thus, crime reduction effects of open-street CCTVs may be much weaker for expressive crimes than instrumental crimes.

Specifically, these explanations can be connected with opportunity theories as follows. According to rational choice perspective, factors that affect crime events are offense-specific. Offenders who commit instrumental crimes may hesitate to commit crime at open-street CCTV implementation sites because they think that the risk from the crime is bigger than the benefit from the crime. In contrast, offenders who commit expressive crime are perhaps more likely to discount risks such as open-street CCTV. Similarly, offenders who commit expressive crimes may be less likely to even recognize the existence of the open-street CCTV during the commission of crime – in other words, having more bounded rationality than instrumental offenders.

Hypotheses regarding the moderating influence of CCTV location type – including Hypotheses 1-1, 1-2, 2-1, 2-2, 3-1, 3-2, 3-3, 3-4, and 3-5 – are derived as follows. First, the degree of recognizing the open-street CCTVs by offenders may be different among locations. For example, offenders may forget the existence of the open-street CCTVs in a complex city center. Secondly, offenders may feel more anonymous within this densely populated area, despite knowledge of the cameras. Hence, the deterrent value of CCTV may be diminished in such locations. Third, the moderating effect of CCTV location type may reflect the fact that certain crimes are more prevalent in some areas than others. For example, violent crimes such as assault – which are presumed to be less influenced by open-street CCTVs – may frequently occur in a complex city center. In contrast, burglary – which is presumed to be more subject to influence by open-street CCTVs – more frequently occur in a residential area.

Specifically, these explanations can be connected with opportunity theories as follows. In line with the rational choice perspective, offenders likely think that downtown has relatively low risk, even with CCTV, due to the anonymity of downtown. Further, the effort to find targets in downtown areas is typically minimal due to high levels of routine activity in downtown areas. In contrast, CCTV could be seen as substantially increasing the risks, especially relative to effort and reward, in residential areas.

Hypothesis 4 is derived from the proposition that offenders may overestimate the reach of open-street CCTV. Consistent with the notion of bounded rationality, offenders do not know the precise viewshed of open-street CCTVs. They may think that open-street CCTVs cover wider areas than the area that the CCTVs cover in reality. Therefore, they may give up committing crimes in the vicinity of open-street CCTV implementation sites due to an incorrect assessment of risk.

CHAPTER III

METHODOLOGY

In this chapter, first, I will explain the research design of this study. Then I will describe the data, measures, and analytic methods of this study. The description of analytic methods includes a detailed discussion of the "overlapping areas problem," which is a major methodological issue in the study of the impact of CCTV.

Research Design

This research used a quasi-experimental time-series design to test given hypotheses presented at the conclusion of the previous chapter. For the design, geographic areas in the city were designated as treatment, buffer, and control areas. The effect of CCTV implementation on crime in target, buffer, and control areas is then examined. For this process, treatment/target areas, buffer areas, and control areas should be clearly defined.

In this study, "target areas" (also referred to as treatment areas) refer to areas that are potentially directly influenced by open-street CCTV. Several methods can be used when designating target areas. First, we can designate target areas based on offender perceptions or the range in which an offender recognizes the existence of open-street CCTV and hesitates to commit his/her offense. This method can measure crime reduction effects of open-street CCTVs accurately, but such offender perceptions are subjective and quite difficult to measure (Ratcliffe et al., 2009). Second, we can designate target areas based on the actual surveillance distance of open-street CCTVs. This method can designate target areas more easily, using GIS (Geographic Information System) and the physical viewshed of open-street CCTV (Ratcliffe et al., 2009).

This research will use the second method following various past studies (e.g., Caplan et al., 20ll; Piza et al., 2014a; Ratcliffe et al., 2009). That is, target areas are the unobstructed, unobscured areas which can be viewed by the open-street CCTVs. To apply this method, the surveillance distance and functionality of the open-street CCTVs in Cincinnati were examined. All open-street CCTVs in Cincinnati were equipped with pan, tilt, and zoom functions. The monitoring officers could read license plates located 200-300 feet away from the open-street CCTVs and see some objects located 3,000 feet away from the open-street CCTVs. However, according to the person in charge of the open-street CCTVs, normally the CCTVs were adjusted to monitor 500 feet – approximately one city block. Hence, 500 feet was regarded as the general surveillance distance of open-street CCTV in this research, though obstructions to view within that range were considered and omitted from target areas (see Figure 3. 1 for a sample target area).

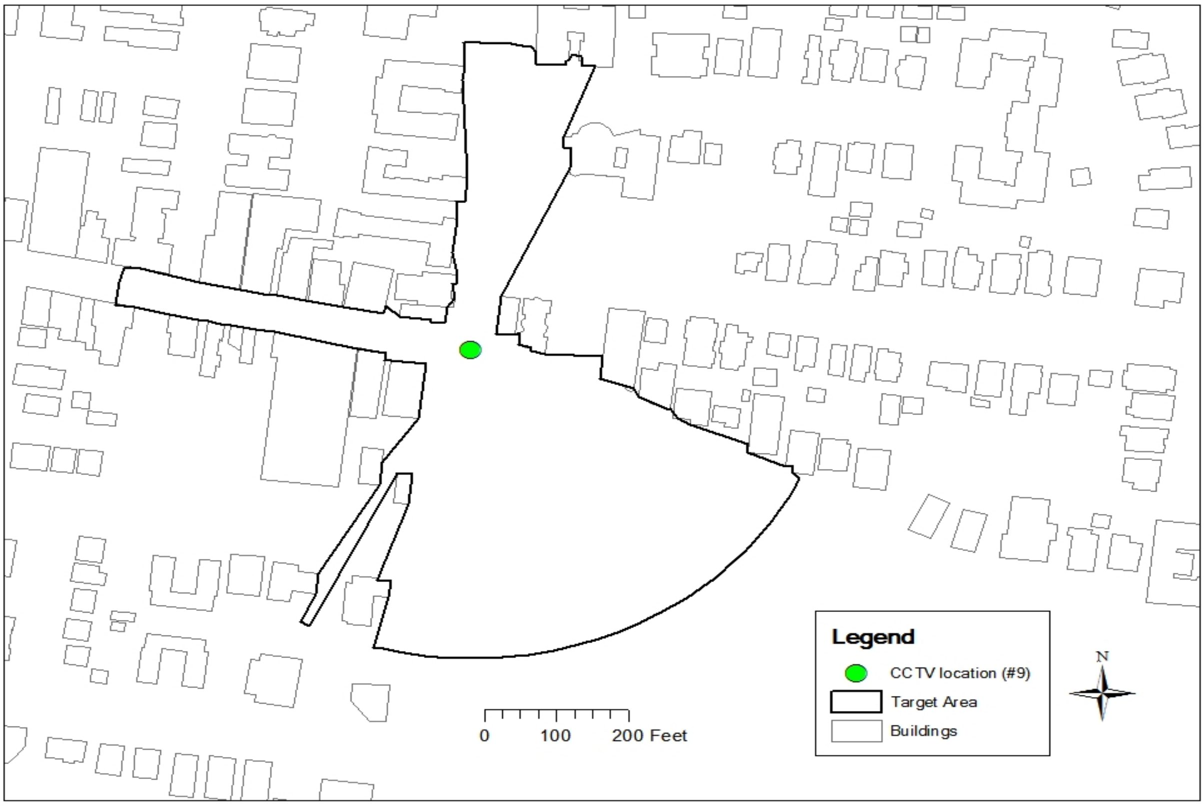

Figure 3. 1. Sample Target Area (#9)

As intended, the open-street CCTVs were sometimes controlled by police officers in a control room. In such instances, the police officers monitored CCTV in real time and dispatched patrol police officers when necessary. However, it is important to note that, in reality, CCTV in Cincinnati tends to be used more frequently in a reactive manner rather than a proactive manner. That is, CCTV is more often used for investigative purposes after the commission of crime as opposed to preventing crime and arresting criminals in the crime scene. Thus, although CCTV had a function of handoff, police officers did not think that the function was typically effective.[2] These issues will be discussed again in relation to the study's findings.

"Buffer areas" in the study's design refer to areas that are potentially indirectly influenced by open-street CCTV. Although buffer areas are not directly within the viewing area of CCTV, the area may experience displacement or diffusion of benefits in accordance with open-street CCTV implementation. For example, an offender may commit a crime in a buffer area instead of target area because he/she is afraid of being caught in the target areas, but the buffer areas is nearby and thus a convenient alternative. Another offender may overestimate the surveillance distance of open-street CCTV and stop his/her prepared offense in the buffer area, thus resulting in diffusion of benefits for the buffer area. This research designated areas within 500 feet from the edge of target areas as buffer areas (see Figure 3. 2). Again 500 feet is the approximate distance of a city block in Cincinnati and is the expected distance in which displacement or diffusion of benefits might be likely. An offender who is deterred in target area is unlikely to displace his/her crime far away from the target area. In addition, diffusion of benefits of open-street CCTV are unlikely to occur far away

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[2] The function of CCTV and police officers' opinion about the effects of CCTV were summarized with the help of Cincinnati Police Officer Roberta Utecht (personal communication, June 10, 2015).

from the implementation sites. Thus, this research assumes that the 500 foot areas surrounding target areas are appropriate designation for buffer areas.

"Control areas" are areas designated by researchers as similar to target areas in various aspects (e.g., SES, race, land use) but not influenced directly or indirectly by open-street CCTV. This research designated areas within 700 feet to 1000 feet from the edge of target areas as control areas (again, see Figure 3. 2 for an example). A control area is similar to a target area due to their relative proximity, but because it is sufficiently far away (outside the buffer), the control area is unlikely to be influenced directly or indirectly by open-street CCTV. In this study, the designated "target," "buffer," and "control" areas are used differently, depending on the hypothesis being tested. Only target areas were used for testing hypotheses 1 to 3. However, for testing hypothesis 4, buffer and control areas, as well as target areas, were used.

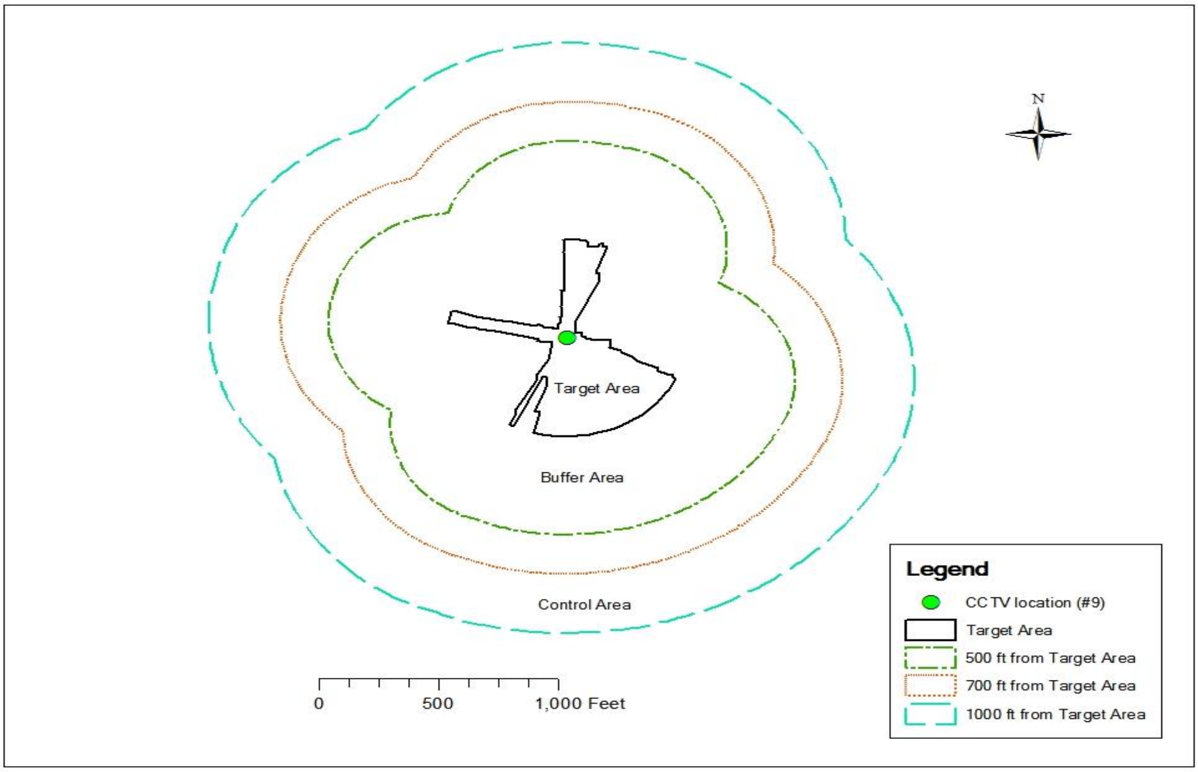

Figure 3. 2. Sample Target Area with Buffer Area and Control Area (#9)

Data

Several sources of data were utilized for this research. First, crime incident data was gathered from University of Cincinnati's Institute of Crime Science (UCICS), which houses updated records of crime incidents from the Cincinnati Police Department[3]. The data secured include the date, location, and the type of crime for incidents reported from 2006 to 2012. Second, information on open-street CCTV installations was gathered from the Cincinnati Police Department, including implementation date and implementation sites. Third, electronic maps of streets and buildings of Cincinnati were gathered from CAGIS (Cincinnati Area Geographic Information system) which is the organization that establishes electronic maps of the Cincinnati area by using GIS. Fourth, information on monthly average temperatures in Cincinnati from 2006 to 2012 was gathered from the website Weather Underground (www.wunderground.com/history). Finally, information on the dates of holidays and observances from 2006 to 2012 was gathered from the website timeanddate.com (www.timeanddate.com/calendar).

Based on the crime incident data and information on open-street CCTVs provided by Cincinnati Police, I was able to geocode crime incident locations and open-street CCTV implementation sites using ArcMap 10.1. Through this process, a total of 280,029 crime incidents were geocoded from the 280,147 total crime incidents reported (success rate: 99.96 %) and 34 open-street CCTV implementation sites were geocoded (success rate: 100 %).

[3] Permission was obtained from Cincinnati Police for the use of the incident data housed at UCICS.

Measures

Dependent Variables

This study used incidents as dependent variables. For each crime type studied, a daily average number of crime incidents for a month was computed for each target area. Daily average numbers of crime incidents for a month is assumed to follow a Normal distribution.[4]

Specifically, this research used nine dependent variables. First, *daytime crime* and *nighttime crime* were used as dependent variables. The variables measured the daily average of all crime incidents per a month in the target area during daytime or nighttime from 2006 to 2012. In this study, daytime and nighttime was designated as follows. First, sunrise and sunset times in Cincinnati during the study period (i.e., from Jan. 1st, 2006 to Dec. 31st, 2012) were gathered from the website timeanddate.com (www.timeanddate.com/sun/usa/cincinnati). Sunrise time ranged between 06:11 to 08:11 and sunset time fell between 07:18 to 19:19 during the study period. The mid-point of each range was then calculated: the mid-points for sunrise and sunset were 07:18 and 19:19, respectively. Crime incidents were designated as daytime or nighttime using the reported time of the incident in relation to these mid-points.

Second, *weekday crime* and *weekend crime* were used as dependent variables. The variables measured average weekday and weekend-day crime incidents per month in the target areas from 2006 to 2012. Finally, five specific types of street crimes were used as dependent variables. They are *assault*, *robbery*, *burglary*, *theft*, and *theft from auto*. The five variables were measured as the daily average number of each type of crime incidents per

[4] Total crime counts per month as opposed to daily averages per month, along with Poisson regression, was considered. However, once crime in overlapping camera areas was considered and averaged across target areas (discussed in further detail below), non-integers resulted.

month for each target area.

Log transformation was conducted to satisfy normality of dependent variable distribution because all dependent variables showed very skewed distributions. Before log transformation, a small constant (0.000001) was added to the values of all dependent variables since the minimum value of all dependent variables was originally zero. Table 3. 1 provides descriptive statistics for all dependent variables including log-transformed variables. The descriptive statistics show that daytime crime, nighttime crime, weekday crime, and weekend crime have standard deviations similar to the means. However, specific types of crime (i.e., assault, robbery, burglary, auto theft, theft from auto) have much greater standard deviations than means. Overall, the skewnesses of the dependent variables in their original metric are much higher than those of transformed dependent variables. The distributions of the transformed dependent variables are much closer to normal than are those of the original dependent variables.

Table 3. 1. Descriptive Statistics for Dependent Variables

	Mean	SD	Min	Max	Skewness
Daytime crime	0.111	0.107	0	0.833	1.721
Nighttime crime	0.076	0.076	0	0.567	1.823
Weekday crime	0.191	0.160	0	1.083	1.279
Weekend crime	0.179	0.195	0	1.375	1.613
Assault	0.004	0.012	0	0.129	3.842
Robbery	0.014	0.025	0	0.233	2.467
Burglary	0.013	0.025	0	0.258	2.824
Auto theft	0.004	0.012	0	0.200	4.310
Theft from auto	0.018	0.033	0	0.267	2.879
Daytime crime (log)	-3.723	3.741	-13.816	-0.182	-2.200
Nighttime crime (log)	-4.679	4.349	-13.816	-0.565	-1.564
Weekday crime (log)	-2.822	3.343	-13.816	0.080	-2.803
Weekend crime (log)	-5.190	5.585	-13.816	0.318	-0.874
Assault (log)	-12.612	3.312	-13.816	-2.048	2.396
Robbery (log)	-10.227	4.986	-13.816	-1.455	0.677
Burglary (log)	-10.544	4.883	-13.816	-1.355	0.830
Auto theft (log)	-12.551	3.388	-13.816	-1.609	2.311
Theft from auto (log)	-10.101	5.081	-13.816	-1.322	0.647

* Descriptive statistics are based on 2,856 monthly repeated measures nested within 34 open-street CCTV target locations.

Key Independent Variables

CCTV implementation was the key independent variable in this study. Specifically, the "CCTV" variable measures whether open-street CCTV was being implemented at a CCTV location in a particular month (1 = Yes; 0 = No). As shown in Table 3.2, 35 open-street CCTVs were installed in 34 areas of Cincinnati from Nov. 2009 to May 2011. Figure 3. 3 displays the precise geographic placement of the CCTVs

Table 3. 2. Open-street CCTVs in Cincinnati

Phase	Number of CCTVs (35)	CCTV Implementation Sites (34)
Phase 1 (Nov. 2009)	8	Downtown (8)
Phase 2 (May 2010)	9	Business district (2), School (university & high school) (5), Residential area (1)
Phase 3 (Oct. 2010)	13	Business district (9), School (university & high school) (2), Residential area (2)
Phase 4 (Feb. 2011)	4	Residential area (4)
Phase 5 (May 2011)	1	Business district (1)

* In Phase 2, two CCTVs were implemented in a same site (i.e., a residential area).

