



FLINT DDACTS PILOT EVALUATION

**MICHIGAN JUSTICE STATISTICS CENTER
SCHOOL OF CRIMINAL JUSTICE
MICHIGAN STATE UNIVERSITY**

JULY 2014

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Michigan Justice Statistics Center

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FLINT DDACTS PILOT EVALUATION

Final Report Outline

ACKNOWLEDGEMENTS

EXECUTIVE SUMMARY

DDACTS OVERVIEW

- Program Description
 - Background
 - Theoretical Framework
 - DDACTS in Flint

PROGRAM OPERATIONS

- Program Implementation and Activities
- Hotspots Identified
 - Program Activities across Hotspots
 - Program Outputs across Hotspots

IMPACT ASSESSMENT

- Defining Target and Non-Target Areas
 - Comparison of Target and Non-Target Areas
 - Estimating the Effect of DDACTS on Violent Crime in Flint
 - Unadjusted Changes in Violent, Pre- and Post-Implementation
 - Comparison Using a Synthetic Control Method
- Sensitivity Analyses
 - Placebo Tests
 - Subgroup Analyses

CONCLUSIONS

TECHNICAL NOTES

- Synthetic Control Strategy
 - Creation of a Synthetic Control Unit
 - Estimating Intervention Effects
 - Covariates for Estimation of a Synthetic Control Unit
- Elaborated Results – Difference-in-Differences Estimates and MSPE Ratios

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EXECUTIVE SUMMARY

In response to the public safety challenges posed by high levels of violent crime and local level law enforcement resource constraints, the Michigan State Police (MSP) have developed the “Secure Cities” initiative as part of its strategic plan. The Secure Cities initiative involves providing additional MSP enforcement resources to Detroit, Flint, Pontiac and Saginaw; using data-driven planning; and developing evidence-informed and evidence-based strategies for addressing high levels of violent crime. One specific strategy has been the implementation of the Data-Driven Approaches to Crime and Traffic Safety (DDACTS) in Flint.

The Flint DDACTS initiative began enforcement activities in January 2012. The current evaluation examined the program as it operated between January 2012 and March 2014. This report presents the findings of the evaluation of the Flint DDACTS program, describing both trends in program activities and the effect of DDACTS on violent crime.

Key Findings

- The DDACTS strategy targeted five hotspots for violent crime in Flint, later expanded to include two additional hotspot areas.
- MSP collected very detailed activity data from the Troopers involved in DDACTS. This reflected exceptional performance output measures.
- A significant level of patrol resources with associated activities occurred in these hotspot areas. Indeed, over 22,000 traffic stops occurred between January 1, 2012 and March 2014 as part of the DDACTS initiative. Nearly three-quarters of the traffic stops occurred in the targeted hotspots. This equated to significant enforcement presence in the hotspot areas with over 600 traffic stops occurring each month in the hotspot areas
- For every 100 traffic stops, there were nearly 95 verbal warnings, 2 citations, 14 arrests for misdemeanor and felony charges, and 17 fugitive arrests.
- The heavy use of verbal warnings appears to reflect concern with maintaining positive relationships with Flint residents.
- The high number of arrests per traffic stop reflects a very high level of enforcement productivity.
- The initial set of analyses focused on the trend in violent crime in the DDACTS hotspot target areas. Violent crime (homicide, aggravated assaults, robberies, criminal sexual conduct, weapons offenses) declined 19 percent in the hotspot areas. The declines were observed in 14 of the 27 months of the DDACTS initiative. The remainder of the city experienced a 7 percent decline in violent crime.
- Robberies declined 30 percent in the hotspot areas. The remainder of the city experienced a 2 percent decline in robberies.
- Several analyses were undertaken to test rival explanations for the decline in violent crime. Specifically, “synthetic” comparison areas consisting of block groups within the city that were not subject to the DDACTS initiative were compared to the trend in violent crime in the hotspot areas. The findings indicated that the comparison areas also experienced a decline in violent crime.

- The finding that the comparison areas also experienced a decline in violent crime suggests two contrasting interpretations. The first is that DDACTS had a crime reduction impact and that the benefits diffused to other areas of the city. This interpretation gains plausibility by the finding that approximately one-quarter of the DDACTS traffic stops, over 1,000 fugitive arrests and an additional 923 felony and misdemeanor arrests occurred outside the hotspot areas. The second interpretation is that some factor other than DDACTS was leading to the observed reduction in violent crime. The results do not allow us to rule out this potential explanation.

Policy Recommendations and Future Directions

- The results are certainly promising and indicate continued implementation, experimentation and ongoing assessment.
- The large number of traffic stops and verbal warnings provide an opportunity for Troopers to express MSP's focus on violence reduction. This opportunity to express a concern for public safety and a focus on reducing gun crime has been suggested in Project Safe Neighborhoods programs in various jurisdictions.
- The Hotspot areas were relatively large and covered a significant portion of the City. This may have diluted some of the impact of the intervention as prior research suggests that highly focused enforcement interventions in small geographic areas have the greatest impact. Identifying specific street blocks with high levels of violence within the larger hotspots and then focusing resources on these high crime street blocks may magnify the impact of the DDACTS strategy. This may include people- (e.g. violent networks) and place-based (e.g., problem-solving, blight reduction, greening) interventions within these street blocks. This may suggest a fruitful area of collaboration with the Flint Police Department (FPD), city of Flint, local residents, and governmental and non-governmental organizations.
- From an evaluation perspective, the impact could be more clearly measured by identifying smaller hotspot areas and systematically rotating enforcement activities. For example, the seven hotspots included in the present DDACTS initiative might be broken into 14 or more target areas. A subgroup of target areas (e.g., 3-4) would receive the DDACTS intervention for a specific period of time (e.g., 30 days) then the focus would move to another set of target areas for a similar period of time. This systematic rotation of the DDACTS intervention would continue over the course of a specified period of time allowing for multiple comparisons of the target area violent crime trends with the remainder of the city. In an ideal evaluation world, the target areas would be randomly assigned for intervention. This would allow the strongest conclusions about the impact of DDACTS. We say this recognizing that the top priority for MSP, FPD, and the city is public safety and that the evaluation goal is one of multiple priorities.
- The evaluation did not include an assessment of the impact on traffic safety. Future assessment should consider this potential effect.
- The largest decline in violent crime in the DDACTS hotspot areas, and the largest divergence from trends in other parts of the city, occurred in the last quarter of 2013. This may indicate increased impact given the duration and the sustained dosage of the DDACTS intervention.

- A large number of firearms seizures occurred, particularly in Hotspot 1. The potential impact on gun crime should be assessed.

DDACTS OVERVIEW

Program Description

Background

Traffic enforcement and crime prevention have traditionally been thought of as separate entities. In the late 1930s, specialized traffic units began to appear in police departments around the United States. Between 1936 and 1941 Los Angeles, Detroit, Atlanta, Chattanooga, Chicago, Cincinnati, Cleveland, Oakland, and Portland all developed specialized units to handle traffic safety (Weiss, 2013). With the growing size of the traffic problem in many cities there was a belief that general patrol was not capable of traffic enforcement because they lacked training and willing skilled supervisors; therefore, specialized traffic units were needed (Kreml, 1954; Weiss, 2013). The creation of these specialized units led many in the law enforcement community to conclude that traffic safety and general crime control were different, and as a result, they have generally been handled separately.

With increasing demands for services, growing operational costs, and limited resources in many jurisdictions, law enforcement executives have to prioritize the allocation of police resources. Addressing crime is often seen as more important than addressing traffic issues for maintaining public safety, and as a result, law enforcement agencies have primarily focused their resources on crime while traffic safety become a secondary issue (NHTSA, 2009).

For years, advocates for traffic safety have argued that traffic enforcement has crime control benefits and have urged law enforcement executives to commit more resources to traffic enforcement and traffic safety programs. The National Highway Traffic Safety Administration (NHTSA) has partnered with a number of law enforcement organizations in an attempt to strengthen law enforcement's role in traffic safety and promote the crime control effects that can

be achieved through traffic enforcement. In 1996, NHTSA along with the International Association of Chiefs of Police (IACP) published the *Highway Safety Desk Book* which advocated for the secondary benefits of traffic enforcement as a way to fight crime by disrupting criminals who use motor vehicles during the commission of a crime (e.g., robbers, drug traffickers, car thieves). They argued that traffic enforcement officers not only kept the roads safe, they also assisted in combating criminal activity.

In 2001, NHTSA and IACP produced another document which stressed the importance of traffic safety programs in “comprehensive law enforcement operations.” *Traffic Safety in the New Millennium* argues that traffic safety initiatives are no less important than those for gang violence, narcotics, and violent crimes and should be given serious consideration by law enforcement executives. In fact, many traffic safety initiatives not only led to reductions in crashes, they also led to other benefits in the communities. They suggest law enforcement agencies make traffic safety an organization-wide commitment, integrating traffic safety throughout all agency operations.

In 2007, Strategic and Tactical Approaches to Traffic Safety (STATS) was offered as a new model for law enforcement traffic safety. The goals of STATS were to: 1) enable law enforcement agencies to provide effective traffic enforcement without depending on federal funding, 2) use data-driven models to allocate enforcement resources, 3) develop strategies for using traffic enforcement to reduce overall criminal activity, and 4) develop and train a new generation of traffic safety professionals (Weiss, 2013, pg. 18).

Using STATS as a guide, in 2008, NHTSA in conjunction with the Bureau of Justice Assistance (BJA) and the National Institute of Justice (NIJ) developed DDACTS. DDACTS escapes conventional ideas about traffic safety and law enforcement by emphasizing traffic

enforcement as an effective strategy for reducing the occurrence of traffic crashes and violations as well as crime in a community. Law enforcement agencies are able to leverage limited resources to provide more effective and efficient services by analyzing crime and traffic data to identify areas with the highest overlapping incidence occurrence then deploying high-visibility traffic enforcement to those areas as a countermeasure to address both crime and traffic safety problems. Since its inception DDACTS has been implemented in a number of cities including Baltimore, MD, Lafourche Parish, LA, Nashville, TN, Rochester, NY, St. Albans, VT, Oakland, CA, Washoe County, NV, and Indianapolis, IN.

DDACTS has seven guiding principles for law enforcement agencies to follow if they plan on implementing the strategy:

1. **Local Partnerships** – There should be partnerships between law enforcement agencies and local stakeholders and community organizations to provide synergistic opportunities for decreasing social harm and improving the quality of life in communities.
2. **Data collection** – Law enforcement agencies should collect current place-based crime, crash, and traffic data coded for type of incident, time of day, and day of the week. Data should include UCR Part I and Part II crimes. Data may also include field interviews, citizen complaints, and dangerous driving behaviors, as well as location of parolees and probationers and individuals with suspended or revoked licenses.
3. **Data analysis** – Law enforcement agencies should create maps that merge crime, crash, and traffic data to identify “hot spots,” areas of high overlap.
4. **Strategic operations** – To increase efficiency, law enforcement should use hot spots to realign workflow and direct agency resources. Realignment should coincide with days of the week and times of the day where crimes and crashes are highest.

5. **Information sharing and outreach** – Law enforcement agencies should share results of analysis, promote community participation, and document their accomplishments. Regular progress reports should be generated and given to management, community members, and government officials.
6. **Monitoring, evaluating, and adjusting operations** – Law enforcement agencies should regularly collect and assess crime and crash data. Operations should be adjusted according to results from data collection.
7. **Measuring Outcomes** – Law enforcement agencies should create goals and objectives during the planning and analysis. Measurements should be able to assess the strategies effectiveness at reducing: crime, crashes, traffic violations, operational costs, and resource deployment. (NHTSA, 2009).

Theoretical Framework

As noted above, with increasing operational costs and diminishing resources, there is a growing need for law enforcement agencies to make decisions about prioritizing their responses to crime and traffic incidents. They have to weigh competing demands for police services against their limited resources. DDACTS is an innovative strategy which uses a problem oriented policing approach to reduce both crime and traffic incidents in areas where the two overlap, allowing law enforcement to address both problems simultaneously despite limited resources. Problem-oriented policing represents a paradigm shift that replaces the reactive, incident-based model of policing with a proactive model which looks to identify the underlying conditions that cause crime and disorder (Weisburd et al., 2010). Emphasis is placed on identifying and analyzing specific crime problems, responding to these problems, assessing that response, and

making adjustments to the response. The DDACTS strategy involves geographically and temporally plotting locations of crimes and motor vehicle crashes to identify places and times of high incidence overlap known as “hot spots.” Once hot spots are identified, law enforcement focuses special attention on those areas through the use of high-visibility traffic enforcement in an attempt to deter crime, traffic violations, and motor vehicle crashes. Crime and traffic data are continuously monitored and evaluated to assess the strategy’s effectiveness and adjust field operations as needed. This strategy also aims to address public safety by reducing social harms that are caused by both crime and traffic crashes (NHTSA, 2009). A number of key elements drive the DDACTS model.

First, DDACTS uses a place-based policing strategy. Traditionally, police focused on the specific people involved in crime incidents such as offenders and victims. In recent years, police have begun shifting their enforcement efforts to situations and places, focusing police strategies on hot spots and crime mapping. When looking at places where crime is concentrated, there is often something about the place which leads to the occurrence of crime (Weisburd, 2008). In place-based policing, places are important for understanding and controlling crime, and emphasis is placed on reducing opportunities for crime at places, not reacting to crime after it occurs. The focus is shifted from the people involved in crime to the contexts of criminal behavior (Weisburd, 2008; Weisburd et al., 2009). According to Weisburd (2008) place-based policing is more efficient than focusing on targeting individuals and provides more stable targets for police than individual offending patterns. The National Research Council’s review of police practices and policies studies found that when resources were focused on crime hot spots they showed strong evidence of police effectiveness (Weisburd, 2008).

