FOCUSING ON VIOLENT CRIME IN MICRO HOT SPOTS USING SATURATION PATROL AND NETWORK-BASED INTERVENTIONS

Final Report

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Submitted by

Kenneth J. Novak
University of Missouri-Kansas City

Andrew M. Fox
State of Washington, Department of Children, Youth, and Families

Bridgette Bryson
University of Missouri-Kansas City

In partnership with:

Ryan Mills

Greg Volker
Major, Kansas City (Mo) Police Department

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EXECUTIVE SUMMARY

The Kansas City, Missouri Police Department (KCPD) launched a *Strategies for Policing Innovation* hot spots policing experiment to test two distinct violence prevention interventions in 2017. Sixteen high-crime micro hot spots were selected as study sites by analyzing police data from KCPD's most violent patrol division (East Patrol Division). The sites, with buffer zones, were randomly assigned as either treatment or control areas: five for saturation patrol, a place-based approach that added 15 minutes of police presence during high-crime periods; five for network-based intervention (NBI), using social network analysis to identify persons central to violent crime for individualized police attention (diversion/services or enforcement actions); and six control areas. Comparable pre- and post-intervention periods were established to measure results and changes over time.

To measure outcomes, KCPD tracked and researchers analyzed pre- and post-intervention high priority calls for service (calls from citizens that require an immediate response from the police) and certain offenses in each micro hot spot. For the NBI and control areas, we constructed offender social networks and analyzed yearly changes in key characteristics of those networks. When the experiment concluded, we reviewed whether KCPD had integrated and sustained the violence-prevention strategies and techniques they had implemented for this study.

Across all analyses, the saturation patrol intervention resulted in fewer high priority calls for service. The changes were not statistically significant; however, it was noted that even a small decrease in such calls could make a meaningful difference in resource

allocation. The NBI also produced a slight decrease in calls for service, but this benefit disappeared in the second year; these differences also were not statistically significant.

In saturation patrol areas, crime decreased, especially when comparing seasonally adjusted crime rates. Violent crime, the focus of this study, did not decrease in treatment areas as much as other offenses; nothing indicated that saturation patrol alone impacted violent crime. In the NBI areas, violent crime increased slightly over time; inexplicably, it decreased slightly in control areas. Across treatments, over time, displacement did not appear to occur. The offender social networks that were constructed did show measurable change occurring over time, indicating that police were doing something different. The first-year change suggested that police were documenting more data than before, resulting in more complete networks. The differences between the treatment and control networks diminished in the second year.

In summary, findings that may interest those considering similar initiatives include the following:

- Saturation patrol resulted in fewer high priority calls for service;
- Saturation patrol resulted in fewer crimes, although the impact was modest;
- Network-based interventions resulted in fewer high priority calls for service during the first year of implementation;
- Network-based interventions resulted in increases in high priority calls for service during the second year of implementation;
- Crime in network-based intervention MHSs experienced few changes in overall crime, and violent crime in these MHSs increased relative to control areas; and

- Measurable changes occurred in the social networks in the NBI micro hot spots during the first year of intervention.

At the SPI project's outset, the expectation was that KCPD would integrate and sustain the techniques and interventions being studied. Instead, other departmental efforts appeared to subsume the interventions. Still, we hope that the benefits gained from using data to focus departmental resources on the people and places most closely associated with violent crime have been clearly recognized, and that this will support the retention of data-driven strategies for informing and monitoring the Department's ongoing violence prevention efforts.

1. INTRODUCTION

In 2014, with support from BJA's Strategies for Policing Innovation (SPI) program, regional stakeholders launched the Kansas City No Violence Alliance (KC NoVA). KC NoVA was a groundbreaking multi-agency crime reduction collaboration that was credited in large part for reducing the city's homicide rate by 21%, bringing it down to its lowest level since the early 1970s. Just one year later, however, that homicide rate had rebounded. An October 2015 editorial in the Kansas City Star announced that according to the most recent Uniform Crime Report, Kansas City was the eighth most violent large city in the US (see Fox & Novak, 2018).

The Kansas City Police Department (KCPD) responded by reaffirming its commitment to the pursuit of innovative, evidence-based methods for reducing violence, preventing victimization, and saving lives, while continuing to avoid resorting to mass incarceration. KCPD sought to preserve the benefits gained from the KC NoVA focused-deterrence project (Fox & Novak, 2018; Fox et al., 2015; Novak et al., 2015), but also to find ways to sustain and even improve upon the program's positive outcomes.

Considering where the greatest impact might be made, KCPD focused attention on its East Patrol Division (EPD). The crime rate for this division was the highest in the department—nearly twice that of Kansas City overall and more than ten times the national average. From 2012 through 2015, EPD's homicide rate had averaged 57 per 100,000 residents; in 2015 alone, it documented 969 aggravated assaults and 526 robberies. Evaluating its options, the department chose to launch a new SPI initiative, concentrating resources on violent crime in the EPD.[1] KCPD adopted offender-based, intelligence-led strategies from KC NoVA and added another promising approach, NBI combined with social network analysis (SNA). They would test these strategies in several selectively chosen micro hot spots (MHS) of violence identified within the district.[2] The planning, implementation, and outcomes of this SPI initiative is the subject of this report.[3]

In October 2016, the SPI team began by selecting the personnel who would carry out the interventions and developing the advanced analytic capacity to measure and analyze their results. The project concluded in July 2020, following the completion of the project assessment and evaluation, as well as this final report. Below, we present the design, implementation, outcomes, and implications of the SPI project.

Section 2 outlines the process by which 16 micro hot spots and their corresponding buffer zones were selected as study sites and then randomly were assigned to one of two different treatment groups or the control group. We present the logic model for this project and the methodology used to measure the impacts of the two interventions studied.

Section 3 describes *saturation patrol* (a version of "hot spots policing"), the first intervention strategy planned. We describe the treatment and its dosage, and present the outcomes and our analysis. Section 4 covers the same ground for the second treatment to

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[1] Shortly afterward, at the federal level, SPI was renamed *Strategies for Policing Innovation*.

[2] KCPD's SPI project operated independently of other ongoing focused deterrence activities in Kansas City.

[3] This *Strategies for Policing Innovation* study was funded with a grant from the Bureau of Justice Assistance (BJA) in collaboration with CNA, a nonprofit research and analysis organization located in Arlington, VA. SPI is a collaborative effort between BJA, CNA (an SPI training and technical assistance provider), state and local law enforcement agencies, and researchers who are testing innovative, evidence-based solutions to chronic crime problems in their jurisdictions. Smart Policing is a strategic approach that brings more science into police operations, leveraging innovative applications of analysis, technology, and evidence-based practices. SPI's goal is to improve policing performance and effectiveness while containing costs, an important consideration in today's fiscal environment. See http://www.strategiesforpolicinginnovation.com/

be tested, network-based intervention (NBI), which in this case used social network analysis (SNA) to inform the treatment and to track change over the course of the study in crime networks in treatment and control MHSs.

Section 5 reports our key findings. Overall, impacts were measured in terms of change over time—that is, changes in numbers of high priority calls for service and crime incidents, and changes in crime networks in treatment and control MHSs, comparing differences between designated pre- and post-treatment periods. Part 6 concludes this report, reviewing the project's influence on policing strategies in the Kansas City Police Department. We discuss the extent of KCPD's adoption of intervention practices and their components, as well as their likely integration and sustainability. We also offer recommendations for others who may be considering or embarking upon these or similar innovative policing strategies.

2. METHODOLOGY

The project research design was aimed at reducing violence in KCPD's high-crime East Patrol Division (EPD). EPD is one of six decentralized patrol divisions in Kansas City. Covering 45.5 square miles (approximately 14% of the total city area), EPD is located east of the central business district; its boundaries include the Missouri River to the north, Independence (MO) to the east, the Metro Patrol Division to the south, and the Center Patrol Division to the west. EPD has a reputation within KCPD as the "high activity" division. In 2017, the area had 36% of the city's criminal homicides, 31% of its assaults, and 26% of its drug/narcotic offenses. The area has a mixture of commercial and residential land use, with many characteristics of concentrated disadvantage including

20.5% multi-family housing units, 37% female-headed households with children, 41.2% African Americans, 24.5% Hispanics, and a median household income of $29,705 (KCPD, 2012). But even within a high-activity, high-crime patrol division, micro hot spots of violent crime were able to be identified.

The SPI approach employed evidence-based strategies (Braga, 2007; Sherman & Weisburd, 1995; Groff et al., 2015; Novak et al., 2016; Ratcliffe et al., 2011; Weisburd et al., 2006) incorporating both place-based and person-based violence prevention methods in a micro hot spot (MHS) network experiment. For purposes of this project, we defined *micro hot spots* as small geographic areas (a group of city blocks or an intersection) with the highest concentrations of violent crime incidents in the district during the two previous years.

Micro Hot Spot Selection

Researchers confirmed EPD's high crime status by evaluating 2015-2016 calls-for-service (CFS) data and violent police incident reports. We focused on violent crimes such as assault, robbery, homicide, sex crimes, and weapons offenses and weighted 2016 data twice as much as 2015 data. Initially, we identified 20 MHSs and inspected each site in person, assuring that no extraneous factors (e.g., co-location of a probation office) were potentially influencing the numbers of CFS and incident reports. Some were excluded for failing to fit project parameters or because their boundaries overlapped. Sixteen MHSs qualified for inclusion in the experiment.

The targeted size for an MHS was one-quarter square mile (1,742,400 ft^2). The MHSs selected ranged between 1,601,466 and 2,389,230 square feet, averaging 1,909,077 square feet.[4] This translated roughly as 3 to 5 city blocks in either direction, with buffer zones added to capture any possible geographic displacement.[5]

Our study examined two distinctly different treatments, each conducted within a separate group of randomly assigned MHSs:

1. *Saturation patrol* - a place-based approach to crime prevention that would increase the dosage of police presence in high crime areas; KCPD officers carrying out the intervention were already familiar with this approach, which was similar to other well-known methods (Sherman & Weisburd, 1995; Telep et al., 2014);
2. *Network-based intervention (NBI)* – an offender-focused approach involving identification of criminal social networks in a specific geographic area with the purpose of strategically interrupting the dynamics of the network through targeted enforcement, diversion, or other actions designed to discourage further crime and delinquency. This innovation was unique to others (see Ratcliffe et

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[4] Our MHS were somewhat larger than those in some prior studies (e.g., Sherman & Weisburd, 1995; Groff et al., 2015), but were considerably smaller than some examined in other locations (see Caeti, 1999; Novak et al., 2016; Ratcliffe et al., 2011; Sherman & Rogan, 1995; Weisburd et al., 2006). This decision was driven in part by the use of SNA. Note that this size is consistent with that of hot spots examined by Taylor et al. (2011) who studied POP strategies in Jacksonville. A hot spot consisting of a single address or street segment would likely yield inadequate data for meaningful SNA, while one consisting of 3-5 street segments could be expected to yield data sufficient for comparing treatment effects of added dosages with the effects of POP strategies. We recommend that anyone defining hot spot sizes be cognizant of the type of treatment(s) being employed.

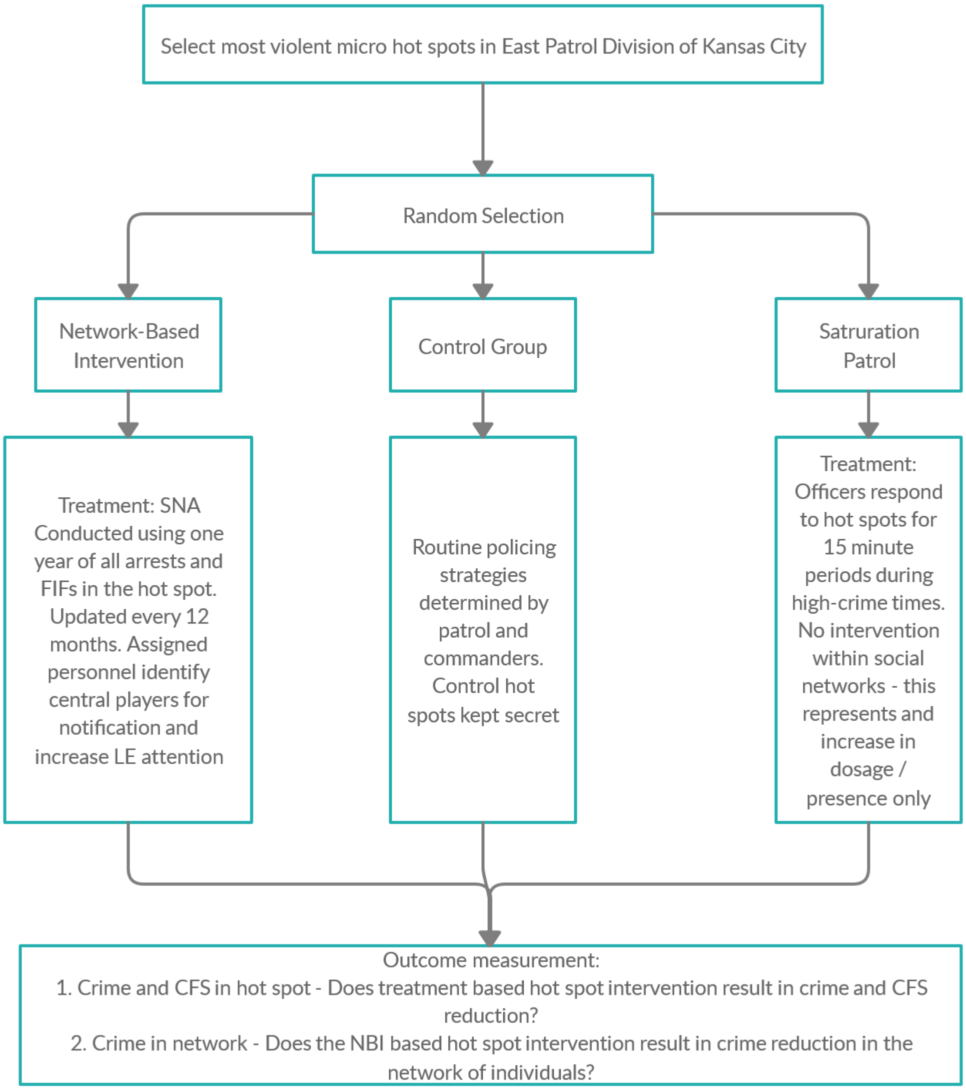
[5] It was important to ensure that no micro hot spots or buffers overlapped anywhere on the map. No universal standard has yet been accepted for the optimal size of buffer zones; our research used Green's (1995) recommendation of approximately two city blocks.

al., 2011) in that KCPD used SNA to identify violent social networks in each NBI-treated and control MHS and the individuals central to them.[6]

The 16 qualifying MHSs were randomly assigned to the place-based saturation patrol group (n=5) which would receive an added 15 minutes of police presence during high crime periods, or the offender-based NBI group (n=5) which would receive SNA-facilitated, network-based interventions (diversion or enforcement), or the control group (n=6) which would experience no change in policing and would be used for comparisons.[7] Figure 1 presents the logic model for this experiment.