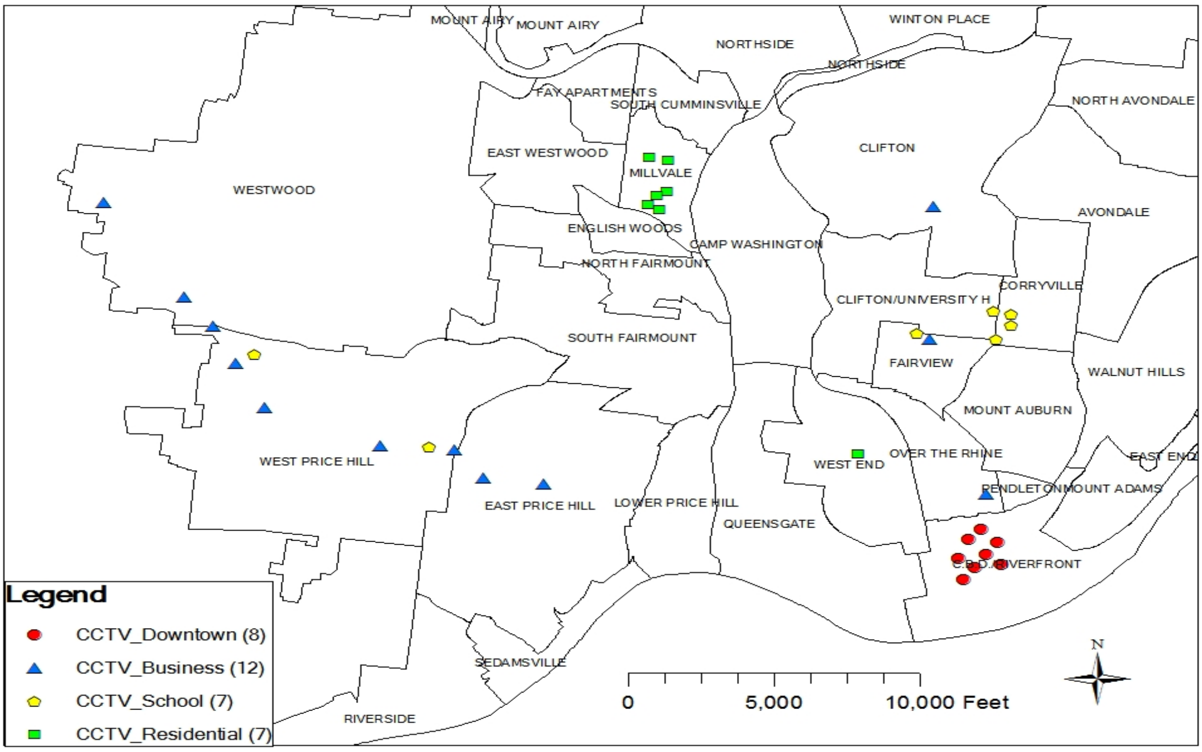

Figure 3. 3. Open-street CCTV Installation Sites

Monthly crime was hypothesized to be related to implementation in CCTV in addition to an overall temporal trend as well as seasonal fluctuations. In order to examine the *temporal trend*, each month of the study was coded sequentially, from 1 to 84. For example, the value of temporal trend for Jan. 2006 is 1 and the value of temporal trend for Dec. 2012 is 84. Seasonal effects were measured with temperature data, under the assumption that there is more outside activity, and thus crime, in warmer weather (Ratcliffe et al., 2009). In this study, *average temperature* for each month of the study was included, based on data from Weather Underground (www.wunderground.com/history).

The types of open-street CCTV sites (i.e., *downtown*, *business district*, *school/university setting*, *residential area*) are also key independent variables since a major aim of the study is to determine whether site-type influences the crime reduction effects of open-street CCTV. Each site type is measured by way of a dichotomous variable (1 = Yes; 0 = No). While the "downtown" site type is self-explanatory, it should be noted that site types designated as "business district" included the Ludlow Avenue Clifton Business District, McMillan Business district, East Price Hill Business District, West Price Hill Business District, Western Hills Plaza Shopping Center, and Over-the-Rhine Main Street. Open-street CCTVs designated as being implemented at "university/school" settings included those installed on the University of Cincinnati campus, Hughes High School, Elder High School, and Western Hills High School. Open-street CCTVs designated as being implemented in "residential areas" were installed at Cincinnati Metropolitan Housing Authority public housing sites.

Table 3. 3 provides descriptive statistics for the key independent variables. The descriptive statistics show that the number of pre-CCTV implementation months are much greater than the number of post-CCTV implementation months. Also, the statistics show that a lot of values of the temperature variable are located close to the mean. Finally, the statistics suggest that the number of CCTV sites for business districts is greater than the number of CCTV sites for downtown, school/university settings, or residential areas.

Table 3. 3. Descriptive Statistics for Independent Variables

	Mean	SD	Min	Max
CCTV	0.358	0.479	0.000	1.000
Temporal trend	42.500	24.251	1.000	84.000
Temperature	55.202	15.984	24.000	81.000
Downtown	0.235	0.424	0.000	1.000
Business district	0.353	0.478	0.000	1.000
School/university	0.206	0.404	0.000	1.000
Residential area (reference group)	0.206	0.404	0.000	1.000

* Descriptive statistics are based on 2,856 monthly repeated measures nested within 34 open-street CCTV target locations.

Bivariate correlations among the dependent variables and key independent variables are shown in Table 3. 4. These correlations indicate that CCTV actually has a significantly *positive* bivariate association with daytime crime and theft from auto, whereas it has the expected significant negative bivariate relationship with nighttime crime, assault, robbery, burglary, and auto theft. The correlations between CCTV and both weekday crime and weekend crime were non-significant.

In addition to the correlations between CCTV and the dependent variables, Table 3. 4 also shows the bivariate correlations among key independent variables. I discuss only a few of these correlations – namely those involving the key independent variable of CCTV. The correlation involving CCTV is positively related to temporal trend and Downtown location, whereas CCTV is negatively related to business district location; other correlations between CCTV and independent variables were non-significant. The correlation between CCTV and temporal trend was especially high (r = 0.816), thus causing concerns about collinearity problems. Hence, I conducted diagnostics of collinearity and found that there was no collinearity problem in this study[5].

[5] In VIF analysis using the key dependent variables (i.e., CCTV, temporal trend, temperature, Downtown, business district, school), all values of VIF were less than 4. In addition, in condition number tests, a condition index over 30 was not found (Besley et al., 1981).

Table 3. 4. Correlation Matrix among the Dependent Variables and Key Independent Variables

	DC	NC	WC	WE	AS	RO	BU	AT	TA	TT	TE	CC	DO	BD	SC
DC	1.000														
NC	.297**	1.000													
WC	.858**	.629**	1.000												
WE	.596**	.643**	.503**	1.000											
AS	.078**	.292**	.172**	.198**	1.000										
RO	.308**	.430**	.406**	.351**	.158**	1.000									
BU	.119**	.296**	.200**	.220**	.066**	.088**	1.000								
AT	.115**	.232**	.171**	.189**	.053*	.085**	.074**	1.000							
TA	.269**	.399**	.365**	.314**	.008	.150**	-.034	.083**	1.000						
TT	.025	-.085**	-.034	-.006	-.044*	-.047*	-.046*	-.056*	-.001	1.000					
TE	.031	.085**	.055*	.057*	.017	-.013	.070**	.026	.036	.046*	1.000				
CC	.059*	-.046*	.014	.022	-.066**	-.053*	-.095**	-.039*	.047*	.816**	.027	1.000			
DO	.339**	.181**	.329**	.232**	-.049*	.064**	-.082**	.005	.293**	.000	.000	.109**	1.000		
BD	.006	.022	-.001	.043*	.020	.110**	-.003	.027	-.056*	.000	.000	-.053*	-.410**	1.000	
SC	-.116**	-.071**	-.090**	-.132**	-.046*	-.037*	-.083**	-.024	-.013	.000	.000	.006	-.282**	-.376**	1.000

* DC: Daytime crime, NC: Nighttime crime, WC: Weekday crime, WE: Weekend crime, AS: Assault, RO: Robbery, BU: Burglary, AT: Auto theft, TA: Theft from auto, TT: Temporal trend, TE: Temperature, CC: CCTV, DO: Downtown, BC: Business district, SC: School

* The results are based on 2,856 monthly repeated measures nested within 34 open-street CCTV target locations.

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

Base Rates of Crime

Beyond the key independent variable described above, base rates of crime incidents are also measured in this study and used 1) to describe the target, buffer, and control areas, and 2) as independent variable in supplemental HLM analyses examining the extent to which CCTV effectiveness might vary depending upon base rates of crime. Base rates are measured as average monthly counts of crime incidents in each target area *before* CCTV implementation (during the 2006-2012 study period). This study considered base-rates as independent variables because crime prevention efforts like open-street CCTV might not show an effect when crime is low (Hinkel, Weisburd, Famega, & Ready, 2013).

Analytic Methods

The analysis of the crime-reduction effectiveness of CCTV will proceed in several major steps where, first, I estimate the "fixed" effect of CCTV across daytime/nighttime, weekday/weekend, five specific types of crime using hierarchical modeling techniques (discussed in more detail below). Then, I compare these fixed slopes using a Z-test. Next, I specify the CCTV coefficient as random and move into a stage of analysis where I examine the extent to which location types moderate the effects of CCTV on my various dependent variables. While not specifically a part of my hypotheses, I also performed supplemental analyses in which I examined the potentially conditional effect of CCTV depending on base rate of crime. Finally, I move into an analysis of displacement and diffusion using WDQ.

The type of hierarchical models estimated here are latent growth curve models, with monthly repeated measures (level 1) nested within target locations (level 2). The level-1 model estimates change in monthly crime counts at target areas as a function of temporal crime trends, seasonal temperature effects, and CCTV implementation (Ratcliffe et al., 2009).

The level-2 model examines whether the effects of CCTV on monthly crime counts vary depending on the characteristics of implementation sites (i.e., downtown, business district, school/university setting, residential area). Specific formulae for the first part of the analysis are as follows:

Level-1:

$$AverageCrimeCount_{it} = \beta_{0i} + \beta_{1i}(TemproalTrend) + \beta_{2i}(Temperature) + \beta_{3i}(CCTV) + r_{it}$$

Level-2:

$$\beta_{0i} = \gamma_{00} + u_{0i}$$
$$\beta_{1i} = \gamma_{10} + u_{1i}$$
$$\beta_{2i} = \gamma_{20}$$
$$\beta_{3i} = \gamma_{30}$$

Where $AverageCrimeCount_{it}$ is the daily average number of crime incidents occurring within the target area for CCTV location *i* at time *t*; β_{0i} is the initial average daily crime count in target area *i*; β_{1i} is the slope coefficient for the temporal trend variable, representing the "growth parameter" for the average daily crime count in target area *i*; β_{2i} is the slope coefficient for the temperature variable; β_{3i} is the slope coefficient for the CCTV variable; r_{it} is the level-1 error; γ_{00} is the mean initial daily average crime count across target areas; γ_{10} is the cross-areas varying slope for the temporal trend, the growth parameter; γ_{20} and γ_{30} are the fixed slopes for the temperature and CCTV variables; u_{0i} and u_{1i} are the level-2 variances for the level-2 intercept and temporal trend slopes, respectively.

In criminology, Z-stat is often used to compare two regression coefficients. This study thus utilizes Z-stat to compare the daytime versus nighttime, weekday versus weekend, and crime-specific crime reduction effects of CCTV at target locations. The formula is as follows (Paternoster et al., 1998).

$$Z = (\gamma_{30A} - \gamma_{30B}) \Big/ \sqrt{(SE\gamma_{30A}\hat{}2 + SE\gamma_{30B}\hat{}2)}$$

Where γ_{30A} is the fixed slope for the CCTV variable in the estimation of dependent variable A (e.g., daytime crime); γ_{30B} is the fixed slope for the CCTV variable in the estimation of dependent variable B (e.g., nighttime crime); $SE\gamma_{30A}\hat{}2$ is the variance associated with γ_{30A}; $SE\gamma_{30B}\hat{}2$ is the variance associated with γ_{30B}.

Before moving into the second stage of the analysis, in which the conditional effect of CCTV across location types in estimated, I specify the effect of the CCTV variable as random, and examine whether the effects of open-street CCTVs are different across CCTV locations. Specific formulae for this step in the analysis are as follows:

Level-1:

$$AverageCrimeCount_{it} = \beta_{0i} + \beta_{1i}(TemproalTrend) + \beta_{2i}(Temperature) + \beta_{3i}(CCTV) + r_{it}$$

Level-2:

$$\beta_{0i} = \gamma_{00} + u_{0i}$$
$$\beta_{1i} = \gamma_{10} + u_{1i}$$
$$\beta_{2i} = \gamma_{20}$$
$$\beta_{3i} = \gamma_{30} + u_{3i}$$

Where AverageCrimeCount$_{it}$ is the daily average number of crime incidents occurring within the target area for CCTV location *i* at time *t*; β_{0i} is the initial average daily crime count in target area *i*; β_{1i} is the slope coefficient for the temporal trend variable, representing the "growth parameter" for monthly crime at target area *i*; β_{2i} is the slope coefficient for the temperature variable; β_{3i} is the slope coefficient for the CCTV variable; r_{it} is the level-1 error; γ_{00} is the mean initial average daily crime count across target areas; γ_{10} is the cross-areas varying slope for the temporal trend, the growth parameter; γ_{20} is the fixed slopes for the temperature variable; γ_{30} is the average cross-areas varying slope for the CCTV variable; u_{0i}, u_{1i}, and u_{3i} are the level-2 variances for the level-2 intercept, temporal trend slopes, and CCTV slopes, respectively.

In the next step of the analysis, I add the dummy variables for sites type (i.e., downtown, business district, school/university setting, residential area) into the growth curve models and look at how those site types interact with CCTV. Specific formulae for this part of the analysis are as follows:

Leve-1:

$$AverageCrimeCount_{it} = \beta_{0i} + \beta_{1i}(TemporalTrend) + \beta_{2i}(Temperature) + \beta_{3i}(CCTV) + r_{it}$$

Level-2:

$$\beta_{0i} = \gamma_{00} + \gamma_{01}(Downtown) + \gamma_{02}(BusinessDistrict) + \gamma_{03}(School) + u_{0i}$$
$$\beta_{1i} = \gamma_{10} + u_{1i}$$
$$\beta_{2i} = \gamma_{20}$$
$$\beta_{3i} = \gamma_{30} + \gamma_{31}(Downtown) + \gamma_{32}(BusinessDistrict) + \gamma_{33}(School) + u_{3i}$$

Where AverageCrimeCount$_{it}$ is the daily average number of crime incidents occurring within the target area for target area *i* at time *t*; β_{0i} is the initial average daily crime count in target area *i*; β_{1i} is the slope coefficient for the temporal trend variable; β_{2i} is the slope coefficient for the temperature variable; β_{3i} is the slope coefficient for the CCTV variable; r_{it} is the residual; γ_{00} is the mean initial average daily crime count in residential areas after controlling for dummy variables indicating Downtown, business district, and school location types; γ_{01}, γ_{02}, and γ_{03} are the mean changes in initial average daily crime count as one moves from residential areas to Downtown, business district, and school location types, respectively; γ_{10} is the varying slope for the temporal trend variable; γ_{20} is the fixed slope for the temperature variable; γ_{30} is the effect of CCTV at residential areas (the reference location); γ_{31}, γ_{32}, and γ_{33} are cross-level interaction effects, indicating the change in the effect of CCTV (relative to the effect in residential areas) in Downtown, business district, and school locations; u_{0i}, u_{1i}, and u_{3i} are the level-2 variances for the intercept, temporal trend slopes, and CCTV slopes, respectively.

In a supplemental stage of the analysis, I add the base-rate variable into the growth curve models in order to explore the extent to which base rates of crime might condition the effect of CCTV. Specific formulae for this part of the analysis are as follows:

Leve-1:

$$AverageCrimeCount_{it} = \beta_{0i} + \beta_{1i}(TemporalTrend) + \beta_{2i}(Temperature) + \beta_{3i}(CCTV) + r_{it}$$

Level-2:

$$\beta_{0i} = \gamma_{00} + \gamma_{01}(Downtown) + \gamma_{02}(BusinessDistrict) + \gamma_{03}(School) + u_{0i}$$
$$\beta_{1i} = \gamma_{10} + u_{1i}$$
$$\beta_{2i} = \gamma_{20}$$
$$\beta_{3i} = \gamma_{30} + \gamma_{31}(Downtown) + \gamma_{32}(BusinessDistrict) + \gamma_{33}(School) + \gamma_{34}(BaseRate) + u_{3i}$$

Where $AverageCrimeCount_{it}$ is the daily average number of crime incidents occurring within the target area for target area *i* at time *t*; β_{0i} is the initial average daily crime count in target area *i*; β_{1i} is the slope coefficient for the temporal trend variable; β_{2i} is the slope coefficient for the temperature variable; β_{3i} is the slope coefficient for the CCTV variable; r_{it} is the residual; γ_{00} is the mean initial average daily crime count in residential areas after controlling for dummy variables indicating Downtown, business district, and school location types and base-rate variable; γ_{01}, γ_{02}, and γ_{03} are the mean changes in initial average crime count as one moves from residential areas to Downtown, business districts, and school locations; γ_{10} is the varying slope for the temporal trend variable; γ_{20} is the fixed slope for the temperature variable; γ_{30} is the effect of CCTV in residential areas; γ_{31}, γ_{32}, γ_{33} are cross-level interaction effects, indicating the change in the effect of CCTV in Downtown, business district, and school locations in relation to residential areas; γ_{34} is a cross-level interaction effect indicating the extent to which base rates of crime interact with CCTV; u_{0i}, u_{1i}, and u_{3i} are the level-2 variances for the intercept, temporal trend slopes, and CCTV slopes, respectively.

For the final part of the analysis – in which I examine possible displacement and diffusion effects (hypothesis 4) – WDQ (Weighted Displacement Quotient) will be used (see Bowers & Johnson, 2003). This study will calculate the value of WDQ for each CCTV location for daytime crime, nighttime crime, weekday crime, weekend crime, and the five specific types of crime. The specific formula is as follows:

$$W\mathrm{DQ} = \frac{\{(B_{t1}/C_{t1}) - (B_{t0}/C_{t0})\}}{\{(A_{t1}/C_{t1}) - (A_{t0}/C_{t0})\}}$$

Where *A* is the number of crime incidents in the target area; *B* is the number of crime incidents in the buffer area; *C* is the number of crime incidents in the control area; *t1* is the time after the installation of CCTV(s); *t0* is the time before the installation of CCTV(s).

The denominator of WDQ is the "success measure" of CCTV implementation in the target areas and the numerator of WDQ is "displacement measure" of CCTV implementation in the buffer areas. If the success measure is positive, it means that open-street CCTV does not have crime reduction effects. In that case, WDQ does not need to be calculated. If the success measure is negative, it means that open-street CCTV has crime reduction effects in the target area. In that case, a displacement measure should be calculated. The positive value of a displacement measure means that displacement emerged in the buffer area and a negative value of a displacement measure means that diffusion of benefits emerged in the buffer area.

WDQ is calculated by using the success measure and the displacement measure. The interpretation of WDQ is as follows (Bower & Johnson, 2003). If the value of WDQ is greater than 1, it means that crime reduction effects in target areas spread to buffer areas, thus, substantial diffusion of benefits emerged in buffer areas. If the value of WDQ is between 0 and 1, it means that crime reduction effects in target areas are greater than diffusion of benefits in buffer areas, thus, only modest diffusion of benefits emerges. In contrast, if the value of WDQ is between -1 and 0, it means that displacement occurred from the target areas to the buffer areas. If the value of WDQ is less than -1, it means that displacement in buffer areas is greater than crime reduction effects in target areas.

