Estimating the Effects of Safe Streets Baltimore on Gun Violence

2007–2022

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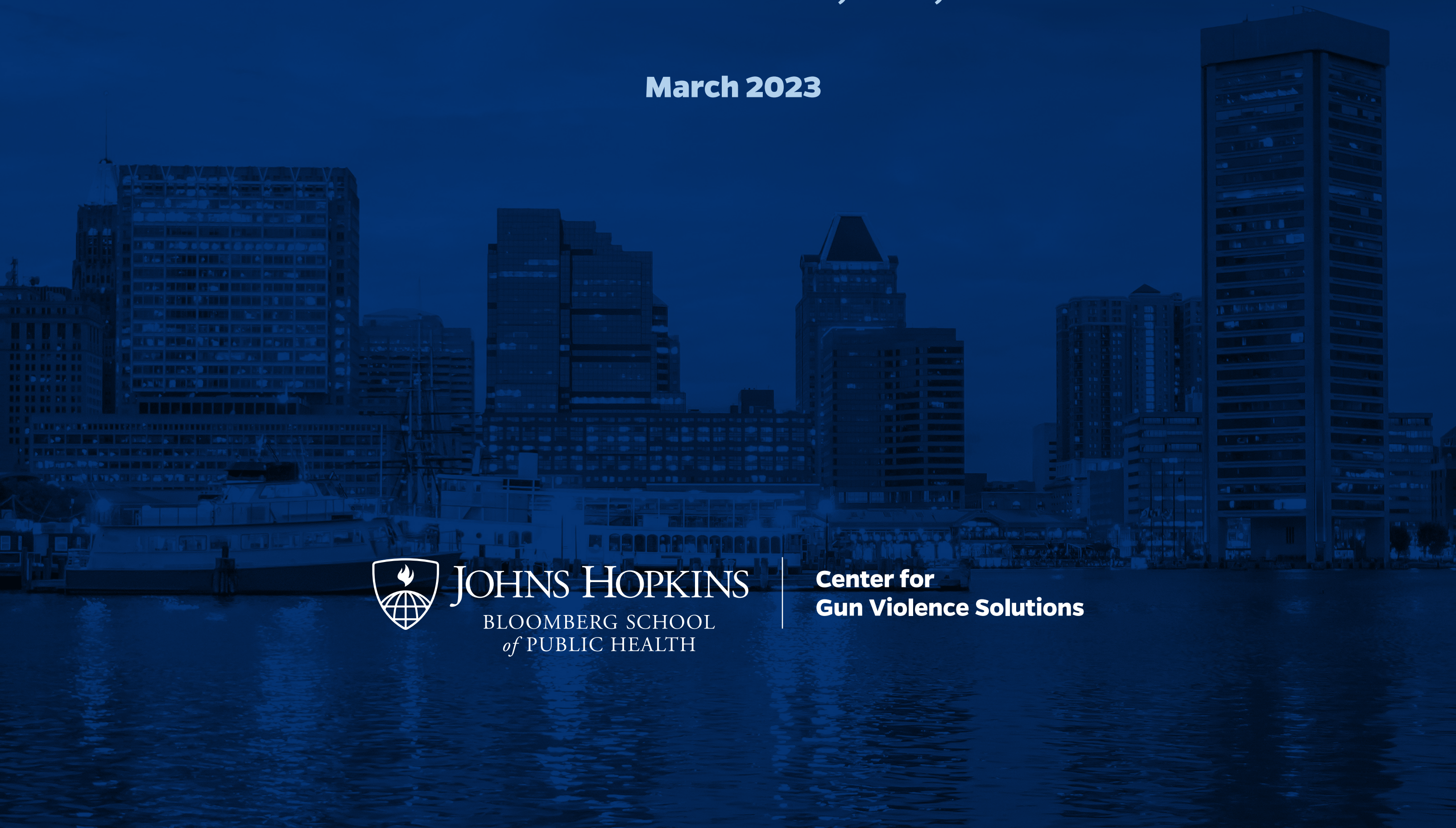

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Executive Summary

Background

Safe Streets Baltimore (Safe Streets) is a community violence intervention (CVI) program designed to reduce gun violence in neighborhoods with high levels of gun violence. Frontline workers are recruited for their ability to connect with individuals at highest risk for involvement in gun violence and mediate disputes, promote nonviolent norms for settling disputes, and connect program participants to services. Baltimore has fully implemented the program in 11 neighborhoods between 2007 and 2021. Six of these sites have been fully operational for less than three years and have not been previously evaluated. Prior evaluations of Safe Streets have shown mixed results across the sites and over time.

Study Methods

To estimate program effects, we analyzed variation in neighborhood-level monthly counts of homicides and nonfatal shootings for the period January 1, 2003 through July 31, 2022. The primary analyses were augmented synthetic control models for each site. This method generated a “synthetic” comparison for each Safe Streets site using a weighted combination of data from neighborhoods that did not implement the program but had similar levels and trends of violence before program implementation. We calculated program effects comparing treated sites to their synthetic controls, estimating what would have happened if Safe Streets had not been implemented. Because confidence in forecasts from statistical models tends to decrease over long periods of time, we generated estimates for the first four years of program implementation for the longer running sites in addition to estimates of the entire time a Safe Streets site has been in operation. We calculated average effects across all sites and within strata of site tenure (longer running and new sites) weighted by the precision of each site’s estimated effects.

Key Findings

During the first four years of program implementation across the five longer-running sites, Safe Streets was associated with a statistically significant average reduction in homicides of 32%. Over the entire study period among these longer-running sites, homicides were 22% lower than forecasted if the program had not been implemented. Three of the five sites had significant reductions ranging from 28% in McElderry Park to 48% in Lower Park Heights. In Sandtown-Winchester, Safe Streets implementation was associated with a significant increase in homicides. Estimates of Safe Streets effects across the six new sites varied with an average reduction of 8% that was not statistically significant.

Over the entire study period across all sites, Safe Streets was associated with a statistically significant 23% reduction in nonfatal shootings. Eight of the 11 sites had program-related reductions in nonfatal shootings. Four sites had significant reductions ranging from 29% in Lower Park Heights to 84% in Franklin Square. Sandtown-Winchester’s site was associated with a 53% reduction in nonfatal shootings over a period of more than seven years.

Conclusions

Safe Streets frontline workers seek to reduce homicides and nonfatal shootings in some of Baltimore's neighborhoods that have long suffered from structural racism, disinvestment, and resulting high rates of gun violence. A rigorous analysis of trends in gun violence provides evidence that Safe Streets has yielded important reductions in homicides and nonfatal shootings in these neighborhoods. Given the extraordinarily high cost of gun violence, we estimate $7.2 to $19.2 in economic benefits for every $1 invested in Safe Streets. Internal reviews of Safe Streets operations, comparisons with CVI programs elsewhere, and current plans to enhance the ecosystem for CVI suggest that there are opportunities to strengthen Safe Streets' ability to consistently produce life-saving effects. Future research designed to tap the experience and insights of Safe Streets frontline workers would enhance such efforts.

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Introduction

Safe Streets Baltimore

Safe Streets Baltimore (Safe Streets) is a community violence intervention (CVI) program designed to reduce gun violence in the most impacted neighborhoods. Safe Streets hires individuals familiar with the communities they serve who often have lived experience similar to the individuals at high risk for gun violence to serve as violence interrupters. Frontline workers and violence prevention coordinators employed by community-based organizations (CBOs) also help to direct program participants to needed services or opportunities that can reduce risks for future involvement in violence.