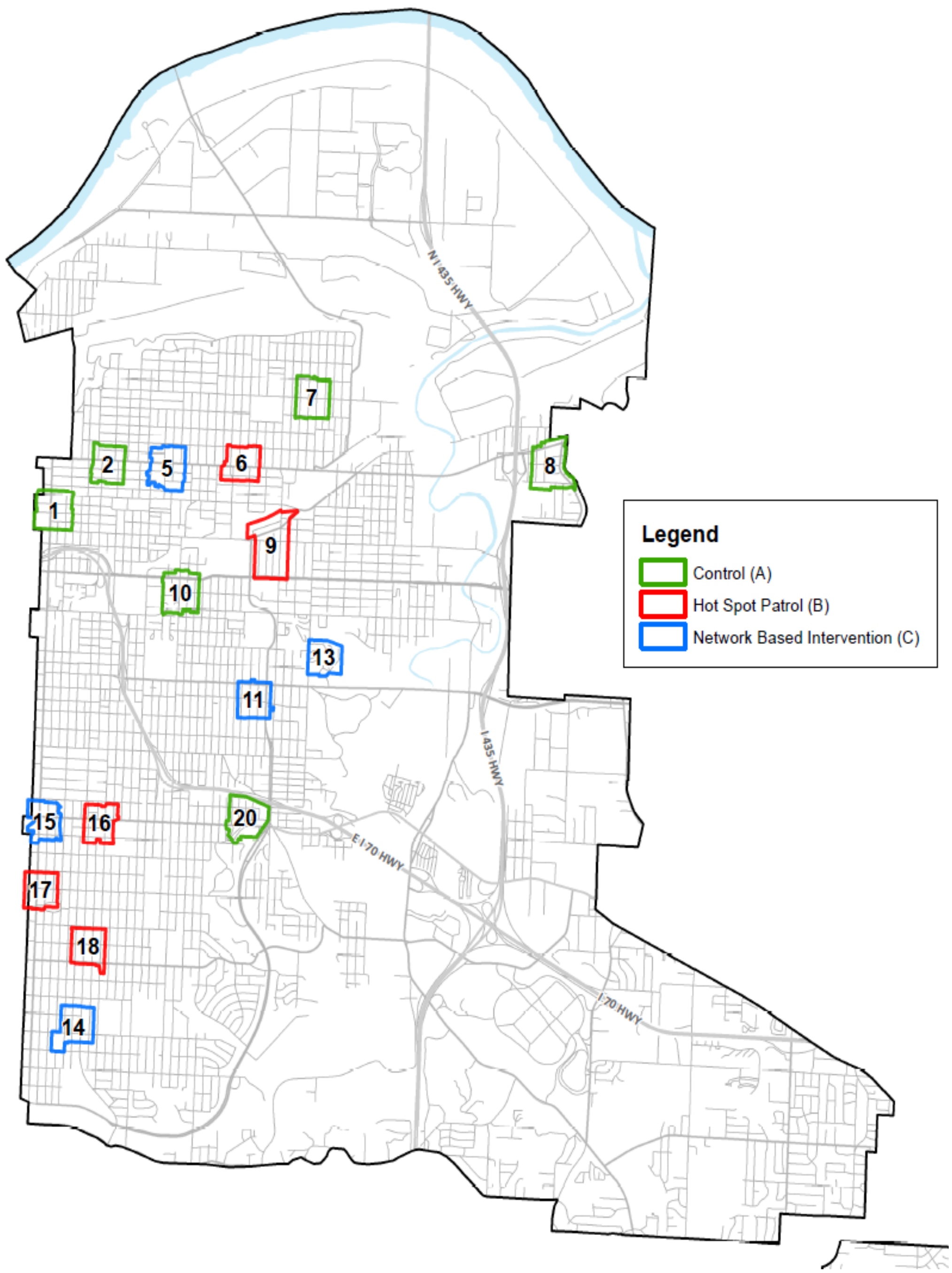
[6] A detailed description of the extant research that formed a foundation for these treatments is presented in Appendices A and B.
[7] This initiative used an experimental design, ranked 5 on the Maryland Scientific Methods Scale.

Figure 1. Kansas City, MO - SPI Logic Model



Each MHS was assigned a number by which it was referenced throughout the study; these had no value other than for tracking purposes. Control MHSs were numbers 1, 2, 7, 8, 10, and 20; saturation patrol MHSs were numbers 6, 9, 16, 17, and 18; and NBI MHSs were numbers 5, 11, 13, 14, and 15 (fig. 2).

Figure 2. Map: KCPD East Patrol Division - Micro Hot Spots



3. SATURATION PATROL INTERVENTION

Saturation patrol is a place-based treatment rooted in the evidence-based hot-spots policing approach.[8] The five MHSs randomly assigned to the saturation patrol group were scheduled to receive an additional 15 minutes of police presence during their high crime periods apart from their usual police coverage.

Treatment & Dosage

To assess the integrity of the study data, KCPD monitored the actual saturation patrol dosage in the five MHSs in the treatment group. Dispatchers recorded officers' locations and the times that they began and ended each visit. In addition, on four separate occasions, the research team conducted field observations. Onsite, researchers took detailed notes, including officers' arrival and departure times, activities performed, and community interactions. To assure that no crucial discrepancies were occurring, researchers' field notes were compared with KCPD's CAD data. We found that, with few minor exceptions, field notes and CAD data were significantly consistent, suggesting a high degree of fidelity in dosage monitoring.

The CAD data were further broken down and analyzed to determine the total intervention dosage across the MHSs in the saturation patrol group. During the treatment period (August 1, 2017 through September 29, 2017) 88 shifts were scheduled, while 60 shifts (68.1%) were actually covered. These were scheduled as overtime shifts, outside

[8] For an overview of hot-spots policing, see Appendix B. More recently, emphasizing the efficacy of selecting smaller geographic locations with concentrated violence, the term *micro hot spots* has come into use; the current study was conducted within the boundaries of clearly defined micro hot spots and their buffer zones.

normal work hours; sometimes no officers were available to fill them. Across the five treatment MHSs, officers made 652 visits throughout the intervention, for a total of 10,090 minutes or 168 hours of intervention time.

The treatment plan called for each MHS in the saturation patrol group to be visited twice daily Sunday through Wednesday and four times daily Thursday through Saturday, every week throughout the intervention period. These visits were in addition to, and not adjacent to or overlapping with, their normal police coverage. When the intervention ended, one MHS (#17) had averaged more than two (2.89) additional visits per day; all others averaged fewer than two—significantly less than planned—which may have affected the results for the saturation patrol MHS group.

Officers were expected to be present in an MHS for precisely 10–15 minutes per visit, in accord with the Koper Curve; this was the period deemed long enough to fully reap treatment benefits but not so long as to degrade the potential for those benefits (Koper, 1995). Seventy-one visits (10.8%) actually lasted fewer than 10 minutes, and 200 visits (30.6%) lasted more than 15 minutes—failing to meet the Koper threshold, in either case.[9] Still, 381 visits (58.4%) had lasted the designated 10–15 minutes, indicating that officers were operating efficiently the majority of the time. Overall, the average time spent per MHS visit fell between 13.86 and 16.65 minutes, with only MHS 16 and MHS 17 averaging more than the threshold time per visit. After removing seven outliers, the average time per visit in the saturation patrol MHSs fell between 13.94 and 15.70 minutes,

[9] Seven of the >15-minute visits lasting longer than an hour could be considered outliers. Overstaying might occur for any number of reasons; for example, if an arrest had been made, it might have taken more than the allotted intervention time to complete the arrest and the required report.

again indicating that officers were working efficiently and were generally meeting the per-visit dosage standard. Altogether, MHSs in this treatment group averaged 9.61 additional visits per day (fig. 3), for a total of 146.8 minutes, or 2.5 hours, of additional police presence per day (fig. 4).

Figure 3. Saturation Patrol Group – Dosage: Added Officer Visits per Day

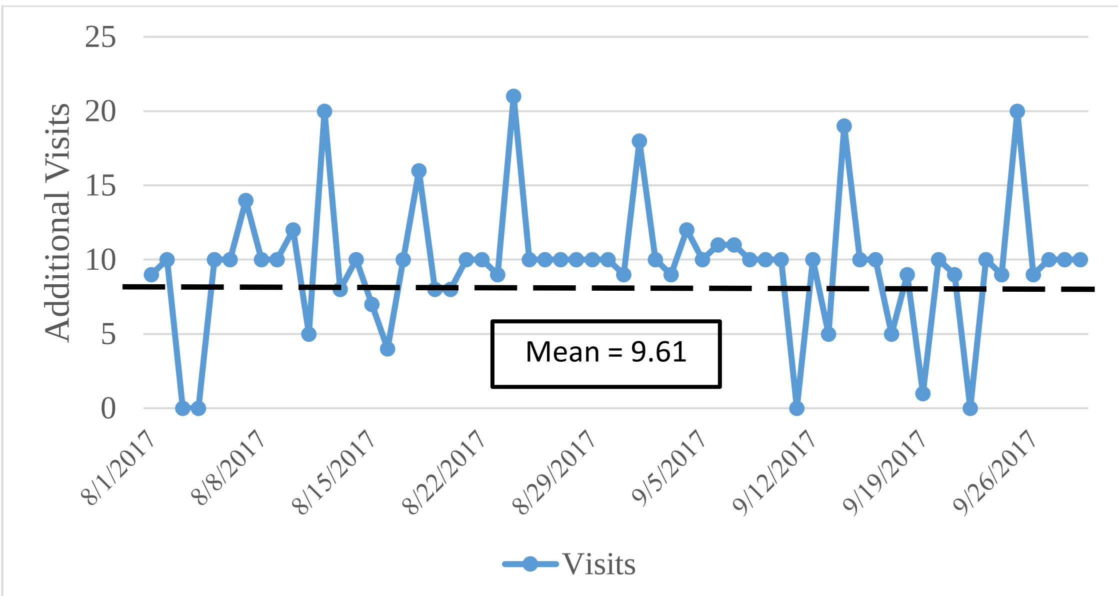
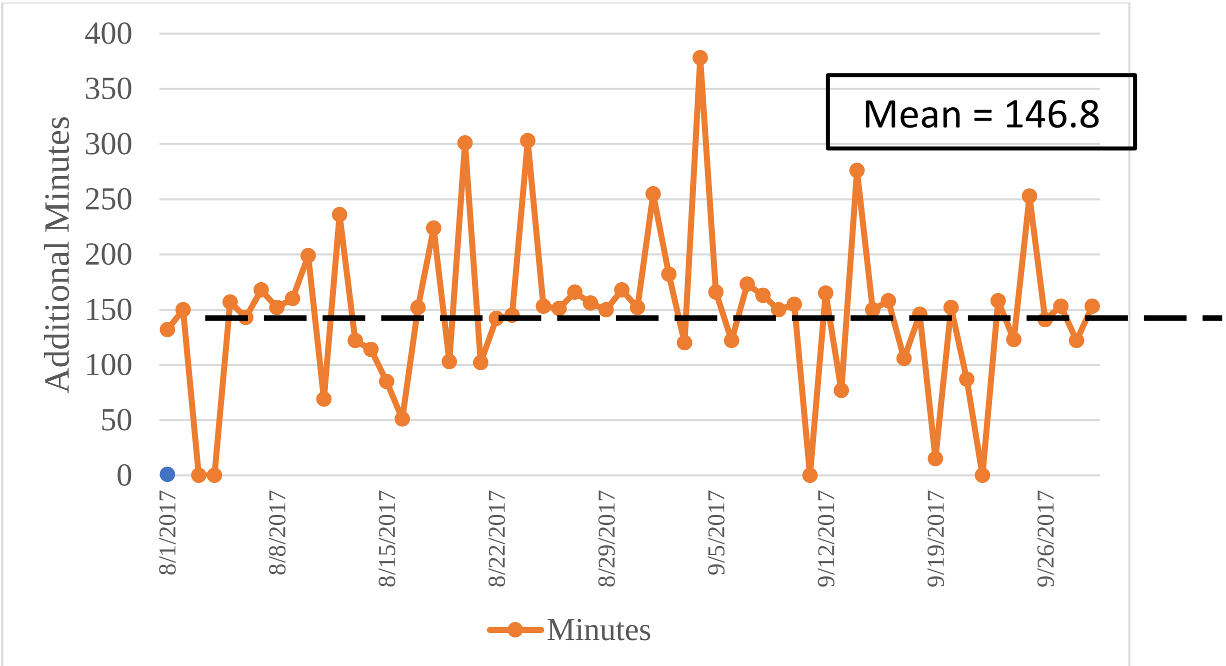


Figure 4. Saturation Patrol Group – Dosage: Added Minutes per Day



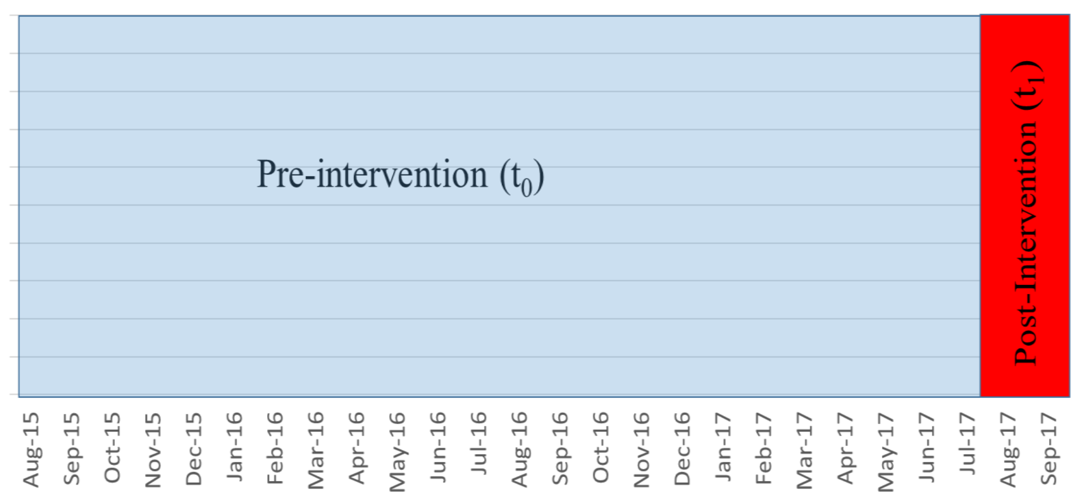
Outcome Analysis

To assess the impact of the saturation patrol treatment on CFS, we collected violent crime reports from EPD's 2015-2019 priority CFS and incident offense data. Violent crimes were the focus of this study. The objective was to determine whether, in geographically concentrated areas, the treatment not only would affect crime, but would affect violent crime specifically.

KCPD triages CFS according to severity. Dispatchers prioritize calls using a scale from 1-5, where 1 is the most serious and 5 is the least serious. CFS are designated priority 1 when an incident is *in progress* or *has occurred* and presents a potential or known danger to human life (e.g., an in-progress shooting or rape). CFS are designated priority 2 when the threat of harm *has not yet occurred* (e.g., a bomb threat or possible domestic violence). Priority 3 CFS are reporting non-life-threatening situations requiring police assistance (e.g., individual welfare checks or 911 calls followed by a hang-up).[10]

We analyzed high priority CFS at levels 1, 2, and 3. To determine the impact of the saturation patrol intervention, the research team estimated a series of models. The first set of analyses focused on high priority CFS, comparing the "pre" period, the 104 weeks before intervention (T_0), to the "post" period, the nine weeks during the intervention (T_1).[11] (See fig. 5.) Next, our analysis was broken down into different models: all high priority CFS, priority 1 CFS, priority 2 CFS, and priority 3 CFS.

Figure 5. Saturation Patrol Group – Pre/Post-Intervention Periods



[10] Priority 4 and 5 calls are low priority requests for service, where officers respond to calls "without undue delay" or "delayed response is acceptable."

[11] For purposes of this report, unless otherwise stated, a "post-intervention" period begins when an intervention is initiated and ends upon its completion.

Next, we compared outcomes by offense type, again during the pre- and post-treatment periods. The set of analyses for incidents and offenses proceeded similarly to those for CFS. Models were estimated for each crime category: all crimes, violent offenses (e.g., murder, robbery, aggravated assault, simple assault), theft (e.g., motor vehicle theft, pocket-picking, purse snatching), disorder (e.g., DUI, intimidation, liquor law violation), and destruction (e.g., arson, vandalism).