Overlapping Area Problems

As I mentioned earlier, the target areas, buffer areas, and control areas used in this study were created using the GIS program. In order to accurately derive crime reduction effects, displacement effects, and diffusion of benefits effects of open-street CCTV through the areas, the areas should not be overlapping. However, overlap among target areas, buffer areas, and control areas occurred in this study because many open-street CCTVs were implemented in close proximity to others (see Figure 3. 4).

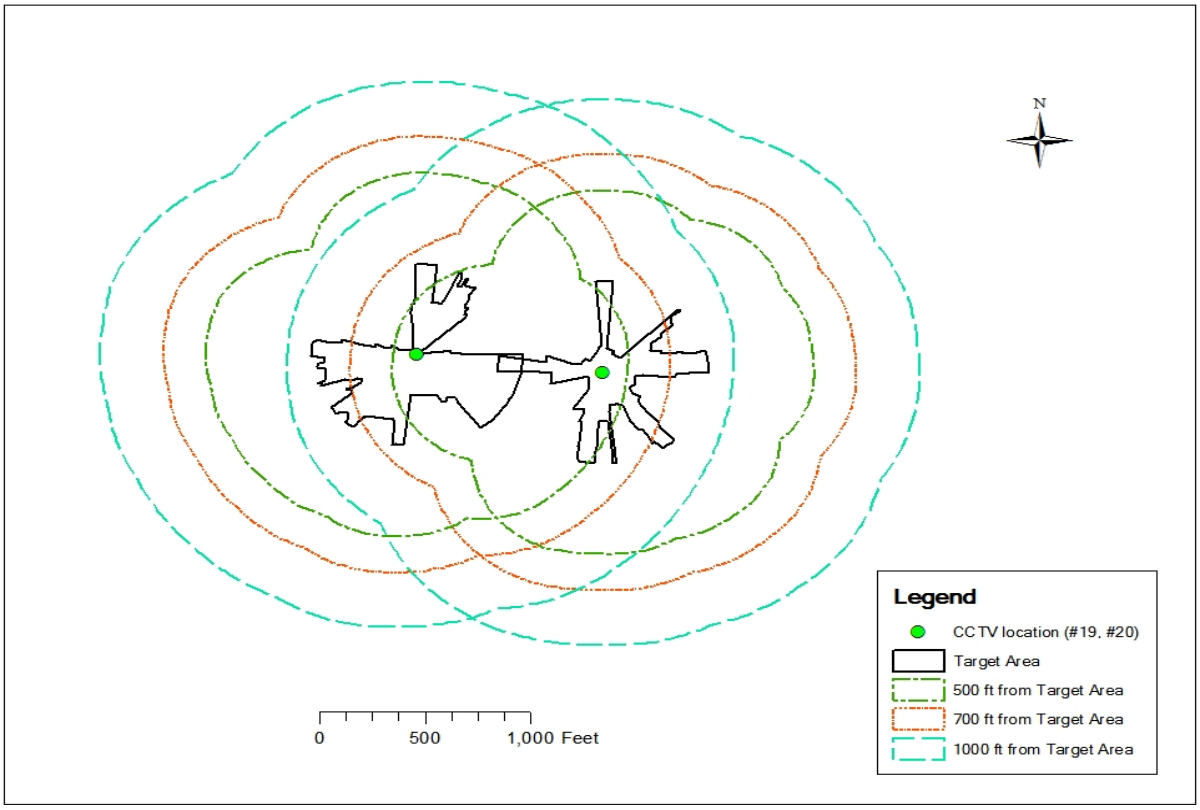

Figure 3. 4. Sample Overlapping Areas (#19, #20)

Overlapping areas may create synergistic effects. Thus, when we measure crime reduction effects, displacement effects, and diffusion of benefits effects of open-street CCTVs in cases of overlapping areas, we should consider such potential synergistic effects. Without taking into account the synergistic effects, we may under- or over-estimate the various effects of CCTV.

In this study, I have three different sorts of analyses that form the basis of my hypothesis tests: 1) tests of the crime reduction effect of CCTV in targets areas; 2) tests of the extent to which site type moderates the effects of CCTV implementation on crime; 3) calculation of WDQ for purposes of assessing displacement and diffusion. For tests of the crime reduction effects of CCTV in target areas and tests of the moderating effects of site type (the first two stages of the analysis), buffer areas and control areas do not need to be considered; only target areas are being considered. Hence, for these analyses it is necessary to address overlapping target areas. Table 3. 5 summarizes the target-area overlap scenario faced in the first two stages of the analysis, the solution utilized in terms of how to measure crime incidents, and the theoretical rationale for the posited solution. In case of overlap between target areas, this study divides the number of crime incidents (or average daily crime incidents for a specific month) within an overlap area by the number of target areas within the overlap, and assigns those crime incidents to each overlapping area. For example, let's think about overlap between target area A and target area B. Ten daytime crime incidents occurred for a month in the pure target area A and six daytime crime incidents occurred for a month in the overlapping area. Then, daytime crime incidents for a month in the target area A is thirteen (i.e., 10 + 6/2 = 13).

Table 3. 5. Decision on Handling Overlap When Assessing CCTV Effectiveness in Target Area

Overlap Scenario	Solution	Theoretical Reason
Overlap between target areas	Divide the number of crime incidents (or average daily crime incidents for a specific month) within an overlap area by the number of target areas within the overlap, and assigns that crime to each overlapping area.	It can be assumed that crime reduction effects will be multiplied in the overlapping areas due to synergistic effects. Hence, if we include all crime in the overlapping areas in each target area, the crime reduction effect of open-street CCTVs may be overestimated. Thus, this study divides the crime in the overlap area and assign a portion of it to each target area.

In calculating WDQ for purposes of assessing displacement and diffusion in the final stage of the analysis, overlap in target, buffer, and control areas need to be considered. Table 3. 6 summarizes overlap scenarios faced in this final phase of the analysis, the solutions utilized in terms of how to measure crime incidents, and the theoretical rationale for the posited solutions.

First, in cases of overlap between target areas, for the purposes of calculating WDQ, this study combines the areas into a single area. Then based on the single area, buffer area and control area are made (see Figure 3. 5). As a result, 34 target areas reduce down to 18 target areas. For WDQ analysis, pre- and post-installation period is important. When combining the overlapping areas, the pre-installation period becomes the period before installation of the initial open-street CCTV, and post-installation period refers to the time after the installation of the final open-street CCTV. For example, if a CCTV within the combined target area was installed in May, 2010 and the other CCTVs within the target area were installed in Feb., 2011, the pre-installation period becomes Jan., 2006 to Apr., 2010 and post-installation period becomes Feb., 2011 to Dec., 2012.

In cases of overlapping buffer areas, for the purposes of calculating WDQ, this study divides the number of crime incidents (or average daily crime incidents for a specific month) within an overlap area by the number of buffer areas within the overlap, and assigns that crime to each overlapping area. In cases of overlap between control areas, this study assigns the total crime incidents in the overlap area to all of the overlapping control areas for the purposes of calculating WDQ. In cases of overlap between a target area and a buffer area, this study assigns the crime incidents in the overlap area to the target area. Fifth, in cases of overlap between a target area and a control area, this study assigns the crime incidents in the overlap area to the target area. Finally, in cases of overlap between a buffer area and a control area, this research assigns the crime incidents in the overlap area to the buffer area.

Table 3. 6. Decisions for Handling Overlapping Areas When Calculating WDQ

Overlap Scenario	Solution	Theoretical Reason
Overlap between two distinct target areas	Combine the overlapping areas into a single area.	It can be assumed that the open-street CCTVs connected by the overlapping areas are related with each other.
Overlap between two distinct buffer areas	Divide the number of crime incidents (or average daily crime incidents for a specific month) within an overlap area by the number of buffer areas within the overlap, and assign that crime to each overlapping area.	It can be assumed that displacement or diffusion of benefits of benefits effects will be multiplied in the overlapping areas due to synergistic effects. Hence, if we include all incidents in the overlapping areas in each of buffer areas, the effects may be overestimated. In this case, we can divide the crime in the overlap among the buffer areas.
Overlap between two distinct control areas	Assign the total crime incidents in the overlap area to all of the overlapping control areas.	Because, theoretically, there is no effect of open-street CCTVs in the control areas, including the area in both control areas does not have any impact on the results of the research.
Overlap between a target area and a buffer area (for a second, distinct target area)	Assign the crime incidents in the overlap area to the target area.	Although crime in this overlapping area (target area A and buffer area B) might consist of crime that has been displaced from target area B, a conservative estimate of WDQ regarding target area A would be to assign all crime in this overlap to the target area A.
Overlap between a target area and a control area (for a second, distinct target area)	Assign the crime incidents in the overlap area to the target area.	Because, theoretically, there is no effect of open-street CCTVs in the control area, this study will assign the crime in the overlap to the target area.
Overlap between a buffer area (for a particular target area) and a control area (for a second, distinct target area)	Assign the crime incidents in the overlap area to the buffer area.	Because, theoretically, there is no effect of open-street CCTVs in the control area, this study will assign crime in the overlap area to the buffer area.

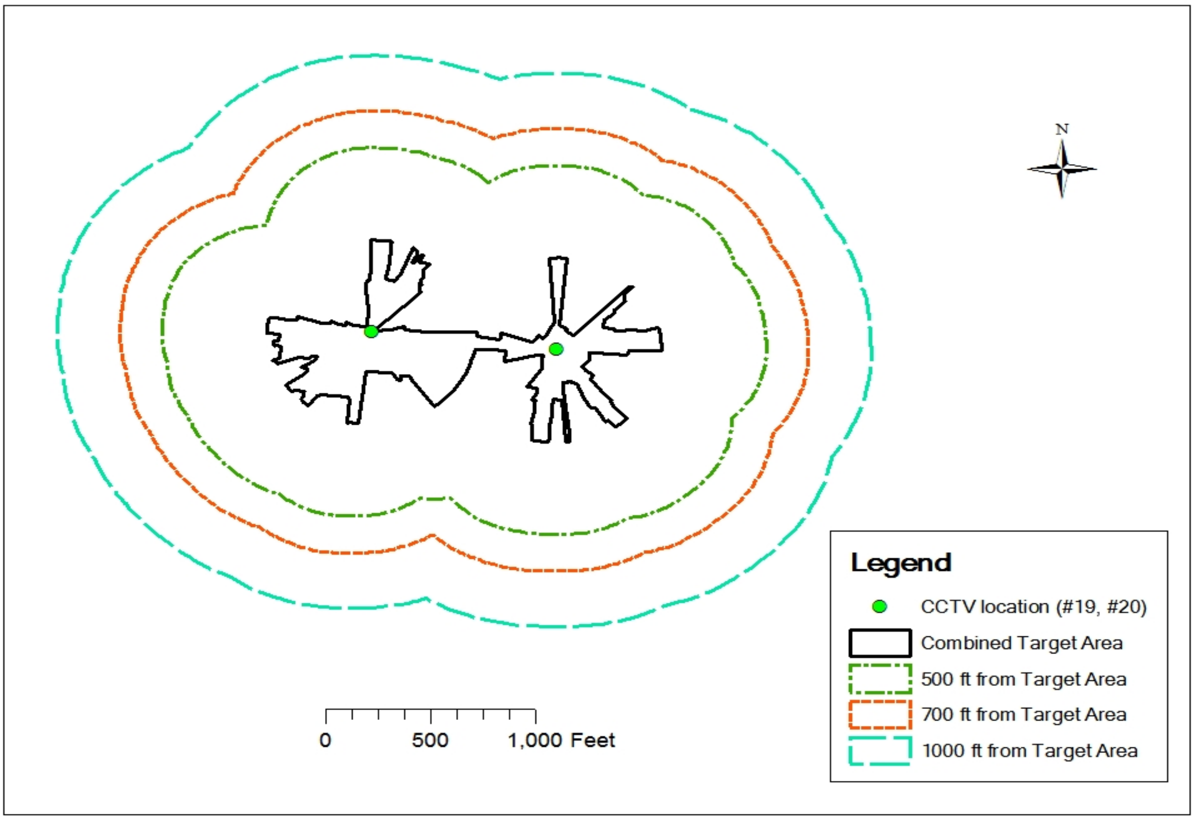

Figure 3. 5. Example of Combined Target Area, Buffer Area, and Control Area

CHAPTER IV

RESULTS

In this chapter, I will present the results from the study's analysis. First, I will discuss base rates for the nine dependent variables. Then, I will present the results from the initial stage of the analysis of the effectiveness of CCTV, where I compare the effects of CCTV across daytime versus nighttime, weekday versus weekend, and across specific crime types. Third, I will present analysis examining how location type moderates the effects of CCTV. Finally, I will present some supplemental analyses regarding the effects of CCTV across different locations.

Base-Rates for Crime in the Target, Buffer, and Control Areas

Before presenting analyses regarding the conditional effectiveness of CCTV, I first present base rates of crime across target, buffer, and control areas. These rates provides some important information about crime that could be useful in understanding the findings that follow regarding the effectiveness of CCTV.

Pre-CCTV Daytime and Nighttime Crime

Table 4. 1 presents characteristics of the 34 CCTV implementation sites and average monthly counts of daytime crime and nighttime crime in each target area *before* CCTV implementation (during the 2006-2012 study period). Overall, more daytime crime occurred than nighttime crime before CCTV implementation. The average monthly crime count of daytime crime in a target area was 3.320, whereas the average monthly crime count of nighttime crime in a target area was 2.392. These pre-CCTV crime counts were different depending on CCTV site settings. For example, the ranking of average monthly crime counts in target areas, from high to low, was: 1) downtown (daytime crime: 5.402, nighttime crime:

3.082), 2) business district (daytime crime: 3.230, nighttime crime: 2.464), 3) university/school setting (daytime crime: 2.622, nighttime crime: 2.062), and 4) residential area (daytime crime: 1.793, nighttime crime: 1.810).

Beyond the difference in averages across types of locations, both daytime and nighttime crime counts showed substantial variability across specific CCTV sites. For example, the average monthly pre-CCTV count of daytime crime ranged from 0.842 (site #25) to 10.355 (site #3), and the average monthly count of nighttime crime ranged from 0.579 (site #21) to 7.923 (site #30). Such variability was also seen when looking *within* specific location types. For example, the average monthly count of daytime crime in downtown sites ranged from 2.902 (site #5) to 10.355 (site #3), and the average monthly count of nighttime crime in downtown sites ranged from 1.261 (site #2) to 5.402 (site #4). Within business districts, average monthly pre-CCTV counts of daytime crime ranged from 0.842 (site #25) to 7.947 (site #27), and average monthly count of nighttime crime ranged from 0.825 (site #26) to 7.923 (site #30). Within university/school CCTV sites, average monthly counts of daytime crime ranged from 0.923 (site #10) to 5.788 (site #11), and average monthly counts of nighttime crime ranged from 0.579 (site #21) to 5.096 (site #11). Finally, average pre-CCTV monthly counts of daytime crime in a residential areas ranged from 0.965 (site #16) to 2.549 (site #33), while average monthly counts of nighttime crime in residential areas ranged from 0.719 (site #16) to 2.923 (site #29).

Table 4. 1. Average Monthly Crime Count of Daytime and Nighttime in 34 Target Areas before CCTV Implementation

Site (#)	Setting	Daytime Crime	Nighttime Crime
1	Downtown	3.232	2.967
2	Downtown	3.580	1.261
3	Downtown	10.355	3.101
4	Downtown	6.337	5.402
5	Downtown	2.902	2.163
6	Downtown	3.804	4.246
7	Downtown	5.659	3.428
8	Downtown	7.348	2.083
9	Business District	2.885	2.577
10	University/School	0.923	1.288
11	University/School	5.788	5.096
12	University/School	1.731	2.635
13	Business District	1.356	1.875
14	University/School	2.875	1.875
15	Residential Area	1.535	1.254
16	Residential Area	0.965	0.719
17	Business District	2.965	2.474
18	Business District	7.421	5.035
19	Business District	1.895	1.316
20	University/School	2.316	1.632
21	University/School	3.684	0.579
22	Business District	3.053	1.579
23	Business District	2.158	1.632
24	Business District	1.175	1.596
25	Business District	0.842	0.842
26	Business District	2.228	0.825
27	Business District	7.947	1.895
28	University/School	1.038	1.327
29	Residential Area	1.962	2.923
30	Business District	4.831	7.923
31	Residential Area	2.107	2.041
32	Residential Area	1.320	1.230
33	Residential Area	2.549	2.590
34	Residential Area	2.115	1.910
Average	Overall	3.320	2.392
	Downtown	5.402	3.082
	Business District	3.230	2.464
	University/School	2.622	2.062
	Residential Area	1.793	1.810

For comparison purposes, Table 4. 2 below presents average monthly counts of daytime crime and nighttime crime *before* CCTV implementation (during the 2006-2012 study period) in the *18 target areas, buffer areas, and control areas that were studied for displacement/diffusion analysis (or, WDQ analysis).* Overall, more daytime crime occurred than nighttime crime in these areas before CCTV implementation. The average monthly count of daytime crime before CCTV implementation in target areas, buffer areas, and control areas was 6.271, 7.113, 5.515, respectively, whereas the pre-CCTV average monthly count of nighttime crime in target areas, buffer areas, and control areas was 4.522, 6.582, 4.325, respectively.

Beyond these averages, both daytime crime and nighttime crime counts in target, buffer, and control areas showed substantial variability across specific CCTV sites. For example, the average monthly pre-CCTV count of daytime crime in target areas ranged from 0.842 (site #14) to 43.217 (#site 1), and the average monthly count of nighttime crime in target areas ranged from 0.825 (site #15) to 24.652 (site #1). Within buffer areas, the average monthly count of daytime crime ranged from 1.544 (site #7) to 29.043 (site #1), and the average monthly count of nighttime crime ranged from 1.289 (site #14) to 21.772 (site #1). Within control areas, average monthly daytime crime ranged from 0.368 (site #6) to 17.231 (site #18), and the average monthly count of nighttime crime ranged from 0.316 (site #6) to 12.815 (site #18).

An important point to emphasize in examining the figures presented in Table 4. 2 is that the daytime and nighttime crime counts in target area #1 and buffer area #1 were much higher than the daytime and nighttime crime counts in other target and buffer areas. This is likely due to the size of these target and buffer areas. These areas were much larger than the other target and buffer areas due to combining eight downtown CCTV areas (using the rules regarding synergy/overlap established in Chapter 3).

