Appendices

These appendices are provided as a supplement to the 2023 Alternatives to Violence Evaluation: Year One Report prepared by the UNC Charlotte Urban Institute.

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APPENDIX A: LOGIC MODEL

Inputs	Activities	Outputs	Short-Term	Intermediate	Long-Term
The financial & human resources needed to operate the program	How resources are used	Units of service resulting from activities	Changes in awareness, knowledge, attitudes, skills, opinions, motivation aspirations, behavioral intent	Changes in behavior, decision-making, policies, social action, enforcement	Changes in conditions: social well-being, health, educational, economic, civic, environmental, etc.
Funding: Wells Fargo Greenlight Fund City of Charlotte YAP staff Violence interrupters (VIs) Outreach workers (OWs) Community-based partner organizations city and county partners	Hire credible OWs and VIs Staff training Street mediation and violence interruption Community outreach Connect ATV clients to community resources Host community events (i.e. events used to reframe narratives about	# of OWs and VIs hired Trained staff # of participants (OW clients) served by the ATV program # of community members served (other youth or individuals engaged in VI mediations) Demographics of clients (Age, Race/Ethnicity, Geographic location, Time in program) # VI mediations (goal ~15/month) # people involved in mediation # caseloads managed (goal of ~15 total) # individuals assessed for eligibility	ATV participants (OW clients) learn nonviolent conflict skills ATV participants have increased their awareness of community resources Community is aware of ATV activities in the neighborhood	ATV participants apply non-violent approaches to conflict resolution ATV participants form pro-social bonds and relationships ATV participants use community resources ATV participants avoid situations involving risk of violence Community is actively involved in anti-violence efforts	Reduced gun-related violence (fewer shootings and gun-related crime/injuries) Reduced non-gun-related violence (fewer non-gun-related violent crime/injuries) Change in community norms towards violence (anti-violence beliefs & attitudes become normative) Improved public perceptions of neighborhood safety

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Referral partners: HAVI, CMS ATV data partners: CMPD, MCPH, Atrium-HAVI	the community and gun violence) Distribute educational materials to community members Data collection and entry Maintain partnerships with city, county, and community-based organizations Coordination with HAVI	#/% individuals meeting selection criteria #/% eligible individuals enrolled in program Avg. # of meetings/touchpoints per client # clients with appropriate closed-loop referrals in response to their identified needs # hours spent in community # events hosted (goal 1-2/month) # materials distributed # community members reached # individuals referred by partners # city/county partners using CRH # partners own and manage program listings on CRH # partners accepting closed-loop referrals # partners co-hosting community events #/% clients referred to from HAVI			

APPENDIX B: METHODOLOGY

B.1 MIXED METHODS APPROACH

As noted in the introduction of the report, an overarching convergent mixed methods design (e.g., Creswell and Plano Clark, 2018) was used to answer process and outcome evaluation questions, with the primary functions of convergence/triangulation and complementarity (e.g., Palinkas et al., 2019).[1] In the convergent design, the quantitative and qualitative data are collected during similar time frames, and are then often analyzed separately before integration (e.g., Fetters et al., 2013).[2]

Integrating Research Findings

The integration of quantitative and qualitative data is a key element of mixed methods designs. Throughout the evaluation data collection and analysis period, the research team discussed similarities and differences identified across data sources/findings. Following the data collection and analysis of each data source the primary investigators facilitated a working session to identify important ideas and takeaways. This process consisted of research team members reviewing findings from each data source presented on flipcharts, identifying common ideas with sticky notes, and then discussion of meaning and alternative explanations for the findings. Following the working session, the primary investigators reviewed key takeaways for the process and outcome evaluations separately, as well as together to develop discussion and recommendation points for the report.

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[1] Creswell, J. W., & Plano Clark, V. L. (2018). Designing and conducting mixed methods research (3rd ed.). Sage Publications.
Palinkas, L.A., Mendon, S.J., Hamilton, A.B. (2019). Innovations in mixed methods evaluations. Annual Review of Public Health, 40, 423-442. https://doi.org/10.1146/annurev-publhealth-040218-044215
[2] Fetters, M.D., Curry, L.A., & Creswell, J.W. (2013). Achieving integration in mixed methods designs—Principles and practices. Health Services Research, 48(6), 2134-2156. https://doi.org/10.1111%2F1475-6773.12117

B.2 ATV STAFF INTERVIEWS

This appendix provides additional detail about methods used for the ATV Staff Interviews.