Results: calls for service

Table 1 displays a series of analyses for CFS, reporting results for all high priority calls and for priority 1, priority 2, and priority 3 calls. Within each model, the mean number of calls pre- and post-treatment is displayed, along with the percentage of change between the two periods. For each model, the total net effect (TNE) and weighted displacement difference (WDD) are presented, along with standard errors (SE), Z(WDD), *p*-values, and confidence intervals (CI). Rows present the mean number of calls in treatment areas, treatment buffer areas, control areas, and control buffer areas. Models compare the mean weekly CFS for 104 weeks pre-treatment to the 9-week post-treatment period.

High priority CFS in the saturation patrol MHSs declined from 50.5 per week to 29.9 per week (40.8%), and CFS in treatment buffer areas declined 30.5%. By comparison, the control area MHSs experienced a 25.3% reduction in CFS and buffer areas fell 28.9%. Standing alone, these results suggest that high priority CFS declined more in the MHSs that had additional police presence than in the control areas, with no apparent spatial displacement. In fact, the TNE indicates a reduction of 10.88 high priority CFS per week in the treatment areas. This is substantively important; however, also note that Z(WDD) = -0.05, suggesting that these reductions are not statistically significant at the .05 level.

Table 1 also presents results for other CFS categories. Priority 1 CFS declined 36.3% in treatment MHSs (compared to only a 9.1% reduction in the control areas); collectively, this translates to a TNE of 4.08 fewer priority 1 calls per week in the treatment MHSs. Priority 2 CFS declined in the treatment MHSs by 30.7%, compared to 15.8% reduction in control areas (TNE = 4.88). Finally, priority 3 CFS declined 67.5% in the treatment MHSs, compared to a 61.8% reduction in the control areas (TNE = 2.32). In total, high priority CFS, regardless of rank, were fewer in the treatment areas than in the control areas, without any detection of harmful spatial displacement. Note, however, that none of the reductions achieved conventional statistical significance as estimated by the series of Z(WDD); also, the strength of the evidence across these models is weak, and therefore may have been observed by chance alone.

Table 1: Saturation Patrol - Calls for Service

	All High Priority			Priority 1			Priority 2			Priority 3		
	Pre	Post	% Change	Pre	Post	% Change	Pre	Post	% Change	Pre	Post	% Change
Treatment	50.5	29.9	-40.8%	12.6	8.0	-36.3%	26.0	18.0	-30.7%	12.0	3.9	-67.5%
Treatment Buffer	59.0	41.0	-30.5%	14.2	12.2	-13.8%	31.2	25.2	-19.1%	13.6	3.6	-73.9%
Control	57.9	43.2	-25.3%	13.7	12.4	-9.1%	30.2	25.4	-15.8%	14.0	5.3	-61.8%
Control Buffer	79.5	56.6	-28.9%	16.1	13.2	-17.9%	42.5	35.8	-15.8%	20.9	7.6	-63.9%
TNE	10.88			4.08			4.88			2.32		
WDD	-1.00			-2.37			-2.44			3.83		
S.E.	20.43			10.12			15.31			8.99		
Z (WDD)	-0.05			-0.23			-0.16			0.43		
p	0.48			0.41			0.44			0.66		
C.I.	-41.05	39.05		-22.20	17.46		-32.44	27.56		-13.79	21.45	

TNE = Total Net Effect

WDD = Weighted Displacement Difference

Z(WDD) = Z score of WDD

Pre = 104 weeks

Post = 9 weeks

The second set of confirmatory analyses compared the 9-week equivalent period to the treatment period, using the same analysis breakdown as above. The intervention occurred between August 1 and September 30, 2017. The analysis compares weekly outcome variable counts during comparable times in previous and subsequent calendar years. This decision was made to account for a natural seasonal fluctuation in crime (Telep et al., 2014). From 2015 through 2018, the 9-week-equivalent pre-treatment periods (August 2, 2015-October 3, 2015 [T_0] and July 31, 2016-October 1, 2016 [T_0]) were analyzed and compared to the post-treatment period (July 30, 2017-September 30, 2017 [T_1]). As with the full sample above, all three sections of priority calls were analyzed in the 9-week equivalence comparison to the 9-week intervention analyses. Figure 6 depicts the pre- and post-treatment periods for the seasonally adjusted set of analyses for the saturation patrol evaluation.

Figure 6. Saturation Patrol – Pre/Post-intervention Periods (Seasonal Adjustment)

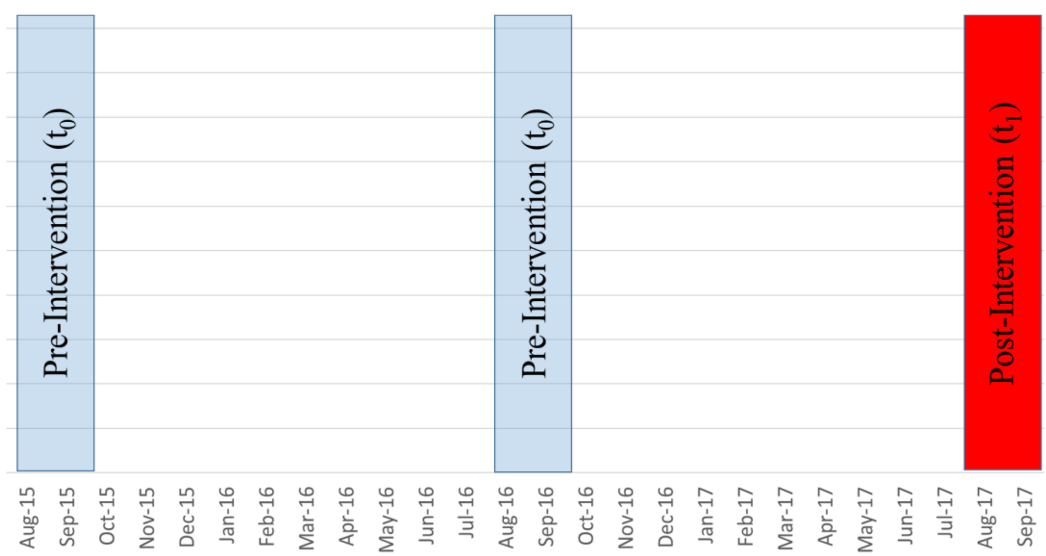


Table 2 displays analyses for the seasonal sample of high priority CFS for the treatment and control MHSs and their buffer areas. The seasonal sample includes two 9-week periods equivalent to treatment times of the year, minimizing seasonal biases in CFS and crime data. (Table 2 is interpreted the same as table 1, above.) The results trend similarly to those in the previous analysis, and the same substantive conclusions develop from this supplemental analysis. High priority CFS were notably reduced in the saturation patrol MHS group, from 59.6 per week to 29.9 per week; this reduction (49.8%) was greater than the reduction observed in the control group (31.6%). Harmful spatial displacement was not detected. Collectively, these results translate to a 10.64 high priority CFS reduction per week in the treatment MHSs. Treatment MHSs experienced measurable declines in priority 1, priority 2, and priority 3 CFS; in each category, the decline in the treatment MHS group exceeded the decline in the control MHS group. The TNE was 5.65 priority 1 CFS per week, 2.84 priority 2 CFS per week, and 2.44 priority 3 CFS per week. As with Table 1, however, none of the changes in Table 2 were statistically significant.

Table 2: Saturation Patrol - Calls for Service (Seasonal Adjustment)

	All High Priority			Priority 1			Priority 2			Priority 3		
	Pre	Post	% Change	Pre	Post	% Change	Pre	Post	% Change	Pre	Post	% Change
Treatment	59.6	29.9	-49.8%	16.7	8.0	-52.0%	29.8	18.0	-39.6%	13.1	3.9	-70.3%
Treatment Buffer	59.6	41.0	-31.2%	15.1	12.2	-19.1%	29.2	25.2	-13.5%	15.3	3.6	-76.8%
Control	63.2	43.2	-31.6%	15.3	12.4	-18.6%	32.6	25.4	-21.9%	15.3	5.3	-65.2%
Control Buffer	83.6	56.6	-32.3%	18.3	13.2	-27.7%	41.5	35.8	-13.8%	23.8	7.6	-68.2%
TNE	10.64			5.65			2.84			2.44		
WDD	-1.33			-3.66			-2.89			5.23		
S.E.	20.89			10.55			15.41			9.37		
Z (WDD)	-0.06			-0.35			-0.19			0.56		
p	0.47			0.36			0.43			0.71		
C.I.	-42.28	39.62		-24.33	17.01		-33.09	27.31		-13.14	23.60	

TNE = Total Net Effect

WDD = Weighted Displacement Difference

Z(WDD) = Z score of WDD

Pre = 18 weeks

Post = 9 weeks

Results: offenses

Table 3 displays a series of models for offenses in saturation patrol and control MHSs showing crimes likely to be affected by increased officer presence (i.e., violent offenses, theft, disorder, property destruction). The models compare average crimes per week for the 104 weeks pre-treatment (T_0) to the nine weeks of treatment (T_1). Overall, compared to the two previous years, reported crimes tended to increase over the treatment time. Treatment MHSs averaged 8.4 crimes per week pre-treatment compared to 10.6 crimes per week post-treatment, for a 26.0% increase. Crime in control MHSs also increased, although only by 10.7%. The TNE of saturation patrol was almost one less crime per week (not statistically significant).

Similarly, violent offenses increased 59% in treatment MHSs compared to 16% in control MHSs. Interestingly, crime in treatment buffer areas decreased 5.1%, while crime in control buffer areas increased 21.3%. The TNE was -0.75, or a modest increase of 0.75 violent crimes per week in treatment areas. Theft offenses increased in treatment MHSs (28.6%) at about the same rate as in control MHSs (25.5%); slight reductions in theft offenses observed in the treatment buffer areas yielded a TNE of 1.46 fewer thefts per week in treatment areas. Disorder offenses declined more in treatment MHSs (32.6%) than in control MHSs (25.2%); treatment buffer areas also experienced reductions during the intervention (36.4%), yielding a slight reduction in treatment MHSs of 0.2 disorder crimes per week. Finally, destruction offenses declined more in treatment MHSs (35.0%) compared to control MHSs (3.9%), yielding a TNE of 0.27 fewer property destruction offenses per week. None of the models estimated in Table 3 achieved statistical significance at the conventional .05 level.

Table 3: Saturation Patrol - Offenses

	All Crimes			Violence			Theft			Disorder			Destruction		
	Pre	Post	%	Pre	Post	%	Pre	Post	%	Pre	Post	%	Pre	Post	%
Treatment	8.4	10.6	26.0%	4.1	6.4	59.0%	2.0	2.6	28.6%	1.3	0.9	-32.6%	1.0	0.7	-35.0%
Treatment Buffer	11.1	10.0	-9.7%	4.7	4.4	-5.1%	4.1	3.4	-12.9%	0.9	0.6	-36.4%	1.6	1.6	-0.6%
Control	9.1	10.1	10.7%	3.9	4.6	16.0%	2.7	3.4	25.5%	1.2	0.9	-25.2%	1.3	1.2	-3.9%
Control Buffer	13.2	16.7	26.5%	5.8	7.0	21.3%	4.8	6.3	32.4%	0.9	1.1	22.0%	1.7	2.2	29.1%
TNE	0.99			-0.75			1.46			0.20			0.27		
WDD	-3.37			0.29			-2.19			-0.65			-0.82		
S.E.	9.44			6.39			5.41			2.78			3.36		
Z (WDD)	-0.36			0.05			-0.41			-0.23			-0.24		
p	0.36			0.52			0.34			0.41			0.40		
C.I.	-21.87	15.13		-12.24	12.82		-12.79	8.41		-6.11	4.81		-7.40	5.76	

TNE = Total Net Effect

WDD = Weighted Displacement Difference

Z(WDD) = Z score of WDD

Pre = 104 weeks

Post = 9 weeks

We conducted confirmatory analyses, examining a 9-week equivalence comparison to the treatment period using the same analysis breakdown as described above for offenses. The models reported in Table 4 provide substantive results similar to those in the larger analysis. When constraining the analyses to seasonally similar periods, however, the TNE of the intervention was slightly (albeit not significantly) more beneficial. For example, the seasonal analysis revealed a negligible increase in total crime in the treatment MHSs (1.6%) and a more substantive 15.9% increase in the control areas, while all crime in the treatment buffer areas decreased 23.4%. Collectively, this indicated 6.63 fewer offenses in the saturation patrol MHSs compared to the control MHSs. Violent crime increased in both treatment and control groups while decreasing in the treatment buffer areas, yielding a modest 1.49 violent crime reduction. Theft, disorder, and destruction offenses all declined when taking control and buffer areas into analytic consideration; however, none of the models examined in Table 4 experienced statistically significant decreases.

Table 4: Saturation Patrol - Offenses (Seasonal Adjustment)

	All Crime			Violence			Theft			Disorder			Destruction		
	Pre	Post	Change	Pre	Post	Change	Pre	Post	Change	Pre	Post	Change	Pre	Post	Change
Treatment	10.4	10.6	1.6%	4.7	6.4	37.9%	2.1	2.6	21.3%	2.4	0.9	-62.8%	1.2	0.7	-45.1%
Treatment Buffer	13.1	10.0	-23.4%	5.7	4.4	-22.4%	4.8	3.4	-28.0%	0.8	0.6	-32.5%	1.7	1.6	-9.3%
Control	8.7	10.1	15.9%	3.9	4.6	16.0%	2.4	3.4	43.9%	1.3	0.9	-33.1%	1.2	1.2	4.3%
Control Buffer	14.5	16.7	15.0%	6.5	7.0	7.7%	5.3	6.3	19.9%	1.1	1.1	0.0%	1.6	2.2	37.9%

	All Crime		Violence		Theft		Disorder		Destruction	
TNE	6.63		1.49		3.92		0.70		0.84	
WDD	-6.45		-0.64		-2.99		-1.33		-1.37	
S.E.	9.70		6.58		5.51		3.02		3.37	
Z (WDD)	-0.67		-0.10		-0.54		-0.44		-0.41	
p	0.25		0.46		0.29		0.33		0.34	
C.I.	-25.45	12.55	-13.53	12.25	-13.78	7.80	-7.25	4.59	-7.98	5.24

TNE = Total Net Effect

WDD = Weighted Displacement Difference

Z(WDD) = Z score of WDD

Pre = 18 weeks

Post = 9 weeks

Summary

We want to highlight the fact that none of the analyses conducted demonstrated statistically significant changes in numbers of CFS or recorded offenses in the saturated patrol treatment MHSs, and the fluctuations that were observed may have occurred by chance alone. In short, violent crime, the focus of this project, was not affected significantly or substantively by the increased presence of officers in the MHS treatment group.

Nonetheless, albeit not nearly of the scope or magnitude anticipated and hoped for, the fact that analysis suggests that the intervention may have had beneficial impacts should not be ignored. Specifically, the implementation of saturation patrol in violent crime MHSs corresponded with a decrease in CFS in high priority situations. While officers were assigned to saturation patrol, a TNE of more than 10 high priority calls per week, including between 4 and 5.65 priority 1 CFS, was realized in the treatment MHSs. High priority CFS represent a drain on organizational resources that is difficult to anticipate and plan for. Strategic deployment of a single officer in a violent MHS quite likely can reduce this burden on resources.

Additionally, taking seasonal fluctuations of crime into account, the strategic deployment of officers in violent crime MHSs yielded a 6.63 reduction in total crimes per week. These changes were not statistically significant and should be interpreted with extreme caution; nevertheless, the results have revealed some crime prevention benefits from enhanced police presence in violent crime MHSs.

