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BRIEF

EXECUTIVE SUMMARY

Detection of Crime, Resource Deployment, and Predictors of Success: A Multi-Level Analysis of CCTV in Newark, NJ

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Introduction

Despite a worldwide popularity for Closed Circuit Television (CCTV), best-practices for its use in policing have been largely understudied. Specifically, little effort has been devoted to understanding how CCTV effects can be maximized. CCTV systems often have a vague mission to "prevent crime" with little consideration given to a number of pertinent issues, such as site selection, proactive monitoring practices, evidence collection, and training (Gill & Spriggs, 2005). The current project sought to fill specific gaps in the CCTV literature through a multi-level analysis of the police-led video surveillance system in Newark, NJ. The project is separated into three components, each focusing on a pertinent, yet under-researched, aspect of CCTV.

The first component is an analysis of the activity of the surveillance unit; specifically, the proactive detection of crime incidents and subsequent response by police. Research questions of component 1 relate to CCTV's ability to increase the "certainty of punishment" in target areas, a key component of deterrence. The second component analyzes the context under which CCTV cameras best deter crime. The statistical analysis tested the influence of several micro-level factors (environmental features, line-of-sight, camera design and enforcement activity) on changes in CCTV viewsheds. The third component is a randomized, controlled trial measuring the effects of coupling proactive CCTV monitoring with directed patrol units: Two patrol units were assigned to exclusively respond to incidents of concern detected on the experimental cameras. The analysis measured the effect of the experimental strategy on levels of proactive surveillance activity and crime incidence.

Research Site

Newark is the largest city in New Jersey, spanning over twenty-six square miles with a population of 277,140: an estimated 11,458 persons per square mile, compared to 1,195 statewide (U.S. Census Bureau, 2010). In 2006, the city made significant investments to upgrade many of its technological capabilities, including the installation of a public CCTV system. One-hundred-forty-six surveillance cameras are located throughout Newark to-date. Two video surveillance operators, under the supervision of a police sergeant, monitor live video footage from the cameras during all shifts from a centralized control room at the police department's communications center. They are tasked with detecting incidents of crime and disorder and then reporting the event via the department's Computer Aided Dispatch (CAD) system. Reported incidents (both CCTV detections and 9-1-1 calls for service) are stored in CAD's "calls pending queue" and addressed in a "differential response" manner by the police dispatcher, with higher priority incidents taking precedence over those with lower priority levels. The manner by which the Newark Police Department staffs its surveillance operation, and the manner by which police respond to detected infractions, parallels the process observed by researchers in other cities (Gill et al., 2005; Norris & Armstrong, 1999a,b; Norris & McCahill, 2006; Ratcliffe et al., 2009; Smith, 2004). Characteristics of Newark's camera deployment, surveillance operation, and the city itself make it representative of a number of medium- to large–sized American cities, which supports the generalizability of this project's findings.

Data Sources

Geographic Information System (GIS) crime and officer activity data were provided by the Newark Police Department's CompStat Unit. CompStat similarly provided GIS files denoting the locations of several crime generators and attractors throughout the city. Additional data not collected by the Newark Police Department was obtained from InfoGroup (www.infogroup.com), a leading provider of residential and commercial information for reference, research, and marketing purposes. Researchers also compiled data from the Video Surveillance Unit's weekly activity reports to allow for an analysis of the process by which the Newark Police Department responds to incidents detected by CCTV. Finally, the CCTV cameras themselves were utilized by researchers in order to create viewsheds of each camera site. A viewshed, capturing the precise area of visibility, offers a more valid measure of CCTV "target areas" than circular buffers or aggregate-level geography. Researchers also utilized the cameras to monitor the camera feeds during a targeted intervention in order to record CCTV operator monitoring activity and the subsequent response by patrol officers.

Results

Component 1. An Analysis of CCTV Detections and Enforcement

The first study component focused on the Newark, NJ surveillance unit's detection of criminal events, subsequent responses and actions taken by patrol units, and its relation to deterrence via certainty of punishment for the period November 2007 through 2010. A total of 8,115 incidents from the weekly Video Surveillance Unit (VSU) reports were included in the analysis: 1,385 CCTV detections and 6,730 calls-for-service (CFS). Four research questions guided the analysis: 1) *Are case process times shorter with CCTV, as compared to calls-for-service?* 2) *Does CCTV produce a heightened level of enforcement compared to calls-for-service?* 3) *How often did surveillance activity occur over the study period?* 4) *What effect did various surveillance barriers have on the occurrence of surveillance activity?*

For research question 1, a series of Mann-Whitney U tests compared the queue time, response time, and total process time (queue time + response time) of CCTV and CFS across eight incident categories. The findings displayed an inconsistent pattern, with results favoring CCTV and CFS in different instances. For example, for overall incidents CFS had significantly shorter time intervals than CCTV incidents while CCTV incidents displayed significantly shorter queue times for both drug and disorder offenses. In sum, CCTV did not consistently demonstrate quicker process times than CFS, and in many instances CFS were processed more quickly than CCTV incidents.

For research question 2, a series of Fisher's Exact tests compared the case closure of CCTV incidents and CFS across three enforcement categories: arrests, other enforcement, and any enforcement (arrests and "other"). A Holm-Bonferroni correction was incorporated to control for multiple comparisons across crime categories. For all enforcement types, most incident categories experienced statistically significant higher closure rates via CCTV than CFS. CFS did not exhibit higher closure rates than CCTV in a single instance. Drug offenses and high-priority incidents were particularly impacted by CCTV, with these two crimes having the highest CCTV-closure rates across all enforcement categories.

The third research question is *"How often did surveillance activity occur over the study period?"* As displayed in Figure A, while detections and enforcement occurred frequently during the beginning of the CCTV operation, surveillance activity became somewhat rare over time. An average of 26.84 CCTV detections occurred per week during camera phase 1. Each subsequent camera phase brought about a reduced amount of detections. Average weekly detections dropped to a low of 2.11 during phase 5, a number more than 92% lower than the phase 1 average. A similar pattern was observed for the enforcement actions. ANOVA tests confirmed that the observed differences for both detections and enforcement were statistically significant ($p<0.01$).