Second, in addition to focusing on the specific places where crime and traffic crashes intersect, the DDACTS model draws on research illustrating the positive crime control effect of directed high-visibility traffic enforcement (McGarrell et al., 2001; Sherman & Rogan, 1995; Stuster, Sheehan, & Morford, 1997; Weiss & Freels, 1996; Weiss & McGarrell, 1999). This can be demonstrated through findings from studies on directed patrol. Directed patrol involves assigning officers to particular high risk areas to engage in proactive investigations and enforcement of suspicious activities. The Kansas City Gun Experiment assigned additional police officers to proactively patrol one high crime neighborhood with specific emphasis on locating and seizing illegal firearms. The treatment neighborhood experienced a 65 percent increase in number of guns seized and a corresponding 49 percent reduction in gun crimes; similar results were not found in the control neighborhood (Sherman & Rogan, 1995). The Pittsburgh police department implemented a directed patrol strategy by increasing police contact through traffic stops and “stop and talks” with pedestrians on the street. Following implementation of these tactics, Cohen and Ludwig (2003) found a 34 percent reduction in shots fired and a 71 percent decline in hospital treated gun shots in the target areas.

In Indianapolis, McGarrell et al. (2001) examined a directed patrol initiative which tested two different strategies. The strategy in the North District used directed patrol to focus on suspicious activities and locations (specific deterrence strategy), while the strategy in the East District focused on maximizing vehicle stops (general deterrence strategy). The finding showed that the specific directed patrol strategy reduced gun crime, while the more general vehicle stops did not. However, homicide in both districts did go down. Under directed patrol programs high crime areas are targeted for additional police resources that focus on illegally carried firearms. Cohen and Ludwig (2003) believe that the positive finding from directed patrol studies are a

result increased police presence in the target areas; the high visibility of officers within these communities deter high-risk people from carrying or using guns in public, in turn reducing gun violence in the communities (For additional studies on the effective of traffic enforcement visibility on crime see: Stuster, Sheehan, & Morford, 1997; Weiss & Freels, 1996; Weiss & McGarrell, 1999).

There is strong evidence that directed traffic enforcement has an effect on crime and researchers suggest targeted traffic enforcement offers a couple of benefits. First, the high-visibility of law enforcement serves as a general deterrent for crime. If there is a notable difference in enforcement activity in the targeted area the perceived risk of getting caught for a crime increases. Second, it disrupts organized crime, particularly in the case of drug and illegal firearms, by making it more difficult to use vehicles in the course of committing a crime. Offenders will be less likely to use a vehicle if they think officers will find contraband or evidence of illegal activity during a stop (NHTSA, 2009; Weiss, 2013). A more visible law enforcement presence gives members of the community an increased sense of safety which can help improve police-community relations (Hardy, 2010).

Finally, DDACTS emphasizes the uses of crime mapping and data to identify the places where targeted traffic enforcement may be needed. The identification of hot spots through spatial clustering techniques provides strong evidence about where crime and crashes occur simultaneously. By using a data-driven process to identify hot spots, law enforcement can easily justify allocation of police resources to those areas and consistently monitor the strategies' progress to determine if and when it needs to be modified (NHTSA, 2009; Hardy, 2010). According to Weiss (2013), crime mapping can help law enforcement agencies better understand how crimes and crashes are related and can be a useful tool for demonstrating to the public

where crime in a community is occurring and the subsequent results from the implementation of DDACTS.

DDACTS in Flint

Over the past couple of years Flint has experienced a rise in gun violence with a sharp increase in murders. In 2012 there were 63 murders in Flint, up from 52 murders in 2011 and almost double the amount from 2009 (36). A FBI study measuring violent crime in Flint from 2006 to 2009 found that within that timeframe there were 145 homicides (138 murder and 7 justified), 5,765 felonious/aggravated assaults, 448 concealed weapons complaints, 2,542 robberies, 11,140 breaking and entering, and 438 other weapons related crimes. For the past six years Flint has been ranked in the top five most dangerous cities in the United States and in 2010 they were ranked number one per capita for homicides. A preliminary analysis conducted by Flint Police Department (FPD) and Michigan State University indicated that drugs were connected to a high proportion of those homicides. Additionally, in 2011 Flint was named the second most violent city per capita in the United States.

Efforts to control the growing violent crime problem have been hampered by the significant decline in the city budget over the past decade and the corresponding reduction in the size of the police force. Since 2003, FPD experienced an approximate 50 percent reduction in their police force, from 242 sworn officers in 2003 to 122 sworn officers by 2011. This time period also saw a corresponding increase in violent crime nearly doubling from 12.2 violent crimes per 1,000 people in 2003 to 23.4 per 1,000 in 2011. Compared to years past FPD is experiencing less citizen support, decreased funding and personnel, and as a result, offer fewer services to the community, making the efficient and effective use of resources important.

The economic challenges, budget restrictions, and diminishing resources led Flint to become more strategic in their approach to responding to and reducing violent crimes in the community by moving toward the use of data-driven crime analysis. In 2012 Michigan's governor Rick Snyder, directed the Michigan State Police (MSP) to offer Flint enhanced tools to support data-driven policing strategies. Data-driven strategies would allow law enforcement to make use of their limited resources by predicting where crime was most likely to occur and strategically positioning resources in those areas as a countermeasure. In response, MSP piloted DDACTS, a data-driven approach to reducing crime and traffic crashes, in Flint. MSP uses the Michigan Incident Crime Reporting System (MICR) to collect crime and crash data and identify, monitor, and evaluate hot spots. MICR is an information sharing system that collects and houses data from law enforcement agencies throughout Michigan. DDACTS was used to maximize MSP's operational efforts by streamlining deployment of troopers to hot spots in Flint and saturating those areas with aggressive high-visibility traffic enforcement in an attempt to reduce violent crime in the city. Subsequently, DDACTS became part of Flint's official public safety plan in 2012.

PROGRAM OPERATIONS

With the explicit goal of reducing violent crime within the City of Flint, DDACTS enforcement activities began in early 2012. During the post-implementation observation period, which extended from January 1st, 2012 to December 31st, 2013, the variety, intensity, and location of program activities varied. This section of the report describes trends in DDACTS enforcement activities during the post-implementation observation period, including program personnel, hotspot identification, and enforcement activities occurring inside and outside of the hotspots. Detailing these trends allows for a better understanding of what the DDACTS intervention entailed, and how the program would be expected to affect violent crime rates.

Program Implementation and Activities

Program Size and Scope

The stated goal of the DDACTS intervention was to reduce violent crime and traffic crashes through the use of high visibility, data-driven traffic enforcement. Per discussions with Michigan State Police (MSP) personnel, DDACTS enforcement activities began in early 2012. Between the start-date of DDACTS activities and the conclusion of the study observation period at year-end 2013 there were several increases in enforcement inputs, escalating the intervention through the addition of new hotspots, personnel, and hours of operation. Using information provided by MSP, a timeline of these shifts is summarized in Table 1.

Table 1. Changes in DDACTS Target Areas and Activities, 2012-2013

	April 2012	August 2012	April 2013	June 2013
Number of Hotspots	5	6	6	7
Total Hotspot Area	7.12 Sq. Mi.	7.68 Sq. Mi.	7.68 Sq. Mi.	9.20 Sq. Mi.
Personnel Allocation	15 Troopers [†] 3 Sergeants	20 Troopers 4 Sergeants	28 Troopers 3 Sergeants	33 Troopers 3 Sergeants ^{††}
Hours of Operation	2pm – 4am	2pm – 4am	6am – 4am	24 Hours

[†] +3-4 Additional troopers Thursday through Saturday.

^{††} +2 Part-time sergeants.

At the outset of DDACTS implementation, MSP had identified five violent crime hotspots in which to focus enforcement activities. As of April 2012 these hotspots covered 7.12 square miles, or about 21 percent of the City of Flint. At this early stage, program activities were restricted to a 14 hour window from the early afternoon through the early morning. During this stage analysts at MSP continued to collect violent crime incident data in the city and identified additional areas where violent crime had intensified. In August of 2012 (or eight months post-implementation) a sixth hotspot was added, increasing the total hotspot area to 7.68 square miles, or 23 percent of the total area of Flint. Five additional state troopers and a sergeant were added to the DDACTS personnel, with the enforcement activities still restricted to the period of 2pm (1400 hours) through 4am (0400 hours).

In April of 2013 (or 16 months post-implementation) the DDACTS intervention was allocated additional personnel and expanded its hours of operation. The program moved from 20 troopers to 28, and added another eight hours of operation. At this point MSP was providing enforcement activities 22 hours per day, from 6am (0600) to 4am (0400). Just two months later, in June 2013, there were several important changes to the intervention scope. Spatial analysis of violent crime incidents suggested the presence of a seventh hotspot, as well as crime displacements from the previously identified hotspots. These displacements resulted in increasing the boundary of several hotspots, and included with the addition of the seventh

hotspots, the total hotspot area increased to 9.20 square miles, or 27 percent of the total area of Flint. The number of personnel was expanded to 33 troopers – a 120 percent increase from the start of the intervention – and hours of operation were expanded to 24 hours per day.

Types of Program Activities and Outputs

Within the DDACTS model traffic enforcement is advocated as a law enforcement tool with applications not just in increasing traffic safety, but also reducing violent crime. This is accomplished by using traffic stops as a mechanism to combat narcotics, guns, and contraband and discover fugitives (NHTSA, 2007, 2009). As such, the operation of the DDACTS enforcement component can largely be characterized as two primary activities with several associated outputs. The primary activities were:

- Traffic stops
- Attempts to locate individual at residence

The outputs measured by MSP in relation to these DDACTS activities were:

- Verbal warnings
- Hazardous citations
- Felons arrested
- Felony counts
- Felony drug counts
- Misdemeanants arrested
- Misdemeanor counts
- Misdemeanor drug counts
- Fugitives arrested
- Felony warrants satisfied
- Misdemeanor warrants satisfied
- Subjects lodged
- Firearms seized
- Stolen vehicles recovered

Daily counts of each DDACTS activity and output were maintained by MSP throughout the post-implementation observation period. The counts detailed which hotspot the activity took place in, including whether it occurred outside of the target area.

Hotspots Identified

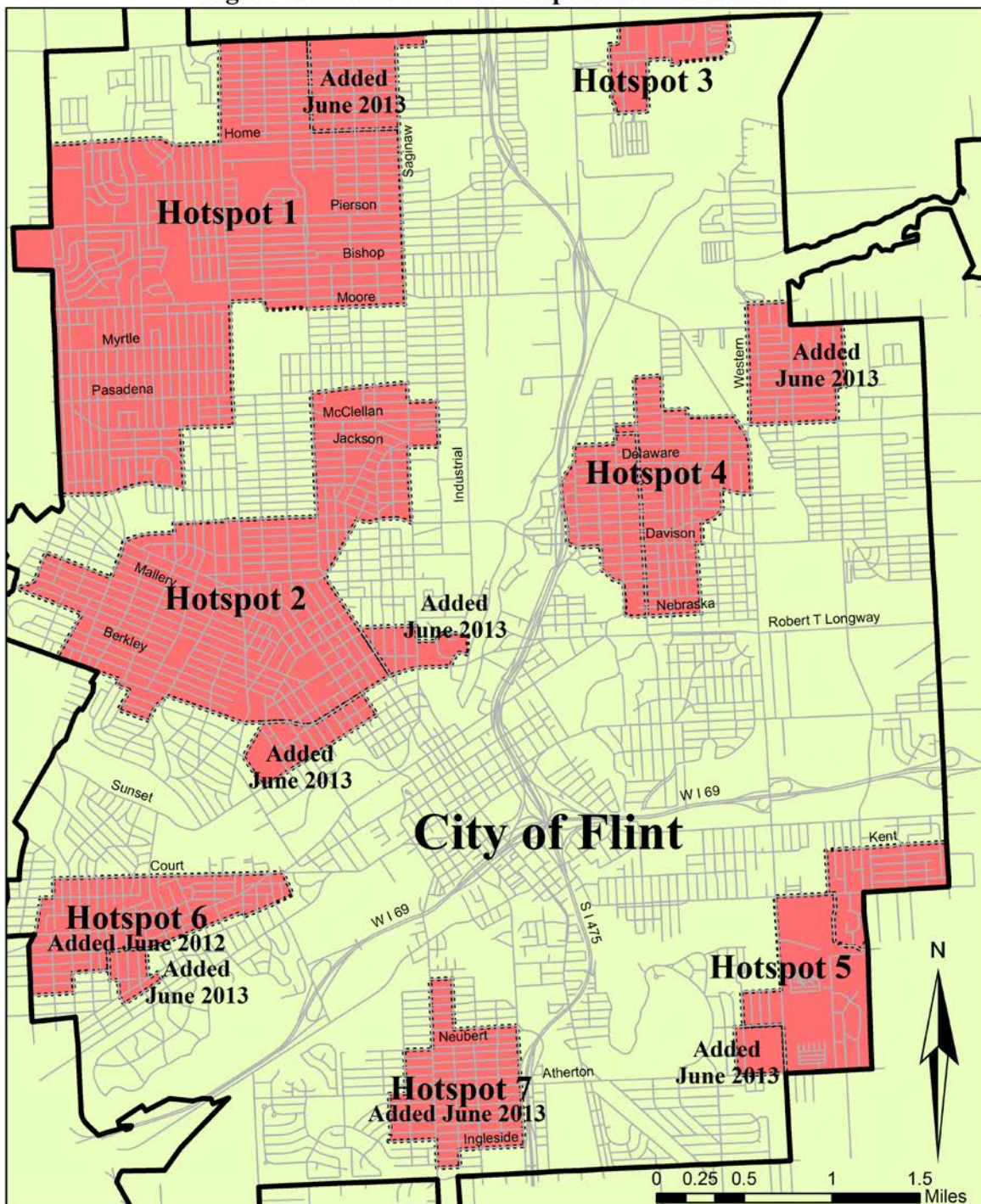
While enhanced traffic enforcement is the mechanism through which DDACTS seeks to lower violent crime, the distinguishing feature of DDACTS from previous traffic enforcement interventions is its focus on particular geographic locations (Weiss, 2013). For DDACTS in Flint, a sophisticated procedure for generating the hotspots was utilized. Leading up to the onset of the intervention in January, 2012, dedicated Geographic Information Systems (GIS) staff at MSP performed spatial analyses of violent crime data in Flint to determine whether and where hotspots may exist. Individual violent crime incidents were geocoded and linked to street segments. A measure of spatial autocorrelation (Moran's I [Moran, 1950]) was used to initially identify clusters of street segments with a relatively high number of violent incidents. Within these clusters of street segments, those with the consistent rates of violence (i.e., repeated incidents within a relatively high violence area) were identified as statistical focus areas. This process was referred to internally as repeat locations analysis. As such, the Flint DDACTS hotspots were generated based on both spatial and temporal factors. The statistical focus areas produced by the repeat locations analysis comprised the anchor points of the DDACTS hotspots.

