Effects of multimodal police and community development interventions on violent crime in a target area of Youngstown, Ohio

by

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ABSTRACT

This research addresses the results of multimodal interventions within a target area on the south side of the city of Youngstown, OH. The Youngstown Police Department (YPD), Youngstown Neighborhood Development Corporation (YNDC), and Youngstown State University (YSU) commenced this strategy due to the disproportionally high rate of violent crime on the city's south side compared with national averages and the city as a whole, in addition to high rates of poverty, urban decay, unemployment, and low rates of formal education. The hypothesis is that intervention reduces specified UCR Part 1 violent crimes. Crime data was analyzed by block group (target area $N = 7$; control area $N = 7$) over thirty-six months. Independent and paired samples t-tests on the limited set of data show the results of intervention to be effective but not statistically significant. Likewise, an innovative crime reduction calculator developed for criminal justice practitioners also showed the interventions to be strongly successful for crime reduction in the target area compared to the control, with overall violent crime being reduced by 29.1%, robberies by 53.6%, and aggravated assaults by 4.0%.

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CHAPTER I

Introduction

The principal measure of crime in the United States is by eight major categories, collectively known as Part I crimes, which help to form the Universal Crime Report (UCR): criminal homicide, forcible rape, robbery, aggravated assault, burglary, larceny-theft, motor vehicle theft, and arson. The city of Youngstown, Ohio, located in the northeast portion of the state and comprising approximately 34 square miles, has experienced violent crime at a rate higher than the national averages for at least the last twenty years (Uniform Crime Reporting Program, 1984 - 2014). As of 2014, the national crime rate (measured per 100,000 people) for overall violent crime was 375.7, with Youngstown's rate at 660.3; for criminal homicide the national rate was 4.5 and Youngstown's 21.6; for robbery the national rate was 102.2 and Youngstown's 204.1; and for aggravated assault ("felonious assault" per the Ohio Revised Code) the national rate is 232.5 with Youngstown's rate at 377.3 (Uniform Crime Reporting Program, UCR, 1984 - 2014).

Disproportionately high to even those rates, however, has been violent UCR Part I crime on the city's south side, particularly the geographical area in Figure 1 bounded by the Mahoning River to the north, Midlothian Boulevard to the south, a non-linear and asymmetrical boundary of Hillman Street/West Myrtle Avenue/Market Street to the west and Shady Run Road to the east (Youngstown Neighborhood Development Corporation, 2017). Collectively, this area became known as the "Byrne area" due to its inclusion in a cooperative Byrne Criminal Justice Innovation Program grant. It comprises approximately 7% of the city's geography and 14% of the city's population yet accounts for 23% of the city's homicides, 29% of aggravated assaults, and 26% of robberies (Youngstown Neighborhood Development Corporation, 2017). Within the aforementioned geographical region of Figure 1 is a smaller hot-spot region hereafter referred to as the "target area" or "Community Based Crime Reduction area" (CBCR), as depicted in Figure 2. It encompasses Florida Avenue to the north, Midlothian Boulevard to the south, Cottage Grove to the west, and Zedaker Street to the east. This particular hot-spot has rates of homicide, aggravated assault, robbery, vacant housing, poverty, unemployment, and absence of formal education attainment higher than both the national and city averages and is the highest concentration of those low rates in the larger Byrne area. (American Community Survey, n.d.; Youngstown Neighborhood Development Corporation, 2017). Locally, these areas are referred to as the "Taft neighborhood" to the east of South Avenue and the "Cottage Grove neighborhood" to the west. These high rates can be seen in Table 1.

In 2016, the Youngstown Neighborhood Development Corporation (YNDC) conducted a house-by-house canvass within the larger Byrne area (Figure 1) and approximately 500 residents answered the in-person survey. The results indicated that 66% of residents felt crime and safety was a concern in their neighborhood and 50% felt that housing and property issues needed addressed to improve their quality of life (Youngstown Neighborhood Development Corporation, 2017). This information gleaned by the survey underscored the need to address the crime and vacant property problem in that area of Youngstown. Not only does the data show that there is a concern of crime in that segment of the city but the residents overwhelming believe that crime and property issues affect their standards of living and that conditions need corrected and improved.

Combating and reducing violent crime is, understandably, an important function of the Youngstown Police Department. Other local entities, such as businesses, neighborhood development organizations, schools, and citizen coalitions also have a vested interest in seeing crime reduced and quality of life improved in their neighborhoods. The President's Task Force on 21st Century Policing acknowledged the benefits that police-community collaboration can foster as it relates to crime reduction. Pillar 4 of the Task Force recommendations, "Community Policing & Crime Reduction", opens with the statement "Community policing is a philosophy that promotes organizational strategies that support the systematic use of partnerships and problem-solving techniques to proactively address the immediate conditions that give rise to public safety issues such as crime, social disorder, and fear of crime" (U.S. Department of Justice, Office of Community Policing Services, 2015, p. 41).

The United States Department of Justice, through the Bureau of Justice Assistance and Office of Justice Programs, offer a highly-competitive grant known as the "Innovations in Community-Based Crime Reduction" grant which invests in the development of practitioner-researcher partnerships to use data, evidence, and innovation to create strategies and interventions that are effective and economical (Bureau of Justice Assistance, n.d.). Because of the high rate of violent crime in the target area on the south side of Youngstown, and the ever-present concern of victimization by the citizens in those neighborhoods, YPD, in cooperation with YNDC, and Youngstown State University (YSU), successfully applied for and was one of twelve cities that won the competitive $150,000 Innovations in Community-Based Crime Reduction planning grant through the Department of Justice. This planning grant was used by the applicants to formulate a multimodal, or multiple methods of activity, strategy to reduce violent crime by focusing extra patrols in the areas with the highest amount of violent UCR Part I crime, listening to and acting on citizens' complaints of crime and/or social disturbance, and reducing or eliminating property dilapidation and blight. After formulating the strategies and conducting a small implementation of them using the planning grant funds, the coalition further applied for and was one of four cities to be awarded the $850,000 "Innovations in CBCR implementation" grant. Overall, this gave YPD, YNDC and YSU the opportunity to utilize $1,000,000 in order to combat crime and blight within the city of Youngstown over a 2-year period beginning in fall of 2017. This initiative became locally known as the Community-Based Crime Reduction (CBCR) Project, or analogously the South Side Revitalization Project, SSRP. (Youngstown Neighborhood Development Corporation, 2017).

The main hypothesis of this thesis is that multimodal interventions conducted by YPD and YNDC will have, conjointly, a significant impact on the reduction of violent crime within the target area. The interventions included data-driven place-based and hot-spot policing, increased emphasis on residential and business blight remediation, and input from the community regarding drivers of crime in their neighborhoods (Youngstown Neighborhood Development Corporation, 2017).

The importance of this thesis is that, should the hypothesis be supported, it will provide police administrators, criminal justice practitioners, and community partners with a foundation for a crime-reduction strategy that is grounded in practical law enforcement operations. Yet, it can be based on established research that also succeeds in cleaning up blighted neighborhoods and involving the community in the process, because adopting more progressive crime-control policies [is] much more likely to result in a substantial reduction in crime (Pratt & Cullen, 2005).

For transparency, the reader should know that the author of this thesis is a nearly 20-year veteran of YPD who has been at the rank of Captain since 2013. Since 2012, the author has been directly involved in studying and employing both research-based and innovative crime-reduction strategies in order improve the efficiency of operations in the Youngstown Police Department as well as reducing the rate of crime in the city of Youngstown while maintaining positive relationships with the community. He was responsible for assisting in the compiling of data for, and co-authoring, both the planning and implementation grants and served as the department's law enforcement coordinator for the life of the CBCR Project. Additionally, the author oversaw and put into operation the law-enforcement based interventions over the life of the project which included personal participation in many of those activities as well as participating with the grant's other partners in their undertakings.

SUMMARY

This chapter highlighted the extent of the violent crime problem in the city of Youngstown and particularly a small area on the city's south side. It detailed the CBCR grant won jointly by YPD, YNDC and YSU and the multimodal programs that would be implemented to help reduce the violent UCR Part I crime in that area. The next chapter will review the academic literature and research that was the basis for the CBCR Project well as for this thesis and why analyzing it will enhance criminal justice studies.

CHAPTER II

Literature Review & Theory

The theory that formed the basis for this research is centered on the seminal work by Cohen and Felson in 1979 known as the "routine activities theory". The theory postulates that in order for crime to occur, three elements must be present: an offender with both criminal inclinations and the ability to carry out those inclinations, a person or object providing a suitable target for the offender, and the absence of guardians capable of preventing violations (Cohen & Felson, 1979). If any one of the elements is removed from the equation then crime is not possible and, subsequently, criminal activity can be reduced or eliminated. Additionally, some places provide more and higher quality opportunities, which means the effects of opportunities on crime vary across the urban landscape based on where those opportunities are located (Felson & Clarke, 1998). More contemporary studies delve deeper into the routine activities' theory as it relates to target selection, which can refer to people, places, or objects. At the neighborhood level, the presence of street drug dealers, building deterioration, and unfavorable conditions typically indicate that residents are poor, [and] possibly depressed…these cues also suggest that police response time is likely slow, thereby enhancing the suitability of the target area (Gialopsos & Carter, 2015).

The interventions that YPD and YNDC used to attempt to reduce crime in the target area of the CBCR Project sought to remove suitable targets for offenders by remediating blight and dilapidation of houses, occupied properties, and vacant properties and introduce additional police presence to the area in order to detect any criminal wrongdoing as well as prevent the further occurrence of crime. The concentration of

UCR Part I crimes in the target area, as well as the extraordinarily high number of vacant and run-down houses and properties provided an ideal opportunity to introduce crime-reduction strategies. By attempting to impact crime on the small micro-spatial level, such as the small block groups the CBCR target area provided, it was posited that the crime-reduction effects would spread to the larger urban landscape.

In order to ensure meaningful crime control interventions are implemented which will have both immediate and sustainable positive effect on crime reductions, a variety of prevention strategies designed to modify local criminal opportunity structures can be implemented to better position [Youngstown] to be effective in its violence prevention efforts (Schnell, Grossman, & Braga, 2019). These intervention strategies must be thoughtfully selected and implemented by police executives based upon the crime-effectiveness of hot-spot and problem-oriented policing strategies with the understanding that broadly implemented and unfocused "order maintenance" strategies do not seem well positioned to generate consistent crime-control gains (Braga & Bond, 2008). Essentially, effective crime control interventions based in accepted research and practice – as opposed to administrative "guess work" in how to reduce crime – needed implemented in the city's most violence-prone areas to help quell the most serious crimes affecting the community and reduce this high rate of violent crime.

The concept of data-driven policing is not new to law enforcement. Fundamentally, line officers, supervisors, and administrators all utilize a rudimentary form of "data-driven" policing without necessarily even reviewing charts, tables, hot-spot maps, or complex computer outputs. That is, those in law enforcement are often thoroughly familiar with what areas of their jurisdictions have the most calls for service and crime, and also which individuals seem to be involved in those same arrays of incidents. However, in the late 1990s, the British national intelligence model (NIM) followed the government policy of using a business process archetype to deal with crime control and employed the ILP (intelligence-led policing) philosophy to introduce intelligence into virtually all aspects of the policing business plan (Carter & Carter, 2009). This philosophy of data-driven policing did not gain popularity in the United States until the terrorist events of 9/11; afterward, the sharing of intelligence and its use as a model for both anti-terrorism operations and crime-control measures surged in academic and popular acceptance as crucially necessary for successful outcomes. The value is the identification of a crime series or significant crimes within a jurisdiction (which, when grouped together, look like a "hot spot" on a map) based on a timely analysis of incident reports and the analysis of data captured via crime reporting. This can provide important information such as such as geographical parameters and modus operandi that can be used to forecast a crime series in the immediate future or aid in problem solving (Carter & Carter, 2009).

In line with intelligence-led models, research has shown that successful initiatives and interventions to reduce crime include a myriad of methodologies. The most widely practiced by state and local law enforcement agencies are targeted patrols based on strategic [long-term] and tactical [short-term] crime data (Braga & Bond, 2008), often referred to as "hot-spot policing". Place-based policing, similar in many ways to hot-spot policing, is another widely-accepted and used strategy in which police resources saturate a particular problem location (such as a house continually selling drugs, a gas station where crimes frequently occur in the parking lot, etc.) and attempt to ameliorate both the obvious criminal activity and any underlying reasons why the crimes may be occurring there to begin with. This strategy is heavily based upon the routine activities theory and there is a growing body of evidence that the more focused and specific the strategies of the police, and the more tailored to the problems they seek to address, the more effective the police will be in controlling crime and disorder (Braga & Schnell, 2013; Braga & Weisburd, 2010; National Research Council, 2004).

In order to be successful, however, research has demonstrated that targeted patrols, such as those just mentioned, must adhere to two operational elements. First, the intervention has to be concentrated in the few hot-spot areas generating a disproportionate amount of the crime; and secondly, intervention must be driven by situational strategies that attempt to modify the criminal opportunity structure at crime and disorder hot-spot locations (Braga & Bond, 2008).