Interviews about ATV program implementation and outcomes were administered with ATV staff. Questions were intended to address the general topics of barriers and facilitators of implementation, fidelity of implementation, and perceived program outcomes.

Sampling and recruitment

All ATV staff members (n = 6) were recruited to participate in program evaluation interviews in person with follow-up text messages.

Participants

Five staff members completed interviews. Participants received $25 gift cards for completing the interview. Due to the small sample, we do not share specific demographic information about the ATV staff participants. However, programs modeled from Cure Violence Global try to hire people from the community where the program is being implemented and often have histories of justice involvement, with the aim of having a team credible to members of the community.

Data Collection

Two members of the evaluation team from the UI visited the YAP office in Beatties Ford in October 2022 to conduct semi-structured interviews with the ATV staff team. We were able to interview five of six staff members. Similar constructs in the survey were covered during the interview but were framed to be more open-ended (i.e., frequencies of specific activities were not requested). Generally, we asked staff members to describe how they conducted core activities, as well as barriers and facilitators to those activities. For example, we asked “What would you say have been the biggest challenges in working with the ATV program and carrying out your tasks?” We then added probes for the different core components as needed. We also asked about perceived program outcomes. Interviews lasted from 30 to 60 minutes—the last two were more focused due to time limitations.

Analysis

Our team used an iterative process to conduct thematic analysis. After transcripts were transcribed verbatim, the two researchers that conducted the interviews generated an initial set of codes and categories independently based on a subset of transcripts. Codes were primarily generated inductively. Deductive coding based on descriptions of core components was also utilized in order to address evaluation questions (e.g., fidelity of implementation).

There was significant overlap in initial codes, even with coding different transcripts. Researcher 1 synthesized and collapsed these codes, then added the first draft codebook into MAXQDA (VERBI Software) then applied the codebook to three transcripts. Once Researcher 1 made a few adjustments, a third researcher independently coded one transcript that was already coded. At this point, Researchers 1 and 3 met for two extended working sessions, in addition to email communications, to resolve differences in code application and finalize the codebook. Changes consisted of shifting subcodes to different categories and clarifying code meanings through memos. The main differences in final application consisted of different amounts of text coded due to researcher coding styles.

Throughout this qualitative analysis process, Researcher 1 documented emergent ideas and possible themes. Once the codebook was finalized, Researcher 1 drafted themes based on the coded transcripts. Researcher 3 reviewed themes, and then discussed and refined themes with Researcher 1.

Final themes developed by the researchers were presented to ATV staff for a member checking session. Small clarifications were made according to feedback.

B.3 ATV STAFF SURVEY

This appendix provides additional detail about methods used for the ATV Staff Survey. Surveys about ATV program implementation and outcomes were administered to ATV staff. Questions were intended to address the general topics of barriers and facilitators of implementation, fidelity of implementation, and perceived program outcomes. The survey focused on fidelity of implementation.

Sampling and recruitment

All ATV staff members (n = 6) were recruited to participate in program evaluation interviews in person with follow-up text messages.

Participants

Three staff members completed the survey through Qualtrics survey software. Participants received $25 gift cards for completing the survey. Due to the small sample, we do not share specific demographic information about the ATV staff participants. However, programs modeled from Cure Violence Global try to hire people from the community where the program is being implemented and often have histories of justice involvement, with the aim of having a team credible to members of the community.

Data Collection

Staff members who indicated interest in the survey received Qualtrics links via email or text message in October 2023. Surveys covered fidelity of implementation (FOI) by asking about specific activity frequency based on core activities listed in the scope of work. Surveys also asked about how the staff perceived ATV, community partnerships, program outcomes, and barriers and facilitators generally (open ended). Surveys included approximately 60 items and took about a half hour to complete.

Analysis

Survey responses (n = 3) were first reviewed individually on a case-by-case basis due to the differing program roles of staff members as well as small sample size. Then responses were viewed side-by-side for major differences in responses. No advanced statistical analyses were utilized due to the small sample. We intended to follow up on any major discrepancies across surveys during the interviews, but there were none. Survey responses were used to supplement other findings during integration.

B.4 ADMINSTRATIVE FOCUS GROUP

This appendix provides additional detail about methods used for the Administrative Staff Focus Group.

Sampling and recruitment

Focus group participants (n = 7) were identified through meetings with administrative staff and recruited via email. Focus group participants were selected to participate based on involvement with ATV program implementation decision-making, including initial program adoption and oversight throughout implementation challenges.