Once the focus areas had been identified, dedicated GIS staff coordinated with crime analysts to expand the small clusters of street segments to encompass nearby street segments. This was done to create larger geographic areas which would be patrolled more effectively by DDACTS enforcement units. The resulting hotspots were then disseminated to MSP post commanders, who would assign DDACTS patrols based on the recommendations of the GIS staff and analysts. To this extent, post commanders were able to exercise discretion regarding where exactly within each hotspot resources and patrols should be allocated. Following the initial identification of hotspots, spatial analysis of violent crime incidents occurred on a continual

basis, suggesting the emergence of new statistical focus areas and the displacement of crime from original hotspots. The program response to these trends was the identification of new hotspots and the expansion of existing hotspots, respectively.

Figure 1 displays the hotspots disseminated to MSP post-commanders to coordinate DDACTS patrol activities. Initially hotspots 1 through 5 were the site of DDACTS enforcement. As the program expanded, hotspots 6 and 7 were added in the South and Southwest areas of Flint. The hotspot expansions in June 2013 are represented by the polygons labeled as “Added in June 2013.” The hotspots utilized by MSP were generally larger than the recommended size for street segment focused hotspots (Eck, Chainey, Cameron, Leitner, & Wilson, 2005). The rationale for using hotspots of this size was to create hotspots consisting of clusters of repeat locations street segments which were amenable to patrol assignments.

Figure 1. Flint DDACTS Hotspots as of June 2013



Program Activities across Hotspots

Throughout the post-implementation observation period, spanning from January 1st, 2012 to the end of March 2014, MSP maintained daily tallies of DDACTS activities and outputs. This data collection included logging the hotspot in which the program activity took place, allowing a depiction of program dosage across the hotspots over time. Table 2 displays summary trends in DDACTS traffic stops across the hotspots over several six-month time frames – January to June 2012, July to December 2012, and January to June 2013, July to December 2013, and January to March 2014.¹ These periods represent meaningful blocks of program activities, as they corresponded to increases in personnel and changes in hotspot scope (see Table 1). Throughout the observation period, there were approximately 22,400 traffic stops by DDACTS personnel in the city of Flint. More than three-quarters of these traffic stops (n = 16,629, 74.1%) took place within the designated hotspots. Hotspot 1 accounted for more than half of all hotspot traffic stops (52.3%). In general, the number of traffic stops increased over time, with the highest six-month totals taking place between July and December 2013.

Table 2. DDACTS Traffic Stops by Hotspot and Time Period, January 2012 through March 2014

Location	Jan – Jun 2012	Jul – Dec 2012	Jan – Jun 2013	Jul – Dec 2013	Jan – Mar 2014	Total
Non-Target Areas	145	971	993	2,456	1,234	5,799
Overall Hotspots	870	3,528	4,262	5,886	2,083	16,629
Hotspot 1	659	2,092	2,534	2,474	945	8,704
Hotspot 2	74	422	485	724	255	1,960
Hotspot 3	43	290	294	511	164	1,302
Hotspot 4	89	494	676	1,513	422	3,194
Hotspot 5	5	119	142	252	92	610
Hotspot 6	0	111	131	220	43	505
Hotspot 7	0	0	0	192	162	354
Entire City Totals	1,015	4,499	5,255	8,342	3,317	22,428

¹ The final three months of the observation period (January to March 2014) were added after preliminary observations suggested that differences between the hotspots and comparison areas were increasing in the later stages of the study (see the impact assessment). These months were included to determine if these trends continued.

Because the hotspots varied in size, the density of traffic stops per square mile were calculated as well, providing an area-normalized measure of program dosage (see Table 3). There are several important points to note in Table 3. The level of program activity varied across the hotspots – certain hotspots received more dosage than others. During the study observation period Hotspot 1 received the heaviest level of traffic stops, averaging over 320 traffic stops per month. Hotspots 2 and 4 followed, with an average of 73 and 118 per month, respectively. Hotspots 5, 6, and 7 received the lowest amount of traffic stops during the observation period. This is largely due to the addition of Hotspots 6 and 7 further into the observation period.

Table 3. DDACTS Post-Implementation Dosage – Average Monthly Traffic Stops and Traffic Stop Density per Square Mile

Location (Square Miles) [†]	Jan – Jun 2012 TS / Density	Jul – Dec 2012 TS / Density	Jan – Jun 2013 TS / Density	Jul – Dec 2013 TS / Density	Jan – Mar 2014 TS / Density	Overall
Non-Target Areas (21.76)	24.17 / 1.01	161.83 / 6.93	165.5 / 7.16	409.33 / 18.81	411.33 / 18.90	214.78 / 9.64
Overall Hotspots (9.20)	145.00 / 20.37	588.00 / 77.33	710.33 / 89.80	981.00 / 106.67	694.33 / 75.50	615.87 / 73.76
Hotspot 1 (3.47)	109.83 / 34.35	348.67 / 109.03	422.33 / 130.58	412.33 / 118.69	315.00 / 90.67	322.37 / 97.33
Hotspot 2 (2.38)	12.33 / 5.82	70.33 / 33.19	80.83 / 37.36	120.67 / 50.63	85.00 / 35.67	72.59 / 32.18
Hotspot 3 (0.20)	7.17 / 34.96	48.33 / 235.81	49.00 / 239.06	85.17 / 415.51	54.67 / 266.71	48.22 / 235.27
Hotspot 4 (1.21)	14.83 / 16.83	82.33 / 93.40	112.67 / 118.45	252.17 / 208.23	140.67 / 116.16	118.30 / 110.0
Hotspot 5 (0.80)	0.83 / 1.15	19.83 / 27.34	23.67 / 31.69	42.00 / 52.30	30.67 / 38.18	22.59 / 29.23
Hotspot 6 (0.62)	--	18.5 / 32.91	21.83 / 38.00	36.67 / 59.05	14.33 / 23.08	18.70 / 31.44
Hotspot 7 (0.50)	--	--	--	32.00 / 64.06	54.00 / 108.10	13.11 / 26.24

Note: TS = Traffic Stops; Density = Traffic Stops / Square Miles

[†] Added for context, this figure represents the final hotspot area set in June 2013. Density calculations reflect the changing hotspot sizes over the course of the observation period.

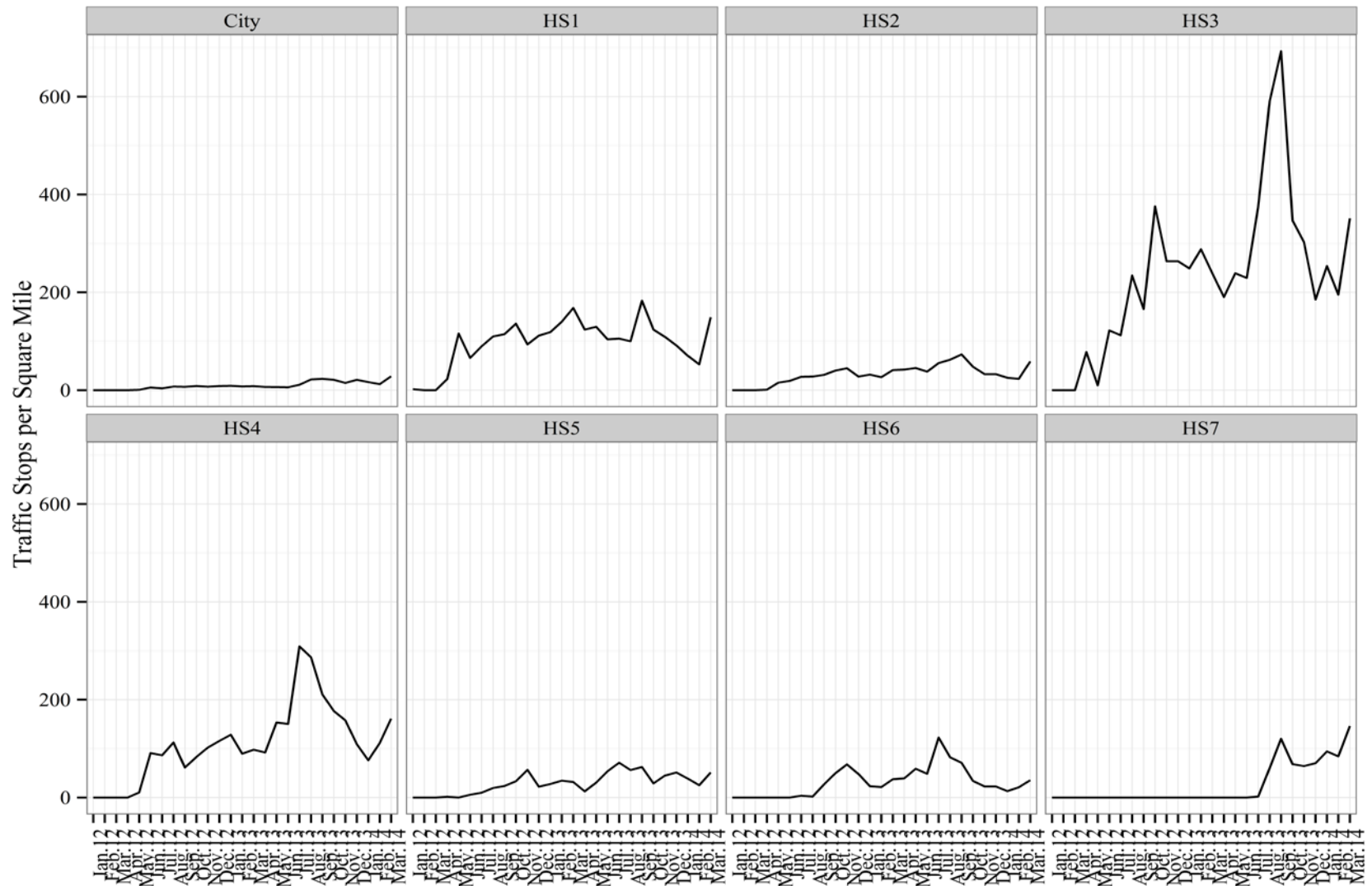
The frequency of DDACTS traffic stops increased in intensity during the study observation period. Considering all of the hotspots together, the peak of program activity occurred between July and December 2013 after increasing in a linear trend since the beginning of implementation. Considering the individual hotspots, all except Hotspot 1 experienced their highest average monthly traffic stops during the July to December 2013 period. The drop in traffic stops in Hotspot 1 during the final time period may simply reflect a slight regression in activity following a period of intense dosage between January and June of that year.

The information displayed in Table 3 also indicates that DDACTS program activities occurred outside of the designated hotspots. There was actually a higher average monthly total of DDACTS traffic stops in the non-target areas of the city than several of the hotspots. This is an important consideration in comparing the hotspot and non-target areas, as the comparison unit actually received some measure of program dosage. It is important to note that the non-target areas of the city were twice as large as the combined hotspots, however, meaning that the designated hotspots received a stronger concentration of traffic stop dosage. An inspection of the traffic stop density (per square mile) indicators suggests that this is the case. The non-target areas of Flint averaged only a handful of traffic stops per square mile during the study period, while the hotspots overall averaged 74 traffic stops per square mile per month.

The traffic stop density measures also provide information about the concentration of DDACTS activities across the hotspots. Comparing the hotspots to each other, Hotspots 3, 4, and 1 experienced the highest average monthly traffic stop density. Although Hotspot 2 had received one of the highest total number of traffic stops, the density of traffic stops was similar to Hotspots 5 and 6, which received relatively low traffic stop totals.

The traffic stop density varied considerably over time. Figure 2 displays monthly trends in traffic stop density across the DDACTS hotspots. In general, the traffic stop density increased over time, indicating that increases in traffic stop frequencies were not solely a result of increasing the size of each hotspot. Hotspots 1, 3, and 4 experienced the highest stable monthly rates of density, with notable spikes in activity leading up to July 2013. Additionally, Figure 2 reiterates that although DDACTS traffic stops occurred outside of the hotspots, the traffic stop density in the non-target areas was considerably lower than any of the designated hotspots.

Figure 2. Monthly Traffic Stop Density per Square Mile, January 2012 – March 2014



Program Outputs across Hotspots

In addition to documenting trends in traffic stop frequency and density across the DDACTS hotspots, it was also possible to measure some of the outputs stemming from these activities. From the data provided by MSP several output measures were selected to characterize some of the intermediate benefits of the traffic stop strategy, as well as describe what the DDACTS personnel were accomplishing with each stop. Two tables display these trends. Table 4 presents summary totals of program outputs, and Table 5 presents rates of four output measures per 100 traffic stops – verbal warnings, hazardous citations, felony and misdemeanor arrests (combined), and arrests of fugitives. These outputs also represent some of the described benefits of intensive traffic stop strategies, such as detecting more serious crime and apprehending fugitives (NHTSA, 2007; Weiss, 2013; Worden & McLean, 2009).

Throughout the evaluation observation period, there were approximately 21,285 verbal warnings issued by DDACTS personnel, as well as 660 citations, 3,300 felony and misdemeanor arrests, and 4,000 arrests of fugitives. The majority of these activities took place within the designated DDACTS hotspots, including 74 percent of the verbal warnings, 67 percent of the citations, 72 percent of the felony and misdemeanor arrests, and 73 percent of the fugitive arrests. As with the traffic stops, the majority of program outputs within the hotspots were generated in Hotspot 1.