Safe Streets was first implemented in the East Baltimore neighborhood of McElderry Park in 2007 and was expanded to two neighborhoods adjacent to McElderry Park, Elwood Park and Madison-Eastend, in 2008. Implementation challenges in Elwood Park and Madison-Eastend led to the program being discontinued in those sites in July 2010. Cherry Hill in South Baltimore implemented Safe Streets in January 2009. Sites were later opened in Mondawmin (2012–2016), Lower Park Heights (2013), and Sandtown-Winchester (2016). Mayor Catherine Pugh called for a significant expansion to Safe Streets in 2019 and six additional sites were opened (Belair-Edison, Belvedere, Brooklyn, Franklin Square, Penn North, and Woodbourne-McCabe). Ten current sites account for 2.6 square miles within a 90-square-mile city (Figure 1). While sites are in the parts of the city where shootings are concentrated, many neighborhoods with high rates of gun violence do not have a Safe Streets site.

Prior Research on the Effects of Community Violence Intervention on Gun Violence

Daniel Webster and his colleagues at the Johns Hopkins Bloomberg School of Public Health have been studying CVI programs in Baltimore since Safe Streets' inception in 2007. The first program evaluation was published in 2012 with data on gun violence through 2010 and focused on the first four sites. We used two-way fixed effects (TWFE) regression models for count data. Models estimated program effects based on changes in the number of homicides and nonfatal shootings in areas with Safe Streets contrasted with changes in these measures in neighborhoods without Safe Streets. These models also controlled for measures of the enforcement of gun and drug laws along with other factors.[1] Significant reductions for both measures of gun violence were found for Cherry Hill (56% for homicides, 33% for nonfatal shootings), for homicides in McElderry Park (26%), and for nonfatal shootings in Elwood Park and Madison-Eastend (33% and 44%). But the homicide reductions in McElderry Park were counterbalanced against an increase in nonfatal shootings (22%), and Madison-Eastend's reduction in nonfatal shootings occurred while homicides rose sharply (170%). This basic pattern of estimated program effects remained when extending data through May 2012.[2, a]

Two additional studies of Safe Streets used data through the end of 2017 to estimate program effects on gun violence. One used the same TWFE regression analytic approach that was used in the prior study.[3] The other used the synthetic control method (SCM) that weighted non-program comparison areas based on how well data from those areas predicted gun violence outcomes in Safe Streets neighborhoods prior to the intervention.[4] Neither analytic approach generated clear evidence that Safe Streets was reducing gun violence across seven program sites.

a It is worth noting that the Elwood Park and Madison-Eastend sites did not have the same resources as the other sites: no building within those neighborhoods for outreach workers and violence interrupters to work from and more workers per supervisor. Problems with implementation led the city to discontinue the program in those neighborhoods after 18–24 months.

The most recent studies[3,4] with non-statistically significant reductions in gun violence associated with Safe Streets may be, in part, due to low statistical power and statistical modeling approaches that did not fit the data well. Indeed, survey data from youth in Safe Streets neighborhoods versus comparison neighborhoods suggest that the program was effective in promoting nonviolent social norms.[5,6] Program participants also reported ways in which Safe Streets was helpful to them making needed changes.[5] Therefore, we undertook the current study with 4.5 years of additional data, six additional Safe Streets sites, and the use of the augmented synthetic control method to create comparison units to forecast counterfactuals and estimate program effects. This method adjusts for bias in pre-treatment model fit in synthetic control models. The improved fit translates to more accurate and precise estimates of program effect and increased statistical power.

Other Studies of Community Violence Intervention Programs

Prior studies of CVI program effects in other cities have included many favorable outcomes; however, not all CVI program sites have demonstrated significant reductions in gun violence. Studies of intervention models in Chicago, now known as Cure Violence, found evidence of significant program-related reductions in shootings in four of seven sites studied in a 2009 report.[7] A subsequent study found evidence of reductions in shootings in four additional sites averaging reductions in homicides of 38% and nonfatal shootings of 15%.[8] Findings from an evaluation of Cure Violence programs in Philadelphia also produced encouraging evidence consistent with significant reductions in gun violence in three police service areas and five hot spots for shootings.[9] There have also been studies of a small number of CVI sites in New York City where there was evidence supporting violence-reducing CVI effects and well as positive changes in norms concerning appropriate ways to respond to conflicts and violence.[10] While these studies offer evidence of the promise of CVI programs, the analytic methods used often do not formally test differences in changes between CVI areas and comparison areas. The current study adds to our understanding of CVI effects on gun violence with more advanced statistical methods that formally test whether levels of gun violence changed in response to Safe Streets implementation in each of 11 sites relative to forecasted counterfactuals and the average effects across sites.

Methods

Study Design

We used a comparative interrupted time-series design to estimate program effects on gun violence that contrasts changes in gun violence in 11 neighborhoods that implemented Safe Streets[b] with neighborhoods with high levels of gun violence that did not receive the program. We used augmented synthetic control models (ASCM) with fixed effects as our primary analytic method for estimating program effects on gun violence and log binomial regression models as a secondary method. While we examined each Safe Streets implementation site as an independent intervention and did not assume homogenous effects across sites, we do present average effects on measures of gun violence from August 2007 through July 2022 and measures of variability in program effects.

TABLE 1.

Fully operational start dates for Safe Streets Baltimore sites.

Site	Fully operational start and end M/Y
McElderry Park	8/2007–present
Cherry Hill	1/2009–present
Lower Park Heights	6/2013–present
Sandtown-Winchester	4/2016–present
Mondawmin	7/2012–6/2016
Belair-Edison	11/2020–present
Franklin Square	6/2021–present
Penn-North	11/2020–present
Woodbourne-McCabe	6/2021–present
Brooklyn	6/2021–present
Belvedere	6/2021–present

In this analysis, the unit is the police post (N=142). Not all police posts were eligible to be controls. To facilitate improved pre-intervention trends, the sum of all homicides and nonfatal shootings in all posts across the full intervention period (2003–2022) was calculated, and only the posts in the top 30th percentile (N=44) were eligible to be a control. Posts that received the BPD Violence Reduction Initiative (VRI) intervention, defined as any post where more than two-thirds of the area of the post was in a VRI catchment area, were further removed as a control, leaving 38 posts eligible.

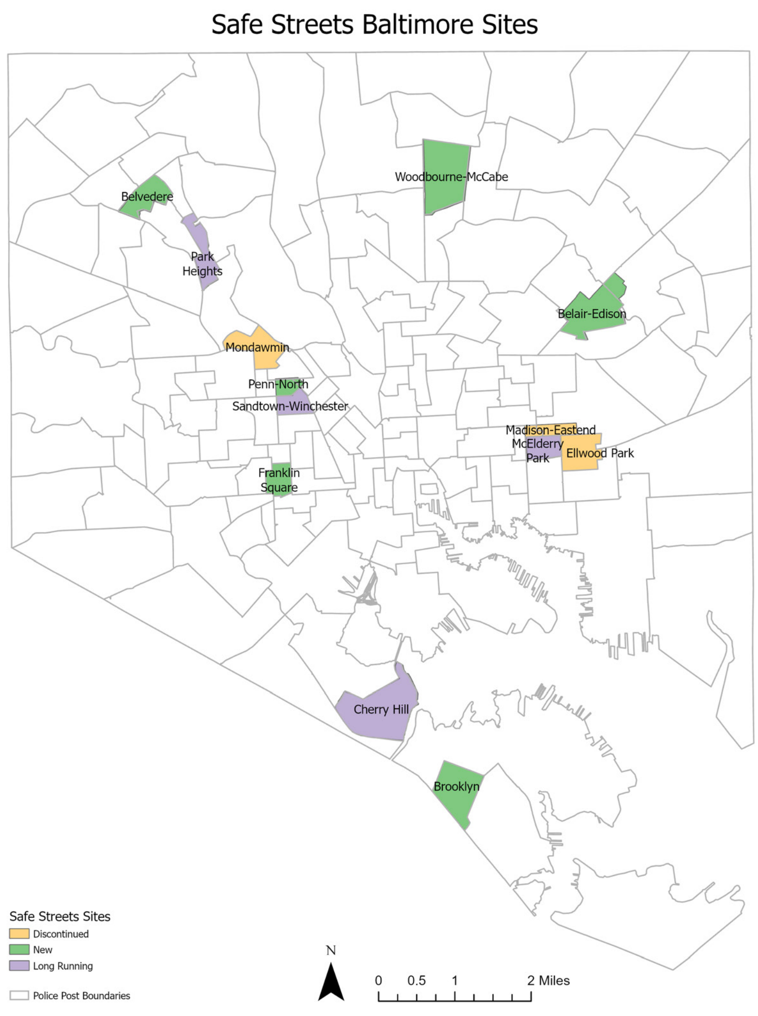
b We examined 10 current Safe Streets sites and the Mondawmin neighborhood site that was implemented July 1, 2012–June 30, 2016. Two sites briefly in place in the early phase of Safe Streets that departed from standard implementation practices, Elwood Park and Madison-Eastend, were not included in the current study.