4. NETWORK-BASED INTERVENTION WITH SNA

Violence can spread like a disease through social networks.[12] Accordingly, borrowing from proven public health strategies, focused deterrence and other violence reduction models have encouraged interventions that are group-based rather than conducted at an individual level. Group-based interventions acknowledge that some violence is the product of social interaction and thus requires a response that accounts for its social nature. With this in mind, the current project introduced such a treatment model using network-based interventions (NBI) supported by social network analysis (SNA).

A number of features characterize NBI combined with SNA. First, once a violent group or network has been identified, one or more specific individuals within it may be prioritized for attention, either diversion services or enforcement. A person's level of priority is related to position within their social network; that is, those who are discovered by SNA to be more central to the crime that is occurring in a particular MHS will be among the first to receive intervention.

Second, NBI is not an "enforcement only" approach. Some higher priority individuals (i.e., more central to the offender network) might not, themselves, be actively violent; for them, an offer of services that could divert them from criminal activity could be the better approach to enabling them to leave the network (or to become a productive prosocial force inside the network).

[12] For a review of the literature pertaining to network-based interventions, see Appendix C.

The aim of NBI is to change the social dynamics that allow violence to spread throughout a community. When understanding violent crime as a network phenomenon, a police officer and a community engagement specialist (CES) working together can design appropriate, effective interventions. The third essential NBI team member is a crime analyst trained in the technique known as SNA. The crime analyst uses all available police data to construct offender social networks that identify the roles of the individuals that comprise them, which in turn informs the actionable decisions made by the officer and CES.

SNA allows law enforcement and researchers to examine organizational structures and social group dynamics that have long been important concepts in the study of crime (Cohen, 1955; Short & Strodtbeck, 1965). SNA helps to quantify the ways in which social structures matter and how certain positions in a given web of social relationships may be of importance—that is, how each position may have more or less significance. One of SNA's objectives is to advance the understanding of offenders and the networks they inhabit. For the current study, the crime analyst used the EPD's police data to construct networks for each randomized NBI and control MHS and to examine how individual positions within each network was related to the likelihood of violent victimization among its members.

For the current study, tasked with achieving NBI objectives, the project team consisted of a sworn KCPD officer, a grant-supported civilian community engagement specialist (CES) with expertise in neighborhood outreach and leveraging social services, and a civilian crime analyst. The officer, while primarily responsible for enforcement-related activities, also contributed to the analysis by gathering further intelligence on individuals identified within the emerging networks and partnering with the CES to plan and carry out diversion activities. The KCPD analyst estimated the boundaries of all of the MHSs and then constructed visual social networks of individuals known to be involved in criminal activity within the NBI MHSs. Collectively, this team was responsible for identifying and prioritizing central individuals within the offender social networks active in the NBI MHSs, and either connecting them with appropriate social services that could help divert them from becoming violent offenders or, when necessary, deploying enhanced law enforcement.

Treatment and Dosage

NBI treatment activity types included, for example, gathering network intelligence, participating in community meetings and events, diversion activities, conflict resolution, and enforcement actions. The officer and CES tracked their respective intervention activities, documenting activity types and dosages for each NBI MHS.[13] If a particular activity occurred in more than one MHS, typically only one tracking form was completed, with total time spent split evenly between them. During 21 months of treatment (July 2017-March 2019), together, the officer and CES completed 816 tracking forms reporting a total of about 1,929 hours of activity.

Figure 7 shows the average number of NBI-related hours per month spent in the treatment MHSs. In year one, MHS 5 and MHS 11 received the most attention, 22.6 and 27 hours per month, respectively. Comparing year one to year two, four of the five

[13] See tracking form, Appendix D.

treatment MHSs increased in the number of hours per month of attention they received. Most significantly, in year one, MHS 15 received about 10.5 hours per month of NBI activities while in year two, this more than doubled, for an average of more than 27 NBI activity hours per month.

Figure 7. NBI Group – Dosage: Ave. Activity Hours/Month (by MHS# & Year)

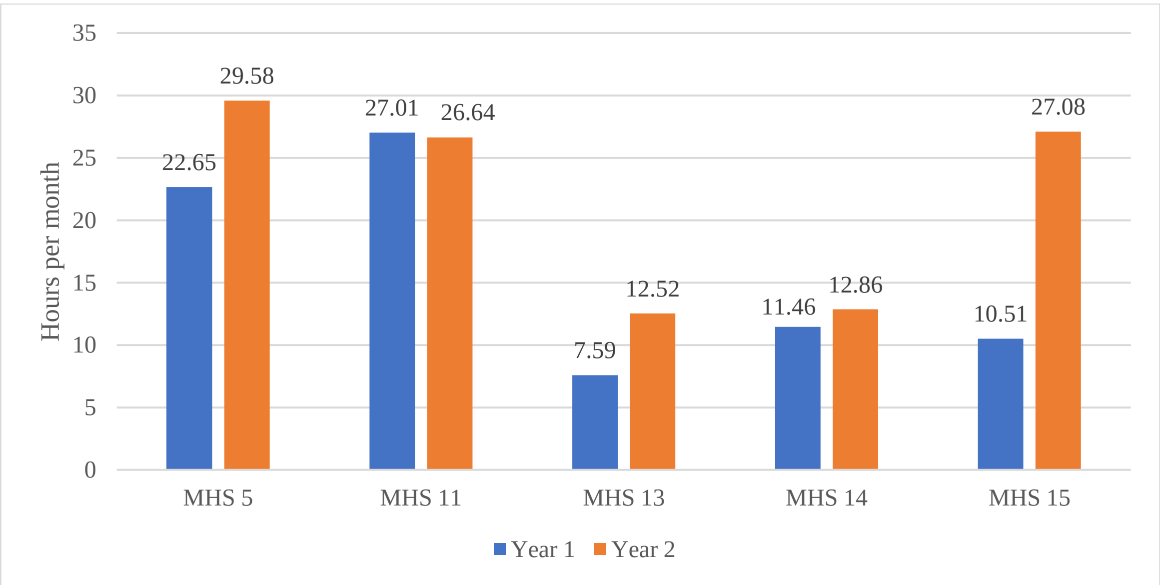
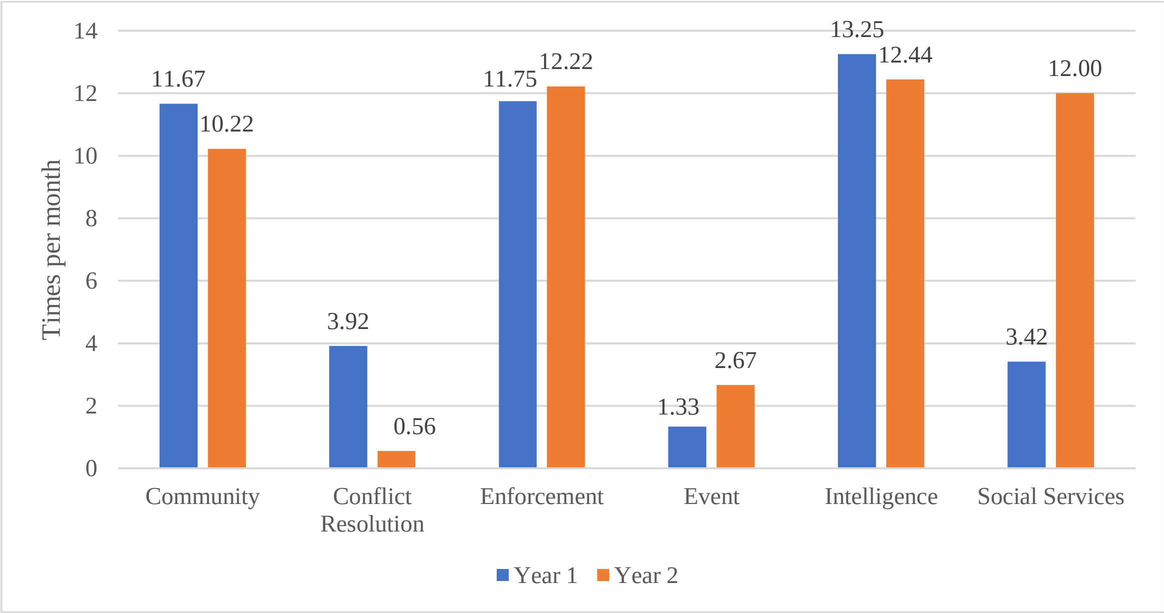


Figure 8 shows the average number of NBI activities per month that occurred across the treatment MHSs, by type, comparing year one to year two. The three most frequently occurring activity types were community engagement, enforcement, and network intelligence; for all three, average monthly activity rates remained fairly consistent from year one to year two.

Figure 8. NBI Group – Dosage: Ave. Number of Activities/Month (by Type & Year)



Outcome Analysis

The analysis used to measure the impact of NBI mirrors the one used to assess saturation patrol (see sec. 3), other than that SNA supplemented the NBI analysis. To assess the impact of the NBI treatment on CFS, violent crime reports were collected from EPD's 2015-2019 priority CFS and incident offense data. As mentioned above, violent crime was the focus of this study; the objective was to determine whether, in geographically concentrated areas, NBI treatment would affect not only crime, but particularly violent crime.

Results: calls for service

Pre- to Y1. Table 5 presents models for all high priority CFS and, broken down, individually for priority 1, priority 2, and priority 3 CFS during the pre-treatment period and year one (Y1); we measured average CFS per week for all MHSs in the NBI and control groups and compared the results in the pre-treatment period with those in year one. The change between those periods was similar in all areas. On average, treatment MHSs experienced a 44.4% decrease in CFS, and control MHSs experienced a 41.7% decrease. Buffer areas for treatment and control MHSs experienced similar declines (47.2% and 43.0%). Treatment MHSs and their corresponding buffer areas outperformed control MHSs and buffer areas, with a modest TNE of 4.84 CFS per week. Priority 1 calls decreased from 12 to 7.5 CFS per week, a 37.4% reduction, compared to a 24.2% decrease in control areas. TNE from the pre-treatment period to Y1 was approximately 3.92 priority 1 CFS per week. The increase in priority 2 CFS was a negligible 0.16 calls per week. Priority 3 CFS had a TNE of 1.22 CFS. None of the models estimated in Table 5 were statistically significant at the 0.05 level.

Table 5: Network-based Intervention - Calls for Service (Pre to Year 1)

	All High Priority Calls			Priority 1			Priority 2			Priority 3		
	Pre	Post	% Change	Pre	Post	% Change	Pre	Post	% Change	Pre	Post	% Change
Treatment	52.0	28.9	-44.4%	12.0	7.5	-37.4%	29.1	18.5	-36.4%	10.9	2.9	-73.4%
Treatment Buffer	62.1	32.8	-47.2%	13.2	7.6	-42.1%	35.0	21.0	-39.9%	14.0	4.2	-70.3%
Control	65.4	38.1	-41.7%	15.4	11.7	-24.2%	34.9	21.5	-38.6%	15.1	5.0	-66.8%
Control Buffer	89.9	51.2	-43.0%	17.0	11.9	-30.3%	49.2	32.7	-33.5%	23.6	6.6	-72.2%
TNE	4.84			3.92			-0.16			1.22		
WDD	13.52			-1.12			5.38			9.26		
S.E.	20.51			9.81			15.56			9.07		
Z (WDD)	0.66			-0.11			0.35			1.02		
p	0.75			0.45			0.64			0.85		
C.I.	-26.67	53.71		-20.35	18.11		-25.11	35.87		-8.51	27.03	

TNE = Total Net Effect

WDD = Weighted Displacement Difference

Z(WDD) = Z score of WDD

Pre = 52 weeks

Post = 52 weeks

Y1 to Y2. Table 6 presents models for all high priority and priority 1, priority 2, and priority 3 CFS in the NBI treatment and control groups, comparing year one to year two. CFS at all priority levels increased in both the treatment and control MHSs. Total high priority CFS in the treatment group increased from 28.9 per week to 35.2 per week (21.7%), while increasing in the control group by only 5.8%; TNE in the treatment group was 8.76 more high priority CFS per week. Priority 1 CFS in the treatment group increased 35.6% compared to 9.9% in the control group. Priority 2 CFS in the treatment group increased from an average of 18.5 per week to 20.8 per week (12.5%), but remained about the same in the control group. Priority 3 CFS in the treatment group increased 44.8%, while increasing only 12.6% in the control group. None of the models presented in Table 6, comparing Y1 to Y2, was statistically significant at the 0.05 level.

Table 6: Network-based Intervention - Calls for Service (Year 1 to Year 2)

	All High Priority Calls			Priority 1			Priority 2			Priority 3		
	Pre	Post	% Change	Pre	Post	% Change	Pre	Post	% Change	Pre	Post	% Change
Treatment	28.9	35.2	21.7%	7.5	10.2	35.6%	18.5	20.8	12.5%	2.9	4.2	44.8%
Treatment Buffer	32.8	38.8	18.4%	7.6	10.0	31.2%	21.0	24.0	14.2%	4.2	4.8	16.4%
Control	38.1	40.3	5.8%	11.7	12.8	9.9%	21.5	21.9	1.9%	5.0	5.6	12.6%
Control Buffer	51.2	56.6	10.5%	11.9	14.5	21.8%	32.7	35.4	8.2%	6.6	6.7	1.4%
TNE	-8.76			-3.55			-4.53			-1.09		
WDD	4.74			1.30			2.18			1.26		
S.E.	17.94			9.28			13.99			6.32		
Z (WDD)	0.26			0.14			0.16			0.20		
p	0.60			0.56			0.56			0.58		
C.I.	-30.43	39.91		-16.89	19.49		-25.25	29.61		-11.13	13.65	

TNE = Total Net Effect

WDD = Weighted Displacement Difference

Z(WDD) = Z score of WDD

Pre = 52 weeks

Post = 30 weeks

Results: offenses

Pre- to Y1. Table 7 presents models for all offenses and four separate offense types (i.e., violent, theft, disorder, property destruction) that were recorded by the police as having occurred in MHSs in the NBI treatment and control groups, comparing the pre-treatment period with year one. Across the crime categories, little measurable impact was found in the treatment group.

Overall, offenses in the treatment group decreased by 5.0%, while offenses in the control group decreased by 9.1%. TNE on all offenses was an increase of 0.76 crimes per week across the treatment MHSs. Violent crime in the treatment group increased by 12.5%, while violent crime in the control group decreased by 9.6%. Similarly, disorder offenses declined more in the control MHSs than in the treatment MHSs, with a TNE of 0.36 more disorder incidents in the NBI group. NBI MHSs outperformed those in the control group when measured by theft offenses and property destruction, with TNEs of 1.23 and 0.32 fewer offenses per week, respectively. None of the models estimated in Table 7 was statistically significant at the 0.05 level.