Table 4. 2. Average Monthly Crime Count of Daytime and Nighttime in 18 Target, Buffer, and Control Areas before CCTV Implementation

Site (#)	Setting	Daytime Crime Target Area	Daytime Crime Buffer Area	Daytime Crime Control Area	Nighttime Crime Target Area	Nighttime Crime Buffer Area	Nighttime Crime Control Area
1	Downtown	43.217	29.043	8.783	24.652	21.772	5.478
2	Business District	2.885	3.981	3.288	2.577	3.923	2.519
3	University/School	7.750	6.212	2.750	7.712	7.154	2.596
4	University/School	1.731	5.154	4.269	2.635	6.519	3.654
5	Business District University/School	4.231	7.308	6.500	3.750	11.712	10.615
6	Residential Area	3.649	3.404	0.368	3.316	2.070	0.316
7	Residential Area	6.947	1.544	2.070	6.526	1.316	2.228
8	Business District	2.965	6.895	7.596	2.474	6.193	9.333
9	Business District	7.421	8.956	3.596	5.035	9.140	3.281
10	Business District University/School	4.211	9.746	5.632	2.947	9.263	4.509
11	Business District University/School	4.860	2.982	12.333	2.175	2.351	4.404
12	Business District	3.053	6.456	2.105	1.579	4.807	2.105
13	Business District	2.158	2.421	1.070	1.632	2.105	1.439
14	Business District	0.842	1.912	12.737	0.842	1.289	4.316
15	Business District	2.228	2.930	1.491	0.825	1.342	1.211
16	Business District	7.947	9.807	1.263	1.895	2.895	1.439
17	Residential Area	1.962	7.596	6.192	2.923	7.654	5.596
18	Business District	4.831	11.685	17.231	7.908	16.977	12.815
	Average	6.271	7.113	5.515	4.522	6.582	4.325

Pre-CCTV Weekday and Weekend Crime

Table 4. 3 presents characteristics of 34 CCTV implementation sites and average monthly counts of weekday crime and weekend crime in each target area *before* CCTV implementation (during the 2006-2012 study period). Overall, more weekday crime occurred than weekend crime before CCTV implementation. The average monthly crime count of weekend crime in a target area was 4.047, whereas the average monthly crime count of weekend crime in a target area was 1.546. This difference may simply be due to a difference between the number of weekdays (i.e., normally five days per a week) and the number of

weekend days (i.e., normally two days per a week) in a month. The pre-CCTV crime counts were different depending on type of CCTV site setting. For example, the ranking of average monthly crime counts in target areas, from high to low, was: 1) downtown (weekday crime: 6.076, weekend crime: 2.242), 2) business district (weekday crime: 3.972, weekend crime: 1.602), 3) university/school setting (weekday crime: 3.445, weekend crime: 1.134), and 4) residential area (weekday crime: 2.457, weekend crime: 1.065).

Beyond these averages, both weekday and weekend crime counts showed substantial variability across CCTV sites. For example, the average monthly pre-CCTV count of weekday crime ranged from 1.044 (site #16) to 9.533 (site #3), and the average monthly count of weekend crime ranged from 0.421 (site #21) to 4.508 (site #30). Such variability was also seen when looking within specific location types. For example, the average monthly count of weekday crime in downtown sites ranged from 3.819 (site #2) to 9.533 (site #3), and the average monthly count of weekend crime in downtown sites ranged from 0.967 (site #2) to 3.707 (site #3). Within business districts, average monthly pre-CCTV counts of weekday crime ranged from 1.211 (site #25) to 9.175 (site #18), and average monthly counts of weekend crime ranged from 0.439 (site #25) to 4.508 (site #30). Within university/school CCTV sites, average monthly counts of weekday crime ranged from 1.442 (site #28) to 7.837 (site #11), and average monthly counts of weekend crime ranged from 0.421 (site #21) to 2.865 (site #11). Finally, average pre-CCTV monthly counts of weekday crime in a residential areas ranged from 1.044 (site #16) to 3.635 (site #29), and average monthly counts of weekend crime in a residential area ranged from 0.614 (site #16) to 1.530 (site #33).

Table 4. 3. Average Monthly Crime Count of Weekday and Weekend in 34 Target Areas before CCTV Implementation

Site (#)	Setting	Weekday Crime	Weekend Crime
1	Downtown	4.482	1.598
2	Downtown	3.819	0.967
3	Downtown	9.533	3.707
4	Downtown	8.022	3.413
5	Downtown	3.913	1.043
6	Downtown	5.457	2.431
7	Downtown	6.413	2.522
8	Downtown	6.971	2.254
9	Business District	3.769	1.673
10	University/School	1.529	0.615
11	University/School	7.837	2.865
12	University/School	3.250	1.038
13	Business District	2.067	1.058
14	University/School	3.471	1.077
15	Residential Area	1.921	0.807
16	Residential Area	1.044	0.614
17	Business District	3.895	1.386
18	Business District	9.175	2.982
19	Business District	2.149	0.974
20	University/School	2.798	1.132
21	University/School	3.789	0.421
22	Business District	3.544	1.035
23	Business District	2.965	0.737
24	Business District	1.877	0.860
25	Business District	1.211	0.439
26	Business District	2.035	0.930
27	Business District	7.018	2.649
28	University/School	1.442	0.788
29	Residential Area	3.635	1.154
30	Business District	7.954	4.508
31	Residential Area	2.762	1.320
32	Residential Area	1.716	0.760
33	Residential Area	3.454	1.530
34	Residential Area	2.667	1.268
Average	Overall	4.047	1.546
	Downtown	6.076	2.242
	Business District	3.972	1.602
	University/School	3.445	1.134
	Residential Area	2.457	1.065

Table 4. 4 presents average monthly count of weekday crime and weekend crime *before* CCTV implementation (during the 2006-2012 study period) within the 18 target,

buffer, and control areas used to calculate WDQ. Overall, more weekday crime occurred in these areas in comparison to weekend crime before CCTV implementation. Pre-CCTV average monthly count of weekday crime in target, buffer, and control areas was 7.651, 9.260, and 6.722, respectively, whereas pre-CCTV average monthly count of weekend crime in target, buffer, and control areas was 2.922, 4.077, and 2.860, respectively. Again, this substantial difference may be due to a difference between the number of weekdays (i.e., normally five days per a week) and the number of weekend days (i.e., normally two days per a week) in a month.

Beyond these averages, both weekday crime and weekend crime counts in target, buffer, and control areas showed substantial variability across CCTV sites. For example, the average monthly pre-CCTV count of weekday crime in target areas ranged from 1.211 (site #14) to 48.609 (site #1), and average monthly count of weekend crime in target areas ranged from 0.439 (site #14) to 17.935 (site #1). Within buffer areas, average monthly count of weekday crime ranged from 1.833 (site #7) to 35.000 (site #1), and average monthly count of weekend crime ranged from 0.947 (site #7) to 14.185 (site #1). Within control areas, average monthly count of weekday crime ranged from 0.491 (site #6) to 21.262 (site #18), and average monthly count of weekend crime ranged from 0.193 (site #6) to 7.954 (site #18).

Again, weekday and weekend crime counts in target area #1 and buffer area #1 were much greater than weekday and weekend crime counts in other target and buffer areas, likely due to the fact that eight downtown CCTV areas were combined in the WDQ stage of analysis.

Table 4. 4. Average Monthly Crime Count of Weekday and Weekend in 18 Target, Buffer, and Control Areas before CCTV Implementation

Site (#)	Setting	Weekday Crime Target Area	Weekday Crime Buffer Area	Weekday Crime Control Area	Weekend Crime Target Area	Weekend Crime Buffer Area	Weekend Crime Control Area
1	Downtown	48.609	35.000	10.022	17.935	14.185	3.870
2	Business District	3.769	5.423	4.000	1.673	2.346	1.654
3	University/School	10.808	9.212	3.365	4.269	3.865	1.712
4	University/School	3.250	8.442	5.442	1.038	2.942	2.327
5	Business District University/School	5.538	11.885	10.404	2.135	6.500	6.269
6	Residential Area	4.754	4.061	0.491	2.105	1.316	0.193
7	Residential Area	8.947	1.833	3.018	4.228	0.947	1.175
8	Business District	3.895	8.912	10.895	1.386	3.965	5.333
9	Business District	9.175	12.316	4.895	2.982	5.219	1.825
10	Business District University/School	4.947	12.895	6.982	2.105	5.746	2.947
11	Business District University/School	5.667	3.649	11.737	1.281	1.526	4.667
12	Business District	3.544	7.579	2.930	1.035	3.386	1.246
13	Business District	2.965	3.140	1.807	0.737	1.263	0.632
14	Business District	1.211	2.114	11.842	0.439	0.974	4.825
15	Business District	2.035	2.535	1.754	0.930	1.605	0.842
16	Business District	7.018	8.947	1.596	2.649	3.474	1.000
17	Residential Area	3.635	10.308	8.558	1.154	4.615	3.019
18	Business District	7.954	18.431	21.262	4.508	9.508	7.954
	Average	7.651	9.260	6.722	2.922	4.077	2.860

Pre-CCTV Offense-Specific Crime Type

Table 4. 5 presents characteristics of 34 CCTV implementation sites and average monthly counts of specific crime types (i.e., assault, robbery, burglary, auto theft, theft from auto) in each target area *before* CCTV implementation (during the 2006-2012 study period). Overall, more robbery, burglary, and theft from auto occurred compared to assault and auto theft before CCTV implementation. The average monthly crime counts of robbery, burglary, and theft from auto in target areas were 0.461, 0.451, and 0.521, respectively, whereas the monthly crime count of both assault and auto theft was 0.132.

These pre-CCTV offense-specific crime counts were different depending on type of CCTV site setting. For example, the ranking of average monthly assault counts in target areas, from high to low, was: 1) residential area (0.199), 2) business district (0.128), 3) downtown (0.109), and 4) university/school setting (0.098). The ranking of average monthly robbery counts in target areas, from high to low, was: 1) downtown (0.592), 2) business district (0.531), 3) university/school setting (0.434), and 4) residential area (0.217). The ranking of average monthly burglary counts in target areas, from high to low, was similar to that of assault: 1) residential area (0.705), 2) business district (0.452), 3) downtown (0.380), and 4) university/school setting (0.275). The ranking of average monthly auto theft counts in target areas, from high to low, was: 1) business district (0.145), 2) downtown (0.136), 3) residential area (0.131), and 4) university/school setting (0.106). The ranking of average monthly theft from auto counts in target areas, from high to low, was: 1) downtown (0.973), 2) business district (0.485), 3) university/school setting (0.483), and 4) residential area (0.101).

Beyond these averages, all the specific crime counts showed substantial variability across CCTV sites. For example, the average monthly pre-CCTV count of assault ranged from 0.000 (site #25) to 0.708 (site #30). The average monthly pre-CCTV count of robbery ranged from 0.123 (site #16) to 2.000 (site #30), and the average monthly count of burglary ranged from 0.043 (site #2) to 1.273 (site #33). The average monthly pre-CCTV count of auto theft ranged from 0.000 (site #21) to 0.523 (site #30), and the average monthly count of theft from auto ranged from 0.018 (site #15) to 2.293 (site #4).

Such variability was also seen when looking within specific location types. Using downtown as one example, the average monthly count of assault in downtown sites ranged from 0.054 (site #5) to 0.228 (site #6). The average monthly count of robbery in downtown sites ranged from 0.431 (site #2) to 0.783 (site #7), and the average monthly count of burglary in downtown sites ranged from 0.043 (site #2) to 0.746 (site #6). The average monthly count of auto theft in downtown sites ranged from 0.033 (site #2) to 0.261 (site #4), and the average monthly count of theft from auto in downtown sites ranged from 0.304 (site #2) to 2.293 (site #4).

Table 4. 5. Average Monthly Crime Count of Specific Crime Types in 34 Target Areas before CCTV Implementation

Site (#)	Setting	Assault	Robbery	Burglary	Auto Theft	Theft from Auto
1	Downtown	0.149	0.540	0.652	0.098	1.141
2	Downtown	0.105	0.431	0.043	0.033	0.304
3	Downtown	0.087	0.500	0.409	0.152	0.460
4	Downtown	0.098	0.630	0.391	0.261	2.293
5	Downtown	0.054	0.609	0.109	0.130	1.250
6	Downtown	0.228	0.533	0.746	0.120	0.322
7	Downtown	0.065	0.783	0.268	0.130	1.058
8	Downtown	0.083	0.714	0.424	0.163	0.953
9	Business District	0.058	0.269	0.365	0.096	0.288
10	University/School	0.048	0.250	0.183	0.019	0.202
11	University/School	0.279	1.000	0.471	0.250	0.663
12	University/School	0.058	0.500	0.154	0.231	1.038
13	Business District	0.106	0.173	0.346	0.038	0.385
14	University/School	0.106	0.423	0.192	0.135	0.462
15	Residential Area	0.123	0.219	0.518	0.061	0.018
16	Residential Area	0.079	0.123	0.237	0.079	0.132
17	Business District	0.175	0.596	0.474	0.175	0.421
18	Business District	0.140	1.000	0.895	0.228	0.667
19	Business District	0.088	0.386	0.333	0.140	0.211
20	University/School	0.070	0.456	0.368	0.053	0.333
21	University/School	0.088	0.175	0.175	0.000	0.070
22	Business District	0.105	0.649	0.193	0.158	0.526
23	Business District	0.018	0.211	0.719	0.070	0.439
24	Business District	0.070	0.140	0.579	0.018	0.316
25	Business District	0.000	0.193	0.053	0.035	0.175
26	Business District	0.035	0.140	0.228	0.088	0.544
27	Business District	0.035	0.614	0.175	0.175	0.526
28	University/School	0.038	0.231	0.385	0.058	0.615
29	Residential Area	0.577	0.462	0.346	0.135	0.077
30	Business District	0.708	2.000	1.062	0.523	1.323
31	Residential Area	0.115	0.172	0.943	0.123	0.066
32	Residential Area	0.115	0.148	0.642	0.107	0.090
33	Residential Area	0.246	0.254	1.273	0.311	0.238
34	Residential Area	0.139	0.139	0.978	0.098	0.090
Average	Overall	0.132	0.461	0.451	0.132	0.521
	Downtown	0.109	0.592	0.380	0.136	0.973
	Business District	0.128	0.531	0.452	0.145	0.485
	University/School	0.098	0.434	0.275	0.106	0.483
	Residential Area	0.199	0.217	0.705	0.131	0.101

Table 4. 6 presents average monthly counts of specific crime types in the 18 target, buffer, and control areas used for WDQ analysis *before* CCTV implementation (during the

2006-2012 study period). Overall, relatively many robberies, burglaries, and thefts from autos occurred in target, buffer, and control areas before CCTV implementation, whereas relatively small numbers of assault and auto theft occurred in target, buffer, and control areas before CCTV implementation. Average monthly counts of robbery, burglary, and theft from auto in target areas were 0.871, 0.851, and 0.983, respectively, whereas monthly counts of assault and auto theft in target areas were 0.249 and 0.251, respectively. Average monthly counts of robbery, burglary, and theft from auto in buffer areas were 0.944, 1.687, and 2.193, respectively, whereas monthly count of assault and auto theft in buffer areas were 0.328 and 0.454, respectively. Average monthly counts of robbery, burglary, and theft from auto in control areas were 0.573, 1.148, and 1.296, respectively, whereas monthly counts of assault and auto theft in control areas were 0.233 and 0.318, respectively.

The specific crime counts in target, buffer, and control areas showed substantial variability across both CCTV site types and specific locations. To provide on example, the average monthly pre-CCTV count of assault ranged from 0.000 (site #14) to 0.870 (site #1) in target areas, from 0.026 (site #14) to 1.212 (site #17) in buffer areas, and from 0.000 (site #13) to 1.462 (site #18) in control areas.

Table 4. 6. Average Monthly Crime Count of Specific Crime Types in 18 Target, Buffer, and Control Areas before CCTV Implementation

Site (#)	Setting	Assault			Robbery			Burglary			Auto Theft			Theft from Auto		
		Target Area	Buffer Area	Control Area	Target Area	Buffer Area	Control Area	Target Area	Buffer Area	Control Area	Target Area	Buffer Area	Control Area	Target Area	Buffer Area	Control Area
1	Downtown	0.870	0.728	0.457	4.739	3.185	0.761	3.043	2.935	0.913	1.087	1.380	0.304	7.783	12.750	3.326
2	Business District	0.058	0.077	0.077	0.269	0.462	0.269	0.365	1.038	0.327	0.096	0.154	0.192	0.288	1.788	1.423
3	University/School	0.365	0.240	0.115	1.481	1.481	0.404	1.038	2.202	0.885	0.327	0.837	0.288	1.481	2.481	1.481
4	University/School	0.058	0.163	0.096	0.500	0.635	0.500	0.154	1.163	1.115	0.231	0.510	0.385	1.038	3.462	2.212
5	Business District University/School	0.212	0.346	0.250	0.596	1.731	1.019	0.538	3.173	2.904	0.173	0.635	0.673	0.846	3.981	4.788
6	Residential Area	0.246	0.132	0.035	0.404	0.211	0.000	1.439	1.623	0.211	0.193	0.175	0.035	0.088	0.193	0.035
7	Residential Area	0.561	0.114	0.088	0.667	0.105	0.105	3.140	0.570	0.982	0.614	0.088	0.263	0.544	0.140	0.351
8	Business District	0.175	0.386	0.474	0.596	1.123	1.053	0.474	2.281	2.807	0.175	0.351	0.439	0.421	0.789	1.246
9	Business District	0.140	0.474	0.158	1.000	1.395	0.263	0.895	3.228	1.193	0.228	0.482	0.228	0.667	1.447	0.526
10	Business District University/School	0.158	0.693	0.228	0.842	1.079	0.561	0.702	3.491	2.193	0.193	0.535	0.509	0.544	1.237	0.632
11	Business District University/School	0.158	0.035	0.018	0.316	0.193	0.561	0.754	1.009	0.333	0.018	0.158	0.228	0.386	1.026	1.386
12	Business District	0.105	0.272	0.053	0.649	0.842	0.123	0.193	2.316	1.351	0.158	0.351	0.105	0.526	0.404	0.351
13	Business District	0.018	0.088	0.000	0.211	0.105	0.000	0.719	0.737	0.351	0.070	0.158	0.123	0.439	0.842	0.614
14	Business District	0.000	0.026	0.035	0.193	0.149	0.579	0.053	0.465	0.368	0.035	0.219	0.158	0.175	0.737	1.351
15	Business District	0.035	0.026	0.053	0.140	0.114	0.105	0.228	0.333	0.579	0.088	0.079	0.088	0.544	0.412	0.579
16	Business District	0.035	0.053	0.018	0.614	0.474	0.070	0.175	0.298	0.649	0.175	0.158	0.123	0.526	0.579	0.456
17	Residential Area	0.577	1.212	0.577	0.462	0.885	0.731	0.346	1.096	1.423	0.135	0.750	0.654	0.077	0.942	0.673
18	Business District	0.708	0.838	1.462	2.000	2.823	3.215	1.062	2.400	2.077	0.523	1.146	0.923	1.323	6.269	1.892
	Average	0.249	0.328	0.233	0.871	0.944	0.573	0.851	1.687	1.148	0.251	0.454	0.318	0.983	2.193	1.296

Comparing Effects of CCTV

This section of the dissertation presents findings from the growth-curve (HLM) analysis of the effects of CCTV on average daily crime counts. Distinct sub-sections provide comparisons of CCTV's effect: 1) on daytime v. nighttime crime; 2) on weekday v. weekend crime; and 3) across five specific offenses.