The data in Youngstown is clear that the larger Byrne area, and specifically the target area, generate a disproportionate amount of crime and property blight in the city. In the case of intervention in the target area, the situational strategies mentioned by Braga and Bond (2008) were included in the CBCR implementation grant: the "small business safety initiative" which addressed employee safety education, crime prevention through environmental design (CPTED), and increased police communication and presence with business owners; the "residential property safety initiative" which addressed safety upgrades to homes, focused deterrence on repeat criminal offenders, and enforcement of rental property registries; the "community empowerment initiative" that sought to create new neighborhood associations and engage residents in local block parties and recreational activities; and the "neighborhood revitalization initiative" to tackle clean-up of vacant properties, demolition of blighted properties, and general neighborhood improvement. Modifying the criminal opportunity structure, as postulated by Braga and Bond (2008) was built-in to several of the strategies and sought to make it less appealing for people and places to be the targets of crime, both by including the element of increased police patrols throughout the neighborhoods and businesses of the target area and also by improving the physical spaces (like vacant housing) where crime was occurring.

Problem-oriented policing (POP) approaches at hot-spots have also demonstrated success (Taylor, Koper, & Woods, 2011). The key difference of a problem-oriented policing approach versus targeted patrols generally lies in exploring the root cause of the crime problem contrasted with saturating an area with extra officers on targeted patrol strategies. For POP stratagems, teams of officers may focus on the offenders, the community, or the need for some kind of environmental crime prevention element. In some cases, the officers will work with residents and other city agencies to develop custom responses to particular problems (Taylor et al., 2011).

As demonstrated in numerous POP-driven studies, collaboration with residential and business property owners to improve security shows statistical significance in reducing crime (Bichler, Schmerler, & Enriquez, 2013). Successes range from decreasing crime and improving the perception of safety in: travel areas (Eriksen, Lin-Kelly, & Maurelli, 2018), hotel nuisance properties (Schneider, 2016), and even entire neighborhoods of a metropolitan area (Carter, 2015).

Another successful data-driven approach to reducing crime, at least within certain small segments of the population, is focused deterrence strategies. The overall idea of focused deterrence strategies is that police can increase the certainty, swiftness, and severity of punishment in a number of innovative ways, often by directly interacting with offenders and communicating clear incentives for compliance and consequences for criminal activity. These approaches all focus on high rate offenders, often gang members or drug sellers (Center for Evidence-Based Crime Policy website, n.d.). With the proper focus of efforts on the problematic people associated with problematic places, police can achieve significant crime reductions while helping to avoid negative community perceptions of their actions. The strategies should be proactive, focused on small places or groups of people in small places, and tailor specific solutions to problems using careful analysis of local conditions which seem to be effective at reducing violent crime (Groff et al., 2015).

Though not typically a direct police intervention, the diminution of blight within neighborhoods is an oft researched form of crime control. Analogous with the socioeconomic conditions of much of the target area on the south side of Youngstown, deteriorated spaces are not only typical of the de-industrialized, disinvested, and underserved neighborhoods where interpersonal firearm violence is most endemic, but may play a causal role in the commission of violence (Jay, Miratrix, Branas, Zimmerman, & Hemenway, 2019). Despite this, findings show that violent crime incidences declined near rehabilitated vacant lots (Kondo, Hohl, Han, & Branas, 2015) and that community engaged physical improvement of neighborhood properties can be an effective violence-prevention strategy (Heinze et al., 2018).

Assessing the proper target area to engage in violent crime reduction interventions should take into consideration several triggers of crime as axioms beyond the current rate of UCR Part I violent crimes. The following are well-researched in criminal justice, sociological, and economic studies, including that neighborhoods with unattended residential and business blight and dilapidation become a magnet for further crime and citizen perception of increased crime (Kelling & Wilson, 1982; Kuo & Sullivan, 2001; Wheeler, Kim, & Phillips, 2018); that high rates of unemployment and low attainment of formal formative and higher education are inextricably tied to an increase in crime (Lochner & Moretti, 2004; Lochner, 2004; Nordin & Almen, 2017); and that rates of poverty within neighborhood populations can have an effect on certain crimes (Hannon, 2005; Hipp & Yates, 2011).

Most experimental interventions and/or research-based grants implement one mode of crime-reduction strategy in a target area and measure it against a formalized control group area that does not receive such an intervention. No existing research was found in the literature review which measured if disparate crime-reduction methodologies, such as those mentioned in the CBCR planning and implementation grants, when conducted simultaneously in the same target area, contributed jointly to violent crime reduction and, if discernable, to what degree. Though not originally applied for as an experimental grant, the unique nature of incorporating the varied crime-control theories and methodologies used in the CBCR Project and being able to measure if they have an aggregated effect on reducing violent UCR Part I crime makes this topic worthy of study.

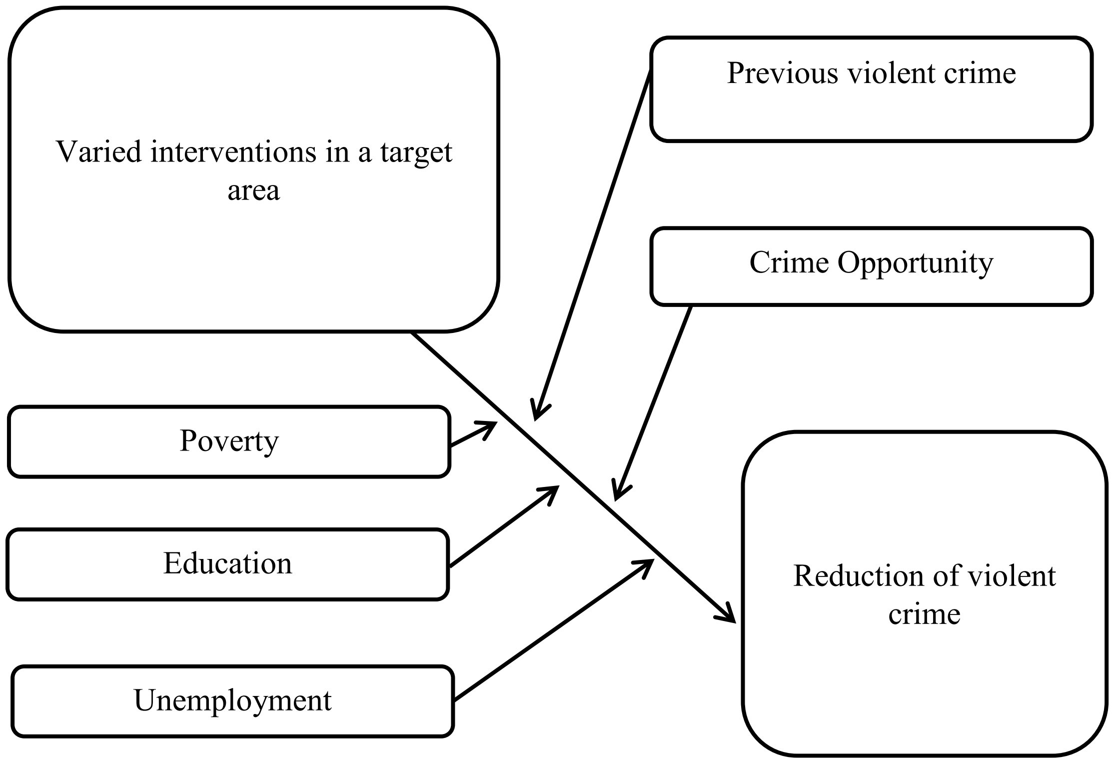

Figure 3. Conceptual framework

SUMMARY

This chapter highlighted the theory, research and literature on which this thesis and the CBCR Project are based to include routine activities theory, hot-spot policing, POP strategies, and focused deterrence interventions. A basic conceptual framework was presented for visualization of the research question. The next chapter will elaborate on the methodologies used to test the hypothesis.

CHAPTER III

Methodology

The core hypothesis for this thesis is that multimodal interventions conducted by YPD and YNDC will have, conjointly, a significant impact on the reduction of violent crime within the target area. The interventions included data-driven place-based and hot-spot policing, increased emphasis on residential and business blight remediation, and input from the community regarding drivers of crime in their neighborhoods (Youngstown Neighborhood Development Corporation, 2017).

During the course of the grant's implementation, which ran from April of 2018 through September of 2019 (18 months total), the Youngstown Police Department used weekly crime maps of the target area, as compiled by the YPD crime analyst, to deploy extra officers (typically, two at a time) to the area over a four-hour period. The four-hour period chosen for the additional patrols was based upon an aggregated three-year look-back of when most of the violent UCR Part I crimes occurred in the target area and the four-hour block with the highest total of UCR Part I crimes was chosen. While on patrol, the officers were encouraged to utilize the crime map information, any supplementary intelligence information provided, communications received by residents about possible criminal activity, and their own observations to conduct proactive traffic and pedestrian stops. This intelligence-led deployment strategy was based upon the previously mentioned works of Braga & Bond (2008), Braga & Schnell (2013) and Taylor et al (2011). The officers were additionally encouraged to stop by homes and businesses within the target area to speak with residents, business owners, and patrons so they could not only make positive police-community connections but also hear the concerns about crime in that area. Collaboration with residents and businesses as part of a crime-reduction strategy is an evidence-based practice YPD and YNDC believed valuable to achieving success (Bichler et al., 2013; Taylor et al., 2011). The officers compiled a log sheet of their activities which was later turned over to the YPD crime analyst for memorialization of the date, time, location, and type(s) of law enforcement activities conducted.

Over the course of the grant implementation, YPD officers participated in 380 total extra patrols in which they spoke with 1,332 residents, made 935 business contacts, conducted 541 traffic stops and 354 investigative stops, towed 46 vehicles, recovered 16 guns, and arrested 123 persons with a total of 42 warrants, 178 misdemeanor charges and 71 felony offenses (Youngstown Police Department [YPD], 2019). During the same 18-month implementation period, YNDC, in cooperation with program partners, had 150 houses demolished, conducted 53 board-ups of vacant properties, participated in 265 separate code enforcement actions, and remediated blight and cleaned 472 properties and/or lots. (Youngstown State University [YSU], 2019)

The data used in this thesis for analysis were compiled from several disparate sources. UCR Part I crime data was filtered out by the crime analyst for YPD using a search feature from all police reports entered by Youngstown Police officers in the department's two record management systems (Motorola NetRMS version 1.95.3 before February 2019; Spillman Flex version 2018.3 beginning February 2019). From there, the data were exported into a Microsoft Excel file and checked for errors manually such as missing addresses or inaccurate dates. Once the data were checked for errors additional information such as time of crime, approximate time of crime (if an exact time was not known), day of week, and method of entry were also entered into the spreadsheet.

The Senior GIS and Data Services Manager and a team of student GIS analysts at Youngstown State University then took the data from YPD and compiled, cleaned, and geocoded it. Point layers were then overlaid with block groups within the city to assign them to the geocoded records which allowed summaries per block group of requested data. This process allowed every crime to be accurately pinpointed to a specific address on a map. Block groups are the smallest units traditionally used for data analysis and often represent several congruent residential blocks. The gathering of vacant property data was compiled by city-wide property surveys conducted by YSU and YNDC from 2008 through present. The data on rate of poverty, unemployment, and educational level all came from the U.S. Census Bureau American Community Survey 2017 five-year estimates and previous years, 2000-2017 (United States Census Bureau, 2017). The aforementioned data were already compiled on block-group level.

IRB approval was sought from YSU's Office of Research and this protocol was deemed to be exempt due to the use of pre-existing data without any contact with research participants and/or subjects. Protocol number 067-20 is associated with this research.

Important to this research was the time periods used for analysis. The beginning of multimodal interventions began in April of 2018 and ran through September of 2019, a total of 18 months. In order to ensure any data analysis was meaningful, an equal pre-intervention period of 18 months was used as the comparison time period. This pre-intervention period ran from October of 2016 through March of 2018. As such, any reference in this research to “pre-intervention”, “prior to intervention”, or similar language refers to October of 2016 through March of 2018; likewise, any reference to “intervention period”, “implementation period”, or similar language refers to April of 2018 through September of 2019.

The YSU GIS Department provided the two main data files used for this thesis, *CBCR Data* (YSU, 2019) and *CBCR Target area weight* (Youngstown State University [YSU], 2019). These are both Microsoft Excel files in “.xlsx” format. *CBCR Data* contains two separate worksheets used in this thesis: “Census Data (2017 ACS 5-Year)”and “Crime Data”. “Census Data (2017 ACS 5-Year)” contains 36 columns and 81 rows of data which represents the 80 block groups throughout the city of Youngstown, plus the column headers. Not all of the data collected was relevant to this particular study. Germane to this thesis were data on which city block group data belonged to (“BlockGroupID”); if the data was in the target area or elsewhere (“CBCRHotSpots”); population per block group (“TotalPopulation”); population over the age of 25 per block group (“Population25Over”); the number of persons per block group who never went to school (“NoSchoolingCompleted”); the number of persons per block group who never completed high school (“NoHighSchoolDiploma”); the number of persons per block group whose income could be verified (“PopulationPovertyStatusDetermined”); the number of persons per block group whose income falls below levels set by the U.S. Census (“BelowPovertyLevel”); the number of vacant lots per block group (“Vacant”); the percentage of land per block group which is vacant (“VacantPct”); and the number of persons per block group who are not employed (“CivilianUnemployed”). Data in this file were all taken from the U.S. Census (United States Census Bureau, 2017).