Table 7: Network-based Intervention - Offenses (Pre to Year 1)

	All Offenses			Violent			Theft			Disorder			Destruction		
	Pre	Post	% Change	Pre	Post	% Change	Pre	Post	% Change	Pre	Post	% Change	Pre	Post	% Change
Treatment	9.3	8.8	-5.0%	4.3	4.9	12.5%	2.9	2.2	-24.3%	0.8	0.6	-16.0%	1.3	1.1	-13.7%
Treatment Buffer	10.9	10.2	-5.7%	4.8	4.7	-2.1%	4.0	3.7	-9.2%	0.7	0.5	-19.4%	1.4	1.4	-0.7%
Control	9.7	8.8	-9.1%	4.3	3.9	-9.6%	2.7	2.8	2.2%	1.4	0.8	-42.8%	1.3	1.3	4.7%
Control Buffer	13.4	13.5	0.3%	5.9	5.6	-4.3%	4.9	5.3	8.4%	0.9	1.0	13.6%	1.8	1.6	-12.8%
TNE	-0.76			-1.31			1.23			-0.36			0.32		
WDD	-0.24			1.10			-1.55			0.22			-0.02		
S.E.	9.19			6.18			5.34			2.58			3.34		
Z (WDD)	-0.03			0.18			-0.29			0.09			-0.01		
p	0.49			0.57			0.39			0.53			0.50		
C.I.	-18.26	17.78		-11.02	13.22		-12.02	8.92		-4.83	5.27		-6.56	6.52	

TNE = Total Net Effect
WDD = Weighted Displacement Difference
Z(WDD) = Z score of WDD
Pre = 52 weeks
Post = 52 weeks

Y1 to Y2. Table 8 compares offenses within NBI and control MHSs in year one to those in year two, taking into consideration fluctuations in the buffer areas. Overall, from year one to year two, crime in the NBI MHSs increased from 8.8 per week to 9.4 per week (6.0%), while decreasing from 8.8 per week to 8.4 per week in the control group (4.2%). Unexpectedly, reported crime decreased in the NBI buffer areas while increasing in the control buffer areas. Ultimately, the TNE for the NBI group was a modest increase of 0.65 crimes per week. Violent crime in the NBI MHSs increased by 7.4% while increasing only 1.3% in the control group, resulting in a TNE of 0.52 more violent crimes per week. Destruction of property increased 22.1% in the NBI MHSs while decreasing 23.3% in the control group, resulting in a TNE of 0.70 more crimes. Conversely, changes in theft and disorder offenses demonstrated a modest improvement in the NBI MHSs relative to the control group. (As before, none of the comparisons here were statistically significant, suggesting that the observed changes may have occurred by chance.)

Table 8: Network-based Intervention - Offenses (Year 1 to Year 2)

	All Offenses			Violent			Theft			Disorder			Destruction		
	Pre	Post	% Change	Pre	Post	% Change	Pre	Post	% Change	Pre	Post	% Change	Pre	Post	% Change
Treatment	8.8	9.4	6.0%	4.9	5.2	7.4%	2.2	2.1	-7.2%	0.6	0.7	12.7%	1.1	1.4	22.1%
Treatment Buffer	10.2	9.6	-6.6%	4.7	4.9	6.0%	3.7	2.8	-24.0%	0.5	0.6	11.1%	1.4	1.2	-9.5%
Control	8.8	8.4	-4.2%	3.9	3.9	1.3%	2.8	2.5	-9.7%	0.8	1.0	20.3%	1.3	1.0	-23.3%
Control Buffer	13.5	15.2	13.1%	5.6	6.2	10.1%	5.3	4.6	-13.0%	1.0	2.1	107.0%	1.6	2.4	51.3%
TNE	-0.65			-0.52			0.47			0.10			-0.70		
WDD	-1.54			0.02			-0.08			-1.09			-0.37		
S.E.	9.16			6.27			5.09			2.70			3.37		
Z (WDD)	-0.17			0.00			-0.02			-0.40			-0.11		
p	0.43			0.50			0.49			0.34			0.46		
C.I.	-19.49	16.41		-12.26	12.30		-10.06	9.90		-6.38	4.20		-6.98	6.24	

TNE = Total Net Effect

WDD = Weighted Displacement Difference

Z(WDD) = Z score of WDD

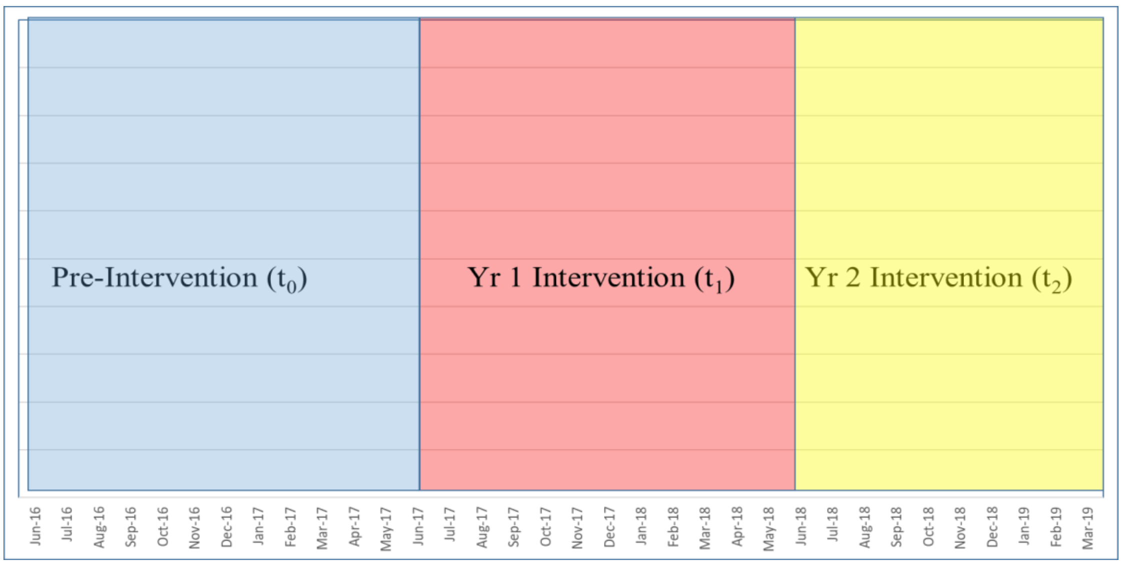
Pre = 52 weeks

Post = 30 weeks

Results: changes in violent MHS social networks

To further understand the impact of the NBI approach, for each MHS in the NBI treatment and control groups, we constructed three one-year networks: pre-treatment (July 1, 2016 through June 20, 2017); treatment year one (July 1, 2017 through June 30, 2018), and treatment year two (July 1, 2018 through June 30, 2019). (See fig. 9.)

Figure 9. Network-based Intervention Periods - Pre, Year 1 & Year 2



As noted above, 16 MHSs were randomly assigned to one of two treatment groups or to the control group. Social networks were constructed only for those in the NBI and control groups.[14] We then examined annual changes in those network structures. The social networks in the treatment groups were modeled several times throughout the project, and the social networks associated with the control group were modeled post-implementation, when the project ended. This meant that project staff and researchers would be blind to the

[14] See Part 2, *Methodology*. Note that the group of MHSs receiving saturation patrol treatment was *not* assessed with SNA; SNA was not part of that group's analytic process.

control group networks and the individuals comprising them, thus assuring that they would not receive unintended treatment or attention from KCPD.

We constructed the social networks by collecting data from EPD incident reports and field interviews (FI) for each of the NBI and control MHSs, for each time period (pre-, Y1, and Y2). Each network was first created to include all suspects involved in any reported incident and all individuals listed on FIs; next, we added all known associates of each of those persons. Whenever two or more people were listed in a single incident or FI report, a connection was created.[15] Constructing pre-treatment, year one, and year two networks for each NBI treatment MHS (n=5) and each control MHS (n=6), we created a total of 33 (i.e., 11 MHSs x 3 one-year periods) distinct social networks for our analysis.

Below, as examples of the networks we created, we have selected two graphic representations from our analyses.[16] Figure 10 represents a two-mode one-year network for an NBI treatment MHS; incidents and FIs are depicted in black, and people are depicted in blue. Figure 11 shows the same network converted to one mode, individuals only, who have been connected through mutual involvement in incident reports or FIs. Each connected cluster of dots is called a *component* (see circle in fig. 10). An *isolate* is a person who is not connected to any other person (see arrow in fig. 11).

[15] Note that in Figure 10 below, an example of a one-mode network representing only people, each dot represents an individual; the lines between the dots represent connections between two individuals.

[16] For a more comprehensive introduction to these SNA concepts, see Appendix E.

Figure 10: Two-Mode One-Year Network (Example)

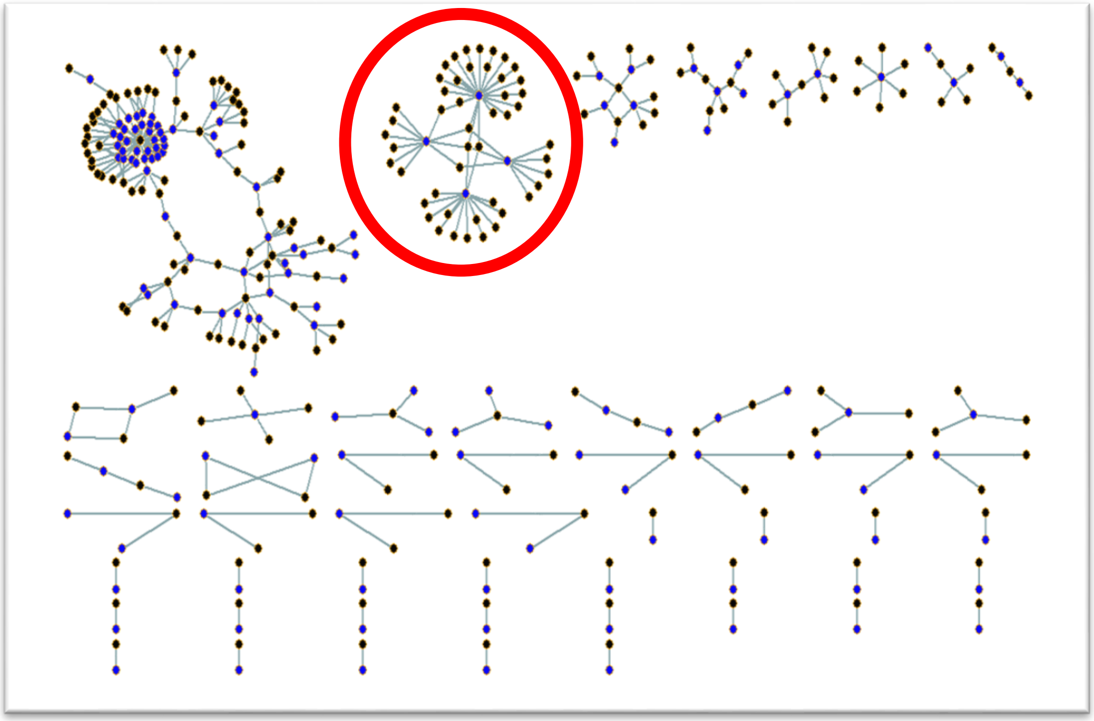
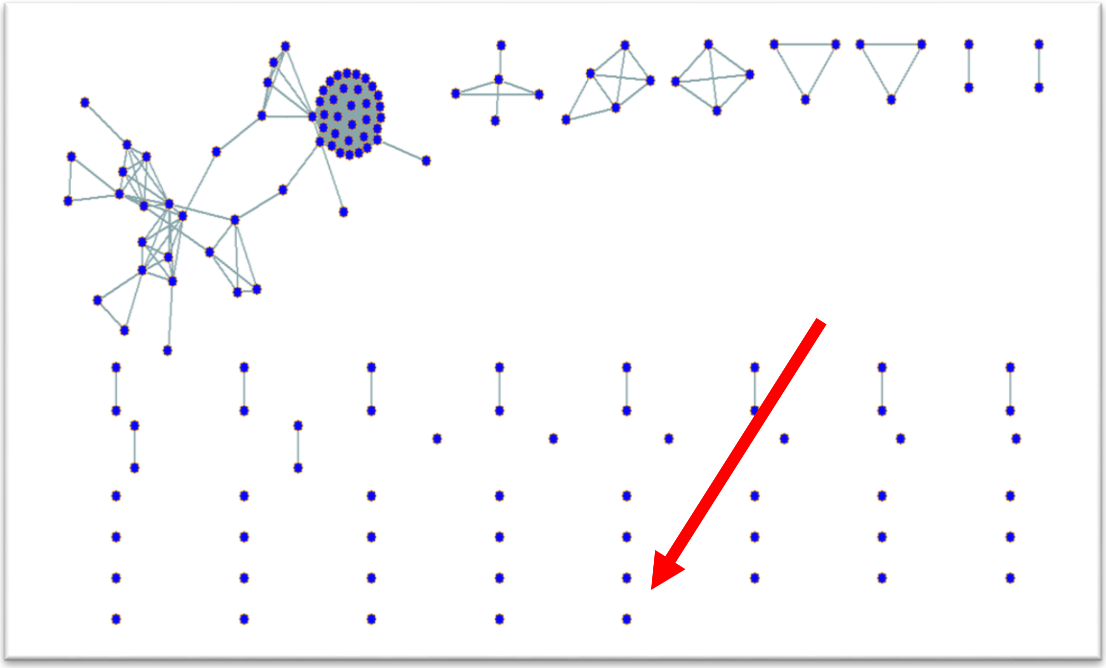


Figure 11: One-Mode One-Year Network (Example)



NBI v. control network comparisons. Comparing pre-treatment and year one NBI treatment networks, we saw some interesting differences.[17] After one year of treatment, network size decreased by 3.2%, and the number of components decreased by 6.4%. The percentage of isolates was reduced in the treatment networks by 13.5%, while in the control networks, the percentage of isolates increased by 18.2%. In terms of network density, the NBI group increased by 8.3%, while the network density in the control group decreased by 53.4%. Degree centralization decreased slightly in the NBI MHS and decreased by 33.5% in the control MHS. Betweenness centralization increased by 87.9% in the NBI MHS and decreased by 27.8% in the control MHS.

These differences in year one tell an interesting story. In the MHSs in the NBI treatment group, we see networks that are slightly denser and more centralized. This indicates that in using the NBI approach, law enforcement was recognizing connections in the network that they had not previously detected. The expansion of this valuable intelligence was almost certainly due to increased officer documentation during this project, as opposed to actual changes in the networks. Looking at the differences between the network characteristics from the year prior to implementation and the second year of the project, however, patterns in the networks in the NBI MHS do not appear to differ much from the control MHS.

[17] See Appendix E for a more detailed explanation of SNA characteristics—including terms and their significance—along with detailed network data from the MHS networks constructed and analyzed for the NBI treatment (Table E1) and control (Table E2) groups. For the tabular presentation of NBI group network data reported above, see Table E1, *Averages*. For control group data, see Table E2.

Summary

When NBI treatment was evaluated across CFS and recorded offenses, we found that it had had little apparent impact. Although high priority CFS decreased in the NBI MHSs, particularly for priority 1 calls, little measurable change was found in offenses occurring there, and the changes that were detected trended in an unexpected direction. As with previous models, none of the comparisons were statistically significant, suggesting that the changes observed may have occurred by chance.

One thing is evident as we viewed these networks: In both the NBI and the control MHS groups, the networks were sparse. Density was generally low, with large numbers of isolates and components. Working with this small number of locations, we were not seeing large, connected networks. There are two possible explanations. First, it could be that networks simply did not exist within the small geographical areas we had identified as EPD MHSs. Alternatively, perhaps such networks did exist, but the official police data lacked the amount of information needed to expose them.

Overall, the network summary indicates that in year one, networks in the MHSs in the NBI treatment group changed in comparison to networks in the control group; then in year two, the networks in the NBI and control groups appeared to have become more similar.

5. FINDINGS AND OBSERVATIONS

To briefly review, in 2017, the Kansas City Police Department implemented an experimental project to reduce crime, particularly violent crime, occurring in micro hot spots (MHS) located within the jurisdiction of KCPD's high-crime East Patrol Division (EPD). The project was designed to test two distinct interventions (treatments). First, in accord with traditional place-based hot-spot interventions, saturation patrol was deployed in five randomly assigned MHSs for a 9-week period, adhering to the Koper Curve. Second, network-based intervention (NBI) was initiated in another group of five randomly assigned MHSs, with the intention of intervening in violent social networks by providing appropriate diversion services and/or enforcement to influential offenders in those networks. Third, six randomized control MHSs were included for comparison. These efforts were monitored and evaluated using a variety of metrics, including average weekly calls for police services (CFS), average weekly offenses reported, average weekly NBI actions and activities, and yearly changes in these metrics and in the characteristics of MHS social networks. Our analysis revealed inconsistent benefits resulting from the interventions.