Table 4. DDACTS Enforcement Activity Outputs by Hotspot and Time Period, January 2012 through December 2013

Location Output	Jan – Jun 2012	Jul – Dec 2012	Jan – Jun 2013	Jul – Dec 2013	Jan – Mar 2014	Total
<i>Non-Target Areas</i>						
Verbal Warnings	143	912	924	2,310	1,150	5,439
Hazardous Citations	2	46	38	100	30	216
Fel & Misd Arrests	27	148	184	424	140	923
Fugitive Arrests	28	201	201	441	203	1,074
<i>Overall Hotspots</i>						
Verbal Warnings	815	3,412	4,068	5,610	1,941	15,846
Hazardous Citations	41	103	126	130	44	444
Fel & Misd Arrests	149	485	448	1,073	235	2,390
Fugitive Arrests	164	675	728	1,026	313	2,906
<i>Hotspot 1</i>						
Verbal Warnings	621	2,021	2,455	2,400	876	8,373
Hazardous Citations	36	61	62	61	28	248
Fel & Misd Arrests	109	270	225	463	96	1,163
Fugitive Arrests	116	382	400	423	148	1,469
<i>Hotspot 2</i>						
Verbal Warnings	74	408	454	675	239	1,850
Hazardous Citations	1	12	10	10	4	37
Fel & Misd Arrests	5	60	61	117	23	266
Fugitive Arrests	18	87	103	142	36	386
<i>Hotspot 3</i>						
Verbal Warnings	37	280	271	489	155	1,232
Hazardous Citations	0	10	20	13	7	50
Fel & Misd Arrests	11	48	43	90	14	206
Fugitive Arrests	6	62	43	83	32	226
<i>Hotspot 4</i>						
Verbal Warnings	79	482	635	1,429	395	3,020
Hazardous Citations	4	9	16	32	3	64
Fel & Misd Arrests	23	77	71	267	72	510
Fugitive Arrests	23	108	130	255	65	581
<i>Hotspot 5</i>						
Verbal Warnings	4	116	134	232	86	572
Hazardous Citations	0	4	11	6	2	23
Fel & Misd Arrests	1	11	16	48	13	89
Fugitive Arrests	1	21	22	49	8	101
<i>Hotspot 6</i>						
Verbal Warnings	0	105	146	202	44	470
Hazardous Citations	0	7	7	4	0	18
Fel & Misd Arrests	0	19	32	57	4	112
Fugitive Arrests	0	15	30	44	4	93

Table 4. (Continued)

Location Output	Jan – Jun 2012	Jul – Dec 2012	Jan – Jun 2013	Jul – Dec 2013	Jan – Mar 2014	Total
<i>Hotspot 7</i>						
Verbal Warnings	0	0	0	183	146	329
Hazardous Citations	0	0	0	4	0	4
Fel & Misd Arrests	0	0	0	31	13	44
Fugitive Arrests	0	0	0	30	20	50
Entire City Totals						
Verbal Warnings	958	4,324	4,992	7,920	3,091	21,285
Hazardous Citations	43	149	164	230	74	660
Fel & Misd Arrests	176	633	632	1,497	375	3,313
Fugitive Arrests	192	876	929	1,467	516	3,980

Table 5 presents rates of these outputs per 100 traffic stops. In general, DDACTS personnel issued verbal warnings to the individuals that they stopped. Indeed, for every 100 traffic stops, DDACTS personnel issued about 95 verbal warnings. The least frequent output stemming from the traffic stops was the issuance of a hazardous citation, with only 3 occurring for every 100 traffic stops. These patterns are consistent with the aggressive, proactive traffic enforcement advocated in the DDACTS model (Worden & McLean, 2009). Falling in between were the two arrest output measures. Approximately 17 of every 100 traffic stops resulted in an arrest of a fugitive, and 14 of every 100 led to a misdemeanor or felony arrest.

Comparing patterns in the hotspots to traffic stops in the non-target areas of Flint, there were slightly higher rates of verbal warnings in the hotspots (95 vs. 94). On the other hand, there were slightly lower rates of hazardous citations (3 vs. 4) and felony or misdemeanor arrests (14 vs. 16) in the hotspots, compared to the non-target areas. Comparing individual hotspots there was some consistency in the rates of verbal warnings, ranging from 93 to 96 per 100 traffic stops. There was relatively less consistency in citations and arrests. In Hotspot 1 only 14 of every

100 traffic stops resulted in a felony or misdemeanor arrest, compared to 18 of every 100 in Hotspot 4 and 22 for every 100 stops in Hotspot 6.

Table 5. DDACTS Post-Implementation Dosage – Outputs per 100 Traffic Stops

Location	Jan – Jun 2012 Rate	Jul – Dec 2012 Rate	Jan – Jun 2013 Rate	Jul – Dec 2013 Rate	Jan – Mar 2014 Rate	Overall Rate
<i>Non-Target Areas</i>						
Verbal Warnings	98.62	93.92	93.05	94.06	93.19	93.79
Hazardous Citations	1.37	4.73	3.82	4.07	2.43	3.72
Fel & Misd Arrests	18.62	15.24	18.53	17.26	11.34	15.92
Fugitive Arrests	19.31	20.70	20.24	17.95	16.45	18.52
<i>Overall Hotspots</i>						
Verbal Warnings	93.68	96.71	95.45	95.31	93.18	95.28
Hazardous Citations	4.71	2.92	2.96	2.21	2.11	2.67
Fel & Misd Arrests	17.13	13.75	10.51	18.23	11.23	14.37
Fugitive Arrests	18.85	19.13	17.08	17.09	15.03	17.48
<i>Hotspot 1</i>						
Verbal Warnings	94.23	96.61	96.88	97.01	92.70	96.20
Hazardous Citations	5.46	2.92	2.45	2.47	2.96	2.85
Fel & Misd Arrests	16.54	12.91	8.88	18.71	10.16	13.36
Fugitive Arrests	17.60	18.26	15.79	17.09	15.66	16.88
<i>Hotspot 2</i>						
Verbal Warnings	100.00	96.68	93.61	93.23	93.73	94.39
Hazardous Citations	1.35	2.84	2.06	1.38	1.57	1.89
Fel & Misd Arrests	6.76	14.22	12.58	16.16	9.02	13.57
Fugitive Arrests	24.32	20.62	21.24	19.61	14.12	19.69
<i>Hotspot 3</i>						
Verbal Warnings	86.05	96.55	92.18	95.69	94.51	94.62
Hazardous Citations	0.00	3.45	6.80	2.54	4.27	3.84
Fel & Misd Arrests	25.58	16.55	14.63	17.61	8.54	15.82
Fugitive Arrests	13.95	21.38	14.63	16.24	19.51	17.36
<i>Hotspot 4</i>						
Verbal Warnings	88.76	97.57	93.93	94.45	93.60	94.55
Hazardous Citations	4.49	1.82	2.37	2.12	0.71	2.00
Fel & Misd Arrests	25.84	15.59	10.50	17.65	17.06	15.97
Fugitive Arrests	25.84	21.86	19.23	16.85	15.40	18.19
<i>Hotspot 5</i>						
Verbal Warnings	80.00	97.48	94.37	92.06	93.48	93.77
Hazardous Citations	0.00	3.36	7.75	2.38	2.17	3.77
Fel & Misd Arrests	20.00	9.24	11.27	19.05	14.13	14.59
Fugitive Arrests	20.00	17.64	15.49	19.44	8.70	16.56

Table 5. (Continued)

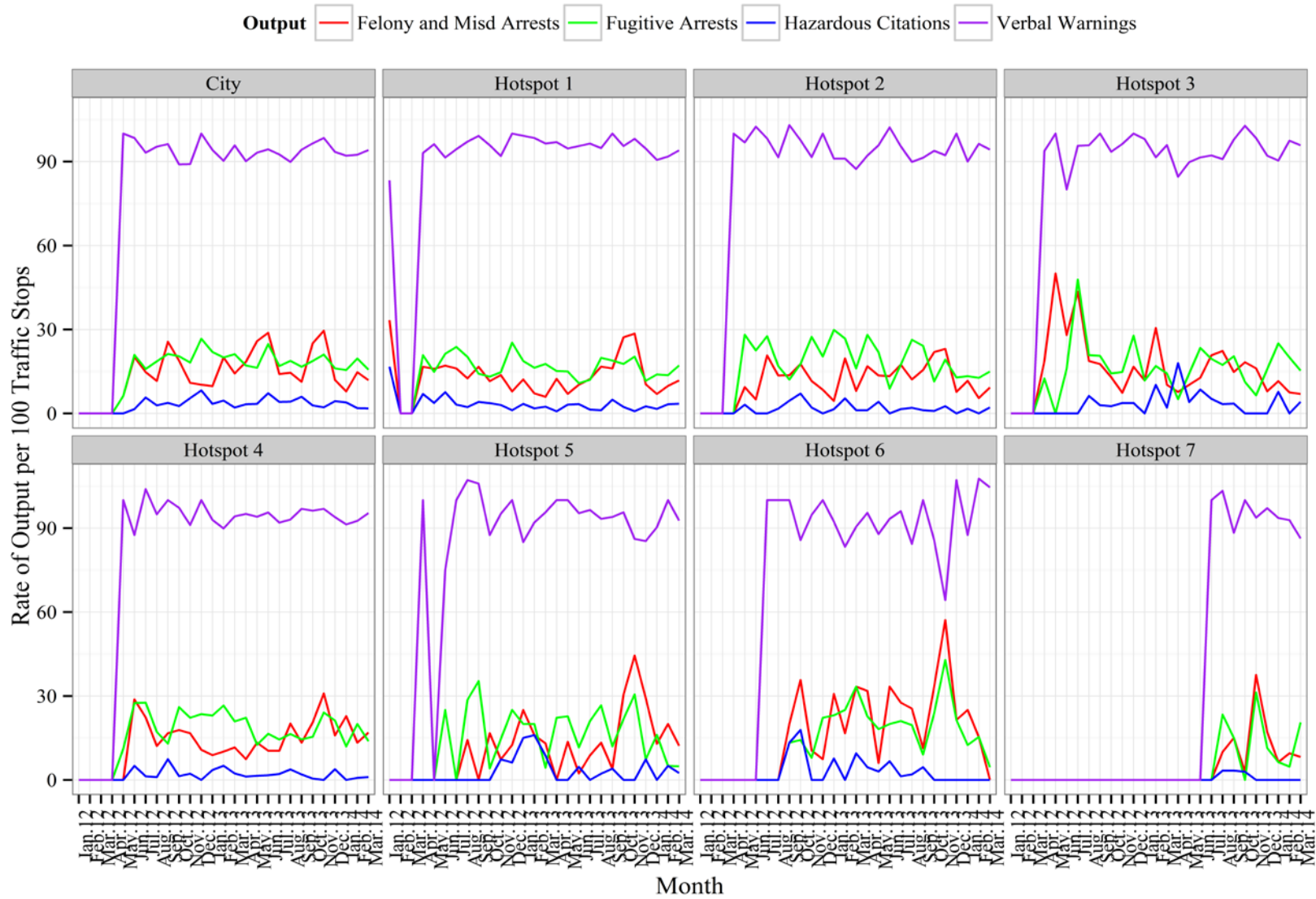
Location	Jan – Jun 2012	Jul – Dec 2012	Jan – Jun 2013	Jul – Dec 2013	Jan – Mar 2014	Overall
	Rate	Rate	Rate	Rate	Rate	Rate
<i>Hotspot 6</i>						
Verbal Warnings	--	94.59	90.84	91.82	102.33	93.07
Hazardous Citations		6.31	5.34	1.82	0.00	3.56
Fel & Misd Arrests		17.12	24.43	25.91	9.30	22.17
Fugitive Arrests		13.51	22.90	20.00	9.30	18.42
<i>Hotspot 7</i>						
Verbal Warnings	--	--	--	95.31	90.12	92.93
Hazardous Citations				2.08	0.00	1.13
Fel & Misd Arrests				16.15	8.02	12.43
Fugitive Arrests				15.63	12.35	14.12

Note: Rates reflect (total outputs during month period ÷ total traffic stops during month period) x 100.

Monthly rates of these outputs per 100 traffic stops were also examined over the course of the study period. Trends in these rates are displayed in Figure 3. The results suggest that verbal warning rates were largely consistent over the course of the study period, rarely dropping below a rate of 90 warnings per 100 traffic stops. The two arrest outputs tended to vary together – when there were more felony and misdemeanor arrests there were more fugitive arrests, as well as the other way around. These trends are in spite of linear increases in the frequency and density of traffic stops over the course of the implementation period. Although there were peaks and valleys in the output rates, the DDACTS personnel were largely consistent within and across hotspots with the outputs of their traffic stops. Additionally, there does not appear to be an appreciable difference between the outputs of DDACTS activities within the hotspots and outside of the hotspots.

The next chapter will detail a statistical analysis of the DDACTS program’s impact on rates of violence in Flint.

Figure 3. Monthly Rate of Outputs per 100 Traffic Stops, January 2012 - March 2014



IMPACT ASSESSMENT

As it was implemented in Flint, the goal of the DDACTS intervention was to reduce violent crime within the designated violent crime hotspots. This section of the report details an analysis of the program's effect to this extent. As with any intervention which purposefully selects enforcement areas, a particular concern is the possibility that underlying differences between the target and non-target areas explains any observed differences in violent crime, rather than those differences being attributable to the intervention. To compensate for this possibility of selection bias, a synthetic control approach (Abadie & Gardeazabal, 2003; Abadie, Diamond, & Hainmueller, 2010) was utilized to estimate a comparison unit similar to the DDACTS hotspots across a variety of important sociodemographic indicators. This approach attempts to estimate the effect of the DDACTS intervention by comparing violent crime rates in the DDACTS hotspots to those in a synthetic control unit which did not receive the intervention.

The following sections describes the manner in which the DDACTS hotspots and comparison areas were defined, presents raw differences in violent crime rates between the treatment and control areas, and then details the synthetic control analysis.