For this research, a combined category was used of those with no education and those who did not complete high school or earn their GED. The new category was named “EduLTHS” (“education less than high school”) and represents that respective percentage of the population. This is based on research that shows that low attainment of formal formative and higher education are inextricably tied to an increase in crime (Nordin & Almen, 2017) and that more than two-thirds of all incarcerated men had not graduated from high school (Freeman, 1996). Essentially, it made good sense to combine the two categories for purposes of comparisons and analysis.

The data file *CBCR Target area weight* provided overall population data in the block groups specific to the target area from 2013-2017. Additionally, five of the seven block groups in the target area were given a “weight”, or percentage of their area which actually fell in the target area. This adjustment is important to the overall analysis because in five of the target area block groups the interventions conducted by YPD and YNDC did not encompass their entire region. Hence, though a crime may have occurred in the block group itself, it may have fallen outside the boundaries of where intervention was occurring. To ensure that rates of crimes were properly calculated for each block group, a “new population” was computed for each of these five block groups and used in data calculations throughout this research. The remaining two of the target area block groups fell entirely within intervention area and were therefore not weighted. Table 2 shows these block groups and the numbers. Population data from 2017, or its weighted equivalent, was used in rate calculations because it is the most recent data available from the United States Census Bureau (United States Census Bureau, 2017).

The "Crime Data" worksheet of the *CBCR Data* Excel file was used to determine how many violent crimes occurred in the block groups studied for this research, both prior to and after intervention. It contains 18 columns and 1,467 rows of data (inclusive of a column-header row). Each row of data is a YPD incident report which was filtered by the YPD crime analyst and forwarded to YSU in the method previously described. Crimes forwarded included the UCR Part I crimes of homicide, aggravated assault, robbery, forcible rape, and arson. Used in this research were the columns which noted whether the crime occurred prior to or during intervention ("Intervention"); if the crime was a homicide, aggravated assault, robbery, forcible rape, or arson ("UCRType"); if the crime occurred in the Taft or Cottage Grove target area block groups, or outside of them ("CBCRTarget"); and which city block group data belonged to ("BlockGroup").

For this research, only the UCR Part I crimes of homicide, aggravated assault, and robbery (all pre- and post-intervention) were used and analyzed. The rationale behind this choice was a practical one. The original grant was applied for as a violent crime reduction project and all interventions which were undertaken by the program partners sought to further that goal. It should go without saying that the Youngtown Police Department, and law enforcement in general, consider all criminal activity worthy of reduction and seek to do so every day with both patrol and follow-up investigative efforts. Nonetheless, because the data showed that certain violent crimes were so prevalent in the studied section of Youngstown for so long, coupled with the citizen concerns over it, only those certain crimes were the aim of the extra enforcement efforts. Hereafter, any mention of “violent crime”, “rates of violent crime”, or similar language will refer to these three offenses collectively.

Within the data provided by YSU in the “Crime Data” worksheet, forcible rape and arson were not included to be analyzed. Forcible rape reduction strategies are quite different than the hot-spot and POP-oriented crime strategies utilized by YSU and YNDC for this grant. As Holtzman and Menning aptly point out, “Most sexual assault prevention focuses exclusively on primary prevention programs. Risk reduction strategies, however, have an equally important role to play in prevention efforts” (2019, p. 7). Though crime prevention educational sessions did occur with the public as part of this grant they were not focused on sexual assault prevention and were more general in nature. Additionally, a common drawback to the collection of data on rape is the date of occurrence listed on a police incident report. It is not uncommon for the victim of a violent sexual assault to wait a period of time, sometimes years, to make a report to the police. The lack of, or delay in, reporting may be due to fears of the victim being blamed, of reprisal, or of a belief that the criminal justice system will not offer an official response (James & Lee, 2014). Once, and if, those incidents are reported, the date listed on the police report is typically the date the report is compiled as opposed to the actual date of the incident. Therefore, collection of the data is often unreliable for purposes of determining crime reduction effectiveness.

Arson, though a serious crime, is typically the function of fire department authorities and not addressed by law enforcement or community organizations and was therefore not included in the analysis of violent crime change in the areas studied.

The crimes of homicide, aggravated assault, and robbery were sorted by several factors for purposes of analysis in this thesis. The hypothesis is, generally, that the interventions by program partners during the intervention period lowered the rates of those violent crimes in the target area. For each block group in the target area, then, each block group number was sorted by crime type, intervention period (pre- or post-), and whether or not it was in the intervention area.

The data from the Excel spreadsheets *CBCR Data* and *CBCR Target area weight* were put into a new Excel file which was used for any statistical tests conducted for this research. The new file was named *0 – CBCR Multimodal Analysis* and contained 32 columns and 15 rows of data (inclusive of a column-header row). Columns/categories of data will be explained as necessary for the remainder of this research as not all were utilized. Rows are the seven block groups of the target area and seven block groups of a selected control area.

The target area of Taft and Cottage Grove in which focused interventions occurred occupy seven block groups. The Taft area contains block group numbers 8011001, 8011002, and 8011003. The Cottage Grove area contains block group numbers 8016001, 8016002, 806003, and 8016004. The rates of violent crime for each of the target area block groups were calculated using their weighted population values for statistical accuracy both pre- and post-intervention ("TViCr0" and "TViCr1", respectively). The individual rates of homicide, aggravated assault, and robbery for each target area block group pre- and post-intervention were noted ("H0r" and "H1r"; "AA0r" and "AA1r"; "R0r" and "R1r", all respectively). Percentages of poverty ("PovertyP"), unemployment ("UnemployedP"), vacant land ("VacantP"), and population with an education less than a high school diploma/GED ("EduLTHSP") were also calculated.

Measuring the changes in the rate of violent crime in the target area before and after intervention is a simple way to see if the multimodal interventions were effective. However, it would not allow us to gain perspective in regards to what may have been happening in other similar parts of Youngstown during the same period of time. For example, if all crime in the city decreased at the same rate as the target area, then the interventions would not have been meaningful. Selecting a comparison, or control area, is the preferred scientific method to determine if the multimodal interventions had an effect. Ideally, the control group "consists of elements that present exactly the same characteristics of the experimental group, except for the variable applied to the latter… this group of scientific control enables the experimental study of one variable at a time, and it is an essential part of the scientific method" (Pithon, 2013, p. 13). In the case of this research, it would be scientifically ideal to have seven additional block groups in the city which could each be matched up to a target area block group in terms of violent crime rate, vacant property percentage, poverty percentage, and so forth. However, such an ideal is lofty in the social sciences. There are limitations on what variables [such as crime rate, vacancy, etc.] that a researcher can control for (Nelson, 2017). Typically, the social sciences – including criminal justice – are concerned with whether an intervention produced the intended effect in practice; as such, the secondary variables [such as education, poverty, etc.] do not confound the effects of the intervention… these secondary variables do not necessarily need to be controlled for in the design or the analysis…randomization obviates even the need to identify the secondary variables (National Research Council, 2012).

The initial Byrne Criminal Justice Innovation grant was not established to be a formal experiment or follow a scientific analysis method post-grant; therefore, there were no formal control areas included in its authoring for comparisons. However, all necessary data to find block groups which could serve as control areas is located in the "Census Data (2017 ACS 5-Year)" and "Crime Data" worksheets of the *CBCR Data* file provided by YSU. The goal was to locate a control block group for each of the seven block groups in the target area. Because the measure of violent crime is the primary focus of this thesis, a 5% error rate (+/- 5%) was used for each of the target area block groups on the measure of total rate of violent crime prior to intervention (*TViCr0*). Secondary to *TViCr0*, the percentage of vacant land and the poverty rate for each block group were given consideration with a goal of also retaining +/- 5% to the matched target area block group. These secondary and tertiary measures proved near-impossible to match perfectly.

For five of the seven target area block groups, multiple other block groups throughout the city were within+/- 5% for *TViCr0*. For these particular block groups, then, the *VacantP* and *PovertyP* were next looked at to see which were within a 5% error in an attempt to find the best control area. Though some were close, only one block group with the potential to serve as a control for Cottage Grove 8016001 reached that 5% error for one variable (*PovertyP*) beyond *TViCr0*.

The Taft block group 8011003 had only one block group in the city which matched its *TViCr0* within +/- 5%. The Cottage Grove block group 8016004 did not have any that were within +/- 5% of its *TViCr0*. Therefore, block group 8021001 was chosen as its control area because it was the closest block group not already being used for another target block group comparison. It is important to note that 8021001 had a *TViCr0* 10.6% higher than Cottage Grove 8016004 but was still the closest of the available choices. Essentially, the *TViCr0* was used as the primary consideration for a control match and then, consequently, an attempt was made to find *VacantP* and *PovertyP* values as close to +/- 5% as possible.

The ease in finding multiple block groups to serve as control areas with +/- 5% for *TViCr0* is based on the fact that these are calculated as rates per 100,000 and there were thousands of crimes committed to contribute to the count. Also, though the target area of Youngstown had the highest crime rates in the city, there were numerous other areas with similarly high rates of crime which allowed for them to be suitable choices. What those other areas did not have, however, were the disproportionally high rates of vacancy and poverty that the target area block groups have, which is what forced the research to consider secondary and tertiary values outside of the desired error rate. This reaffirms the reason the target area was chosen for intervention in the first place and underscores Nelson's notion that, in the social sciences, there are often not many variables we have the luxury of controlling for (Nelson, 2017).

In the YSU data files, control areas did not contain an area name as they were not initially part of the grant. Therefore, the name designation for each as "CTL" followed by the neighborhood and associated block group it controlled for was assigned. As an example, "CTLT2" is the control area for Taft block group 8011002, just as "CTLCG3" is the control area for Cottage Grove block group 8016003. The visual representation of where each block group falls with the city of Youngstown is found on a map as Figure 4.

For all variables, $N = 14$ representing the block groups used for this thesis (seven in the target area and seven used as controls). It is an apparent and recognized limitation of this research that the number of samples is low. However, as mentioned in the introduction section, a primary goal of this analysis is to provide a practical application to law enforcement professionals and community organizations wishing to engage in crime-reduction efforts based on established academic research and effective practices. This typically entails a "before and after" comparison which is how the data in this research has been organized.

The dependent variable (DV) in this analysis was the violent UCR Part 1 crime rates (*TViCr1*) as gathered by YPD and YSU. *TViCr1* represents the rate of the violent UCR Part 1 crimes homicide, aggravated assault, and robbery per 100,000 for each block group in the target area as well as the control areas selected. These rates were current as of the end of September 2019.

The independent variable (IV) for this research was the block groups in the city of Youngstown's target area and the control area (*CBCRArea*). This IV was a categorical variable with binary properties. The value of 0 ($N = 7$) represents the control block groups outside of the CBCR target area for each of the 36 months of this study. The value of 1 ($N = 7$) represents the CBCR target area for each of the 36 months of this study. This "target area" (Figure 2) represents the geographical area where intervention, such as saturation patrols in hot spot areas, blight remediation, and community engagement took place. The target area, by block groups, represents approximately 3% of the square mileage of the city of Youngstown while the control areas represent approximately 7%.

When analyzing data, the standard practice is to check and ensure that data within the variable are normally distributed. This is an important function because it describes how the values of a dataset are dispersed and, ideally, it should be a symmetric distribution where most of the observations cluster around a central peak and other values taper off in either direction (commonly known as the "bell curve") (Frost, 2019). If the distribution of data is not symmetrical, a transformation of the data can be done to normalize it. Though the bell curve is a visual depiction of the normal distribution of data, the skewness and kurtosis values of the data depict normalcy numerically. Skewness represents the horizontal "lean" of the distribution while kurtosis refers to the vertical "peak" or "flatness" of those same points (Rogers, 2017). Though these concepts can be visually represented, from a statistical perspective normalcy of data is any skewness between the values of 2 and -2 and any kurtosis less than -2 (Ghasemi & Zahediasl, 2012; Tabachnick & Fidell, 2018; Rogers, 2017). As a note of caution, however, the above rule is generally applicable with larger datasets which are admittedly absent in this research.

One common way of normalizing data is to remove outliers, or points that are far away from the main distribution of points which can distort statistical summaries, such as the mean and standard deviation (Rogers, 2017). However, due to the very small data set of this research ($N = 14$ for each variable, or $N = 7$ for each studied area) the removal of even one outlier to attempt to normalize the distribution eliminates between 7% and 14% of the data. Therefore, those interpreting the results of this study should keep in mind that statistical tests are conducted on variables which may not be normally distributed.

Eight different independent samples t-tests were conducted on the data found in *0 – CBCR Multimodal Analysis*. This form of a t-test compares two independent groups (here, the block groups of the target area and the control area) in order to determine if there is statistical evidence that the associated population means (here, the rate of violent crimes) are statistically significant (Tabachnick & Fidell, 2018; "Independent Samples t Test," 2019). The eight independent samples t-tests were conducted on the rate of total violent crime (pre- and post-intervention), rate of homicide (pre- and post-intervention), rate of aggravated assault (pre- and post-intervention), and rate of robbery (pre- and post-intervention), and all within both the target area and the control area. Essentially, these tests will show if there is a statistically significant difference between the data before and after intervention for each measurement in each area.