Participants

Focus group participants included seven current or former employees of the City of Charlotte, Mecklenburg County, and Youth Advocate Program (YAP).

Data Collection

Prior to the focus group discussion, all participants received study information via email. The discussion took place online via Zoom and lasted for about one hour. The questions addressed: facilitators and barriers of implementation, changes since day one of implementation, sustainment-related constructs (e.g., champions of the program), and perceived impact on the community. These questions were predominantly created based on implementation science literature broadly (e.g., facilitators/barriers) and sustainment literature specifically (Palinkas et al., 2020).[3] One researcher from the Urban Institute ATV evaluation team facilitated the discussion, and another took notes and recorded the discussion.

Analysis

The discussion recording was transcribed verbatim. Two researchers independently coded the transcript, resulting in similar initial codes. The codebook was refined and finalized in MAXQDA. Next, each researcher wrote out main emergent ideas and discussed. Because there was just one focus group, we refer to findings from the focus group as major ideas rather than themes. These ideas were later used in the triangulation processes for more comprehensive understanding of evaluation findings.

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[3] Palinkas, L. A., Chou, C.-P., Spear, S. E., Mendon, S. J., Villamar, J., & Hendricks Brown, C. (2020). Measurement of sustainment of prevention programs and initiatives: the sustainment measurement system scale. *Implementation Science, 15*(1). https://doi.org/10.1186/s13012-020-01030-x

B.5 CURE VIOLENCE GLOBAL (CVG) ADMINSTRATIVE DATA

YAP provided the evaluation team CVG data through the City of Charlotte. The evaluation team analyzed or referenced data from the following sets of forms completed by ATV staff:

- Daily logs
- Interruption follow-ups
- Participant case notes
- Participant goal setting
- Participant intake assessments
- Participant goals
- RNR assessments
- Success stories
- Violence interruptions
- Violent incidents

The evaluation team identified key data points from these data sources, then cleaned and analyzed the data (descriptive statistics). Open-ended notes were used for context to better understand on-the-ground operations of program staff but were not formally analyzed. It is important to note varying degrees of data quality that led to the exclusion of some metrics from reporting.

B.6 CRIME INCIDENTS DATA

This section provides details about the matching methods and difference-in-difference quasi-experimental design used to assess community-level changes in crime.

Matching NPAs

The main report discussed how we utilized eight variables from the Quality of Life (2022) and CMPD Crime Incidents (2022a) datasets to create a representative match on the three NPAs within the treatment (ATV) area. After removing all NPAs classified as being contiguous to the treatment NPAs within the Beatties Ford area, we then perform three standard matching procedures (known as nearest, optimal, and genetic) to determine if a match would run and, if it could, how "close" the NPAs in the corresponding comparison group matched with the treatment NPAs (those in the Beatties Ford area. After finding that the base techniques of nearest and genetic provided the most promising options, we then ran another nearest and genetic match procedure with some changes to the respective models. The nearest procedure is specified to use the glm distance measure and probit link function in addition to setting the ratio at 3 (the number of NPAs to match per NPA for the treatment). The genetic method is specified using the Euclidean distance option, setting the population size at 500, and setting the ratio at 3. The results of these two models can be found in Table B.6.1.

Table B.6.1

Comparing Means of Nearest Neighbor and Genetic Matching Techniques

		Nearest Neighbor			Genetic Matching		
	Treatment	Control	Std. Diff.	Diff.	Control	Std. Diff.	Diff.
VC Rate (2018)	3.135	2.220	0.631	0.916	2.447	0.474	0.689
VC Rate (2017)	3.929	2.471	1.335	1.458	2.486	1.321	1.443
PC Rate (2018)	6.772	6.608	0.031	0.164	7.249	-0.091	-0.477
PC Rate (2017)	7.288	6.374	0.206	0.914	7.141	0.033	0.148
AA Pct.	82.670	69.002	0.931	13.668	77.998	0.318	4.672
Pop. Growth (Pct)	3.544	3.257	0.010	0.287	1.343	0.075	2.200
HH Income	27.179	36.777	-0.445	-9.598	24.278	0.135	2.901
Bachelors (Pct)	8	15.444	-0.492	-7.444	9.667	-0.110	-1.667