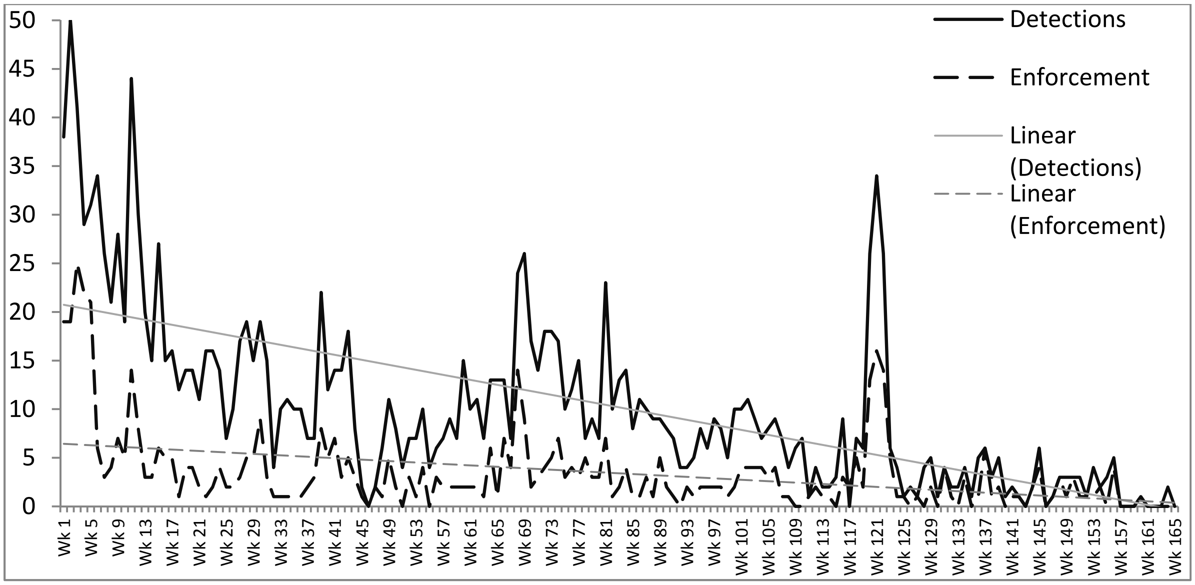

Figure A: Weekly surveillance detections and enforcement actions.

Phase	WEEKLY ACTIVITY		
	Frequency	**Mean Detections**	**Mean Enforcement**
TOTAL	165	10.19	3.41
1 (11 Cameras)	19	26.84	9.47
2 (60 Cameras)	20	12.70	3.00
3 (111 Cameras)	71	9.83	2.93
4 (137 Cameras)	19	7.53	3.68
5 (147 Cameras)	36	2.11	1.22
F	-	51.05	17.01
p	-	0.00	0.00

Table A: ANOVA results for the average number of weekly detections and enforcement actions across the camera installation periods.

CATEGORY	TOTAL PROCESS MINUTES			
	CCTV Mean Rank	9-1-1 Mean Rank	Z	p.
Overall	4864.08	4228.64	-8.46	0.000**
Violence	1756.24	1867.74	1.34	0.181
Disorder	916.24	1049.14	4.76	0.000**
Drugs	415.35	610.27	9.87	0.000**
Other	628.37	652.54	0.82	0.411
High	1734.43	1205.52	-12.12	0.000**
Intermediate	2355.28	2242.17	-2.54	0.020**
Low	725.26	827.23	3.34	0.001**

***statistically significant after holm-bonferroni correction*

Table B: Mann-Whitney U Test of differences of mean ranks of total process minutes.

	OVERALL ENFORCEMENT				
	CCTV		9-1-1		p.
	Obs. (Exp.)	% Obs. (% Exp.)	Obs. (Exp.)	% Obs. (% Exp.)	
OVERALL					
Yes	459 (273.1)	33.1% (19.7%)	1141 (1326.9)	17.0% (19.7%)	0.000**
No	926 (1111.9)	66.9% (80.3%)	5589 (5403.1)	83.0% (80.3%)	
VIOLENCE					
Yes	32 (23.6)	18.3% (13.5%)	471 (479.4)	13.3% (13.5%)	0.069
No	143 (151.4)	81.7% (86.7%)	3078 (3069.6)	86.7% (86.5%)	
DISORDER					
Yes	204 (179.8)	32.3% (28.5%)	370 (394.2)	26.8% (28.5%)	0.011**
No	427 (451.2)	67.7% (71.5%)	1013 (988.8)	73.2% (71.5%)	
DRUGS					
Yes	173 (113.1)	44.5% (29.1%)	141 (200.9)	20.4% (29.1%)	0.000**
No	216 (275.9)	55.5% (70.9%)	550 (490.1)	79.6% (70.9%)	
OTHER					
Yes	50 (30.6)	26.3% (16.1%)	159 (178.4)	14.4% (16.1%)	0.000**
No	140 (159.4)	73.7% (83.9%)	948 (928.6)	85.6% (83.9%)	
HIGH					
Yes	128 (39)	42.2% (12.9%)	179 (268)	8.6% (12.9%)	0.000**
No	175 (264)	57.8% (87.1%)	1903 (1814)	91.4% (87.1%)	
INTERMEDIATE					
Yes	268 (180.3)	30.6% (20.6%)	617 (704.7)	18.0% (20.6%)	0.000**
No	608 (695.7)	69.4% (79.4%)	2806 (2718.3)	82.0% (79.4%)	
LOW					
Yes	63 (58.7)	30.6% (28.5%)	345 (349.3)	28.2% (28.5%)	0.505
No	143 (147.3)	69.4% (71.5%)	880 (875.7)	71.8% (71.5%)	

***statistically significant after holm-bonferroni correction*

Table C: Fisher's Exact test for overall enforcement.

The fourth research question is *"What effect did various surveillance barriers have on the occurrence of surveillance activity?"* A series of negative binomial regression models were conducted in order to identify factors that influenced the weekly occurrence of CCTV detections and enforcement actions. In the first model, the number of weekly detections served as the dependent variable; in the second model, weekly enforcement actions was the dependent variable. The detections model found camera phase, footage requests, after layoffs, after gunshot detection, and temperature to be statistically significant. Footage requests was the only statistically significant variable to be associated with increased detection levels; all other variables were associated with decreased levels. "Camera Phase" (an ordinal variable from 1 to 5 denoting the installation phase of the CCTV system) and "layoffs" a dichotomous variable identifying if the week was after the November 2010 layoffs or not) had the largest effect on detections, as evidenced by their Incident Rate Ratios (IRR). In particular, each one unit increase in "Camera Phase" was associated with a 47% reduction in weekly detection (IRR=0.53) levels while the period after the layoffs was associated with an 87% reduction (IRR=0.13).