Daytime v. Nighttime Crime

Table 4. 7 presents the results from hierarchical linear growth curve models of daytime and nighttime crime with level-1 variables only. The results can be interpreted as follows. First, the fixed-effects panel of Table 4. 7 shows that the coefficient associated with the temporal trend was not significant for either daytime or nighttime crime. This means that neither daytime crime nor nighttime crime had a significant increasing or decreasing trend during the study period, after controlling for seasonal effects (i.e., temperature) and the implementation of CCTV. Second, the coefficient of temperature was not significant for daytime crime but it was significantly positive for nighttime crime. This means that monthly average temperature did not have a significant impact on daytime crime, but it had a significantly positive impact on nighttime crime after controlling for temporal trend and CCTV implementation. In case of nighttime crime, for each one unit temperature increase, the average daily nighttime crime was multiplied by 1.0249 (i.e. $e^{0.0246}$). Here, the exponentiated coefficient was examined for interpretation purposes because the dependent variable was logged. Third, the coefficient for the CCTV variable was not significant for either daytime crime or nighttime crime. This means that the implementation of CCTV did not significantly influence daytime crime and nighttime crime during the study period after controlling for temporal trend and temperature variables.

Table 4. 7. Hierarchical Linear Models of Daytime and Nighttime Crime, Level-1 Variables Only

Fixed Effect	Daytime		Nighttime	
	Coefficient	**SE**	**Coefficient**	**SE**
Intercept, γ_{00}	-3.8856**	0.3966	-5.6137**	0.4372
Temporal trend, γ_{10}	-0.0007	0.0046	-0.0073	0.0057
Temperature, γ_{20}	0.0033	0.0039	0.0246**	0.0045
CCTV, γ_{30}	0.0306	0.2287	-0.3197	0.2681
Random Effect	Variance Component	Chi-square	Variance Component	Chi-square
Intercept, u_{0i}	3.1735**	230.9765	3.5196**	193.9115
Temporal trend slope, u_{1i}	0.0000	35.9821	0.0002*	52.0573
Level 1, r_{it}	10.8797		14.8971	

* The results are based on 2,856 monthly repeated measures nested within 34 open-street CCTV target locations.
*p < 0.05, **p < 0.001

The random-effects panel of Table 4. 7 shows that the variance component for the intercept was significant for both daytime crime and nighttime crime. This means that both daytime crime and nighttime crime had significant variation across CCTV sites, after controlling for temporal trend, temperature, and CCTV implementation. The variance component of the temporal trend slope was not significant for daytime crime, but it was significant for nighttime crime. This suggests that the temporal trends of daytime crime were not significantly different across CCTV sites, but the temporal trends of nighttime crime were significantly different depending on CCTV sites.

Although Z-stat was proposed as the means for comparing the effect of open-street CCTV on daytime crime versus nighttime crime (see Chapter III), no Z-stat test was actually performed in this regard. It is not meaningful to compare the two effects of open-street CCTVs because, as shown above, the two effects were non-significant. As a result, this study does not provide evidence to support Hypothesis 1 – that the effects of CCTV would be greater for daytime as opposed to nighttime crime.

Weekday v. Weekend Crime

Table 4. 8 presents the results from hierarchical linear growth-curve models of weekday and weekend crime with level-1 variables only. The fixed-effects panel of Table 4. 8 shows, first, that the coefficient for the temporal trend was not significant for either weekday crime or weekend crime. This means that neither weekday crime nor weekend crime had a significant increasing or decreasing trend during study period, after controlling for temperature and CCTV implementation. Second, the coefficient of temperature was not significant for weekday crime, but it was significantly positive for weekend crime. Thus, monthly average temperature did not have a significant impact on weekday crime, but it had a significantly positive impact on weekend crime after controlling for temporal trend and CCTV. In the case of weekend crime, average daily weekend crime (per month) was multiplied by 1.0249 (i.e. $e^{0.0246}$) per one unit of monthly temperature increase (again, the exponentiated coefficient was examined because the dependent variable was logged). Third, the coefficient of CCTV variable was non-significant for both weekday crime and weekend crime. Thus, the implementation of CCTV did not significantly influence either weekday crime or weekend crime during study period, after controlling for temporal trend and temperature variables.

Table 4. 8. Hierarchical Linear Models of Weekday and Weekend Crime, Level-1 Variables Only

Fixed Effect	Weekday		Weekend	
	Coefficient	**SE**	**Coefficient**	**SE**
Intercept, γ_{00}	-2.8382**	0.3440	-6.4028**	0.5682
Temporal trend, γ_{10}	-0.0074	0.0043	-0.0042	0.0069
Temperature, γ_{20}	0.0048	0.0035	0.0246**	0.0059
CCTV, γ_{30}	0.1797	0.2064	0.0966	0.3490
Random Effect	Variance Component	Chi-square	Variance Component	Chi-square
Intercept, u_{0i}	2.2558**	206.3285	5.9021**	189.0474
Temporal trend slope, u_{1i}	0.0001	44.1614	0.0000	31.0810
Level 1, r_{it}	8.8416		25.3972	

* The results are based on 2,856 monthly repeated measures nested within 34 open-street CCTV target locations.
*p < 0.05, **p < 0.001

The random-effects portion of Table 4. 8 shows that the intercept's variance component was significant in both the weekday crime and weekend crime models. This suggests that both weekday crime and weekend crime had significant variation depending on CCTV sites, after controlling for temporal trend, temperature, and CCTV. On the other hand, the variance component for the temporal trend slope was non-significant for both weekday crime and weekend crime, thus suggesting that temporal trends of weekday and weekend crime were similar across CCTV sites.

As with the daytime/nighttime comparison of the effects of CCTV, a Z-stat analysis of the effect of CCTV on weekday crime versus weekend crime was not conducted. It was ultimately not meaningful to compare these two effects of open-street CCTVs since, as shown above, they were both non-significant. As a result, this study does not produce evidence to support Hypothesis 2 – that the effect of CCTV would be greater for weekday crime as opposed to weekend crime.

Across Crime Type

Table 4. 9 presents the results from hierarchical linear growth curve models of specific crime types (i.e., assault, robbery, burglary, auto theft, theft from auto) with level-1 variables only. The results show, first, that the coefficient of temporal trend was non-significant for assault, robbery, burglary, and theft from auto, but it was significantly negative for auto theft. Thus, assault, robbery, burglary, and theft from auto did not exhibit a significant increasing or decreasing trend, but auto theft had a significantly decreasing trend during study period (after controlling for temperature and CCTV variables). In case of auto theft, for each monthly increment over the course of the study period, the average daily auto theft was multiplied by 0.9839 (i.e. $e^{-0.0162}$). Also shown in Table 4. 9, the coefficient of temperature was not significant for assault, robbery, auto theft, and theft from auto, but it was significantly positive for burglary. In case of burglary, average daily burglary was multiplied by 1.0257 (i.e. $e^{0.0254}$) per unit increase in average monthly temperature.

Table 4.9 also shows the effects of CCTV across specific crimes. Results suggest that the implementation of CCTV did not significantly influence robbery, auto theft, and theft from auto but it significantly decreased assault and burglary during study period, after controlling for temporal trend and temperature. In case of assault, average daily assault was multiplied by 0.6057 (i.e. $e^{-0.5013}$) in months in which CCTV was implemented (in comparison to months prior to implementation). In case of burglary, average daily burglary was multiplied by 0.3538 (i.e. $e^{-1.0391}$) in months when CCTV was implemented versus months prior to implementation.

The random-effects portion of Table 4. 9 shows that the variance component of intercept was significant for all the five specific types of crime. This means that all the five types of crime had significant variation across CCTV sites, after controlling for temporal trend, temperature, and CCTV implementation. The variance component of the temporal trend slope was not significant for assault and theft from auto, but it was significant for robbery, burglary, and auto theft. Thus, the temporal trends of robbery, burglary, and auto theft were significantly different depending on CCTV sites during study period, after controlling for temperature and CCTV implementation.

Table 4. 9. Hierarchical Linear Models of Specific Crime Types, Level-1 Variables Only

Fixed Effect	**Assault**		**Robbery**		**Burglary**		**Auto Theft**		**Theft from Auto**	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Intercept, γ_{00}	-12.5773**	0.3073	-9.9150**	0.4889	-11.7998**	0.5131	-12.4225**	0.3289	-10.2390**	0.5239
Temporal trend, γ_{10}	0.0008	0.0043	-0.0020	0.0069	0.0054	0.0077	-0.0162*	0.0051	-0.0116	0.0063
Temperature, γ_{20}	0.0020	0.0037	-0.0011	0.0055	0.0254**	0.0052	0.0075	0.0039	0.0088	0.0054
CCTV, γ_{30}	-0.5013*	0.2169	-0.4679	0.3235	-1.0391*	0.3103	0.4054	0.2259	0.4051	0.3177
Random Effect	Variance Component	Chi-square	Variance Component	Chi-square	Variance Component	Chi-square	Variance Component	Chi-square	Variance Component	Chi-square
Intercept, u_{0i}	1.2414**	119.0786	3.7737**	150.8252	4.9627**	202.4048	1.5125**	127.7679	5.1226**	195.8670
Temporal trend slope, u_{1i}	0.0000	34.6278	0.0003*	52.5639	0.0008**	95.1806	0.0002*	66.4468	0.0000	29.7433
Level 1, r_{it}	9.8551		21.7806		19.9443		10.8517		21.0600	

* The results are based on 2,856 monthly repeated measures nested within 34 open-street CCTV target locations.
*p < 0.05, **p < 0.001

As presented above, this study shows that open-street CCTV has crime reduction effects on assault and burglary but it does not have crime reduction effects on robbery, auto theft, and theft from auto. Comparison of the effects of open-street CCTV on assault and burglary can be conducted by Z-stat. The specific calculation is as follows.

$$Z = \frac{(-0.5013)-(-1.0391)}{\sqrt{(0.2169^\wedge 2 + 0.3103^\wedge 2)}} = 1.4205$$

Since the Z score (i.e., 1.4205) is between -1.96 and 1.96, this study concluded that the effects of open-street CCTV on assault and burglary were not significantly different (at the p < .05 level, using a two-tailed test).

In sum, the crime reduction effects of open-street CCTV on assault and burglary were greater than the effects for robbery, auto theft, and theft from auto. In addition, the crime reduction effects of open-street CCTV on assault and burglary were not significantly different.

Random Effects of CCTV

The CCTV effects in the models presented above were fixed in order to more appropriately compare any significant effects across daytime v. nighttime conditions, weekday v. weekend conditions, and across crime types. However, in the next stage of analysis, the effects of CCTV will be examined across location type (i.e., downtown, other business district, university/school, residential area). Before examining whether the effects of CCTV vary across such locations, it is helpful to first present the variance components for CCTV in models with level-1 variables only. Thus, Table 4. 10 presents the variance components for CCTV, along with the variance component for other level-1 variables. The table does not include fixed effects because they are almost identical to the tables presented in the analyses above.

The results from Table 4. 10 show that the variance component of the CCTV slope was significant in the estimation of daytime crime, but it was non-significant in all other models – models estimating nighttime crime, weekday crime, weekend crime, assault, robbery, burglary, auto theft, and theft from auto. Additionally, the variance components of the intercepts, for all dependent variables, were significant. This pattern is similar to the level-1 models in which the CCTV slope was fixed (see above). The variance components for the temporal trend slopes reported in Table 4. 10 were a little different from level-1 models presented earlier (models in which CCTV's slope was fixed). In the models shown in Table 4. 10, variance components of temporal trend slope for daytime crime, burglary, and auto theft were significant whereas variance components of temporal trend slope for nighttime crime, weekday crime, weekend crime, assault, robbery, and theft from auto were not significant in the level-1 models in which CCTV is specified as random.

Table 4. 10. Random Effects in Hierarchical Linear Models of Daytime, Nighttime, Weekday, Weekend Crime, and Specific Crime Types, Level-1 Variables Only

Random Effect	Daytime		Nighttime		Weekday		Weekend	
	Variance Component	Chi-Square	Variance Component	Chi-square	Variance Component	Chi-square	Variance Component	Chi-square
Intercept, u_{0i}	2.7606**	160.4025	4.1184**	166.9464	2.3166**	161.6887	6.9237**	169.3577
Temporal trend slope, u_{1i}	0.0004*	50.8707	0.0001	26.6292	0.0001	35.9015	0.0002	34.6939
CCTV slope, u_{3i}	1.7223**	66.2844	0.3322	24.5966	0.0322	28.4787	0.4301	31.7012
Level 1, r_{it}	10.7544		14.8701		8.8393		25.3651	

Random Effect	Assault		Robbery		Burglary		Auto Theft		Theft from Auto	
	Variance Component	Chi-square	Variance Component	Chi-square	Variance Component	Chi-square	Variance Component	Chi-square	Variance Component	Chi-square
Intercept, u_{0i}	1.2187**	99.9756	4.3389**	138.9426	4.1597**	141.7588	1.5946**	106.8793	6.2390**	178.7045
Temporal trend slope, u_{1i}	0.0002	41.1976	0.0005	46.3670	0.0009*	55.1944	0.0003*	48.1535	0.0004	40.8312
CCTV slope, u_{3i}	0.3443	26.8168	0.3111	36.2388	1.3933	47.0909	0.0415	29.9554	1.5004	47.1158
Level 1, r_{it}	9.8101		21.7502		19.8483		10.8503		20.9504	

* The results are based on 2,856 monthly repeated measures nested within 34 open-street CCTV target locations.
*p < 0.05, **p < 0.001

Location Type and the Effects of CCTV

This section of the dissertation presents findings from the growth-curve (HLM) analysis regarding potential variation in the effects of CCTV on average daily crime counts across location type (i.e., downtown, business district, university/school, residential area). Successive sub-sections provide results regarding CCTV's effect at various location types: 1) on daytime and nighttime crime; 2) on weekday and weekend crime; and 3) on five specific offenses.

Daytime and Nighttime Crime

Table 4. 11 presents the results from hierarchical linear growth curve models of daytime and nighttime crime with level-1 and level-2 variables. The results show how the effects of CCTV on daytime and nighttime crime vary by location type. None of the coefficients representing the location-related effects of CCTV (i.e., CCTV (Intercept), CCTV (Downtown), CCTV (Business district), CCTV (School)) in the fixed effects panel of Table 4. 11 were significant for either daytime crime or nighttime crime. Thus, the effects of CCTV on daytime and nighttime crime did not vary by location type; the implementation of CCTV did not significantly influence daytime crime and nighttime crime in any location type during the study period, after controlling for temporal trend, temperature, and location types.

For main effects of location types on daytime crime, Downtown was significantly positive in the fixed effects panel of Table 4. 11, whereas the other two location types were not significant. This means that significantly more average daily daytime crime occurred in downtown in comparison to the reference category (residential areas). The fixed effects panel of Table 4. 11 also shows that there were no significant main effects of location types on nighttime crime.

The coefficients of temporal trend and temperature in the fixed effects panel of Table 4. 11 show results similar to the fixed effects of level-1 models in which CCTV was fixed (see Table 4. 7). That is, neither daytime crime nor nighttime crime had a significant decreasing or increasing temporal trend during the study period, after controlling for temperature, CCTV implementation, and location types. Also, monthly average temperature did not have a significant impact on daytime crime, but it had a significantly positive impact on nighttime crime, after controlling for temporal trend, CCTV implementation, and location types.

Table 4. 11. Hierarchical Linear Models of Daytime and Nighttime Crime: The Effects of CCTV by Location Type

Fixed Effect	Daytime		Nighttime	
	Coefficient	**SE**	**Coefficient**	**SE**
Intercept, γ_{00}	-4.8804**	0.6487	-5.6892**	0.7665
Downtown, γ_{01}	2.7302**	0.8366	1.1680	0.9679
Business District, γ_{02}	0.5605	0.7706	-0.0895	0.8793
School, γ_{03}	0.8590	0.8659	-0.8046	0.9921
Temporal trend, γ_{10}	-0.0009	0.0057	-0.0072	0.0056
Temperature, γ_{20}	0.0030	0.0039	0.0243**	0.0045
CCTV (Intercept), γ_{30}	0.2169	0.4580	-0.8948	0.4756
CCTV (Downtown), γ_{31}	-0.5602	0.4664	0.9322	0.5766
CCTV (Business district), γ_{32}	0.2469	0.4356	0.4752	0.5396
CCTV (School), γ_{33}	-0.6291	0.4849	0.8032	0.6001
Random Effect	Variance Component	Chi-square	Variance Component	Chi-square
Intercept, u_{0i}	1.9928**	110.2406	3.7435**	143.6229
Temporal trend slope, u_{1i}	0.0004*	50.9643	0.0001	26.6263
CCTV slope, u_{3i}	1.9741**	68.9516	0.2448	22.0465
Level 1, r_{it}	10.7346		14.8709	

* The results are based on 2,856 monthly repeated measures nested within 34 open-street CCTV target locations.
*p < 0.05, **p < 0.001

The random-effects panel of Table 4. 11 shows results similar to the random effects of level-1 models in which CCTV was random (see Table 4. 10). That is, the variance components of the intercept for both daytime crime and nighttime crime were significant. The variance component of the temporal trend slope for daytime crime was significant, whereas the variance component of the temporal trend slope for nighttime crime was not significant. In addition, the variance component of the CCTV slope was significant in the estimation of daytime crime, but it was non-significant in estimating nighttime crime.

Weekday and Weekend Crime

Table 4. 12 presents the results from hierarchical linear growth curve models of weekday and weekend crime with level-1 and level-2 variables, highlighting the effects of CCTV on weekday and weekend crime vary by location type. The coefficients for all CCTV-location interactions, shown in the fixed effects panel of Table 4. 12, were non-significant for weekday crime. This means that the implementation of CCTV did not significantly influence weekday crime in any location type during the study period, after controlling for temporal trend, temperature, and location types.

Regarding weekend crime, the coefficients of CCTV (Intercept) and CCTV (School) were non-significant, whereas the coefficients of CCTV (Downtown) and CCTV (Business district) were significantly positive for weekend crime. Thus, although CCTV does not significantly influence weekend crime in residential areas (the reference group), the effects of CCTV on weekend crime varied by location type. That is, the crime-reduction effects of CCTV on weekend crime were significantly smaller in downtown and business districts (i.e., the coefficients were significantly more positive) in comparison to the effects in residential areas.

For main effects of location types on weekday crime, Downtown was significantly positive among the coefficients of in the fixed effects panel of Table 4. 12, whereas the other two location types were not significant. This means that significantly more average daily weekday crime occurred in downtown in comparison to residential areas (the reference location). There were no significant main effects of location types on weekend crime in the fixed effects panel of Table 4. 12. This means that location types did not influence average daily weekend crime.

The coefficients of temporal trend and temperature in the fixed effects panel of Table 4. 12 show results similar to the fixed effects of level-1 models in which CCTV was fixed (see Table 4. 8). That is, neither weekday crime nor weekend crime had a significant decreasing or increasing temporal trend during the study period, after controlling for temperature, CCTV implementation, and location types. Also, monthly average temperature did not have a significant impact on weekday crime, but it had a significantly positive impact on weekend crime, after controlling for temporal trend, CCTV implementation, and location types.