The table provides both the standardized (Std. Diff.) and raw differences (Diff.) in means between the treatment and comparison group for the nearest neighbor and genetic matching techniques that returned 3 comparison NPAs per treatment NPA. While it is accepted practice that the difference in standardized means should be around .1 between the treatment and comparison groups, the uneven distribution of the data, specifically the skewed nature of the Beatties Ford NPAs compared to non-treatment NPAs on these measures, means that we are simply looking for the lowest scores as they imply a greater level of closeness between the treatment and comparison groups. Six of the standardized and raw difference scores are lower for the genetic matching technique compared to the nearest neighbor method, illustrating the former should be the preferred method used for the analysis. This is augmented by five of the standardized difference in means scores being either below or close to the .1 threshold discussed earlier.

Why focus on historical crime data?

The first question that may be posed in this selection of variables is why the focus is on historical crime data. The reason for this is two-fold. First, we cannot use variables in the analysis that are also used during the matching process. Therefore, we cannot have more recent crime data (specifically on violent crime), as post-2018 crime represents one of the outcomes of interest. Second, the previous literature notes that it is beneficial for researchers to use up to 60 months of crime data when performing this type of program evaluation.

Why use general crime categories instead of specific crimes?

Another question stems from the use of general crime categories instead of specific crimes (e.g., homicide, aggravated assault). We initially intended to match particular types of crimes, such as rates of homicide and aggravated assault. After creating the dataset, however, it became apparent that some of these violent forms of crime are rare and, consequently, are coded as "missing". Even if we recorded these variables as zero, having no observations for a variable that is supposed to be utilized in the matching process decreases the likelihood that researchers will obtain a satisfactory outcome. To make the matching process as straightforward as possible, therefore, we instead elected to match using the general categories.

The means for matched areas for violent crime aren't very close. Is this a concern?

Some readers may look at the unstandardized difference in means for the violent crime rates and notice that they remain above the preferred .1 difference that was mentioned earlier. The theory of standardization, like many statistical concepts, inherently requires several assumptions that are not met by our analysis, specifically the notion of normality. Put another way, that standard of having a difference equal to or less than .1 implicitly makes the assumption that the data in which you are matching is considered to be normally distributed. This, however, is not the case with our data. For example, the violent crime rate for NPAs within the Beatties Ford area are considered to be in the upper 90^{th} percentile within the dataset and the percentage of African Americans is in the 99.9th percentile. Simply put, the significant skew in the makeup and characteristics of the treatment NPAs means that the standardized difference does not represent a significant issue (though it is certainly something we strived to improve).

Outcomes of Interest

The next step in the process was to create the dataset for analysis. This subsection begins by outlining how we calculated the dependent variables (outcomes of interest) before discussing the primary independent variables of the study (treatment status and time). Similar to the Matching Procedures, these steps represent an overview of the process. The corresponding code can be provided upon request.

Given the violence prevention focus of the ATV program, we utilized four different crime outcomes: aggravated assault with a gun, non-fatal gunshot injuries, homicide with a firearm, and violent crime. Table B.6.2 summarizes outcomes of interest, data sources, and notes from analysis.

Table B.6.2

Variables and Corresponding Datasets for Outcome Variables for the Analysis

Outcome	Data Set	Notes
Aggravated assault (gun)	CMPD, Charlotte Open Data Portal (CMPD, 2022b)	Filtered the category of '"Aggravated Assault-Gun" in the Offense Description variable of the Violent Crime dataset grouped by NPA, month, and year.
Aggravated assault (non-gun)	CMPD, Charlotte Open Data Portal (CMPD, 2022b)	Filtered three variables associated under Aggravated Assault (with a knife, with other weapon, and fists, feet, etc.) in the Offense Description variable of the Violent Crime dataset; summarized by NPA, month, and year.
Non-fatal gunshot injury	CMPD, Charlotte Open Data Portal (CMPD, 2022b)	Filtered the category of '"Non-Fatal Gunshot Injury" in the Offense Description variable of the Violent Crime dataset grouped by NPA, month, and year.
Homicide with a firearm	CMPD, Charlotte Open Data Portal (CMPD, 2022c)	Filtered all homicides that included any type of firearm in the Weapon variable of the Homicide dataset; summarized by NPA, month, and year.
Violent Crime	CMPD, Charlotte Open Data Portal (CMPD, 2022b)	Filtered the category of '"Violent Crime" in the Offense Description variable of the Violent Crime dataset grouped by NPA, month, and year.