Saturation Patrol

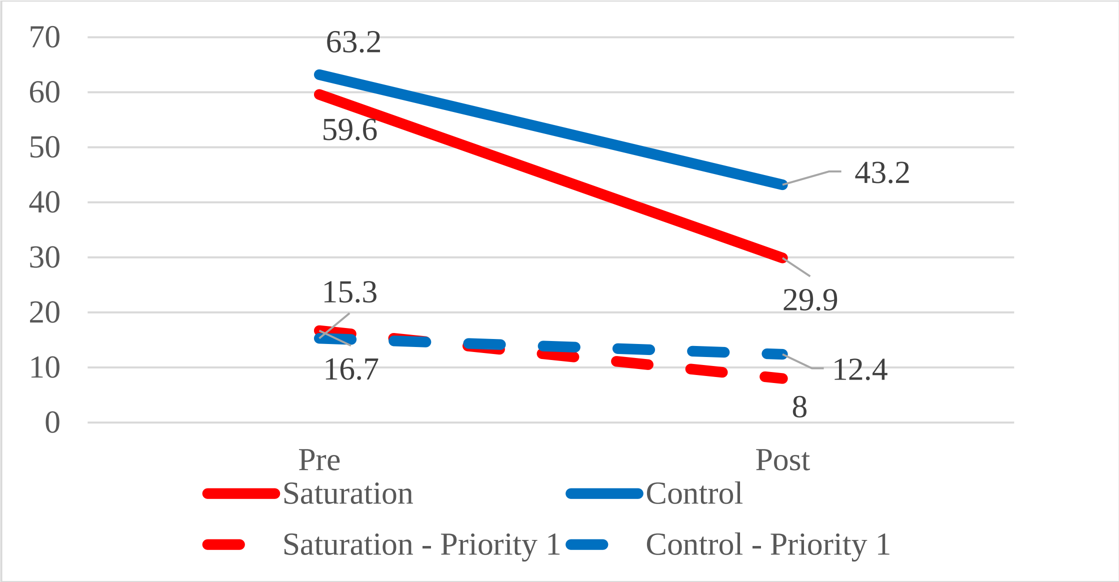
The impact of the saturation patrol treatment was measured across high priority CFS and crime/offense reports (including violent crime, theft, disorder, and destruction offenses). Treatment MHSs were compared to control MHSs, and spatial buffer zones were estimated to detect crime displacement. Rates of CFS and crime in the treatment periods were compared to trends in the two years prior to each intervention, and also to the same periods in previous years when compensating for seasonal fluctuations in crime. Findings 1 and 2 pertain to saturation patrol in MHSs in the treatment and control groups.

Finding 1: Saturation patrol resulted in fewer high priority calls for service.

Across all analyses, saturation patrol resulted in fewer high priority CFS. The total net effect (TNE) of saturation patrol was an average of about 10.75 fewer high priority calls per week; the decrease in priority 1 CFS accounted for approximately five of these. The positive results were tempered slightly by the fact that the changes were not statistically significant. Nevertheless, saturation patrol MHSs consistently outperformed control MHSs, without displacing CFS to adjacent areas. Figure 12 displays the average number of all high priority and priority 1 CFS per week in both saturation patrol and control MHSs (seasonally adjusted). Although CFS decreased over time in both MHS groups, the decrease observed in the treatment group was greater, yielding a TNE of 10.64 fewer high priority calls per week, including 5.65 fewer priority 1 calls.[18]

[18] See Table 2 for CFS results with buffer zones accounted for.

Figure 12: Saturation Patrol Group - Pre/Post Change in Ave. CFS/Week (Seasonally Adjusted)



High priority CFS represent a significant drain on policing resources; thus, reductions in their numbers is a meaningful outcome. In this study, saturation patrol required assignment of one officer to provide a physical presence in each treatment MHS for a relatively brief period (about 15 minutes), two to four times per day. This in itself represents an allocation of resources, but one that compares favorably to high priority CFS, each of which involves a response by at least one two-person unit, and often two or three such units. Emergency high priority calls are also unscheduled, resulting in unpredictable "blackout time" during which several patrol units may be out of service and unavailable to respond to other calls. Saturation patrol in violent MHSs can lower the CFS workload and help relieve the burden on personnel resources, an important and measurable benefit.

Finding 2: Saturation patrol resulted in fewer crimes, although the impact was modest.

Overall, crime decreased during the weeks when saturation patrol was occurring. This was especially obvious when comparing seasonally adjusted crime rates, where the treatment resulted in an average of 6.63 fewer crimes per week. Violent crime in treatment MHSs did not decrease by as much as other offenses did, however, and the TNE of saturation patrol on violent crime was weak and inconsistent. Our results demonstrated no indication that saturation patrol in MHSs alone impacted violent crime.

Network-based Intervention

The network-based intervention (NBI) in this study used social network analysis (SNA) to identify and understand networks of individual offenders engaged in crime, particularly violent crime, in the five randomized MHSs that comprised the NBI treatment group. As noted above, by definition, an MHS is a small geographical area where a disproportionate number of crimes and other problems are concentrated. For this study, police used SNA intelligence to identify and prioritize the most central people within the MHS networks to be recipients of either diversion (e.g., services) or enforcement actions. The logic of this approach: If an MHS's violent social network can be effectively disrupted strategically at individual levels, fewer violent crimes will be committed by those inhabiting that network—in fact, fewer CFS and crimes should be experienced in the MHS overall.

The NBI treatment was initiated in June 2017, and networks were re-estimated in June 2018. To examine the impact, rates of CFS and crime in the pre-intervention year were compared to those in year one, and year one was compared to year two. As with the saturation patrol intervention, trends in the MHSs in the NBI group were compared to those in the control group, by year (pre-treatment through year two). Unlike the saturation patrol intervention, however, the NBI intervention was examined using supplemental SNA. This allowed us to determine whether and how the structures of social networks in the treatment MHSs had changed over time. Specifically, we examined yearly changes in the NBI networks, comparing them to yearly changes in the control networks. The objective was to determine whether the NBI intervention had produced any measurable changes in the networks of offenders who were operating in the treatment areas. Findings 3 through 6 pertain to the NBI intervention in MHSs.

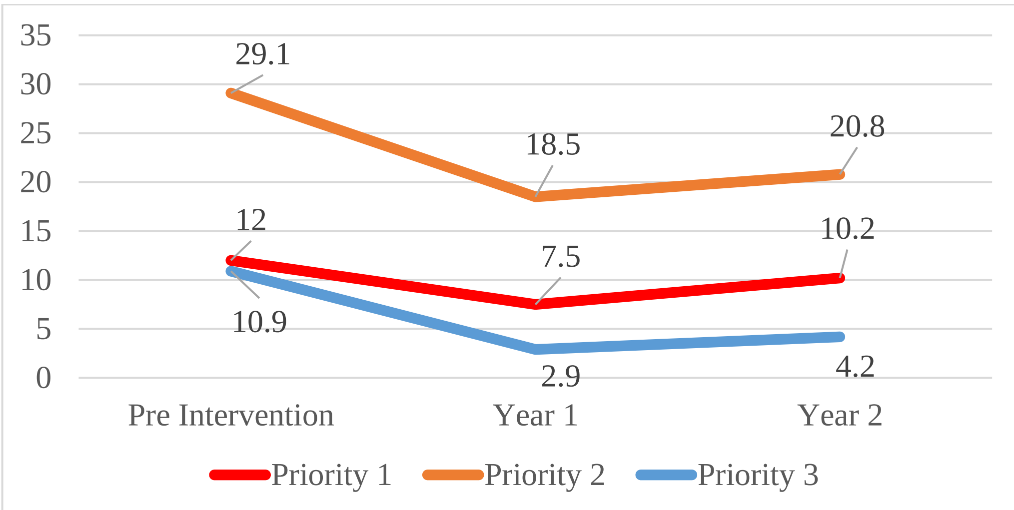
Finding 3: Network-based interventions resulted in fewer high priority calls for service during the first year of implementation.

As with saturation patrol, the first year of NBI treatment resulted in a decrease in the average number of high priority CFS per week of about 4.84, with priority 1 calls, those reporting the most dangerous situations, decreasing the most. We found a 37.4% decrease in the treatment group compared to a 24.2% decrease in the in the control group, with no displacement. This represented a significant savings in patrol resources, particularly with emergency CFS.

Finding 4. Network-based interventions resulted in increases in high priority calls for service during the second year of implementation.

The beneficial reductions in high priority CFS observed in year one were partially erased in year two, when numbers of calls regressed nearly to pre-treatment averages. All types of CFS declined in year one, then trended upward in year two. The year-two decay was not enough to return high priority calls to pre-treatment levels, but the trend did turn in an unexpected and undesirable direction. Figure 13 presents the trends in priority 1, priority 2, and priority 3 CFS for each study period.[19]

Figure 13. NBI Group - Yearly Change in Average Weekly CFS



The year-two decay in the CFS results is difficult to explain. One possible cause could be a second-year implementation difference. SNA findings indicated no change in the NBI network structures in year two when compared to the control group networks, but the reversal in results does coincide with a difference in how the SPI officer operated after becoming part of a division Impact Squad.[20] Possibly this merger diluted the officer's focused attention on NBI MHSs during the second year of implementation.

[19] Figure 13 summarizes Findings 3 and 4.
[20] For information how Impact Squads function and their possible impact on treatment, see section 6, subsection *NBI with SNA*.

Finding 5: Crime in network-based intervention MHSs experienced few changes in overall crime, and violent crime in these MHSs increased relative to control areas.

The impact of NBI on crime is unclear. There was little evidence indicating that NBI efforts had reduced crime within the treatment MHSs. Comparing the pre-period with year one, the TNE on overall crime was negligible, increasing in the treatment MHSs by an average of about 0.76 crimes per week. Violent crime increased in NBI MHSs by 12.5%, while decreasing in control areas by 9.6%; the TNE was 1.31 additional violent crimes per week in the treatment group. This is frustrating given that the focus of this intervention was disruption of violent crime. This finding engenders skepticism about the efficacy of the approach as a violent crime reduction strategy for high crime areas.

Figure 14 presents annual changes in the average weekly number of all offenses reported for the NBI treatment group relative to the control group, comparing pre-treatment and treatment periods.[21] Although from pre-treatment to year one, the average number decreased in the treatment MHSs, it decreased even more in the control MHSs. In year two, crime in the control group's MHSs continued to decline while crime in the NBI treatment MHSs rebounded to pre-project levels. Examining only violent crime (fig. 15), we see the average weekly number increasing slightly over time while violence in control areas declined slightly over time.

[21] Figure 14 summarizes findings 5 and 6.

Figure 14. NBI v. Control Group - Yearly Change in Average Weekly Offenses

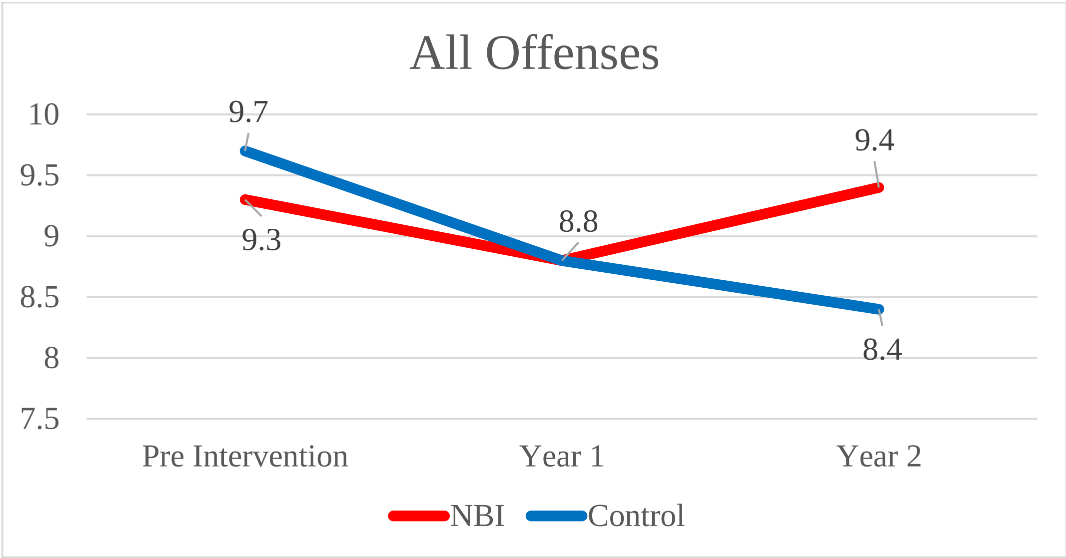
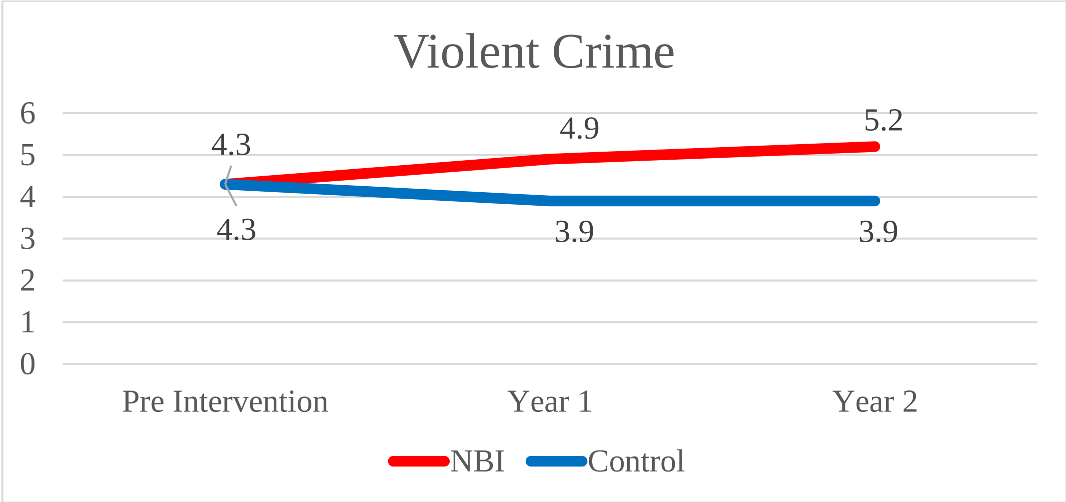


Figure 15. NBI v. Control Group - Yearly Change in Average Weekly Violent Crime



The logic of modeling deviant social networks within violent crime MHSs is that intervening with those who are most central within these networks will affect the crime rates of these small geographic areas. Such a beneficial outcome was not observed in this case, however. The intervention here lasted two years, but largely ran out of steam in its second half. The original premise was that the understanding and practice of NBI would become operationalized throughout the agency. Instead, the NBI intervention was largely subsumed by other agency priorities. In this case, the NBI treatment dosage was clearly too little to have a measurable or meaningful impact on violent crime in the targeted locations.

Finding 6. Measurable changes occurred in the social networks in the NBI micro hot spots during the first year of intervention.

Networks in the NBI treatment MHSs increased in *density* and in *betweenness centralization*, contrary to what we saw in the MHSs in the control group. Since NBI was a police-based intervention, these changes were likely the result of changes in policing practices. The control group networks showed what normally would have happened in those networks had officers not been intervening. The measurable changes in the NBI treatment group's networks indicated that officers were doing something different.