Table 4. 12. Hierarchical Linear Models of Weekday and Weekend Crime: The Effects of CCTV by Location Type

Fixed Effect	Weekday		Weekend	
	Coefficient	**SE**	**Coefficient**	**SE**
Intercept, γ_{00}	-3.4583**	0.5894	-6.6551**	0.9440
Downtown, γ_{01}	1.8952*	0.7514	1.8605	1.1766
Business District, γ_{02}	0.3692	0.6886	-0.0198	1.0619
School, γ_{03}	0.1912	0.7745	-1.0187	1.2012
Temporal trend, γ_{10}	-0.0072	0.0045	-0.0034	0.0070
Temperature, γ_{20}	0.0048	0.0035	0.0247**	0.0059
CCTV (Intercept), γ_{30}	-0.1974	0.3336	-0.9151	0.5436
CCTV (Downtown), γ_{31}	0.3301	0.3889	1.3102*	0.6022
CCTV (Business district), γ_{32}	0.4377	0.3658	1.3325*	0.5702
CCTV (School), γ_{33}	0.6126	0.4057	0.8486	0.6303
Random Effect	Variance Component	Chi-square	Variance Component	Chi-square
Intercept, u_{0i}	1.9232**	129.0531	5.8534**	138.5560
Temporal trend slope, u_{1i}	0.0001	35.9148	0.0001	34.6929
CCTV slope, u_{3i}	0.0266	25.5109	0.1824	27.7434
Level 1, r_{it}	8.8344		25.3593	

* The results are based on 2,856 monthly repeated measures nested within 34 open-street CCTV target locations.
* $p < 0.05$, ** $p < 0.001$

The random-effects panel of Table 4. 12 shows results similar to the random effects of level-1 models in which CCTV was random (see Table 4. 10). That is, the variance components of the intercept for both weekday crime and weekend crime were significant. In contrast, the variance component of the temporal trend slope for both weekday crime and weekend crime was non-significant. In addition, the variance component of the CCTV slope was not significant for either weekday crime or weekend crime.

Across Crime Type

Table 4. 13 presents the results from hierarchical linear growth curve models of specific crime types (i.e., assault, robbery, burglary, auto theft, theft from auto) with level-1 and level-2 variables. The coefficients for CCTV in the fixed-effects panel of Table 4. 13 indicate that the effects of CCTV on assault, burglary, auto theft, and theft from auto did not vary by location type, whereas the effects of CCTV on robbery varied by location type.[6] Specifically, although the coefficient of CCTV (Intercept) for assault was significantly negative, the other CCTV-related coefficients were not significant. This means CCTVs have crime reduction effects on assault in residential areas, and the effects of CCTV on assault in other location types were not significantly changed in comparison to the effects in residential areas. For robbery, the coefficient of CCTV (Intercept) was significantly negative and the coefficient of CCTV (Business District) was significantly positive. Thus, the crime-reduction effects of CCTV on robbery was significant in residential areas (the reference group) and the effects of CCTV on robbery were significantly smaller in business districts (significantly more positive) in comparison to residential areas.

There were no significant main effects of location types on assault and auto theft in the fixed effects panel of Table 4. 13. This means that location types did not influence average daily nighttime crime. In contrast, Downtown was significantly positive among the main effects of location types on robbery in the fixed effects panel of Table 4. 13, whereas the other two location types were not significant. This means that significantly more average

[6] When the models were grand mean centered, the results were slightly changed. In grand mean centered models, the coefficients of CCTV (Intercept) for assault and robbery were not significant and the coefficient of CCTV (Intercept) for burglary was significant. However, all other results were very similar to the non-centered models for this study.

daily robbery occurred in downtown than in residential areas (the reference group). All main effects of location types on burglary were significantly negative. This means that significantly less average daily burglary occurred in downtown, business district, and university/school locations in relation to that which occurred in residential areas. On the other hand, all main effects of location types on theft from auto were significantly positive. This means that significantly more average daily burglary occurred in downtown, business district, and university/school locations than in residential areas.

The coefficients of the temporal trend and the temperature in the fixed effects panel of Table 4. 13 show similar results from the fixed effects of level-1 models in which CCTV was fixed (see Table 4. 9). That is, the coefficient of the temporal trend was non-significant for assault, robbery, burglary, and theft from auto, but it was significantly negative for auto theft. Additionally, the coefficient of the temperature was not significant for assault, robbery, and theft from auto, but it was significantly positive for burglary and auto theft.

The random-effects panel of Table 4. 13 shows results similar to the random effects of level-1 models in which CCTV was random (see Table 4. 10). That is, the variance components of the intercepts, for all dependent variables, were significant. Variance components of the temporal trend slope for burglary and auto theft were significant, whereas variance components of temporal trend slope for assault, robbery, and theft from auto were not significant. Additionally, the variance component of the CCTV slope was significant in the estimation of burglary[7], but it was non-significant in all other models – models estimating assault, robbery, auto theft, and theft from auto.

[7] This was different than model in Table 4. 10.

Table 4. 13. Hierarchical Linear Models of Specific Crime Types: The Effects of CCTV by Location Type

Fixed Effect	Assault		Robbery		Burglary		Auto Theft		Theft from Auto	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Intercept, γ_{00}	-11.7771**	0.4863	-11.3561**	0.7410	-9.6143**	0.7671	-12.2511**	0.4476	-12.6141**	0.7497
Downtown, γ_{01}	-0.7822	0.5886	2.7951*	0.9023	-2.8493*	0.9205	-0.3055	0.4750	4.3095**	0.9138
Business District, γ_{02}	-1.0216	0.5390	1.2629	0.8275	-2.4297*	0.8347	-0.2766	0.4097	2.4709*	0.8317
School, γ_{03}	-1.2186	0.6062	1.4503	0.9303	-3.1549*	0.9419	-0.0558	0.4711	2.2443*	0.9374
Temporal trend, γ_{10}	-0.0001	0.0049	-0.0022	0.0077	0.0041	0.0080	-0.0162*	0.0053	-0.0107	0.0068
Temperature, γ_{20}	0.0022	0.0037	-0.0004	0.0055	0.0255**	0.0052	0.0077*	0.0039	0.0087	0.0054
CCTV (Intercept), γ_{30}	-0.8349*	0.3531	-1.1289*	0.5269	-1.3476	0.6698	0.1048	0.3938	0.1456	0.5242
CCTV (Downtown), γ_{31}	0.1429	0.3820	0.6089	0.5974	0.2136	0.8423	0.4807	0.4842	0.5965	0.5642
CCTV (Business district), γ_{32}	0.6781	0.3612	1.5084*	0.5621	0.3275	0.7807	0.3850	0.4507	-0.2894	0.5331
CCTV (School), γ_{33}	0.5161	0.3995	-0.0882	0.6232	0.9291	0.8727	0.2286	0.5025	0.6768	0.5899
Random Effect	Variance Component	Chi-square	Variance Component	Chi-square	Variance Component	Chi-square	Variance Component	Chi-square	Variance Component	Chi-square
Intercept, u_{0i}	1.0876**	86.9344	2.5717**	89.1991	4.0545**	130.0256	1.7084**	108.7433	3.0251**	98.9515
Temporal trend slope, u_{1i}	0.0002	41.1977	0.0007	46.5191	0.0009*	55.1917	0.0003*	48.1446	0.0003	40.7288
CCTV slope, u_{3i}	0.3450	27.7151	0.4309	28.9045	1.6075*	46.9116	0.0515	29.0445	0.8795	41.4533
Level 1, r_{it}	9.8104		21.6925		19.8435		10.8517		20.9742	

* The results are based on 2,856 monthly repeated measures nested within 34 open-street CCTV target locations.
*p < 0.05, **p < 0.001

Supplemental Analyses: Overall Trends in Crime across the Camera Locations

In this section, I present analyses to supplement the HLM analyses of CCTV effects presented in the previous sections – as a way to better understand the minimal effects of CCTV revealed in the growth curve models. Specifically, I present figures showing overall trends of crime across the camera locations. The figures present, in graphical form, average daily crime counts per month in 34 CCTV target areas for the period of 12 months before and after CCTV implementation. Overall, the figures show that open-street CCTVs may have had some short-term crime reduction effects, but minimal-to-no long-term effects.

In addition to presenting figures showing trends across all camera locations, trends are shown for several specific sites with particularly higher base rates of crime in comparison to other target areas. These are shown as a way to discern whether cameras might have hypothesized crime-reduction effects at sites with relatively more crime that are washed out in HLM analysis due to many sites having low base rates (Hinkle, Weisburd, Famega, & Ready, 2013).

Daytime and Nighttime Crime Before and After CCTV

Figure 4. 1 presents overall trends in daytime and nighttime crime across all the camera locations. The daytime crime trend line shows that daytime crime was increasing before CCTV implementation, and it declined during the four months immediately following CCTV implementation. After that short time period, it then began to increase again. The nighttime crime trend line was similar to the daytime crime trend line. Nighttime crime was trending upward before CCTV implementation. During the three months following CCTV implementation, crime declined, but then began an increasing trend again. These findings suggest that CCTV implementation might reduce daytime crime and nighttime crime on a

short-term basis, but those effects are not sustained for the long-term.

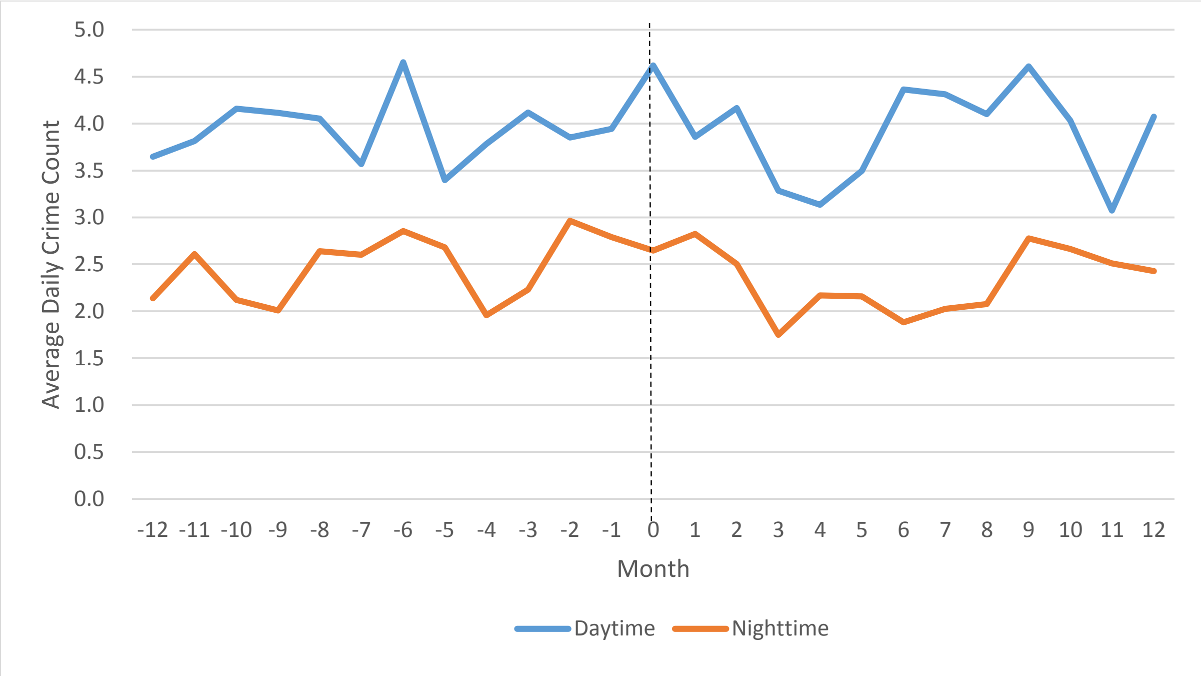

Figure 4. 1. Overall Trends in Daytime Crime and Nighttime Crime across the Camera Locations

Weekday and Weekend Crime Before and After CCTV

Figure 4. 2 presents overall trends in weekday and weekend crime across all of the camera locations. The weekday crime trend line shows that weekday crime was increasing before CCTV implementation. Weekday crime then decreased during the three months after CCTV implementation, but then began to increase, reaching pre-implementation levels during the period nine-months after CCTV installation.

The weekend crime trend line demonstrates a decreasing trend before CCTV implementation. Weekend crime then actually increased for two months after CCTV implementation. Then, it displayed a sharp decrease for one month, but then began an increasing trend that spanned the period three to ten months after CCTV implementation.

These findings suggest that CCTV implementation might also reduce weekday crime and weekend crime on short-term basis, but those effects are not sustained for the long-term.

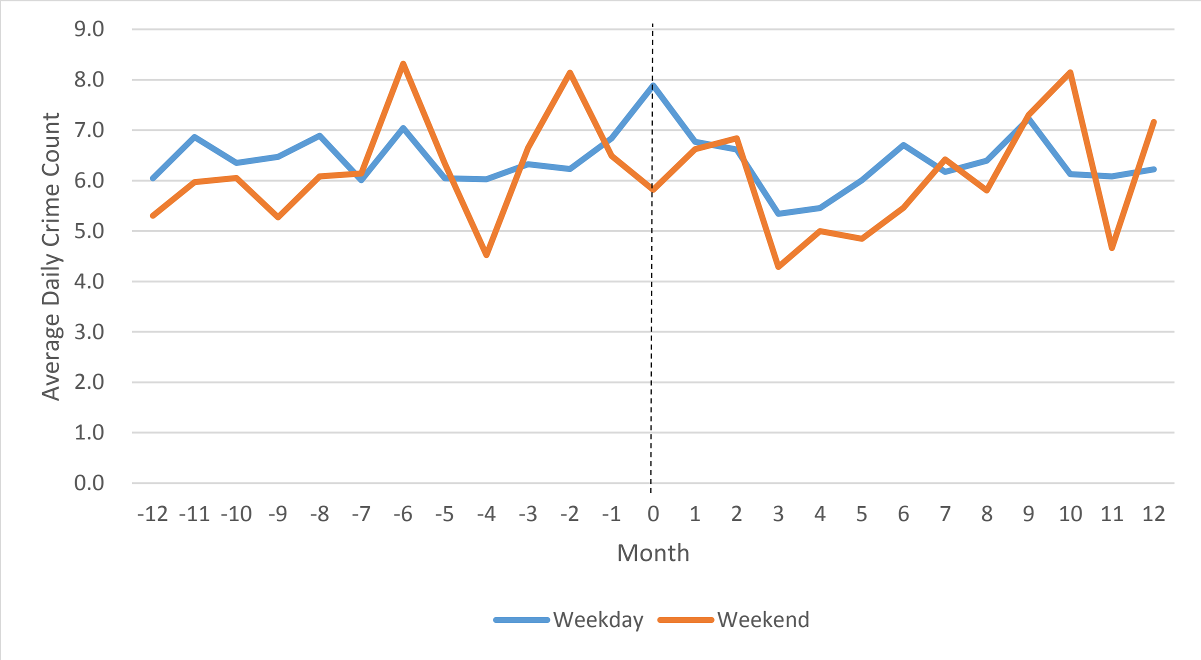

Figure 4. 2. Overall Trends in Weekday Crime and Weekend Crime across the Camera Locations

Specific Crime Types Before and After CCTV

Figure 4. 3 presents overall trends in specific crime types (i.e., assault, robbery, burglary, auto theft, theft from auto) across all of the camera locations for a period spanning 12 months before and after CCTV implementation. The assault trend line shows that assault was generally decreasing for about five months before CCTV implementation. Upon installing CCTV, assault increased for one month before a slow decreasing trend for four months. But then assault increased for several months before beginning another decline. In general, assault went up and down throughout the before- and after period displayed in Figure 4. 3. This same sort of pattern of short increments of increasing and decreasing trends, over and over both before and after CCTV implementation, is observed for robbery, burglary, auto

theft, and theft from auto as well. Overall, these crime-specific findings support the HLM results that the cameras are having little overall effect, especially long-term. Fluctuations in crime occurred before and after implementation. That said, when a particular type of crime was relatively high when CCTV was implemented, CCTV appeared to reduce crime for the short-term. Whether this is a true short-term effect of CCTV of just part of an overall pattern of "up and down" crime cannot be fully determined.

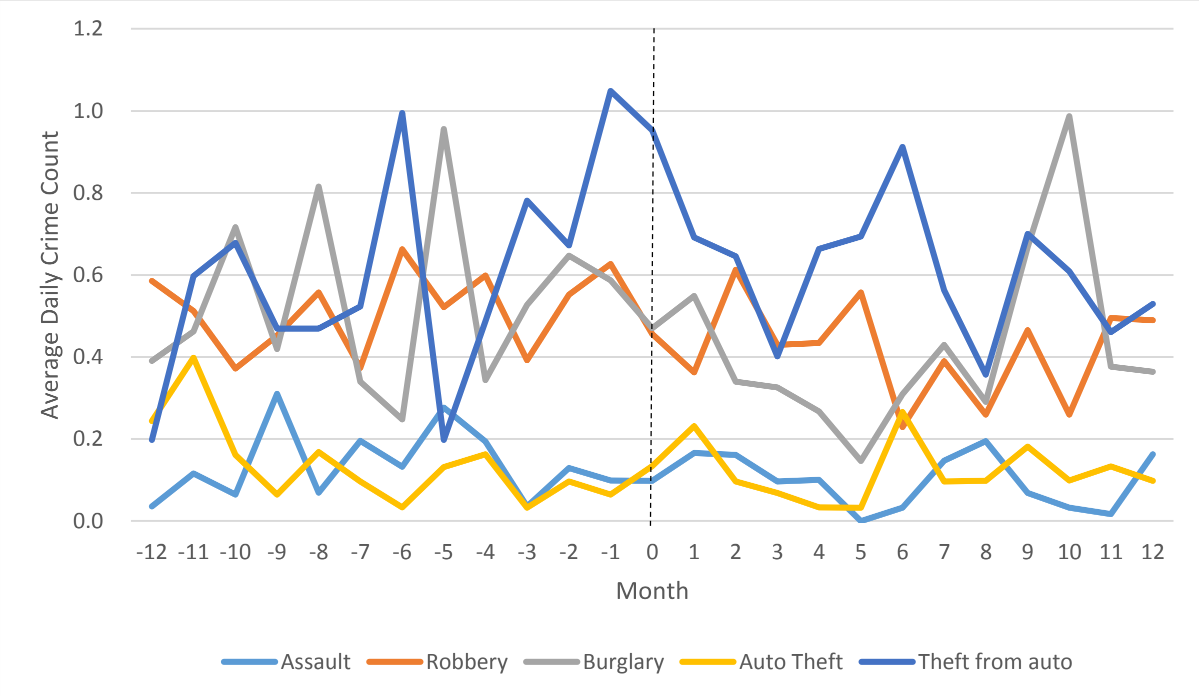

Figure 4. 3. Overall Trends in Specific Types of Crime across the Camera Locations

Trends at High-Crime Locations

Figure 4. 4 and Figure 4. 5 presents overall trends in daytime and nighttime crime for site #3 and # 30, respectively. These sites were selected for further examination because they had relatively high crime rates for daytime crime and nighttime crime, respectively. I explore these sites in more detail based on the assumption that open-street CCTV might provide more crime reduction effects in sites with high crime rates than sites with low crime rates (Hinkle

et al., 2013).

