JUSTICE & SECURITY **STRATEGIES**

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We thank the Denver Police Department, the Denver ATF Office, and their law enforcement partners for their willingness to provide data and information regarding the Crime Gun Intelligence Center and the Regional Anti-Violence Enforcement Network. Their cooperation was invaluable and without it we would not be able to complete this report.

JUSTICE & SECURITY **STRATEGIES**

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SECTION 1:

INTRODUCTION, BACKGROUND, AND METHODOLOGY

INTRODUCTION

In 2012 the Bureau of Alcohol, Tobacco, Firearms, and Explosives (ATF) and the Denver Police Department (DPD) began informal discussions about thwarting violent crime that was emerging in the Denver metropolitan area. ATF's Supervisory Agent Jeff Russell and DPD's Commander Mark Fleecs formulated a pilot project that would eventually become the Denver Crime Gun Intelligence Center (CGIC), and in 2019 expand to the Regional Anti-Violence Enforcement Network (RAVEN) (J. Russell, personal communication October 2020).

Denver's CGIC was conceived as a program that would "focus on gun violence" -- emphasizing shooters and those who commit gun-related crimes (J. Russell, personal communication October 2020). Using data- and forensic-driven approaches, an interagency collaboration was developed between ATF and DPD. Relying on research on gun violence and crime lab forensics, ATF and DPD leveraged the ATF's National Integrated Ballistics Information Network (NIBIN) to identify critical links between gun casings, gun-related incidents, and those using firearms. NIBIN information and eTrace were used to link ballistics evidence recovered from firearms and casings to other shooting incidents. They showed the ability to identify heretofore unknown perpetrators and generate forensic evidence leading to the arrest and convictions of gun-crime offenders.

Within a year, the Denver District Attorney's Office[1] and a number of other local agencies began participating in CGIC, including the Aurora Police Department, the Lakewood Police Department, the Colorado Bureau of Investigation, the Colorado Attorney General's Office, the Colorado Department of Corrections Division of Adult Parole, and the United States Attorney's Office, District of Colorado (White & Franey, 2014).

To augment the activities of CGIC, the Bureau of Justice Assistance (BJA) and the District of Colorado's Project Safe Neighborhood's Task Force provided grant funding in 2015 and 2016 to expand operations for processing ballistic evidence (Schaible & Six, 2017). Additionally, ATF provided financial support for the installation of the ShotSpotter acoustic detection system, which was first implemented on January 8, 2015. Four years later, in January 2019, the CGIC initiative expanded into the Regional Anti-Violence Enforcement Network (RAVEN). The goal of this expansion was to increase the number of regional partnerships that would extend ballistic evidence collection and processing, as well as enabling cross-agency partnerships for strategic violent crime prevention.

This report presents the results from two types of evaluations – a process evaluation and impact evaluation of CGIC/RAVEN. For the process evaluation, we focus on the CGIC/RAVEN activities and NIBIN-related information in Denver, Aurora, and Lakewood as well as contextual information provided from interviewees participating in RAVEN.

For the impact evaluation, we focus only on the observed effects on crime in the City of Denver. Specifically, using a quasi-experimental design, we examine whether CGIC and RAVEN led to changes in the level and trends of gun crime: serious violent crime with a firearm, homicide with a firearm, robbery with a firearm, and aggravated assault with a firearm.

This report is divided into four major sections. We first provide a background on the CGIC concept, review the literature regarding its effectiveness and describe our methodology. Second, we discuss the findings from the process evaluation, which tells the story of how Denver evolved from a CGIC to a large network known as RAVEN. Third, we discuss the impact of CGIC and RAVEN on crime throughout the Denver area. Fourth, we discuss the conclusions, limitations of the study, and provide a series of recommendations for future research and policy

BACKGROUND

Many municipalities across the nation have experienced increases in violent crime, particularly homicides, over the last decade. The majority of this increase occurred between 2014 and 2016 (BJS, 2020). The total national violent crime rate from 2014 to 2016 increased by 7 percent, while homicides rose 23 percent, robberies rose 2 percent, and aggravated assaults increased by 8 percent during the same time period (BJS, 2020, p.1). According to the Police Executive Research Forum (2017), firearm crime was predominantly responsible for driving these crime rates, particularly the aggravated assault and homicide rates.

In an effort to curb rising violent crime rates, legislators have enacted a variety of laws, such as expanding background checks, banning certain types of firearms, and limiting magazine capacities. Violent firearm crime rates have continued to rise in recent years despite these efforts. Law enforcement agencies have employed their own strategies to reduce firearm-related violent crime, such as the use of specialized units, increased use of closed circuit television cameras, and cross-jurisdictional enforcement partnerships (Police Executive Research Forum, 2017). These strategies, too, have produced mixed results.

In 2013, a new and innovative method, the Crime Gun Intelligence Center (CGIC), was activated in Denver for combating firearms-related crime. Unlike other police-based programs that emphasize intuition and enforcement-led tactics and strategies, the Denver CGIC relied upon science to assist in identifying and tracking gun casings, guns, and shooters. Taking a nuanced approach that begins with the gun casing itself, the Denver CGIC sought to disrupt the shooting cycle by using forensic science and data analysis to identify, investigate, and prosecute shooters as well as their sources of crime guns. A key feature of the Denver CGIC is the collaboration among several different agencies with the same multi-pronged goals: real-time collection, processing, and analysis of crime guns and cartridge casings; identification of active shooters; disruption of criminal networks; and violence prevention.

The CGIC concept in Denver required the timely collection of ballistic evidence and submission into NIBIN. Once a NIBIN hit was generated, detectives from DPD's Intelligence Unit began follow-up and investigation. Denver's early CGIC program concentrated on NIBIN operations to inform real-time investigative leads to arrest and prosecute firearm offenders quickly and efficiently (J. Russell, personal communication October 2020).

In 2014 and 2015 word about the success of the Denver CGIC spread to Washington, D.C. and law enforcement agencies across the country. At ATF headquarters, the use of evidence-based approaches became part of its 'business model' and the Denver CGIC was a prominent example of that approach (Bureau of Alcohol, Tobacco, Firearms and Explosives, 2015). Importantly, ATF analysts in the Denver office began to create a database for NIBIN information that eventually became NESS – NIBIN Enforcement Support System. This system is now used nationally and is available for online use by ATF and local law enforcement agencies.

By 2015 the Bureau of Justice Assistance (BJA) and ATF developed a full grant program to enable law enforcement agencies to create their own CGICs. Under the competitive program local agencies could receive $750,000 to $1,000,000 to establish its CGIC. As of 2020, at least 25 local jurisdictions have established CGICs using funds and technical assistance from BJA and ATF (The Police Foundation, 2020).

Denver has continued to evolve its program by incorporating a number of investigative strategies, tactics, technologies, and partnerships. Based on their experiences with the CGIC process from 2013 to 2017, Denver CGIC participants decided to expand the model to include additional surrounding agencies and merge the local Metro Gang Task Force with the CGIC. In January 2019, Denver rebranded the CGIC as the Regional Anti-Violence Enforcement Network (RAVEN) and began functioning as the centralized firearm crime unit in the Denver metropolitan area.

RAVEN is currently comprised of 13 separate agencies and a number of partners. Participating agencies provide a representative to RAVEN who is responsible for communicating about violent, firearm, and gang-related crime in their respective jurisdictions. In addition, the RAVEN task force leverages federal resources to assist participating agencies in solving and combating violent crime in the Denver Metro area. Figure 1 presents a timeline of many of the key events from CGIC/RAVEN through 2019.

The adaptation and expansion efforts of RAVEN served as the first example of the CGIC model moving from a conceptual framework to a set of investigative processes and practices.

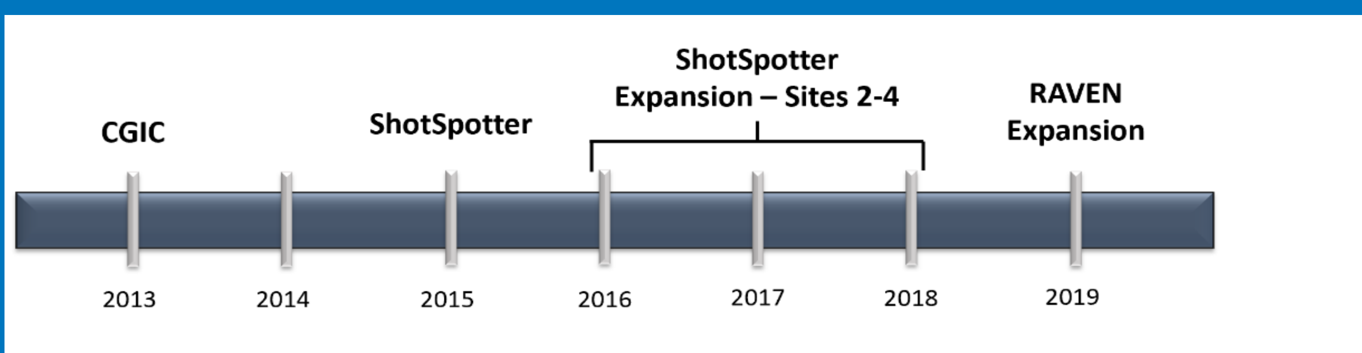


FIGURE 1. TIMELINE OF EVENTS IN DENVER CGIC/RAVEN

Review of the CGIC Concept

The Denver CGIC was the first in the nation and remains a model for other agencies. Currently, at least 25 local jurisdictions have established CGICs using funds and technical assistance from the BJA and the ATF. The primary intent of CGICs is to disrupt the shooting cycle by using forensic science and data analysis to identify, investigate, and prosecute shooters and their sources of crime guns. A key feature of these CGICs is collaboration among several different agencies with the same multi-pronged goals: real-time collection, processing, and analysis of crime guns and cartridge casings; identification of active shooters; disruption of crime; and violence prevention. Successful CGIC operations include collaborative efforts among several partners and stakeholders, often including ATF offices, law enforcement agencies; crime labs; probation and parole departments; gang task force officers and gang units; federal, local, and state prosecutors' offices; crime and intelligence analysts; the community; and research partners (Police Foundation, 2017). Figure 2 provides an overview of the CGIC workflow and processes.

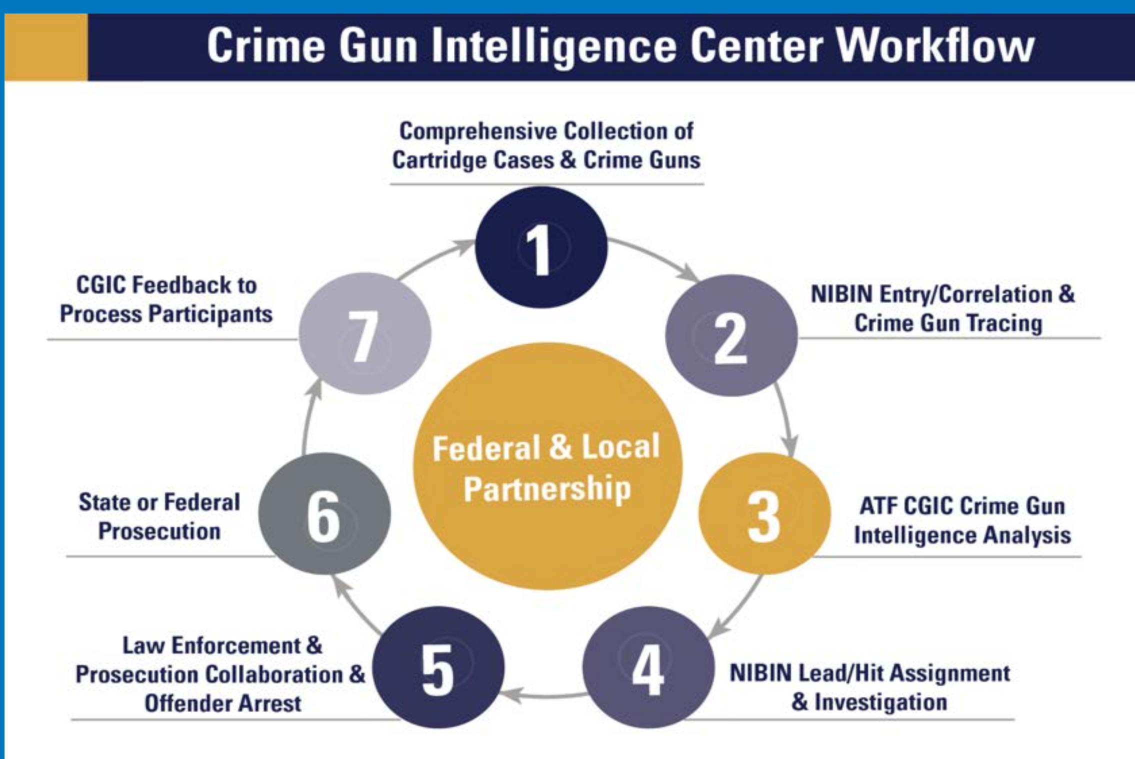


FIGURE 2. CGIC WORKFLOW AND PROCESSES
Source: https://crimegunintelcenters.org/cgic-process/

A cornerstone of the CGIC strategy is leveraging the National Integrated Ballistic Information Network (NIBIN) technology hosted by ATF. NIBIN is a national network of digital images of fired cartridge casings, often taken from crime scenes and recovered crime guns. This network allows law enforcement agencies to upload cartridge casings and other ballistic evidence to the national database; once uploaded, examiners are able to match ballistic evidence to previously submitted cartridge casings to link multiple crime incidents (Koper, Vovak, & Cowell, 2019).

The NIBIN correlation process occurs in several parts. First, officers collect fired cartridge casings from crime scenes or from recovered crime guns. Those casings are then transferred to firearm examiners and technicians for submission into the Integrated Ballistic Identification System (IBIS). The IBIS technology identifies significant markings on the shell casing or bullet, which are deposited by different components of the firearm, such as the firing pin or ejector. The digitally examined casing or bullet is then submitted to NIBIN for correlation analysis. Once the correlation analysis is complete by image analysis software, a list of potential matches is generated. The list of correlations is divided by confidence levels ranging from low to high and subsequently examined by an operator. Once the operator confirms the probability of a match between casings and/or bullets, the correlation is reclassified as a Potential Candidate for Comparison (PCC) and is then examined through a microscope by a firearm examiner. At this point, a NIBIN lead is generated and may provide new investigative avenues with the linkage provided by NIBIN (Koper et al., 2019., pp. 8-9).

By comparing the digital images from spent casings, NIBIN gives investigators the ability to identify linkages among incidents involving discharged or recovered firearms. From these incidents, investigators are able to re-start ‘cold’ cases and to generate lists of potential suspects, victims, and associates across incidents and jurisdictions that may be otherwise unavailable. Further, the NIBIN database links to the ATF’s eTrace system that traces firearm information from manufacture through purchaser to identify if firearms are trafficked or stolen (Kraft, 2018). All of this information is used in follow-up investigation and may assist arrest and prosecution of gun crime offenders.

Previous Evaluations of CGIC

Since the CGIC concept is relatively new, few studies have evaluated the degree to which CGICs assist law enforcement in reducing the extent of gun crime. However, there are several existing studies that provide promising results. Since 2017 researchers have conducted evaluations of CGICs in Milwaukee, Los Angeles, Washington D.C., Chicago, and Denver.

The Police Executive Research Forum (2017) conducted an early evaluation of CGICs operating in Denver, Chicago, and Milwaukee. Taking a 'case study' approach, PERF described the components and processes existing within each of the CGICs. The study demonstrated that coupled with other federal resources and technology, NIBIN was an effective investigative tool in generating leads and identifying patterns of firearm-related crime (Police Executive Research Forum, 2017). Specifically, the utility of NIBIN was elevated when agencies submitted ballistic evidence frequently and consistently. In the early stages of implementation, Denver was able to integrate NIBIN operations into their existing crime lab in order to streamline NIBIN processing, hit triaging, and investigative lead follow-up. This capability significantly increased DPD's ability to process ballistic evidence and NIBIN leads in the recommended 24-48-hour window. While Milwaukee and Chicago did not have the capacity to process ballistic evidence in-house, they were able to implement a successful CGIC program by investigating NIBIN leads immediately and enlisting state crime labs for review of NIBIN leads.

Researchers from the National Police Foundation and George Mason University examined the impact of Milwaukee's CGIC from 2014 to 2017. They found clearance rates for non-fatal shootings increased during the study period due to NIBIN-related evidence. Further, NIBIN arrests had a statistically significant negative effect on shootings in subsequent time periods. Cases with NIBIN links helped investigators focus on chronic offenders who were responsible for large portions of gun violence throughout the city. Investigators made one arrest for every 1.3 homicides with a NIBIN link and one arrest for evert 2.7 NIBIN-related incidents overall (Koper et al. 2019).

An evaluation of Los Angeles' CGIC by Justice & Security Strategies, Inc. also showed promising results. In the Los Angeles Police Department (LAPD), four of 21 patrol divisions (77th Street, Southeast, Southwest, and Harbor) experienced the CGIC treatment, with the primary focus on 77th Street Division. Relative to the pre-CGIC period, 77th Street Division recorded an 18.9 percent decrease in homicides and a 7.7 decrease in firearm-related homicides. Despite robberies increasing during the same period, firearm-related robberies decreased 3.1 percent. Interviews with CGIC personnel supported the idea that investigators focused their interventions on the most chronic and violent firearm offenders. In the three divisions of Southeast, Southwest, and Harbor, violent crime steadily increased in the post-CGIC period; however, firearm-related violent crime remained relatively stable. Despite several additional interventions occurring in Los Angeles during the same timeframe, these results are encouraging (Uchida, Quigley, & Anderson, 2019).

Washington D.C.'s Metropolitan Police Department (MPD) received funding to enhance its existing CGIC program by improving the speed of evidence processing and the capacity to use NIBIN and NIBIN-related evidence. Researchers examined the effects of the enhancements as well as the relationship between ShotSpotter alerts and shots fired calls for service from 2017-2019. Specifically, the four outcome measures observed were (1) case clearance rates, (2) prosecutorial outcomes, (3) detectives' perceptions, and (4) causal effect on violent crime. The study findings suggested that NIBIN leads may have contributed to advancing the investigative process, but they found no discernible difference between prosecutorial outcomes. The researchers found slightly higher clearance rates when NIBIN information was available relative to cases without NIBIN information. Finally, the study did not find statistically significant reductions in violent crime. The researchers theorized that these results were due to the short observational period in which the full effects of these outcomes may not have been realized (Mei, Owusu, Quinney, Ravishankar, & Sebastian, 2019).

Particularly germane to the current research, Schaible and Six (2017) evaluated Denver's CGIC for Fiscal Year 2015-2016. This evaluation examined several facets of CGIC covering the period of January 1, 2010 to June 30, 2016. There were several notable findings from this research. First from participant surveys across two waves, they found many CGIC partners participated almost monthly, participated in cooperative activities, and formed a robust cross organizational network. They found that NIBIN entries and NIBIN hits increased dramatically after CGIC started. They noted improvements in arrest rates for violent crimes with firearms with a NIBIN hit. Promisingly, they found that neighborhood NIBIN hit rates were associated with higher neighborhood arrest rates for firearm and gang offenses. Further, the number of NIBIN related arrests in a neighborhood were related to lower firearm and gang violent offenses the following year (Schaible & Six, 2017).

An important limitation of the prior evaluations of CGIC is that these studies mostly relied on simple pre-post intervention analysis or correlational evidence between the use of NIBIN information and case outcomes. While this evidence is vital for providing initial results and exploring the mechanisms at work within CGIC, these designs are not suited for determining whether implementing a CGIC program yields measurable decreases in violent gun crime. In ideal circumstances, a randomized controlled experiment would be the "gold standard" for determining whether CGICs reduce violent gun crime; however, the nature of a CGIC collaboration and extensiveness of its operation makes such studies infeasible. An alternative strategy is to use a quasi-experimental design to offer some control over threats to internal validity. While quasi-experimental designs may still be vulnerable to some threats to internal validity, they still offer considerably more protection than non-experimental designs (see Campbell & Stanley, 1963; Cook & Campbell, 1979; Shadish, Cook, & Campbell, 2002).

In order to fill this important gap in the understanding of CGIC, the current study employs a quasi-experimental design, the Interrupted Time Series (ITS) design, to examine whether establishing a CGIC results in decreases in gun-related violent crime. Specifically, we consider whether Denver's CGIC led to observed decreases in homicide with a firearm, robbery with a firearm, aggravated assault with a firearm, and a composite measure – serious violent crime with a firearm. Further, this evaluation examines the impact of the recent expansion of CGIC into RAVEN using the same methods and outcomes.

METHODOLOGY

This process and impact evaluation of the Denver CGIC and RAVEN takes a multi-method approach. Using quantitative and qualitative data, we examine a number of important issues that cover:

- The origins of the CGIC concept, Denver's development of the CGIC model,
- The addition and use of new technologies associated with the CGIC process,
- The expansion to RAVEN,
- The agencies and personnel involved in CGIC/RAVEN,
- How the CGIC/RAVEN program currently operates,
- The successes or difficulties experienced by the CGIC/RAVEN, and
- The impact of CGIC/RAVEN on crime.

An initial process evaluation of CGIC completed in 2017 serves as the baseline for this study (Schaible & Six, 2017). A key aspect of the current study is the development of CGIC since the initial review. For this component of the evaluation, we rely on data from DPD's Computer-Aided Dispatch (CAD) system and crime incidents, ATF's NIBIN Enforcement Support System (NESS), and qualitative information from interviews with key stakeholders and personnel involved in the operation of CGIC and RAVEN, as well as prior YouTube videos and other Internet sources. Our analysis of the data examines CGIC implementation; use of technologies, such as ShotSpotter, NIBIN, and eTrace; ballistic evidence recovered; the CGIC expansion to RAVEN; and trends in crime and calls for service during the course of the CGIC program.

Process Evaluation Research Questions

For the process evaluation, we describe the activities of the Denver CGIC and RAVEN team. We ask a number of research questions:

1. How was CGIC implemented and operationalized?
   - What technologies were introduced into the Denver CGIC?
   - What were the effects of the Denver CGIC implementation and new technology?

2. How did CGIC evolve over time?
   - What was the purpose of the RAVEN expansion?
   - What was the effect of the RAVEN expansion?

3. What were the perceptions of the partners?
   - What were the challenges of CGIC and how did they overcome them?
   - How did the partners view the implementation, changes, and expansion of CGIC?

For the impact evaluation, we ask:

4.
   - What were the impacts of CGIC and RAVEN on violent firearm crimes?

Description of Data

For the process and impact evaluation, JSS relied on data from a variety of sources to capture the timeline, development, and outcomes achieved by the Denver CGIC.

Denver Incidents and Calls for Service

The Denver Police Department provided data on all crime incidents and calls for service spanning January 1, 2010 to June 30, 2020. The DPD recorded 609,671 incidents during this period.[2] The DPD also provided ArcGIS shape files for each of the 78 neighborhoods in the city of Denver. The incident data were used to report monthly crime counts for the entire city.

ATF NESS Data on Firearm Investigative Activity

Denver's ATF coordinator provided JSS staff with 2010-2019 data on firearm investigative activities in the Denver area. The ATF provided JSS staff with a data dictionary to assist in defining the data during analysis. Based on the data dictionary, we conducted a frequency analysis of guns and casings recovered, test fires, NIBIN hits, eTrace queries, and eTrace hits by year.

Interviews

To better assess the internal mechanisms of the CGIC/RAVEN program, we conducted semi-structured interviews with various personnel from ATF, the Denver Police Department, the United States Attorney's Office, the Denver District Attorney's Office, and other participating organizations. To ensure that our interviews encompassed important personnel associated with CGIC/RAVEN, we conducted a snowball sample, where we asked participants to identify additional personnel who would be good candidates for an interview. After initially contacting eight CGIC-involved individuals regarding interviews on September 1, 2020, we reached out to 21 additional recommended individuals for an interview. In total, 28 individuals were contacted and 21 agreed to participate in the interviews (a response rate of 71.4%).