Four different paired samples t-tests were conducted on the data found in *0 – CBCR Multimodal Analysis*. A paired samples t-test is used when a researcher wants to compare a measurement taken at two different times with an intervention administered between those times (Tabachnick & Fidell, 2018; "Paired Samples t Test," 2019). These tests are commonly used to determine if there is a statistical difference between two points in time when an intervention is introduced.

Three separate bivariate statistics tables were conducted on the dependent variable, independent variable, and selected demographics. Also known as a "Pearson Correlation", this test measures the strength and direction of relationships between variables (Tabachnick & Fidell, 2018; "Pearson Correlation," 2019). It can also help determine if there is a statistical significance between variables. One Pearson Correlation was conducted on the total rates of violent crime both pre- and post-intervention, the entirety of the target and control areas, and the population, vacancy, poverty, unemployment, and education less than high school demographics. One additional Pearson Correlation was conducted for each of the target and control areas, separately, with the same crime and demographic numbers associated with their respective territories.

As with the independent and paired t-tests, the results will be of limited value statistically-speaking. Pearson Correlations assume normal distribution and no outliers, which have been noted to be problematic with the small sample size of the present research. Additionally no p-value was practical to calculate to show the statistical significance of the correlations for the same reasons (Tabachnick & Fidell, 2018).

While the above statistical analyses were conducted on the data to measure statistical significance for the results of intervention, there have been several mentions already that the data set is small and potentially unreliable for such tests. The primary goal of the Byrne Criminal Justice Innovation grant was to reduce violent crime through multimodal interventions and provide law enforcement and community groups a valid way to do so which was based on academic research and effective practices. What most administrators want to know is, simply, this: did the interventions reduce violent crime in the targeted areas? Statistical analyses play an important role in these outcomes; however, not every police department or neighborhood revitalization group will have access or capabilities to conduct these types of tests. In essence, they simply want to know if what they did worked and how effective it was (or wasn't).

To provide criminal justice practitioners with such a tool to make this determination, noted researchers and professors Jerry Ratcliffe and Andrew P. Wheeler published research titled “A simple weighted displacement difference test to evaluate place based crime interventions” (Wheeler & Ratcliffe, 2018). The research was based in statistics used for some time to measure whether place-based intervention reduced crime in a treatment area relative to a control area, while taking into account potential spatial displacement of crime, [which have been] used across a range of crime prevention evaluations (Bowers & Johnson, 2003; Guerette, 2009; Ariel, Weinborn, & Sherman, 2016). From their research, in conjunction with Ratcliffe’s book *Reducing Crime*, Ratcliffe designed and published a macro-enabled Microsoft Excel spreadsheet titled *ABC spreadsheet calculator* (Ratcliffe, 2019). This free, downloadable spreadsheet permits to user to “evaluate the outcome of crime reduction operations that take place in a geographic area. The spreadsheet is optimized to work with operations that are focused in areas such as neighborhoods, housing projects, or crime hot spots” (Ratcliffe, 2019). It provides an overview of crime reduction efforts in an easy-to-read-and-interpret fashion.

Wheeler and Ratcliffe do not make any claim that this spreadsheet is the “end-all, be-all” new test for evaluating the effectiveness of crime-reduction interventions. They note that a big limitation is that the control area and treatment area need to have relatively similar counts of crime and that it may not be able to identify statistically significant crime reduction, which is a problem endemic to all micro place-based policing research (Wheeler & Ratcliffe, 2018). Despite some drawbacks, however, they note that the test is reasonable enough to use in practice, provides effective analysis, and that “the perfect need not be the enemy of the good” (Wheeler & Ratcliffe, 2018, p. 8).

All descriptive data, t-tests, and bivariate correlations were derived using the data analysis tools in Microsoft Excel (version 14.0.4760.1000, 32-bit). Additional analysis was conducted using the *ABC spreadsheet calculator* (version 1.4).

SUMMARY

This chapter highlighted the approaches undertaken by program partners for the Byrne Criminal Justice Innovation grant to reduce violent crime and specified how the data was collected. It explained the methodology of how and why certain data were selected, which populations samples were used and why, and which statistical tests and programs were used to analyze the data. The next chapter will present the results of the data analysis relative to the hypothesis.

CHAPTER IV

Results

The hypothesis of this research is that the multimodal interventions undertaken by YPD and YNDC in the specified target area of Youngstown were successful in reducing the violent crimes of homicide, aggravated assault, and robbery compared to the control areas which were selected as a comparison. Concerns regarding limitations on the analysis of the data using traditional statistical tests were expressed because of the very small sample size of the number of block groups analyzed for the dependent variable ($N = 14$). Nonetheless, for practitioners and community partners to engage in a successful crime-reduction program does not always necessitate that it be “statistically significant” – only that “it works”.

The following is an overview of the tables used in presentation of the results. After this brief description of each of the tables, a more detailed description is brought forth. Tables 3, 4 and 5 were generated in order to gain a perspective regarding the crime and census data in both the target and control areas. Table 3 is a summary of the block groups used in this research and the counts of appropriate violent crimes in each while Table 4 depicts the rates of violent crime for those same block groups. Table 5 is a summary of the census data for the block groups used in this research. Table 6 shows the differences in total violent crime as well as census data of the matched control area census blocks for each corresponding target area census block. As previously remarked, six of the seven control groups were within +/- 5% for total violent crime prior to intervention, yet matching the additional considerations of vacancy percentage and poverty percentage to find a "perfect" match within the desired error rate proved impossible.

Table 7 separately lists the rates of violent crime in the target and control areas before intervention, after intervention, and the percentage of change within each. Table 8 summarizes the rates of violent crime in the target area after intervention, the control area after intervention, and the percentage of difference between their rates.

Descriptive statistics were then calculated on the count of the total violent crime in addition to the individual crimes of homicide, aggravated assault, and robbery in the target and control areas, both pre- and post-intervention. Tables 9 (target) and 10 (control) contain this output.

Likewise, descriptive statistics were then calculated on the rates of the total violent crime in addition to the individual crimes of homicide, aggravated assault, and robbery in the target and control areas, both pre- and post-intervention. Tables 11 (target) and 12 (control) contain this output.

Table 13 shows the results of the eight independent t-tests for rate of total violent crime as well as homicide, aggravated assault, and robbery, before and after intervention, for the target and control areas.

Table 14 depicts the results of the four paired samples t-tests conducted on the combined pre- and post-intervention rates of total violent crime, homicide, aggravated assault, and robbery for the target and control areas.

Table 15 displays the bivariate correlations conducted on the total rates of violent crime both pre- and post-intervention (the dependent variable), the entirety of the target and control areas (the independent variable), and the population, vacancy, poverty, unemployment, and education less than high school demographics. Tables 16 and 17 show the results of the bivariate correlations conducted with the same crime and demographic numbers but calculated separately for the target area and control area, respectively.

Figures 5-8 are screenshots of the output from Ratcliffe's *ABC spreadsheet calculator* (Ratcliffe, 2019). Each snapshot depicts what source data was input and the simple-to-understand explanation of the effectiveness (or lack of) from intervention. Though a table is typically utilized when reporting this type of data, it was important to include the visual depiction of what a user would see if s/he were testing any similar hypothesis. Except for the crime numbers which were input for each calculation, all other information depicted in the output was automatically generated by the *ABC spreadsheet calculator*.

Rates, Counts & Demographics

Table 3 shows that the count of all violent crimes, both pre- and post-intervention, were higher in the control area rather than in the target area. Post-intervention, it can be seen that, except for homicides (which remained identical in both areas to pre-intervention levels), the count of crime dropped for total violent crime, aggravated assaults, and robberies in the target area. The control area also had decreases in counts of total violent crime and aggravated assaults but saw a rise in robberies.

However, the rate of crime, as measured by the population and figured per 100,000 people to conform to UCR Part I reporting standards, is a more proper measurement of crime increase or decrease. Table 4 shows that the total rate of violent crime (homicides, aggravated assaults, and robberies), which was used as a primary measure for selecting the area for intervention to begin with, is higher in the target area pre-intervention (2,115/100,000) than the control area (2,035/100,000), even though the individual rates homicides and aggravated assaults were slightly lower than the control area. Post-intervention, only the rates of homicides remained the same for both areas, with the target area still having a lower rate of homicides than the control area (77 and 102 per 100,000, respectively). The rate of crime for aggravated assault dropped in both areas while the rate of robberies dropped for the target area but rose for the control area. Overall, Table 4 shows that the total rate of violent crime dropped for both the target area (from 2,115 to 1,500 per 100,000) and the control area (from 2,035 to 2,009 per 100,000).

Demographically, the weighted population of the target area (population where the interventions took place since the entire block groups were greater than the intervention boundaries) was lower than the control area, but the percentage of those living in poverty, of vacant properties, of unemployment, and of those having an education less than high school were all higher (Table 5). This accentuates the additional reasons why the target area was chosen for crime and blight intervention over other parts of the city.

It's worthy of noting once again that the Byrne Criminal Justice Innovation grant was not initially established as a formal research experiment. However, in an attempt to measure its effectiveness from a standpoint of methodological rigor, a control area was chosen for comparison. One control block group was selected per block group in the target area with attempts to keep the total rate of violent crime and the demographics of vacant land percentage and poverty percentage within +/- 5%. Table 6 shows that the Taft neighborhood block groups (8011001, 8011002 and 8011003) had control block groups within +/- 5% for total violent crime (8023002, 8139003 and 8024001, respectively) but they failed to come within the error rate for vacant land or poverty. The Cottage Grove block groups of 8016001, 8016002 and 8016003 likewise had control block groups within +/- 5% for total violent crime (8141002, 8043001 and 8021002, respectively) but block group 8016004 had no comparison within the same error rate, with the closest being 8021001 which was 10.6% higher. Also, the pairing of 8016001 and 8141002 was the only one among the seven pairs to have a selected demographic within +/- 5% (*Poverty %* at -0.9%). Though not used as a basis for selecting the control areas, the percentage of those unemployed was within +/- 5% between block groups 8011003/8024001 (Taft neighborhood/control) and 8016003/8021002 and 8016004/8021001 (Cottage Grove/controls).

Table 6 provides good perspective to the crime, blight, and poor socio-economic conditions of the target area and why it is worthy of multimodal intervention. Its rates of violent crime are higher (as seen here versus most of the closest control areas, and additionally seen in Table 4), it’s vacant property more plentiful, more people are impoverished, unemployed, and lack formal education (all also reflected in Table 5). This data helps to reaffirm the research that areas with more vacant and blighted land (Kelling & Wilson, 1982), higher unemployment and lower rates of formal education (Lochner &

Moretti, 2004), and higher rates of poverty (Hannon, 2005) tend to have higher violent crime rates as spoken on in the literature review of Chapter II.

So were the multimodal interventions successful as this research hypothesizes? Previous research indicates that crime interventions and blight remediation do have an effect, separately, in reducing violent crime when carefully planned and executed in the proper target areas (Braga & Schnell, 2013; Jay et al., 2019; Taylor et al., 2011; National Research Council, 2004). Table 7 begins to provide perspective to answering our hypothesis. There, we can see that the rates of total violent crime and aggravated assault each dropped post-intervention in both the target (-29.1% and -4.0%) and control areas (-1.3% and -6.8%). The rate of homicide stayed steady between the target and control areas (0% change) and the rate of robbery decreased in the target area (-53.6%) but rose in the control area (6.3%). Table 8 shows that, post-intervention, our dependent variable of total violent crime post-intervention (33.9%) as well as the rates of homicides (32.5%), aggravated assaults (13.0%), and robberies (73.0%) were the specified amounts higher than the target area. These numbers alone support the hypothesis that multimodal interventions did have an effect in reducing violent crime.

Statistical Tests

In the target area, the total count of violent crime pre- and post-intervention, homicides pre- and post-intervention, aggravated assaults pre- and post-intervention, and robberies pre- and post-intervention (N = 7 for each) all fell within the statistical range of normalcy with regards to skewness (Table 9) and all but total violent crime post-intervention (-0.09) were positively skewed. None, however, were normally distributed with regards to kurtosis (less than -2, Tabachnick & Fidell, 2018). Transformations of this data were not attempted due to the small sample size.

In the control area, the total count of violent crime pre- and post-intervention, homicides pre- and post-intervention, aggravated assaults post-intervention, and robberies pre- and post-intervention ($N = 7$ for each) all fell within the statistical range of normalcy with regards to skewness (Table 10) and all but aggravated assaults post-intervention (-0.92) were positively skewed. None, however, were normally distributed with regards to kurtosis. Aggravated assaults pre-intervention fell outside both statistical ranges of normalcy (2.06 skewness and 4.55 kurtosis, Tabachnick & Fidell, 2018). Transformations of this data were not attempted due to the small sample size.