Data Sources

The primary outcomes were homicides and nonfatal shootings (NFS). Total gun violence was also assessed. Incident level data for these outcomes were obtained from the Baltimore Police Department (BPD) and Open Baltimore (OB). Data on the catchment area of Safe Streets sites and the dates of site implementation were provided by the Mayor's Office of Neighborhood Safety and Engagement (MONSE). The catchment area of most Safe Streets sites was drawn to align with police post boundaries, but there are minor differences between the Safe Streets catchment area and the police post boundaries. Police post boundaries were used because they more reliably include both sides of the main streets bordering Safe Streets sites where gun violence tends to cluster. Two sites, Penn North and Belair-Edison, do not directly align with police posts. To address this, faux police posts were created that represented Safe Streets site boundaries, and changes in outcomes in that area were assessed. Surrounding police posts that the Safe Streets site overlapped with were shrunk to accommodate the new faux posts. Geocoding of point data and aggregation to police post polygons were completed using ESRI ArcGIS Pro 2.8.0.

FIGURE 1.

Map of locations of current and former Safe Streets sites.



Covariates were selected based on prior evaluations of Safe Streets and other violence prevention interventions. Covariates were included in all models to improve model fit and attempt to isolate the impacts of Safe Streets specifically. Incident level data for drug possession arrests, drug trafficking arrests, and weapon possession were obtained from BPD and OB. Additional covariates included violence prevention initiatives led by the BPD that overlapped with the study period: Violent Crime Impact Section zones (VCIS), Violence Reduction Initiatives (VRI), and CeaseFire. These are all hot spot policing initiatives directed at gun violence. Details on the implementation of these initiatives were provided by BPD and MONSE. The East Baltimore redevelopment efforts were included as two covariates, one indicating the area where the redevelopment occurred and one indicating potential extended effects of the redevelopment on posts adjacent to those in the redevelopment catchment area. Details on this redevelopment were obtained from the East Baltimore Development Inc. (EBDI) website.

Measures

Data for all outcomes, exposures, and covariates span from January 1, 2003, to July 31, 2022. Incident level data for arrests, homicides, and NFS were geocoded or mapped to police posts and summed for each BPD post where the incident occurred by month and year during the study period. All other covariates were assigned as binary variables, where the variable was coded as ‘1’ if the intervention was present in that post during that month and ‘0’ otherwise. For newer sites, models were run using two different start dates: the date the site opened and the date the site was considered fully staffed and operational. For older sites, models were run using two different end dates: one censored at four years from implementation and one uncensored. Due to the staggered adoption of Safe Streets, in censored models, Safe Streets sites were eligible to be a control if they were implemented more than four years from the start date of the site being evaluated.

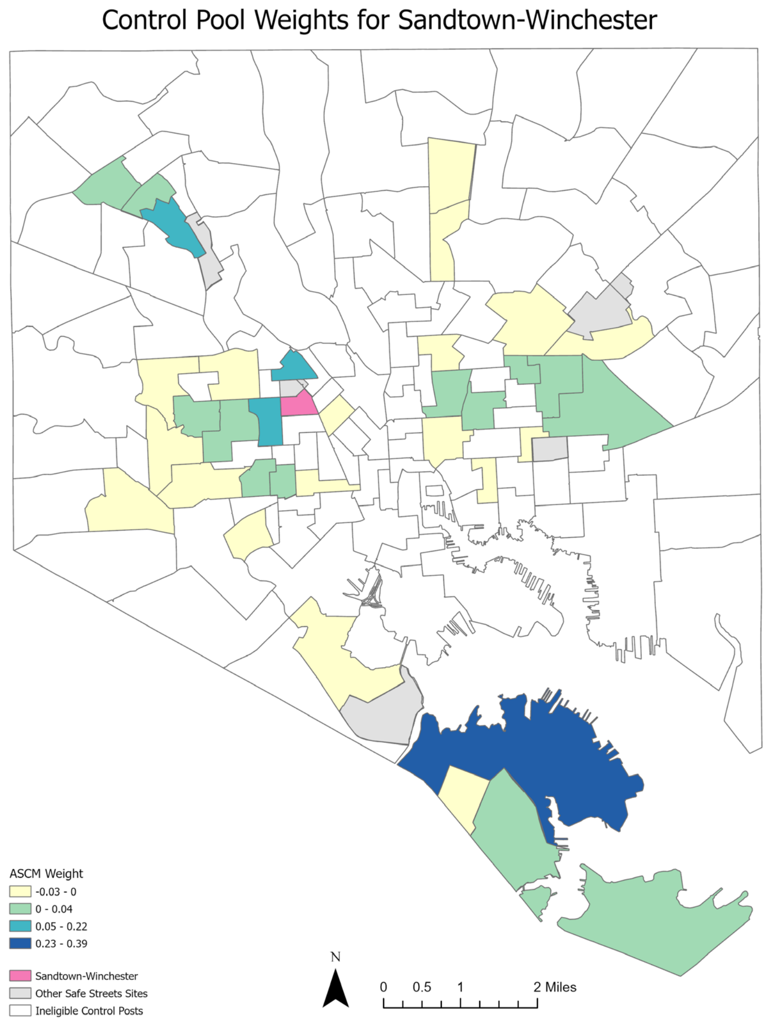
Analytic Strategy

Augmented Synthetic Control Models

Key to accurately evaluating the effects of Safe Streets is finding appropriate control areas to compare outcomes to. This is challenging because Safe Streets is implemented in higher violence areas than non-intervention areas. To try to account for this, ASCM were the primary analysis method used. Synthetic Control Models (SCM) are statistical models used to evaluate the effect of an intervention by comparing the treated unit—in this case neighborhood police post—to a weighted combination of control units. Control unit weights are used to create a synthetic control that most closely matches the pre-intervention trends of the outcome in the treated unit. This weighted combination of controls is known as the synthetic control and is created from what is referred to as a pool of potential controls. SCM are an improvement over interrupted time series analyses as they account for time-varying covariates that co-occur during the pre-intervention period. SCM however are only appropriate when the synthetic unit’s pre-treatment outcomes closely match the treated unit’s pre-treatment outcomes. When it is not feasible to construct a close match, ASCM are an extension of SCM that estimate and adjust for bias in pre-treatment fit. Pre-treatment fit of these models is measured by the difference between the synthetic control’s and the treated Safe Streets’ outcome prior to the intervention, also referred to as the root mean square prediction error (RMSPE), where a smaller number indicates a better fit. Figure 2 provides a map with an example of the weights for police posts serving as controls for the Sandtown-Winchester Safe Streets site.

FIGURE 2.

Example of weights for police posts serving as controls for the Sandtown-Winchester Safe Streets site.