These findings were likely due to the SPI project as officers began noting and documenting *connections* in the field. The increase in network *density* meant that more connections between individuals were being identified and documented in administrative data. An increase in *betweenness centralization* meant that connections between groups were also being recognized and documented.[22] Both of these indicators suggested that during the first year of the project, officers were becoming increasingly focused on the network of offenders engaged in crimes in the NBI MHSs. In the second year, however, network patterns in the treatment group looked more similar to those in the control MHSs,

[22] For more information about social network analysis and these indicators, see Appendix C (SNA literature review) and Appendix E (an overview of NBI with SNA, including an explanation of these terms).

suggesting that the strength of the intervention had diminished rather than carrying over to the second year, as hoped.

The reality of this as a possibility is important to keep in mind when using police-generated intelligence to estimate violent social networks. Initial SNA models may present only rudimentary network structures, although these are useful for planning early interventions. Executing strategies designed to focus attention on individuals with key positions within offender networks will necessarily change the overall network structure, and these changes must be reflected as they occur—that is, as the structure develops into a denser, more centralized network. A network becomes more dense as additional documentation reveals connections between more and more of its people, and the network's centralization increases as more connections between clusters of people emerge. When implementing NBI crime prevention approaches, then, it is important to continuously re-estimate the model over time as the social network reacts to external (police) forces, to ensure that the intelligence drawn from it reflects the most current, valid representation of the social network as it exists on the street.

6. INTEGRATION AND SUSTAINABILITY

Saturation patrol, network-based interventions, and the use of micro hot spots, as implemented in this SPI study, were integrated into the Kansas City Police Department's organizational culture and practices to varying degrees and only up to a point, post-treatment. Some principles associated with the strategies gained partial penetration within the organization. For example, most officers understood the logic and saw the value of saturation patrol; for many, this strategy passed the officers' "sniff test." A smaller number of officers remained disinterested in the content of the post-study debriefing and the "why" behind these approaches, taking the attitude that "I don't need to know why I'm doing this—just tell me what to do and I'll do it." Interestingly, there were no differences in program fidelity across these two groups; both engaged in the activities with a high degree of compliance and fidelity. But the latter group represents a missed opportunity to translate evidence-based approaches into day-to-day practices and so, moving forward, those strategies are less likely to be integrated and sustained by the police.

Saturation Patrol

We believe that for this (or indeed, any) policing strategy to be sustainable, it needs to be widely understood, supported, and practiced. We suggest that officers assigned to general policing functions be assigned to patrol micro hot spots during their regular shifts, between other calls and obligations. Each visit should be brief (10-15 minutes, to conform to the Koper Curve); thus, officers could provide added policing presence (saturation patrol) in violent micro hot spots while in service but not otherwise engaged. This could accomplish several objectives. First, saturation would be achieved with existing resources, without needing to schedule overtime or create special units. Second, officers assigned to general policing would better understand the micro hot spots within their coverage areas, and the hot spots would be reinforced and better defined as their networks routinely incorporated the officers' latest intelligence. Third, MHS saturation patrol would become part of the general policing responsibility rather than "someone else's job." Full integration of a proven, well-defined, data-driven violence reduction practice into day-to-day policing could help transform the cultural understanding of the job into one that better balances effective deterrence with enforcement.

Alternatively, some police departments might find it more feasible to implement sustained saturation policing by creating with a dedicated unit, similar to other specialized units (e.g., traffic, street narcotics). Such a unit would partner with crime analysts to identify micro hot spots, track MHS policing activities, and measure strategic outcomes. This has certain drawbacks: Special units can be expensive to maintain and they often divert personnel from other important functions. Such drawbacks can compromise the benefits or returns on investment of the reduced calls for service that were highlighted in this report. Also, separation of duties may compromise sustainability; whenever a function is "someone else’s job," others are less likely to be aware of and value those activities, their goals, and underlying rationale, and so are unlikely to support and engage in them.

Regardless of the specific operational approach taken, all officers need to be well-informed about the goals and objectives of saturation patrol in micro hot spots. The philosophy and demonstrated success of the strategy must be communicated to those most directly involved. Officers should be encouraged to understand and appreciate the "why," not only the "how." Explaining the expected outcomes (e.g., reductions in high priority CFS and some types of crime) provides greater context for the activities they are assigned to perform. The significant impact of using data and data-driven decision making on workload and resource allocation then becomes self-evident, not only to those directly involved, but to the wider organization and the public. In the current project, officers engaged in saturation patrol in micro hot spot policing were debriefed and the goals and logic of the approach were explained to others.

Micro Hot Spots

Like other police departments, KCPD uses calls for service and jurisdictional crime trends to influence staffing and allocate patrol operations. Once the current study ended, it was unclear whether or not the micro hot spot approach, as defined and implemented here, would be sustained despite having shown some resource allocation benefits. The practice of purposefully defining micro hot spots as small, concentrated geographic areas of disproportionate crime has not appeared to have taken hold.

NBI with SNA

The use of network-based intervention with SNA as a strategy in itself thus far has been sustained. Several KCPD analysts are now trained and routinely produce SNA products for investigative and patrol applications. (Note, however, that these seem to have been adopted more for retrospective investigations and are not yet commonly used for proactive crime prevention.) Midway through this experiment, each of the Department's six patrol divisions incorporated a dedicated Impact Squad to initiate and conduct preventive strategies. Each Squad consisted of a supervisor and four to six officers who were otherwise unencumbered by general policing services (e.g., responding to CFS), their time kept free for prevention activities. On occasion, the Impact Squads did make use of the NBI approach pioneered in the SPI project. This was most often the case in the East Patrol Division, where the SPI project was carried out, given Squad members' direct experience with the strategy.

When NBI was operationalized, it became clear early on that its application in the treatment micro hot spots would require a dedicated NBI-trained officer. This person became not only the assigned SPI officer for implementing NBI, but also the strategy's designated subject matter expert and champion, responsible for interpreting and promoting its goals and methods among peers. This role was critical to the success of the project, and it also gave the NBI approach credibility and an opportunity to take root.

The benefits of this arrangement came with a logistical drawback, however. KCPD policy required that more than one officer be involved in virtually all enforcement activities, such that most patrol officers were assigned to two-person units. When enforcement actions within the treatment MHSs' violent networks were required, rather than acting alone, the SPI officer had to ensure that a second officer would be available, on overtime, to assist or partner during the action. Obviously, this protocol frequently resulted in delays and logistical complications.

After the first year, the SPI officer was reassigned to EPD's Impact Squad. This helped to solve the above problems. The officer gained quicker access to backup for NBI enforcement actions, and the audience for communicating the rationale and logic behind NBI became broader. This has implications for sustainability of NBI innovations because more members of the organization were exposed to the SPI approach – greater exposure increases the likelihood of sustainability. On the downside, however, the SPI officer's responsibilities expanded to include the Squad's other efforts, and even when those priorities fell outside NBI actions, the SPI officer was expected to become involved. No longer being dedicated full-time to SPI duties turned out to be a reasonable trade-off, however, for resolving the logistical complications of the previous arrangement.

The midpoint organizational shift to reliance on Impact Squads seemed to benefit the Department overall. Supervisors and officers in EPD's Impact Squad in particular gained exposure to NBI and gradually came to understand its purpose, tactics, and utility. We are unaware of any plan to continue to train analysts or officers on the construction or use of SNA in this context, however. At this time, KCPD seems unlikely to continue the SPI interventions initiated in this study. Nonetheless, we hope that the benefits gained from using data to focus departmental resources on those people and places most closely associated with violent crime have been apparent and sufficient to support retention and further integration of data-driven strategies to inform and monitor the results of the Department's continuing violence prevention efforts.

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Appendix A. Analytic Strategy

To determine the impacts of the saturation patrol and NBI interventions, we used Wheeler and Ratcliffe's (2018) Weighted Displacement Difference (WDD) estimator. Wheeler & Ratcliffe (2018) define the WDD as: WDD=(T_{t1}- T_{t0}) - (C_{t1}- C_{t0}) + (TB_{t1}- TB_{t0}) - (CB_{t1}- CB_{t0}). In this equation, C=control, T=treatment, TB=treatment buffer, CB= treatment buffer, t_0=pre-intervention, and t_1=post-intervention. The variance is estimated as: V(WDD)=T_{t1}+ T_{t0} + C_{t1}+ C_{t0} + TB_{t1} + TB_{t0} + CB_{t1} + $CB_{t0.}$ An estimate of Z is therefore: Z(WDD)=WDD/ $\sqrt{V(WDD)}$.

WDD calculates whether place-based interventions in treatment areas differ significantly from comparison areas, taking into consideration spatial displacement or diffusion of benefits. WDD requires both pre- and post-treatment crime counts from four separate geographic areas, the (a) treatment area, (b) control area, (c) treatment buffer area, and (d) control buffer area. WDD is an improvement over similar estimation strategies because it enables researchers to estimate standard error, Z scores, and subsequent *p* values following a normal distribution, thereby estimating whether changes in crime counts in treatment areas are significantly different from those in control areas.

Further, Wheeler & Ratcliffe (2018) provide guidance interpreting the strength of evidence of Z(WDD) when crime counts are relatively low, specifically:

If Z(WDD) = -1.3, then weak evidence of a reduction

If Z(WDD) = -1.6, then evidence of a reduction

If Z(WDD) = -2.3, then strong evidence of a reduction

If Z(WDD) = -3.1, then very strong evidence of a reduction

Included in our analyses is a rough estimate of the change in the number of crimes and calls per week, or Total Net Effect (TNE).[23] The key estimate measure to consider is the relative change of crime in treated hot spots and control areas while taking spatial displacement into consideration. Neutral (or 0) values indicate no impact. Positive TNE values indicate a positive response to the intervention; the larger the absolute value, the greater the effect. Negative TNE values indicate an ineffective response; the larger the absolute value of a negative TNE, the greater the ineffectiveness. That is, given a value of -5 for one outcome and -7 for another outcome, the -7 TNE would be an even worse negative response than the -5 TNE. Overall, for example, since our analyses focused on weeks, if the TNE were 4.2, then 4.2 fewer crimes per week were reported for the intervention area, resulting in a positive response to the intervention (Guerette, 2009). The WDD and TNE estimations were repeated for all periods of analysis.[24]

[23] Guerette & Bowers (2009) define the Total Net Effect as: $TNE=(T_{t0} * (C_{t1}/C_{t0}) – T_{t1}) + (TB_{t0} * (C_{t1}/C_{t0})-TB_{t1})$. In the above equation, TB=treatment buffer, C=control, T=treatment, t_0=pre-intervention, and t_1=post-intervention.
[24] For T_0, T_1, and T_2, see figure 5, *Outcomes Analysis* section.

Appendix B. Hot Spots Policing: Literature Review

Saturation patrolling, or deterrence policing, is the accelerated use of patrols in designated areas, meant to discourage crime and increase the public's sense of safety. The Kansas City Preventive Patrol Experiment (KCPPE) was one of the earliest studies (1972-73) to test the strategy's effectiveness. Researchers analyzed and compared outcomes for three conditions: (a) proactive patrol (three times the routine patrol presence), (b) reactive patrol (police presence only in response to calls for service, no preventive patrols), and (c) routine patrol (an area's norm, no change). They concluded that "the three experimental patrol conditions appeared not to affect crime, service delivery, and citizen feelings of security in ways the public and the police often assume they do" (Kelling et al., 1974, p. 3). Many then came to believe then that random patrol, previously assumed to be the "backbone of policing," was ineffective.

Later, however, others suggested that the KCPPE study had methodological limitations that had probably masked certain treatment impacts. For example, Sherman & Weisburd (1995) criticized the study for having weak statistical power and being deficient in determining exact treatment dosages, and other more recent studies have shown hot-spots policing, an evolved form of deterrence policing, to be effective for crime prevention. In Minneapolis, studying crime and disorder within small geographic units of analysis, Sherman, Gartin, and Buerger (1989) observed that 50% of such calls for service were originating from only 3% of all possible geographic locations (e.g., property parcels, street segments, intersections) which they referred to as "hot spots." Subsequently, Weisburd and Telep (2014) began labelling such areas experiencing high rates of crime as "micro-units of geography." Regardless of the terms used for concentrated high-crime locations, law enforcement increasingly leaned towards strategies that focused resources on small geographic areas with comparatively high levels of crime. Policymakers, ever in pursuit of more effective and efficient use of resources, began to seek hot-spots-based crime reduction strategies.

In 2007, Braga published a meta-analysis of hot-spots policing studies, an overview of the different treatments employed that includes each study's research design and definition of "hot spots." Braga concluded that the "extant evaluation research seems to provide fairly robust evidence that hot-spots policing is an effective crime prevention strategy" (p.18). Telep and Weisburd (2014) conducted a deeper review of some of the studies included in Braga's meta-analysis, including the Jersey City Problem-Oriented Policing in Violent Places experiment (Braga et al., 1999), the Jersey City Drug Market Analysis Program (Weisburd & Green, 1995), the Oakland Beat Health Study (Mazerolle, Price, & Roehl, 2000), a problem-oriented policing intervention in Lowell, Massachusetts (Braga & Bond, 2008), an experimental study in Jacksonville, Florida (Taylor & Woods, 2011), and foot patrol studies in Philadelphia and Kansas City (Ratcliffe et al., 2011; Novak et al., 2016). Although these studies had implemented hot-spots policing in different ways, each of their outcomes indicated that the underlying strategy was effective for crime prevention.

As a place-based approach, hot-spots policing involves systematically identifying and linking small high-crime locations and then focusing policing resources in those areas (Telep & Weisburd, 2014; Weisburd & Telep, 2014). Tactics used have included problem-oriented policing, third-party policing, and merely scheduled increases in police presence. Studies of specific hot-spots policing approaches have not always indicated exactly what officers ought to be doing when patrolling treatment areas. Regardless of the approach employed, when testing its effectiveness, it is important to define the treatment clearly and to ensure treatment fidelity and accurate measurement of the treatment dosage. Telep, Mitchell, & Weisburd (2014) conducted a study to examine how officers might optimize the directed patrol dosage, as some critics were questioning whether having officers spend time in hot spots would detract from time spent on proactive policing (i.e., generally increasing police presence and fostering community engagement). Their study showed the opposite to be true. Within the specified hot-spot areas, officers were increasing the levels of community engagement in facilitating crime prevention and reduction solutions.

Although this is all valuable information, additional research continues to be needed to better understand specific aspects of hot-spots policing, such as the optimal period an officer should spend in an area, how to sustain proactivity, and whether or not unrelated calls for service should be accepted while in the treatment area. Some researchers have identified unaddressed aspects of hot-spots policing, but so far only one has offered specific guidance. Koper (1995) set out to determine the optimal length of time police should be present in a hot spot and the point at which police presence ceases to add a benefit. Koper found that 10 minutes was the minimum threshold for effectiveness and that more than 15 minutes ceased to be effective (p. 668). Others have conducted variations on Koper’s study; nearly all concur that determining and adhering to a strict, accurate dosage is crucial for effectiveness and that outcomes are significantly affected when treatment dosage is not measured and correctly applied (Weisburd & Telep, 2014; Sherman et al., 1995).

Some have questioned whether crime reductions found in hot-spots treatment areas might be due to displacement—the relocation of crime from a treated area to another nearby. Several studies have shown that the phenomenon of crime displacement is not that common. In 1995, Sherman & Weisburd studied the issue and concluded “displacement is merely a rival theory explaining why crime declines at a specific hot spot if it declines” (p. 629). Braga’s 2007 meta-analysis also found little evidence of spatial displacement in its hot-spots policing studies (Telep, Mitchell & Weisburd, 2014).