In the enforcement model, camera phase was again associated with a decrease in the weekly counts (IRR=0.53) as was temperature (IRR=0.99). "Year 2010" (a dichotomous variable identifying if the week was in the year 2010 or not) was associated with a doubling of weekly enforcement levels (IRR=2.42). Year 2010 was conceptualized as the period when the police department was shifting resources in preparation for the impending police layoffs; it was thus unexpected for the "year 2010" and "after layoffs" variables to be correlated with enforcement in opposite directions. Newark Police officials provided a potential explanation for this seemingly counterintuitive observation. A number of officers in administrative posts were reassigned to patrol duties throughout 2010 in order to prepare them to take over for the street officers who were slated for termination. The immediate effect was an increased number of officers patrolling the streets of Newark; the "replacements" were on the street along with the officers currently assigned to patrol (who would later be terminated), which Newark police officials suggested may have enhanced the department's ability to respond to CCTV detections, leading to higher levels of enforcement actions.

Due to our inability to disaggregate the footage requests variable into disks requested for investigatory purposes and disks request as the result of an arrest, two additional models were run excluding this variable. This was done as an additional test of the covariate influence, particularly by testing which covariates maintained significance absent the footage requests. In both the detections and enforcement models, camera phase, after layoffs, year 2010, and temperature all maintained statistical significance with similar IRR values as the previous model. In the updated detections model, "after gun-shot detections" was no longer statistically significant.

COVARIATES	DETECTIONS				ENFORCEMENT ACTIONS			
	β	S.E.	95% C.I.		β	S.E.	95% C.I.	
			Lower	Upper			Lower	Upper
Constant	4.27**	0.24	3.79	4.75	3.36**	0.36	2.66	4.06
Camera Phase	-0.45**	0.07	-0.59	-0.32	-0.49**	0.10	-0.69	-0.29
After Gun-Shot Detection	-0.29	0.17	-0.61	0.04	-0.25	0.26	-0.76	0.26
After Layoffs	-2.18**	0.76	-3.66	-0.69	-21.41	14218.83	-27889.82	27846.99
Year 2010	0.16	0.20	-0.24	0.56	0.77**	0.31	0.17	1.37
Temperature	-0.01**	0.00	-0.02	-0.01	-0.01**	0.00	-0.02	0.00
Precipitation	0.02	0.03	-0.05	0.08	-0.02	0.05	-0.12	0.07
***p<0.01, *p<0.05*								

Table D: Negative binomial regression results for weekly surveillance detections and surveillance enforcement actions, without the footage requests covariate.

Component 2: The Impact of Micro-Level Feature on Camera Effect

This component moves beyond the typical research question of *"Does CCTV work?"* to *"In which context does CCTV work best?"* Units of analysis were the viewsheds of the individual CCTV cameras, which accounted for two particular obstructions: 1) immovable objects (e.g. traffic signs and telephone poles), and 2) foliage (e.g. leaves from trees and bushes).

The dependent variable in this analysis was crime level changes within each viewshed, from the one-year pre-installation period to the one-year post-installation period. All of the disaggregate crime types (robbery, murder, shootings, auto theft, and theft from auto) were combined to create an "overall crime" category. Robbery, murders, and shootings were combined to create a "violent crime" category. Auto theft and theft from auto were combined to create a "property crime" category. Finally, robbery, auto theft, and theft from auto were each included on their own as disaggregate categories. Murder and shootings were not disaggregated due to their relatively sparse occurrence.

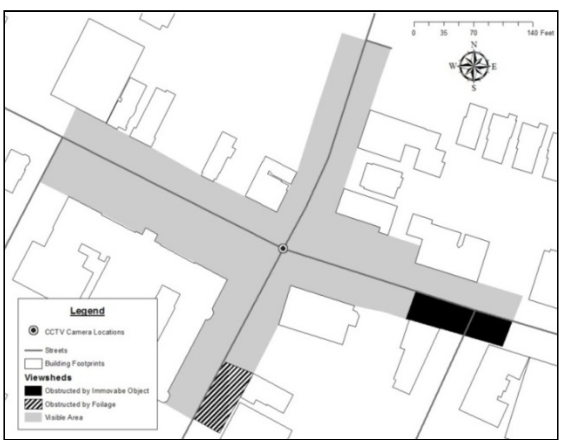

Figure B: Example viewshed with denoted areas of obstruction.

Crime levels were measured via Location Quotients (LQ), which measure the occurrence of crime in a target area compared to its occurrence over a larger area. LQs controlled for two important factors: 1) the size of the target area and 2) crime incidence within a control area. LQ values below 1 suggest the area to have less crime than is more generally found across the aggregate geography; LQ values greater than 1 suggest a crime concentration. Two separate LQs were calculated for each viewshed, for the one-year "pre" and for the one-year "post" periods. Each viewshed's "pre" LQ was subtracted from the "post" LQ, creating a "Change in Location Quotient" (ΔLQ) variable. Negative ΔLQ values were considered as evidence of crime reductions while positive ΔLQ values suggest increased crime levels (Caplan et al., 2011a). ΔLQ values were calculated for all six crime categories.

Sixteen independent variables were grouped into four categories: environmental features (nine), line-of-sight (three), enforcement activity (three), and camera design (one). For the analysis, ΔLQ values of viewsheds were utilized as dependent variables in Ordinary Least Squares (OLS) regression models with these sixteen independent variables as covariates. We conducted six separate models, one for each of the crime categories. Statistically significant variables differed across crime types. Environmental features were statistically significant in the violent crime, property crime, robbery, auto theft, and theft from auto models. Bars were associated with reduced levels of violent crime and robbery. Liquor stores were associated with increased levels of robbery. Schools were associated with increased levels of auto theft while corner stores were related to auto theft reductions. Both corner stores and retail stores were related to increased levels of theft from auto, with retail stores also being associated with increased levels of property crime.

Line-of-sight variables were statically significant in the violent crime, robbery, auto theft, and theft from auto models. Immovable obstructions were associated with increased levels of auto theft. Conversely, immovable obstructions were associated with decreased crime levels in the violent crime, robbery, and theft from auto models. The "foliage obstruction" variable was not statistically significant in any other six models (though it approached significance at $p<0.10$ in the violent crime model).

"Camera enforcement" was the only variable in the enforcement category to achieve statistical significance. The camera enforcement variable was significant in the overall crime, violent crime, and theft from auto models. Camera enforcement was associated with decreased crime levels in each instance.