The overall trends for daytime crime and nighttime crime in site #3 and #30 were somewhat different from overall trends in daytime crime and nighttime crime across all the camera locations. Specifically, the daytime crime trend line in site #3 shows that daytime crime was increasingly sharply in the several months leading up to implementation but then was actually decreasing immediately before CCTV implementation, and that declining trend continued into one month after implementation. Crime then increased somewhat, but then when into a three-month decline that lasted until 5-months post CCTV implementation. After that point, crime increased rather sharply. When examining the entire period 12 months before and after CCTV implementation at this site with high baseline daytime crime, it appears that crime was, overall, higher in the post-implementation period. As such, CCTV did not appear to work, even in the case of a high base rate.

Site #30 is also examined since it had very high base rates of nighttime crime. For site #30, the nighttime crime trend line shows that nighttime crime, despite its relatively high levels, had generally been decreasing quite a bit over the course of the 12 months leading up to CCTV implementation (though with fluctuations). That said, there was an increasing trend one month prior to the cameras being installed. That uptick in crime continued on month after CCTV implementation, but then nighttime crime started to decline. Crime went up and down on an almost monthly basis for the remainder of the time period post-implementation. Overall, once again, there is little evidence that nighttime crime was all that different before and after CCTV implementation, even at this site which had relatively high base rates of nighttime crime.

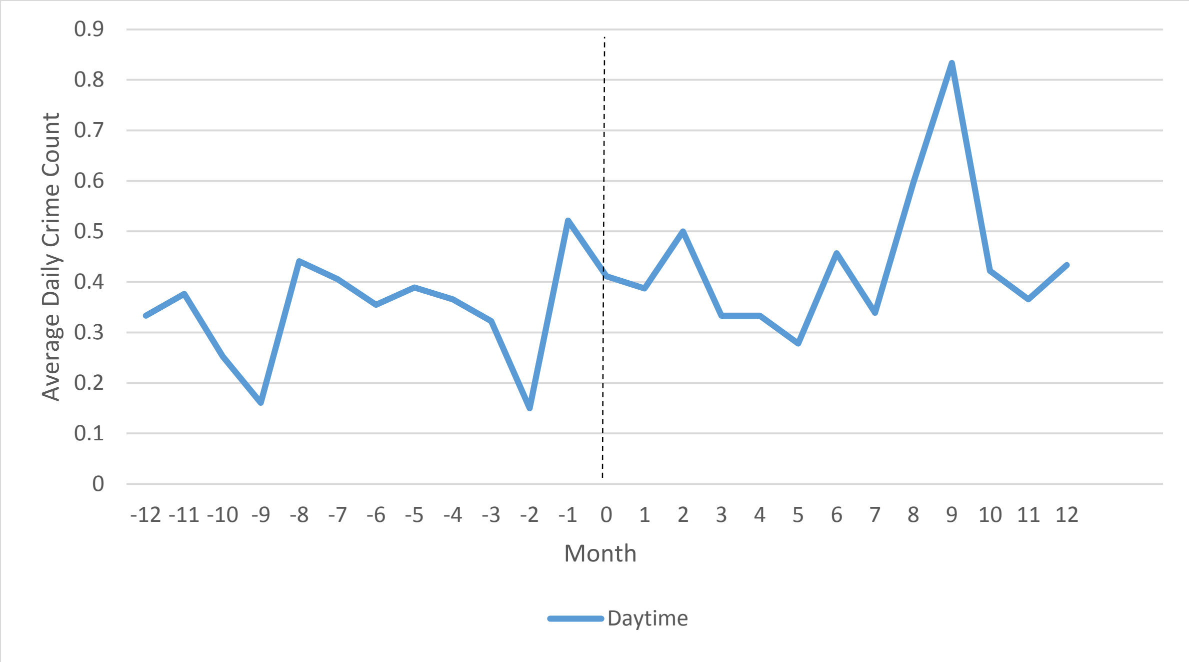

Figure 4. 4. Overall Trends in Daytime Crime in Site #3

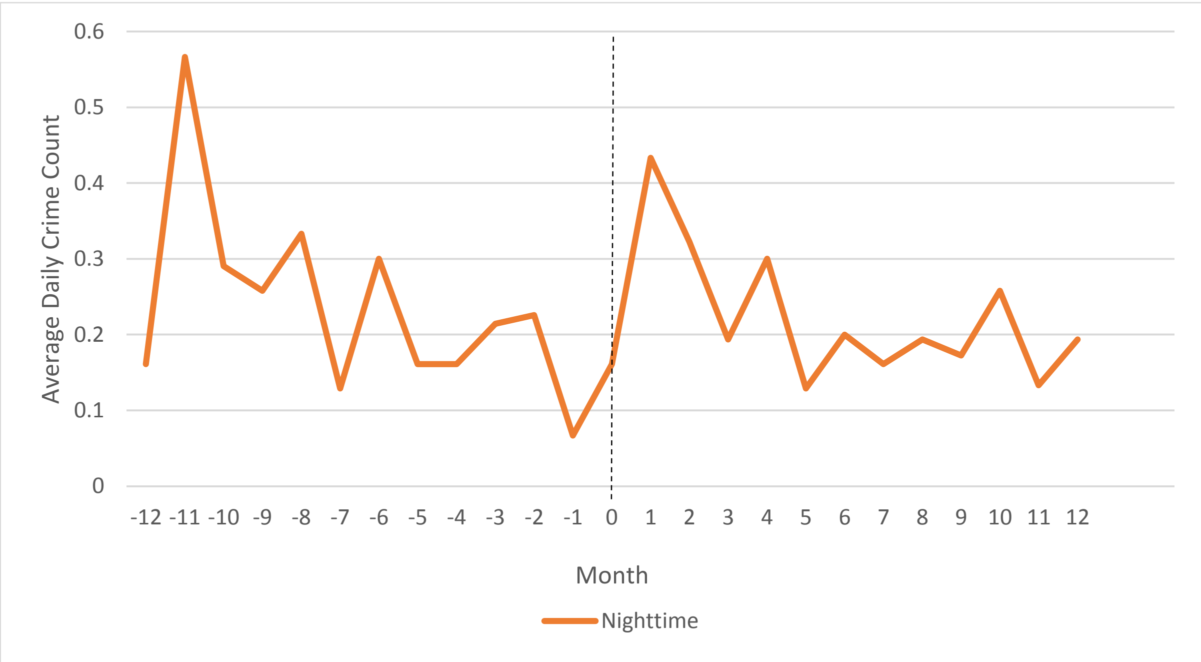

Figure 4. 5. Overall Trends in Nighttime Crime in Site #30

CCTV and Base Rate of Crime: Further Analysis

In this section, I present HLM analyses which include base-rate of crime as a level-2 variable to better understand how CCTV interacts with base-rates. Table 4. 14 reports interaction effects between base rate and CCTV implementation, stemming from HLM models of all dependent variables – daytime crime, nighttime crime, weekday crime, weekend crime, assault, robbery, auto theft, and theft from auto. The models that were estimated included location types, along with base-rate of crime as level-2 variables. The location types were included as both main effects and interaction effects with CCTV, whereas base-rate was included in an interaction with CCTV (the main effect of base rate is reflected in the intercept in these models). The models also included temporal trend, temperature, and CCTV as level-1 variables. However, for purposes of this section, I present only the coefficients regarding the interaction effects between CCTV and base-rates. Importantly, it should be noted that the "base rate" variable in each model refers to the specific base crime rate that is related to the outcome measure (i.e., in daytime crime model, the base rate included in interaction with CCTV is the base rate of daytime crime; in the assault model, the base rate included in interaction with CCTV is the base rate of assault).

In terms of the interaction between CCTV and base-crime rates, all coefficients for interaction effects except those in the nighttime crime and auto theft models were significantly positive. Thus, the crime-reduction effect of CCTV for daytime crime, weekday crime, weekend crime, assault, robbery, burglary, and theft from auto decreased (i.e., the coefficient moved in the more strongly positive direction) as base-rate of the crimes in the CCTV location increased. Such findings provide little support for the suggestion that crime-reduction effects may not be detected when base rates are low as opposed to high.

Table 4. 14. Hierarchical Linear Models of Daytime, Nighttime, Weekday, Weekend Crime, and Specific Crime Types: The Effects of CCTV by Base-Rate

Fixed Effect	**Daytime**		**Nighttime**		**Weekday**		**Weekend**	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
CCTV (Base-Rate), γ_{34}	0.2297*	0.0729	0.1290	0.1319	0.1547*	0.0622	0.5620*	0.2128

Fixed Effect	**Assault**		**Robbery**		**Burglary**		**Auto Theft**		**Theft from Auto**	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
CCTV (Base-Rate), γ_{34}	3.4714**	0.8300	4.4060**	0.5602	9.2750**	0.7896	2.1325	1.3525	1.1185*	0.4649

* The results are based on 2,856 monthly repeated measures nested within 34 open-street CCTV target locations.
*$p < 0.05$, **$p < 0.001$

WDQ Analysis

Table 4. 15 presents WDQ values across the 18 CCTV sites used for analysis of displacement and diffusion; WDQ values are presented with respect to each dependent variable. Table 4. 16 then summarizes the values presented in Table 4. 15 in terms of how the value can be classified across the four substantively important categories of WDQ value (strong displacement, small displacement, small diffusion of benefits, strong diffusion of benefits).

Overall, in cases where WDQ values were computed (i.e., in cases where success measure[8] was negative in a CCTV site), CCTV tends to bring about diffusion of benefits rather than displacement[9]. Among the 80 total WDQ values computed in this study, 18 values indicated displacement (i.e., WDQ < 0) and 62 values indicated diffusion of benefits (i.e., WDQ > 0). More specifically, nine WDQ values indicated strong displacement effects (WDQ < -1), and nine WDQ values indicated small displacement effects (i.e., -1 < WDQ < 0). In contrast, 40 WDQ values indicated strong diffusion of benefits effects (WDQ > 1), and 22 WDQ values indicated small diffusion of benefits effects (i.e., 0 < WDQ < 1).

Overall, these findings suggest that open-street CCTV implementation brought about diffusion of benefits rather than displacement effects. Inspection of the WDQ values associated with each dependent variable results in similar conclusions for all but two: auto

[8] In WDQ formula, the denominator is the "success measure" of CCTV implementation in the target areas. If success measure is negative, it means that open-street CCTV has crime reduction effects in the target area (see Chapter III for full details).

[9] This study computed WDQs for all cases in which success measure was negative in a CCTV site following precedent (Ratcliffe et al, 2009).

theft and theft from auto.

Among eight total WDQ values produced for auto theft, four WDQ values indicated displacement effects (i.e., WDQ < 0) and four WDQ values indicated diffusion of benefits effects (i.e., WDQ > 0). Specifically, three WDQ values indicated strong displacement effects (i.e., WDQ < -1) and one WDQ value indicated small displacement effects (i.e., -1 < WDQ < 0). In contrast, two WDQ values indicated strong diffusion of benefits effects (WDQ > 1) and two WDQ values indicated small diffusion of benefits effects (i.e., 0 < WDQ < 1). These findings suggest that open-street CCTV implementation brings about both diffusion of benefits and displacement in regards to auto theft. Similarly, among total six WDQ values produced for theft from auto, three WDQ values indicated displacement effects and three WDQ values indicated diffusion of benefits effects. More specifically, two WDQ values indicated strong displacement effects, one WDQ value indicated small displacement effects, and three WDQ values indicated strong diffusion of benefits effects (WDQ > 1). Thus, open-street CCTV implementation seems to bring about both diffusion of benefits and displacement with respect to theft from auto.

Table 4. 15. WDQ Values for Each Dependent Variable in 18 CCTV Sites

CCTV Sites	Dependent Variable								
	Daytime Crime	Nighttime Crime	Weekday Crime	Weekend Crime	Assault	Robbery	Burglary	Auto Theft	Theft from Auto
1						0.046	0.394	0.884	
2	-2.257		-0.141						
3	1.267	0.708	0.990		5.000	1.100	2.766		-8.154
4		5.157	76.744	2.069		-2.750			
5						3.307	5.814		
6					-0.250	0.289			
7	0.040	-0.318	-0.152	-0.648	-4.250	0.203		-0.385	
8						2.596	7.778	-3.000	1.008
9		1.600			1.688	4.313	7.816	-3.308	
10	1.574	5.317	3.553	1.530			3.488	2.679	
11	0.615	0.361	0.261	1.796	0.286				8.444
12	2.221	1.923	2.063	1.210	2.528	0.909	13.000	2.352	-1.476
13	1.701	1.276	0.382	4.579	5.000	0.500	0.563		1.672
14		1.668						-14.000	
15		0.466	3.692		0.750	2.250	-0.693		-0.854
16	0.013				1.500				
17		0.992	-0.805			0.419			
18							-2.714	0.795	

* Vacant cell means that there is no WDQ value because success measure of the case is positive.

Table 4. 16. Classification of WDQ Values for Each Dependent Variable

	Dependent Variable									
WDQ Size	**Daytime Crime**	**Nighttime Crime**	**Weekday Crime**	**Weekend Crime**	**Assault**	**Robbery**	**Burglary**	**Auto Theft**	**Theft from Auto**	**Total**
WDQ < -1	1	0	0	0	1	1	1	3	2	9
-1 < WDQ < 0	0	1	3	1	1	0	1	1	1	9
0 <WDQ <1	3	4	3	0	2	6	2	2	0	22
1 < WDQ	4	6	4	5	5	5	6	2	3	40
Total	8	11	10	6	9	12	10	8	6	80

*Each cell is filled with classified counts.

Summary

In this chapter, I presented results from several types of analysis: 1) HLM analyses with level-1 variables only for daytime versus nighttime crime, weekday versus weekend crime, and across specific crime types; 2) HLM analyses with level-1 variables and level-2 location type variables for daytime crime, nighttime crime, weekday crime, weekend crime, and specific crime types; 3) supplemental analyses for overall trends in crime across the camera locations; 4) HLM analyses with a level-2 base rate variable in interaction with CCTV as well as level-1 variables and level-2 location type variables. Results will be summarized and interpreted in the following concluding chapter.

CHAPTER V

DISCUSSION AND CONCLUSIONS

In this chapter, I will first summarize findings in Chapter IV in relation to each hypothesis and discuss possible reasons for the findings. Next, I will examine the policy implications of the findings. Finally, I will discuss the limitations of this study and provide suggestions for future research.

Support for Hypotheses

This study examined a total of 13 hypotheses. Three hypotheses centered around the crime reduction effects of CCTVs on daytime versus nighttime crime and three hypotheses were about the expected crime reduction effects of CCTVs on weekday versus weekend crime. Additionally, six hypotheses dealt with the expected relative crime reduction effects of CCTVs on specific crime types. Finally, one hypothesis was about displacement versus diffusions of benefits effects caused by the implementation of CCTV. In this section, I will discuss whether the findings supported each hypothesis. When going over support for the hypotheses, I will review the theoretical rationale provided for each hypothesis and discuss findings in terms of support/non-support for that theory.

Daytime and Nighttime Crime

As mentioned above, I examined three hypotheses about the crime reduction effects of CCTVs on daytime versus nighttime crime. Table 5. 1 summarizes whether this study supports each of the hypotheses – related to daytime versus nighttime crime. As shown in Table 5. 1, the first hypothesis (hypothesis 1) was: *Crime reduction effects of open-street CCTVs will be greater during the daytime than the nighttime.* According to opportunity theory, the implementation of CCTV makes offenders feel greater risk, works as stronger guardianship for targets, and provides increased surveillance during the daytime than the nighttime. Thus, the crime reduction effects of CCTVs were expected to be greater during daytime than nighttime.

However, this study does not provide support for the first hypothesis because CCTV did not show crime reduction effects on either daytime or nighttime crime after controlling temporal trend and temperature in the HLM analyses (see Table 4. 7). The supplementary graphical analysis of overall trends in daytime and nighttime crime across the camera locations showed results compatible with findings from the HLM analyses. That is, the overall trends showed that, while the implementation of CCTV might have brought about short-term crime reduction effects, it did not appear to bring about long-term crime reduction effects on either daytime or nighttime crime (see Figure 4. 1).

The second hypothesis (hypothesis 1-1) was as follows: *Crime reduction effects of open-street CCTVs during the daytime will vary depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The reduction effects will be greatest in residential areas and lowest in downtown districts.* According to opportunity theory, implementation of CCTV provides offenders relatively lower risk in downtown areas due to the overall anonymity experienced in downtown locations, whereas CCTV provides much higher risk in residential areas. Further, even with CCTV providing some risk, offenders can find targets (rewards) more easily in downtown areas due to higher levels of routine activity in downtown areas in comparison to residential areas. This study did not provide evidence in support of this second hypothesis. The effects of CCTV on daytime crime was not significant in residential areas (the reference group), and it did not vary by location type in the HLM analysis (see Table 4. 11).

The third hypothesis on daytime/nighttime crime (hypothesis 1-2) was as follows: *Crime reduction effects of open-street CCTVs at nighttime will vary depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The reduction effects will be greatest in residential areas and lowest in downtown districts.* The theoretical rationale for this hypothesis was the same as the second hypothesis. That is, according to opportunity theory, implementation of CCTV makes offenders feel relatively less risk in downtown areas due to the anonymity of downtown, whereas it makes offenders feel relatively greater risk in residential areas. Further, offenders can find targets more easily in downtown as opposed to residential areas. This study did not provide evidence in support of the third hypothesis. The effects of CCTV on nighttime crime was not significant in residential areas, and it did not vary by location type in the HLM analysis (see Table 4. 11).

Table 5. 1. Support for Hypotheses in Relation to Daytime versus Nighttime Crime

Hypotheses	Support
Crime reduction effects of open-street CCTVs will be greater during the daytime than the nighttime.	X
Crime reduction effects of open-street CCTVs during the daytime will vary depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The reduction effects will be greatest in residential areas and lowest in downtown districts.	X
Crime reduction effects of open-street CCTVs at nighttime will vary depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The reduction effects will be greatest in residential areas and lowest in downtown districts.	X

* ○: support, X: non-support

Weekday and. Weekend Crime

As mentioned earlier, I examined three hypotheses about crime reduction effects of

CCTVs on weekday and weekend crime. Table 5. 2 summarizes whether this study supports the hypotheses in relation to weekday versus weekend crime. As shown in Table 5. 2, the first hypothesis about weekday/weekend crime (hypothesis 2) was as follows: *Crime reduction effects of open-street CCTVs will be greater during weekdays than during the weekends*. According to opportunity theory, much more criminal opportunity is produced during the weekends than during weekdays because major entertainment and cultural events are concentrated on weekends compared to weekdays. Thus, offenders may more likely to commit crime during weekends than weekdays, even with CCTV. As a result, the crime reduction effects of CCTVs was expected to be greater during weekdays than weekends.

This study did not provide evidence for this hypothesis because CCTV did not reduce either weekday or weekend crime after controlling temporal trend and temperature in the HLM analyses (see Table 4. 8). The supplementary descriptive, graphical analysis of overall trends in weekday and weekend crime across the camera locations showed results compatible with the HLM analyses: the overall trend lines showed that the implementation of CCTV perhaps brought about short-term crime reduction effects, but not long-term crime reduction effects on weekday or weekend crime (see Figure 4. 2).