Note. After the variables have been created and merged together, we then create standardized rates on all five of these variables in order to run the DiD analyses. The standardized rate is calculated by dividing the count of these offenses by the estimated population in 2020 and then multiplying this number by 500.

We accessed data on homicide with a firearm from the Homicide dataset provided by Charlotte Mecklenburg Police via the City of Charlotte Open Data Portal (CMPD, 2022c). The dataset includes daily counts of all murder and non-negligent manslaughter victims (as defined by the FBI) at the point (address) level. The first issue was to filter the data to only focus on homicides by looking at the weapon variable in the dataset. The second step required us to then aggregate the daily address-level data into something that could eventually be merged with the other variables. We, therefore, elected to aggregate the total number of homicides committed with a firearm to the respective NPA for each calendar month.

The other four outcomes of interest, aggravated assault with a gun, aggravated assaults without a gun, non-fatal gunshot injuries, and violent crime, all use the Violent Crime dataset provided by Charlotte Mecklenburg Police through the City of Charlotte Open Data Portal (CMPD, 2022b). Unlike the previous dataset, which provided daily address-level data, the Violent Crime dataset is updated every month and is already aggregated to three possible levels of analysis: CMPD jurisdiction, Neighborhood Profile Area (NPA), and

Violent Crime Hotspot. Here, the crime categories are broader as they include all of the Part 1 crimes as classified by FBI Uniform Crime Reporting (UCR) standards and include homicide, rape, attempted rape, armed robbery, strong arm robbery, aggravated assault, and violent crime (total violent crime types combined).

The first step in the process was to filter the type of crimes, and this leads us to Aggravated Assaults. Unlike the other crimes in this dataset, there are unique subcategories for specific types of aggravated assaults that a perpetrator could initiate, including using a gun, knife, other weapon, and fists/feet/etc. We elected to use two types of aggravated assaults for our analysis. One with a total count of aggravated assaults without a gun (all subcategories combined except for the gun subcategory) and a more specific measure that only includes aggravated assaults with a gun. Additional filters were performed for Non-Fatal Gunshot Injuries and the total count of violent crime before all four variables were merged by the NPA, calendar month, and calendar year. We then merged this dataset with the Homicide data using the same variables to join (NPA, calendar month, and calendar year) before filtering the resultant dataset to only include the time period between 2019-2022.

The preceding steps resulted in a dataset that included the monthly counts of various crimes of interest over approximately four years. However, the variation in the total population of the NPAs implies that relying solely on counts could lead to misleading results. We, therefore, create a standardized rate on the number of a particular crime per 500 residents within an NPA based on the population in 2020. This was calculated for all the outcomes of interest, and the resulting summary table is provided in Table B.6.3.

Table B.6.3

Summary Statistics on Outcome Variables

	Comparison NPAs (N = 374)				Treatment NPAs (N = 143)			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Aggravated (Gun)	0.843	1.190	0	8.319	0.711	0.911	0	5.217
Aggravated (Non)	0.288	0.403	0	2.510	0.274	0.299	0	1.163
Non-Fatal Gun	0.126	0.252	0	1.425	0.132	0.248	0	1.551
Homicide (Gun)	0.042	0.148	0	1.693	0.044	0.113	0	0.775
Violent Crime	1.439	1.292	0	8.757	1.260	1.016	0	6.421

Independent Variables

The final steps in the process of preparing the data is to merge the resultant crime dataset with the matched dataset and to create a final variable accounting for the implementation of the ATV program. We begin by merging the crime outcomes with the matched dataset created using the procedure discussed both in the main report and at the beginning of Appendix B.6. This represented a straightforward process as we simply matched on the NPA. Treatment status, a binary indicator of whether an NPA is considered part of the Beatties Ford area (coded as 1) or the comparison group (coded as 0), represents the main independent variable.

Table B.6.4

Summary Statistics on Binary Independent Variables

	Comparison (N = 374)		Treatment (N = 143)	
	Count	Percent	Count	Percent
Pre ATV	281	75.13	105	73.43
Post ATV	93	24.87	38	26.57

This brings us to the intervention variable, i.e., the time when the ATV program was implemented in the treatment areas. We create a single binary intervention variable with 0 representing any month prior to September 2021 and 1 representing any month after this date. Importantly, we limit the overall sample to only include 24 months prior to intervention (September 2019) and 12 months after intervention (August 2022). Updated summary statistics on the specific time frame and demarcated by treatment status can be found above. One timeframe to note is when the ATV program experienced significant staff turnover after the initial start to the program. While it is beyond the scope of this analysis to speculate exactly what this entailed or the impact on day-to-day activities within the program itself, it is important to note. A new team was on-boarded the last week of December 2021. Core components were re-implemented in February, 2022, with training taking place prior to this.