All interviews were conducted via RingCentral (a video conference application) or by phone depending on the preference of the interviewee. Interviews were completed between September 9, 2020 and October 4, 2020 and averaged about 25 minutes in length. Participants were informed about the purpose of the interviews and provided with a statement regarding confidentiality. In all but one interview, one member of the JSS staff interviewed the participant while another JSS staff member recorded notes.

Of the 21 interviews conducted, most involved personnel from local police departments participating in the CGIC program. Personnel from these departments included investigators, crime analysts, Lieutenants, Captains, and Chiefs/Deputy Chiefs. Five attorneys from both local District Attorney offices and the United States Attorney Office participated in the interviews. Lastly, four individuals with various roles in the ATF were interviewed.

TABLE 1. COUNT OF AGENCY TYPES IN CGIC INTERVIEWS

AGENCY TYPE	COUNT	PERCENT
ATF	4	19%
Local Police Department	12	57%
Attorneys (Local and Federal)	5	24%
TOTAL	21	100%

IMPACT EVALUATION METHODOLOGY

Outcomes

We consider four main outcomes in this study: homicides with firearms, robbery with firearms, aggravated assaults with firearms, and serious violent crimes with firearms. The main goal of CGIC is to reduce violent gun crime; therefore, it is reasonable to expect that impacts of CGIC should be observed in the crime statistics compiled by the DPD. A criminal event is considered to involve a firearm if the DPD recorded the presence or use of any handgun, rifle, or other non-homemade firearm. Serious violent crimes with firearms is an aggregate measure of homicides, sexual assaults, robberies, and aggravated assaults involving a firearm. While reliance on official police reports may understate the extent of crime experienced by residents, underreporting of criminal events is much lower for serious crime (see Mosher et al., 2011; O'Brien, 1985).

Research Design

CGIC began operations in January 2013, and RAVEN began operations in January 2019. Because these interventions have fixed start dates, an Interrupted Time Series (ITS) design was used to evaluate the effectiveness of the interventions. The ITS design is a strong quasi-experimental design that allows for control over many of the threats to internal validity that compromise conclusions about interventions (see Campbell & Stanley, 1963; Cook & Campbell, 1979; Shadish et al., 2002). One of the key features to a time series design is a sequence of observations taken before and after the intervention occurs. For the purposes of this evaluation, we reserve the period of January 2010 to December 2016 (84 months) for examining the impact of CGIC and January 2017 to June 2020 (42 months) for examining the impact of RAVEN. Importantly, there are very few post-intervention observations for RAVEN, so any results from this intervention should be interpreted as preliminary.

This part of the evaluation is limited to the City of Denver and the neighborhoods within the city limits. While additional law enforcement agencies in the local area are involved in the CGIC and RAVEN initiatives, these agencies came onboard after the January 2013 start date. It is entirely possible that these agencies have also experienced benefits from participating in CGIC/RAVEN, but due to time and resource limitations, a full impact analysis of crime trends from these other agencies exceeds the scope of this report

Plan of Analysis: Impact Evaluation

Hotspot maps and neighborhood thematic maps provide information about the distribution of gun crime throughout the city. Additionally, local polynomial graphs for the four outcome variables (serious violent crime with a firearm, homicide with a firearm, robbery with a firearm, and aggravated assault with a firearm) are examined to understand the trend in these crimes over time. These graphs also provide an opportunity to check for non-linearities in the crime trends. Additional information on the local polynomial graphs can be found in Appendix 1.

Ordinary Least Squares (OLS) and negative binomial segmented regression analysis with Newey-West models adjusted for standard errors are used to estimate the impact of CGIC over the years 2010 to 2016 and RAVEN over the years 2017 to June 30, 2020 on the four measures of gun crime. Additional information on the segmented regression approach can be found in the technical appendix.

Finally, a series of multilevel models (or mixed effects models) is used to examine the impact of CGIC across the neighborhoods of the city of Denver. The advantage of these models is that CGIC may have a different impact on the incident counts in each neighborhood. These models can be used to determine whether the observed citywide impacts of CGIC are also observed at the neighborhood level. More information on the multilevel models can be found in the technical appendix.

SECTION 2:

IMPLEMENTING CGIC AND RAVEN

INTRODUCTION

This section is primarily focused on how the Denver Crime Gun Intelligence Center (CGIC) and the Regional Anti-Violence Enforcement Network (RAVEN) were implemented. We want to know whether and how the Denver Police Department, ATF, and its law enforcement partners followed the principles they established and the types of activities that were undertaken.

This section provides details about the city of Denver and the police department; describes Denver's violent crime problem; and then lays out the fine points of CGIC. Tables, graphs, and charts illustrate the activities of the CGIC team in terms of the numbers of guns and casings seized, the number and types of ShotSpotter events that occurred during implementation, and the perceptions of those who participated on the team. We then turn to a description of the expansion to the Regional Anti-Violence Enforcement Network (RAVEN), which occurred in 2019.

The Site: Denver, CO

As of 2019, the city of Denver recorded a population of 727,211 residents. According to the U.S. Census Bureau (2019), the demographic breakdown of Denver's population is made up of White (76 percent), Black (9 percent), Asian (4 per cent), American Indian (1 percent), and two or more races (4 percent). Hispanic or Latino make up 30 percent. The reported median household income as of 2019 was $63,793 with a poverty rate of 14 percent.

The Denver Police Department is the largest police agency in the Rocky Mountain region, with about 1,500 officers and about 300 civilians. Police personnel cover an area of 154.9 square miles and the Department has an annual budget of $426 million.

During the years of the CGIC and RAVEN implementation, the Denver Police Department was led by two Chiefs – Robert White (2012-2018) and Paul Pazen (2018-present). Chief Pazen currently oversees the department with assistance from one deputy chief and three division chiefs.

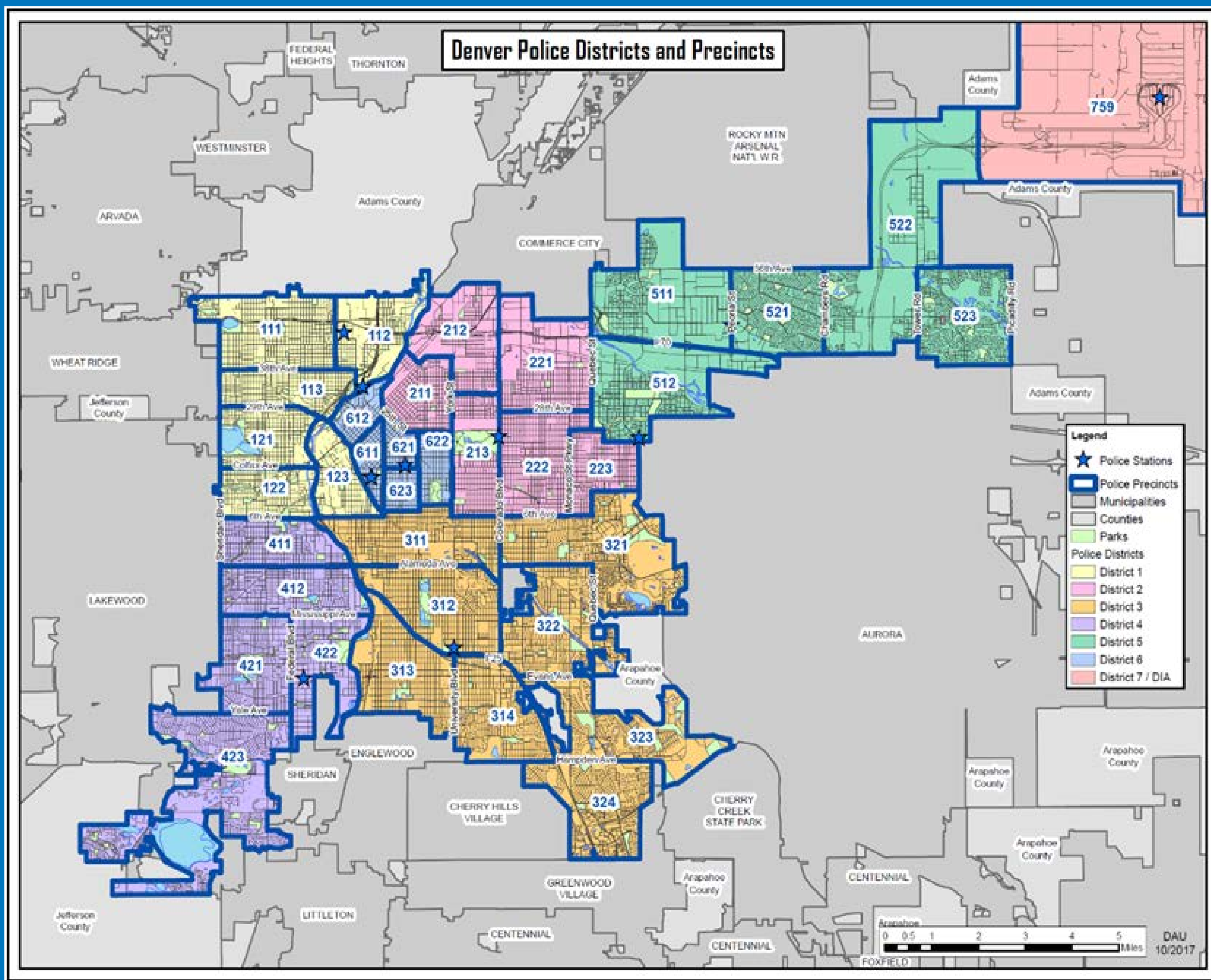


FIGURE 1. DENVER POLICE DISTRICTS AND PRECINCTS
SOURCE: DENVERGOV.ORG

DPD is comprised of six major police stations that are organized by Districts: District 1 Station (NW), District 2 Station (N Central), District 3 Station (SE), District 4 Station (SW), District 5 Station (NE), and District 6 Station (Downtown). Additionally, Denver PD covers District 7, which consists of the Denver International Airport. Figure 1 provides a map of the DPD's Police Districts and Precincts.

DPD has its own fully functioning crime lab with eight separate units that utilize criminal intelligence databases in firearms, DNA, and fingerprinting. Firearms Unit personnel conduct examinations of firearms, ammunition, fired bullets, spent cartridge cases and shot shells, shot and wadding.

Currently, all fired cartridge cases recovered at crime scenes are evaluated by the Firearms Unit for entry into NIBIN. Those items that are entered are correlated (searched) automatically against all entries made in Colorado. Hits identified during correlation review are confirmed through hands-on, microscopic comparisons. Once verified, a notification of the hit is sent to the investigating detectives for each incident that has been linked.

Crime Rates

To contextualize the Denver CGIC implementation, we provide information about the extent of crime experienced prior to and during the intervention period. Table 1 displays the crime rates in Denver for homicide, sexual assault, robbery, and aggravated assault from 2010 to 2012. Counts of homicide, sexual assault, robbery, and aggravated assault were standardized into rates by dividing the counts by the Denver population (727,211) and multiplying by 100,000. Homicide and sexual assault rates remained relatively stable over this period, but robberies and aggravated assaults increased by 36.1 percent and 15 percent respectively from 2010 to 2012.

TABLE 1. CRIME RATES IN DENVER BY YEAR AND CRIME TYPE

YEAR	HOMICIDE	SEXUAL ASSAULT	ROBBERY	AGGRAVATED ASSAULT
2010	5.1	72.5	137.7	307.2
2011	5.9	75.5	166.1	319.7
2012	5.4	76.7	187.3	353.3
AVG.	**5.5**	**74.9**	**163.7**	**326.7**

TABLE 2. GUN INVOLVED CRIME RATES IN DENVER BY YEAR AND CRIME TYPE

YEAR	HOMICIDE	ROBBERY	AGGRAVATED ASSAULT
2010	2.5	43.7	79.9
2011	3.3	60.6	86.9
2012	3	71.2	99.8
AVG.	**2.9**	**58.5**	**88.9**

Table 2 displays the firearm-related homicide, robbery, and aggravated assault rates in Denver for 2010 to 2012. Firearm homicide climbed slightly from 2010 to 2012 while firearm robbery and aggravated assault made larger gains.

Figure 2 displays kernel density hot spot maps for firearm-involved violent crime from the pre-CGIC period (2010-2012). Kernel density hot spot maps provide useful information on the spatial distribution of firearm involved violent crime. Kernel density estimation (KDE) is a method of spatial smoothing that uses a kernel function to generate a spatial density based on the locations of crime incidents (see Levine, 2013). Most violent firearm crime occurred in the Northwest sections of Denver's jurisdiction with additional minor hot spots in the Southeast corner and the far Northeast. Homicides and robberies appear to be concentrated in the northern and western areas of Denver, while aggravated assaults are less concentrated. From the maps, we can see that there are four hot spots for firearm-related aggravated assaults that occur throughout the city of Denver.

Shots Fired

Figure 3 (page 26) displays the kernel density analysis for shots fired and shots heard calls for service (CFS) during the pre-CGIC period. Similar to the violent crime KDE analysis, most of the shots fired CFS occurred in the Northwest portions of the city.

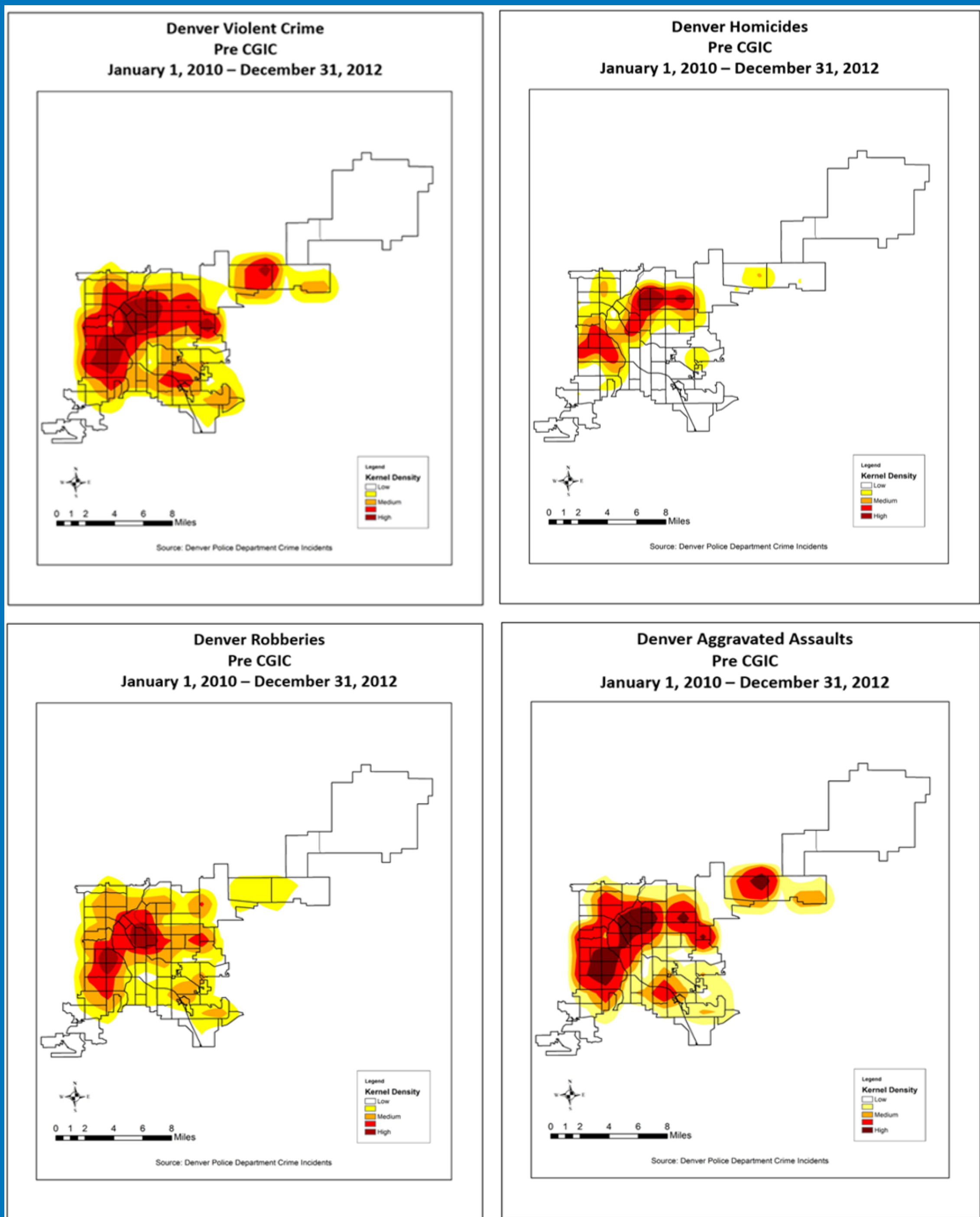


FIGURE 2. KDE HOTSPOT MAP,
GUN-INVOLVED VIOLENT CRIME,
PRE-CGIC, 2010-2012

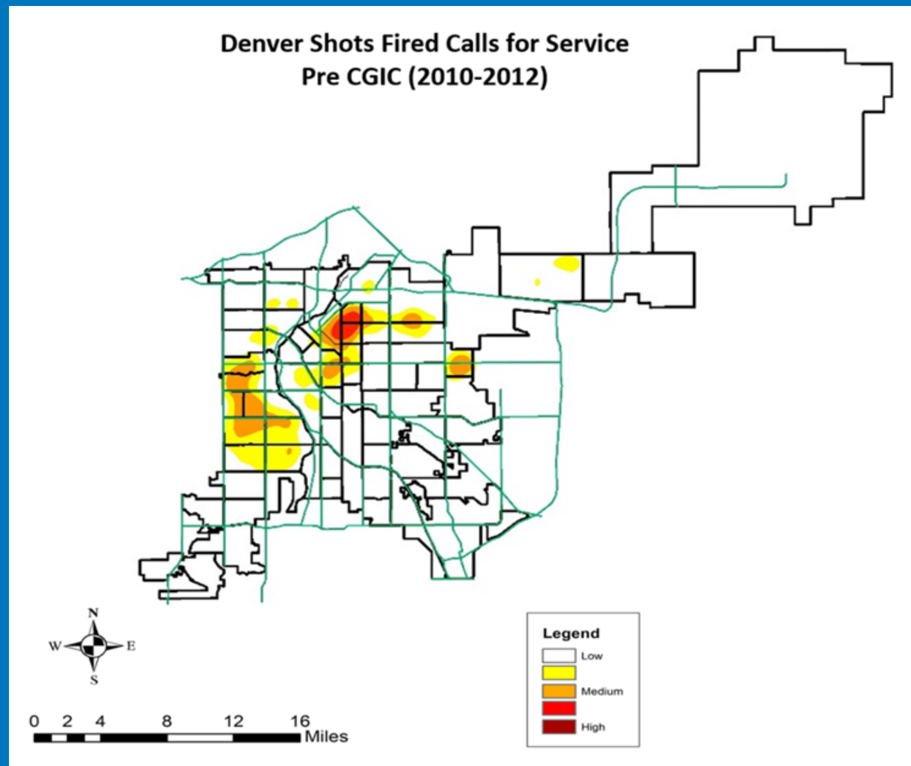


FIGURE 3. SHOTS FIRED CALLS FOR SERVICE, PRE-CGIC (2010-2012)

CGIC IMPLEMENTATION (2013-2016)

ATF Supervisory Agent Russell and Commander Fleecs began implementing their new model on January 1, 2013. The initial program involved a collaborative effort with two ATF personnel, part-time DPD detectives, and administrative support from Denver, Aurora, and Lakewood Police Departments. Up to this point, the Denver crime lab used NIBIN to link shootings together, but did not have the resources or personnel to follow up on these leads. CGIC implementation allowed the Denver PD to assign personnel on a part-time basis specifically to NIBIN investigative follow-up from the DPD's Gang Bureau. With assistance from ATF, the Denver crime lab was able to increase the speed of NIBIN searches and allow Denver investigators to pursue NIBIN leads within a matter of days. According to the PERF report, prior to CGIC the time from the crime to the NIBIN hit would typically last a few weeks (Police Executive Research Forum, 2017).

Support for the Concept

CGIC "made sense … because ATF, through NIBIN and a lot of technology [forensic ballistic evidence], could be used to stop violent gun crime as quickly as possible."

During our interviews, two major reasons emerged that demonstrated the support for the concept of a crime gun center. First, there was a belief that the focus on drugs and long-term investigations had not resulted in a reduction in violent crime. One interviewee mentioned that in 2013 the Metro Gang Task Force was involved in "multi-year investigations" and could not assist with the problems of violence "right now." Second, the idea of using new technology stood out among chiefs and line detectives. One interviewee said that CGIC "made sense … because ATF, through NIBIN and a lot of technology [forensic ballistic evidence], could be used to stop violent gun crime as quickly as possible." In Washington, D.C., support came from ATF Director B. Todd Jones, as the concept fit into his notion of Frontline, the business model for the agency.

Early Struggles

As with many new projects, however, the Denver CGIC experienced a few early struggles regarding inter-department coordination and policy, finding the right personnel, and obtaining buy-in from the various personnel and agencies involved. In terms of policy, one CGIC-involved individual mentioned the transition from the Metro

Gang Task Force investigation tactics to the CGIC model: "… Trying to blend together something new while keeping your own identity, you run into problems, personality issues, personnel problems. For me, at my level, it's trying to find out which system works best." But he realized that "the operations plan of ATF's had more depth [than Metro Gangs] …Even though that was a struggle, at the end of the day it's a benefit to the task force to have something like that in place."

Bringing all involved departments and personnel up to speed on NIBIN and the CGIC process was difficult at the outset but critical for early program success. Getting officers to understand the importance of collecting firearm evidence and streamlining procedures for NIBIN correlations was a key development. According to one CGIC interviewee: "The biggest part is getting departments on board with the NIBIN process and streamlining it between the department and labs. [Now] Aurora has come up with NIBIN operations for gun related crimes and found guns."

CGIC was seen as a cutting-edge method for investigating violent firearm crime in real time.

Finding the right personnel was more of a long-term process for the Denver CGIC. One CGIC interviewee mentioned that some investigators struggled to learn the technology or work at the right pace for CGIC: "Lots of … personnel have moved on to different jobs and have been replaced by individuals that management wanted - people who are like-minded and want to pursue the same goals as us. With that change has come that expertise." The interviewee noted that, "guys came in with expertise that we didn't have and have been super hard working. This has helped a lot. This has helped a lot in the collaboration."

Early Successes

"Arresting shooters helped establish the program," said Supervisory Agent Russell. This meant working closely with Denver's crime lab to obtain NIBIN hits and leads and then working with detectives to do the follow up investigations. During the first few months of the project, ATF staff worked at Denver's crime lab in the morning and then went out to investigate with DPD's detectives in the afternoon. ATF's commitment to the program and their ability to show the value of linking casings to incidents to shooters were strong indicators of how and why the crime gun center could succeed.

In addition, CGIC was seen as a cutting-edge method for investigating violent firearm crime in real time. Early CGIC implementation efforts were aimed at processing firearm evidence quickly through forensics so that investigators could pursue incidents with NIBIN leads within a few days of their occurrence. Interviews with CGIC-involved personnel revealed that the implementation was successful after the group cleared early hurdles. Once policy differences had been settled and the NIBIN process had been streamlined, CGIC-involved personnel believed that they had created an effective program for quickly responding to and investigating firearm crime.

ShotSpotter Implementation

As part of efforts to increase the amount of firearm forensic evidence recovered, the city of Denver and ATF installed the ShotSpotter acoustic firearm detection network. Essentially, ShotSpotter relies on a series of fixed-location sensors designed to detect gunfire. These sensors are deployed within a specific area, typically a high gun crime location. When a gun is fired within this area, information from multiple sensors are then used to triangulate the location of the gunshot. By producing timely intelligence on the location of gunshots, ShotSpotter enables police departments to respond faster in order to apprehend offenders and to receive more precise location information to increase the likelihood of obtaining ballistic forensic evidence.

The four ShotSpotter areas examined in this report are presented in Figure 4. The first site that received the technology was the North Area outlined in blue. This area began operation on January 8, 2015. The West Area outlined in red was the second area that implemented ShotSpotter on April 23, 2016. The Montbello Area, outlined in purple, started operating on September 21, 2016. Finally, the East Colfax area outlined in light green came online on March 30, 2018. [The newest area of Downtown Denver began on July 9, 2020 and because of its recency is not a part of this evaluation.] Analysis of calls for service, shots fired, and incident data all indicate that the Denver CGIC and DPD command staff strategically placed ShotSpotter in high crime areas with high levels of firearm activity. The hot spot kernel density map displaying shots fired calls for service from 2010-2012 supports this decision (see Figure 5). ShotSpotter locations identically overlay high density shots fired areas within Denver's jurisdiction.