In the target area, the total rate of violent crime pre-intervention, homicides pre- and post-intervention, aggravated assaults pre- and post-intervention, and robberies pre- and post-intervention ($N = 7$ for each) all fell within the statistical range of normalcy with regards to skewness (Table 11) and all but total violent crime post-intervention (-2.20), aggravated assault post-intervention (-0.35) and robbery post-intervention (-0.22) were positively skewed. None, however, were normally distributed with regards to kurtosis. Total violent crime post-intervention fell outside both statistical ranges of normalcy (-2.20 skewness and 5.34 kurtosis, Tabachnick & Fidell, 2018). Transformations of this data were not attempted due to the small sample size.

In the control area, the total rate of violent crime pre- and post-intervention, homicides pre- and post-intervention, aggravated assaults pre- and post-intervention, and robberies pre- and post-intervention ($N = 7$ for each) all fell within the statistical range of normalcy with regards to skewness (Table 12) and all but aggravated assaults crime post-intervention (-0.11) were positively skewed. None, however, were normally distributed with regards to kurtosis (less than -2, Tabachnick & Fidell, 2018). Transformations of this data were not attempted due to the small sample size.

The descriptive statistics which were calculated above help support the position that such a small data set ($N = 14$) is far from ideal in being able to have a normal distribution of data to analyze. Researchers are not always given the luxury of having perfect data sets, however, and especially in social sciences the data we are given to analyze is challenging to control for (Nelson, 2017).

Independent t-tests were performed to determine if the means of the target and control areas were significantly different from each other with respect to the dependent variable and other individual crime measures (Table 13). An alpha of $p < .10$ was used instead of the "conventional" $p < .05$ because of small sample size. Fisher (1973) contends that the selected level for statistical significance is, in large part, based on personal opinion taking into context the entirety of the research at hand. For this study, it would mean that 10% of the time, the results discovered would have been happened upon only by "chance" or other factors not considered or controlled for. As held previously, this research has limited samples and a larger significance threshold is deemed appropriate in context.

The chosen alpha $p < .10$ notwithstanding, no mean differences were significant between the target and control areas with regards to total violent crime pre-intervention ($p = .95$) or post-intervention ($p = .18$); homicides pre-intervention ($p = .55$) or post-intervention ($p = .62$); aggravated assaults pre-intervention ($p = .38$) or post-intervention ($p = .60$); or robberies pre-intervention ($p = .41$) or post-intervention ($p = .20$). These independent t-tests help illustrate that, statistically, there exists no difference in these rates of violent crimes pre- and post-intervention. For all measures pre-intervention this helps support the selection of control areas for target areas (i.e., selected areas had no significant differences). Notably, the p-values for the difference between the target and control areas for total violent crimes post-intervention ($p = .18$) and robberies post-intervention ($p = .20$) are closest to the selected alpha of $p < .10$ and, though statistically insignificant, still correlate well to the results in Tables 7 and 8 which show that those same areas had the highest percentage of overall change compared to the control area. The reliability of these tests requires variables which are both normally distributed (most are only normal in regards to skewness) and contain no outliers. As such, results signifying lack of statistical differences should be taken with reservation.

Paired t-tests were performed to determine if the means of the target and control areas were significantly different from each other when pre- and post-intervention measures were combined (Table 14). An alpha of $p < .10$ was again selected for the analysis. No mean differences were statistically significant between the target and control areas with regards to total violent crime pre- and post-intervention combined ($p = .16$); homicides pre- and post-intervention combined ($p = .41$); aggravated assaults pre- and post-intervention combined ($p = .18$); or robberies pre- and post-intervention combined ($p = .67$). Similar to some of the independent t-tests in Table 13, several measures of the paired t-tests (total violent crime pre- and post-, $p = .16$ and aggravated assaults pre- and post-, $p = .18$) also begin to approach the desired alpha of $p < .10$ to show that there is a difference between the areas when pre- and post-intervention values are combined. Again, the reliability of these tests requires variables which are both normally distributed (most are only normal in regards to skewness) and contain no outliers. As such, results signifying lack of statistical differences should be taken with reservation.

A bivariate correlation was conducted on the dependent variable, independent variable and demographics in order to show the direction and magnitude of their relationships. Given the limited sample size and exploratory nature of this bivariate analysis, no p-values were calculated. Standardized measures of strength-of-relationship (Tabachnick & Fidell, 2018) are still applicable, however, and are used in the interpretation of results: a weak relationship if values are 0-0.29; a moderate relationship if they are 0.30-0.59; and a strong relationship if they are 0.60-0.99. A "1" indicates a perfect relationship. Table 15 shows the correlation matrix of the results of the Pearson's r correlation coefficients, some of which are described hereafter.

The independent variable *CBCRArea* (where intervention occurred: 1 = Target, 0 = Control) is moderately and negatively correlated (r = -0.37) with the dependent variable of *TViCr1* (total rate of violent crimes post-intervention). Therefore, as the intervention increases, the total rate of violent crime decreases. Similarly, *Vacant %* is also negatively correlated with *TViCr1*, though the relationship is weaker (r = -0.26). *Poverty %* had a very weak and positive correlation (r = -0.03) with *TViCr1*, which could indicate that as the total rate of violent crime increases, so does the percentage of those living in poverty. *Unemployment %* also had a moderate, negative relationship (r = -0.35) with the dependent variable. A strong, positive correlation (r = 0.61) was discovered between the dependent variable and total violent crime pre-intervention. This could be interpreted to signify that as violent crime pre-intervention begins to rise, so does violent crime post-intervention. One outcome of that interpretation is that the rate of violent crime is a strong indicator for future crime, though more sophisticated statistical testing would be necessary to explore such a notion. Statistical significance of any correlations in Table 15 is unknown and results should be interpreted appropriately.

A bivariate correlation was then conducted within the target area with the dependent variable and demographics in order to show the direction and magnitude of their relationships (Table 16). Given the limited sample size and exploratory nature of this bivariate analysis, no p-values were calculated. *Vacant %*, *Population*, and *Poverty %* all had moderate, positive correlations with the dependent variable ($r = 0.55$, $r = 0.38$, $r = 0.31$, respectively) so it may be connected that as violent crime rises after intervention (if, in fact, it would), then the population will be increasing as will the percentage of vacant properties and the rate of poverty. Statistical significance of any correlations in Table 16 is unknown and results should be interpreted appropriately.

Lastly, a bivariate correlation was then conducted within the control area with the dependent variable and demographics in order to show the direction and magnitude of their relationships (Table 17). Given the limited sample size and exploratory nature of this bivariate analysis, no p-values were calculated. Strong, negative correlations were found between the dependent variable and *Vacant %* ($r = -0.70$) and a moderate, negative correlation was found between the dependent variable and *Population* ($r = -0.47$). In contrast to the results within the target area (Table 16), these results may be interpreted that as the rate of violent crime goes up in the control area, population and vacancy may in fact decrease. Interestingly, a very strong, positive relationship ($r = 0.94$) was calculated between the rate of violent crime before intervention and the rate after. Though not a predictive statistical test, it may be interpreted that there is a very strong possibility that as the rate of violent crime rises in the control area pre-intervention, so will it rise post-intervention. Statistical significance of any correlations in Table 17 is unknown and results should be interpreted appropriately.

Though there are notable shortcomings with the size of the dataset that was available for analysis with this research, most of the statistical tests conducted herein support the hypothesis that the multimodal interventions undertaken by YPD and YNDC reduced violent crime aggregately, and some individually, in the target area relative to the control area. The independent t-tests of Table 13 supported the selection of control areas for each target area block group by indicating that, in the pre-intervention period, there was no statistical significance ($p < .10$) to any difference between the means of the target and control areas. In post-intervention, however, several measures had tendencies approaching statistical significance for a difference emerging. Likewise, though statistical significance at $p < .10$ was not achieved with the limited data, the paired t-tests had important measures, most notably total rate of crime in two areas, which were approaching the alpha level. Lastly, though p-values were not determined for the bivariate correlation tests, many measures showed moderate relationships to supporting the hypothesis, such as the independent variable of the area for intervention correlating with a reduction in overall rates of crime post-intervention.

Ratcliffe's *ABC spreadsheet calculator*

Statistical significance aside, did the interventions work? That is the bottom line that most criminal justice practitioners will want to know. Statistically, with the limited data available for this research, it could be said "No". However, the research of Wheeler and Ratcliffe (2018) and Ratcliffe (2019) provides a straight-forward Microsoft Excel spreadsheet to provide administrators, crime analysts, researchers, and anyone interested an easy way to get a statistically-sound answer.

The program utilizes counts of crimes as opposed to rates since it provides a "real reduction" statement referencing how many crimes it calculates were reduced (if any). The "real reduction" is calculated by the following formula:

(Activity area % change – Control area % change) x (Activity before number); result rounded (Wheeler & Ratcliffe, 2018).

Figure 5 shows the results of the inputting the homicide data into the program. There was no change in either the target ($N = 2$, before and after) or control area ($N = 4$, before and after) so the operation (in this case, multimodal intervention) was deemed to have no effect. This is supported by crime count data in Table 3 and by corresponding rates in Table 4.

Figure 6 shows the results of inputting the aggravated assault data into the program. This crime was reduced in both the target ($N = 1$) and control area ($N = 3$); however, since the control area decreased by 6.8% as opposed to the 4% of the target area, the multimodal interventions were deemed unsuccessful in reducing this particular crime for the CBCR program. This is supported by crime count data in Table 3 and by corresponding rates in Table 4.

Figure 7 displays the results after inputting the robbery count data into the program. This crime in the activity area decreased by 53.6% ($N = 15$) while it increased in the control area by 6.3% ($N = 2$). The target area thus "outperformed" the control area by 59.8% with a "real reduction" calculated to be 17 robberies. This is supported by crime count data in Table 3 and by corresponding rates in Table 4.

Lastly, Figure 8 displays the results after inputting the counts of total violent crime data (homicides + aggravated assaults + robberies) into the program. Conjointly, total violent crime in the target area was decreased by 29.1% ($N = 16$) while total violent crime in the control area decreased by only 1.3% ($N = 1$). This resulted in the target area "outperforming" the control area by 27.8% and resulting in a real reduction of 15 total violent crimes.

All of the above calculations done in Ratcliffe's spreadsheet are verified by the data available in Table 7 which itself was calculated from YSU's *CBCR Data* spreadsheet. By Ratcliffe's "real-world measures", the hypothesis that multimodal interventions conducted by the CBCR program partners in the target area would reduce overall violent crime was supported.

SUMMARY

This chapter highlighted the results of descriptive, independent and paired t-, and bivariate correlation statistical tests conducted on crime and demographic data for the CBCR Project. Cautions on interpreting the statistical outputs were emphasized due to limitations with the data. A practical analysis of the raw data was conducted and the hypothesis that crime would be reduced in the target area by engaging in multimodal interventions was supported. The next chapter will summarize the overall findings of this research, further discuss limitations, and consider recommendations for future research.

CHAPTER V

Conclusions

"Well, did it work?"

Undoubtedly, this question has been asked by countless chiefs of police, police captains, mayors, council persons, community leaders, news media, researchers, professors, and an array of other interested parties after a well-publicized violent crime reduction effort has concluded. Did crime decrease? Were there less shootings? Were less people robbed? How long will the reduction last? Was our money well spent? These and a multitude of other similar questions have been asked after large grants, such as the CBCR Project, concluded and the final numbers were tallied and reports were disseminated. "Did it work", however, is a relative viewpoint depending on who asked and what "work" actually means to them. Is it sufficient enough that crime numbers go down in the area where operations occurred? Or, does the person making the inquiry require that crime not only decreased, but did so with statistical significance such that we can rule out other possibilities besides the intervention? Because the audience asking these questions is often a diverse one with interests ranging from the practical to the political and from the academic to the highly-scientific, any similar endeavor to this violence-reduction effort should attempt to answer the questions of "did it work?" from several angles to provide the most extensive, yet practical, perspective possible.

The hypothesis for this research was reasonably simplistic in what it sought to explain – that multimodal interventions in a high-crime area reduce overall crime in that same area relative to when, and where, intervention was not present. Unique to this particular CBCR grant, which set it apart from a plethora of previous hot-spot and POP-based studies, was that the multitude of crime-reduction activities were not tied to law enforcement efforts alone – blight remediation was a companion pillar in the process along with community-engagement events and educational sessions. This unique multimodality of an approach was chief among the reasons that YPD, YNDC and YSU won the $1 million competitive grant from the Department of Justice and precisely why its operational efforts are worthy of analysis.

As evident from Chapter IV, the hypothesis has been supported by the evidence presented in this study: multimodal interventions to reduce violent crime in a micro-hot spot of Youngstown, Ohio were successful for the crimes analyzed. Relating the successful interventions back to Cohen and Felson's "routine activities theory" (1979), on which this research is grounded, YPD helped the program achieve success by increasing the presence of guardians (police officers) in the target area where the violent crime was occurring. They worked nearly 400 extra shifts, spoke to well over a thousand residents, and made hundreds of business contacts, traffic stops and arrests over the course of the intervention period which would not have occurred but for the CBCR Project. Likewise, YNDC successfully demolished over a hundred vacant houses and remediated hundreds of blighted and run-down properties which helped remove people and/or objects that may have provided suitable targets for crime, as the routine activities theory postulates. Both organizations, in conjunction with YSU, also helped educate residents in the target area about how they could make safety upgrades through environmental design, how to help themselves from personally becoming victims of crime, among other crime prevention strategies, thus removing themselves as "suitable targets". This is not to say, though, that this particular research or the data utilized were perfect; on balance, recognizing the limitations will help ensure future research improves over the present study.