For ASCM, outcomes were modeled as three-month moving averages to smooth out the volatility of homicides and nonfatal shootings, and arrests were modeled as yearly averages. For log binomial regression models, outcomes were not smoothed and arrests were modeled as monthly counts that were lagged by one month. An additional covariate indicating the period after the uprising spurred by the killing of Freddie Gray while in police custody and the increase in homicides and NFS that followed was included in regression models. This variable was coded as ‘1’ for all police posts starting May 2015. Additional interaction variables of the post-unrest variable and arrest variables were also included in regression models to estimate any differences in the effects of drug or weapon arrests on homicides and NFS after the 2015 unrest occurred. These interaction variables were also lagged by one month.

ASCM calculate the average treatment effect, or intervention effect. To interpret these estimates, this value is transformed into a percent change based on the observed monthly average of the outcome prior to Safe Streets implementation. To estimate the average treatment effect of implementing Safe Streets across all sites and implementation periods, we calculated mean effects across all sites and within strata (longer running and new sites) weighted by the inverse of the variance of each site's estimated effects using a random-effects meta-analysis (REMA). We specified a random-effects model to account for differences in implementation and context relevant to gun violence across sites and over time. ASCM analyses and visualizations were performed in R 4.2.1 using the augsynth, meta, and ggplot2 packages.

Log Binomial Regression Models

To supplement ASCM, we used negative binomial regression models to estimate program effects. Negative binomial regression models were used to model over-dispersed count outcomes, meaning the variability in the outcome is greater than the mean of the outcome. This is common for rare outcomes such as homicides and nonfatal shootings (HNFS). Models included fixed effects for police post to control for baseline differences in levels of gun violence, year to control for unmeasured factors that influence yearly trends in citywide violence, and month to control for seasonal cycles in gun violence.

Unlike the ASCM, Safe Streets sites that were implemented later were not eligible to be comparison units in the regression models. Sites were also not removed for exposure to VRI and instead VRI was modeled as a binary covariate coded as '1' if more than two-thirds of the post area was in a VRI catchment area. Models were similarly run using both the start date and full implementation date of the newer sites, but no models were censored at four years from implementation.

The coefficients of the regressions were transformed into incident rate ratios (IRRs) so the results can be interpreted as percentage change in the outcome, similar to ASCM. An IRR equal to 1.00 indicates no effect and IRRs below or above 1.00 can be viewed in terms of percentage change relative to a 1.00. For example, IRR = 0.80 indicates a 20% reduction in shootings associated with an intervention and IRR = 1.20 indicates a 20% increase in shootings associated with an intervention. Data management and log binomial regression analyses were performed in Stata/SE 15.1.

Results

In the five Safe Streets sites that operated for at least four years, the program was associated with statistically significant reductions in homicides in three sites ranging from 28% in McElderry Park to 48% in Lower Park Heights. The estimated 24% reduction in homicides associated with program implementation in Mondawmin approached statistical significance. Sandtown-Winchester's Safe Streets implementation was associated with a significant increase in homicides. Our weighted average of site-specific estimates within the strata of long-running sites indicated an average homicide reduction of 22%. When our models forecasted program effects over just the first four years of implementation within each of the longer running sites there was an average 32% reduction in homicides that was statistically significant (Table 2).

Appendix Figures 1A–22A depict how much lower or higher each measure of gun violence was in each Safe Streets site relative to their synthetic controls for each month over the course of the study period. Vertical lines separate pre- and post-implementation. The pre-intervention period shows how well the model predicted gun violence prior to implementation, and the post-intervention period estimates program effects. For Cherry Hill, the implementation period 2009–2016 shows more consistently lower homicide counts than the predicted counterfactual, but inconsistent effects during 2017–2022 (Figure 2A). Lower Park Heights, in contrast, had consistently lower homicides than the predicted counterfactual for 2015–2022 (Figure 3A). Mondawmin's estimated program effects on homicides was initially in the direction of more homicides in late 2012 and 2013, then shifted to significantly lower homicides than the synthetic control for most of the remaining period the site was open from 2014–2016 (Figure 5A).

Estimates of program effects on homicides per month for the six newer sites are more varied and less precise as evidenced by wide 95% confidence intervals. Penn North's site was associated with a statistically significant 53% reduction in homicides, and Belvedere's site was associated with a 40% reduction in homicides. However, our model estimated Safe Streets implementation was associated with a statistically significant 27% increase in homicides in Brooklyn and an 103% increase in homicides in Belair-Edison. The weighted average of program effects for the six new sites indicated an 8% reduction in homicides that was not statistically significant (Table 2, Figure 3).

Site-specific estimates for Safe Streets' effects on nonfatal shootings varied significantly across sites. One long-running site and three new sites had statistically significant reductions in nonfatal shootings ranging from a 29% reduction in Lower Park Heights to an 84% reduction in Franklin Square. Belvedere was the only site where the program was associated with a significant increase in nonfatal shootings (459%; Table 3). The large estimate suggesting harmful program effect in Belvedere was largely due to a sharp decline in nonfatal shootings in the synthetic control for that site. The weighted average of program effects across longer running sites reveals a statistically significant average reduction in nonfatal shootings of 19%. Among the new sites, the average estimated program effect was also a 90% reduction in nonfatal shootings. The weighted average of program effects across all sites estimated a statistically significant 23% reduction in shootings associated with program implementation (Table 3, Figure 3).[c]

c If Belvedere is dropped from the analysis, the other 10 sites, both old and new, experienced a 27% reduction in nonfatal shootings associated with full program implementation.

TABLE 2.

Augmented synthetic control model estimates for Safe Streets effects on homicides.

Safe Streets Site	Monthly Average During Program	Average Monthly Treatment Effect	95% Confidence Interval	Percent Change
Long-running Sites				
McElderry Park	0.24	**-0.10**	**-0.17, -0.02**	**-28%**
Cherry Hill	0.24	**-0.16**	**-0.29, -0.02**	**-39%**
Lower Park Heights	0.15	**-0.14**	**-0.23, -0.04**	**-48%**
Sandtown-Winchester	0.34	**0.10**	**0.04, 0.16**	**+44%**
Mondawmin	0.29	-0.09	-0.18, 0.00	-24%
Average effects weighted by precision				
Total implementation period	0.25	-0.07	-0.16, 0.03	-22%
Censored at 4 years of implementation	0.21	**-0.10**	**-0.17, -0.03**	**-32%**
New Sites				
Belair-Edison	0.33	+0.17	-0.10, 0.43	+103%
Penn North	0.17	**-0.19**	**-0.32, -0.06**	**-53%**
Woodbourne-McCabe	0.31	-0.06	-0.21, 0.10	-15%
Franklin Square	0.37	-0.08	-0.51, 0.34	-18%
Brooklyn	0.62	**0.13**	**0.01, 0.25**	**+27%**
Belvedere	0.14	-0.09	-0.19, 0.00	-40%
Average effects weighted by precision				
New sites	0.34	-0.03	-0.15, 0.09	-8%
All sites	0.26	-0.05	-0.12, 0.02	-16%

bold indicates statistical significance at $p < 0.05$

TABLE 3.

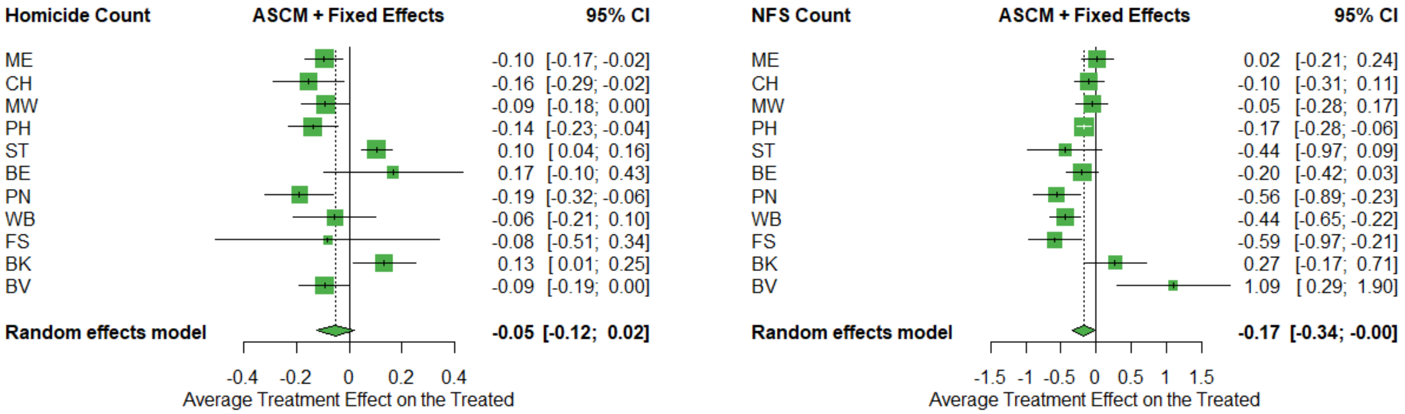
Augmented synthetic control model estimates for Safe Streets effects on nonfatal shootings.