Still, researchers should know what to look for and how to measure for potential displacement. Green (1995), for example, has proposed that right-sized buffer zones surrounding treatment areas are crucial in any examination of place-based policing strategies, adding that buffer areas typically should be about two city blocks wide. In a more recent study, Gibson, Slothower, and Sherman (2017) defined the purpose of buffer zones as "to test for any displacement of crime or incidents into the immediate surrounding areas [or the contrary] and ‘diffusion of benefits’ of reduction in crime and disorder in areas surrounding treatment hot spots” (p. 6). For some researchers, identifying buffer zones and measuring displacement has actually suggested that the benefits of an effective intervention may be as likely as (or more likely than) crime to be displaced (Clarke & Weisburd, 1994). The National Research Council of the National Academies reviewed many displacement studies, and only one, the Hope study (1994), found a statistically significant amount of crime displacement. The Council’s review suggested that, rather than crime displacement, the diffusion of crime control benefits was more prominent and appeared to have a larger impact (Skogan & Frydl, 2004). In foot patrol studies, as well, diffusion of crime control benefits seems to have occurred following treatment (Novak et al., 2016).

Finally, Cohen and Felson's (1979) Routine Activities Theory has established a theoretical foundation for hot-spots policing, setting out three criteria that are apt to result in crimes of opportunity when they occur simultaneously: (a) motivated offenders, (b) suitable targets, and (c) the absence of capable guardians (p. 470). Theoretically, altering any one of these elements would disrupt opportunity and thereby reduce crime. Hot-spots policing intervenes by adding police presence (thus disrupting "c"). The intervention has been considered an improvement over the one-size-fits-all standard policing model that Weisburd and Eck (2004) considered ineffective: "This new openness to innovation and widespread experimentation in new practices [has been] part of a renewed confidence in American policing that could be found among not only police professionals but also scholars and the general public" (p. 43).

Appendix C. Social Network Analysis: Literature Review

Social network analysis (SNA) is a technique for examining the social relationships of individuals or groups by using dots and lines to visually represent the data in networks. Dots, or *nodes*, represent individuals or groups within networks, and the lines between nodes (ties) represent the relationships between them. More than just a set of research tools, SNA is widely recognized as a “broad intellectual approach” (Wellman, 1983, p.156), useful for exploring the relationships among individuals, neighborhoods, organizations, countries, and anything else that conceivably might be connected. SNA focuses on and measures interdependencies among people (Wasserman & Faust, 1994); these *patterns of interdependencies* are viewed as important pieces of a puzzle (see Papachristos & Wildeman, 2014).

For example, Papachristos, Braga, and Hureau (2012) used SNA to show that in Chicago, 70% of that city’s nonfatal gunshot victimizations had occurred within co-offending networks that contained less than 6% of its population. The same study demonstrated *social contagion*, showing that being socially connected with a perpetrator or victim of violent crime increased one’s own probability of future involvement in violence, whether as a perpetrator or a victim. Previous research has demonstrated that using SNA to process police intelligence for decision making is more efficient than processing police intelligence alone. This is especially true with multijurisdictional crime. SNA enables the visualization of geographical and social aspects of criminal networks; it reveals both the big picture and the details of a known criminal population.

An important advantage of using SNA to examine the social structures of criminal populations is that it exposes the identities of individuals who are most central in their networks, those who have the greatest influence on other members. Bouchard and Konarski (2014) used SNA to analyze a co-offending network[25] in order to evaluate law enforcement's strategy for dismantling the network by targeting the six individuals thought to be its most influential members. Constructing the co-offending network visually, they discovered that ten additional gang members were at least as central as the six originally targeted by police. Core analysis showed that just four of the original six actually ranked at the top in terms of influence, and the individual who ranked highest had been entirely overlooked. This clearly demonstrates how intervention decisions based on police intelligence alone can fall short of achieving law enforcement objectives and contribute to an ineffective allocation of resources.

Research has shown that understanding social networks, particularly deviant social networks that include but are not limited to gangs, is essential for discovering crime patterns. Such research has also shown that membership in offender networks is linked with vulnerability to crime victimization, specifically violent crime victimization (Papachristos & Wildeman, 2014; Papachristos, Braga, & Hureau, 2012). A person's affiliation with and position within a deviant social network is a risk factor for victimization, just as other demographic characteristics, social factors, lifestyle choices, and ecological factors differentially expose individuals to victimization. Identifying deviant social networks and understanding their structures and the individual positions

[25] Co-offending networks are those with two or more members who have committed a crime together.

within them allow law enforcement analysts to calculate victimization risk in order to tailor mitigating crime prevention strategies to local circumstances. SNA offers the means of comprehending and measuring such group structures and individuals' roles within them (Haynie, 2001; Snijders et al., 2009).

The position an individual holds within a gang is most often determined by that person's number of friends in the gang and involvement in gang activities. Klein (1971) proposed four position types that gang members may occupy: hard core, inner core, outer fringe, and fringe-fringe. Yablonsky (1962) used the artichoke as a metaphor for understanding the implications of gang structure for law enforcement: It is necessary to peel away the outer layers (fringe), he asserted, to get to the heart (core). The differences between fringe and core gang members have implications for their respective behaviors (Klein, 1995). Core members are more involved in formal gang activity, more likely to be arrested, and more violent, and their delinquent careers start earlier. SNA provides the tools needed for identifying the position an individual might occupy within a gang and in one's social world, the latter likely consisting of both gang and non-gang members.

Morselli (2009) conducted case studies using SNA with police data to understand the organization of criminals and gangs. Investigating the Hell's Angels, using electronic surveillance to track associations between individuals, Morselli identified the members who were more central to the network and others who operated on its periphery. Interestingly, individuals who would be considered full members in the biker gang did not necessarily have the most connections, even though they held strategic positions and were crucial in connecting different parts of the gang network. This suggested that individuals' contributions to or leverage in the network were not dependent on them having the most connections (Morselli, 2010). Social networks and one's position within them are shown to determine individuals' access to resources (material and intellectual) and deviant opportunities (Granovetter, 1973; Fleisher, 2002). This suggests that police interventions aimed at breaking up a gang should not simply target the most central members in a given network; others in fringe positions may also be highly instrumental in perpetuating the gang (Bright et al., 2015; Hashimi & Bouchard, 2017).

Data from police investigation case studies have been used to understand the centrality and roles of individuals within gang networks, providing significant new insights into their social structures. This has had two limitations, however. First, the selection of the data collected is unique to each investigation and therefore is not consistently replicable in any practical way. Second, the selection of individuals included in a given network is determined by police for variable investigative reasons that cannot be assessed, while for research to be replicated and generalized, systematic selection criteria are needed. When acknowledged by researchers, both limitations can be managed. Still, social networks constructed in the context of a specific investigation will focus on key people and their roles and relationships—persons who are already known to investigators. Inevitably, such networks become evident only after a crime is committed. Although SNA in these circumstances still helps to clarify the social relationships of victims, suspects, and witnesses, post-incident analysis will fall short of exploiting SNA's significant potential for informing and helping to cultivate meaningful crime prevention and intervention strategies.

Appendix D. SPI Activity Tracking Form

Micro Hot Spot

- ☐ MHS #5 (Independence AV/Norton AV)
- ☐ MHS #11 (E 24 ST/Denver AV)
- ☐ MHS #13 (Wheeling AV/Park Tower DR)
- ☐ MHS #14 (E 43 ST/ Benton BL)
- ☐ MHS #15 (E 31 ST/Prospect AV)

Tracking Done By ____________________

Date ____________________

SPI TRACKING FORM

Time (Start) ____________________ (Stop) ____________________(Total Time) ____________________

Location ____

Activities engaged in

- ☐ Custom Notification
- ☐ Community Meetings
- ☐ Conflict Resolution
- ☐ Neighborhood Accountability Board
- ☐ Enforcement Activities
- ☐ Community Event
- ☐ Intelligence Gathering
- ☐ Directed Patrol
- ☐ Other:____________________

Brief description of the activity

Related CRNs/FIFs

Contacts' Information (Name/Race/Sex/DOB/Address/Etc)	Resides in MHS area?	SPI Target?	Relationship to SPI
(1)________________________________	☐	☐	____________
(2)________________________________	☐	☐	____________
(3)________________________________	☐	☐	____________
(4)________________________________	☐	☐	____________
(5)________________________________	☐	☐	____________
(6)________________________________	☐	☐	____________
(7)________________________________	☐	☐	____________
(8)________________________________	☐	☐	____________
(9)________________________________	☐	☐	____________
(10) ________________________________	☐	☐	____________

Follow-ups needed ☐ Yes ☐ No

Follow-up notes

Appendix E. Network-based Intervention w/ SNA: An Overview

Social network analysis was used with the NBI treatment to measure certain characteristics of the offender networks and to help identify the flow of information and individuals' roles and degrees of influence within them. *Density* is the most commonly used measure of a network's cohesion; a density measure is the proportion of ties (i.e., direct connections between members) that exist over the total number of ties that could potentially exist (Wasserman & Faust, 1994; de Nooy, Mrvar & Batagelj, 2011). If everyone in the network was tied to everyone else, the density of that network would be 1; if no one was connected to anyone else, the density would be 0. Thus, the closer the density measure is to 1, the denser and more cohesive the network. (See Table E1, NBI SNA – Treatment Group Descriptives and Table E2, NBI SNA – Control Group Descriptives, below.)

We next examined each network's level of *centralization*. Centralization measures and describes the *flow of information throughout the network*. High levels of network centralization indicate role differentiation in the network (i.e., not everyone in the network is equal). The greater the number of roles, the more some individuals in the network will be advantaged with respect to access to information (and/or whatever else the network has to offer). Centralization refers to the entire network, while *centrality* refers to a specific node (individual or group) in the network. As in the previous section, the four measures of centralization used in the present study are *degree* centralization, *closeness* centralization, *betweenness* centralization, and *eigenvector* centralization. Only degree centralization and betweenness centralization are represented in the tables below, but the other two measures are also explained here for context.

First, degree centralization is a measure ranging from 0 to 1, with 1 indicating the most centralized network. The *degree* of a node is the number of ties it has to other nodes in the network. Thus, degree centralization is calculated as the variation in degree among nodes divided by the maximum possible variation in a network of the same size (de Nooy, Mrvar & Batagelj, 2011; Wasserman & Faust, 1994). The more variation in degree there is in a network, the more centralized that network is. This might seem counterintuitive at first, but if everyone had equal access to all other individuals in a network, then the network would inherently not be centralized; instead, everyone would have equal access to information. For this reason, more diversity in positions and degree will mean more overall network centralization generally (de Nooy, Mrvar & Batagelj, 2011).

The second measure of centralization is *betweenness centralization*. Betweenness can best be understood in terms of the flow of information. If information were to flow through a network, as it often does, who are the people that information would have to flow through most frequently, and who are the individuals through whom information does not flow? As with the previous centralization indices, the betweenness centralization measure is calculated as the variation in betweenness centrality measures (the individual-level measure of betweenness) divided by the maximum possible variation in betweenness centrality in a network of the same size. Again, higher variation is an indication that the network is more centralized—that information must flow in distinct ways and not through random avenues.

The final centralization measure to be presented is *eigenvector centralization*. Eigenvector centralization adds the weight of who your associates know. Thus, it is not just *who* you know, but *how connected* your friends are to others in the network. Eigenvector centralization is calculated as the variation in eigenvector centrality (individual measure of eigenvector centralization) divided by the maximum possible variation in eigenvector centrality (de Nooy, Mrvar & Batagelj, 2011)

Table E1: NBI SNA - Treatment Group Descriptives

	Year Prior	Year 1	Year 2
NBI Hot Spot 5			
People	136	91	76
Components	21	16	16
Isolates	44	32	31
Density	1.40%	2.10%	1.60%
Degree Centralization	0.061	0.115	0.079
Between Centralization	0.005	0.015	0.003
NBI Hot Spot 11			
People	156	142	114
Components	23	17	23
Isolates	40	42	32
Density	5.30%	1.70%	1.52%
Degree Centralization	0.195	0.076	0.066
Between Centralization	0.014	0.032	0.007
NBI Hot Spot 13			
People	122	126	162
Components	22	23	23
Isolates	72	40	76
Density	0.50%	1.40%	1.00%
Degree Centralization	0.019	0.051	0.084
Between Centralization	0.001	0.008	0.005
NBI Hot Spot 14			
People	40	73	29
Components	8	10	2
Isolates	19	32	25
Density	2.60%	5.00%	0.50%
Degree Centralization	0.135	0.134	0.033
Between Centralization	0.011	0.003	0.000
NBI Hot Spot 15			
People	111	115	184
Components	20	22	31
Isolates	53	45	80
Density	1.10%	1.60%	0.83%
Degree Centralization	0.053	0.082	0.073
Between Centralization	0.002	0.004	0.005

T1	**7/1/16 to 6/30/17**
T2	**7/1/17 to 6/30/18**
T3	**7/1/18 to 6/30/19**

Average	Year Prior	Year 1	Year 2	Pre-Y1 change	Pre-Y2 change
People	113	109	113	-3.2%	0.0%
Components	19	18	19	-6.4%	1.1%
Isolates	46	38	49	-16.2%	7.0%
% Isolates	40.4%	34.9%	43.2%	-13.5%	7.0%
Density	2.2%	2.4%	1.1%	8.3%	-50.0%
Degree Centralization	0.093	0.092	0.067	-1.1%	-27.6%
Between Centralization	0.007	0.012	0.004	87.9%	-39.4%

Table E2. NBI SNA – Control Group Descriptives

	Year Prior	Year 1	Year 2
Control Hot Spot 1			
People	88	63	91
Components	12	9	17
Isolates	36	40	32
Density	1.8%	0.9%	2.3%
Degree Centralization	0.076	0.039	0.169
Between Centralization	0.011	0.001	0.014
Control Hot Spot 2			
People	131	139	125
Components	22	19	21
Isolates	57	64	61
Density	0.80%	0.90%	0.80%
Degree Centralization	0.039	0.049	0.033
Between Centralization	0.002	0.002	0.001
Control Hot Spot 7			
People	141	113	81
Components	18	22	16
Isolates	35	40	30
Density	6.30%	1.30%	1.50%
Degree Centralization	0.203	0.042	0.074
Between Centralization	0.054	0.002	0.004
Control Hot Spot 8			
People	119	94	42
Components	12	13	8
Isolates	33	31	20
Density	8.80%	3.60%	2.30%
Degree Centralization	0.239	0.172	0.052
Between Centralization	0.0253	0.057	0.002
Control Hot Spot 10			
People	66	81	77
Components	11	14	16
Isolates	41	41	35
Density	0.80%	1.40%	1.10%
Degree Centralization	0.038	0.076	0.029
Between Centralization	0.001	0.002	0.001

T1	**7/1/16 to 6/30/17**
T2	**7/1/17 to 6/30/18**
T3	**7/1/18 to 6/30/19**

Control Hot Spot 20

People	37	56	66
Components	10	12	13
Isolates	10	19	25
Density	3.80%	2.30%	2.10%
Degree Centralization	0.107	0.089	0.073
Between Centralization	0.005	0.007	0.005

Average	**Year Prior**	**Year 1**	**Year 2**	**Pre-Y1 change**	**Pre-Y2 change**
People	97.0	91.0	80.3	-6.2%	-17.2%
Components	14.2	14.8	15.2	4.7%	7.1%
Isolates	35.3	39.2	33.8	10.8%	-4.2%
% Isolates	36.4%	43.0%	42.1%	18.2%	15.6%
Density	3.7%	1.7%	1.7%	-53.4%	-54.7%
Degree Centralization	0.117	0.078	0.072	-33.5%	-38.7%
Between Centralization	0.016	0.012	0.005	-27.8%	-72.5%