Statistically, the major findings of this study demonstrated that it was possible to find a successful control area for our target area based upon the rate of violent crime, though other demographics such as vacancy and poverty presented an obstacle. Finding any "perfect" control area would be an anomaly due to the fact that the rates of violent crime, poverty, and vacancy were so extreme in the target area compared to the rest of the city. Post-intervention, the straightforward and uncomplicated results in Table 7 demonstrate that the target area's rates total violent crime, aggravated assault and robbery dropped and all but aggravated assault greatly out-performed the control area. The statistical findings presented in Tables 9-12 painted a clear picture that our data was not normally distributed and the results of further, more complex statistical tests would have to be interpreted with caution. The independent and paired samples t-tests did not produce any results of statistical significance, despite some measures approaching such an end. The three bivariate correlations generally showed associations that supported the hypothesis: a moderate, negative correlation (r = -0.37) exists between the dependent variable of total rate of violent crime post-intervention and the intervention area (Table 15); a weaker, but negative correlation (r = -0.26) exists between the percentage of vacant land and crime rates post-intervention (Table 15); and as crime rises, so does the percentage of vacant land (r = 0.55) and poverty (r = 0.31) (Table 16). In spite of these correlations by and large supporting the hypothesis, they too should be interpreted prudently due to the small and non-normalized nature of the data.

One point of concern is the lack of a “true” control area in order to more properly analyze the effects of intervention. Here, seven block groups were chosen which matched the target area block groups within 5% of total violent crime. During the period of time being studied, however, interventions to these control areas by both YPD and YNDC continued: YPD did not cease saturation patrols to hot-spot zones outside of the CBCR area when the need arose, nor did YNDC cease all blight remediation in other parts of the city. It would be irresponsible to deny extra patrols, code enforcement, and quality-of-life improvement pursuits throughout other areas simply for the purpose of studying its effects in a concentrated locale. Valid, however, is that the intensity and amplified frequency of such activities throughout the rest of the city did not compare to the very directed, planned, and significant efforts which took place within the target area.

The oft-opined about small data set ($N = 14$) is perhaps the study’s largest inadequacy. It limits statistical testing in a number of ways: normalization of data becomes difficult if not impossible; outliers which can skew more complex bivariate and multivariate testing cannot be practically controlled for; p-values become virtually meaningless in some testing; and more complex multivariate and predictive testing cannot be undertaken. A recommendation to correct for the small data set is to expand on each crime per block group by taking into account the crime rate per month, per quarter, or anything smaller than simply “pre-intervention” and “post-intervention” which aggregates all of the data into eighteen month each. As an example, if crime rates per month were used, instead of each block group being $N = 1$ for rate of robbery post-intervention, it would be $N = 18$. Total rate of violent crime pre- or post-intervention, then, would be $N = 54$ per block group and $N = 378$ for the entire target or control area.

Drilling down to a smaller timeframe, such as per week, would add even further detail. With a larger data set, statistical significance would be meaningful for correlations and multivariate regression analysis could be conducted with potential predictors (such as the census data) to measure the degree to which all of the measures may be related.

In addition to the unique nature of studying the effects of disparate multimodal interventions in the same target area simultaneously, this study was also the first found in the literature which used Ratcliffe's *ABC spreadsheet calculator* (Ratcliffe, 2019; Wheeler & Ratcliffe, 2018) for a key portion of the project's analysis. Moreover, the program was used in the practical approach intended by Ratcliffe's design: did crimes increase or decrease in the operational area compared to the control area, and by how much? In every-day policing and practice, these are the numbers that administrators care about. The results supported the hypothesis that the multimodal interventions reduced crime in the target area (Figures 5-8) and matched results which were statistically calculated in Table 7. Overall violent crime was reduced by 29.1%, robberies by 53.6%, aggravated assault by 4%, and the count and rate of homicides remained steady.

Ratcliffe's *ABC spreadsheet calculator* has its limitations too, chief among them being that the inputs and results are based upon crime count as opposed to rate of crime. Because rate of crime is based upon population size (per 100,000 people) its results are relevant nationwide and a more appropriate measure of overall crime for a given area compared with another. Additionally, within the same area, population could change over the period of a particularly long, longitudinal study and a straightforward crime count would be less accurate. At the time of this thesis, however, population data was not available for 2018 and 2019 from the U.S. Census Bureau so it was impossible to determine if there was any change and a need to apply weighting, if so.

A vast amount of detailed, cleaned, and geocoded data for dozens of measures related to crime, housing, demographics, and more is available from the Youngstown Police Department and YSU, including further data within the CBCR Project. So how can future research benefit from this expansive amount of data and build on the hypothesis presented here? One suggestion is to further explore the individual effects of the multimodal interventions on crime reduction. Just as the aggregated effects of multimodal interventions on violent crime had not been previously explored until this research, nor yet has how much each effect within the same area reduces crime.

The lack of the capability to distinguish which particular intervention has a more significant effect on reducing crime is a common shortcoming discussed for nearly all such interventions. This study utilized saturation patrols, increased community engagement, rapid addressing of code violations, demolition of abandoned houses, and more. The data gathered may have a story yet to tell – which actual intervention has a stronger effect on crime reduction? Did a traffic stop on the corner of Street X and Avenue Y reduce crime around it for a longer period of time than the children's event held at the church parking lot down the road? This particular study falls short of addressing such detailed analyses and the data in the dependent variable accounted for crime reduction from all interventions collectively.

Hot spots interventions, such as the CBCR Project, do not typically show strong evidence of the geographic displacement of crime to areas nearby (Telep, Mitchell, &

Weisburd, 2014) but enough detailed data has been gathered for the grant that looking at any potential displacement effect would be worthwhile. Lastly, because it has been shown that the operations did reduce violent crime counts and rates post-intervention, re-checking the crime rates after the hot-spot interventions have ceased – for example, one year from program termination – would be a valuable endeavor to ascertain if the effects of previous increased patrols, improved communication with the residents and the business community to foster meaningful relationships, and the remediation of blight had a longitudinal effect on keeping the crime rate lower than pre-intervention levels.

Though highly successful in reducing overall violent crime and robberies in the target area, the reduction in aggravated assaults was less than the control area and homicides remained steady in both. In what ways is it possible that administrators of similar operations can address these potential shortcomings to an otherwise successful program? Gun violence and homicides tend to be target-specific in nature, so augmented focused deterrence efforts on those who commit or are known to commit gun crimes is an effective strategy to reducing both (Braga & Schnell, 2013; Braga & Weisburd, 2010; Groff et al., 2015). Chief among these strategies are increased parole and probation visits, inspection of the violator's residence by appropriate authorities, and strict sentencing of the offender if s/he is found with a weapon or in violation of their probation or parole (Braga, Kennedy, Waring, & Piehl, 2001; Skogan & Frydl, 2004). Crimes such as homicide and aggravated assault which are directed at specific victims require focused interventions which specifically target the offenders, and augmenting the multimodal interventions presented herein with those strategies will further the success of those operations in whatever cities or towns implement them.

For too long, the city of Youngstown has endured a fiercely disproportionate amount of violent crime that has affected the lives of its citizens in ways which we cannot begin to adequately reflect upon in this thesis. Though the final answer to eliminating all such crimes will remain elusive to even the most gifted academic or the wisest philosopher, we as researchers and practitioners in the field of criminal justice have many of the keys to help open that door. Our use of intelligence-led policing models and data-driven strategies, coupled with our community and academic partnerships, are leading the way to realizing the ever-elusive goal of a crime-free society. Inherent to our strategy, however, must be the continued communication with, and eliciting the cooperation of, a community that not only needs our help but wishes to be part of the solution. Though the solutions we come up with together may not be perfect or may not follow traditional conventions, if we build them collectively using the lessons we have learned we know that success will come. Then, when they ask the inevitable question of "Well, did it work?" we can confidently answer:

"Yes, it did".

SUMMARY

This chapter highlighted the results of statistical testing conducted within the target area of the CBCR Project and, though the data had limitations, a trend was observed toward statistical significance. A more practical test was conducted on the change in crime over the life of the project which showed that it was a success in crime reduction. The benefits of this thesis are that it demonstrates that, though data may be limited, real crime reduction measures do not have to be perfect to be good.

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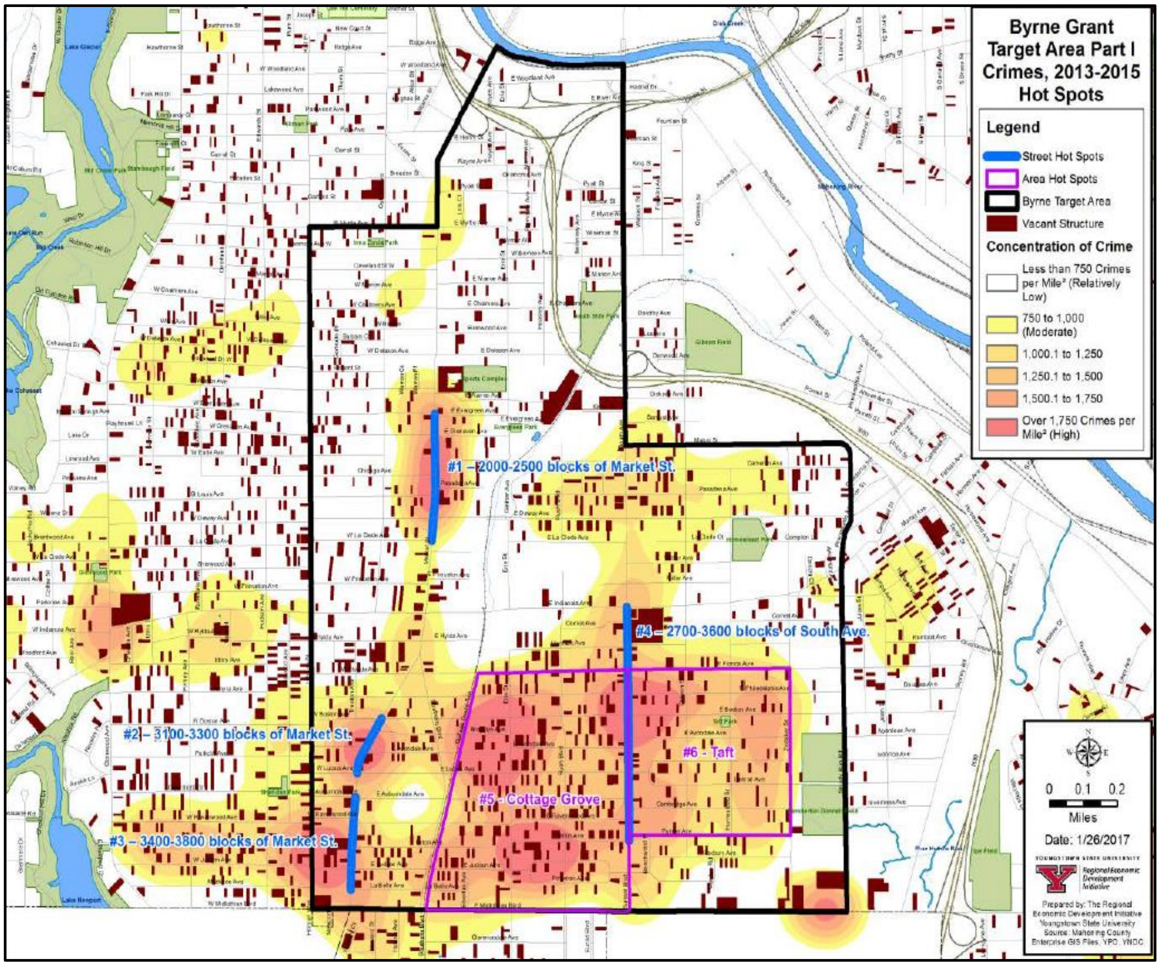

Figure 1. Byrne area (Youngstown Neighborhood Development Corporation, 2017).