Site	Monthly Average During Program	Ave. Monthly Treatment Effect	95% Confidence Interval	Percent Change
Long-running Sites				
McElderry Park	0.77	0.02	-0.21, 0.24	+2%
Cherry Hill	0.47	-0.10	-0.31, 0.11	-18%
Lower Park Heights	0.41	**-0.17**	**-0.28, -0.06**	**-29%**
Sandtown-Winchester	0.40	-0.44	-0.97, 0.09	-53%
Mondawmin	0.42	-0.05	-0.28, 0.17	-11%
Average effects weighted by precision				
Total implementation period	0.56	**-0.13**	**-0.21, -0.05**	**-19%**
Censored at 4 years of implementation	0.47	**-0.11**	**-0.22, -0.00**	**-19%**
New Sites				
Belair-Edison	0.75	-0.20	-0.42, 0.03	-21%
Penn North	0.54	**-0.56**	**-0.89, -0.23**	**-51%**
Woodbourne-McCabe	0.49	**-0.44**	**-0.65, -0.22**	**-47%**
Franklin Square	0.12	**-0.59**	**-0.97, -0.21**	**-84%**
Brooklyn	0.59	0.27	-0.17, 0.71	+85%
Belvedere	1.33	**1.09**	**0.28, 1.90**	**+459%**
Average effects weighted by precision				
New sites	0.65	-0.15	-0.57, 0.28	-19%
All sites	0.57	**-0.17**	**-0.34, -0.00**	**-23%**

bold indicates statistical significance at $p < 0.05$

FIGURE 3.

Augmented synthetic control model estimates for the site-specific and average overall effects of Safe Streets Baltimore on homicides and nonfatal shootings.



Our estimates of Safe Streets effects on our global measure of gun violence—homicides plus nonfatal shootings—are not based on a sum of the estimates for the models for homicides and nonfatal shootings; they are modeled as a separate outcome. Estimated program effects on total gun violence are more variable and show less evidence of significant program effects than the separate models for homicides and nonfatal shootings (Appendix Table 1A). Model prediction error, measured by RMSPE, was also greater for the sum of homicides and nonfatal shootings than for each separate component for 10 of the 11 sites (Appendix Table 2A).

Estimates of program effects in the newest Safe Streets sites were sensitive to the date of implementation used in the models. The models above used the dates when the sites were deemed to be fully operational. In models that used the dates sites were first opened, estimated program effects for the new sites were all in the positive direction (12% to 21% more acts of gun violence than the synthetic control forecasted); however, these increases were not statistically significant (data not shown).

Our secondary method of estimating the effects of Safe Streets on gun violence using log binomial regression generated aggregate effect sizes in the general range of those generated from the random effects model of the site-specific ASCM (Table 4). In the regression models, Safe Streets implementation was associated with a non-significant 10% reduction in homicides and statistically significant reductions of 23% for nonfatal shootings and 18% in total gun violence (HNFS). Models that estimated each site's effects independently generated program effect estimates with wide confidence intervals with varying consistency with the estimates generated by the augmented synthetic control models especially for the six new sites (Appendix Tables 3A–5A). Regression models indicated that Cherry Hill and Lower Park Heights were sites that had the most certain positive impact in reducing gun violence. Program effect estimates for Sandtown-Winchester and Franklin Square on nonfatal shootings approached statistically significant declines.

TABLE 4.

Log binomial regression estimates for the aggregate impact of Safe Streets Baltimore (SSB) on each measure of community gun violence.

	IRR (% change)	95% CI IRR (% change)	p value
Homicides	0.899 (-10%)	0.701, 1.141 (-30%, +14%)	0.381
Nonfatal shootings	**0.768 (-23%)**	**0.645, 0.915 (-36%, -8%)**	**0.003**
Total gun violence	**0.822 (-18%)**	**0.709, 0.952 (-29%, -5%)**	**0.009**

bold indicates statistical significance at $p < 0.05$

Discussion

The current study built upon prior evaluations of Safe Streets by examining data through July 2022, generating estimates of initial program effects in six new sites and employing new statistical methods to generate more precise and accurate estimates of program effect than were used in prior evaluations. Our findings support the hypothesis that Safe Streets Baltimore has reduced homicides and nonfatal shootings over the many years the program has operated in some of Baltimore's most under-resourced neighborhoods. The average reductions ranged from 16% to 23% with larger reductions in homicides during the first four years of the longer running sites.

While the overall pattern of findings is very encouraging, implementation of Safe Streets in each neighborhood that has long struggled to curtail gun violence did not always lead to fewer shootings. During some times and places, program implementation is associated with increases in gun violence or long stretches of no program effect. Particularly noteworthy were the delays in getting all six new sites fully staffed and operational and disappointing program outcomes in those sites during 2019–2020. There is some evidence that program effects in reducing homicides may have waned in some long-running sites (e.g., McElderry Park) after four or more years of implementation.

While there are many strengths to this study, we acknowledge limitations that are common in evaluations of community violence intervention programs. First, neighborhoods were not selected at random for program implementation; thus, selection bias could confound estimates of the program's causal effects. We used ASCM for site-specific estimates that generate weights for data from untreated neighborhoods that minimize prediction error to generate counterfactuals upon which to estimate program effects. These models generally performed well and generated estimates with smaller confidence intervals than was the case for the regression models. Model fit was better for long-running sites than for newer sites.

Second, as with all studies of this type, our research design and statistical models assume that Safe Streets effects will be limited to the neighborhoods where workers are assigned. But conflicts between individuals and groups commonly cut across neighborhood boundaries, and mediations or other program activities geared toward promoting nonviolence may have violence-reducing effects in other neighborhoods. This may bias estimates of program effects toward the null. We also did not have individual-level data for program participants, those with whom violence interrupters regularly engaged. Our prior research that included anonymous interviews with Safe Streets participants revealed many ways in which Safe Streets supported their efforts to reduce their risks of violence through job opportunities, access to social services, and assistance with mediating conflicts.[5]

Third, the evaluation team did not have access to program implementation data on staffing levels, worker pay, training, dismissals of workers, or changes in supervisors and site directors over the course of the study period. Our analyses, therefore, do not measure the relationship between program capacity, implementation metrics, and gun violence outcomes. A recent internal evaluation of Safe Streets identified many problems that have likely weakened program effectiveness over the years. These included high staffing turnover, persistent vacancies at some sites, low salaries of workers ($40,000–$45,000 for violence interrupters), gaps in worker training, and weaknesses in program oversight. Most workers worry about losing their jobs due to uncertainties in program funding and experience significant trauma witnessing or being a victim of violence.[11] Workers went without cost of living raises for many years. Tragically, three Safe Streets workers were murdered over a span of 14 months in 2021 and 2022. These conditions may contribute to the difficulty in recruiting and retaining staff and may contribute to some workers occasionally engaging in criminal activities that damage the credibility of the program. There has been increased attention to the importance of investing in and supporting frontline community violence intervention workers with pay increases, support for dealing with trauma, better training, and career counseling. In addition to program implementation and staff support challenges, little is known about how factors such as different neighborhood conditions or violence dynamics may impact Safe Streets' ability to reduce gun violence. More research is needed to better understand what policies, practices, and conditions enhance or weaken community violence intervention program implementation effectiveness in Baltimore and in other cities.