Model Selection

We measure the influence of the ATV program (treatment) by utilizing regression analysis, which estimates the relationship between one or more covariates (independent variables) and an outcome of interest (dependent variable). As all the dependent variables are rates, and therefore considered continuous, we can utilize ordinary least squares (OLS) as the base regression model. As we are comparing changes in these crime outcomes before and after the implementation of the ATV program between treatment and comparison groups, we implement Difference-in-Difference (DiD) modeling (Donald and Lang 2007). This analysis determines the impact of treatment by comparing differences in outcomes between treatment and control groups across the time period of study (also referred to as the differential impact of treatment). We run five DiD regression models for the outcomes of interest mentioned above.

Uncertainty represents the final point of consideration; for this, we turned our attention to how to estimate the standard errors for the models. Standard errors represent the average distance between the observed values (the observations we see in the data) and the predicted values from the regression model. Put another way, standard errors allow researchers to ascertain how "incorrect" the predicted values of the coefficients in the model are expected to be from the "true" estimates (Polanitzer, 2021).[4] To this end, there are two primary schools of thought when considering how to estimate standard errors and, consequently, the confidence intervals, after implementing a matching technique. The first method would see us weighting the model and using clustered standard errors while the second method relies on a bootstrapping sampling technique (Liang & Zeger, 1986; Efron & Tibshirani, 1993).[5] While both estimation methods have support within the literature, we chose to bootstrap the standard errors (Austin & Small 2014; Greifer, 2023).[6]

As stated above, we utilize ordinary least squares (OLS) to test whether ATV service areas witness a decrease in crime rates after the implementation of the program. More specifically, we utilize a specialized form of regression known as DiD modeling in order to more explicitly compare the differences in outcomes between treatment and control groups across the time period of study (also referred to as the differential impact of treatment). This brings up an important point on our modeling choice that we expand upon shortly. We use OLS regression as the dependent variables are rates, i.e., continuous. There is the option, however, of keeping the crime outcomes as basic monthly counts. To account for this possibility, we ran five additional regression models using a mixed effects

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[4] Polanitzer, R. (2021, November). *Data science one on one—part 9: Standard errors of coefficients*. Medium. https://medium.com/@polanitzer/data-science-one-on-one-part-9-standard-errors-of-coefficients-ef64079804b9

[5] Liang, K-Y., & Zeger, S.L. (1986). Longitudinal data analysis using generalized linear models. *Biometrika, 73*(1), 13-22. https://doi.org/10.1093/biomet/73.1.13; Efron, B., & Tibshirani, R.J. (1993). An Introduction to the Bootstrap. Chapman and Hall.

[6] Austin, P.C., & Small, D.S. (2014). The use of bootstrapping when using propensity-score matching without replacement: A simulation study. *Statistics in Medicine*. https://doi.org/10.1002/sim.6276; Greifer, N. (2023, March). *Estimating effects after matching*. MatchIt. https://kosukeimai.github.io/MatchIt/articles/estimating-effects.html

negative binomial regression.[7] In addition, the unit of analysis (NPA month) leaves us with a number of missing observations. While it was important to utilize the month level in order to achieve the most robust models possible, there were missing data points for some of the outcomes of interest (specific types of crimes) for particular months that caused our data to be unbalanced, i.e., not every NPA had data on all of the types of crime that we wanted to study. We dealt with this imbalance by utilizing bootstrapped standard errors, but we also include a mixed effects model with random effects at the NPA level to directly address this possible methodological issue.[8]

Regression Models

Table B.6.5

OLS Difference-in-Difference Regression Models on Crime Outcomes

	Assault (Gun)	Assault (Non)	Gunshot	Homicide	Violent Crime
Treatment (ATV)	-0.246	0.022	0.017	0.008	-0.238
	(0.157)	(0.048)	(0.036)	(0.015)	(0.157)
Post-Treatment	-0.239	-0.009	0.012	0.016	-0.199
	(0.132)	(0.055)	(0.027)	(0.015)	(0.154)
Status x Post	0.443	0.001	0.021	-0.040*	0.351
	(0.263)	(0.082)	(0.056)	(0.018)	(0.296)
Intercept	0.974***	0.283***	0.119***	0.026**	1.564***
	(0.105)	(0.026)	(0.018)	(0.008)	(0.106)
Obs. (N)	388	388	388	388	388

Note: Bootstrapped, clustered, standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[7] While we maintain that it is more appropriate to use a standardized rate in lieu of a count for the specific crime types of interest, running the additional regressions constitutes an important robustness check to illustrate that the findings are not an aberration. As can be seen in the Appendix, the overall results do not change in terms of directionality or significance from the OLS regressions.