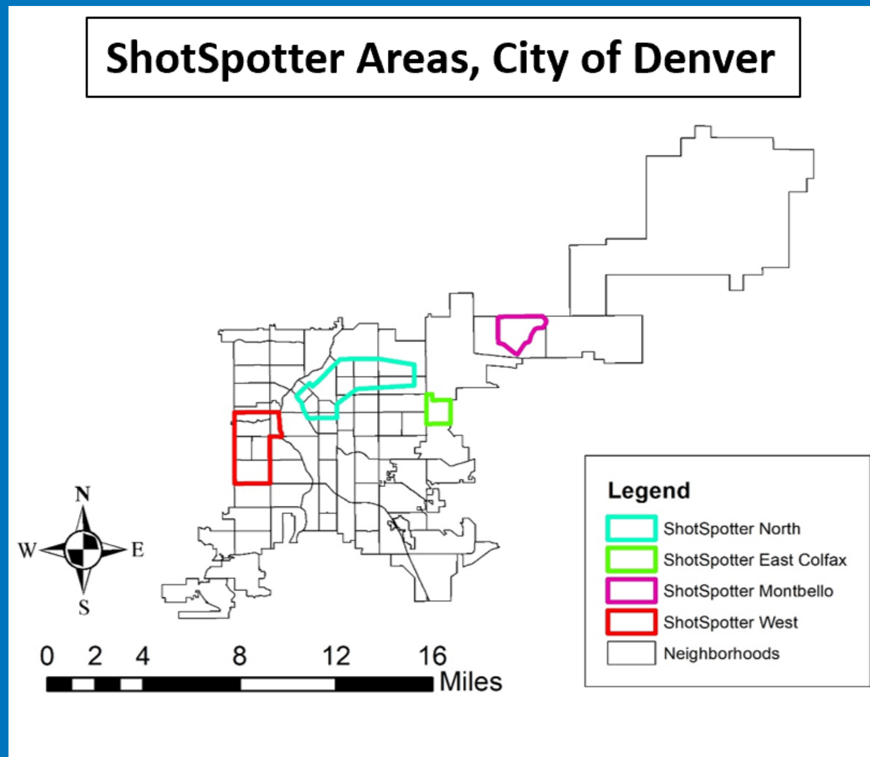


FIGURE 4. SHOTSPOTTER DETECTION AREAS, DENVER, 2015-2018

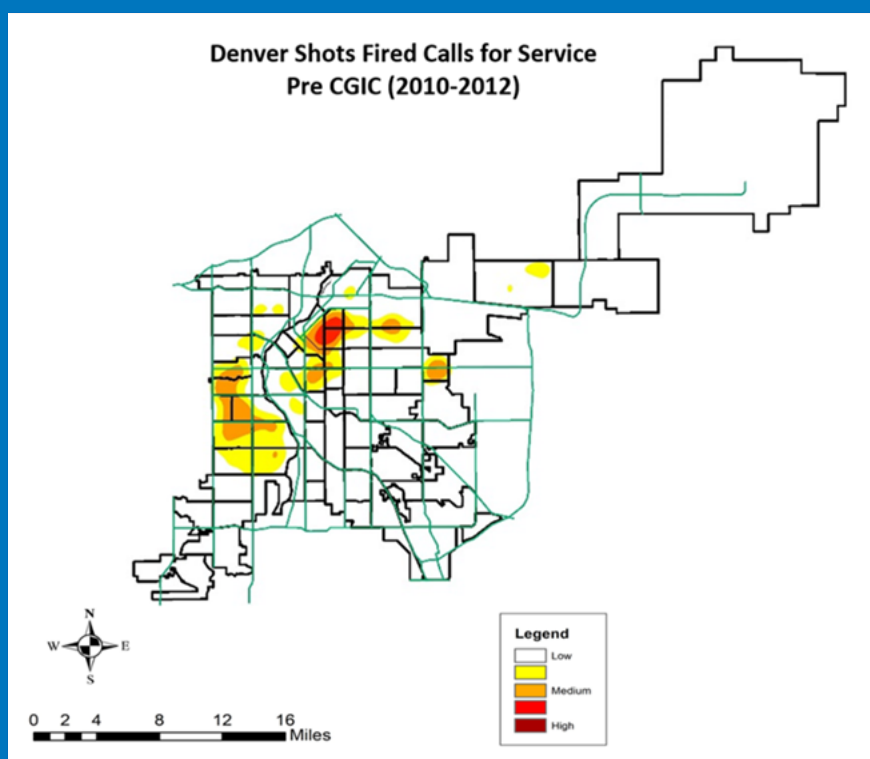


FIGURE 5. SHOTS FIRED CALLS FOR SERVICE, DENVER, PRE-CGIC, 2010-2012

ATF Data on Firearm Investigative Activity, 2013-2016

Data from the ATF's NESS show that firearm investigative activity increased steadily following the implementation of the Denver CGIC in 2013. Guns and casings recovered (Table 3), the number of ballistics tests (Table 4), NIBIN hits (Table 5), the number of eTrace queries (Table 6), and the number of eTrace hits (Table 7) increased substantially in the post-CGIC period (2013-2016) compared to the pre-CGIC period (2010-2012).

TABLE 3. GUNS AND CASINGS RECOVERED BY AGENCY, 2010-2016

YEAR	AURORA PD	DENVER PD	LAKEWOOD PD
2010	89	425	12
2011	92	599	12
2012	153	681	23
2013	282	919	15
2014	270	942	29
2015	446	1,407	46
2016	448	1,853	32
TOTAL	1,780	6,826	169

TABLE 4. BALLISTIC TESTS BY AGENCY, 2010-2016

YEAR	AURORA PD	DENVER PD	LAKEWOOD PD
2010	54	286	8
2011	61	356	5
2012	124	412	9
2013	207	642	10
2014	156	552	12
2015	308	758	9
2016	245	958	18
TOTAL	1,155	3,964	71

TABLE 5. NIBIN HITS BY AGENCY, 2010-2016

YEAR	AURORA PD	DENVER PD	LAKEWOOD PD
2010	4	15	0
2011	1	35	0
2012	8	37	3
2013	9	56	0
2014	14	57	1
2015	23	115	2
2016	29	181	6
TOTAL	88	496	12

TABLE 6. ETRACE QUERIES BY AGENCY, 2010-2016

YEAR	AURORA PD	DENVER PD	LAKEWOOD PD
2010	1	2	0
2011	0	1	0
2012	1	4	0
2013	2	17	0
2014	5	28	0
2015	17	49	2
2016	20	104	2
TOTAL	46	205	4

TABLE 7. ETRACE HITS BY AGENCY, 2010-2016

YEAR	AURORA PD	DENVER PD	LAKEWOOD PD
2010	0	2	0
2011	0	1	0
2012	1	4	0
2013	2	17	0
2014	5	28	0
2015	17	48	2
2016	20	103	2
TOTAL	45	203	4

TABLE 8. YEARLY AVERAGES FOR FIREARM INVESTIGATIVE ACTIVITY, PRE-CGIC VS. POST-CGIC

FIREARM-RELATED CRIME INVESTIGATIVE ACTIVITY	PRE-CGIC	POST-CGIC
Ballistic Evidence Recovered	695	1,672 (+140.6%)
Test Fires	438	969 (+121.2%)
NIBIN Hits	34	123 (+262.5%)
eTrace Queries	3	62 (+1,950.0%)
eTrace Hits	3	61 (+1,933.3%)

Table 8 displays the yearly averages for each firearm investigative activity metric for the pre-CGIC period (3 years) and the post-CGIC period (4 years). The Denver CGIC more than doubled the amount of ballistic evidence recovered and test fires, tripled the number of NIBIN hits, and essentially added eTrace practices to their investigative procedures after CGIC implementation in 2013.

Results of ShotSpotter Implementation

Table 9 presents the number of alerts generated in each ShotSpotter area by year along with the percentage of the total number of alerts. The final year provides the most reasonable estimate of the distribution of the alerts across location, as all ShotSpotter areas are active throughout the entire year. The West Area is the largest area, approximately 6.5 square miles, and receives the most alerts, 43 percent of all alerts. The North Area is the second largest at approximately 3 square miles and receives 32 percent of all alerts. The Montbello Area covers about 2.0 square miles and receives 20 percent of all alerts. Finally, the East Colfax Area covers 1.1 square miles and is responsible for 5 percent of all alerts.

As previously discussed, the ShotSpotter system screens events to identify likely gunfire events. The type of event detected is then passed along to the 911 call center as part of the ShotSpotter alert. Table 10 provides the type of events identified in the ShotSpotter alerts. The percentages of both single gunshot events and multiple gunshot events fluctuated over the years. Interestingly, the percentage of firecracker or gunshot events appeared to increase as additional sites came online. (Note: Single gunshot and multiple gunshot events are given a higher priority in terms of responding to the call. Firecracker or gunshot events are given lower priority.)

After the alerts arrive at the 911 call center, these alerts are then converted to calls for service with a designation of "ShotSpotter" as the source of the call. Importantly, this conversion process is not 1:1 as some alerts for repeat events are combined into a single call for service, while other alerts do not generate a call for service at all. Across the 5-year sample period, ShotSpotter recorded 6,858 calls for service across all four locations.

Table 11 displays the distribution of ShotSpotter-initiated calls for service from 2015-2019. As expected, the larger and earlier implemented areas recorded the most ShotSpotter calls for service. The West location recorded 43 percent of all ShotSpotter calls for service, followed by North (35 percent), Montbello (17 percent), and East Colfax (5 percent).

	2015		2016		2017		2018		2019		TOTAL	
Area	N	%	N	%	N	%	N	%	N	%	N	%
North	492	100%	497	40%	506	29%	505	24%	570	24%	2,570	32%
West	N/A	N/A	444	36%	846	49%	991	47%	1,120	47%	3,401	43%
Montebello	N/A	N/A	300	24%	394	23%	405	19%	474	20%	1,573	20%
East Colfax	N/A	N/A	N/A	N/A	N/A	N/A	200	10%	204	9%	404	5%
TOTAL	492		1,241		1,746		2,101		2,368		7,948	

TABLE 9. NUMBER OF SHOTSPOTTER ALERTS BY AREA AND YEAR. CITY OF DENVER, 2015-2017

	2015		2016		2017		2018		2019		TOTAL	
Type of Alert	N	%	N	%	N	%	N	%	N	%	N	%
Single Gunshot	172	35%	514	41%	460	26%	728	35%	838	35%	2,712	34%
Firecracker or Gunshot	39	8%	91	7%	272	16%	300	14%	391	17%	1,093	14%
Multiple Gunshots	281	57%	636	51%	997	57%	1,073	51%	1,124	48%	4,111	52%
Other	0	0%	0	0%	17	1%	0	0%	15	1%	32	0%
TOTAL	492		1,241		1,746		2,101		2,368		7,948	

TABLE 10. TYPE OF SHOTSPOTTER ALERT BY YEAR. CITY OF DENVER, 2015-2017

	2015		2016		2017		2018		2019		TOTAL	
Area	N	%	N	%	N	%	N	%	N	%	N	%
North	467	100%	497	51%	489	30%	452	25%	510	26%	2,415	35%
West	N/A	N/A	414	42%	766	47%	884	48%	873	45%	2,937	43%
Montebello	N/A	N/A	73	7%	374	23%	347	19%	402	21%	1,196	17%
East Colfax	N/A	N/A	N/A	N/A	N/A	N/A	162	9%	148	8%	310	5%
TOTAL	467		984		1,629		1,845		1,933		6,858	

TABLE 11. NUMBER OF SHOTSPOTTER CALLS FOR SERVICE BY AREA AND YEAR. CITY OF DENVER, 2015-2017

Summary of CGIC Implementation

ATF data on firearm investigative activity, Denver data on ShotSpotter, and interviews with CGIC-involved personnel indicate that the initial CGIC implementation in Denver was successful. Indicators of firearm investigative activity increased substantially following CGIC implementation in 2013. This met Denver's goal of processing more firearm-related evidence via NIBIN post-implementation. Denver relied on shots fired calls for service data to implement shot spotter in high volume firearm crime areas. This effort appeared successful as well given the increases in firearm evidence acquisition due to ShotSpotter-initiated calls notifying the CGIC team of firearm-related activity. Lastly, interviews with CGIC-involved personnel revealed that despite early hurdles, the CGIC implementation was successful in allowing investigators to pursue NIBIN leads in a timely manner and provide an avenue for firearm crime suppression efforts.

THE EXPANSION TO RAVEN

The Denver CGIC model had become the standard for the rest of the country in 2016. BJA and ATF were touting Denver as the model to follow, particularly the workflow process that emanated from the ATF Governing Board's Best Practices. Two years later, in 2018, CGIC personnel believed they could benefit the local law enforcement community by expanding their service area to the entire Denver metropolitan region. Command staff from multiple agencies convened to develop a plan to combine existing task forces in order to better leverage resources and personnel. Because of the rise in violent crime in the area and the need for actionable intelligence via NIBIN leads, the Regional Anti-Violence Enforcement Network (RAVEN) was created and then implemented in 2019.

The expansion to RAVEN "allowed for more collaboration and made everything more effective."

The evolution of RAVEN consisted of combining the ATF CGIC and the Metro Gang Task Force (FBI and Colorado agencies) under one umbrella for combating violent crime. The RAVEN team was able to leverage local, state, and federal resources by partnering with a number of local law enforcement agencies in the Denver Metro area. One interviewee said that the expansion to RAVEN "allowed for more collaboration and made everything more effective." With a reestablished mission, goals, and a new sense of identity, the RAVEN team was able to increase investigative activity in a number of ways. As it relates to the new goals set forth by RAVEN, one interviewee stated:

"It's simple, meaningful, and inspires investigators to get behind it and believe in the mission. I think we're doing that now. I see potential to get even better."

The expansion to RAVEN generated some procedural changes, but none of the interviewees perceived these changes as burdensome. Essentially, the transition to RAVEN required each participating agency (12 departments) to assign an investigator to the RAVEN task force.

Benefits

We asked participants to weigh the pluses and minuses of the RAVEN program in terms of how it benefits their department compared to any additional workload or costs associated with CGIC. Overwhelmingly, all of the interviewees identified CGIC/RAVEN as exclusively beneficial or stated that benefits outweighed the burdens.

Interviewees discussed challenges that stem from combining two groups, much like the early formation of CGIC in 2013. Adding new agencies meant incorporating them into the team, but because of the strength of the original collaboration, the transition was not difficult. Overall, RAVEN meant an increase in expertise and sharing of knowledge about gun-crimes and this was cited as a big benefit. One supervisor indicated that, "switching to RAVEN, doubled if not tripled our group in size… It creates a lot more work on supervisors to try to keep everything together. So many people doing so many things and everybody has two offices so it's a bit more complicated to make sure we're working together and not duplicating work… The good part is so many people are working there with expertise in different areas. Now we can go to anybody with questions."

We tabulated the benefits of RAVEN from our interviews. Table 12 displays the frequency of those benefits. Of the 171 total comments from all of the interviews, most interviewees referenced higher quality investigations, better and more available resources, and better and more-well trained personnel compared to standard operations.

BENEFITS OF CGIC	FREQUENCY	PERCENT
More Effective Investigations	38	22.2%
Increased/Better Resources	36	21.1%
Better/More Well-Trained Personnel	33	19.3%
Improved Inter-Department Communication	15	8.8%
Improved Speed/Efficiency with Cases	14	8.2%
Quick Response to Violent Crime	11	6.4%
Better Technology	11	6.4%
Other Miscellaneous Items	11	6.4%
Training Programs	2	1.2%
TOTAL COMMENTS	171	100.0%

TABLE 12. BENEFITS OF CGIC ACCORDING TO INTERVIEWS

Satisfaction

Interviewees were asked to rate their satisfaction with their roles and responsibilities within the program in addition to their satisfaction with the program as a whole. While some team members provided a detailed description of their thoughts on the program, others supplemented this discussion with a numeric ranking. Of the 15 interviewees that provided a numeric score, satisfaction ranged from 7 to 10, with an average score of 9. Table 13 provides a frequency distribution of the satisfaction scores. A score of 10 was the most frequently offered satisfaction score (n=6). For some interviewees, the reason for not giving a score of 10 was their reluctance "to give anything a perfect score."

SCORE	FREQUENCY
10	6
9.5	1
9	2
8.5	1
8	4
7.5	0
7	1

TABLE 13. INTERVIEWEE SATISFACTION SCORES WITH CGIC PROGRAM (N=15)

Challenges

While interviews with members of the Denver RAVEN team highlighted several benefits of the program, they also identified a few key areas that could be improved. Table 14 displays the frequency of topics listed as "areas for improvement" during the CGIC interviews.

TABLE 14. AREAS FOR IMPROVEMENT ACCORDING THE CGIC INTERVIEWS

AREAS FOR IMPROVEMENT	FREQUENCY	PERCENT
Need More/Better Communication	36	35.0%
Additional Funding	15	14.6%
Other Miscellaneous Items	14	13.6%
Better Case Tracking and Automation	8	7.8%
Need for Specialized Personnel	6	5.8%
Required Training	6	5.8%
Need for Additional Personnel	5	4.9%
Increased Caseloads	4	3.9%
Politics of Agencies	4	3.9%
Personnel Turnover	3	2.9%
COVID-19/Protest-related Issues	2	1.9%
TOTAL COMMENTS	103	100.0%

"The only thing I would say is just give us more stats that I can tout ... just like a monthly count… how many guns [were seized], how many search warrants were done for the whole task force, so I can show that it's successful."

Interviewees commonly stated that communication efforts were positive overall but that they could definitely identify room for improvement. Most communication issues were related directly to the distribution of data and information, discussions regarding current assignments, and general communication about success stories. One interviewee commented, "The only thing I would say is just give us more stats that I can tout ... just like a monthly count… how many guns [were seized], how many search warrants were done for the whole task force, so I can show that it's successful."

Some interviewees cited inter-department communication issues as a current area for improvement whereas other interviewees felt that there needs to be more communication between jurisdictions on "who-is-working-on-what". Interviewees felt that it would be helpful to have information on case resolution, but this information is not currently collected. Likewise, the largest gap in communication appears to be between the RAVEN team and prosecutors at the local level. On the prosecution side, it was noted that "stuff has slipped through cracks or been forgotten about because we don't have the same intimate relationship with RAVEN that we do with DPD [the Denver Police Department].” This sentiment was expressed on the law enforcement side as well: “It would help if we did get the same DA all the time, but they won’t allow that.”

Additional funding, resources, and personnel were discussed on a number of occasions during interviews. While members of the RAVEN team acknowledged that they do have technology and resources that assist in meeting the goals of the program, several individuals cited a need for acquiring more funding.

ATF Data on Firearm Investigative Activity, 2017-2019

While challenges exist in terms of communication and relationships, the work of the RAVEN team continues to improve and shows the value of the collaboration. Table 15 displays the number of guns and casings recovered by Aurora, Denver, and Lakewood Police Departments from 2017-2019. The number of ballistic evidence items recovered by CGIC operations steadily increased from 2017-2019, with Lakewood recording the greatest overall increase from 2017-2019 (262 percent).

Table 16 displays the number of test fires conducted by Aurora PD, Denver PD, and Lakewood PD from 2017-2019. Test fires conducted by the Denver CGIC steadily increased from 2017-2019, with Lakewood recording the greatest overall increase from 2017-2019 (336 percent)

TABLE 15. GUNS AND CASINGS RECOVERED BY AGENCY, 2017-2019

YEAR	AURORA PD	DENVER PD	LAKEWOOD PD
2017	402	2,077	58
2018	740	2,453	177
2019	768	2,522	210
TOTAL	1,910	7,052	445

TABLE 16. BALLISTIC TESTS BY AGENCY, 2017-2019

YEAR	AURORA PD	DENVER PD	LAKEWOOD PD
2017	133	1,079	36
2018	362	1,225	112
2019	355	1,297	157
TOTAL	850	3,601	305

TABLE 17. NIBIN HITS BY AGENCY, 2017-2019

YEAR	AURORA PD	DENVER PD	LAKEWOOD PD
2017	45	220	2
2018	55	302	10
2019	33	365	11
TOTAL	133	887	23

TABLE 18. ETRACE QUERIES BY AGENCY, 2017-2019

YEAR	AURORA PD	DENVER PD	LAKEWOOD PD
2017	21	100	1
2018	24	138	3
2019	27	117	6
TOTAL	72	355	10

TABLE 19. ETRACE HITS BY AGENCY, 2017-2019

YEAR	AURORA PD	DENVER PD	LAKEWOOD PD
2017	17	96	1
2018	17	123	3
2019	3	96	3
TOTAL	37	315	7

Table 17 displays the number of NIBIN hits acquired by Aurora PD, Denver PD, and Lakewood PD from 2017-2019. Similar to ballistic evidence collection and test fires, NIBIN hits steadily increased from 2017-2019 for Denver and Lakewood, while NIBIN hits in Aurora steadily declined.

Table 18 displays the number of eTrace queries conducted by Aurora PD, Denver PD, and Lakewood PD from 2017-2019. While the number of eTrace queries steadily increased from 2017-2018, there was a slight drop off in 2019 after the RAVEN expansion.

Table 19 displays the number of eTrace hits obtained by Aurora PD, Denver PD, and Lakewood PD from 2017-2019. The number of eTrace hits steadily increased from 2017-2018 but dropped off by 28.7 percent (n=41) from 2018 to 2019. Comparatively, the number of eTrace queries dropped by only 9.1 percent from 2018 to 2019, so this decrease in eTrace hits is larger than expected if the hit rate were stable between 2018 and 2019.

Finally, Table 20 displays the yearly averages for each firearm investigative activity metric for the post-CGIC period (4 years) and the RAVEN period (3 years). RAVEN more than doubled the amount of ballistic evidence recovered, more than tripled NIBIN hits, and more than doubled eTrace queries relative to the CGIC period. Test fires increased by just over 86 percent, and eTrace hits increased by 67 percent. Despite CGIC activity increasing drastically from the pre-CGIC time period, RAVEN was able to achieve a comparable increase in firearm-related investigative activity.

TABLE 20. YEARLY AVERAGES FOR FIREARM INVESTIGATIVE ACTIVITY, POST-CGIC VS. RAVEN

FIREARM-RELATED CRIME INVESTIGATIVE ACTIVITY	POST-CGIC	RAVEN
Ballistic Evidence Recovered	1,672	3,500 (+109.3%)
Test Fires	969	1,809 (+86.7%)
NIBIN Hits	123	409 (+231.8%)
eTrace Queries	62	150 (+143.9%)
eTrace Hits	61	102 (+67.2%)

Post-Implementation Crime Rates

The main focus of the Denver CGIC was firearm crime suppression in the Denver metro area. Using data from the Denver CAD system, we examined firearm-related violent crime rates from 2010-2019. Using Denver's 2019 population estimate (727,211) we calculated Denver's crime rates by dividing the counts by the population and multiplying by 100,000. Figures 6 through 8 below display the results of our analysis. Firearm-related homicides and aggravated assaults steadily increased from 2010 to 2019. Firearm-related robberies increased and decreased several times between 2010 and 2016, increased again in 2017, and decreased substantially in 2019 (see Figure 7 on page 43).

While firearm-related crime rates increased during the post-implementation period, it is likely that CGIC stifled an even higher increase that would have occurred if the program had not been implemented in 2013. The Denver CGIC processed increasing amounts of firearm-related evidence and created a task force specifically focused on investigating firearm-related crime. The Denver CGIC's leverage of cutting-edge technology and multi-agency collaboration is a highly effective model for identifying firearm-related crime issues, so the program's involvement is likely a benefit to the Denver metro area during a period of increased firearm violence.

"…how do we say we are impacting violent crime when we have an increasing violent crime rate? We can say it's not increasing at as high of a rate because of our impact.".