Variables	1/VIF	OVERALL CRIME			VIOLENT CRIME			PROPERTY CRIME		
		β	S.E.	t	*β*	S.E.	t	*β*	S.E.	t
Environmental Features										
Bars	0.763	-0.045+	0.027	-1.710	-0.195**	0.066	-2.950	-0.026	0.025	-1.010
Liquor Stores	0.833	0.013	0.011	1.190	0.027	0.027	1.020	0.007	0.010	0.660
Corner Stores	0.726	0.006	0.018	0.330	0.019	0.045	0.430	0.002	0.017	0.090
Retail Stores	0.468	0.011	0.007	1.660	-0.013	0.017	-0.780	0.019*	0.006	3.010
Schools	0.822	0.023	0.017	1.330	0.001	0.044	0.020	0.025	0.017	1.470
Take Outs	0.647	-0.005	0.019	-0.280	0.016	0.046	0.350	-0.016	0.018	-0.890
Transit Stops	0.692	0.007	0.038	0.180	-0.031	0.095	-0.320	0.000	0.037	0.000
At-Risk Housing	0.783	-0.001	0.005	-0.210	0.004	0.014	0.280	-0.001	0.005	-0.130
Parking Lots	0.835	-0.001	0.005	-0.240	0.012	0.012	0.960	-0.003	0.005	-0.550
Line of Sight										
% Immovable Obstruct	0.710	-0.004	0.009	-0.480	-0.047*	0.022	-2.140	0.000	0.008	0.020
% Foliage Obstruct	0.785	-0.003	0.005	-0.560	-0.024+	0.013	-1.780	-0.001	0.005	-0.160
Overlap	0.879	0.125	0.135	0.920	0.232	0.339	0.690	0.135	0.130	1.040
Enforcement Activity										
Detections	0.259	0.013	0.008	1.530	0.015	0.021	0.750	0.011	0.008	1.420
Camera Enforcement	0.209	-0.045*	0.020	-2.210	-0.121*	0.051	-2.390	-0.027	0.020	-1.400
Unrelated Arrests	0.788	0.000	0.001	-0.050	0.000	0.002	0.300	0.000	0.001	-0.770
Camera Style										
Dome	0.863	0.157	0.152	1.040	0.088	0.383	0.230	0.097	0.147	0.660
R-squared (Adjusted)		0.122 (-0.018)			0.296 (0.183)			0.161 (0.027)		
Power (1-β err prob)		0.638			0.997			0.814		
*+p<.10; *p<.05; **p<.01*										

Table E: OLS results for aggregate crime categories (Viewsheds)

In addition, we explored any potential displacement or diffusion of benefits effects relative to the CCTV cameras. For most crime categories, catchment areas exhibited positive ΔLQ values, suggestive of displacement, more frequently than negative ΔLQ values. The proportion of catchment areas with positive ΔLQ values was 10% greater than those with negative ΔLQ values in the overall crime (55% vs. 45%), violent crime (57% vs. 42%), and robbery (60% vs. 40%) categories. This is in contrast to the viewsheds, in which violent crime was the only category where the proportion of viewsheds with positive ΔLQ values was 10% higher than those with negative ΔLQ values (52% vs. 42%). Auto theft was the only category for which the proportion of catchment zones exhibiting negative ΔLQ values, suggestive of diffusion of benefits, was 10% higher than those with positive ΔLQ values (57% vs. 42%). Contrary to the main analysis, a test of the influence of the independent variables on crime changes within catchment zones was very limited due to the low number of observations. Overall, the events per predictor variable (EPV) of the catchment models ranged from 2.18 (violent crime and robbery) to 2.62 (auto theft and theft from auto).

Variables	1/VIF	ROBBERY (Squared) β	S.E.	t	AUTO THEFT β	S.E.	t	THEFT FROM AUTO β	S.E.	t
Environmental Features			-	-		-	-		-	-
Bars	0.763	-2.469*	0.983	-2.510	-0.021	0.027	-0.780	-0.040	0.049	-0.820
Liquor Stores	0.833	0.686+	0.396	1.730	0.011	0.011	1.020	-0.003	0.020	-0.150
Corner Stores	0.726	0.009	0.674	0.010	-0.033+	0.019	-1.770	0.072*	0.034	2.120
Retail Stores	0.468	-0.098	0.246	-0.400	0.009	0.007	1.280	0.037**	0.012	3.040
Schools	0.822	0.444	0.646	0.690	0.042*	0.018	2.360	-0.008	0.032	-0.240
Take Outs	0.647	-0.252	0.687	-0.370	0.006	0.019	0.340	-0.052	0.034	-1.500
Transit Stops	0.692	0.331	1.409	0.240	-0.017	0.039	-0.430	0.022	0.070	0.310
At-Risk Housing	0.783	0.082	0.201	0.410	-0.002	0.006	-0.420	0.004	0.010	0.370
Parking Lots	0.835	0.154	0.180	0.860	-0.006	0.005	-1.130	0.002	0.009	0.260
Line of Sight										
% Immovable Obstruct	0.710	-0.698*	0.324	-2.160	0.021*	0.009	2.310	-0.037*	0.016	-2.270
% Foliage Obstruct	0.785	-0.303	0.196	-1.540	0.000	0.005	-0.090	-0.002	0.010	-0.170
Overlap	0.879	1.891	5.021	0.380	0.056	0.139	0.400	0.182	0.251	0.720
Enforcement Activity										
Detections	0.259	0.128	0.306	0.420	0.002	0.008	0.250	0.026+	0.015	1.690
Camera Enforcement	0.209	-0.901	0.752	-1.200	0.010	0.021	0.500	-0.088*	0.038	-2.350
Unrelated Arrests	0.788	-0.012	0.025	-0.500	0.000	0.001	-0.710	-0.001	0.001	-0.430
Camera Style										
Dome	0.863	-1.854	5.677	-0.330	0.168	0.158	1.070	-0.081	0.284	-0.280
R-squared (Adjusted)		0.206 (0.079)			0.203 (0.076)			0.203 (0.075)		
Power (1-β err prob)		0.934			0.929			0.923		
*+p<.10; *p<.05; **p<.01*										

Table F: OLS results for individual crime categories (Viewsheds)

CRIME CATEGORY	VIEWSHEDS WITH NEG. ΔLQ	CATCHMENT ZONES	CATCHMENT ZONES WITH NEG. ΔLQ	CATCHMENT ZONES WITH POS. ΔLQ
Overall Crime	55	40	18 (45.00%)	22 (55.00%)
Violent Crime	50	35	15 (42.85%)	20 (57.14%)
Robbery	54	35	14 (40.00%)	21 (60.00%)
Property Crime	58	41	19 (46.34%)	22 (53.65%)
Auto Theft	54	42	24 (57.14%)	18 (42.85%)
Theft From Auto	61	42	21 (50.00%)	21 (50.00%)

Table G: Number of viewsheds with negative ΔLQ values and resutling catchment zones.