[8] The overall results did not change between the standard regression model and the mixed level model. Therefore, we include the standard regression model in the main report and the mixed effects model in the Appendix for the interested reader.

Table B.6.5 provides the regression estimates for the five regression models run for this analysis. All models implement a difference-in-difference design to run a linear regression that utilizes three independent variables: a binary indicator to determine if an NPA is within the treatment (ATV) area, the binary indicator that delineates whether the time period is before (0) or after (1) the program was implemented, and finally the interaction between the two. This final interactive effect is the "difference" coefficient, representing the primary point of interest for these models. As discussed in the main report, we only report the interactive term on homicides with a firearm as it is the only coefficient significant at the .05 level. As standard in the social sciences, however, running an OLS regression model with bootstrapped standard errors does not represent the only type of model that can be run for our analysis.

Table B.6.6

Mixed-Level Difference-in-Difference Linear Regression Models on Crime Outcomes

	Assault (Gun)	Assault (Non)	Gunshot	Homicide	Violent Crime
Treatment Status	-0.255	0.020	0.015	0.008	-0.254
	(0.187)	(0.060)	(0.047)	(0.015)	(0.231)
Intervention	-0.229	-0.011	0.012	0.016	-0.189
	(0.154)	(0.069)	(0.024)	(0.010)	(0.114)
Treat x Intervention	0.436	0.004	0.023	-0.040**	0.350
	(0.252)	(0.116)	(0.032)	(0.014)	(0.310)
Intercept	0.982***	0.282***	0.119***	0.026***	1.572***
	(0.170)	(0.034)	(0.011)	(0.005)	(0.185)
RE (NPA)	0.051	0.005	0.001	0.000	0.123
	(0.049)	(0.003)	(0.001)	(0.000)	(0.070)
Obs. (N)	388	388	388	388	388

Note: Robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The next two series of models represent possible alternatives to the main models utilized for this analysis. The first alternative continues to use a linear regression, but this time we employ a mixed-level model that utilizes random effects at the NPA level.[9] Put another way, the first alternative model is a mixed level linear regression model with random effects at the NPA level and robust standard errors. The coefficients for these models are reported in Table B.6.6. As alluded to earlier in this Appendix, moving from a linear regression model to a mixed level model with random effects does not impact the overall conclusion of the analysis. Similar to Table B.6.6, homicides with a firearm remain the only statistically significant outcome at the .05 level. While the significant appears to be of greater magnitude (it is now significant at the .001 level), the coefficient itself and the directionality of the interactive term remain the same between the two models. The other possible alternative is to not transform the crime outcomes into a standardized rate. In other words, we could keep the variables as simple monthly counts instead of creating a rate based on the population of the neighborhood. Using the monthly counts instead of the standardized rate, however, introduces one additional problem.

[9] There is another option of implementing fixed effects at the NPA level (the panel variable). We posit that random effects are more appropriate for this study for an important theoretical distinction: Kreft and De Leeuw (1998) differentiate these concepts by claiming that fixed effects are constant across units while random effects vary. As we do not assume that the influence of the NPAs will be similar, we therefore utilize the multilevel model with random effects at the neighborhood level.