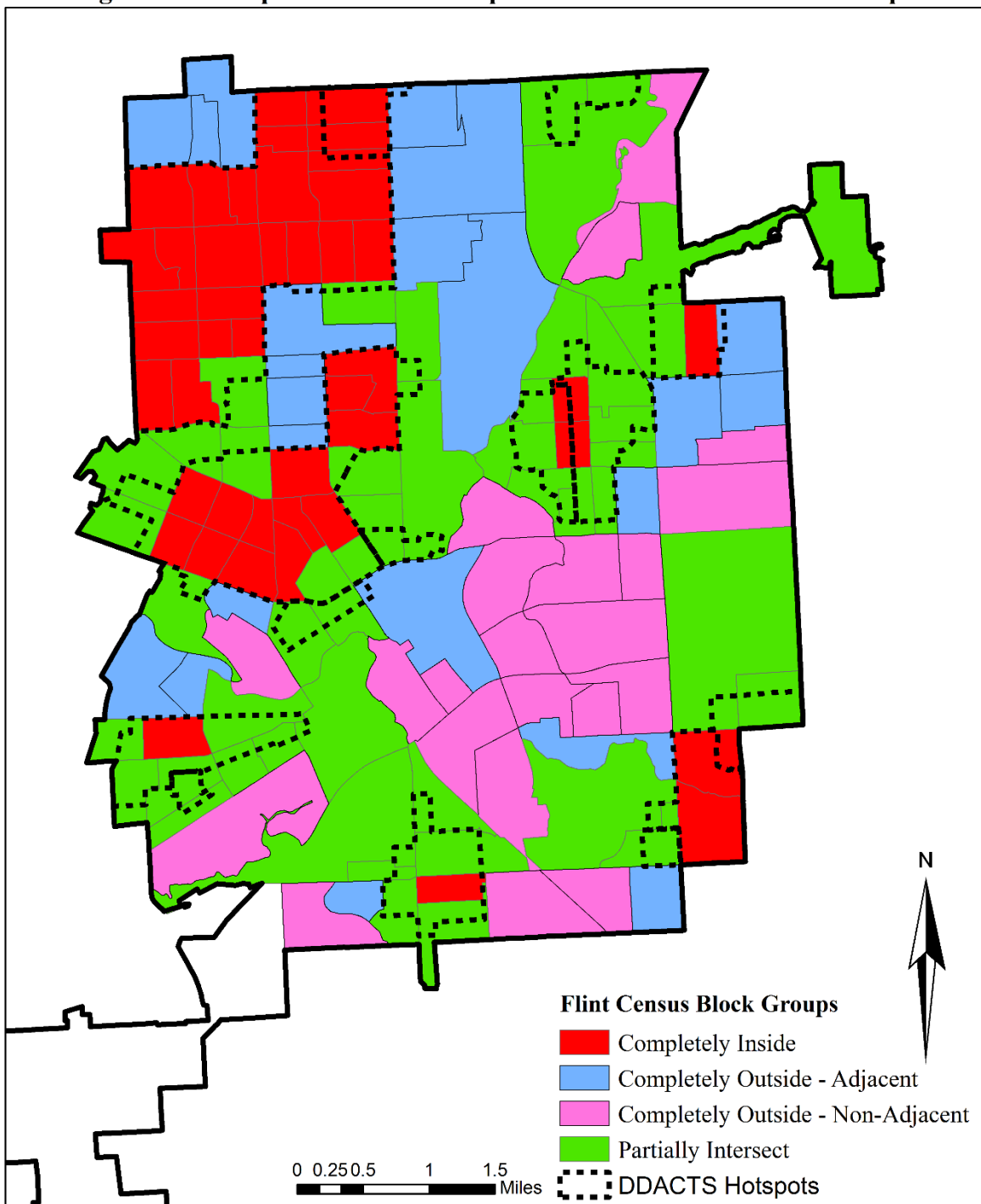
Defining the Target and Non-Target Areas

In Flint, the DDACTS hotspots were created by using spatial statistics to identify clusters of street segments with consistently high levels of violence. From these statistical focus areas, GIS staff and crime analysts at MSP added adjacent street segments to create broader hotspots which were amenable to patrol assignments (see Figure 1). For the purposes of an impact assessment several considerations were made in selecting the appropriate unit of analysis. Because of the possibility that the areas of Flint designated to be hotspots were significantly different from the areas not selected, a unit large enough to capture relevant sociodemographic

variables was desired. To this extent, the 2010 Census block groups were selected as the unit of analysis. *Those block groups that intersected the designated hotspots were defined as the target areas, and those not intersecting the hotspots were defined as the comparison areas.*² In order to capture variation in violent crime rates over time, the block group-month was used as the primary unit of analysis. The overlap between the block groups and the DDACTS hotspots is displayed in Figure 4.

² Simply using the hotspots themselves as the unit of analysis, while intuitive, was not the optimal approach. The customized geographic boundaries of the hotspots complicated measuring key characteristics, such as population density, which made it difficult to characterize how similar or different the hotspots were from the remainder of the city.

Figure 4.Overlap of DDACTS Hotspots and Flint Census Block Groups



In defining the target areas as those block groups that intersected the hotspots, the block groups shaded in red and green were considered as the target area, and those in blue and purple as the non-target areas. Although the block groups did not exactly correspond to the hotspot boundaries, there were several benefits to this approach. First, this approach allowed the ability to collect sociodemographic measures from the American Community Survey, which made measuring and controlling for differences between the target and non-target areas possible. Second, compared to using individual street segments as the units of analysis, splitting the hotspots into several block faces is more consistent with how DDACTS patrols were assigned in practice. Third, because a relatively small amount of DDACTS enforcement activities took place outside of the hotspots, defining the hotspots comparison areas as those block groups not intersecting the hotspots at all decreases the likelihood that these units received the intervention.

Comparison of the Target and Non-Target Areas

In order to compare the DDACTS hotspots to the non-target areas of the city, estimates of sociodemographic variables were gleaned from the American Community Survey (United States Census Bureau, 2013). The measures represent 5-year estimates, corresponding to the period of 2008 to 2012. A series of sociodemographic variables were selected based on their relation to violent crime rates in previous research, as well as their utilization in a recent evaluation of a community-based violence prevention program (Wilson, Chermak, & McGarrell, 2010). Descriptive statistics for the Flint block groups are displayed in Table 6.

The first column of Table 6 displays baseline descriptive statistics for each of the sociodemographic measures corresponding to all of the block groups. The next four columns break out the block groups by their relation to the DDACTS hotspots – whether they completely or partially intersected them, or were outside of the hotspots but immediately adjacent to one, or

completely outside of the hotspots and not adjacent to hotspots. The bolded values in Table 6 indicate that the types of block group locations were different from one another at a statistically significant threshold ($p < .05$). The results presented in Table 6 indicate that the block groups intersecting the DDACTS hotspots were significantly different from those that did not. Of the 19 covariates compared, the block groups were significantly different on 14 of them. More specifically, the block groups completely inside of the hotspots tended to be more densely populated, had a larger proportion of African-American residents, a larger proportion of female headed households with children under the age of 18, higher rates of public assistance, higher unemployment, and a higher violent crime rate just prior to the intervention.

Table 6. Descriptive Statistics for 2010 Flint Census Block Groups in Relation to DDACTS Hotspots (N = 131)

	All Block Groups	Completely Inside Hotspot	Partially Intersect Hotspot	Completely Outside Adjacent	Completely Outside Non-Adjacent
Measure	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Total Population	788.21 (319.10)	680.00 (279.51)	834.59 (334.20)	785.00 (291.87)	914.96 (317.44)
Population Density per Square Mile	4515.99 (2315.24)	5434.88 (2272.44)	4106.18 (1914.07)	4120.65 (2775.58)	3875.22 (2250.12)
% Male	48.23 (8.09)	46.68 (8.65)	48.02 (6.94)	48.90 (7.03)	51.12 (9.59)
% Age 15-24	16.00 (7.93)	17.50 (7.11)	15.90 (8.16)	14.53 (6.63)	14.61 (9.94)
% White	37.61 (33.70)	16.25 (25.63)	52.16 (32.04)	30.24 (31.26)	58.22 (27.43)
% African-American	56.83 (35.07)	77.84 (27.37)	42.84 (33.52)	63.70 (35.05)	36.25 (27.98)
% No HS Diploma	62.22 (11.77)	58.21 (12.96)	63.50 (9.16)	61.74 (11.47)	68.16 (11.91)
% Married	29.29 (12.03)	24.49 (12.21)	30.28 (9.95)	30.00 (12.14)	34.29 (12.80)
% Below Poverty	40.15 (18.47)	47.82 (19.12)	39.88 (16.17)	31.16 (15.13)	33.96 (19.14)
% Female Headed HH with Children und. 18	19.50 (13.61)	25.59 (14.16)	16.85 (12.43)	17.22 (9.60)	14.80 (14.51)
% Public Assistance	13.25 (10.89)	17.38 (12.15)	12.32 (9.01)	9.65 (7.88)	10.28 (12.10)
% Unemployed	27.46 (14.56)	32.68 (15.14)	25.59 (13.62)	26.41 (12.42)	21.77 (14.71)
% Professionals	22.53 (20.18)	20.90 (21.86)	21.77 (16.81)	25.04 (20.85)	24.94 (23.01)
% Renter Occupied	32.88 (14.85)	32.86 (14.13)	32.38 (14.29)	33.46 (14.76)	33.40 (18.18)
% Vacant	24.24 (13.55)	28.11 (10.70)	24.06 (15.72)	25.11 (12.10)	16.02 (12.39)
% HH Income < \$25k	49.03 (17.77)	55.47 (17.37)	47.75 (16.43)	45.65 (16.40)	41.94 (19.33)
% HU with 5+ Units	8.43 (13.68)	5.75 (13.57)	7.23 (10.88)	12.44 (15.57)	12.35 (16.06)
% HH Rent > 30% of Income	68.01 (24.66)	78.43 (19.98)	63.00 (21.18)	72.41 (19.28)	52.99 (33.77)
Violent Crime Rate 2011 per 1,000 [†]	26.84 (22.89)	35.34 (30.20)	25.98 (18.08)	23.74 (13.57)	14.53 (14.49)
N	131	44	44	21	22

Note: Bolded values indicate statistically significant difference ($p < .05$) in an analysis of variance; HH = Households; HU = Housing Units; †Rate includes homicide, aggravated assault, robbery, criminal sexual conduct, weapons offenses.

These differences between the areas of Flint comprising the DDACTS hotspots and the comparison areas represent a challenge in measuring the effect of the intervention for several reasons. It is possible that some of these differences observed in Table 6 may explain both selection of the area as a DDACTS hotspot and the violent crime rate before and after the intervention had been implemented, which would confound the estimation of the program's effect (Morgan & Winship, 2007). In the analyses that follow, attempts are made to compensate for this issue by building a comparison unit which is similar to the block groups intersecting the DDACTS hotspots, with the only difference being that this comparison unit did not receive the intervention.³

Estimating the Effect of DDACTS on Violent Crime in Flint

This section of the report details two analyses of DDACTS effect on violent crime in Flint. In each analysis the dependent variable is the rate of violent crimes per 1,000 residents. The violent crimes considered in the analyses are homicides, aggravated assaults, robberies, criminal sexual conduct, and weapons offenses, as well as combinations of these crime types. In the first analysis offered, general trends in violent crime rates prior to, and after the implementation of DDACTS are compared for both the target and non-target areas. The second analysis attempts to estimate the effect of the DDACTS intervention through a synthetic control strategy.

³ Because there were DDACTS activities conducted outside of the designated hotspots, it is more accurate to say that the attempted comparison is between the DDACTS hotspots and areas of the city which received a significantly smaller dose of the intervention.

Unadjusted Changes in Violence, Pre- and Post-Implementation

Table 7 presents average monthly rates of violent crime for the DDACTS target area and the comparison area, comparing rates for the 24 months prior to DDACTS, and for 27 months after implementation.⁴ Comparisons are made for general violent crime rates, as well as rates for individual violent crimes. This simple comparison indicates that violent crime was decreasing between the pre- and post-implementation periods for the entire city. In general, the decreases tended to be larger for the block groups intersecting the hotspots, relative to those that did not. The total violent crime rate decreased in the target area block groups by 19 percent, from an average of 2.74 violent crimes per month to 2.21. In the comparison areas the decrease was more modest, from an average of 1.64 per month to 1.52, or a 7 percent decrease.

When restricting the violent crimes considered to assaultive violence in the form of homicides, aggravated assaults, and robberies, similar decreases were observed. Between the pre- and post-implementation periods the monthly rate of these violent crimes decreased by 20 percent in the target area and by 7 percent in the comparison area. Considering individual violent crimes, the decreases were concentrated among aggravated assaults, robberies, and weapons offenses. While aggravated assaults and weapons offenses declined in both the target and non-target areas, monthly robbery rates decreased by 30 percent in the target areas, but remained stable for the comparison. Homicide rates did not change following DDACTS implementation, and rates of criminal sexual conduct actually increased for both the target and non-target areas of Flint.

⁴ Hotspots 1 through 5 were initially identified at implementation in January 2012. Hotspots 6 and 7 were identified later, and thus did not have similar pre- and post-intervention observation periods. In these analyses, Hotspots 6 and 7 are treated as part of the comparison area until their respective implementation points.

Table 7. Changes in Monthly Violent Crime Rates per 1,000 residents, Pre- and Post-DDACTS Implementation

	All Violent Crimes [†]			Homicide, Assault, Robbery		
	Pre	Post	% Chg	Pre	Post	% Chg
DDACTS Hotspots	2.74	2.21	-19.34	2.39	1.92	-19.67
Comparison Areas	1.64	1.52	-7.32	1.42	1.31	-7.75
	Homicides			Aggravated Assaults		
	Pre	Post	% Chg	Pre	Post	% Chg
DDACTS Hotspots	0.06	0.05	-16.67	1.58	1.34	-15.19
Comparison Areas	0.03	0.03	±0.00	0.90	0.81	-10.00
	Robberies			Criminal Sexual Conduct		
	Pre	Post	% Chg	Pre	Post	% Chg
DDACTS Hotspots	0.76	0.53	-30.26	0.09	0.10	+11.11
Comparison Areas	0.48	0.47	-2.08	0.08	0.09	+12.50
	Weapons Offenses					
	Pre	Post	% Chg			
DDACTS Hotspots	0.20	0.19	-5.00			
Comparison Areas	0.13	0.11	-15.38			

Note: % Chg = Percent Change; [†] The combination of homicides, aggravated assaults, robberies, criminal sexual conduct, and weapons offenses.