	Mean	SD	Min	Max	# Negative (%)	# Positive (%)
DEPENDENT VARIABLES						
ΔLQ Overall Crime	0.005	0.563	-1.840	1.643	55 (47.01%)	62 (52.99%)
ΔLQ Violent Crime	-0.072	1.570	-6.310	2.739	50 (42.74%)	62 (52.99%)
ΔLQ Property Crime	-0.043	0.553	-1.739	1.133	58 (49.57%)	57 (48.72%)
ΔLQ Robbery	-0.079	1.719	-6.037	3.548	54 (46.15%)	57 (48.72%)
ΔLQ Auto Theft	-0.033	0.607	-2.295	1.570	54 (46.15%)	60 (51.28%)
ΔLQ Theft From Auto	-0.067	1.095	-3.676	3.782	61 (52.14%)	48 (41.03%)

Table H: Statistical summary of ΔLQ values in viewsheds.

Component 3: The effects of a dedicated team of patrol units dispatched by CCTV operators.

The final component was a randomized experiment designed for the purpose of overcoming specific "surveillance barriers" common to CCTV, namely a high camera to operator ratio and the lack of an immediate response to CCTV-detected incidents due to the differential-response nature of police dispatch. An additional camera operator was funded to monitor a subset of Newark's CCTV cameras over 40 separate four-hour tours of duty in the Summer of 2011. Two patrol units were assigned to the operators, and were tasked with exclusively responding to incidents of concern detected on the experimental cameras.

Units of analysis began as camera viewsheds, which were constructed during the early stages of study component 2. Viewsheds that overlapped or lay directly adjacent (less than one-city block) to each other were grouped together into singular "schemes" for the purpose of the experiment. To obtain an appropriate target area for the intervention (with only 2 cars available to respond to incidents of concern), researchers created a standard deviation ellipse utilizing all of camera sites present within the high risk camera schemes. Overall, 38 schemes fell within the boundary of the standard deviation ellipse and were chosen for inclusion in the experiment.

A randomized block design was utilized in the assignment of schemes to the experimental and control groups. Schemes were matched into pairs based on their level of three calls-for-service types: violent crime, narcotics incidents, and social disorder incidents. Location quotients (LQ), rather than raw counts of incidents, were calculated to determine the pairing of schemes (to control for the different size of the schemes). The separate LQ values were summed to create a composite value capturing the overall level of crime activity. Calls-for-service data were measured for the period July 2010 through September 2010 to reflect the period in 2011 that the Newark Police Department wished to conduct the experiment.

The schemes were grouped into 18 different pairs based on their composite LQ values; the schemes with the highest and second highest composite LQ values were grouped together; the schemes with the third highest and fourth highest values were grouped together, and so on. One group of each pair was then randomly selected to the treatment group with the other being assigned to the control group.

In addition to conducting an outcome evaluation, we conducted a process evaluation in an attempt to contextualize program effects and any policy implications generated from the findings (Sherman & Eck, 2002). The process analysis primarily focused on the activity of the experimental operators and patrol officers. Data were collected for the process analysis through qualitative methods. Researchers observed the activity of the CCTV operators from within the control room, as well as the response of the responding officers via the CCTV camera feeds, and used a pre-constructed form to record specific aspects of their observations.

Experimental operators conducted a total of 237 targeted surveillances, defined as an operator observation "that lasted more than one minute on an individual or group of individuals" (Norris & Armstrong, 1999a: p. 161). In more than half (54.01%) of the surveillances, operators did not observe any illegal activity, or other behavior providing probable cause or reasonable suspicion for officers to respond to the incident. In 109 incidents (45.99%), operators did observe events worthy of a police response. Operators did not report the observed infractions in 35 of the 109 (32.11%) incidents. Of the 74 detections, 64 (86.49%) resulted in an enforcement action by the police. Thirty-nine of the enforcement actions were arrests. The remaining 25 enforcement incidents were with record checks or field interrogations. Ten of the reported detections did not result in an enforcement action. In 7 of these incidents, the suspects left the scene before the officers' arrival. In one additional incident, the suspect ran from the officers upon their arrival on scene, with the resulting foot chase not leading to apprehension of the suspect. In the other two incidents, the officers used their discretion to not pursue the incident when it was reported by the operators.

On average, operators conducted targeted surveillances for an average of 17.41 minutes. In the 74 incidents in which a detection was reported to the police officers, operators reported the incident an average of 10.68 minutes into the surveillance. These figures suggest that operators did not "rush" to interpret the situations under surveillance, but took extended periods of time to decide whether to dispatch the patrol officers (though the standard deviation suggests a high level of variability). The process analysis also highlighted certain aspects of the CCTV operation that impeded upon the experimental strategy: specifically, arrest processing times, the presence of visible obstructions in camera viewsheds, and poor lighting around camera locations.

Two research questions drove the outcome evaluation of the experiment. The first was *"What effect did the experimental strategy have on levels of surveillance activity?"* A series of ANOVA tests were utilized to explore this question. An average of 9.55 detections per week occurred during the 11-week experiment period. This was more than three times the average weekly detections of any of the five 11-week periods before the experiment and the three 11-week periods following the experiment. These findings were statistically significant at $p<0.01$. We obtained similar findings regarding enforcement.

The CCTV system generated 6.82 enforcement actions per week during the experiment period, more than three times the amount of any other of the eight 11-week periods. Again, the results were statistically significant ($p=0.00$). The previous ANOVA tests included all surveillance activity that occurred during the experiment period--activity of the experiment personnel and the regular operators working during the non-experiment tours. To further test the effect of the experimental strategy on surveillance activity, we conducted additional ANOVA tests that excluded all non-experiment personnel activity during the 11-week experiment period. In these tests, the activity of the experiment personnel alone are compared to that of the "normal" CCTV produce residual deterrence effects (Sherman, 1990; Telep et al., 2012; Wyant et al., 2012). The first time period was comprised of the actual experiment tours of duty (Wednesday through Saturday, 8pm to midnight from 7/20/11 to 10/1/11). The second time period was the entire days (e.g. 24 hour period) the experimental tours took place (Wednesday through Saturday, from 7/20/11 to 10/1/11). The third time period was the entire 11-week experimental period of July 20, 2011 through October 1, 2011.

operation during the non-experiment period. For both detections and enforcement, findings concurred with the previous models. Weekly averages of detections and enforcement were much higher during the experiment period than during any of the other periods. Findings again were significant at $p<0.01$.