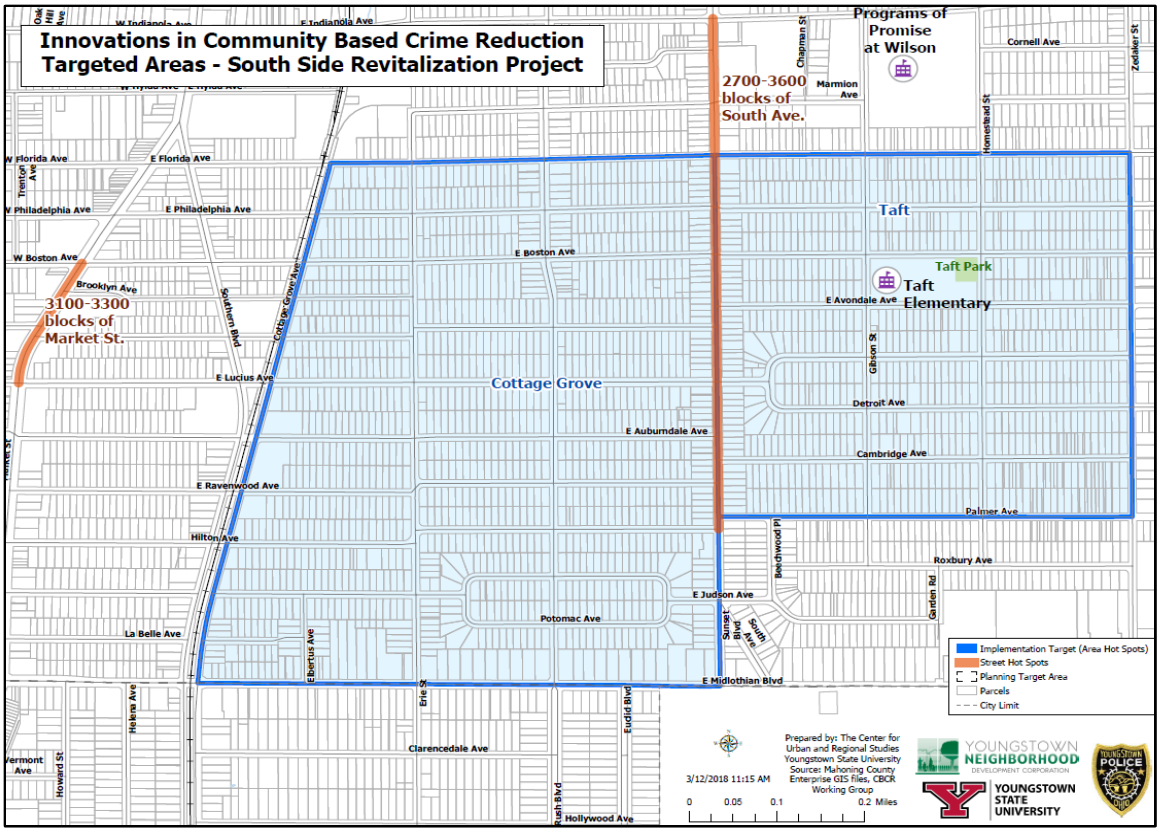

Figure 2. CBCR target hot spot (Youngstown Neighborhood Development Corporation, 2017).

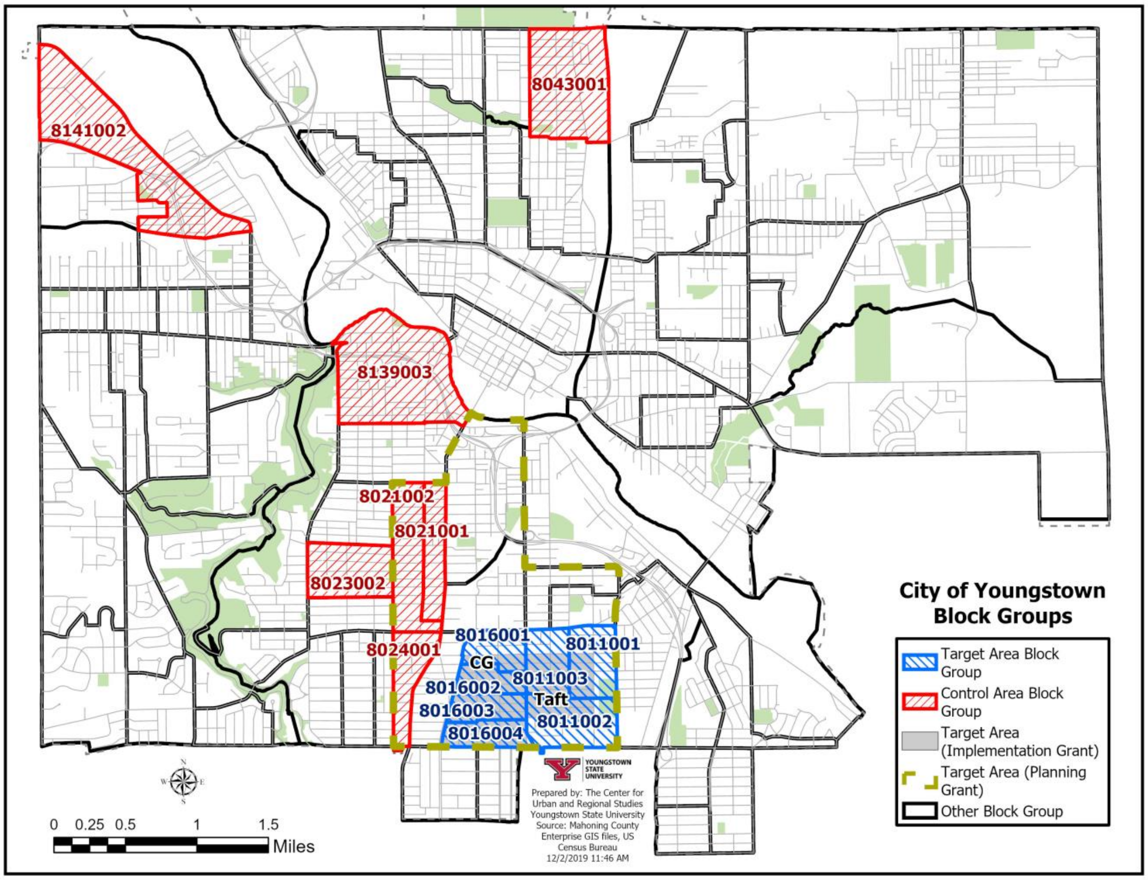

Figure 4. Block groups in the city of Youngstown with target area block groups shaded in blue forward-slashes and control area block groups shaded in red back-slashes (YSU, 2019).

CRIME OVERVIEW: Activity vs. control area

Crime in the activity area remained unchanged.
Crime in the control area remained unchanged.
There was less than 1% difference between control and activity areas.

Compared to the control area, the operation had no effect.

SOURCE DATA:

	Before	After
Activity area	2	2
Control area	4	4

Figure 5. Output for effectiveness of intervention on counts of homicide using Ratcliffe's *ABC spreadsheet calculator* (Ratcliffe, 2019).

CRIME OVERVIEW: Activity vs. control area

Crime in the activity area decreased by 1, a change of 4%

Crime in the control area decreased by 3, a change of 6.8%

The control area outperformed the activity area by 2.8%

Compared to the control area, the operation was not a success.

SOURCE DATA:

	Before	After
Activity area	25	24
Control area	44	41

Figure 6. Output for effectiveness of intervention on counts of aggravated assault using Ratcliffe's *ABC spreadsheet calculator* (Ratcliffe, 2019).

CRIME OVERVIEW: Activity vs. control area

Crime in the activity area decreased by 15, a change of 53.6%
Crime in the control area increased by 2, a change of 6.3%
The activity area outperformed the control area by 59.8%
This translates to a real reduction of about 17 crimes.
Compared to the control area, the operation was a success.

SOURCE DATA:

	Before	After
Activity area	28	13
Control area	32	34

Figure 7. Output for effectiveness of intervention on counts of robbery using Ratcliffe's *ABC spreadsheet calculator* (Ratcliffe, 2019).

CRIME OVERVIEW: Activity vs. control area

Crime in the activity area decreased by 16, a change of 29.1%

Crime in the control area decreased by 1, a change of 1.3%

The activity area outperformed the control area by 27.8%

This translates to a real reduction of about 15 crimes.

Compared to the control area, the operation was a success.

SOURCE DATA:

	Before	After
Activity area	55	39
Control area	80	79

Figure 8. Output for effectiveness of intervention on count of total violent crime (homicide + aggravated assault + robbery) using Ratcliffe's *ABC spreadsheet calculator* (Ratcliffe, 2019).

Table 1

Crime Rate and Demographic Comparisons

Crime	U.S.	City	Byrne	CBCR
Murder[a]	5.00	39.00	67.00	42.50
Aggravated Assault[a]	238.00	383.00	850.00	679.40
Robbery[a]	102.00	224.00	570.00	382.10
Vacant Housing[b]	12.20	20.10	33.00	35.70
Poverty[b]	7.60	38.00	53.30	55.30
Unemployment[b]	4.70	16.80	24.10	24.90
Education < HS[b]	13.00	17.00	21.30	22.30

[a] 2015 crime rates (*Source*. YNDC, 2017)
[b] 2016 Census data (*Source*. United States Census Bureau, 2017)

Table 2

Weighted Population of Target Area Block Groups

Block Group	Area	Population	Weighted	% of total Pop
8011001	Taft	640	206	32%
8011002	Taft	960	288	30%
8011003	Taft	643	411	64%
8016001	Cottage Grove	542	190	35%
8016002	Cottage Grove	591	591	100%
8016003	Cottage Grove	485	485	100%
8016004	Cottage Grove	441	429	97%

Note. Weighted population is population within block group subject to intervention activities
Source. Data file "CBCR Target area weight" (YSU, 2019)

Table 3

Violent Crime Counts for Target and Control Areas

Geography	Total Violent Crime[a] Pre	Total Violent Crime[a] Post	Homicides Pre	Homicides Post	Aggravated Assaults Pre	Aggravated Assaults Post	Robberies Pre	Robberies Post
Target	**55**	**39**	**2**	**2**	**25**	**24**	**28**	**13**
8011001	5	3	0	0	0	2	5	1
8011002	5	1	0	0	3	0	2	1
8011003	19	6	1	1	8	3	10	2
8016001	3	3	0	0	1	3	2	0
8016002	9	10	0	1	4	5	5	4
8016003	5	8	0	0	3	4	2	4
8016004	9	8	1	0	6	7	2	1
Control	**80**	**79**	**4**	**4**	**44**	**41**	**32**	**34**
8023002	11	8	2	1	5	2	4	5
8139003	7	7	0	0	6	5	1	2
8024001	23	23	1	0	13	8	9	15
8141002	14	12	0	1	5	7	9	4
8043001	10	10	1	2	7	8	2	0
8021002	6	7	0	0	4	6	2	1
8021001	9	12	0	0	4	5	5	7

Note. Pre-intervention period is October 2016 through March 2018 and post-intervention period is April 2018 through September 2019
[a] Total Violent Crime represents the number of homicides + number of aggravated assaults + number of robberies
Source. Data file "CBCR Data" (YSU, 2019)

Table 4

Violent Crime Rates per 100,000 Population for Target and Control Areas

Geography	Total Violent Crime[a] Pre	Total Violent Crime[a] Post	Homicides Pre	Homicides Post	Aggravated Assaults Pre	Aggravated Assaults Post	Robberies Pre	Robberies Post
Target	**2115**	**1500**	**77**	**77**	**961**	**923**	**1077**	**500**
8011001[b]	2424	1454	0	0	0	970	2424	485
8011002[b]	1737	347	0	0	1042	0	695	347
8011003[b]	4625	1461	243	243	1947	730	2434	487
8016001[b]	1576	1576	0	0	525	1576	1050	0
8016002	1523	1692	0	169	677	846	846	677
8016003	1031	1649	0	0	619	825	412	825
8016004[b]	2098	1865	233	0	1399	1632	466	233
Control	**2035**	**2009**	**102**	**102**	**1119**	**1043**	**814**	**865**
8023002	2529	1839	460	230	1149	460	920	1149
8139003	1659	1659	0	0	1422	1185	237	474
8024001	4842	4842	211	0	2737	1684	1895	3158
8141002	1525	1307	0	109	545	763	980	436
8043001	1460	1460	146	292	1022	1168	292	0
8021002	985	1149	0	0	657	985	328	164
8021001	2320	3093	0	0	1031	1289	1289	1804

Note. Pre-intervention period is October 2016 through March 2018 and post-intervention period is April 2018 through September 2019
[a] Total Violent Crime represents the number of homicides + number of aggravated assaults + number of robberies
[b] Block group using weight population to represent the population within the block group subject to intervention activities
Source. Data file "CBCR Data" (YSU, 2019)

Table 5

Demographic Profile of Target and Control Areas

Geography	Population	Weighted Pop[a]	Poverty %	Vacant Property %	Unemployment %	Edu LTHS %
Target Area	**4302**	**2600**	**58.1%**	**35.5%**	**16.7%**	**42.2%**
8011001	640	206	31.8%	10.6%	26.2%	66.0%
8011002	960	288	46.2%	23.1%	21.2%	50.2%
8011003	643	411	54.6%	33.4%	4.4%	64.8%
8016001	542	190	69.2%	47.3%	37.3%	32.7%
8016002	591	591	67.5%	38.1%	6.3%	29.9%
8016003	485	485	90.9%	44.7%	16.1%	22.8%
8016004	441	429	46.5%	51.3%	5.4%	29.0%
Control Area	**3932**	**3932**	**46.9%**	**27.2%**	**7.1%**	**24.7%**
8023002	435	435	39.3%	29.8%	5.3%	24.2%
8139003	422	422	40.3%	34.3%	6.2%	24.3%
8024001	475	475	43.8%	15.4%	3.6%	30.0%
8141002	918	918	68.3%	19.2%	0.0%	23.7%
8043001	685	685	42.0%	30.6%	12.7%	21.2%
8021002	609	609	28.1%	37.5%	14.8%	31.2%
8021001	388	388	66.2%	23.9%	7.0%	18.4%