RAVEN personnel were aware of this rise in crime as well and how they saw it within the impact of CGIC: "…how do we say we are impacting violent crime when we have an increasing violent crime rate? We can say it's not increasing at as high of a rate because of our impact.". Some CGIC-involved personnel believed that the increase in violent firearm crime indicated a vital need for CGIC/RAVEN, not a failure on the part of the program: "RAVEN is vital. The most important or salient example right now: Denver is on track for an unprecedented number of homicides this year [2020] and most are firearm related. Without RAVEN and without CGIC, I don't even know what my office would be doing."

FIGURE 6. DENVER FIREARM HOMICIDE RATE, 2010-2019

FIGURE 7. DENVER FIREARM ROBBERY RATE, 2010-2019

FIGURE 8. DENVER FIREARM AGGRAVATED ASSAULT RATE, 2010-2019

Summary of RAVEN Expansion

The data provided from NESS and interviews with RAVEN personnel revealed that CGIC's regional expansion was successful. Results from the CGIC evaluation demonstrated a dramatic rise in firearm-related investigative activity during the initial stages of CGIC implementation; the RAVEN expansion demonstrated a continued increase in firearm-related investigative activity from 2017 through 2019. Insights from our interviews indicated that RAVEN team members were working collaboratively and in unison to meet the initial goals of the CGIC and the goals of the RAVEN expansion. "I think that was the only thing that was an issue – the collaboration piece. It was a gradual improvement as people moved out and were replaced by likeminded individuals. Not a dramatic difference. Just a slow process of bringing newer guys in." The added expertise, resources, and technology stemming from the RAVEN expansion supported these goals. "The bigger things I've seen from CGIC to RAVEN is that we have access to a lot more money with RAVEN than we had with CGIC. And I know they go hand in hand – before we became RAVEN, we didn't have the funds we have now. With these funds, we've been able to do so much. New applications for finding phone data or new apps for searching through Facebook or social media data, or there's a ton of different things we have that have been super helpful in having funding - money to pay overtime for the TFOs. The TFOs and local law enforcement investigators know more than anybody else. Having the money to keep these TFOs and have them help us and us help them through the investigations has been super helpful."

Despite early challenges regarding collaboration, personnel, and developing a mission, RAVEN was clearly able to overcome any barriers and successfully expand to a comprehensive project.

SECTION 3:

THE IMPACT OF CGIC AND RAVEN

INTRODUCTION

This section presents the results from the impact evaluation of CGIC/RAVEN. We focus on the observed effects on crime in the City of Denver. Specifically, we examine whether the start dates of CGIC and RAVEN were associated with changes in the level and trend of gun crime: serious violent crime with a firearm, homicide with a firearm, robbery with a firearm, and aggravated assault with a firearm. First, we provide a brief explanation regarding our methods, including the statistical techniques used in the analysis (segmented regression and multilevel models). The results section follows which discusses the results of the descriptive analysis, segmented regression analysis, and multilevel models. In the final section, we provide a brief summary of the results, a discussion of the limitations of the study, and a series of recommendations for future research and policy.

Methods and Statistical Terminology

For the analyses, we used a variety of statistical techniques to determine the impact of CGIC and RAVEN on crime in Denver (both city-wide and within neighborhoods). First, mapping tools are used to visually show the differences between the pre-CGIC period and post-CGIC period. We use Kernel Density estimates, a function in ArcGIS (a mapping platform) that calculates the density of occurrences of crime in a neighborhood. Basically, these estimates allow us to identify hot spots in Denver prior to and after the implementation of CGIC.

“Local Polynomial Trend Graphs” are used to show the trends and patterns in specific crimes over a ten-year time frame. For example, these graphs are used to show the monthly trends in firearm-related robberies from 2010 to 2019. This technique extracts trends by “smoothing” the statistical “noise” in the data series.

To determine the actual impacts of CGIC and RAVEN we use “segmented regression analyses” (part of the Interrupted Time Series analyses). Specific models called “Ordinary Least Squares (OLS) Newey-West models” are used to determine whether changes occurred over time because of the activities of CGIC. In the narrative, we indicate whether the CGIC intervention is statistically significant or not. If so, it will be highlighted in bold. To avoid statistical bias and inappropriate standard errors we use another technique – the “negative binomial Newey-West model” for violent crime with a firearm. This procedure is a better match to the data than the OLS Newey-West Model and also confirms statistical significance or not.

It can be difficult to understand the impact of the program from the results of the regression models, particularly the negative binomial models. For this reason, we produce “observed vs. counterfactual” plots to understand the impact of CGIC. From the results of our model, we can plot “predicted values” that summarize the data we observe. We also use the model to estimate the “counterfactual” -- what we would see in the data had CGIC not been created. We get this by extrapolating the crime trends that occurred prior to the start of CGIC. The difference between the observed and counterfactual plots shows us how CGIC affected crime over time.

Additionally, we analyzed data at the neighborhood level to see whether effects took place in the 78 neighborhoods identified by DPD. Thematic maps are used to show the monthly average of violent crime with a firearm in each of the 78 neighborhoods over ten years. We then use multilevel models to determine how the program affected crime in each neighborhood. We first get results that tell us about the overall impact of CGIC across all 78 neighborhoods. We then use the model to generate “Empirical Bayes” (EB) estimates of the change in crime for each of the 78 neighborhoods. These EB estimates are mapped to show how different neighborhoods respond to CGIC.

Results: Violent Firearm Crime Hot Spots

We use hot spot maps to provide useful visualizations of firearm-involved violent crime in Denver. The mapping technique, referred to as Kernel Density estimation, is a method of spatial smoothing that uses a kernel function to generate a spatial density based on the locations of crime incidents (see Levine, 2013). Hotspot maps are compared for the pre-CGIC (2010 – 2012) and post-CGIC (2013 – 2019) periods to determine whether the spatial distribution of crime changed after the implementation of CGIC.

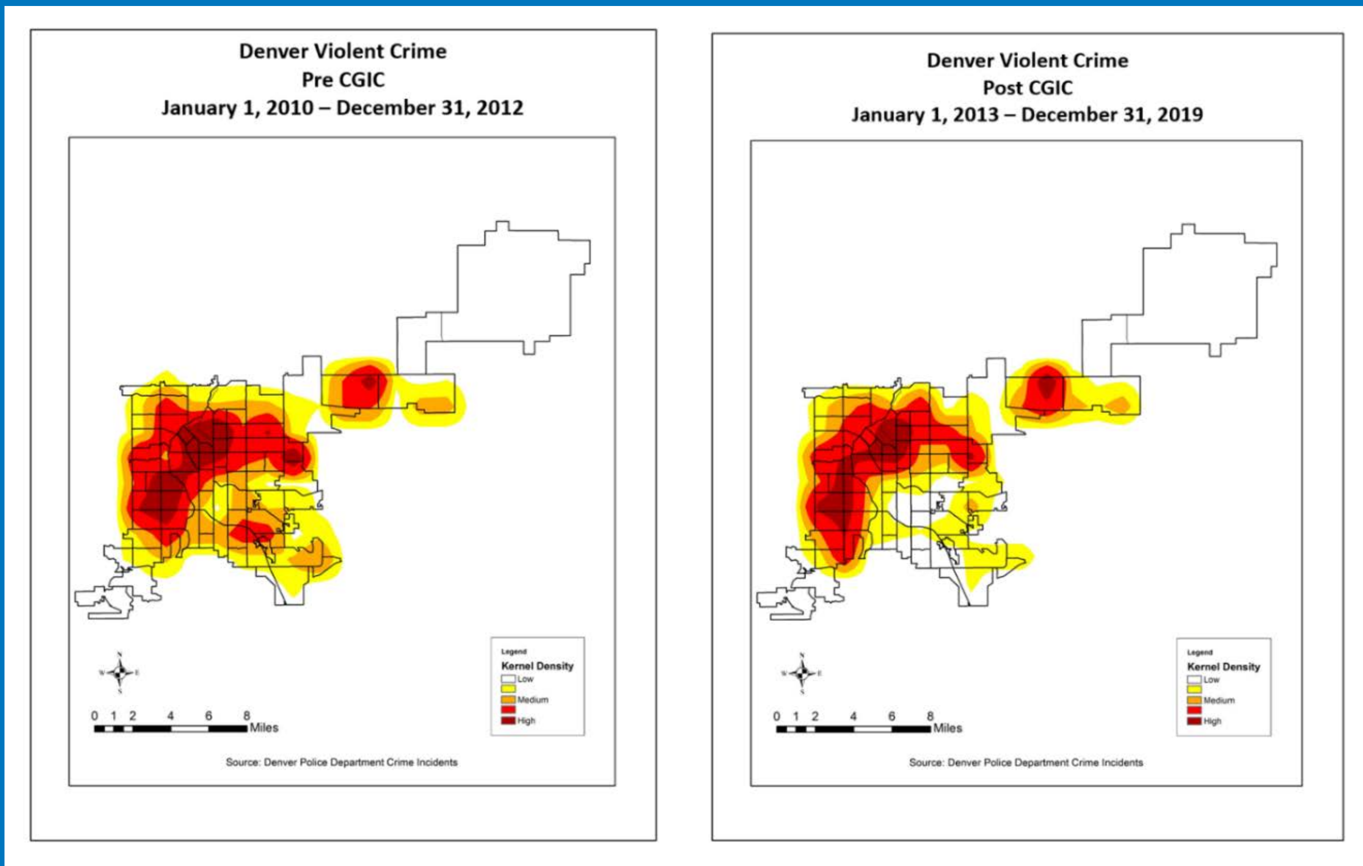


FIGURE 1. PRE- AND POST – CGIC KERNEL DENSITY MAP FOR VIOLENT CRIME WITH A FIREARM, CITY OF DENVER, 2010 – 2019

Figure 1 displays violent firearm-related crime for the pre- and post-CGIC periods. In the pre-CGIC map, the concentration of violent crime with a firearm appears strongest in the western and northern areas of the city. The concentration of crime is smaller in the southeastern portion of the city, but there are some smaller elevated crime areas in the northwestern section of the city (towards the airport) and east of the northern hotspot. After CGIC began, the density of violent crime with a firearm appears to have decreased in the lower crime areas in the southeastern and eastern portions of the city. Crime appears to have increased in the hotspot near the airport. The northern and western hotspots appear similar to the concentrations observed pre-CGIC.

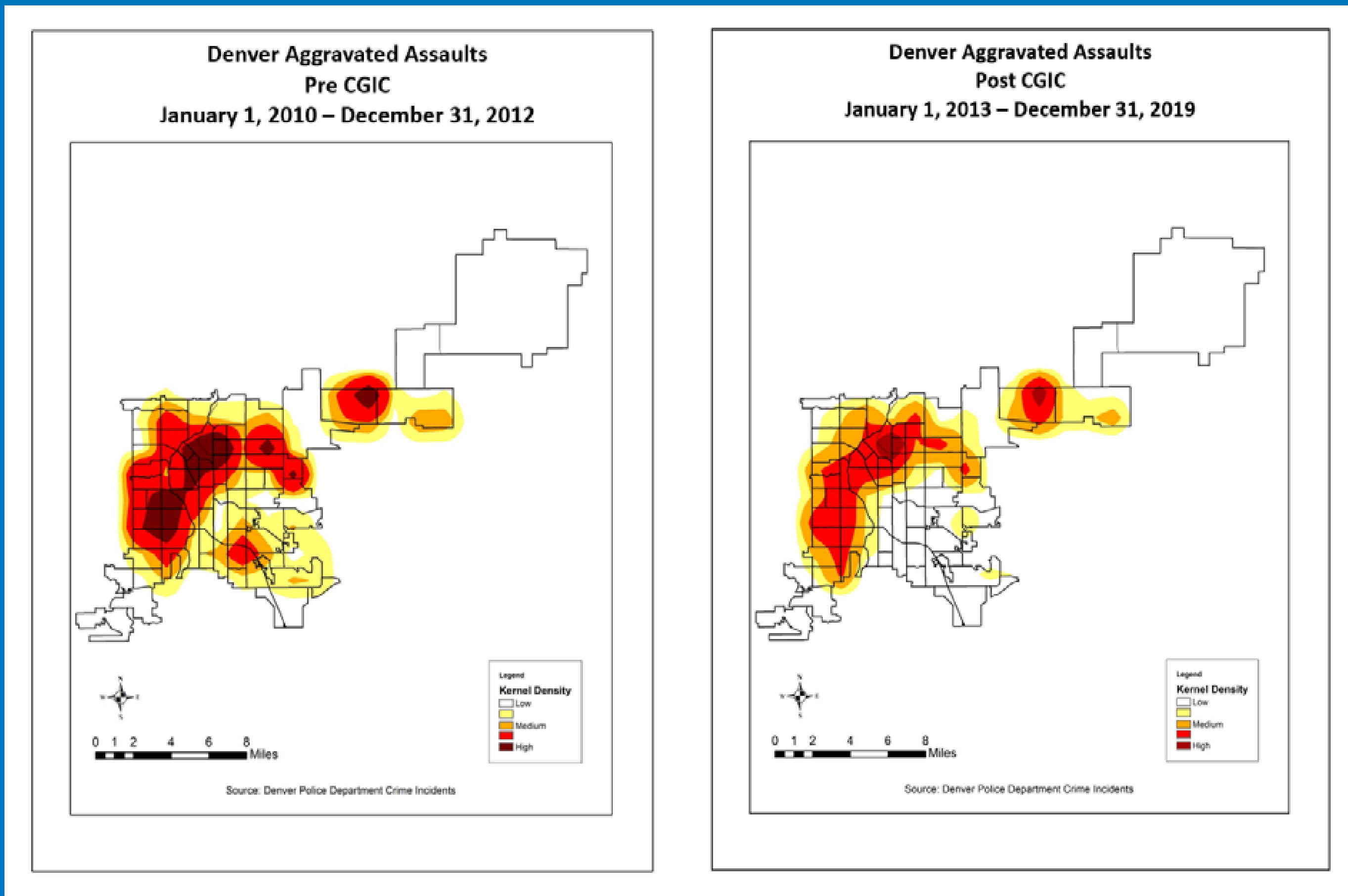


FIGURE 2. PRE- AND POST – CGIC KERNEL DENSITY MAP FOR AGGRAVATED ASSAULTS WITH A FIREARM, CITY OF DENVER, 2010 – 2019

The density of aggravated assaults committed with a firearm is displayed in Figure 2. In the pre-CGIC map, the density appears similar to the density of the composite measure of violent crime. The map for firearm-related aggravated assaults shows the same hotspots in the north, west, and northeast areas of the city. The main difference appears to be that aggravated assaults with a firearm are much more concentrated within these hotspots. In the post-CGIC map, all of the same hotspots are visible, but it appears that the relative concentration of crime in these hotspots is lower.

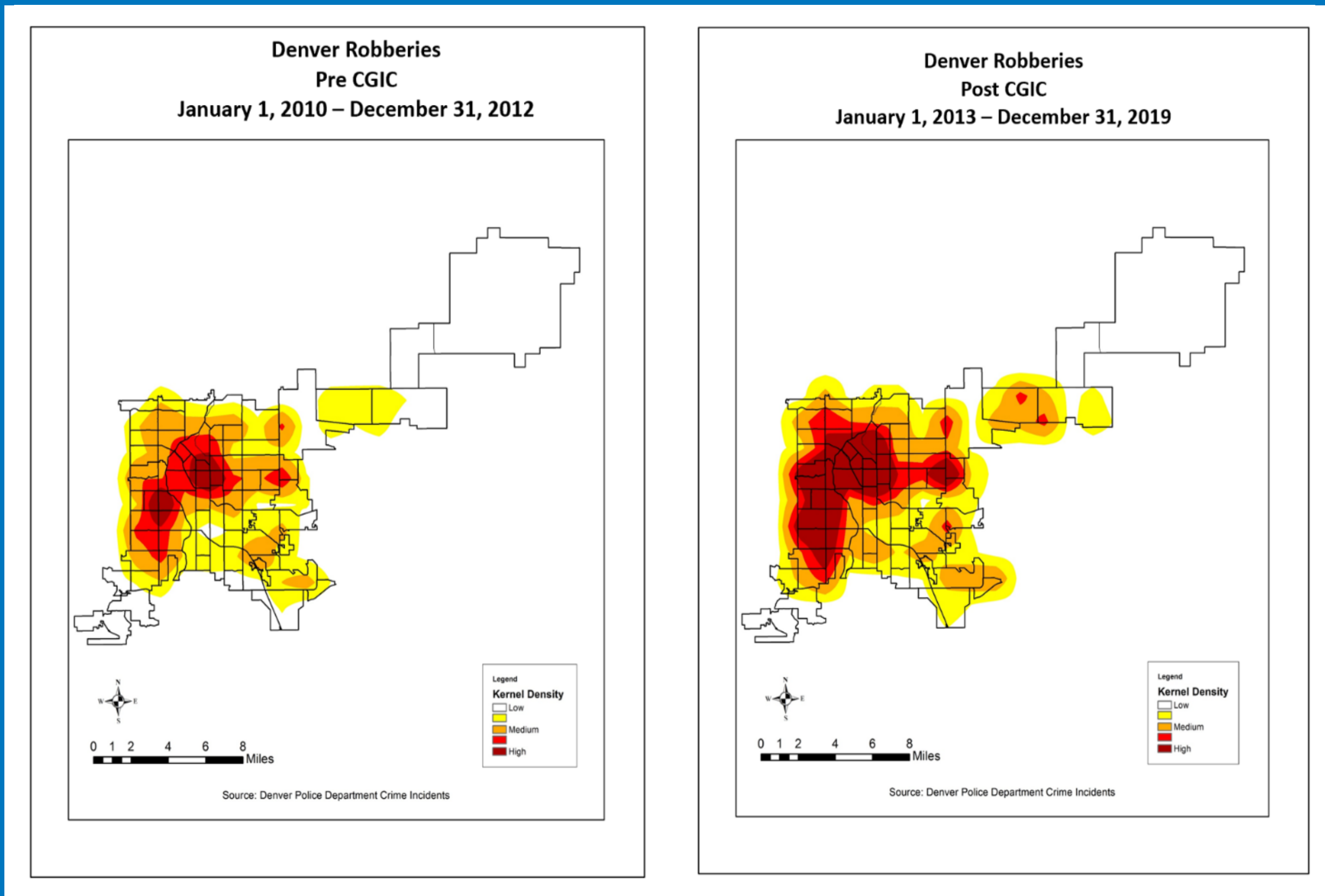


FIGURE 3. PRE- AND POST – CGIC KERNEL DENSITY MAP FOR ROBBERIES WITH A FIREARM, CITY OF DENVER, 2010 – 2019

Figure 3 displays the pre- and post-CGIC hotspot maps for robberies with a firearm. In the first panel, there appears to be only two main hotspots during the pre-CGIC period, the north and west areas. The density of crime appears low in most of the city, particularly in the south and eastern regions of the city. Interestingly, the hotspot near the airport observed for violent crime and aggravated assaults does not appear for robbery. In the post-CGIC map, the concentration of robbery appears much higher. The western and northern hotspots appear to have grown considerably in size. It is also noteworthy that even the lower concentration areas appear "hotter" than before CGIC.

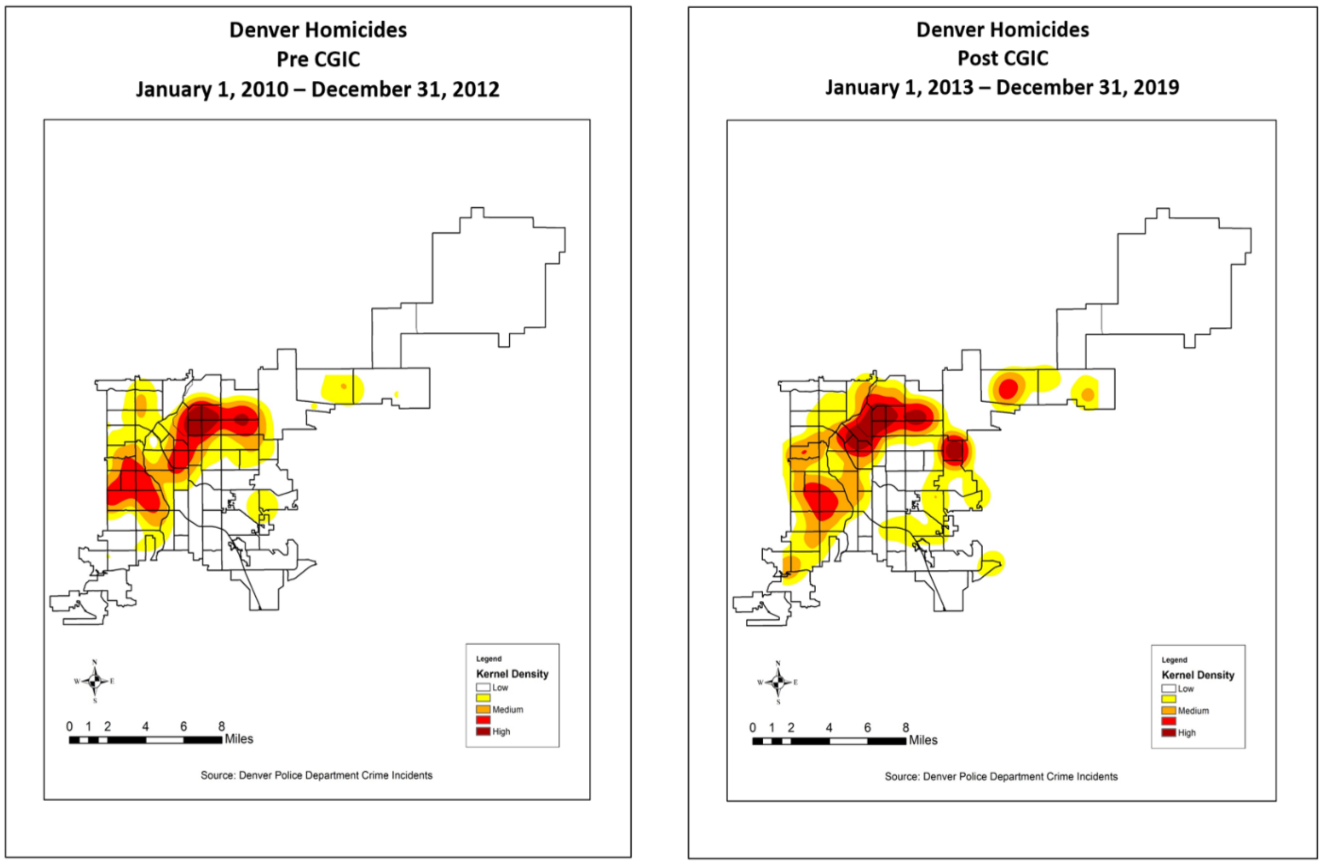


FIGURE 4. PRE- AND POST – CGIC KERNEL DENSITY MAP FOR HOMICIDES WITH A FIREARM, CITY OF DENVER, 2010 – 2019

Finally, Figure 4 displays firearm-related homicides in the pre-and-post CGIC periods. In the pre-CGIC map, there appears to be two main hotspots in the western and northern areas of the city as observed the other maps. In the post-CGIC map, the western hotspot appears to have shrunken slightly, while the northern hotspot appears to have grown and expanded further east. A new hotspot has emerged slightly south and east of the northern area.

Results: Local Polynomial Trend Graphs

To examine the four outcomes under consideration – serious violent crime with a firearm, homicide with a firearm, robbery with a firearm, and aggravated assault with a firearm, local polynomial models are used to estimate the trends in these crimes over time across the city of Denver.