The second research question of the outcome evaluation was *"What effect did the experimental strategy have on observed crime levels in target areas compared to control areas?"* The small sample size coupled with the concise time period of the analysis caused the experiment to be underpowered. Increasing sample size is typically considered as the most straightforward way to increase statistical power. However, as noted by Weisburd et al. (1993), increasing sample size may negatively affect field experiments by creating too large of a treatment group to be adequately treated. We, therefore, decided to not increase our sample size at the outset of the experiment. To increase statistical power, we set the alpha level for statistical significance to .10, rather than the traditional level of .05, in order to minimize the chance of making a Type II error of falsely failing to reject the null hypothesis (Lipsey, 1990). Indeed, other underpowered experiments have similarly incorporated alpha levels of .10 in order to protect against Type II errors (see Weisburd & Green, 1995).

Crime level changes were calculated via an Inverted Odds Ratio (IOR), which measures the crime increase/decrease within the target area with that of a control area. The statistical significance of the IORs was measured through a t-test as well as a count (Poisson or negative binomial) regression model. Crime changes were measured across three time periods, in recognition of previous research suggesting that proactive police activity may

Two crime categories experienced statistically significant reductions during the experiment tours. Violent crime reduced over 60% in the target areas compared to the controls. The t-test for violent was statistically significant at $p = 0.047$. However, the regression model did not achieve significance, meaning regression to the mean may have influenced the reduction. Disorderly behavior, a subset of the overall disorder category, achieved a statistically significant reduction of over 50% according to both the t-test ($p=0.04$) and the regression model (p=0.06). No other categories achieved statistical significance.

Two violent crime categories achieved statistical significance in the "days" period. Overall violence experienced a statistically significant 40% reduction, according to the t-test (p=0.061) as well as the regression model (p=0.084). Fights reduced over 70% in the target areas compared to the control areas, with statistical significance reported by the t test (p=0.014) but not the regression model (p=0.23).

Three crime categories achieved statistically significant reductions during the "11-week" period. Fights achieved a statistically significant reduction of over 60% according to both the t-test (p=0.028) and the regression model (p=0.04). Similarly, the reduction of shootings also achieved statistical significance in both the t-test (p=0.029) and the regression model (p=0.090). Finally, overall disorder reduced 27% in treatment areas relative to control areas as per both the t-test (p=0.089) and regression model (p=0.058).

Weighted Displacement Quotients noted that diffusion of benefits effects were observed in four instances: overall violence during the "tours," fights during the "days," and overall disorder, fights, and shootings during the "11-weeks." Conversely, overall violence during the "days" did not experience any real displacement or diffusion effects, and disorderly behavior experienced a displacement effect greater than the achieved reduction in the target area during the "tours."

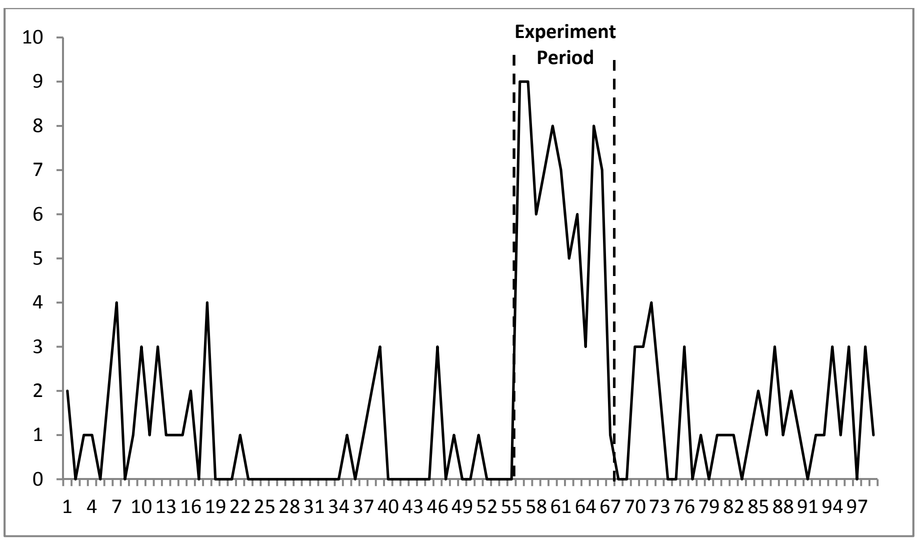

Figure C: Weekly CCTV enforcement. 6/20/10-5/26/12

r u t g e r s c p s . o r g

Violence			
	TOURS	**DAYS**	**11-WEEKS**
IOR	0.39	0.59	0.74
T-Test *p.*	0.05	0.06	0.19
Regression *p.*	0.13	0.08	0.42
Social Disorder			
	TOURS	**DAYS**	**11-WEEKS**
IOR	0.52	0.81	0.72
T-Test *p.*	0.19	0.37	0.09
Regression *p.*	0.13	0.33	0.06
Narcotics			
	TOURS	**DAYS**	**11-WEEKS**
IOR	1.15	0.76	1.01
T-Test *p.*	0.94	0.94	0.95
Regression *p.*	0.85	0.55	0.97
Fights			
	TOURS	**DAYS**	**11-WEEKS**
IOR	0.17	0.32	0.36
T-Test *p.*	0.12	0.06	0.03
Regression *p.*	0.42	0.23	0.04
Shootings			
	TOURS	**DAYS**	**11-WEEKS**
IOR	n.a.	0.13	0.26
T-Test *p.*	0.85	0.01	0.03
Regression *p.*	0.7	0.07	0.09
Disorderly Behavior			
	TOURS	**DAYS**	**11-WEEKS**
IOR	0.52	0.89	0.80
T-Test *p.*	0.04	0.64	0.23
Regression *p.*	0.06	0.62	0.22
Panhandling			
	TOURS	**DAYS**	**11-WEEKS**
IOR	n.a.	0.19	0.12
T-Test *p.*	0.91	0.22	0.12
Regression *p.*	0.93	0.46	0.22

Table I: IOR values and significance test *p.* values for tours, days, and 11-week periods.

Policy Implications

Findings from this project have practical implications for the use of Video Surveillance by law enforcement. All three components highlighted the fact that proactive surveillance activity and enforcement are directly related to the effectiveness of CCTV. The findings of component 2 suggest that CCTV effects may be at least partly related to the environmental composition of target areas. Similarly, the process evaluation included in component 3 illustrated that visible obstructions in viewsheds can present hardships to the proactive monitoring function of CCTV operators.