Comparison using a Synthetic Control Method

In order to compensate for differences between the hotspots and the non-target areas which could have contributed to both selection into the intervention and violent crime rates, a synthetic control approach was utilized (Abadie & Gardeazabal, 2003; Abadie, Diamond, & Hainmueller, 2010). The synthetic control method applies weights to the Flint block groups which were not in the hotspots to favor those which were more similar to the hotspots, and down-weight those which were dissimilar. These weighted block groups are then combined to create a synthetic control unit which resembles the hotspots prior to the implementation of DDACTS (see the Technical Notes section for a complete discussion of the method).

Table 8 presents descriptive statistics for the block groups intersecting the DDACTS hotspots, the non-target areas of Flint, and the estimated synthetic control unit. The results in Table 8 suggest that the synthetic control approach produced a comparison unit very similar to the block groups that intersected the DDACTS hotspots. This synthetic control unit (synthetic hotspots column) was much more similar to the actual hotspots than the original non-target block groups (non-target areas column). By comparing violent crime rates between the DDACTS hotspots and the synthetic comparison there will be stronger validity in claiming that any observed differences in violence were due to the intervention and not any other factor.

Table 8. Predictor Means for DDACTS Hotspots and Synthetic Comparison Prior to DDACTS Implementation

Predictor Variable	DDACTS Hotspots [†]	Synthetic Hotspots	Non-Target Areas ^{††}
Population Density	3650.22	3018.81	3928.73
% Male	0.48	0.48	0.50
% Age 15-24	0.17	0.17	0.15
% White	0.25	0.25	0.45
% African-American	0.70	0.70	0.49
% No HS Diploma	0.60	0.60	0.65
% Married	0.26	0.26	0.33
% Below Poverty	0.46	0.46	0.33
% Female Headed HH with Children und. 18	0.23	0.23	0.16
% Public Assistance	0.16	0.16	0.10
% Unemployed	0.31	0.31	0.24
% Professionals	0.22	0.19	0.25
% Renter Occupied	0.34	0.34	0.33
% Vacant	0.28	0.28	0.21
% HH Income < \$25k	0.54	0.54	0.43
% HU with 5+ Units	0.07	0.07	0.11
% HH Rent > 30% of Income	0.73	0.73	0.62
Violent Crime Rate 2011 per 1,000	25.42	25.39	19.23

[†]Defined as census block groups which intersected the hotspots.

^{††}“Comparison Areas” are all of the Flint block groups that did not intersect a DDACTS hotspot. These comprise the “donor pool” which could have contributed to the estimation of the synthetic hotspot comparison.

In order to estimate the effect of DDACTS on violent crime, the violent crime rates between the block groups intersecting the DDACTS hotspots and the synthetic comparison unit were compared. These rates are displayed in Figure 5. The dark solid line represented the violent crime rates in the hotspots, and the gray dotted line represents the synthetic comparison. The violent crime rate for the synthetic comparison represents the predicted violent crime rate in the DDACTS hotspots had the program never been implemented. A visual inspection of the trends suggests that following DDACTS implementation the violent crime rate began to decline in the hotspots, particularly after July of 2012. The violent crime rates in the comparison area, while demonstrating a larger variance, also decreased after this period, but began increasing in June of 2013.

Figure 5. Violent Crime Rates (per 1,000) for DDACTS Hotspots and Synthetic Comparison Area, January 2010- March 2013

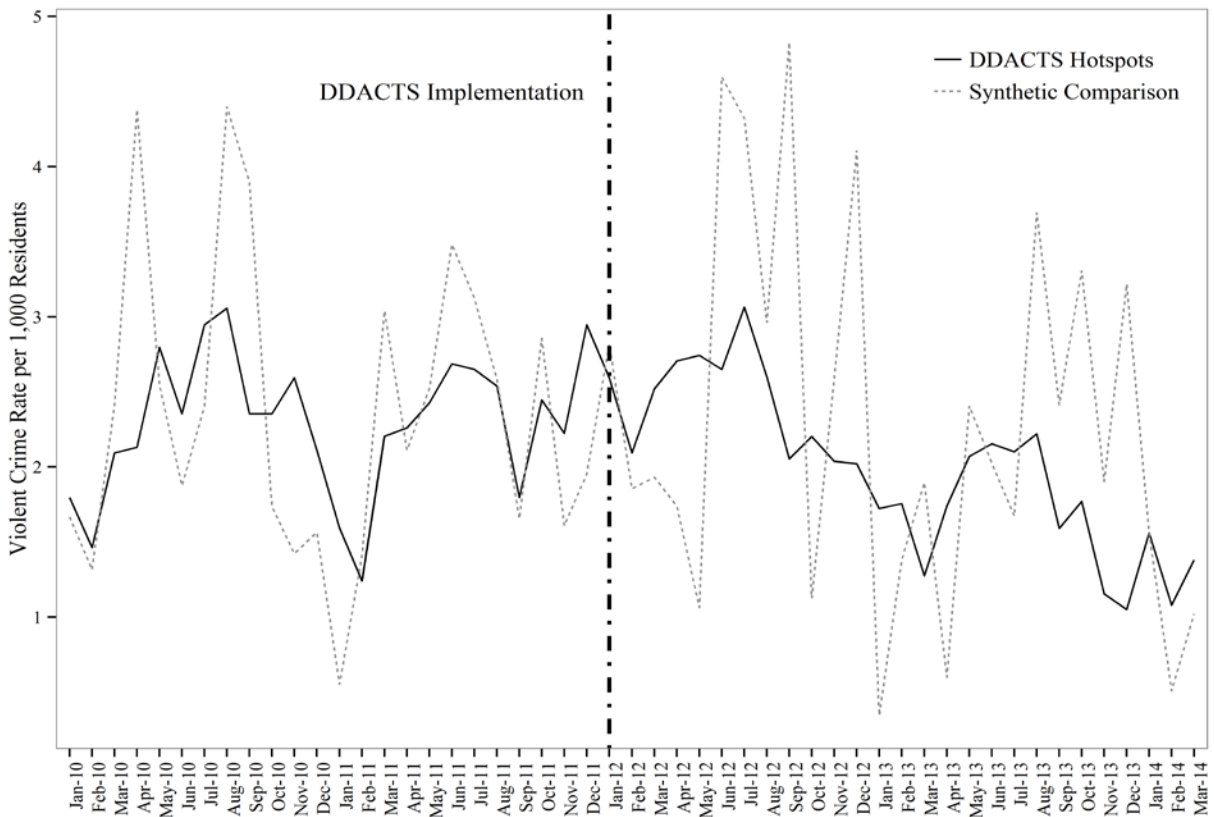
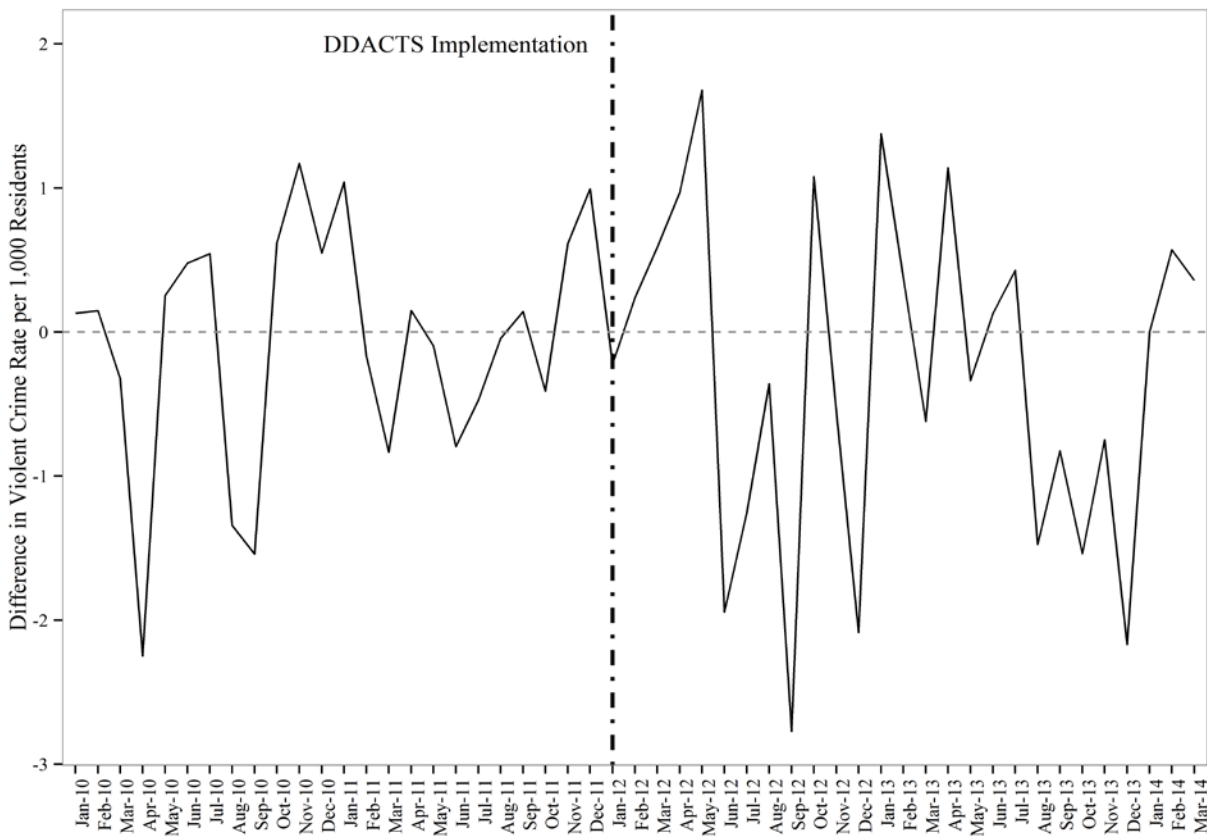


Figure 6 displays an alternative representation of the program effect by more directly plotting the difference between the hotspots and the synthetic comparison. The line represents the difference between the violent crime rate in the DDACTS hotspots and the synthetic comparison for each month. Any value below zero (the gray dashed line) indicates that the violent crime rate was lower in the hotspots than in the comparison area. During the post-intervention period, the DDACTS hotspots experienced a lower violent crime rate than the estimated synthetic comparison in 14 of the 27 months.

Figure 6. Difference in Violent Crime Rate (per 1,000 Residents) between DDACTS Hotspots and Synthetic Comparison, January 2010 – March 2013



The average difference between the violent crime rate in the DDACTS hotspots and the synthetic comparison during the post-implementation period can be used as a summary statistic of the program's effect. These average differences are displayed in Table 9 for each of the violent crime measures across each of the hotspots. Negative values indicate that the post-implementation violent crime rate in the DDACTS hotspots was lower than in the synthetic comparison, on average. Positive values indicate that the crime rate was higher in the hotspots. The overall effect for DDACTS on the combined violent crime rate suggests that after implementation the monthly violent crime rate decreased by -0.30 crimes per month. Considering individual offenses, the largest decreases were observed for robberies and weapons offenses. There were more mixed effects for the individual hotspots, as several experienced higher violent crime rates relative to their synthetic comparisons. The most consistent decreases in crime rates were for robberies, which declined in 5 of the 7 hotspots. On the other hand, homicides were higher in all of the DDACTS hotspots, as well as criminal sexual conduct in 5 of 7 hotspots. These effects suggest that the intervention was associated with a slight increase in homicide and criminal sexual conduct rates. Caution, however, should be used in interpreting the homicide and criminal sexual conduct offense patterns because of the low base rates of these two types of violent crime.

Similarly, these differences (both increases and decreases) must be interpreted with caution, as the certainty of the results are tempered by how similar the pre-DDACTS violent crime rate was in the estimated synthetic comparison to the actual hotspots. The measure of this similarity, the mean squared prediction error (MSPE) ratio, was not particularly high for these effects. See the Technical Notes for an expanded discussion.

Table 9. Average Monthly Differences in Violent Crime Rates per 1,000 between DDACTS Hotspots and Synthetic Comparisons

Crime→ Hotspot ↓	All Violent Crimes	Homicide Agg Aslt, Robbery	Homicide	Agg. Assault	Robbery	Criminal Sexual Conduct	Weapons Offenses
Overall	-0.30	-0.07	0.00	0.07	-0.03	-0.00	-0.11
Hotspot 1	-0.02	0.32	0.03	0.20	-0.10	0.03	-0.09
Hotspot 2	0.11	0.19	0.01	0.06	0.03	0.04	-0.03
Hotspot 3	1.23	1.06	0.03	1.05	-0.22	0.17	0.02
Hotspot 4	-0.25	0.11	0.02	0.29	-0.16	-0.04	0.02
Hotspot 5	-0.08	-0.03	0.01	0.14	-0.24	0.02	0.02
Hotspot 6	-0.02	-0.04	0.01	0.01	0.02	-0.01	0.04
Hotspot 7	0.24	0.01	0.03	0.08	0.06	0.07	-0.01

Note: A separate synthetic comparison was selected for each of the DDACTS hotspots; the values for hotspots 6 and 7 reflect the different implementation points.

Negative values bolded -Negative values indicate lower rates in DDACTS hotspots relative to the synthetic comparison

Sensitivity Analyses

In order to assist the interpretability of the results and to increase the validity of the comparisons a series of sensitivity analyses were performed. These tests add new comparisons or restrict the comparisons involved to provide a check on situations in which the DDACTS program would be expected to have the strongest effects. If the DDACTS hotspots perform better than the synthetic controls in these scenarios, or if the program effect is stronger than in the general analysis above, then there will be increased confidence in claiming that DDACTS was responsible for any observed changes in violent crime.