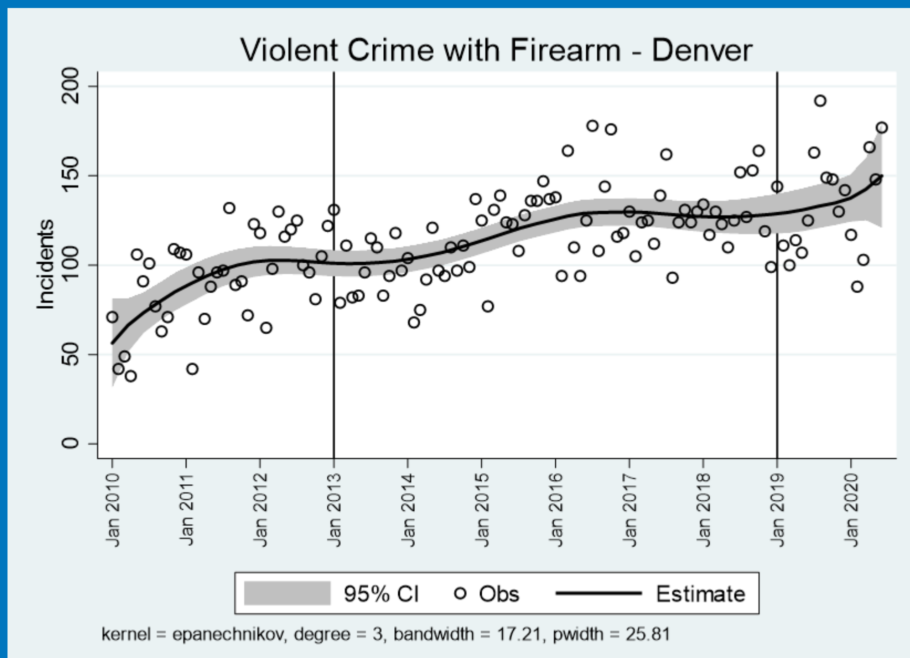


FIGURE 5. LOCAL POLYNOMIAL ESTIMATE OF TREND IN VIOLENT CRIME WITH A FIREARM, CITY OF DENVER, 2010 – Q2 2020

Figure 5 presents the trend in violent crime with firearm incidents across the city of Denver from January 1, 2010 to June 30, 2020. Each point is a monthly count of incidents. The solid horizontal line is the estimated trend in crime incidents across years. The grey shaded area shows the 95% confidence interval in the estimated trend. The first solid vertical line represents the month that CGIC began operation (January 2013) and the second vertical line represents the month that RAVEN began operation (January 2019). The trend for violent crime with a firearm trends upwards through 2013 and then flattens slightly for the remainder of the year. The trend then moves upwards through the middle of 2016 where it flattens out again. There appears to be a slight uptick again near the conclusion of the series, but this may be a data artifact as this occurs when the confidence interval widens due to a lack of observations at the end of the series.

FIGURE 6. LOCAL POLYNOMIAL ESTIMATE OF TREND IN HOMICIDE WITH A FIREARM, CITY OF DENVER, 2010 – Q2 2020

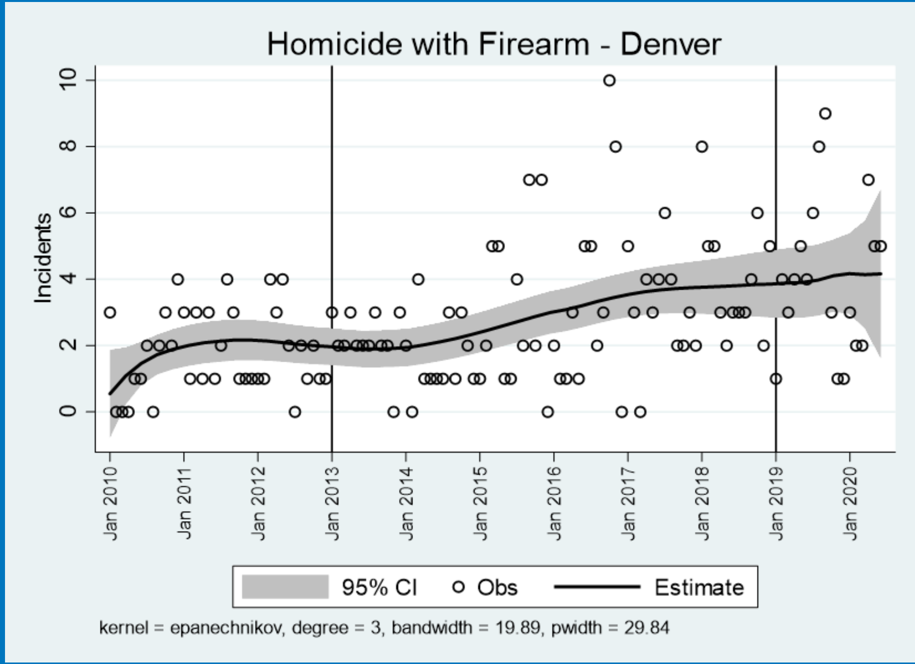


Figure 6 shows the trend in homicide with a firearm over the same time period. This trend is mostly flat until January 2015, where there is a slight increasing trend until January 2017. After this, the trend remains flat through the rest of the series. Interestingly, the variance of the observations appears to increase after January 2015, with the largest spread occurring near January 2017 and June 2019.

The trend for robbery with a firearm is presented in Figure 7. There is an immediate decrease near the beginning of the series, but this is likely a data artifact due to the limited number of observations at the beginning of the series. After this, the increasing trend appears to flatten out and even decrease starting near the start date for CGIC. Early in 2014, this decreasing trend stops, and the series begins a slowly increasing trend through 2018. There appears to be a slight decreasing trend following the onset of RAVEN, but again this decrease occurs near the end of the series and may be a data artifact.

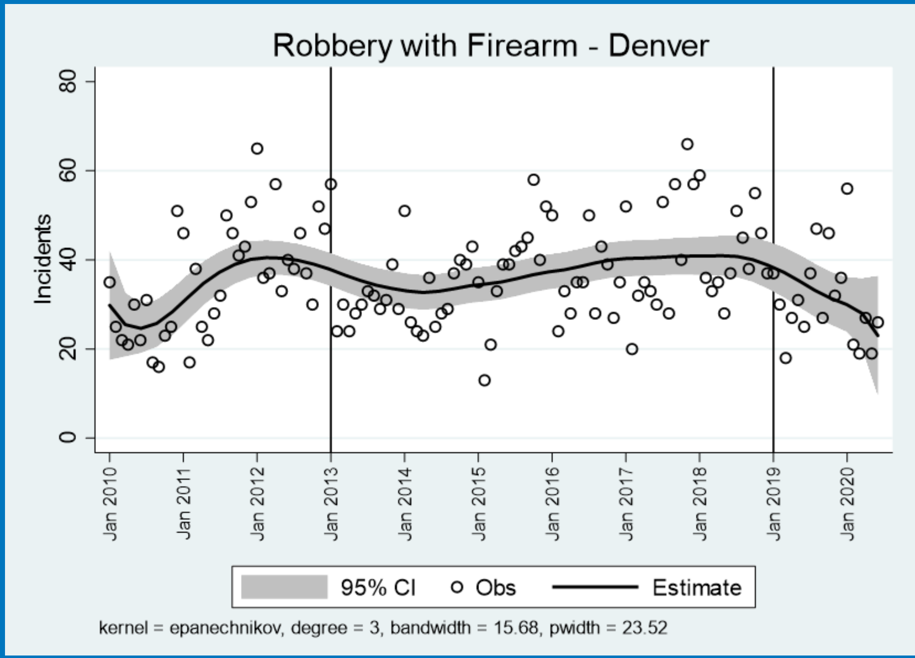


FIGURE 7. LOCAL POLYNOMIAL ESTIMATE OF TREND IN ROBBERY WITH FIREARM, CITY OF DENVER, 2010 – Q2 2020

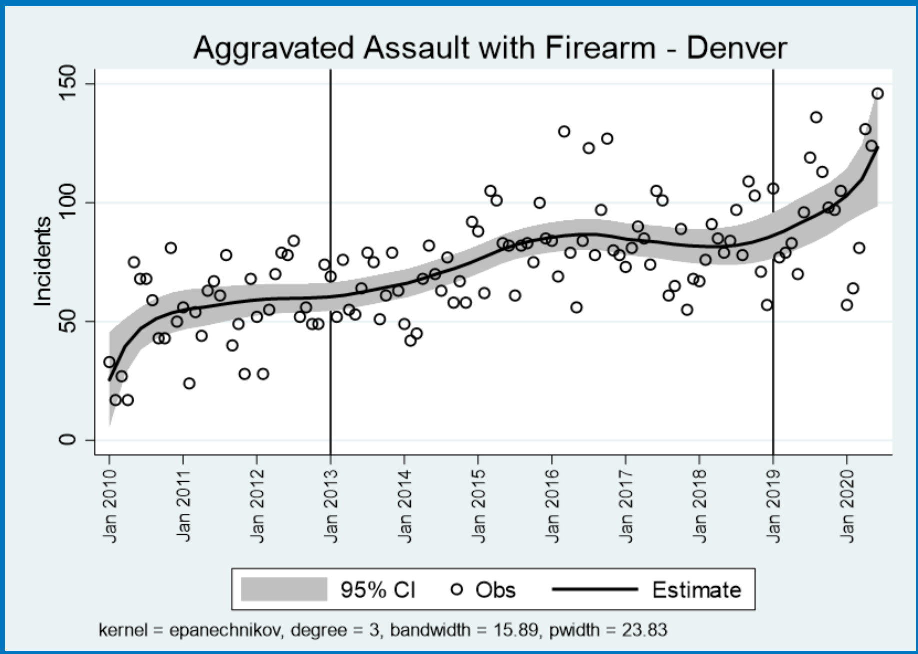


FIGURE 8. LOCAL POLYNOMIAL ESTIMATE OF TREND IN AGGRAVATED ASSAULTS WITH FIREARM, CITY OF DENVER, 2010 – Q2 2020

Finally, Figure 8 presents the trend in aggravated assaults with a firearm. There appears to be a rapid increase at the beginning of the series, which is very likely a data artifact. After this in the middle of 2010, robberies with a firearm show an increasing trend through the beginning of 2016. After this, the trend flattens out through the start date of RAVEN with a sharp upwards trend starting around the same time. Again, as the confidence intervals widen at this point, the sharpness of this upwards trend may be a data artifact.

None of these graphs demonstrated considerable non-linearity for the purposes of modeling the trend in crime in the time series models. Therefore, only linear time trends are included in the final models that are presented in the remainder of the report.[3] Importantly, there was a system change in Denver's Records Management System that occurred in July 2013. However, none of the trends observed in the four outcome variables appear to be affected by this change.[4]

Time Series Results

These local polynomial graphs provide important diagnostic information for the segmented regression analysis. Before considering the segmented models, it is important to examine descriptive statistics for the monthly observations of the city of Denver. Descriptive information for the monthly observations is presented in Table 1. There were 126 total monthly observations across the series (January 2010 – June 2020). Over this time period, Denver experienced an average of 74 aggravated assaults, 36 robberies, and 3 homicides with a firearm per month. In total, Denver experienced about 113 serious violent crimes with firearms per month over this time.

TABLE 1. DESCRIPTIVE STATISTICS FOR MONTHLY GUN-INVOLVED CRIME (*N* = 126)

Variable	Mean	SD	Min	Max
Violent Crime with Firearm	113.17	28.80	38	192
Homicide with Firearm	2.76	2.03	0	10
Robbery with Firearm	35.83	11.42	13	66
Aggravated Assault with Firearm	73.85	24.41	17	146

TABLE 2. OLS NEWEY-WEST MODELS FOR CGIC ON CRIMES WITH FIREARM (N = 84)

Violent Crime with Firearm

Variable	*b*	*SE*
Constant	67.114***	(8.561)
Time	1.332***	(0.381)
Intervention	-26.199**	(9.012)
Intervention × Time	-0.311	(0.445)
Model		
F(3, 80)	15.92***	

*p <.05, **p <.01, ***p <.001

Homicide with Firearm

Variable	*b*	*SE*
Constant	1.540**	(0.484)
Time	0.013	(0.022)
Intervention	-0.537	(0.659)
Intervention × Time	0.034	(0.034)
Model		
F(3, 80)	1.83	

*p <.05, **p <.01, ***p <.001

Robbery with Firearm

Variable	*b*	*SE*
Constant	22.884***	(3.075)
Time	0.680***	(0.141)
Intervention	-16.997***	(4.124)
Intervention × Time	-0.518**	(0.175)
Model		
F(3, 80)	8.85***	

*p <.05, **p <.01, ***p <.001

Aggravated Assault with Firearm

Variable	*b*	*SE*
Constant	42.354***	(7.369)
Time	0.622	(0.315)
Intervention	-8.596	(6.878)
Intervention × Time	0.189	(0.331)
Model		
F(3, 80)	34.91***	

*p <.05, **p <.01, ***p <.001

Table 2 presents the results from the initial OLS Newey-West models for the impact of CGIC on all the outcome variables over the period of January 2010 to December 2016. The top left panel shows the results from the model for violent crime with a firearm. The coefficient for the CGIC intervention is statistically significant suggesting that when CGIC began, there was a drop of about 26.2 violent crimes with firearms. However, the coefficient for the time × intervention interaction is not significant, indicating that CGIC did not have an impact on the overall upwards trend in violent crimes with a firearm. It is important to caution that these effects are approximate because OLS regression does not correct for the count-based nature of the outcome variable.

The second top right panel of Table 2 provides the results for the impact of CGIC on homicide with a firearm. In this model, neither the coefficient for the intervention nor the coefficient for the intervention × time interaction is statistically significant, indicating that CGIC did not have an impact on homicide with a firearm. The bottom left panel of Table 2 shows the impact of CGIC on robbery with a firearm. The coefficient for the intervention is significant, indicating that CGIC resulted in a decrease of nearly 17 robberies with a firearm. Further, the coefficient for the interaction of intervention and time is significant, which suggests that CGIC resulted in a decrease of about 0.54 robberies with a firearm per month, thereby attenuating the previously increasing trend. Finally, the bottom right panel of Table 2 shows the impact of CGIC on aggravated assault with a firearm. Neither the coefficient for the intervention and the intervention × time interaction is statistically significant in this model.

TABLE 3. OLS NEWEY-WEST MODELS FOR RAVEN ON CRIMES WITH FIREARM (*N* = 42)

Violent Crime with Firearm

Variable	*b*	*SE*
Constant	88.231	(58.876)
Time	0.403	(0.627)
Intervention	-9.245	(16.834)
Intervention × Time	0.973	(1.416)
Model		
F(3, 38)	0.71	

*p<.05, **p<.01, ***p<.001

Homicide with Firearm

Variable	*b*	*SE*
Constant	0.982	(4.301)
Time	0.027	(0.043)
Intervention	-0.149	(1.163)
Intervention × Time	0.000	(0.094)
Model		
F(3, 38)	0.24	

*p<.05, **p<.01, ***p<.001

Robbery with Firearm

Variable	*b*	*SE*
Constant	12.884	(27.828)
Time	0.300	(0.282)
Intervention	-12.378*	(5.809)
Intervention × Time	-0.534	(0.523)
Model		
F(3, 38)	3.48*	

*p<.05, **p<.01, ***p<.001

Aggravated Assault with Firearm

Variable	*b*	*SE*
Constant	71.770	(38.783)
Time	0.096	(0.407)
Intervention	3.559	(9.550)
Intervention × Time	1.463	(1.162)
Model		
F(3, 38)	2.26	

*p<.05, **p<.01, ***p<.001

Table 3 shows the impact of RAVEN on the outcome variables over the period of January 2017 to June 2020. Due to the short observational period, many of the parameters fail to achieve statistical significance. None of the coefficients in the model for violent crime with a firearm (top left panel), homicide with a firearm (top left panel), or aggravated assault with a firearm (bottom right panel) is statistically significant. **The only coefficient carrying a significant effect is in the model for robbery with a firearm (bottom left panel). In this model, the coefficient for the intervention was statistically significant suggesting that RAVEN may have led to a decrease of 12.4 robberies with firearms when it began.**

While the initial results from the OLS Newey-West models are encouraging, these models are not appropriate as the outcome variables are counts. Although standard OLS regression is useful for diagnostic purposes as well as providing some initial estimates, OLS regression with count variables may lead to biased coefficients and inappropriate standard errors, which can mask the true intervention effects. As previously mentioned, one of the important differences between the standard OLS and the negative binomial model is that the coefficient needs to be transformed in order to interpret it. One of the strategies for interpreting the b coefficients is by calculating $(e^b - 1) * 100$, which is interpreted as the percentage change in the outcome associated with a one-unit change in the covariate. For the intervention variable which changes from 0 to 1 in the month that the intervention occurs, this calculation produces the percentage change in crime when the intervention began. For the intervention × time variable, this calculation gives the percentage change each month after the intervention began. The final negative binomial Newey-West for the impact of CGIC on the outcome variables for the period of January 1, 2010 through December 31. 2016 is presented in Table 4.

TABLE 4. NEGATIVE BINOMIAL NEWEY-WEST MODELS FOR CGIC ON CRIMES WITH FIREARM (*N* = 84)

Violent Crime with Firearm		
Variable	*b*	*SE*
Constant	4.223***	(0.116)
Time	0.015**	(0.005)
Intervention	-0.270**	(0.094)
Intervention × Time	-0.006	(0.005)
Joint Test $\chi^2(2)$	8.340*	
Model		
LL	-473.707	

*p <.05, **p <.01, ***p <.001

Homicide with Firearm		
Variable	*b*	*SE*
Constant	0.417	(0.322)
Time	0.008	(0.015)
Intervention	-0.202	(0.319)
Intervention × Time	0.008	(0.016)
Joint Test $\chi^2(2)$	1.370	
Model		
LL	-166.089	

*p <.05, **p <.01, ***p <.001

Robbery with Firearm		
Variable	*b*	*SE*
Constant	3.176***	(0.104)
Time	0.020***	(0.004)
Intervention	-0.479***	(0.119)
Intervention × Time	-0.015**	(0.005)
Joint Test $\chi^2(2)$	21.560***	
Model		
LL	-383.314	

*p <.05, **p <.01, ***p <.001

Aggravated Assault with Firearm		
Variable	*b*	*SE*
Constant	3.753***	(0.167)
Time	0.012	(0.007)
Intervention	-0.138	(0.122)
Intervention × Time	-0.002	(0.007)
Joint Test $\chi^2(2)$	1.990	
Model		
LL	-347.714	

*p <.05, **p <.01, ***p <.001

The negative binomial Newey-West models for violent crime with a firearm are presented in the top left panel of Table 4. The joint test of whether the coefficients of both the intervention variable and the intervention × time interaction was statistically significant, suggesting the existence of an intervention effect. The coefficient of the intervention effect is statistically significant, indicating a drop of 23.7 percent in violent crimes with a firearm when CGIC began. For homicide with a firearm (top right panel) and aggravated assault with a firearm (bottom right panel), there is no indication of an intervention effect as the joint test as well as the individual coefficients for intervention and intervention × time are not statistically significant. **Finally, for robbery with a firearm (bottom left panel), the joint test is statistically significant suggesting that CGIC had an impact on robberies. The intervention coefficient is also statistically significant indicating that robberies with a firearm dropped by 38.1 percent when CGIC came online. Further, the coefficient for the intervention × time interaction is statistically significant, suggesting that CGIC reduced robberies with a firearm by 1.5 percent per month. This effect slowed the previous increasing trend in this crime.**

In order to illustrate the impact of CGIC on violent crime, we produced observed vs. counterfactual plots. These graphs show what happened (observed) versus what could have happened (counterfactual). The difference between the two shows the effect of CGIC.

Figure 9 shows the observed vs. counterfactual plot for the model of CGIC on serious violent crime with a firearm. The dashed vertical line represents the start date of CGIC. To the left of this line is the pre-existing trend based on the model. The solid line represents the estimated trend and the dots are the monthly observations. To the right of the dashed vertical line, there is a solid line and a dashed line. The solid line shows the modeled trend after the intervention and the dots are the monthly observations. This represents the outcome that was observed – the level and trend of violent crime with a firearm after CGIC. The dashed line represents the "counterfactual," what we would expect to see based on the model if CGIC was not implemented. In this analysis, the counterfactual is found by projecting the pre-existing trends over the remainder of the series. The difference between the two lines represents the "treatment effect" of CGIC, the decrease in violent crime with firearms that can be attributed to the intervention. From this graph, the drop in violent crime with a firearm starting in January 2013 is clear – this

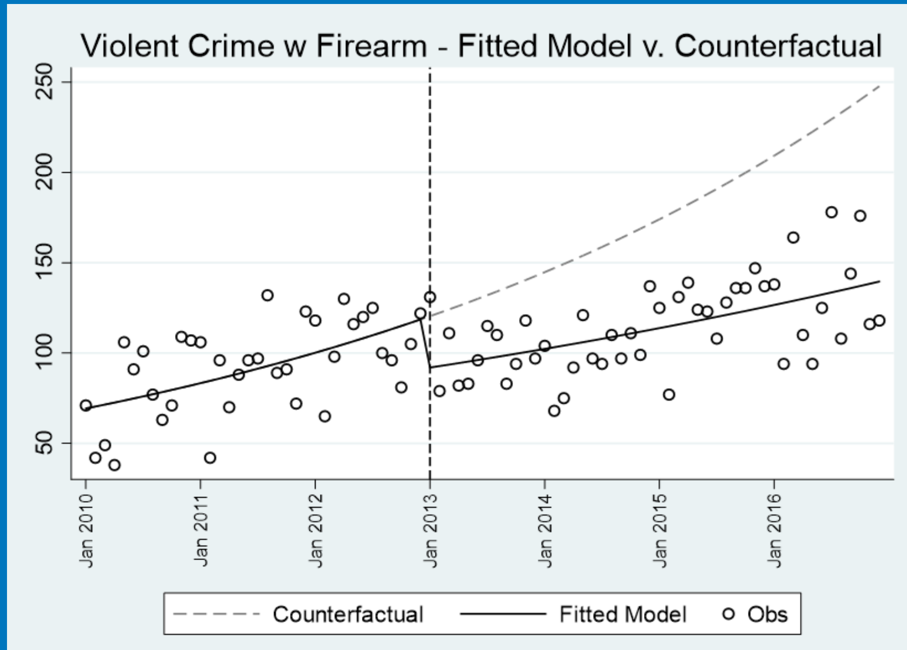


FIGURE 9. OBSERVED VS. COUNTERFACTUAL PLOT FOR GLM NEWEY-WEST MODEL FOR CGIC ON VIOLENT CRIME WITH A FIREARM, CITY OF DENVER, 2010-2016

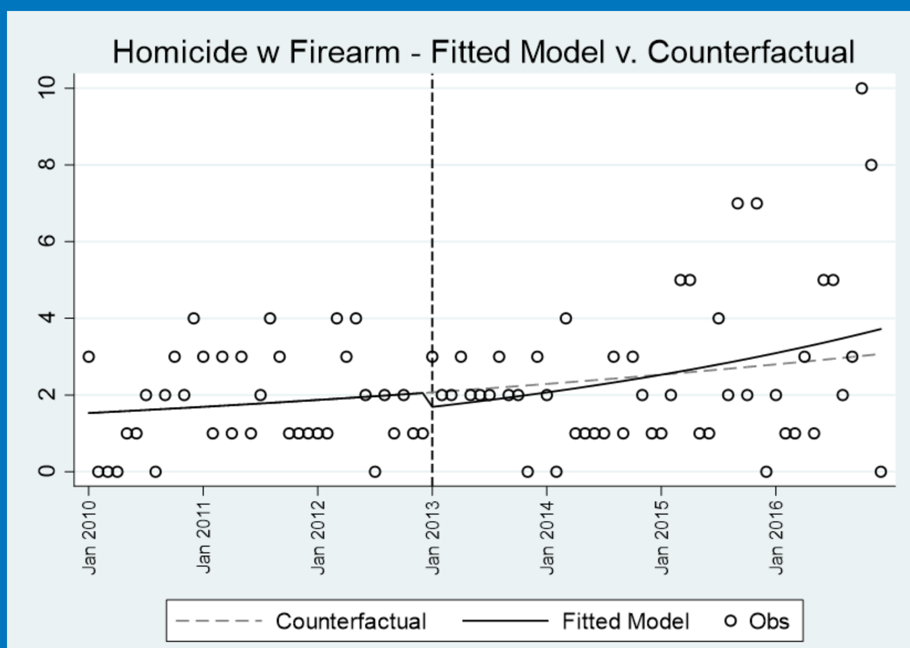


FIGURE 10. OBSERVED VS. COUNTERFACTUAL PLOT FOR GLM NEWEY-WEST MODEL FOR CGIC ON HOMICIDE WITH A FIREARM, CITY OF DENVER, 2010-2016

drop is due to the significant coefficient for the intervention. There is only a slight difference in the trends between the observed and the counterfactual condition. This is because the coefficient for the intervention x-time interaction was not statistically significant.