Research suggests CCTV deployment should be preceded by an in-depth analysis of the spatial distribution and nature of crime patterns (Ratcliffe, 2006; Welsh & Farrington, 2002). Findings of this project suggest that police should also account for the composition of the environment when installing cameras. Police can utilize easily applied analytical tools and methods, such as Risk Terrain Modeling (RTM; Caplan et al., 2011b), to incorporate such findings in the selection of camera sites. In the case of theft from auto, for example, the concentration of corner stores and retail stores could be combined into a composite map which is then "subtracted" from a map of theft from auto hotspots. As displayed in Figure C, this process would result in a map showing the areas throughout the city most conducive to CCTV effect, with high levels of theft from auto absent environmental features that may negatively influence CCTV effect.

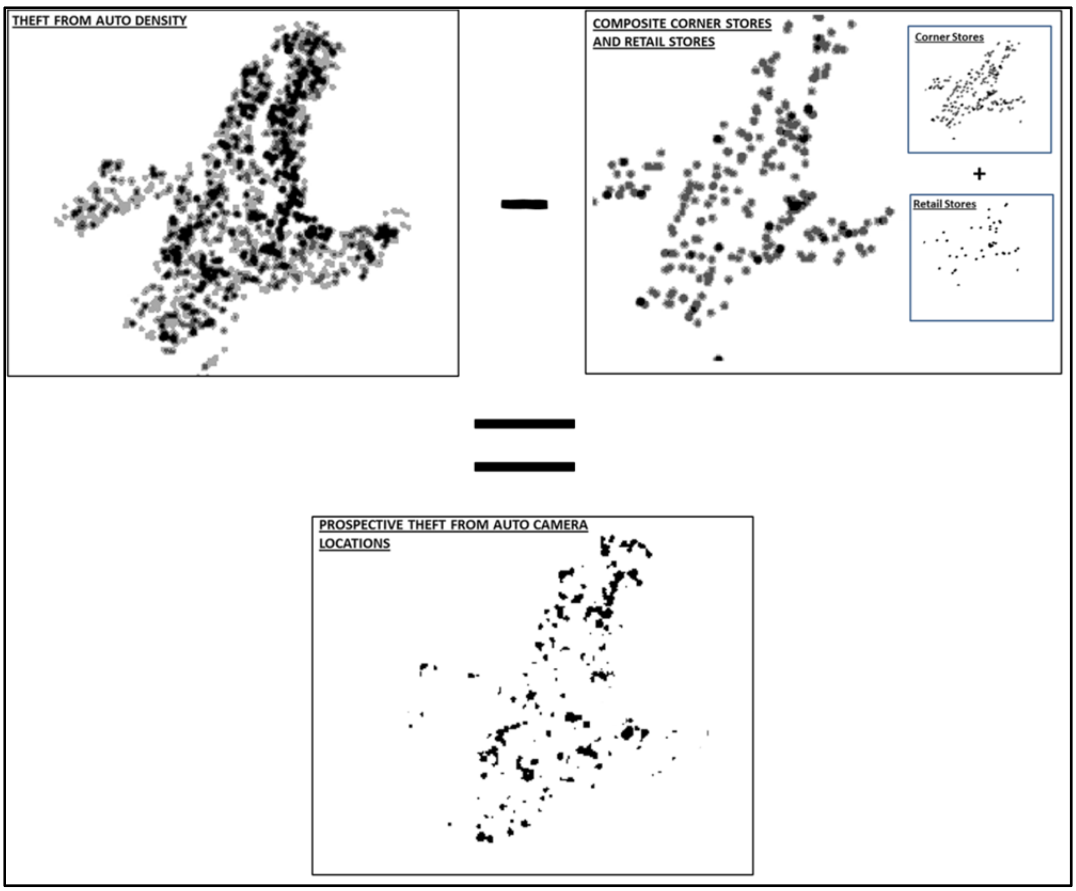

Figure C: RTM camera site selection maps.

Findings from component 2, as well as the process analysis of component 3, point to the importance of maintaining camera visibility by minimizing the presence of visible obstructions within camera viewsheds. Examples of in-depth audits of prospective camera sites by practitioners have begun to emerge. In Baltimore, for example, city officials visited each prospective camera site for the purpose of identifying physical obstructions (La Vigne et al., 2011: p. 25). Practitioners can build upon such exercises, and fine-tune their site selection process, using easily applied GIS techniques. For example, Figure D shows two maps of prospective camera sites and resulting viewsheds. The prospective camera site in map "A" largely covers portions of both Bloomfield Ave. and N. 6th St. While the prospective camera in map "B" covers a similar area, it also covers a parking lot on N. 6th St. and approximately half the block of 1st Ave. to the west of N. 6th St.— both of which are obstructed from the view of the camera in map "A." These subtle, yet potentially important, differences can be accounted for by decision-makers selecting a street-corner for CCTV. If an analysis of crime incidents reveals that a disproportionate number of crimes occur within the parking lot, then map "B" offers the ideal camera site, since the lot is not obstructed from view. However, if the analysis finds that crime clusters on Bloomfield Ave., then the camera in map "A" may be more effective.

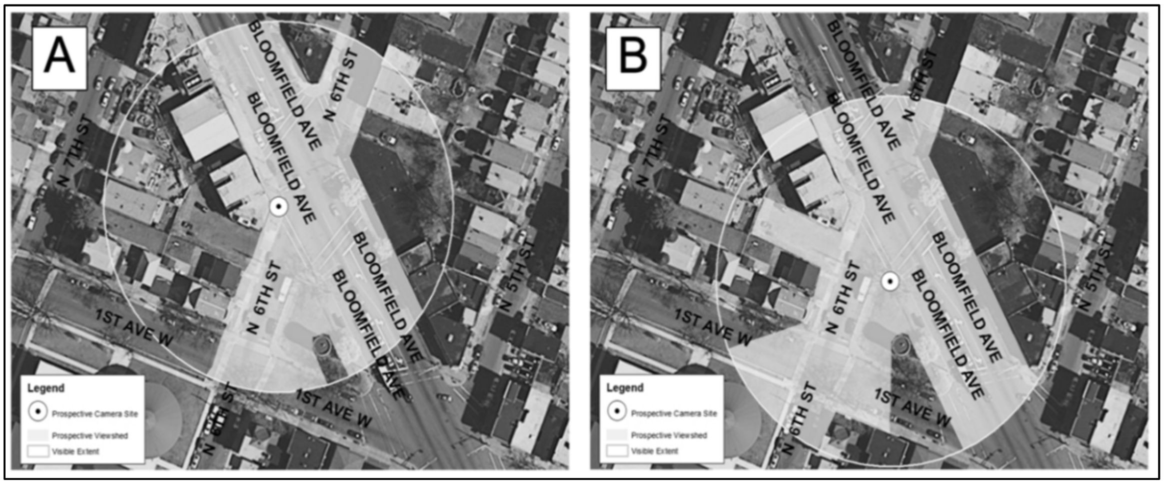

Figure D: Line-of-sight of prospective camera sites.