Figure B.6.1

Monthly Counts of Crime Outcomes

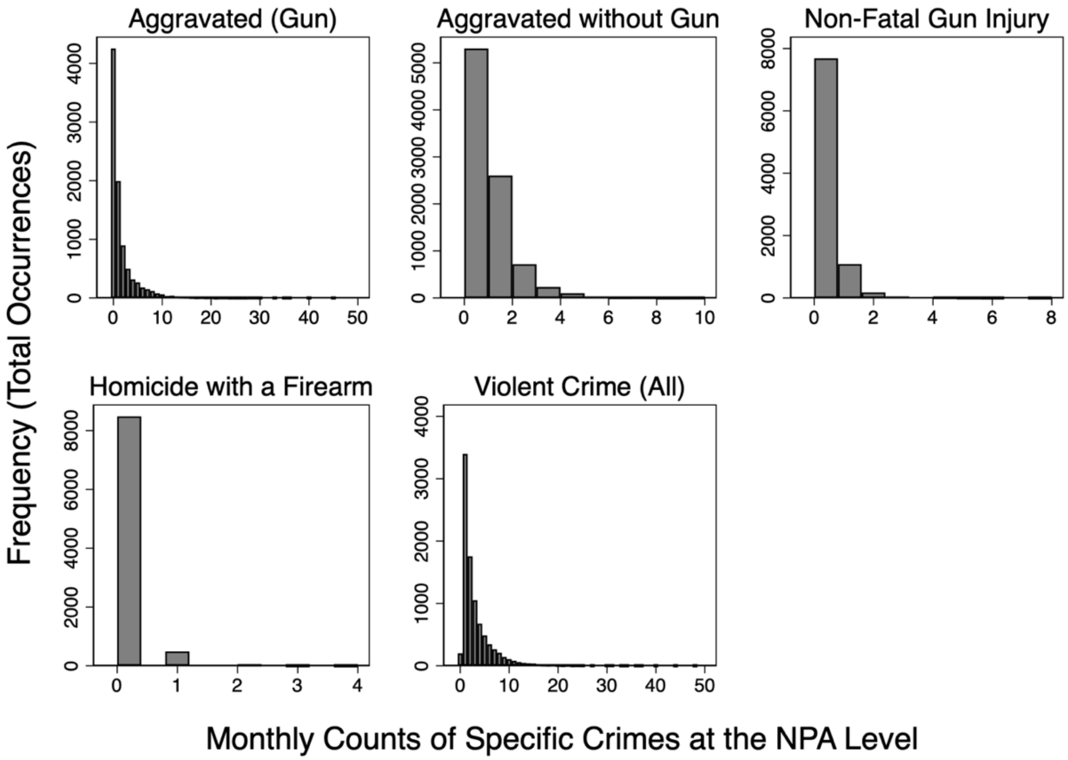

Figure B.6.1 illustrates the skewed nature of the count data across the crime outcomes of interest. Put another way, these figures provide evidence that the data on these dependent variables do not follow a normal distribution. Instead, they are concentrated toward the lower end of the possible number of crimes committed per month. This overdispersion of the data means that we cannot run a basic Poisson regression. Instead, we a mixed level negative binomial regression with random effects at the NPA level with robust standard errors.

Table B.6.7 provides the coefficients for the mixed level negative binomial DiD regression models. As a reminder, the outcome variables are kept as their standard count format instead of transforming them to become standardized rates using the 2020 estimates of the neighborhood population. This table, similar to Table B.6.6, provides support for the original models used in the report. The interactive effect for homicides with a firearm remains the only significant independent variable (once again at the more robust .01 level compared to the .05 level of the original model).

Table B.6.7

Mixed-Level Difference-in-Difference Negative Binomial Regression Models on Crime Outcomes

	Assault (Gun)	Assault (Non)	Gunshot	Homicide	Violent Crime
Treatment Status	0.094	0.370	0.363	0.624	0.171
	(0.303)	(0.373)	(0.525)	(0.593)	(0.302)
Intervention	-0.101	-0.197	0.112	0.580**	-0.081
	(0.149)	(0.216)	(0.204)	(0.216)	(0.064)
Treat x Intervention	0.295	0.135	0.098	-1.648**	0.155
	(0.254)	(0.346)	(0.232)	(0.530)	(0.195)
Intercept	0.891***	-0.287	-1.150***	-2.641***	1.383***
	(0.118)	(0.209)	(0.153)	(0.290)	(0.129)
Alpha	-0.040	-1.216**	-0.243	0.636	-1.394***
	(0.206)	(0.407)	(0.253)	(0.473)	(0.235)
RE (NPA)	0.077*	0.237***	0.234*	0.186	0.129**
	(0.037)	(0.069)	(0.096)	(0.254)	(0.044)
Obs. (N)	388	388	388	388	388
Log-Lik.	-825.008	-494.638	-332.330	-129.554	-937.446

Note: Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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APPENDIX C: HOMICIDE HEAT MAP

This map illustrates the density of homicides with a firearm prior to ATV program implementation, where yellow indicates the highest density.