Figure 10 shows the observed vs. counterfactual plot for homicide with a firearm. In contrast to the previous graph for violent crime with a firearm, there is little difference between the observed and the counterfactual trends. Since the coefficients for the intervention and intervention × time interaction are not statistically significant, the slight deviations between the observed and counterfactual lines is nothing more than a statistical artifact.

Figure 11 shows the observed vs. counterfactual plot for robbery. **There is a clear effect from CGIC on the decrease in crime starting in January 2013. This is because the coefficient for the intervention was statistically significant. Unlike the previous graph, there is also a clear change in the trend of crime in this graph. Specifically, robberies with a firearm is expected to increase at a steady pace based on the pre-existing trend. Instead, after CGIC started, the trend in robberies with a firearm is nearly flat across the rest of the series. This change in the trend is due to the significant coefficient for the intervention × time variable. It is apparent in this graph that while the trend in robberies with a firearm did not begin decreasing after CGIC began, there was a sufficient impact to nearly flatten a pre-existing increasing trend.**

The final observed vs. counterfactual plot for aggravated assault with a firearm is presented in Figure 12. While there appears to be a slight drop in aggravated assaults, the coefficient for the intervention was not statistically significant, and this difference is only a statistical artifact. There is also no impact on the post-intervention trend as the coefficient for the intervention x-time interaction was not statistically significant.

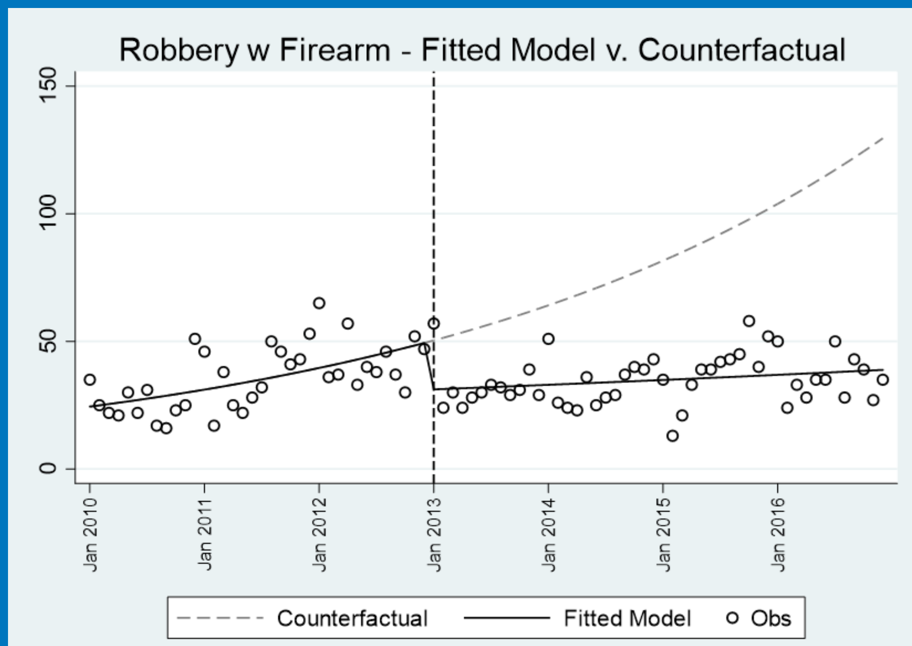


FIGURE 11. OBSERVED VS. COUNTERFACTUAL PLOT FOR GLM NEWEY-WEST MODEL FOR CGIC ON ROBBERY WITH A FIREARM, CITY OF DENVER, 2010-2016

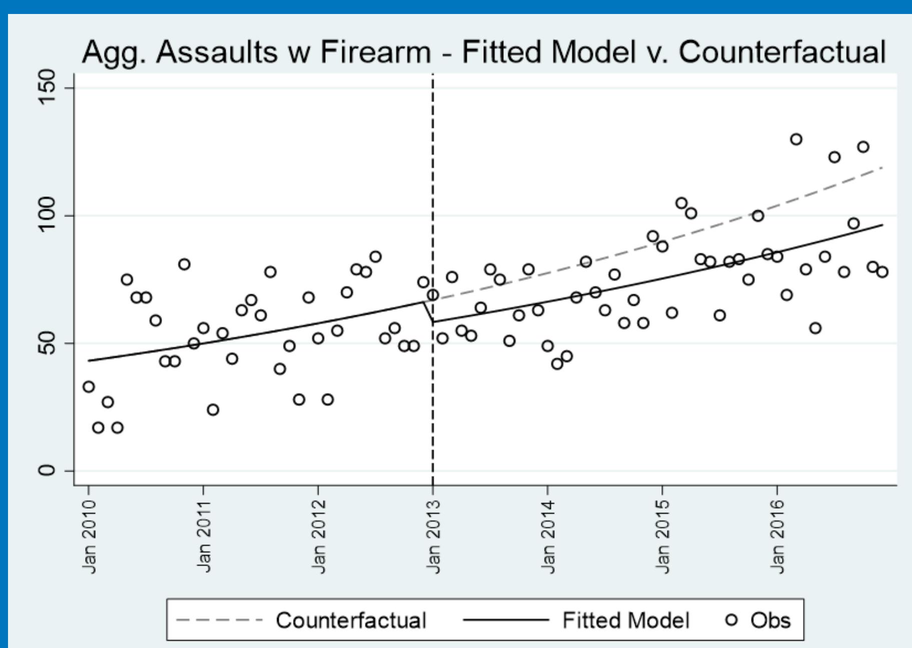


FIGURE 12. OBSERVED VS. COUNTERFACTUAL PLOT FOR GLM NEWEY-WEST MODEL FOR CGIC ON AGGRAVATED ASSAULT WITH A FIREARM, CITY OF DENVER, 2010-2016

TABLE 5. GLM NEWEY-WEST MODELS FOR RAVEN ON CRIMES WITH FIREARM (*N* = 42)

Violent Crime with Firearm

Variable	*b*	*SE*
Constant	4.537***	(0.437)
Time	0.003	(0.005)
Intervention	-0.071	(0.124)
Intervention × Time	0.007	(0.010)
Joint Test $\chi^2(2)$	0.650	
Model		
LL	-246.672	

*p<.05, **p<.01, ***p<.001

Homicide with Firearm

Variable	*b*	*SE*
Constant	0.553	(1.181)
Time	0.008	(0.012)
Intervention	-0.044	(0.293)
Intervention × Time	-0.000	(0.024)
Joint Test $\chi^2(2)$	0.030	
Model		
LL	-103.173	

*p<.05, **p<.01, ***p<.001

Robbery with Firearm

Variable	*b*	*SE*
Constant	3.003***	(0.692)
Time	-0.315	(0.166)
Intervention	-0.016	(0.017)
Intervention × Time	3.003	(0.692)
Joint Test $\chi^2(2)$	7.530*	
Model		
LL	-194.018	

*p<.05, **p<.01, ***p<.001

Aggravated Assault with Firearm

Variable	*b*	*SE*
Constant	4.282***	(0.448)
Time	0.001	(0.005)
Intervention	0.053	(0.099)
Intervention × Time	0.014	(0.011)
Joint Test $\chi^2(2)$	2.320	
Model		
LL	-230.359	

*p<.05, **p<.01, ***p<.001

The negative binomial Newey-West models for RAVEN are presented in Table 5. Similar to the results that were observed in OLS models, there was no significant intervention effects for violent crimes with a firearm (top left panel), homicide with a firearm (top right panel), or aggravated assault with a firearm (bottom right panel). Interestingly, in the model for robbery with a firearm, the joint test of coefficients is statistically significant, but the individual coefficients for the intervention and the intervention x-time interaction were not statistically significant. This suggests that while an intervention effect is present, there is insufficient statistical power to determine what type of effect is present. Further, while the coefficient for the intervention did not reach statistical significance, the observed p-value approached significance (p = .058). It is anticipated that with additional observations, RAVEN may have a significant impact on robbery with a firearm. Observed vs. counterfactual plots are omitted for RAVEN as none of the intervention or intervention × time variables are significant in the models.

Multilevel Results

The results from the citywide segmented regression models provide evidence that CGIC had an impact on violent crime with a firearm and robbery with a firearm. It remains possible that the same crime reductions were not seen for every neighborhood within Denver. In order to assess the impact of CGIC at the neighborhood level, we conducted a series of multilevel models for the impact of CGIC on serious violent crime with a firearm, homicide with a firearm, robbery with a firearm, and aggravated assault with a firearm.

Descriptive statistics for each month across neighborhoods are presented in Table 6. There are 84 monthly observations for each of the 78 neighborhoods for a total of 9,360 observations. On average, each neighborhood experiences 1.43 serious violent crimes with a firearm per month, with a low of zero and a high of 41. On average, neighborhoods experience 0.03 homicides with a firearm per month with a low of zero and a high of three. Each neighborhood experiences between zero and eight robberies with a firearm, with an average of 0.46 across all monthly observations. Finally, neighborhoods experience between 0 and 37 aggravated assaults with a firearm with an average of 0.92 per month across all observations.

TABLE 6. NEIGHBORHOOD-LEVEL STATISTICS FOR MONTHLY GUN-INVOLVED CRIME (*N* = 9,360)

Variable	Mean	SD	Min	Max
Violent Crime with Firearm	1.43	2.51	0	41
Murder with Firearm	0.03	0.20	0	3
Robbery with Firearm	0.46	0.83	0	8
Aggravated Assault with Firearm	0.92	2.12	0	37

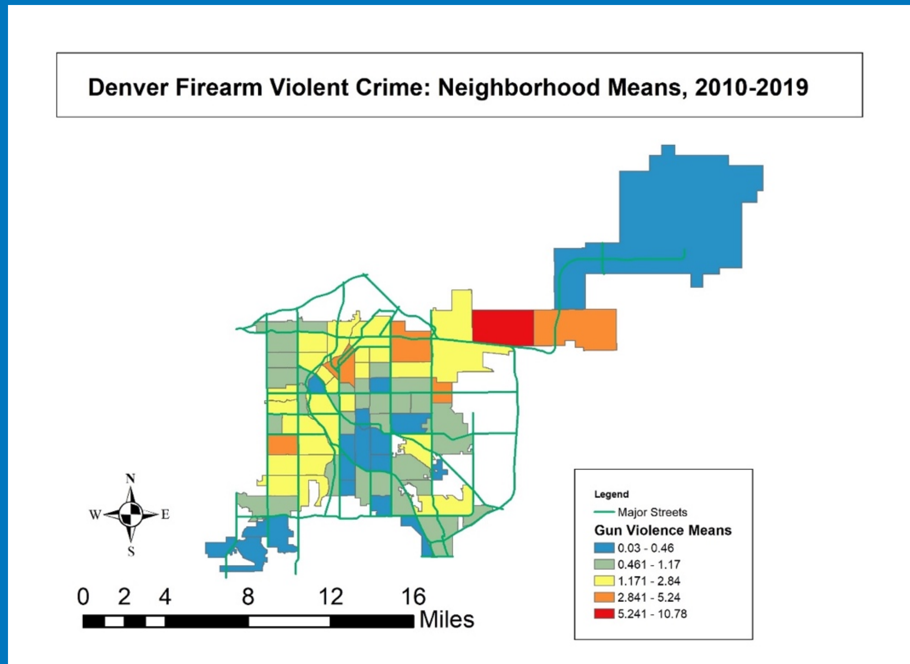


FIGURE 13. NEIGHBORHOOD MONTHLY MEANS FOR VIOLENT CRIME WITH A FIREARM, CITY OF DENVER, 2010-2019.

In order to better visualize the differences between the neighborhood averages of the four outcome variables, a series of neighborhood thematic maps were constructed. Figure 13 presents the monthly average of violent crime with a firearm for each of the 78 neighborhoods across the years 2010 to 2019. The Montbello neighborhood had the highest monthly average with 10.8 violent crimes with a firearm per month. The Westwood and Gateway – Green Valley Ranch neighborhoods had approximately 5.2 violent crimes with a firearm. Five Points and Northeast Park Hill had 4.5 and 4.2 violent crimes with a firearm per month. At the other extreme, Indian Creek, Wellshire, and Country Club neighborhoods had the lowest monthly averages with 0.03, 0.07, and 0.09 violent crimes with a firearm, respectively.

Figure 14 shows the neighborhood monthly averages for homicide with a firearm for each of the 120 months from 2010-2019. The range of values is much smaller as all neighborhoods have an average of less than 0.2 homicides with a firearm per month. Sixteen neighborhoods do not experience a homicide with a firearm for the entire observational period. The Northeast Park Hill neighborhood had the highest average with 0.18 homicides with firearms per month, followed by Five Points (0.16), Montbello (0.15), and East Colfax (0.15).

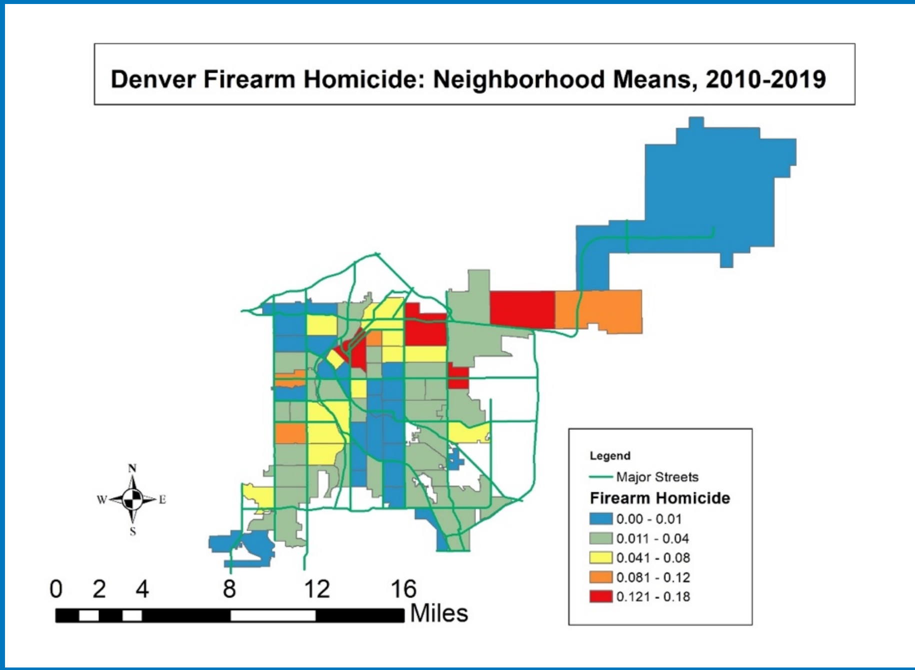


FIGURE 14. NEIGHBORHOOD MONTHLY MEANS FOR VIOLENT CRIME WITH A FIREARM, CITY OF DENVER, 2010-2019.

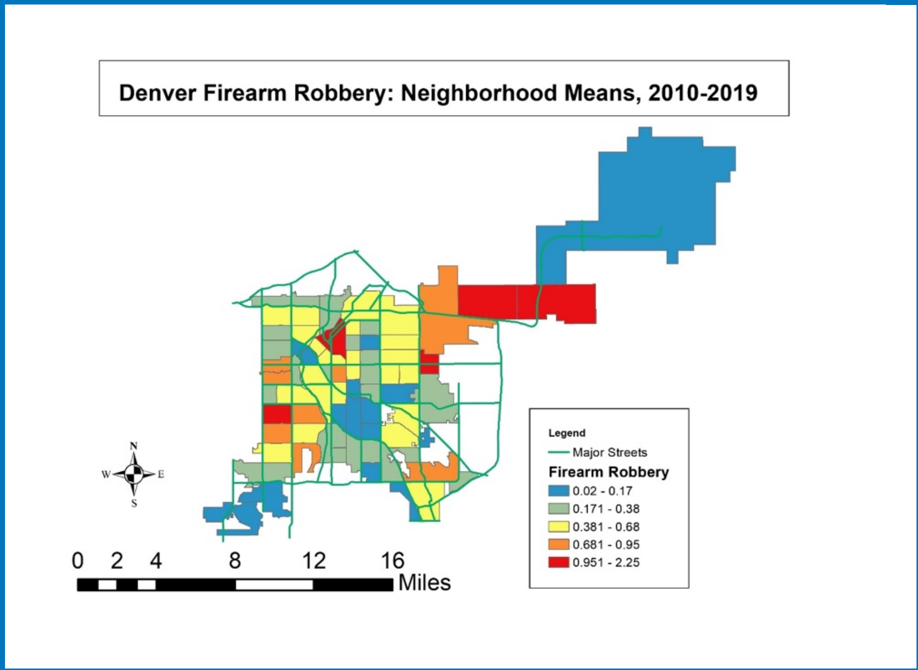


FIGURE 15. NEIGHBORHOOD MONTHLY MEANS FOR ROBBERY WITH A FIREARM, CITY OF DENVER, 2010-2019

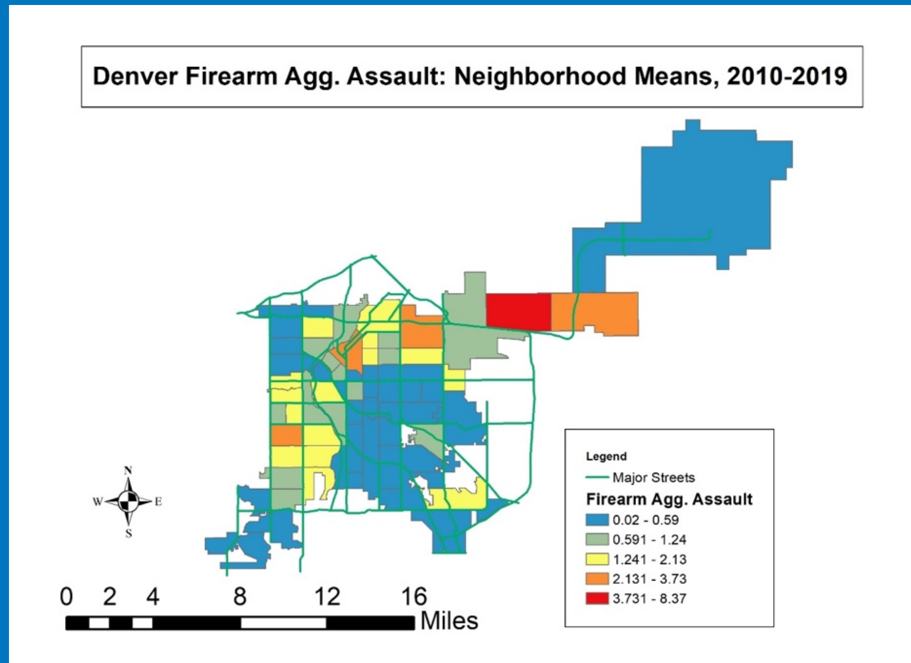


FIGURE 16. NEIGHBORHOOD MONTHLY MEANS FOR AGGRAVATED ASSAULT WITH A FIREARM,CITY OF DENVER, 2010-2019.

Figure 15 presents the monthly average number of robberies with a firearm for each neighborhood. The neighborhoods of Montbello (2.25), East Colfax (1.40), Westwood (1.40), and Gateway – Green Valley Ranch (1.33) had the highest monthly averages. In contrast, Indian Creek (0.02), Wellshire (0.02), Auraria (0.04), and Hilltop (0.06) had the lowest monthly averages.

Finally, Figure 16 shows the neighborhood monthly averages for aggravated assaults with a firearm. By a considerable margin, Montbello had the highest average at 8.37 aggravated assaults with a firearm per month. Gateway – Green Valley Ranch (3.73), Westwood (3.69), Northeast Park Hill (3.28), and Five Points (3.00) had high averages. In contrast, Indian Creek (0.02), Country Club (0.02), Wellshire (0.05), and Rosedale (0.08) all had very low monthly averages.

Following the recommendations of Raudenbush and Bryk (2002), the multilevel models for the Denver neighborhoods were constructed using a “bottom-up” procedure where random effects are introduced sequentially into the base models. Unfortunately for all models, the random effects for the coefficients for time and the intervention × time interaction were so small that they resulted in models that were unable to be estimated.[5] For this reason, random effects were specified only for the coefficients for the constant and the coefficient for the intervention.

TABLE 7. FINAL MIXED MODEL FOR CGIC ON VIOLENT CRIMES WITH FIREARMS (*N* = 6,552; 78)

Violent Crime with Firearm		
Variable	*b*	*SE*
Fixed Effects		
Constant	-0.540***	(0.136)
Time	0.015***	(0.003)
Intervention	-0.322***	(0.077)
Intervention × Time	-0.006	(0.003)
	Variance	SE
Random Effects		
Constant	0.960	(0.172)
Intervention	0.122	(0.032)

*p <.05, **p <.01, ***p <.001

Table 7 provides the final multilevel model for the impact of CGIC on violent crimes with firearms. As with the citywide models, the coefficient for the intervention was statistically significant, indicating that on average, neighborhoods experienced a drop of 27.5 percent in violent crimes with firearms when CGIC began. However, there was considerable variability in this coefficient across neighborhoods as noted by the large variance of the random effect for the intervention coefficient compared to its standard error.

To examine the range of impacts of CGIC across neighborhoods, Figure 17 displays a map of the Empirical Bayes estimates for the intervention coefficient for each neighborhood. Importantly, the EB estimates are used primarily for diagnostic purposes, so it is inadvisable to interpret their numeric values. However, the approximate magnitude of the EB estimates can still provide useful information about the distribution of the coefficient across neighborhoods. **About 60 percent of the neighborhoods had negative values for the EB estimates, suggesting that violent crime with a firearm decreased in the majority of neighborhoods.** In some neighborhoods, such as Montbello, Westwood, Five Points, Northeast Park Hill, and East Colfax, the coefficients were positive, suggesting an increase in violent crime with a firearm after the start of CGIC. In fact, many of the neighborhoods with high monthly averages also had positive coefficients, suggesting that CGIC was mostly effective in low to medium crime neighborhoods.

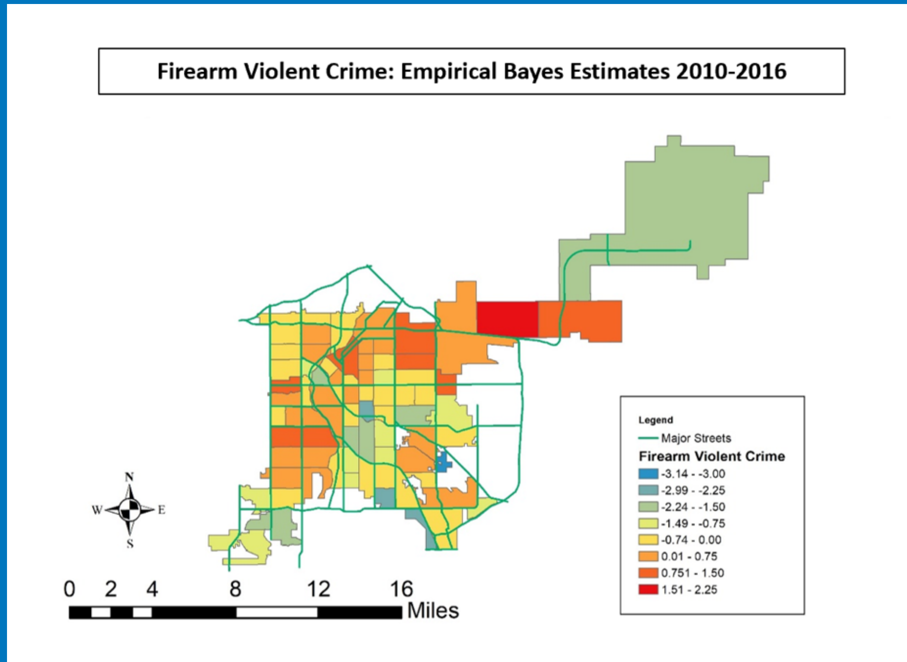


FIGURE 17. EMPIRICAL BAYES ESTIMATES OF CGIC ON VIOLENT CRIME WITH A FIREARM, CITY OF DENVER, 2010 – 2016

Table 8 provides the results from the multilevel models of CGIC on homicide with a firearm. As with the citywide model, the coefficients for intervention and intervention × time were not statistically significant, indicating that CGIC did not have an impact on homicide with a firearm. Further, although the random effect for the intervention coefficient is sizable, the standard error is also large, implying that the variance in the coefficient is not notable.