In addition to these significant program implementation challenges, Safe Streets has had relatively modest City investment in the program over the course of the 15 years Safe Streets Baltimore has been in existence. The task of preventing gun violence is daunting in neighborhoods long suffering from structural racism and public and private disinvestment in a city with deep problems in policing. Baltimore is still scarred from the in-custody killing of Freddie Gray, the uprising it spurred, the wide-scale corruption of BPD's Gun Trace Task Force, and the persistent police abuses highlighted in the U.S. Department of Justice's Consent Decree. A convergence of social and economic forces including historic increases in gun purchases and the growing availability of privately made firearms (a.k.a., "ghost guns") to underage youth and other prohibited persons have led to a surge of gun violence in most cities in the U.S. Given these challenges, it is remarkable that Safe Streets appears to have reduced gun violence by 23%. It is reasonable to expect increased and more consistent violence-reducing effects of Safe Streets with stable funding, increased investment in workers, improved oversight, and increased access to critical services and supports for individuals to step away from violence.

Gun violence has taken an enormous toll on Baltimore City for decades cutting lives short, leaving entire communities traumatized, and greatly weakening the local economy. Because of the stark racial disparities in gun violence and incarceration, programs such as Safe Streets that work to reduce violence through non-incarceration approaches promote health equity and social justice. Additionally, a recent study estimated that the social and economic costs of gun violence in the United States translate to approximately $4.8 million for every person shot.[12,d] Another approach used by economists based on citizens' stated willingness to pay taxes for efforts to reduce gun violence results in a cost estimate of $1.8 million for every shooting in 2022 dollars.[13] Baltimore City, state, and federal governments have allocated between $500,000 and $750,000 per year per Safe Streets site over the course of the program. The estimated three shootings prevented (one fatal and two nonfatal) per Safe Streets site per year suggests social and economic benefits of $7.2 to $19.2 per every dollar spent on the program, depending on the method used to estimate the costs of shootings.

d The study estimated annual costs of $557 billion for gun violence resulting from approximately 40,000 deaths and 76,000 persons who are shot but survive.

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Appendix

Table 1A. Augmented synthetic control model estimates for the impact of Safe Streets Baltimore (SSB) on total gun violence (homicides plus nonfatal shootings).

Safe Streets Site	Monthly Average During Program	Average Monthly Treatment Effect	95% Confidence Interval	Percent Change
Long-running Sites				
McElderry Park	1.01	0.08	-0.14, 0.30	+9%
Cherry Hill	0.71	-0.22	-0.81, 0.37	-23%
Lower Park Heights	0.57	-0.32	-0.71, 0.06	-36%
Sandtown-Winchester	0.73	-0.55	-1.53, 0.44	-43%
Mondawmin	0.72	-0.03	-0.37, 0.30	-5%
Average effects weighted by precision				
Total implementation period	0.80	-0.08	-0.29, 0.12	-9%
Censored at 4 years of implementation	0.68	-0.12	-0.28, 0.04	-15%
New Sites				
Belair-Edison	1.08	-0.24	-0.53, 0.06	-18%
Penn North	0.71	**-0.80**	**-1.18, -0.43**	**-53%**
Woodbourne-McCabe	0.79	**-0.75**	**-1.05, -0.44**	**-48%**
Franklin Square	0.49	-0.22	-0.62, 0.18	-31%
Brooklyn	1.21	**0.26**	**0.09, 0.42**	**+27%**
Belvedere	1.47	**0.61**	**0.16, 1.05**	**+70%**
Average effects weighted by precision				
New sites	0.99	-0.19	-0.63, 0.24	-16%
All sites	0.83	-0.18	-0.43, 0.08	-18%

bold indicates statistical significance at $p < 0.05$

Table 2A. Model fit measured by Root Mean Squared Prediction Errors (RMSPE) for each site-specific augmented synthetic control model for monthly homicides, nonfatal shootings, and total gun violence (homicides plus nonfatal shootings).

Safe Streets Site	Homicides	Nonfatal Shootings	Total Gun Violence[1]
McElderry Park	.2047	.3724	.3985
Cherry Hill	.2095	.4278	.3578
Mondawmin	.2036	.3435	.3513
Lower Park Heights	.1389	.2501	.3252
Sandtown-Winchester	.1584	.3042	.3943
Belair-Edison	.2361	.5395	.6031
Penn North	.3168	.5357	.6723
Woodbourne-McCabe	.3385	.4587	.6504
Franklin Square	.2762	.5730	.6350
Brooklyn	.2891	.3858	.4730
Belvedere	.3165	.5313	.6360

Table 3A. Log binomial regression estimates for the impact of Safe Streets Baltimore on homicides.

Safe Streets Site	IRR (% change)	95% CI (% change)	p value
McElderry Park	0.69 (-31%)	0.38, 1.24 (-62%, +24%)	0.215
Cherry Hill	**0.57 (-43%)**	**0.34, 0.97 (-66%, -3%)**	**0.039**
Lower Park Heights	0.73 (-27%)	0.39, 1.37 (-61%, +37%)	0.329
Sandtown-Winchester	1.33 (+33%)	0.77, 2.32 (-23%, +132%)	0.310
Mondawmin	1.25 (+25%)	0.65, 2.39 (-35%, +139%)	0.500
Belair-Edison	1.00 (0%)	0.44, 2.27 (-56%, +127%)	0.992
Penn North	0.84 (-16%)	0.30, 2.38 (-70%, +138%)	0.745
Woodbourne-McCabe	1.21 (+21%)	0.48, 3.07 (-52%, +207%)	0.686
Franklin Square	1.41 (+41%)	0.56, 3.58 (-44%, +258%)	0.468
Brooklyn	2.11 (+111%)	0.95, 4.67 (-5%, +367%)	0.066
Belvedere	0.50 (-50%)	0.12, 2.06 (-88%, +106%)	0.334

bold indicates statistical significance at $p < 0.05$

Table 4A. Log binomial regression estimates for the impact of Safe Streets Baltimore on nonfatal shootings.

Safe Streets Site	IRR (% change)	95% CI (% change)	p value
McElderry Park	1.00 (0%)	0.69, 1.47 (-31%, +47%)	0.986
Cherry Hill	**0.66 (-34%)**	**0.46, 0.97 (-54%, -3%)**	**0.033**
Lower Park Heights	**0.55 (-45%)**	**0.34, 0.87 (-66%, -13%)**	**0.011**
Sandtown-Winchester	0.63 (-37%)	0.39, 1.02 (-61%, +2%)	0.058
Mondawmin	1.10 (+10%)	0.65, 1.86 (-35%, +86%)	0.729
Belair-Edison	0.98 (-2%)	0.51, 1.86 (-49%, +86%)	0.947
Penn North	0.94 (-6%)	0.46, 1.91 (-54%, +91%)	0.867
Woodbourne-McCabe	0.80 (-20%)	0.33, 1.88 (-67%, +88%)	0.605
Franklin Square	0.25 (-75%)	0.06, 1.03 (-94%, +3%)	0.055
Brooklyn	0.90 (-10%)	0.38, 2.10 (-62%, +110%)	0.804
Belvedere	1.54 (+54%)	0.81, 2.96 (-19%, +196%)	0.188

Table 5A. Log binomial regression estimates for the impact of Safe Streets Baltimore on total gun violence (homicides plus nonfatal shootings).