[a] Weighted population is population within block group subject to intervention activities
Source. United States Census Bureau, 2017

Table 6

Error Rates for Selection of Control Areas

Target	Control	Total Violent Crime[a] Pre	Vacancy %	Poverty %	Unemployed %	Edu LTHS %
8011001	8023002	4.3%[b]	19.1%	7.6%	-20.9%	-41.8%
8011002	8139003	-4.5%[b]	11.2%	-5.9%	-15.0%	-25.8%
8011003	8024001	4.7%[b]	-18.1%	-10.9%	-0.8%[b]	-34.8%
8016001	8141002	-3.2%[b]	-28.1%	-0.9%[b]	-37.3%	-8.9%
8016002	8043001	-4.1%[b]	-7.5%	-25.5%	6.4%	-8.7%
8016003	8021002	-4.4%[b]	-7.3%	-62.9%	-1.3%[b]	8.4%

Note. Pre-intervention period is October 2016 through March 2018
[a] Total Violent Crime represents the number of homicides + number of aggravated assaults + number of robberies
[b] Achieved targeted +/- 5%
Source. Data file "CBCR Data" (YSU, 2019)

Table 7

Changes in Rates of Crime in Target and Control Areas Pre- and Post-Intervention

	Target Area			Control Area		
Crime	Pre	Post	% change	Pre	Post	% change
Total Violent Crime[a]	2,115	1,500	-29.1%	2,035	2,009	-1.3%
Homicide	77	77	0.0%	102	102	0.0%
Aggravated Assault	961	923	-4.0%	1,119	1,043	-6.8%
Robbery	1,077	500	-53.6%	814	865	6.3%

Note. Pre-intervention period is October 2016 through March 2018 and post-intervention period is April 2018 through September 2019
[a] Total Violent Crime represents the number of homicides + number of aggravated assaults + number of robberies
Source. Data file "CBCR Data" (YSU, 2019)

Table 8

Changes in Rates of Crime Between Target and Control Areas Post-Intervention

Crime	Target	Control	% change
Total Violent Crime[a]	1,500	2,009	33.9%
Homicide	77	102	32.5%
Aggravated Assault	923	1,043	13.0%
Robbery	500	865	73.0%

Note. Post-intervention period is April 2018 through September 2019
[a] Total Violent Crime represents the number of homicides + number of aggravated assaults + number of robberies
Source. Data file "CBCR Data" (YSU, 2019)

Table 9

Descriptive Statistics of Violent Crime Count in Target Area (N = 7)

Crime	Mean	Median	SD	Min	Max	Skewness	Kurtosis
Total Violent Crime[a] Pre	7.86	5.00	5.40	3.00	19.00	1.78[b]	3.49
Total Violent Crime[a] Post	5.57	6.00	3.31	1.00	10.00	-0.09[b]	-1.59
Homicide Pre	0.29	0.00	0.49	0.00	1.00	1.23[b]	-0.84
Homicide Post	0.29	0.00	0.49	0.00	1.00	1.23[b]	-0.84
Aggravated Assault Pre	3.57	3.00	2.76	0.00	8.00	0.43[b]	-0.37
Aggravated Assault Post	3.43	3.00	2.23	0.00	7.00	0.13[b]	0.52
Robbery Pre	4.00	2.00	3.00	1.00	9.00	1.61[b]	2.45
Robbery Post	1.86	1.00	1.57	0.00	15.00	0.68[b]	-1.16

Note. Pre-intervention period is October 2016 through March 2018 and post- intervention period is April 2018 through September 2019

[a] Total Violent Crime represents the number of homicides + number of aggravated assaults + number of robberies

[b] Achieves statistical normalcy as indicated in Tabachnick & Fidell, 2018

Table 10

Descriptive Statistics of Violent Crime Count in Control Area (N = 7)

Crime	Mean	Median	SD	Min	Max	Skewness	Kurtosis
Total Violent Crime[a] Pre	11.43	10.00	5.74	6.00	23.00	1.61[b]	2.88
Total Violent Crime[a] Post	11.29	10.00	5.59	7.00	23.00	1.89[b]	3.99
Homicide Pre	0.57	0.00	0.79	0.00	2.00	1.11[b]	0.27
Homicide Post	0.57	0.00	0.79	0.00	2.00	1.11[b]	0.27
Aggravated Assault Pre	6.29	5.00	3.15	4.00	13.00	2.06	4.55
Aggravated Assault Post	5.86	6.00	2.12	2.00	8.00	-0.92[b]	0.80
Robbery Pre	4.57	4.00	3.31	1.00	9.00	0.61[b]	-1.43
Robbery Post	4.86	4.00	5.08	0.00	15.00	1.53[b]	2.62

Note. Pre-intervention period is October 2016 through March 2018 and post-intervention period is April 2018 through September 2019

[a] Total Violent Crime represents the number of homicides + number of aggravated assaults + number of robberies

[b] Achieves statistical normalcy as indicated in Tabachnick & Fidell, 2018

Table 11

Descriptive Statistics of Violent Crime Rate in Target Area (N = 7)

Crime	Mean[c]	Median[c]	SD[c]	Min[c]	Max[c]	Skewness	Kurtosis
Total Violent Crime[a] Pre	2,145	1,737	1,180	1,031	4,625	1.91b	4.16
Total Violent Crime[a] Post	1,435	1,576	500	347	1,865	-2.20	5.34
Homicide Pre	68	0	116	0	243	1.23b	-0.82
Homicide Post	59	0	103	0	243	1.41b	0.28
Aggravated Assault Pre	887	677	638	0	1,947	0.50b	0.16
Aggravated Assault Post	940	846	553	0	1,632	-0.35b	0.47
Robbery Pre	1,190	846	874	412	2,434	0.98b	-1.05
Robbery Post	436	485	275	0	825	-0.22b	-0.15

Note. Pre-intervention period is October 2016 through March 2018 and post-intervention period is April 2018 through September 2019

[a] Total Violent Crime represents the number of homicides + number of aggravated assaults +number of robberies

[b] Achieves statistical normalcy as indicated in Tabachnick & Fidell, 2018

[c] Values are rates per 100,000 population

Table 12

Descriptive Statistics of Violent Crime Rate in Control Area (N = 7)

Crime	Mean[c]	Median[c]	SD[c]	Min[c]	Max[c]	Skewness	Kurtosis
Total Violent Crime[a] Pre	2,188	1,659	1,283	985	4,842	1.79b	3.60
Total Violent Crime[a] Post	2,193	1,659	1,332	1,149	4,842	1.67b	2.32
Homicide Pre	117	0	174	0	460	1.54b	2.06
Homicide Post	90	0	125	0	292	0.97b	-0.93
Aggravated Assault Pre	1,223	1,031	730	545	2,737	1.78b	3.77
Aggravated Assault Post	1,076	1,168	392	460	1,684	-0.11b	0.40
Robbery Pre	849	920	614	237	1,895	0.69b	-0.34
Robbery Post	1,026	474	1,127	0	3,158	1.32b	1.23

Note. Pre-intervention period is October 2016 through March 2018 and post-intervention period is April 2018 through September 2019
[a] Total Violent Crime represents the number of homicides + number of aggravated assaults + number of robberies
[b] Achieves statistical normalcy as indicated in Tabachnick & Fidell, 2018
[c] Values are rates per 100,000 population

Table 13

Comparison for Rate of Violent Crimes (independent t-tests)

Crime	Mean	SD	p-value[b]
Total Violent Crimes[a] Pre			
Target Area	2,145	1,180	0.95
Control Area	2,188	1,283	
Total Violent Crimes[a] Post			
Target Area	1,435	500	0.18
Control Area	2,193	1,332	
Homicides Pre			
Target Area	68	116	0.55
Control Area	117	174	
Homicides Post			
Target Area	59	103	0.62
Control Area	90	125	
Aggravated Assaults Pre			
Target Area	887	638	0.38
Control Area	1,223	730	
Aggravated Assaults Post			
Target Area	940	553	0.60
Control Area	1,076	392	
Robberies Pre			
Target Area	1,190	874	0.41
Control Area	849	614	
Robberies Post			
Target Area	436	275	0.20
Control Area	1,026	1,127	

Note. Pre-intervention period is October 2016 through September 2019
[a] Total Violent Crime represents the number of homicides + number of aggravated assaults + number of robberies
[b] alpha for the analysis is $p<.10$

Table 14

Paired Comparison for Rate of Violent Crimes (paired t-tests)

Crime	Mean	SD	p-value[b]
Total Violent Crimes[a] Pre & Post			
Target Area	1,790	945	0.16
Control Area	2,191	1,256	
Homicides Pre & Post			
Target Area	64	106	0.41
Control Area	103	146	
Aggravated Assaults Pre & Post			
Target Area	913	574	0.18
Control Area	1,150	568	
Robberies Pre & Post			
Target Area	813	735	0.67
Control Area	938	877	

Note. Pre-intervention period is October 2016 through March 2018 and post-intervention period is April 2018 through September 2019

[a] Total Violent Crime represents the number of homicides + number of aggravated assaults + number of robberies

[b] alpha for the analysis is $p<.10$

Table 15

Bivariate Statistics of Violent Crime Measures in Target and Control Areas with Selected Demographics

Crime	Total Violent Crime[a] Pre	Total Violent Crime[a] Post	CBCRArea	Population[b]	Vacant %	Poverty %	Unemployment %	EduLTHS %
Total Violent Crime[a] Pre	1							
Total Violent Crime[a] Post	0.61	1						
Target Area (1=yes)	-0.02	-0.38	1					
Population	-0.22	-0.02	-0.52	1				
Vacant %	-0.39	-0.26	0.36	-0.06	1			
Poverty %	-0.20	0.03	0.33	0.13	0.34	1		
Unemployment %	-0.33	-0.35	0.48	-0.63	0.14	0.03	1	
EduLTHS %	0.42	-0.30	0.58	-0.49	-0.31	-0.30	0.33	1

Note. Given limited sample size and the exploratory nature of this bivariate analysis, no p-values were calculated.
[a] Total Violent Crime represents the number of homicides + number of aggravated assaults + number of robberies
[b] Weighted population is used to represent the population within the block group subject to intervention activities
Sources. Data files "CBCR Data" and "CBCR Target area weight" (both YSU, 2019)

Table 16

Bivariate Statistics of Violent Crime Measures in Target Area with Selected Demographics

Crime	Total Violent Crime[a] Pre	Total Violent Crime[a] Post	Population[b]	Vacant %	Poverty %	Unemployment %	EduLTHS %
Total Violent Crime[a] Pre	1						
Total Violent Crime[a] Post	0.00	1					
Population	-0.07	0.38	1				
Vacant %	-0.26	0.55	0.42	1			
Poverty %	-0.43	0.31	0.48	0.64	1		
Unemployment %	-0.38	-0.26	-0.83	-0.22	-0.01	1	
EduLTHS %	0.75	-0.41	-0.48	-0.81	-0.72	0.06	1

Note. Given limited sample size and the exploratory nature of this bivariate analysis, no p-values were calculated.
[a] Total Violent Crime represents the number of homicides + number of aggravated assaults + number of robberies
[b] Weighted population is used to represent the population within the block group subject to intervention activities
Sources. Data files "CBCR Data" and "CBCR Target area weight" (both YSU, 2019)

Table 17

Bivariate Statistics of Violent Crime Measures in Control Area with Selected Demographics

Crime	Total Violent Crime[a] Pre	Total Violent Crime[a] Post	Population[b]	Vacant %	Poverty %	Unemployment %	EduLTHS %
Total Violent Crime[a] Pre	1						
Total Violent Crime[a] Post	0.94	1					
Population	-0.41	-0.47	1				
Vacant %	-0.71	-0.70	-0.18	1			
Poverty %	0.06	0.17	0.29	-0.66	1		
Unemployment %	-0.46	-0.35	-0.13	0.75	-0.65	1	
EduLTHS %	0.25	0.15	0.06	0.07	-0.64	0.15	1

Note. Given limited sample size and the exploratory nature of this bivariate analysis, no p-values were calculated.
[a] Total Violent Crime represents the number of homicides + number of aggravated assaults + number of robberies
[b] Weighted population is used to represent the population within the block group subject to intervention activities
Sources. Data files "CBCR Data" and "CBCR Target area weight" (both YSU, 2019)

APPENDIX

Dear Investigators

Your protocol entitled Multimodal effects of violent crime reduction in a micro-target area of Youngstown Ohio has been reviewed and it is deemed to meet the criteria of an exempt protocol. You will be using pre-existing data without any contact with research participants/subjects.

The research project meets the expectations of 45 CFR 46.104(d)(2) and is therefore approved. You may begin the investigation immediately. Please note that it is the responsibility of the principal investigator to report immediately to the YSU IRB any deviations from the protocol and/or any adverse events that occur. Please reference your protocol number 067-20 in all correspondence about the research associated with this protocol.

Good luck with your research.

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