The second hypothesis about weekday and weekend crime (hypothesis 2-1) was the following: *Crime reduction effects of open-street CCTVs during weekdays will vary depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The reduction effects will be greatest in residential areas and lowest in downtown districts.* Again, according to opportunity theory, implementation of CCTV makes offenders feel relatively less risk in downtown areas in comparison to residential areas due to the anonymity of downtown. Also, offenders can find targets more easily in downtown districts due to high levels of routine activity in downtown areas in comparison to residential areas. This study did not produce evidence in support of these expectations. The effects of CCTV on weekday crime were not significant in residential areas (the reference group), and the effects of CCTV on weekday crime did not vary by location type in the HLM analysis (see Table 4. 12).

The third hypothesis about weekday and weekend crime (hypothesis 2-2) was similar to the hypothesis just described, except in relation to weekend crime as opposed to weekday crime: *Crime reduction effects of open-street CCTVs during weekends will vary depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The reduction effects will be greatest in residential areas and lowest in downtown districts.* This study did provide evidence in support of this hypothesis. The effects of CCTV on weekend crime were significantly smaller in downtown areas and business districts in comparison to residential areas in the HLM analysis (see Table 4. 12).

Table 5. 2. Support for Hypotheses in Relation to Weekday versus Weekend Crime

Hypotheses	Support
Crime reduction effects of open-street CCTVs will be greater during weekdays than during the weekends.	X
Crime reduction effects of open-street CCTVs during weekdays will vary depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The reduction effects will be greatest in residential areas and lowest in downtown districts.	X
Crime reduction effects of open-street CCTVs during weekends will vary depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The reduction effects will be greatest in residential areas and lowest in downtown districts.	○

* ○: support, X: non-support

Across Crime Type

I examined six hypotheses about crime reduction effects of CCTVs on specific crime types. Table 5. 3 summarizes whether this study supports hypotheses about the effects of CCTV on crime-specific offenses. As shown in Table 5. 3, the first crime-type hypothesis (hypothesis 3) was: *Crime reduction effects of open-street CCTVs are different between crime types (i.e., assault, robbery, burglary, auto theft, theft from auto). The reduction effects of robbery, burglary, auto theft, theft from auto will be greater than the reduction effects of assault.* According to opportunity theory, offenders who commit expressive crimes such as assault may overestimate the benefits and underestimate the risks from their crimes, whereas offenders who commit instrumental crimes such as robbery, burglary, auto theft, and theft from auto may overestimate the risks and underestimate the benefits from their crimes. Also, offenders who commit expressive crime may be less likely to recognize the existence of the open-street CCTVs due to more bounded rationality. Thus, crime reduction effects of CCTV were expected to be greater on instrumental crime than on expressive crime.

However, this study did not provide evidence for this hypothesis. CCTV did not have crime reduction effects on most instrumental crimes (i.e., robbery, auto theft, theft from auto), though it did reduce burglary. Additionally, CCTV appeared to have crime reduction effects on the expressive crime of assault (see Table 4. 9). Finally, the Z-test did not show a significant difference between the crime reduction effects of CCTVs on burglary versus assault. The supplementary graphical analysis of overall trends in specific types of crime across the camera locations showed results similar to the HLM analyses. Assault and burglary appeared to decrease more than robbery, auto theft, and theft from auto after the implementation of CCTV. However, for all crime types, the overall trends showed that the implementation of CCTV perhaps created short-term crime reduction effects, but there was less evidence of such effects for the longer-term (see Figure 4. 3).

The remaining hypotheses (hypothesis 3-1 to hypothesis 3-5) centered around the conditional effects of CCTV on specific crime types across locations types: *Crime reduction effects of open-street CCTVs for assault/robbery/burglary/auto theft/theft from auto will vary depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The reduction effects will be greatest in residential areas and lowest in downtown districts.* This study did not provide evidence for this hypothesis in relation to assault, burglary, auto theft, and theft from auto. The effects of CCTV on assault were significantly negative in residential areas (the reference group), but the effects of the other location types did not vary in relation to the effect in residential areas in the HLM analysis (see Table 4. 13). The effects of CCTV on burglary, auto theft, and theft from auto were not significant in residential areas (the reference group) and did not vary by location type in the HLM analysis (see Table 4. 13).

On the other hand, this study did provide evidence of this hypothesis in relation to robbery. The effects of CCTV on robbery was significantly negative in residential areas (the reference group), and the effects were significantly smaller (i.e., the coefficient increased) in business districts than in residential areas in the HLM analysis (see Table 4. 13).

Table 5. 3. Support for Hypotheses in Relation to Crime-Specific Offenses

Hypotheses	Support
Crime reduction effects of open-street CCTVs are different between crime types (i.e., assault, robbery, burglary, auto theft, theft from auto). The reduction effects of robbery, burglary, auto theft, theft from auto will be greater than the reduction effects of assault.	X
Crime reduction effects of open-street CCTVs for assault will vary depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The reduction effects will be greatest in residential areas and lowest in downtown districts.	X
Crime reduction effects of open-street CCTVs for robbery will vary depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The reduction effects will be greatest in residential areas and lowest in downtown districts.	○
Crime reduction effects of open-street CCTVs for burglary will vary depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The reduction effects will be greatest in residential areas and lowest in downtown districts.	X
Crime reduction effects of open-street CCTVs for auto theft will vary depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The reduction effects will be greatest in residential areas and lowest in downtown districts.	X
Crime reduction effects of open-street CCTVs for theft from auto will vary depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The reduction effects will be greatest in residential areas and lowest in downtown districts.	X

* ○: support, X: non-support

Displacement v. Diffusion of Benefits

I examined one hypothesis about displacement versus diffusion of benefits. The hypothesis was as follows: *Open-street CCTV implementation brings about diffusion of benefits effects rather than displacement effects. This effect is expected to be seen regardless of daytime/nighttime, weekday/weekend, and crime types.* According to opportunity theory, offenders may overestimate the reach of open-street CCTV due to bounded rationality. Thus, they may give up committing crimes in the vicinity of open-street CCTV implementation sites due to an incorrect assessment of risk. As a result, diffusion of benefits effects caused by CCTV implementation were expected to be greater than displacement effects. This study provided some support for this hypothesis. WDQ analyses showed that when CCTV had crime reduction effects in target areas, diffusion of benefits occurred rather than displacement for daytime crime, nighttime crime, weekday crime, weekend crime, assault, robbery, and burglary. In cases of auto theft and theft from auto, the frequency of diffusion of benefits and displacement was same.

Compatibility with Past Research

Many findings of this study are compatible with past studies. First, the null effects of CCTVs on daytime crime, nighttime crime, weekday crime, and weekend crime are compatible with the results of several past studies. Although many past studies concluded that CCTV had crime reduction effects on overall crime (e.g., Cho, 2009; Ratcliffe et al., 2009), some past studies concluded that CCTV did not have crime reduction effects on overall crime (e.g., Cerezo, 2013). Regarding more crime-specific findings, the null effects of CCTVs on robbery and theft from auto revealed here are compatible with some past studies on robbery (e.g., Gill & Hemming, 2004; Yim & Hong, 2008) and theft from auto (e.g., Caplan et al., 2011). Regarding location-specific findings, the null effects of CCTVs in residential areas, downtown areas, business districts, and university/school settings for daytime crime, nighttime crime, weekday crime, burglary, auto theft, and theft from auto in this study can be said to be somewhat compatible with the results of past studies which showed that CCTV had crime reduction effects only in certain highly-specific locations types, like car parks (e.g., Welsh & Farrington, 2009). In short, the many null effects of CCTV shown in this study are not incompatible with some past research. That said, the findings that CCTV did not have crime reduction effects on auto theft are different from past studies. All previous studies examining auto theft showed that CCTV had significant crime reduction effects on auto theft (e.g., Caplan et al., 2011; Welsh & Farrington, 2009).

While null results regarding the effects of CCTV were common, the few instances of significant crime-reduction effects shown in this research are also compatible with some past research. For example, the significant crime reduction effects of CCTVs on assault and burglary that were found here are compatible with several past studies on assault (e.g., Cho, 2009; Gill & Hemming, 2004) and burglary (e.g., Goodwin, 2002). Also, the significant crime reduction effect of CCTVs on robbery specifically in residential areas that was revealed here is compatible with past studies in which CCTV had crime reduction effects on robbery (e.g., Cho, 2009; Park & Choi, 2009).

Finally, like past studies (Caplan et al, 2011; Cho, 2009; Kim, 2008), whether spatial diffusion of benefits occurred after implementation of open-street CCTVs depended on crime type. Here, diffusion of benefits occurred rather than displacement for daytime crime, nighttime crime weekday crime, weekend crime, assault, robbery, and burglary; but, the frequency of diffusion of benefits was the same as that of displacement for auto theft and theft from auto. In addition, the findings of this study were similar to past studies which showed that although displacement may happen after the implementation of open-street CCTVs, diffusion of benefits is stronger than the displacement (e.g., H.H. Park et al., 2012).

Null Effects: Possible Reasons

It is worth noting that the absence of crime reduction effects of CCTV on daytime crime, nighttime crime, weekday crime (in non-residential locations), weekend crime, robbery (in non-residential locations), auto theft, and theft from auto in this study may be due to poor implementation of CCTV for crime prevention (e.g., inappropriate density of cameras or, inadequate signage indicating the implementation of CCTV) or the fact that Cincinnati police don't really use the cameras for prevention purposes as much as they do for investigative purposes.[10] Paradoxically, the results may indicate that we should not expect a significant reduction in crime solely with the implementation of CCTV (Piza et al., 2014).

Another possibility of null crime reduction effects of CCTVs may be due to an increase in police recognition of crime incidents after the implementation of CCTV. Let's take an example of burglaries in a CCTV target area. A victim of a burglary may be reluctant to report the burglary to the police before the implementation of CCTV because he/she think that the police cannot solve the burglary problem. However, the victim may be likely to report to the police after the implementation of CCTV because he/she think that the police can solve the burglary with the assistance of CCTV.

Finally, null effects may emerge because long-term as opposed to short-term effects are really being examined in this study. Some of the supplemental analyses indicated that there might be more evidence of short-term effects. Hence, examining solely short-term effects in this study might have led to significant effects of CCTV.

Policy Implications

The findings in this study have several important policy implications. First, implementation of open-street CCTV alone may not be sufficient for crime reduction in most situations. As Piza et al. (2014) pointed out, the mere existence of CCTV may not bring about significant crime reduction effects. Thus, supplementary efforts may be needed to make crime reduction effects of CCTV significant. For example, if adequate signage indicating the

[10] As mentioned in Chapter III, Cincinnati Police use open-street CCTV for more investigative purposes that crime prevention purposes according to Cincinnati Police Officer Roberta Utecht (personal communication, June 10, 2015).

implementation of CCTV is installed in areas surveilled by CCTV – in order to make potential offenders more easily recognize the existence of CCTV – it might increase the crime reduction effects of CCTV (Wilson & Sutton, 2004). Also, using CCTV in conjunction with more proactive policing could potentially increase the crime reduction effects of CCTV. For example, more real-time monitoring of CCTV by police could better detect offenders' suspicious behaviors, thus deterring future potential offenders and, in turn, increasing the crime reduction effects of CCTV (Piza et al., 2014; Piza et al, 2014b).

Second, despite the fact that CCTV alone does not have broad-ranging crime reduction effects in this study, open-street CCTV does appear to be a good crime prevention measure against assault and burglary. In this regard, this study confirmed past research which found that open-street CCTV had significant crime reduction effects on assault and burglary. Therefore, if assault or burglary is troublesome in some areas, open-street CCTV might be a good solution for the problem. Although CCTV has some clear limitations in terms of reducing assault in domestic settings, CCTV might be a surprisingly good measure to prevent assaults that occur in outside spaces (i.e., outside of bars; in places where people are loitering).

Third, in general, open-street CCTV should be implemented in residential areas rather than in downtown areas or business districts, especially in order to reduce weekend crime. This study showed that the effects of CCTV on weekend crime were significantly smaller in downtown areas and business districts in comparison to residential areas. Thus, if we would like to reduce weekend crime by using CCTV, implementation of the CCTV in residential areas will be more effective than the implementation in downtown areas or business districts. The implementation of CCTV in downtown areas or business districts may bring about little or no crime reduction effects on weekend crime.

Fourth, open-street CCTV should also be implemented more so in residential areas rather than in business districts in order to most effectively reduce robbery. This study showed that the effects were significantly smaller in business districts than in residential areas. Thus, if we would like to reduce robbery by using CCTV, implementation of the CCTV in residential areas will be more effective than the implementation in business districts. The implementation of CCTV in business districts may bring about little or no crime reduction effects on robbery.

Fifth, CCTV might be most effective in situations in which there are low as opposed to high base rates of crime. In this study, the crime-reduction effect of CCTV for daytime crime, weekday crime, weekend crime, assault, robbery, burglary, and theft from auto decreased (i.e., the coefficient moved in the more strongly positive direction) as base-rate of the crimes in the CCTV location increased. These results are consistent with the findings that CCTV is more effective in residential areas than downtown areas and business districts against some kind of crime (since residential areas had the lowest base rates of crime, on average). However, importantly, the results are contrary to the suggestion that crime-reduction effects may not be detected when base rates are low as opposed to high.

Finally, another implication of this study's findings is that we do not need to be highly concerned about displacement when we use open-street CCTV as a crime prevention measure. WDQ analyses showed that when CCTV had crime reduction effects in target areas, diffusion of benefits occurred rather than displacement for daytime crime, nighttime crime, weekday crime, weekend crime, assault, robbery, and burglary. In cases of auto theft and theft from auto, the frequency of diffusion of benefits and displacement was the same. That is, this study indicated that in most cases, the implementation of CCTV brings about diffusion of benefits rather than displacement. Thus, when we implement open-street CCTV, we should not ignore the possibility of displacement, but we also do not need to view this possibility as inevitable or even likely.

Limitations of the Present Study and Suggestions for the Future Study

Like other studies, this study has several limitations that should be mentioned. First, the relatively small number of target areas is a limitation of this study. The hierarchical analysis employed here included both level-1 and level-2 units of analysis. The level-1 sample in this study is relatively sufficient because there are 84 level-1 repeated measures for each of the level-2 target areas. In contrast, there is a relatively small sample size for level 2 (n=34). While this level-2 sample size is a bit larger than a previous HLM analysis of repeated measures across CCTV locations (Ratcliffe et al., 2009), future research would benefit from larger sample sizes at level 2 in order to get more precise results.

Second, this study considered synergistic effects between CCTVs to get more precise findings about crime reduction effects of open-street CCTVs. Although the consideration of synergistic effects can give more precise information, it may also cause biased results if the methods to handle synergistic effects (i.e., the decisions made about crime in overlapping areas) may not reflect synergistic effects perfectly. Future work can consider alternative methods for measuring synergistic effects.

Third, in examining daytime versus nighttime crime, this study assumed that the viewshed of CCTVs is the same during day and night. However, illumination probably changes the shape of the viewshed. Thus, changes in illumination could be confounding the comparison of the effectiveness of CCTV on daytime versus nighttime. Therefore, future studies of the effectiveness of CCTV for reducing daytime versus nighttime crime should explore ways to consider the difference between the viewshed of CCTV during day and night to get more precise results.

Fourth, though the multiple time series design used in this study is strong in terms of guarding against many threats to internal validity, a principal threat to internal validity affecting this study is likely to be "local history" – there may be certain historical events happening at the CCTV sites that confound the effects of CCTV on crime. But with multiple sites, it is highly unlikely that local history will be similar. So consistent findings across sites would suggest strong internal validity. In fact, though location *type* (e.g., downtown, business district, school, residential area) was significant in some models, for most models estimated in this study, the effects of CCTV did not vary across the 34 sites after controlling temporal trend, temperature, and location types (e.g., see the variance components for CCTV in Tables 4. 11, 4. 12, and 4.13). Thus, I tentatively conclude that local history was not a problem in this study, but future work might consider ways to explore this possibility more fully.

Fifth, this study designated "500 feet" from the target area as the buffer area distance because 500 feet is the approximate distance of a city block in Cincinnati and is the expected distance in which displacement or diffusion of benefits might be likely. Also, the 500-foot designation is the same as that used in Ratcliffe et al.'s research (2009) – the previous study that most closely resembles this one in terms of research design. However, it is possible that a different distance is more appropriate. The buffer area may need to be larger or smaller, depending on the actual area where crime-reduction effects versus displacement or diffusion of benefits could emerge. In short, using 500 feet might have influenced the findings. In general, future work should attempt to examine more fully how the designated buffer distance can affect conclusions.

Sixth, this study assumes independence of samples when using the Z-test in order to examine the difference between the CCTV coefficients across models. However, this assumption is not necessarily appropriate. Hence, the Z-test conducted to examine the difference between the effects of CCTV on assault and robbery in this study may be biased. Future research could address this limitation by developing and using a more appropriate comparison.

Seventh, all dependent variables of this study were from count data. Hence, the most appropriate distribution for the variables may be a Poisson distribution. However, this study used a normal distribution for the dependent variables instead of a Poisson distribution because using a Poisson distribution became problematic when examining synergistic effects. That is, when considering synergistic effects, the values of the dependent variables were non-integers instead of counts. Future work might specifically compare the results of the crime-reduction effectiveness of CCTV when using linear versus Poisson-based regression models.

Finally, the focus on the crime reduction effects of open-street CCTV instead of the processes by which CCTV is most effective is another limitation of this study. This study examines whether open-street CCTV has crime reduction effects by comparing crime incidents before and after the implementation of open-street CCTV. Hence, this study does not examine *how* open-street CCTV might lead to reducing crime. Piza et al. (2014b) has suggested that the trend to focus only on effectiveness in terms of comparing crime before and after implementation of open-street CCTV might hinder our understanding of which processes influence deterrence. Thus, more future work needs to examine the process of crime reduction effects of open-street CCTV, including the processes behind any crime-reduction effects of CCTV in Cincinnati.

Conclusion

Despite the limitations noted above, this study provides an important contribution in terms of addressing the conditional nature of the effectiveness of open-street CCTVs. In particular, this study examined differences in the effects of CCTV between daytime crime and nighttime crime, between weekday crime and weekend crime, and across specific-crime offenses. The findings showed that, overall, open-street CCTV did not have crime reduction effects on daytime crime, nighttime crime, weekday crime, weekend crime, robbery, auto theft, and theft from auto, whereas it had significant crime reduction effects on assault and burglary. That said, once location type was considered, condition effects were apparent. For example, the crime reduction effects of open-street CCTVs during weekends varied depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The reduction effects were be greater in residential areas and weaker in business districts and downtown areas. Also, the crime reduction effects of open-street CCTVs for robbery varied depending on implementation sites (i.e., downtown, business district, school/university setting, residential area). The effects were greater in residential areas in comparison to business districts.

This study also considered displacement and diffusion of benefits. Diffusion of benefits effects caused by CCTV implementation were expected to be greater than displacement effects. In fact, WDQ analyses indicated that when CCTV had crime reduction effects in target areas, diffusion of benefits occurred rather than displacement for daytime crime, nighttime crime, weekday crime, weekend crime, assault, robbery, and burglary.

Although the findings of this study supported only some of its hypotheses, they still produced important information to build upon in future research. That is, the effectiveness of open-street CCTVs may be conditional based on the timing of the crime, the type of crime, and characteristics of implementation sites.

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