Safe Streets Site	IRR	95% CI	p value
McElderry Park	0.95 (-5%)	0.68, 1.33 (-32%, +33%)	0.779
Cherry Hill	**0.66 (-34%)**	**0.48, 0.91 (-52%, -9%)**	**0.012**
Lower Park Heights	**0.62 (-38%)**	**0.42, 0.91 (-58, -9%)**	**0.015**
Sandtown-Winchester	0.87 (-13%)	0.58, 1.23 (-42%, +23%)	0.380
Mondawmin	1.19 (+19%)	0.79, 1.81 (-21%, +81%)	0.423
Belair-Edison	0.96 (-4%)	0.56, 1.65 (-44%, +65%)	0.893
Penn North	0.97 (-3%)	0.54, 1.73 (+46%, +73%)	0.907
Woodbourne-McCabe	0.90 (-10%)	0.45, 1.79 (-55%, +79%)	0.753
Franklin Square	0.45 (-55%)	0.16, 1.24 (-84%, +24%)	0.122
Brooklyn	1.20 (+20%)	0.64, 2.26 (-36%, +26%)	0.574
Belvedere	1.25 (+25%)	0.69, 2.27 (-31%, +127%)	0.470

bold indicates statistical significance at $p < 0.05$

The vertical dotted lines in Figures 1A–22A indicate Safe Streets implementation dates.

Figure 1A. Difference between McElderry Park's augmented synthetic control for homicides and a 3-month moving average for homicides in McElderry Park.

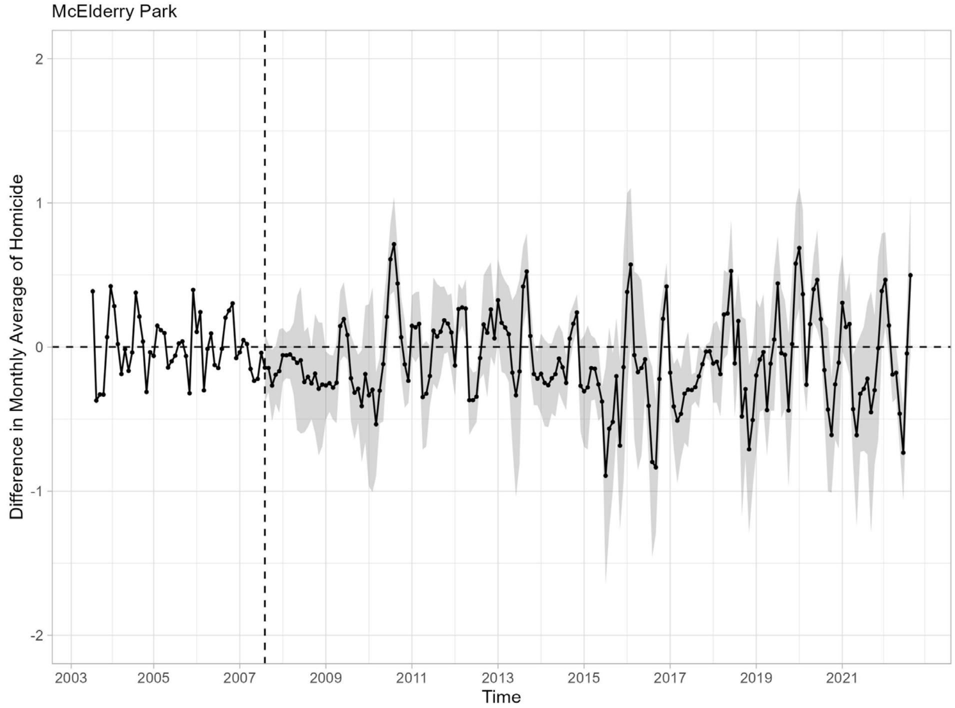

Figure 2A. Difference between Cherry Hill's augmented synthetic control for homicides and a 3-month moving average for homicides in Cherry Hill.

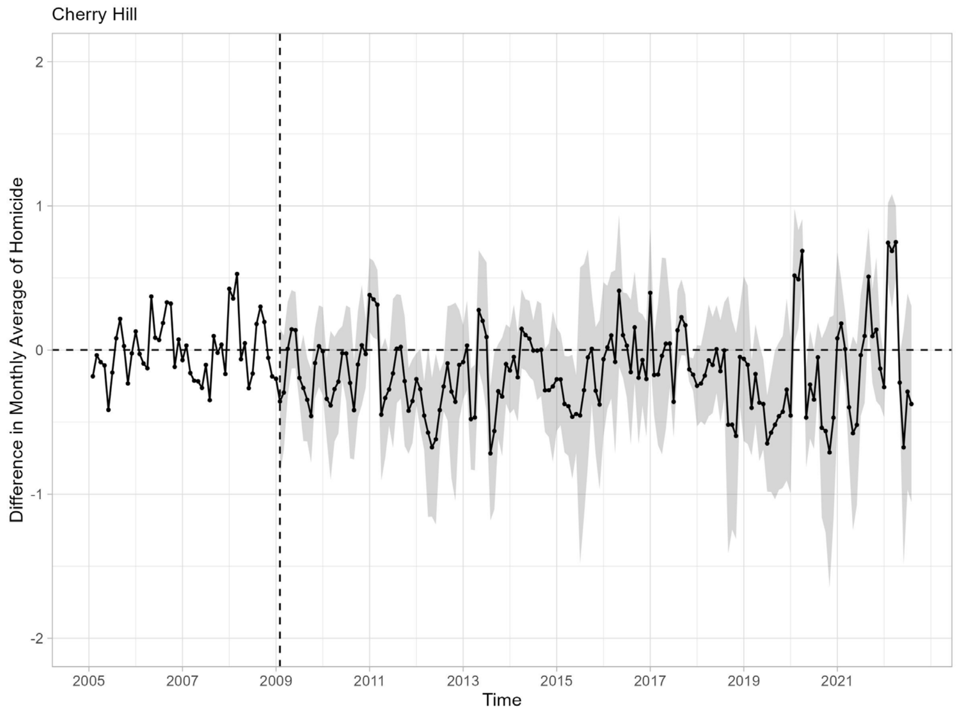

Figure 3A. Difference between Lower Park Heights' augmented synthetic control for homicides and a 3-month moving average for homicides in Lower Park Heights.

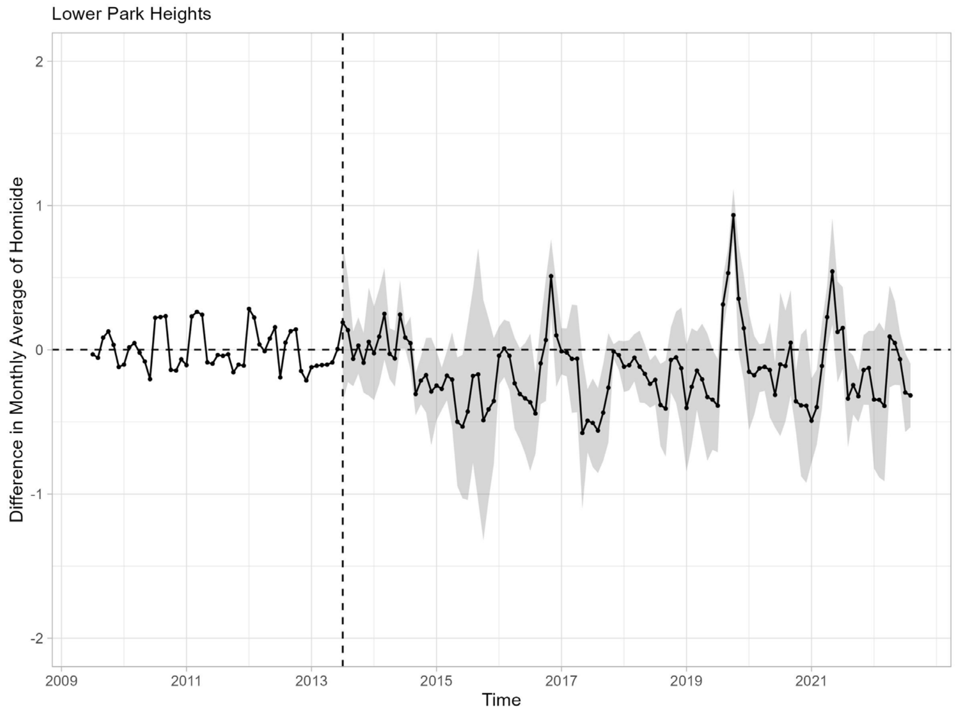

Figure 4A. Difference between Sandtown-Winchester's augmented synthetic control for homicides and a 3-month moving average for homicides in Sandtown-Winchester.