Placebo Tests

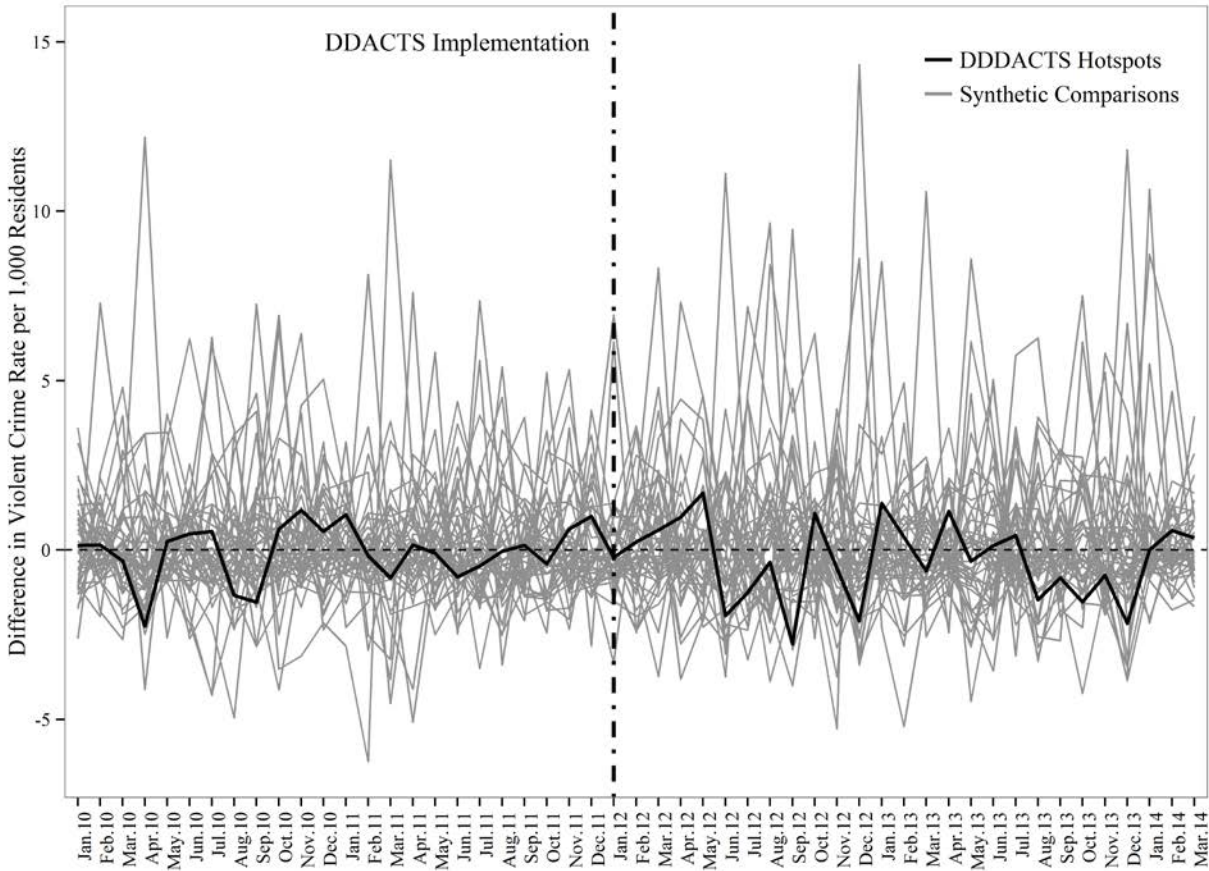
The first set of sensitivity checks involves what Abadie and colleagues (2010) refer to as a placebo test, or permutation test. In this scenario each of the 43 non-target block groups completely outside of the hotspots are treated in the analysis as if they had actually been a DDACTS hotspot. A synthetic comparison for each of these non-target units is estimated and the violent crime rates are compared. Because these comparison units did not actually receive an

intensive dose of the intervention, they are considered “placebo” units. If the DDACTS intervention had a strong effect on violent crime, then it would be expected that the actual hotspots would demonstrate a larger reduction in the violent crime rate than any of the placebo comparison units. The results of the placebo tests are displayed in Figure 7.

Displayed in Figure 7 are trends in the difference in the violent crime rate between the treatment unit and the synthetic comparison units. The dark line represents the estimates differences for the actual DDACTS hotspots (i.e., this line is identical to that presented in Figure 6), while the grayed lines represent the estimates differences for each of the placebo units and their synthetic comparison. A visual inspection of Figure 7 suggests that although there is an evident negative effect for the actual DDACTS hotspots, it does not stand out from the estimated differences in the placebo units which did not receive the intervention in force. When comparing the size of the intervention effect (the MPSE ratio) across the DDACTS hotspots and each of the placebo units, there were 9 placebo units which had larger effect than the actual treatment unit. This entails that if the DDACTS intervention was randomly assigned to the actual hotspots or any of the non-target block groups, one would expect to find an effect as large as in the actual hotspots 23 percent of the time (10/44). This figure falls above the common minimum thresholds in criminological research (i.e., 5 percent).⁵

⁵ Some of these larger effect sizes are positive effects, meaning that the placebo unit had a significantly higher violent crime rate than its synthetic counterpart after the implementation of DDACTS. Restricting the analysis to the 26 placebo units that experienced a negative effect, the actual DDACTS treatment unit had the fourth largest effect size, meaning that there were three placebo units with stronger estimated effects. In this case, if the intervention had been randomly assigned to these placebo units, one would expect to observe an effect as large as or larger than the actual hotspots 12 percent of the time. This figure again falls above the commonly used threshold of 5 percent for identifying a statistically significant effect.

Figure 7. Estimated Difference in Violent Crime Rate (per 1,000 Residents) for DDACTS Hotspots and Synthetic Placebo Comparisons, January 2010 – March 2014



Subgroup Analyses

The second set of sensitivity checks involve dividing the Flint block groups intersecting the DDACTS hotspots into smaller units which are expected to demonstrate stronger or weaker intervention effects. To conduct the analyses above, the DDACTS hotspots were defined as any Flint block groups which intersected a hotspot boundary. The inclusion of block groups which only partially intersected the hotspots may be expected to depress the treatment effect, as smaller differences within these units may mask larger differences in those block groups which fell completely inside the hotspot boundaries. To check whether this was the case, the block groups intersecting the hotspots were divided into two groups – those completely inside the hotspots,

and those partially intersecting the hotspots. A synthetic comparison unit was estimated for each of these DDACTS treatment units. If the intervention was responsible for a reduction in crime after the implementation period, then one would expect to see a larger effect for the block groups completely inside of the hotspots, and a smaller effect for those only partially intersecting the hotspots. The results of these comparisons are displayed in Table 10.

As with previous tables, the effects represent average monthly differences in the violent crime rate per 1,000 residents when comparing the DDACTS hotspots with their synthetic comparison. Negative values (bolded) indicate that the crime rate was lower in the hotspots following implementation, and positive effects mean that the rate was higher. The results of the synthetic comparisons suggests that there was an estimated increase in violent crime rates among the block groups which were completely inside the hotspots. There was an estimated decrease in the violent crime rate in the block groups which partially intersected the hotspots. These patterns are contrary to what would be expected if DDACTS was largely responsible for the observed decreases in violent crime.

To provide a subsequent check on the sensitivity of the results, the analysis was restricted to block groups which intersected the DDACTS hotspots which received the most intense enforcement activities throughout the post-implementation period. Based on the previous examination of traffic stop density per square mile (Table 3), it was determined that hotspots 1, 3, and 4 received more intense program activities, relative to the other DDACTS hotspots. If DDACTS activities were associated with a decrease in crime, it would be expected that there would be a strong, negative effect observed for the block groups intersecting those hotspots, relative to their estimated synthetic controls. The results presented in Table 10 indicate that there was an increase in the violent crime rate in these intensive dosage hotspots following the onset of

the intervention, and this was the case for most of the individual violent crimes. The difficulty in interpreting this effect is a matter of causal direction. It could be that flare ups in violence resulted in intensifying patrol in these hotspots. The alternative is that the most intensive implementation did not have the violence reduction impact desired through DDACTS.

Table 10. Average Monthly Differences in Violent Crime Rates per 1,000 between DDACTS Hotspots Subgroups and Synthetic Comparisons

Crime → Hotspot ↓	All Violent Crimes	Homicide Agg Aslt, Robbery	Homicide	Agg. Assault	Robbery	Criminal Sexual Conduct	Weapons Offenses
Comp. Inside	0.37	0.25	0.00	0.11	0.11	0.01	0.02
Partially Intersect	-0.08	0.04	0.01	0.03	-0.07	0.02	0.02
Intensive Dosage	0.19	0.26	0.01	0.33	-0.07	0.01	-0.03

Note: “Intensive dosage” corresponds to the block groups which intersected hotspots with the most intense DDACTS activities, which were Hotspots, 1, 3, and 4.

Negative values bolded - Negative values indicate lower rates in DDACTS hotspots relative to the synthetic comparison

CONCLUSION

In response to high rates of violent crime and reductions in police resources due to city budgetary restrictions, MSP implemented a promising law enforcement strategy known as Data Driven Approaches to Crime and Traffic Safety (DDACTS) in Flint, Michigan. The results of this evaluation demonstrate that MSP invested considerable resources and generated significant outputs in terms of traffic stops, warnings, citations, fugitive arrests, and similar indicators. The target areas experienced substantial decreases in violent crime. Indeed, the target areas experienced a 19 percent reduction in violent crime and a 30 percent reduction in robberies. This compared to 7 and 2 percent reductions, respectively, in the rest of the city. On the other hand, more stringent evaluation methods that compared the target hotspots to matched comparison areas did not reveal significant differences between the trends in the target hotspots and the matched comparison areas. These findings are consistent with two plausible interpretations. One is that the DDACTS strategy had a violence reduction impact that beneficially diffused to other parts of the city. The alternative interpretation is that some other factor was influencing violent crime in Flint and the impact was observed in the DDACTS target areas as well as in areas of Flint most similar to the DDACTS target areas.

These results suggest cautious optimism in the use of DDACTS to address violent crime. Clearly, reductions of 19 and 30 percent in total violent crime and robberies are impressive and suggest future implementation and experimentation with DDACTS as a promising strategy for addressing violent crime. At the same time, the lack of observed impact when the DDACTS hotspot areas were compared with other similar areas of the city suggest that caution is warranted and more evidence needs to be considered before conclusions can be drawn about the efficacy of DDACTS as strategy for reducing violent crime.

TECHNICAL NOTES

Synthetic Control Strategy

The purpose of the current analysis is to estimate the effect of the DDACTS intervention on incidents of violent crime within the Flint block groups. In the event that areas of Flint had been randomly assigned to receive the DDACTS intervention, it would be possible to estimate the average treatment effect by calculating the difference in the average number of violent crimes between the hotspots (treatment) and the rest of the city (control).⁶ When areal units are not randomly assigned to receive the intervention, it raises the possibility that the observed difference in violent crime between the treatment and control units is not due to the intervention, but rather underlying differences between the units. Given that DDACTS hotspots were selected based on the clustering of violent crime incidents within small geographic areas, it is likely that block groups with a high intensity of violent crime were different from those without such concentrations. Covariates such as sociodemographic characteristics of the block groups may affect both the assignment to receive DDACTS and violent crime outcomes, confounding the estimation of treatment effects.

In the absence of random assignment, one possible means to estimate the effect of an intervention is to utilize a synthetic control unit. Developed by Abadie and colleagues (Abadie & Gardeazabal, 2003; Abadie, Diamond, & Hainmueller, 2010), the synthetic control approach weights members of a comparison group to construct a single synthetic control unit which closely resembles the treatment unit prior to the onset of the intervention. The resulting synthetic control unit approximates what would have happened to the outcome of interest in the treatment group had the intervention never been implemented. In the context of the current analysis, the

⁶ Per Morgan and Winship (2007), $E[\delta] = E[Y^1 - Y^0]$ where $E[Y^1]$ represents the average number of violent crime incidents in the DDACTS hotspots, and $E[Y^0]$ is the average violent crime incidents in the control areas.

synthetic control strategy constructs a synthetic comparison unit to the DDACTS hotspots through a weighted average of the Flint block groups which did not intersect a hotspot. This synthetic comparison unit estimates how the crime rate would have varied within the hotspots in the absence of the DDACTS intervention.

Creation of a Synthetic DDACTS Control Unit

Drawing on the model of Abadie and colleagues (2010), suppose that $J+1$ represents the number of Flint block groups under observation. The DDACTS hotspots are referred to as unit $j = 1$.⁷ The remaining block groups, units $j = 2$ to $J + 1$ are considered as the “donor pool” which can contribute to the estimation of the synthetic control unit. Units $J + 1$ are observed for time periods $t = 1, \dots, T$, in which the DDACTS intervention is implemented at $T_0 + 1$. That being said, T_0 reflects the number of pre-intervention time periods and T_1 the number of post-intervention periods. Further, $1, 2, \dots, T_0$ are pre-intervention observation periods, and $T_0 + 1, T_0 + 2, \dots, T$ are post-intervention periods.

The synthetic control approach asserts that when the goal of a study is to estimate the effect of an intervention as it is applied to an aggregate-level unit, a combination of comparison units may provide a more accurate counterfactual than any single comparison unit (Abadie et al., Forthcoming). A synthetic control unit is defined as a weighted average of the comparison units available in the donor pool (Abadie et al., 2010). The synthetic control unit is constructed as a $(J \times 1)$ vector of weights $W = (w_2, \dots, w_{J+1})$, for which $0 > w_j > 1$ and $w_2 + \dots + w_{j+1} = 1$. Any given value for W represents a possible synthetic control unit. Abadie and colleagues (2010,

⁷ Per Abadie, Diamond, and Hainmueller (2011, Forthcoming), synthetic control methods can consider a single treatment unit or multiple treatment units. In either case, a synthetic control unit is estimated for each treatment unit separately. For the current analysis, two approaches were taken: First, all block groups intersecting the DDACTS hotspots were aggregated prior to analysis, indicating that $J + 1$ units were available for analysis. In a secondary approach, block groups intersecting each of the seven hotspots were aggregated and analyzed separately. Each treatment unit drew from the same donor pool of block groups which did not intersect DDACTS hotspots.

Forthcoming) define the optimal value for W as one in which the characteristics of the synthetic control best approximate the pre-treatment characteristics of the treated unit.