TABLE 8. FINAL MIXED MODEL FOR CGIC ON HOMICIDE WITH FIREARMS (*N* = 6,552; 78)

Violent Crime with Firearm		
Variable	*b*	*SE*
Fixed Effects		
Constant	-4.285***	(0.323)
Time	0.007	(0.011)
Intervention	-0.426	(0.386)
Intervention × Time	0.010	(0.014)
	Variance	SE
Random Effects		
Constant	0.757	(0.332)
Intervention	0.228	(0.315)

*$p < .05$, **$p < .01$, ***$p < .001$

Figure 18 presents a map of the EB estimates for the intervention effect for CGIC on homicide with a firearm across Denver neighborhoods. Although 73 percent of neighborhoods showed negative coefficients, indicating a drop in homicides with a firearm, the size of these coefficients were minimal. It appears that many of these negative coefficients represent slight expected decreases in neighborhoods nearly free of gun homicides. While some neighborhoods show slight increases in homicide with a firearm, the size of the effects suggest a marginal increase in neighborhoods with high rates of gun homicide. Again, this suggests that CGIC did not have an impact on homicide with firearms across neighborhoods.

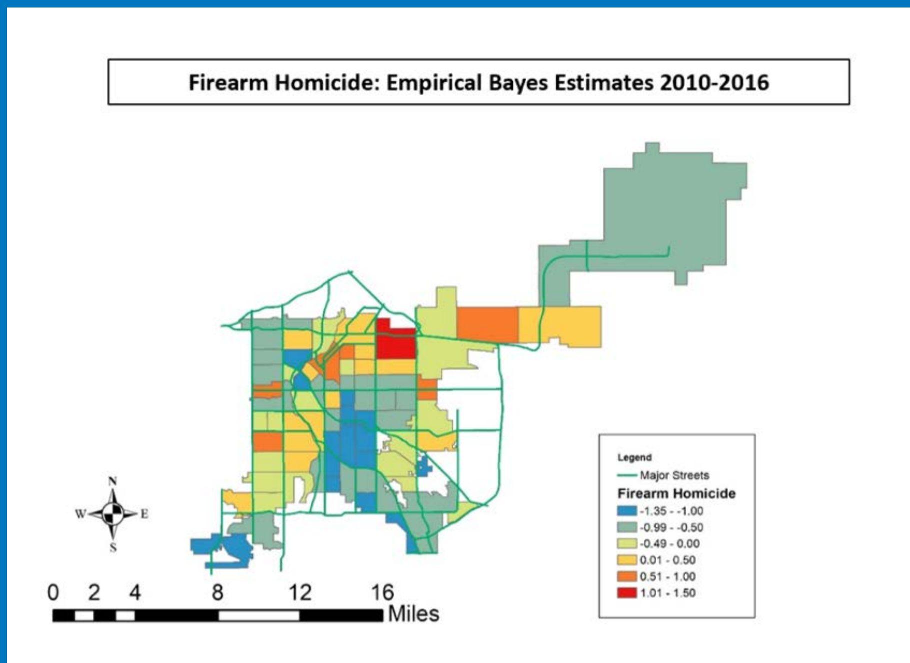


FIGURE 18. EMPIRICAL BAYES ESTIMATES OF CGIC ON HOMICIDE WITH A FIREARM, CITY OF DENVER, 2010 – 2016

Table 9 shows the results from the multilevel model of CGIC on robbery with a firearm. As seen with the citywide models, the coefficient for the intervention is statistically significant, suggesting there was a drop of 40.7 percent robberies with a firearm when CGIC came online. The variance of the random effects for the intervention effect was large compared to its standard error, suggesting that there is notable variance in the impact of CGIC across neighborhoods. The coefficient for the intervention × time interaction was also statistically significant, indicating that robbery with a firearm decreased by 1.5 percent per month after CGIC began.

The variance of the coefficient for the intervention × time interaction variable was near zero, which indicates that each neighborhood experienced this same downward trend in robberies with a firearm.

TABLE 9. FINAL MIXED MODEL FOR CGIC ON ROBBERY WITH FIREARMS (*N* = 6,552; 78)

Violent Crime with Firearm		
Variable	*b*	*SE*
Fixed Effects		
Constant	-1.472***	(0.131)
Time	0.020***	(0.003)
Intervention	-0.523***	(0.087)
Intervention × Time	-0.015***	(0.003)
	Variance	SE
Random Effects		
Constant	0.696	(0.165)
Intervention	0.043	(0.020)

*p <.05, **p <.01, ***p <.001

The map of the EB estimates for the impact of CGIC on robbery with a firearm is presented in Figure 19. **Approximately 73 percent of neighborhoods had a negative coefficient for the intervention, indicating that the onset of CGIC was accompanied by a decrease in robbery with a firearm in the majority of neighborhoods. Again, the largest effects appear to be in neighborhoods with low averages of robberies with a firearm. Specifically, the largest negative effects were observed in the Indian Creek, Wellshire, Auraria, Hilltop, and Southmoor Park neighborhoods.** The largest positive effects were seen in Montbello, Westwood, East Colfax, and Five Points – all neighborhoods with high averages of robberies with a firearm. It is important to mention, however, that all neighborhoods still experience the 1.5 percent per month decrease in robberies with a firearm, as this effect was constant across neighborhoods.

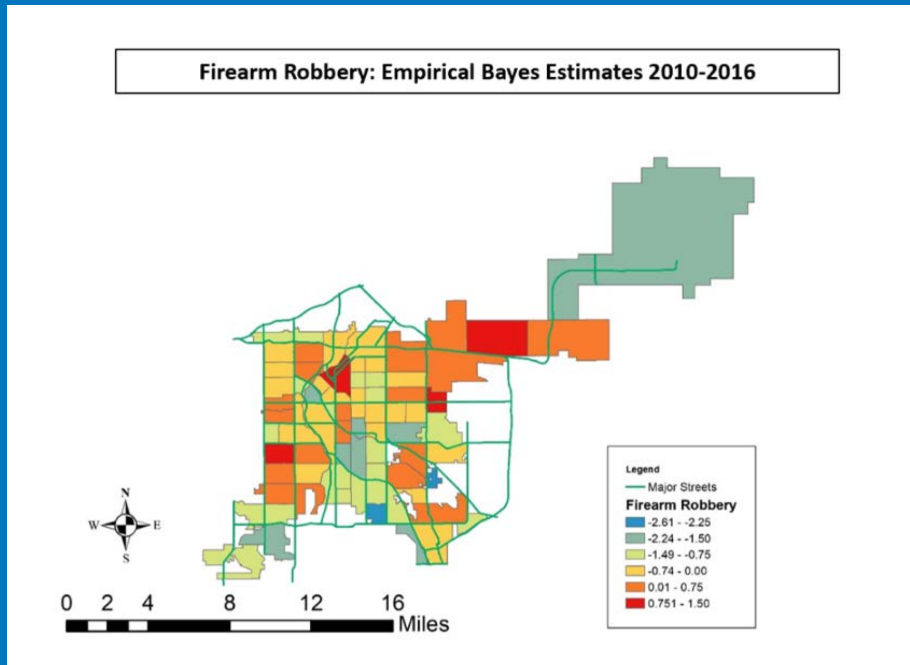


FIGURE 19. EMPIRICAL BAYES ESTIMATES OF CGIC ON ROBBERY WITH A FIREARM, CITY OF DENVER, 2010 – 2016

The final multilevel model for the impact of CGIC on aggravated assaults with a firearm is presented in Table 10. Similar to the city-wide model, the coefficient for the intervention and the intervention × time interaction is not statistically significant. This indicates that on average CGIC did not have an impact on aggravated assault with a firearm. However, the size of the variance in the intervention coefficient across neighborhoods is large compared to its standard error, which suggests that there may be considerable variance in this effect across neighborhoods.

TABLE 10. FINAL MIXED MODEL FOR CGIC ON AGG. ASSAULT WITH FIREARMS (*N* = 6,552; 78)

Violent Crime with Firearm		
Variable	*b*	*SE*
Fixed Effects		
Constant	-1.175***	(0.160)
Time	0.011**	(0.004)
Intervention	-0.173	(0.116)
Intervention × Time	-0.001	(0.005)
	Variance	SE
Random Effects		
Constant	1.264	(0.200)
Intervention	0.223	(0.062)

*p <.05, **p <.01, ***p <.001

The EB estimates of the coefficient of the intervention for each neighborhood is presented in Figure 20. Approximately 49 percent of neighborhoods show decreases in aggravated assaults with a firearm after CGIC began. Indian Creek, Country Club, and Southmoor Park neighborhoods have very large negative EB estimates, although these neighborhoods experience very few aggravated assaults with a firearm. The largest positive EB estimates are in the Montbello, Westwood, Northeast Park Hill, and Five Points neighborhoods and these experience high levels of aggravated assaults with a firearm.

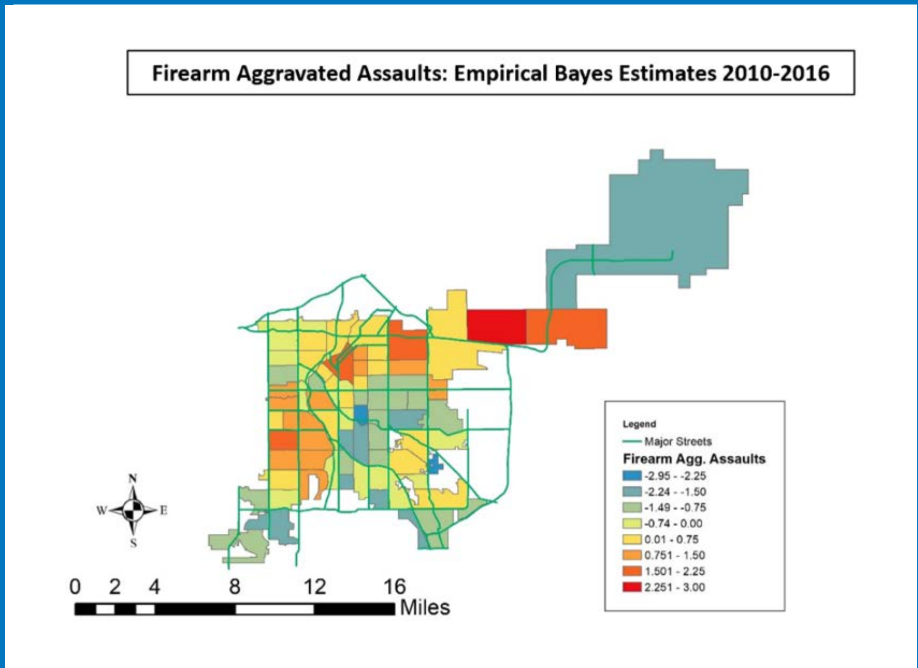


FIGURE 20. EMPIRICAL BAYES ESTIMATES OF CGIC ON AGGRAVATED ASSAULT WITH A FIREARM, CITY OF DENVER, 2010 – 2016

Summary of Findings

Using our regression models we estimated the impact of CGIC and RAVEN -- both the immediate impact associated with the start of the intervention and the longer-term impact on the trend in crime over time. **We found that there was an immediate drop in violent crime with a firearm when CGIC began. There was also an immediate drop in robbery when CGIC began, and the start of CGIC was associated with the halting of a pre-existing upwards trend in robbery.**

Since violent crime with a firearm is a compound measure of several crime types, it seems likely that the impact of CGIC on violent crime with a firearm was predominately due to its impact on robbery with a firearm. There was no observed effect of CGIC on homicide with a firearm or aggravated assault with a firearm. There were no significant effects for RAVEN on any outcome variable, but this may be due to the limited number of post-intervention observations. The coefficient for the intervention was nearly significant in the model for robbery with a firearm and might reach statistical significance after more observations are available.

We also examined whether CGIC had an impact across neighborhoods and used a series of multilevel models to do so. The Empirical Bayes (EB) estimates of the impact of CGIC were then mapped to provide a visual depiction of the variance in the impact of CGIC across neighborhoods. **Similar to the citywide models, we found that the intervention was statistically significant for violent crime with a firearm, indicating that on average across neighborhoods, violent crime with a firearm decreased when CGIC began. Further, the combination of the coefficient for the intervention and the intervention × time interaction were statistically significant in the model for robbery with a firearm.** This suggested that across neighborhoods, on average, robbery with a firearm decreased when CGIC began and then the upward citywide trend in robbery was reduced.

The EB estimates maps revealed an interesting pattern for both models; the impact of CGIC appear to be greatest in low and medium crime neighborhoods, while CGIC was associated with increases in crime in the high crime neighborhoods. This finding may be in part a statistical artifact as a small drop in the number of crime incidents is associated with a large percentage decrease in low and medium crime neighborhoods. It is also likely that unmeasured neighborhood effects, such as demographic or social factors may moderate the effectiveness of CGIC in particular neighborhoods.

SECTION 4:

SUMMARY AND CONCLUSION

INTRODUCTION

The Denver Police Department (DPD), the Bureau of Alcohol, Tobacco, Firearms, and Explosives (ATF), and several other partners from local, state, and federal criminal justice agencies created a collaborative network called the Crime Gun Intelligence Center in 2013 designed to combat gun crime throughout the Denver Metro Area. The 'focus on gun violence' and using data- and forensics-driven approaches are key components of the Denver CGIC, and now are ingrained in all of the CGICs across the country.

One of the key components of CGIC is analyzing and compiling ballistics information though the National Integrated Ballistics Information Network (NIBIN). By working with ATF, the DPD was able to obtain intelligence packages, which in turn led to investigations that identified and arrested shooters within the Denver region. By using NIBN and eTrace, they were able to track crime guns and identify linkages between cases within and across jurisdictions.

This report provided the results of the process and impact evaluations for CGIC and RAVEN. Using quantitative and qualitative data from DPD and ATF, we were able to answer critical research questions about the implementation and effects of CGIC and RAVEN.

For the process evaluation, we interviewed 21 people associated with the CGIC/RAVEN program and obtained useful perceptions about their work. Using incident data, calls for service data, and information from ShotSpotter we were able to determine the activities of the CGIC/RAVEN team. By showing that implementation occurred as planned, we were then able to determine the effects and impact of the team on serious violent crimes with a firearm, homicide with a firearm, robbery with a firearm, and aggravated assault with a firearm.

Process Evaluation Summary

From our analysis of quantitative data and through the perceptions of those who work in the program, we were able to answer questions about the implementation and effects of CGIC and how it transformed into RAVEN.

Research Question 1:

- *How was CGIC implemented and operationalized?*
- *What technologies were introduced into the Denver CGIC?*
- *What were the effects of the Denver CGIC implementation and new technology?*

The Denver CGIC was the first CGIC implemented in the United States. As such the initial CGIC implementation effort was conceptual and was developed in real-time by a handful of people from participating agencies. Eventually, prosecutor offices at the local and federal level, and the Aurora and Lakewood Police Departments joined the program. Together they formulated policies and procedures designed to streamline firearm evidence collection, create an investigative team specifically designed to follow-up on NIBIN leads, disseminate NIBIN hit information to the CGIC team, and increase collaboration between involved agencies. Information gleaned from ATF NESS data and interviews indicate that the Denver CGIC was successful in achieving these goals.

The Denver CGIC introduced technologies such as NIBIN, eTrace, and ShotSpotter to local law enforcement. ATF data on NIBIN hits and eTrace queries/hits indicate that the Denver CGIC was able to increase their use of these technologies to identify shooters and illegal firearm dealers in the Denver Metropolitan area. Data from the Denver CAD system indicate that the ShotSpotter systems were implemented based on calls for service data and were successful in assisting the CGIC in obtaining firearm-related evidence.

Overall, the Denver CGIC's early implementation efforts were successful after overcoming hurdles in policies and coordination and getting the right people in place. Local agencies required a blend of training and personnel changes to build a CGIC that collectively supported the ATF's policies and procedures for CGIC investigations. The forensics process was streamlined with the support of additional ATF personnel, so the Denver CGIC was able to quickly identify NIBIN hits and follow-up on those hits within a few days of firearm incidents occurring.

Research Question 2:

- *How did CGIC evolve over time?*
- *What was the purpose of the RAVEN expansion?*
- *What was the effect of the RAVEN expansion?*

Denver's CGIC program experienced several positive changes that contributed to its evolution. The initial program involved a collaboration between two ATF personnel, part-time DPD detectives, and administrative assistance from Denver, Aurora, and Lakewood police agencies. Up to this point, the Denver crime lab had used NIBIN to link shootings together, but did not have the resources or personnel to follow up on these leads. With assistance from ATF personnel the Denver crime lab was able to increase the speed of NIBIN searches and allow Denver investigators to pursue NIBIN leads within a matter of days.

Importantly, ATF analysts in the Denver office recognized the need for collecting, compiling, and using data. As a result, they created a database that would eventually become NESS, the NIBIN Enforcement Support System. Now used nation-wide, the system assists all CGICs in keeping track of ballistic evidence (casing caliber, traces, etc.), incidents, dates, law enforcement agency, crime guns, linkages, and other useful information. From this system, 'actionable intelligence' and intelligence packages are generated that include incidents that are linked to a casing.

Following the streamlining of ballistic forensic processing, DPD deployed ShotSpotter in an effort to receive more precise location information to increase the likelihood of obtaining ballistic forensic evidence. The implementation of ShotSpotter, first in the North area and then in four subsequent areas of Denver, allowed investigators to increase comprehensive casing collection and NIBIN ballistic processing. ShotSpotter event record data indicate that the sensors were able to assist DPD in recovering casings, recovering firearms, and eventually arresting suspects.

The most recent evolution of the CGIC program occurred when it expanded to RAVEN, a regional network of local, state, and federal partners to target and prosecute firearm offenders. This allowed the Denver CGIC to provide assistance to neighboring jurisdictions on violent firearm crime and increase the scope of NIBIN searches. This expanded effort increased collaboration in the Denver metropolitan area. Data on firearms-related investigative activity reflected this increased collaboration as the number of NIBIN hits, amount of firearm evidence, and other CGIC-related measures increased compared to the 2013-2018 CGIC operations. Interviews with RAVEN-involved personnel also reflected this result, as they overwhelmingly supported the program and praised its results.

Research Question 3:

- *What were the perceptions of the partners?*
- *What were the challenges of CGIC and how did they overcome them?*
- *How did the partners view the implementation, changes, and expansion of CGIC?*

Interviews with the CGIC team and partners provided a range of perceptions and themes regarding CGIC implementation. The interviews revealed that CGIC experienced challenges early on with inter-department coordination and policy, having the right personnel, and obtaining buy-in from the various personnel and agencies involved. The local and federal partners that were involved in the initial stages of CGIC indicated that the agencies differed in terms of tactics and policy. In addition, CGIC was comprised of investigators that had expertise with narcotics investigations, and this mentality did not align with the emerging goals of the CGIC. Many CGIC partners were unfamiliar with the concept of NIBIN and associated technologies to target violent firearm offenders. In an effort to overcome these initial challenges, the CGIC team coordinated several meetings. These meetings facilitated open communication and provided the team with an opportunity to develop strategies to overcome these challenges. Specifically, CGIC administrators were able to coordinate tactical policy decisions and develop strategies to phase out task force members who did not share the same vision as the core CGIC team. Many interviewees cited this as a major turning point for the evolution of Denver's CGIC program. As a result of this "good turnover", more experienced firearm and violent crime investigators were incorporated into CGIC. Less emphasis was placed on drug-related crimes and more focus placed on gun-crime. Their expertise facilitated officer buy-in, as they were able to share their knowledge base surrounding NIBIN and the importance of processing firearms ballistic evidence. Coupled with a shared mission and values, the newly enlisted CGIC team members facilitated the growing success of Denver's CGIC program.

Interviewees overwhelmingly discussed these 'turning points' as crucial moments for the evolution of CGIC. Many of the CGIC team members expressed that these pivotal decisions increased the communication, efficiency, and overall expertise of the CGIC as a whole.

Impact Evaluation Summary

The impact evaluation asked a straightforward question:

Research Question 4:
What were the impacts of CGIC on RAVEN on violent firearm crimes?

We used a research design that showed how CGIC intervened in the pattern of violent crimes used with a firearm. The interrupted time series design is a quasi-experimental approach that allows for control over many of the threats to internal validity that compromise conclusions about interventions. That is, the design is stronger than a simple pre- post-comparison of crime rates or simple regression analyses because it considers a number of variables like time and date of the intervention.

In the analysis, we used citywide segmented negative binomial regression models with robust Newey-West corrected standard errors to estimate the impact of CGIC and RAVEN. We looked at the immediate impact associated with the start of the intervention and the longer-term impact on the trend in crime over time.

Findings from these models indicated that there was an immediate drop in violent crime with a firearm when CGIC began. There was also an immediate drop in robbery when CGIC began, and the start of CGIC was associated with the halting of a pre-existing upwards trend in robbery. Since violent crime with a firearm is a compound measure of several crime types, it seems likely that the impact of CGIC on violent crime with a firearm was predominately due to its impact on robbery with a firearm. There was no observed effect of CGIC on homicide with a firearm or aggravated assault with a firearm. There were no significant effects for RAVEN on any outcome variable, but this may be due to the limited number of post-intervention observations. The coefficient for the intervention was nearly significant in the model for robbery with a firearm and might reach statistical significance after more observations are available.

In order to explore whether the impact of CGIC differed across neighborhoods, a series of multilevel models were examined. The Empirical Bayes (EB) estimates of the impact of CGIC were then mapped to provide a visual depiction of the variance in the impact of CGIC across neighborhoods. Similar to the citywide models, the coefficient for the intervention was statistically significant for violent crime with a firearm, indicating that on average across neighborhoods, violent crime with a firearm decreased when CGIC began. Further, the coefficient for the intervention and the intervention × time interaction were statistically significant in the model for robbery with a firearm, suggesting that across neighborhoods, on average, robbery with a firearm decreased when CGIC began and then the upward citywide trend in robbery was reduced. The EB estimates map revealed an interesting pattern for both models; the impact of CGIC appear to be greatest in low and medium crime neighborhoods, while CGIC was associated with increases in crime in the high crime neighborhoods. This finding may be in part a statistical artifact as a small drop in the number of crime incidents is associated with a large percentage decrease in low and medium crime neighborhoods. However, it is also likely that unmeasured neighborhood effects, such as demographic or social factors may moderate the effectiveness of CGIC in particular neighborhoods.

Limitations

As with any research, several limitations need to be considered when interpreting the key findings.

Within the process evaluation, we did not measure all of the components involved in the use of NIBIN and the subsequent steps that were involved in an investigation. For example, we did not track the investigative follow up, triaging practices, or clearance rates. While firearm-related investigative activity appeared to increase over time, we cannot say whether the CGIC model was directly responsible for an increase in violent firearm crime clearance, faster or more efficient investigations, or higher quality evidence/information. Our interviews indicate that CGIC-involved personnel believe the program has helped in this manner, but we did not measure these outcomes quantitatively.

Another limitation of the present study was our inability to evaluate case outcomes. As noted in the interviews, Denver's CGIC and RAVEN program does not currently track cases that involve charges filed, cases that went to court, and dispositions of the cases themselves.

For the impact evaluation, there were additional limitations. First, it was not possible to assess the impacts of CGIC and RAVEN on communities outside of Denver (e.g., Lakewood, Aurora and other jurisdictions). Further, while the focus of this evaluation has been on firearm crime, it is possible that CGIC had important impacts on other types of crime. Many serious offenders do not specialize in only one or two types of offenses committed (see MacDonald, Haviland, Ramchand, Morral, & Piquero, 2014), and it is possible that removing habitual gun offenders from the community may have impacts on non-gun crime as well.