Another takeaway from this project is that camera enforcement has a positive impact on a camera's ability to generate deterrence. An implication is that levels of enforcement should be maximized. A seemingly obvious solution would be to staff the surveillance unit with more operators. Despite the likely benefits this would generate—in respect to increased detections and enforcement—the current fiscal situation of many police departments likely prevents the assignment of additional personnel to the surveillance unit. A more viable solution would be to incorporate the video surveillance function into current proactive operations of the department.

In this respect, the Newark Police Department commonly deploys "suppression" units for the purpose of identifying and addressing criminogenic conditions which may generate violence. Since most camera detections are of narcotics or disorder, suppression units could be integrated into the surveillance operation so that they are notified when a camera captures an incident of concern. In addition, a few police officers from a given unit could be assigned to monitor surveillance cameras in support of the operations of the unit as a whole. For example, a main strategy of the Newark Police Department is "Command Field Day," where officers assigned to administrative posts (e.g. "Human Resources" or "Legal Affairs") are deployed to motorized and foot-patrol in various high-crime areas throughout the city at least one day per week. The officers are not assigned to any police precinct, but rather remain under the command of their (administrative) unit's supervisor and are given responsibility for proactively patrolling specific areas. It may be worthwhile to assign one of the officers to the surveillance unit for the purpose of monitoring any cameras that fall within the target area being patrolled by their unit. By focusing on a small number of cameras within a concise geography, the officers may be able to detect incidents of concern that may have gone unnoticed by the regular surveillance operators (who are responsible for monitoring a much larger number of cameras).

Qualifications and Suggested Future Research

This project has important policy implications for CCTV use by police. However, this study, like most others, has specific limitations that should be mentioned. In component 1, the control group was limited to calls-for-service occurring within CCTV areas. On the one hand, exclusively including calls-for-service from CCTV areas controls for the environment; since the geography is identical for both the treatment and control group, differences cannot be attributed to the disproportionate influence of criminogenic features (e.g. crime attractors or generators) on either group. However, calls-for-service occurring outside of CCTV areas are completely unrelated to CCTV, and thus may have been a more appropriate comparison and something to consider for future research. Additional limitations relate to the covariates utilized in the negative binomial regression models. Specifically, the data did not allow for identification of the precise days that the surveillance unit was below full strength. The dichotomous "after layoffs" and "year 2010" variables were included as proxy measures for when CCTV operators were most likely to be temporarily assigned to other assignments. The models may have improved had the data included precise dates that less than two operators were on duty.

In component 2, the results of OLS models highlighted the importance of understanding the micro-level environment of CCTV areas in order to contextualize observed crime changes. It should be noted, however, that the β coefficients across the models were small for all covariates. This is partly a byproduct of the dependent variable, which measured the change in Location Quotients (LQ) from the "pre" to the "post" period. The average ΔLQ values were well below 1 for all models. When such small values are utilized as dependent variables in OLS, the resulting coefficients of model covariates are likely to be similarly small. However, the regression coefficients may also suggest that the effects of the covariates on crime levels are very modest. Furthermore, each model generated relatively low r^2 values, meaning most of the variance in the dependent variables went unexplained. Limitations were also present in other aspects of the methodology. For one, the viewshed creation occurred during the months of April through September, which may have somewhat compromised the digitizing of visible obstructions. While researchers accurately captured the presence of foliage obstructions during these warm-weather months, in certain instances we were unable to determine if any immovable obstructions (e.g. a bus shelter or telephone pole) were blocked from view by the foliage. This may have resulted in immovable obstructions being underrepresented in our models. We were additionally unable to control for changes in the land use of facility types that may have occurred during the intervention period, a problem commonly faced in environmental criminology studies (see De Souza & Miller, 2012). Furthermore, our analysis of displacement was hampered by the very small number of catchment areas.

In component 3, we largely attributed the increased surveillance activity to the lowering of the camera to operator ratio. This was due to the findings of the negative binomial regression models incorporated in component 1, which found the "camera phase" and "after layoffs" (a proxy measure for when operators were likely to be temporarily reassigned from the surveillance function) variables to be most strongly associated with reductions in weekly levels of surveillance activity. However, a contributing factor to the surveillance activity increase may have been high levels of motivation on the part of the experimental surveillance operators. Since these individuals were new to the operation, they may have approached the surveillance function with a level of zeal higher than that of operators who have worked in the surveillance unit for a considerable amount of time. A second limitation revolved around the low statistical power associated with tests of research question 2, as previously discussed. While increasing the alpha is an acceptable approach in this case, it would have been desirable to conduct the experiment over a longer period to produce adequate statistical power to allow for the more conservative 95% confidence interval.

Conclusion

A simple truth about video surveillance often gets lost; cameras in-and-of themselves cannot stop a crime. A camera can only deter potential offenders either through its presence or the promise of swift action in response to a crime. While the initial installation of a camera may *signify* an increased risk to offenders, the threat may quickly ring hollow. If over time, potential offenders notice that the camera is not accompanied by increased police response or presence, they may believe that they are at no more risk of punishment. This project was a modest attempt to explore how video surveillance effect can be maximized in this regard. While the research focused on the city of Newark, the policy implications can inform police agencies around the globe. In addition, the research methods are replicable, and we encourage other researchers to repeat the study in other jurisdictions. The recent economic downturn has created a situation in which police resources are extremely limited, and in many cases dwindling. While an impartial review of the empirical evidence should discount the notion of CCTV as a "panacea," video surveillance does have the potential to effectively address issues of public safety within certain contexts and when proactively integrated into existing police function.

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Piza, E., Caplan, J. and Kennedy, L. (in press). Is the Punishment More Certain? An Analysis of CCTV Detections and Enforcement. *Justice Quarterly.* Advance online publication, 9/11/12. DOI: 10.1080/07418825.2012.723034