More specifically, let k represent the number of predictor variables which the researcher wishes the treatment unit and the synthetic control to be matched on. Let X_1 be a $(k \times 1)$ vector representing the pre-treatment characteristics of the treated unit, and X_0 be a $(k \times J)$ matrix containing the pre-treatment characteristics of each unit in the donor pool. Let m represent individual predictor variables (i.e., $m = 1, \dots, k$), and X_{1m} represent the value of the m -th variable for the treatment unit, and X_{0m} be a $(1 \times J)$ vector with values for the m -th variable for each comparison unit in the donor pool. In addition, let v_m represent the importance weight applied to each variable m , whereas variables which more strongly predict the outcome indicator are weighted more heavily than those which do not (see Abadie et al. [Forthcoming] for a formal definition of the importance weights). The optimal estimated value for W is the one which minimizes

$$\sum_{m=1}^k v_m (X_{1m} - X_{0m}W)^2, \quad (1)$$

which represents the sum of the importance-weighted squared discrepancies between X_1 and X_0W for each covariate m .

Estimating Intervention Effects

The synthetic control approach focuses on two outcomes. Using the language of a potential outcomes framework, let Y_{jt}^N refer to the outcome observed for unit j at time t if that unit is not exposed to DDACTS, and let Y_{jt}^D refer to the outcome that would be observed if unit j was exposed to DDACTS at time t . The treatment effect during the post-intervention period would be defined as $\alpha_{1t} = Y_{jt}^D - Y_{jt}^N$, or the difference between the outcomes for unit j during

the post-intervention period when the unit was and was not exposed to DDACTS. Values for Y_{jt}^N for any unit actually receiving DDACTS during the post-intervention period represent an unobservable counterfactual (Abadie et al., 2011). Fortunately, the implementation of the synthetic control approach defined above allows for the estimation of a counterfactual treatment unit which was not exposed to the intervention.

Generalizing from the potential outcomes above, let Y_{jt} represent the outcome of unit j at time t . Let Y_1 be a $(T_1 \times 1)$ vector of the post-intervention observations of the outcome indicator for the DDACTS treatment unit, and Y_0 be a $(T_1 \times J)$ matrix of post-intervention outcomes for each unit $j + 1$. Per Abadie and colleagues (2010, 2011, Forthcoming), the synthetic control estimator for the effect of the intervention at time t is given by

$$\hat{\alpha}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j Y_{jt}, \quad (2)$$

which estimates α_{1t} through a comparison of outcomes for the treatment unit and its synthetic control at each period t during the post-intervention period.

Further, scholars have expanded upon the work of Abadie and colleagues to suggest additional intervention effect indicators using the synthetic control framework. Faller, Glynn, and Ichino (2013) define the synthetic estimate as the average difference between the treatment unit and the synthetic control unit during the post-intervention period, or

$$\bar{\alpha}_1 = \frac{1}{T_1} \sum_{T_0+1}^{T_1} \hat{\alpha}_{1t}. \quad (3)$$

Further, the synthetic estimate for the pre-intervention period can be subtracted from this value for a difference-in-difference estimator. These estimators are used to describe the effect of the DDACTS intervention on violent crime. The construction of the synthetic control unit and the

impact analysis were conducted using the ‘Synth’ package in the R statistical computing environment (Abadie et al., 2011; R Core Team, 2014).

Covariates for Estimation of Synthetic Control Unit

In order to construct a synthetic control unit which resembled the DDACTS treatment unit, a set of sociodemographic characteristics were collected for each of the 131 Census Block Groups in the city of Flint.⁸ The sociodemographic data were gleaned from 5-year estimates from the American Community Survey, corresponding to 2008-2012 (United States Census Bureau, 2013). The covariates selected were a reflection of community characteristics which have been demonstrated to correlate with violent crime, and similar to those which were used in comparable evaluation research (Wilson, Chermak, & McGarrell, 2010). The block group covariates utilized were:

- Total population
- Population density per square mile
- Proportion of the population that was male
- Proportion of the population that was age 15-24
- Proportion of the population that was white
- Proportion of the population that was African-American
- Proportion of the population over the age of 25 without a high school diploma
- Proportion of the population over the age of 15 that was married
- Proportion of individuals in the population who were living below poverty
- Proportion of households that were headed by females with children under the age of 18
- Proportion of households that were receiving public assistance
- Proportion of the population that was over the age of 16 and unemployed
- Proportion of the population over the age of 16 that was employed in professional occupations
- Proportion of housing units that were occupied by renters
- Proportion of the housing units that were vacant

⁸ There are actually 132 block groups in the city of Flint. One block group (Block Group 1 of Census Tract 9801) was excluded from the analysis because it had a population of zero. This made it impossible to calculate rates of violent crime, unless the block group were assigned an arbitrary population count. Because this block group represented an outlier and it was situated outside of the DDACTS hotspots, it was excluded from the impact analyses. During the entire four year observation period there were only 28 violent crimes which took place there, or 0.003percent of all violent crimes during the observation period.

- Proportion of households with income less than \$25,000
- Proportion of households with rent greater than 30 percent of household income
- Violent crime rate per 1,000 residents in 2011

Elaborated Results – Difference-in-Difference Estimates and MSPE Ratios

Throughout the Impact Assessment section of the report, the effect of DDACTS on violent crime was examined using the average monthly difference in violent crime between the hotspots and their estimated synthetic comparisons following the implementation of DDACTS (i.e., the synthetic effect, Equation 3 above). In addition to these synthetic effects, two additional values of interest were calculated; these were difference-in-differences estimates (DID) and mean square prediction error (MSPE) ratios. Each of these measures are described and presented in turn.

Difference-in-differences estimates (DID) provide a compliment to the presentation of the synthetic effects by further adjusting the effect estimate for stable differences between the DDACTS hotspots and their synthetic comparison unit. Additionally, DID estimates account for changes in the outcome variable trends over time which were unrelated to the intervention (Imbens & Wooldridge, 2009). For each outcome variable considered (i.e., combined violent crimes, homicides, aggravated assaults, etc.) the DID estimate is calculated as:

$$\hat{\alpha}_{DID} = \bar{\alpha}_1 - \bar{\alpha}_0 \quad (4)$$

Where, expanding on Equation 3 above, $\bar{\alpha}_1$ represents the average difference in the outcome variable between the treatment unit and the control unit during the post-intervention period, and $\bar{\alpha}_0$ represents the same average difference during the pre-intervention period. The DID estimate is calculated by subtracting the average difference in the treatment and control groups prior to the intervention from the difference between the groups following the intervention (Imbens & Wooldridge, 2009).

In this sense, a DID estimate is more robust to pre-intervention differences between the treatment and control groups than the synthetic estimates. For instance, a large negative difference between the hotspots and the synthetic comparison unit following the onset of DDACTS would not seem as impressive if there was already a sizable negative difference prior to the intervention, indicating that the observed differences were likely not attributable to the intervention. On the other hand, a relatively small difference during the post-intervention period would look more impressive if there was a large positive difference during the pre-intervention period.

The mean square prediction error (MSPE) ratio provides a similar check on the synthetic estimates presented in the Impact Assessment section of the report. As described by Abadie and colleagues (2010), the MSPE is defined as the average squared difference between the outcome variable in the treatment unit and in the synthetic comparison unit. The synthetic control estimation attempts to minimize the MSPE during the pre-intervention period (Abadie et al., 2010), meaning that the estimated synthetic control experiences similar levels of the outcome variable to the treatment unit prior to the onset of the intervention. During the post-intervention period, a high MSPE is indicative of a large difference in the outcome variable between the treatment and control units. But like with the DID estimates, a large post-intervention MSPE is less impressive if there was a large MSPE during the pre-intervention period as well. Similarly, a large post-intervention MSPE is given more credence if there was a relatively small pre-intervention value, suggesting that any differences would be attributable to the intervention. To this extent, the ratio of the post-intervention MSPE to the pre-intervention MSPE is a check on the size of the intervention effect (Abadie et al., 2010).

The DID estimates and MSPE ratios for the synthetic effects estimated for each violent crime in each of the hotspots are presented in Table 11. There are several points to note. Concerning the overall difference between the DDACTS hotspots and their synthetic comparison, there is a negative DID estimate (-0.23), suggesting that the DDACTS intervention was associated with a modest decrease in violent crime rates. For these hotspots, the post-intervention MSPE was 1.41, and the pre-intervention MPSE was 0.68, resulting in an MSPE ratio of 2.08. Each of these values is quite small (Abadie and colleagues, 2010), indicating that while the synthetic control procedure succeeded in producing a comparison unit with similar pre-DDACTS violent crime rates to the hotspots, the difference between them following the intervention was not particularly large. Among the placebo tests described in the sensitive checks section of the Impact Assessment, the observed MSPE ratio of 2.08 was the 10th largest ratio among the placebo units. These results suggest that although the intervention was associated with some decrease in overall violent crime, the decrease was rather modest.

Table 12 presents similar estimates for the subgroup analyses portion of the sensitivity checks. Considering the block groups which fell completely inside the DDACTS hotspots, the DID estimate suggests that after compensating for the pre-intervention difference in violent crime rates, there was a slight increase in violent crime in the hotspots during the post-intervention period (0.14). The MSPE ratio again suggests that this effect was not particularly pronounced (2.52), but relatively large among the observed effects. On the other hand, the DID estimate for the block groups partially intersecting the hotspots was essentially null (-0.03). Concerning the hotspots receiving most intense program activities, the DID estimate indicates that there was a similar null relationship between the DDACTS intervention and violent crime rates (0.04, MSPE 2.62).

Table 11. Synthetic Effect and Difference-in-Differences Estimates for DDACTS Intervention on Crime Rates per 1,000 Residents

Hotspot	All Violent Crime	Assault, Homicide, Robbery	Homicide	Aggravated Assault	Robbery	CSC ^{†††}	Weapons Offenses
	Synth [†] , DID ^{††} MSPE Ratio	Synth, DID MSPE Ratio	Synth, DID MSPE Ratio	Synth, DID MSPE Ratio	Synth, DID MSPE Ratio	Synth, DID MSPE Ratio	Synth, DID MSPE Ratio
Overall	-0.30, -0.23 2.08	-0.07, -0.18 0.97	0.00, 0.08 0.08	0.07, 0.09 0.96	-0.03, -0.13 0.67	-0.00, -0.01 1.88	-0.11, -0.12 2.30
Hotspot 1	-0.02, 0.01 1.56	0.32, 0.15 1.76	0.03, 0.03 2.18	0.20, 0.06 0.96	-0.10, -0.17 0.88	0.03, 0.03 3.14	-0.09, -0.11 2.56
Hotspot 2	0.11, 0.20 1.70	0.19, 0.30 0.94	0.01, 0.01 0.51	0.06, 0.14 0.66	0.03, -0.02 0.40	0.04, -0.01 0.70	-0.03, -0.05 1.90
Hotspot 3	1.23, 1.33 5.64	1.06, 1.17 4.01	0.03, 0.02 5.36	1.05, 1.02 3.76	-0.22, -0.03 2.75	0.17, 0.15 4.81	0.02, 0.02 5.80
Hotspot 4	-0.25, -0.36 2.26	0.11, -0.17 0.58	0.02, -0.02 0.52	0.29, 0.12 2.06	-0.16, -0.16 1.21	-0.04, -0.07 3.10	0.02, -0.03 5.15
Hotspot 5	-0.08, -0.13 3.74	-0.03, -0.07 2.41	0.01, -0.02 3.96	0.14, 0.18 3.08	-0.24, -0.23 1.64	0.02, 0.05 1.95	0.02, -0.07 1.71
Hotspot 6	-0.02, 0.10 2.09	-0.04, 0.13 0.93	0.01, -0.01 0.80	0.01, -0.02 0.43	0.02, 0.11 1.87	-0.01, -0.04 3.04	0.04, -0.03 2.46
Hotspot 7	0.24, 0.03 0.47	0.01, -0.04 0.71	0.03, -0.00 0.49	0.08, -0.13 0.50	0.06, -0.05 1.37	0.07, 0.06 1.95	-0.01, -0.10 1.44

Note: Hotspots 6 and 7 did not begin DDACTS activities until July 2012 and July 2013, respectively. This information is incorporated into synthetic effect estimates.

[†]Estimates reflect the average difference between the violent crime rate for the DDACTS hotspots and their synthetic comparisons during the post-implementation period. Negative effects mean crime rates were lower in the DDACTS hotspots, while positive effects mean higher rates.

^{††}DID = Difference-in-Differences.

^{†††}CSC = Criminal Sexual Conduct.

Table 12. Synthetic Effect and Difference-in-Differences Estimates for DDACTS Intervention on Crime Rates per 1,000 Residents

Hotspot	All Violent Crime	Assault, Homicide, Robbery	Homicide	Aggravated Assault	Robbery	CSC ^{†††}	Weapons Offenses
	Synth [†] , DID ^{††} MSPE Ratio	Synth, DID MSPE Ratio	Synth, DID MSPE Ratio	Synth, DID MSPE Ratio	Synth, DID MSPE Ratio	Synth, DID MSPE Ratio	Synth, DID MSPE Ratio
Completely Inside	0.37, 0.14 2.52	0.25, 0.17 1.21	0.00, -0.01 1.72	0.11, 0.02 1.01	0.11, -0.10 0.50	0.01, -0.02 2.12	0.02, -0.05 2.00
Partially Intersect	-0.08, -0.03 2.39	0.04, -0.13 1.53	0.01, 0.02 0.29	0.03, 0.03 1.25	-0.07, -0.02 0.84	0.02, 0.03 1.19	0.02, -0.05 3.80
Intensive Dosage	0.19, 0.04 2.62	0.26, -0.10 1.16	0.01, 0.03 0.44	0.33, 0.13 1.70	-0.07, -0.21 0.87	0.01, -0.00 0.96	-0.03, -0.06 3.03

Note: “Intensive dosage” corresponds to the block groups which intersected hotspots with the most intense DDACTS activities, which were Hotspots, 1, 3, and 4.

[†]Estimates reflect the average difference between the violent crime rate for the DDACTS hotspots and their synthetic comparisons during the post-implementation period. Negative effects mean crime rates were lower in the DDACTS hotspots, while positive effects mean higher rates.

^{††}DID = Difference-in-Differences.

^{†††}CSC = Criminal Sexual Conduct.

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