A second important limitation is the use of the time series design. As discussed previously, the time series design is a strong quasi-experimental design that protects against many threats to internal validity. However, they are vulnerable to the threat of history. This means that events that occur simultaneously cannot be distinguished from the CGIC intervention. The use of a control area or site would have been useful, but because CGIC and RAVEN are regional initiatives, there were no suitable control area available. This means that the threat of history remains a critical concern in the research design.

Implications for Future Research

There is a clear need for additional process evaluations of CGIC sites. The present evaluation was able to glean useful information regarding implementation hurdles from the interviews with CGIC/RAVEN personnel. While some obstacles like training requirements might be unique to Denver, other sites may share common implementation hurdles. CGIC evaluations should attempt to identify these common themes so consistent policies can be developed or improved in early stages of these initiatives. The current study can only to speak to the successes and challenges specific to Denver. More research in this area may assist in determining common obstacles concerning implementation and other related processes. In addition, multisite studies would provide a broader knowledge base for future CGIC programs.

Future process evaluations should consider placing more emphasis on tracking investigation data regarding time to clearance, sentence lengths, quality of evidence, triaging procedures, exceptional clearance, and investigative techniques to develop a clearer picture of CGIC efforts compared to outputs. We strongly recommend incorporating data collection for assessing this aspect of CGIC. To accomplish this without burdening CGIC personnel, researchers should attempt to build early relationships with prosecutor offices (District Attorneys and U.S. Attorneys) to streamline case outcome data collection. Another option is to include these data in NESS with the help of ATF. Information could be collected in a centralized CGIC database for the serviced area, or collected in local jurisdictional databases based upon the incident locations. The present study was not able to obtain information on case-related variables, so this limited our ability to speak to the role of CGIC in improving case quality or case clearance.

While the limitations of this impact evaluation are problematic, it is encouraging that this impact evaluation found a positive impact for CGIC on some types of violent firearm crime. This positive finding suggests that additional research on CGIC is warranted. A key concern is whether the impact of CGIC is generalizable to other jurisdictions. It remains possible that the decreases in violent crime observed in this study are unique to the CGIC program implemented in Denver. The funding provided by BJA for other evaluations of CGIC in other jurisdictions will help toward this goal.

Another recommendation is for future research to investigate further the mechanism of action responsible for producing positive impacts. We identify three main mechanisms that CGIC may lead to crime reductions. First, as intended, CGIC may lead to the collection of additional firearm forensic evidence, which in turn leads to the removal of habitual gun offenders from the community. Second, CGIC leads to additional information sharing and strategic planning towards responding to gun crime among partners. Collaborating agencies may be more likely to coordinate responses to gun crime beyond sharing NIBIN information. Third, establishing a CGIC may help agencies re-orient priorities around apprehending and convicting gun offenders. In this instance, establishing a CGIC represents the beginning of an organizational value-shift that leads to additional resources being spent on addressing gun crime. It is likely that all three processes operate simultaneously, and the impact of CGIC reflects all of these processes. Additional research efforts to model "dosage-response curves" associated with NIBIN usage, to identify the impact of NIBIN information on the likelihood of arrest and conviction, and to estimate the impact of removing habitual gun offenders from the community will help clarify whether the expected mechanism of action is responsible for the reductions in gun crime.

A final recommendation is that additional research is needed to understand the variance in the impact of CGIC strategies across neighborhoods. In the multilevel models, it appeared that the largest impacts for CGIC were observed in the low and medium crime neighborhoods. This suggests that other unmeasured neighborhood factors may be interacting with the impact for CGIC. Collective efficacy (see Sampson, 2004; 2012; Sampson, Raudenbush, & Earls, 1997; Swatt, Varano, Uchida, & Solomon, 2013; Uchida, Swatt, Solomon, & Varano, 2015) is one potential confounding variable. In low collective efficacy neighborhoods with high gun crime, removing several habitual gun offenders may not provide citizens with sufficient safety to foster and develop informal social ties. In neighborhoods with higher collective efficacy and lower average gun crime, apprehending and incarcerating relatively few habitual gun offenders may result in a "tipping point" effect, where gun crime is low enough that community members feel less fearful and start engaging in informal social control. Research on these moderating community factors would be very helpful for understanding the conditions under which a CGIC can be successful.

Recommendations for Future Policy

The main conclusion from this research for future policy is that there is evidence to suggest that Crime Gun Intelligence Centers are associated with tangible reductions in firearm-related violent crime. While a considerable amount of research remains to be conducted, policymakers should consider establishing a CGIC as part of a coordinated response to addressing violent crime. It is also important to recognize that there is considerable variance regarding the types of crimes that are impacted by CGIC and the neighborhoods where CGIC may be effective. For this reason, policymakers should pay particular attention to the nature and location of firearm crime during the development of CGIC.

Prior studies suggest that the main mechanism through which CGIC achieves crime reductions is through the apprehension, prosecution, and removal of chronic offenders within the community. For this reason, the bulk of CGIC operations should focus on identifying and targeting these offenders for prosecution. Cross-jurisdiction coordination and information sharing should yield considerable benefit at apprehending chronic offenders that may operate in adjacent jurisdictions. In that regard, expanding CGIC collaboration to additional local law enforcement agencies, as done with RAVEN, may be beneficial. While the results of the evaluation suggest that the RAVEN expansion of Denver's CGIC did not have detectable effects in the city of Denver, the limited number of post-intervention observations tempers this conclusion. With additional observations and increased statistical power, it is likely that positive impacts will be observed.

Finally, seeing that the impact of CGIC is constrained to particular locations and offenses, policymakers should consider establishing a CGIC as part of a comprehensive strategy for combating gun crime. This may include additional enforcement efforts in high crime communities, as well as social service and community interventions designed to steer potential offenders away from violent crime. A coordinated strategy should also include community outreach efforts designed to increase collective efficacy within neighborhoods to improve informal social control among neighborhood residents to accelerate crime reductions after initial violence reductions are achieved.

ENDNOTES

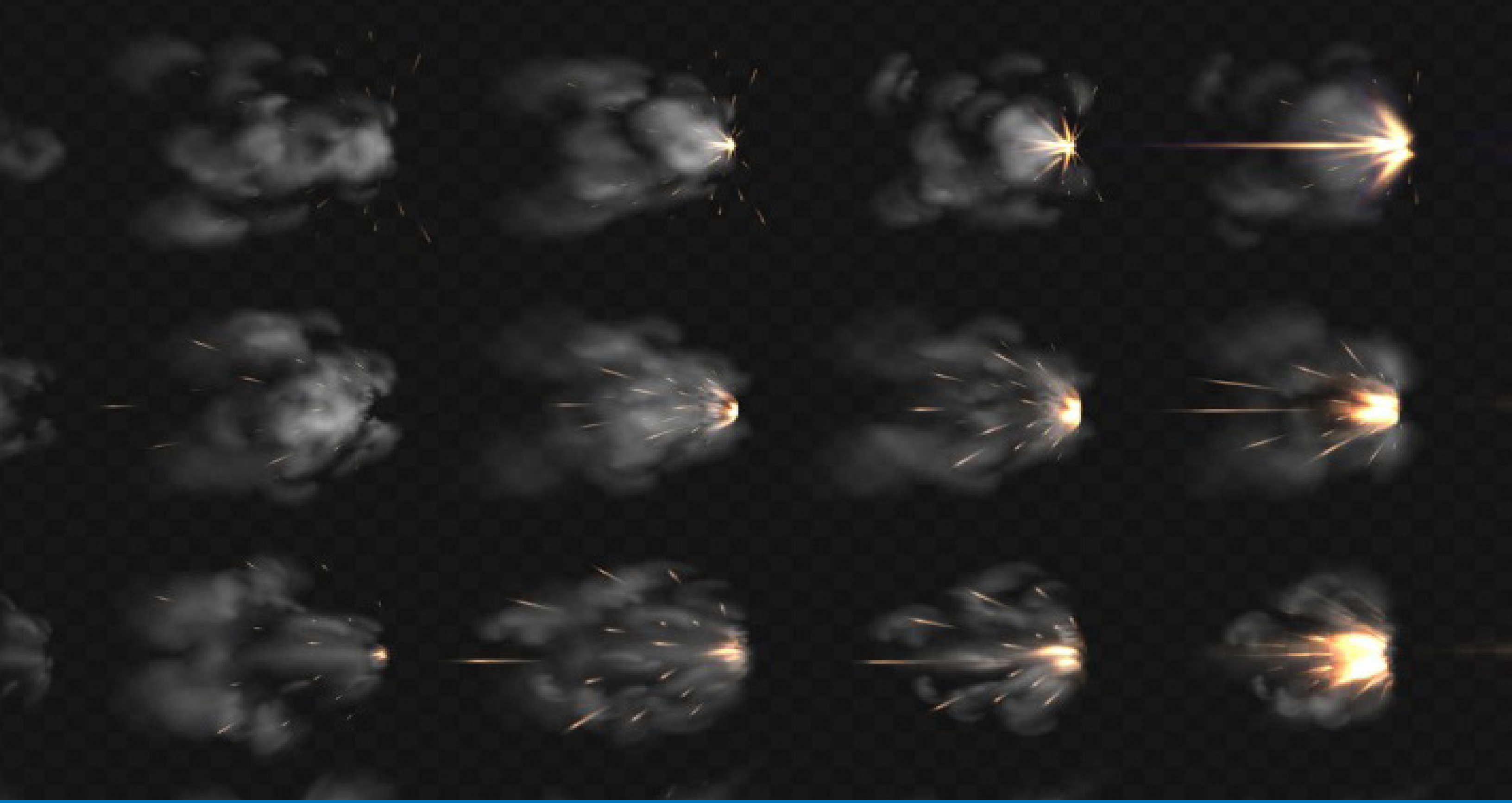
1 See the YouTube video from November 22, 2013 for a discussion that included ATF Supervisory Agent Russell, DPD Commander Mark Fleecs, and Denver District Attorney Mitch Morrissey: https://www.youtube.com/watch?v=I6ssYQBZvFo

2 Incidents involving multiple victims or multiple crimes are disaggregated to ensure that multiple victim incidents were not understated in the final counts.

3 We estimated additional diagnostic models including quadratic and cubic functions for the initial crime trend and found no substantive differences in our results. As such only the models including linear trends are presented.

4 There were some observed impacts in the trends for the total incident counts due to the system change, but these appear to be constrained to simple assaults and other non-serious crime types. We also detected similar impacts for the system change in case clearance, suggesting possible measurement effects of case clearance. For this reason, case clearance by crime type is not included as potential outcomes for the impact of CGIC and RAVEN. To ensure that similar effects did not pollute the measurement of the treatment effect of CGIC, we ran additional models including a dichotomous variable for the system change in July 2013. This dichotomous variable did not substantively alter the conclusions of any of the models and this variable is omitted from the results presented here.

5 One of the reasons that Raudenbush and Bryk (2002) recommend a bottom-up approach is that random effects near zero can cause models to fail to converge or result in other estimation problems.



SECTION 5

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APPENDIX 1:

METHODS AND ANALYSIS STRATEGY

INTRODUCTION

The purpose of this appendix is to provide additional information regarding the methodology and data analysis strategy used to estimate the intervention effects associated with CGIC/RAVEN. The material contained in this appendix is not required to understand the results of the analysis but provides additional details about the methods and analysis strategy for interested readers. Some of this material will overlap with the information included in the technical appendix for the ShotSpotter impact evaluation.

Local Polynomial Graphs

Local polynomial regression models are non-parametric regression models and require very few distributional assumptions about the functional form between the outcome and response variable. These models combine features of other non-parametric models, such as lowess regression models and kernel regression models. The basic specification of this model is that for each observation point a local neighborhood of nearby observations are selected according to the size of the bandwidth of the local polynomial model. The bandwidth is often a user-specified parameter, but Stata 15.0 incorporates a "rule of thumb" bandwidth selection strategy to simplify this parameter. The points lying within the bandwidth receive a weight according to the distance from the center of the local neighborhood – e.g., points nearer to the focal point are given higher weights compared to points that are further away. The exact weight depends on a kernel function, in this case, the Epanechnikov kernel. From these weighted points, a non-linear regression surface is estimated – in this instance, a cubic function is used. Once these local regression models are completed for all points, the resulting regression models are then averaged to produce a smooth response surface between the two variables. Further, this procedure can be used to generate 95% confidence intervals around the smoothed estimate (see Fan & Gijebels, 1996; Fox, 2008; and StataCorp, 2013 for further discussion of this model).

In this analysis, the outcome variables are related to a time variable with a value of 1 at t=1 and increments by 1 each subsequent month. The benefit of this approach is that the local polynomial model yields a smoothed estimate of the time trend for each outcome variable. Prior experience with these models shows that the estimated time trends are responsive to local non-linearities in the data while still providing a sufficiently smoothed trend line that allows for sensible interpretation.

Segmented Regression Analysis

The basic specification for a Segmented Regression model for ITS designs is a regression model that includes an intercept, a variable for time, a variable for the intervention, and a variable representing the interaction between time and the intervention (see Linden, 2015; Ramsay, Brown, Hartman, & Davey, 2003; Shardell, Harris, El-Kamary, Furuno, Miller, & Perencevich, 2007; Wagner, Soumerai, Zhang, & Ross-Degnan, 2002). A visual depiction of the segmented regression approach is illustrated in Figure 1. The intercept (b0) captures the value of the outcome variable at time = 0 and in the absence of a trend can be interpreted as the mean of the outcome variable prior to the intervention. The time variable takes a value of one at the start of the observational period and then increments by one each period thereafter. The coefficient of this variable (b1) captures the linear trend prior to the intervention. The intervention variable takes a value of zero before the intervention and a value of one after the intervention occurs. The coefficient of this variable (b2) captures the immediate increase or decrease associated with the intervention. If the there is no change in trend after the intervention, this variable captures the average treatment effect associated with the intervention. The intervention × time interaction variable takes a value of zero before the intervention and during the initial month of implementation and then increments by one each month thereafter. The coefficient for this variable (b3) captures the change in the trend after the intervention occurs.

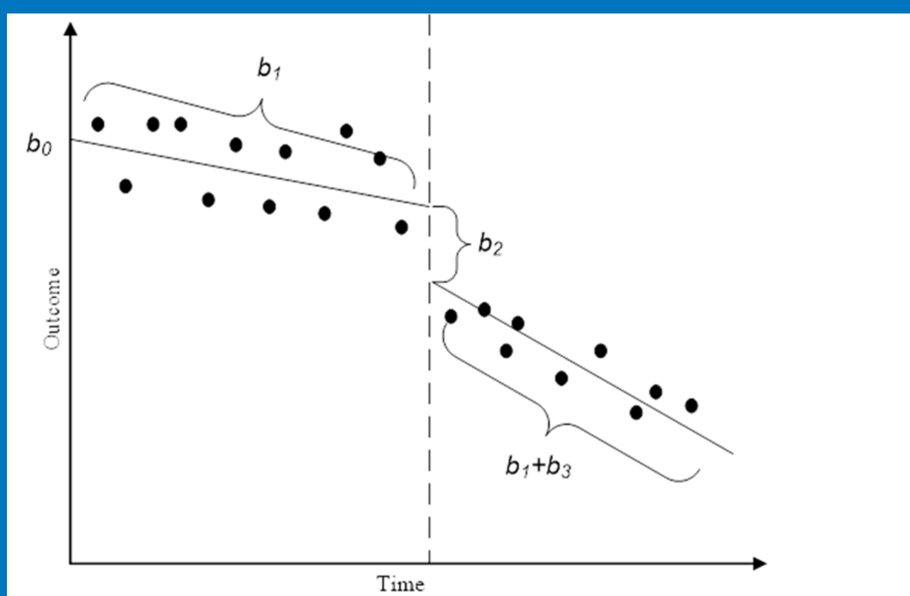

FIGURE 1. REPRESENTATION OF THE PARAMETERS OF A SEGMENTED REGRESSION MODEL

This basic specification is used relating the outcome variables to the intervention variables. This model, however, still does not correct for temporal autocorrelation – where the observations of the outcome remain correlated even after adjusting for relevant covariates. Temporal autocorrelation is so named because observations nearer in time are likely more similar than observations that are more temporally distant.

In this application, temporal dependence is a nuisance and the focus of correcting for temporal dependence is on correcting standard errors rather than formally modeling temporal dependence with ARIMA and related models. For this reason, Newey-West adjusted standard errors are used to remove the impact of temporal dependence (see Linden, 2015). Cumby and Huizinga (1991, 1992) tests for autocorrelation and prior OLS Newey-West models confirmed that the appropriate lag for the Newey-West models is 5 for aggravated assaults with a firearm and 1 for all other models. The computed standard errors from these models are also robust to heteroscedasticity.

Because the dependent variables under investigation represent counts of events, a negative binomial Newey-West model is needed. The negative binomial model is one of a number of distributions related to the Poisson distribution that is specifically designed for count variables. The main difference between the standard Poisson and the negative binomial distribution is that the negative binomial distribution introduces an additional term to control for over-dispersion – when the mean of the Poisson distribution is not equal to its variance (see Cameron & Trivedi, 1998). Following the recommendation of Long and Freese (2014), (exp(b) – 1) can be interpreted as the percentage change in the count of events for a one unit increment in the independent variable.

Multilevel Models

It is also possible that an intervention has different impacts in separate areas of the city. To assess this possibility, the segmented regression approach described above can be embedded within a multilevel model for neighborhoods. Following the multi-equation growth model formulation popularized by Raudenbush and Bryk (2002), the model can be written as follows:

$$\text{Level 1: } y_{ti} = \pi_{0i} + \pi_{1i}Time + \pi_{2i}Intervention + \pi_{3i}Intervention\ x\ Time + e_{it}$$

$$\begin{aligned} \text{Level 2: } \pi_{0i} &= \beta_{00} + r_{0i} \\ \pi_{1i} &= \beta_{10} + r_{1i} \\ \pi_{1i} &= \beta_{20} + r_{2i} \\ \pi_{3i} &= \beta_{30} + r_{3i} \end{aligned}$$

In this model, the π parameters capture the impact of each variable of the segmented regression model. These parameters vary across neighborhoods – meaning that for each neighborhood there is a unique initial level of crime, initial crime trend, impact on crime after the intervention, and impact on the trend in crime after the intervention. The β terms in the second level are the "fixed effects" and represent the mean coefficient for each variable. The r terms are the "random effects" which capture the variance in each parameter across neighborhoods. Each coefficient is assumed to be normally distributed with a variance that is estimated from the data. Through substituting the Level 2 equations into the Level 1 equations, it can be shown that the fixed effects (β00, β10, β20, and β30) are equivalent to the corresponding coefficients in the original segmented regression model (b0, b1, b2, and b3 respectively). While the values for each neighborhood are not directly estimated in the initial model, these can be obtained afterwards using the estimated model and the original data. The most common strategy for obtaining these estimates results in "Empirical Bayes" (EB) estimates which can then be used for other purposes (see Raudenbush & Bryk, 2002, p. 85-94). While the EB estimates have many desirable statistical properties, they may shrink the estimates too much towards the overall parameter means. Further, they may result in inaccurate estimates when the Level-2 models are misspecified. For these reasons, the focus of interpreting the EB is to examine the patterns of effects across neighborhoods rather than directly interpreting the magnitude of the effect.

In terms of estimating this model, Raudenbush and Bryk (2002) recommend a “bottom-up” approach where additional random effects are sequentially added to the subsequent models. This is necessary because random effects with near-zero variances often lead to models that are either unstable or are unable to be estimated. This strategy determined that the random effects for the coefficient for time and the intervention × time interaction effect have variances approaching zero and were unable to be estimated. For this reason, the final models include random effects for only the intercept and coefficient for the intervention. While robust standard errors are used in these models, it is unfortunately not possible to correct for temporal or spatial autocorrelation in these models and it remains possible that these effects distort the estimated standard errors.

As before, the outcome variables are counts of events and an adjustment is necessary. Again, the outcome is modeled using a functional form appropriate for count variables – in this case using a standard Poisson distribution. As Rabe-Hesketh and Skrondal (2012) illustrate, including a random-effects coefficient introduces unobserved heterogeneity into the model and relaxes the requirement that the mean is equal to the variance in Poisson models. The interpretation of these coefficients follows the same strategies as outlined for the negative binomial models.

APPENDIX 2:

INTERVIEW QUESTIONS

Interview Instrument

Denver CGIC/RAVEN

Name ____ **Affiliation** ____________
Rank or Title _______________
Date of Interview ____________
Interviewer _________________

1. When did you begin working on/with CGIC/RAVEN and in what capacity?
    a. How long have you been with your current department/agency?
    b. What was your role in the department prior to CGIC/RAVEN?
2. What is your current role within CGIC/RAVEN? Has that role changed since you started? How?
    a. What is your current assignment? (Other than CGIC/RAVEN)
        i. How long have you been in your current assignment?
        ii. How much of your time is dedicated to CGIC/RAVEN operations?
3. Some programs/technologies can benefit police, but they may also create burdens in the form of extra paperwork, data collection, or inter-department coordination. In your view, is CGIC/RAVEN beneficial overall to your agency?
    a. What investigative/procedural burden(s) existed for firearm-related crime before CGIC/RAVEN that was changed by CGIC/RAVEN?

    b. Have there been any issues with collaboration with other departments/agencies? How do you think these collaboration efforts could be improved?

    c. Are there any current issues that need to be addressed to maximize the benefit of CGIC/RAVEN?

    d. What has been the most beneficial aspect of CGIC/RAVEN?

    e. Was there a particular 'turning point' or 'aha' moment where things improved dramatically?

4. How has CGIC/RAVEN evolved since you have been with the program? Is there anything you would like to see changed? What improvements would you like to see in the future?
5. In your view, what successes or good outcomes have been achieved by CGIC/RAVEN for the local law enforcement community?
6. Tell me about one of your best "success stories" from CGIC/RAVEN.
7. How would you rate your satisfaction with your responsibilities/role in CGIC/RAVEN? (0 to 10 or explanation of what you like/do not like)

8. Can you identify one or two additional personnel involved in CGIC and/or RAVEN that you think we should interview?

ABOUT JUSTICE & SECURITY STRATEGIES, INC. (JSS)

Justice & Security Strategies, Inc. (JSS) is a minority-owned business that specializes in crime and public policy issues, with an emphasis on law enforcement. JSS has conducted applied research for over 23 years.

Dr. Craig D. Uchida is the President and Founder of JSS where he oversees contracts and grants with cities, counties, criminal justice agencies, foundations, and foreign nations. He is a nationally known expert in policing and has conducted numerous studies with law enforcement agencies across the country.

Experience in Applied Research

JSS serves as the Research Partner for a number of law enforcement agencies and community-based organizations across the country. JSS is currently the Research Partner for the Baltimore Police Department (BPD) on its Crime Gun Intelligence Center program. JSS has worked extensively with the Los Angeles Police Department (LAPD) as its Research Partner for over 11 years. Currently, JSS is working with LAPD's homicide detectives to improve the solvability of its cases. In addition, JSS is assisting LAPD with the transition from the UCR data collection system to the National Incident-Based Reporting System (NIBRS) through a BJS grant.

Other JSS work includes a partnership with the Miami-Dade County government to reduce crime in the southern part of the county through collective efficacy; a partnership with the Bronx County District Attorney's Office to enhance the capabilities of the Crime Strategies Unit; and JSS provides training and technical assistance on body-worn cameras to law enforcement agencies through a contract with the Bureau of Justice Assistance.

JSS has worked with more than 75 police agencies across the country since its inception in 1997. The larger departments include Atlanta, Austin, Baltimore, Colorado Springs, Dallas, Fairfax County (VA), Honolulu, Jersey City, Kansas City (MO), Los Angeles, Long

Beach, City of Miami, Miami-Dade County, Minneapolis, Nashville, Newark, Oklahoma City, Phoenix, San Francisco, Seattle, and Washington, DC. Medium-size departments include Cambridge (MA), Concord (CA), Fort Lauderdale (FL), Hialeah (FL), Hollywood (FL), Inglewood (CA), Little Rock, Miami Gardens (FL), Redlands (CA), Salt Lake City, and the US Virgin Islands. Small departments include Everett (MA), Hoover (AL), Somerville (MA), Spartanburg (SC), and Westwood (MA).

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