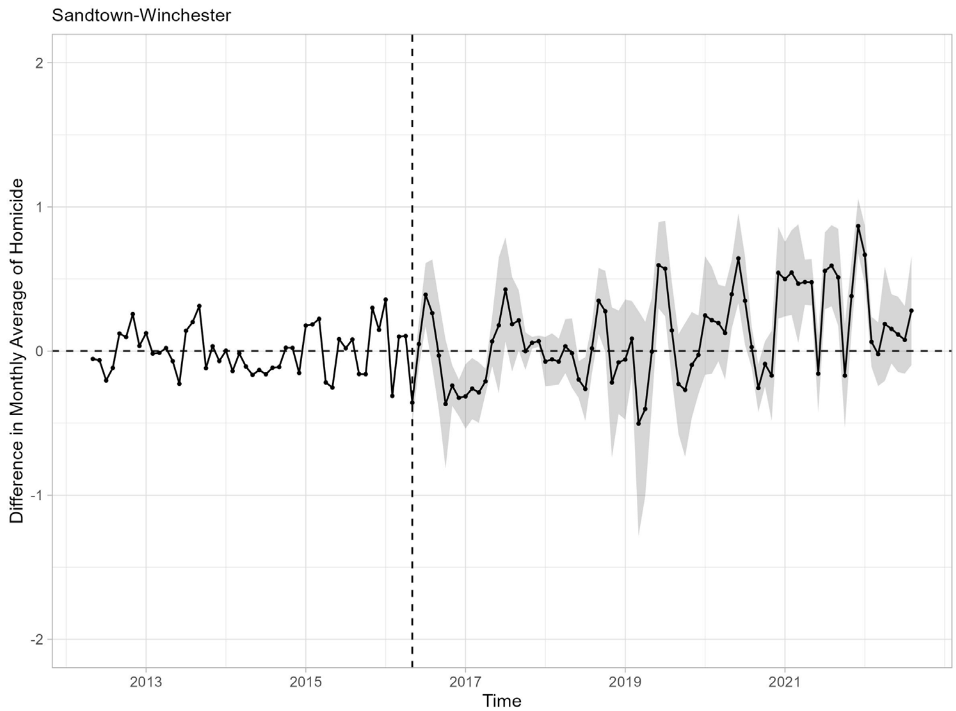

Figure 5A. Difference between Mondawmin's augmented synthetic control for homicides and a 3-month moving average for homicides in Mondawmin.

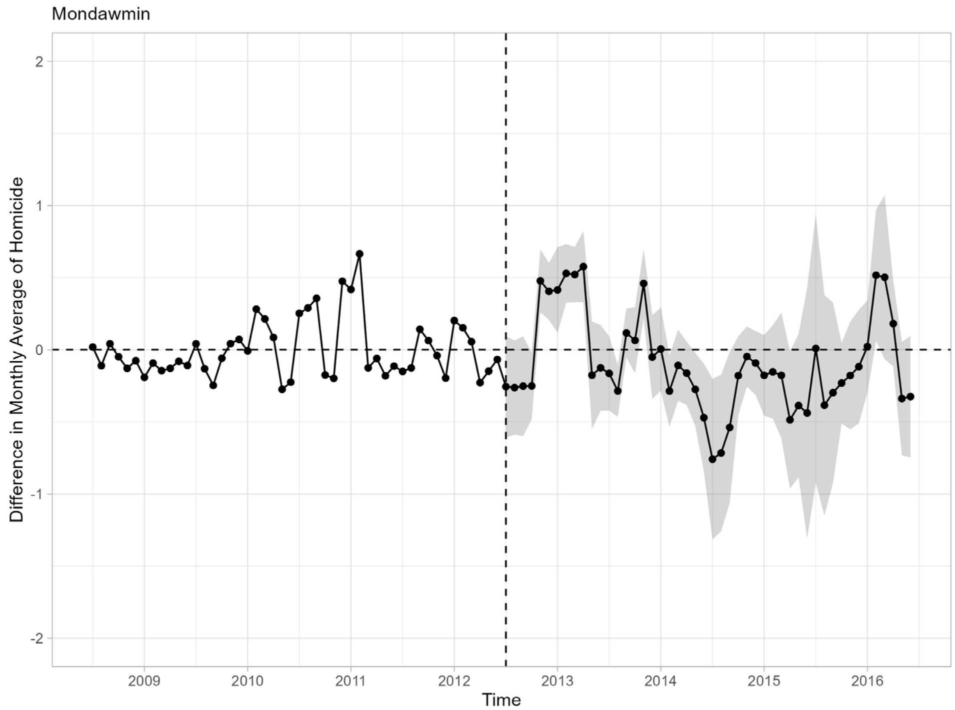

Figure 6A. Difference between Belair-Edison's augmented synthetic control for homicides and a 3-month moving average for homicides in Belair-Edison.

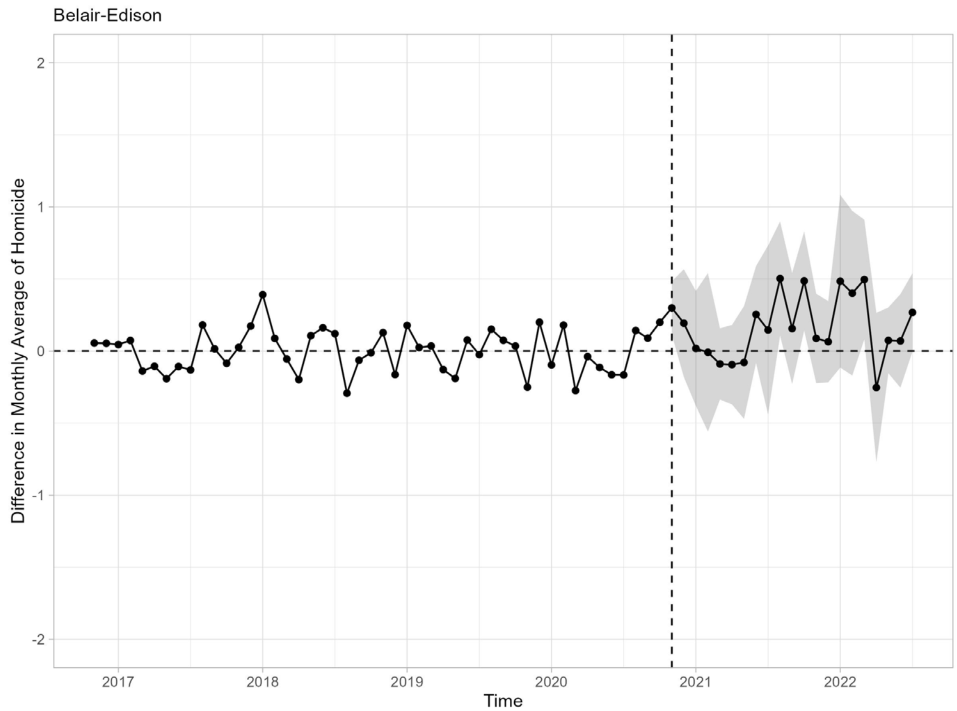

Figure 7A. Difference between Penn North's augmented synthetic control for homicides and a 3-month moving average for homicides in Penn North.

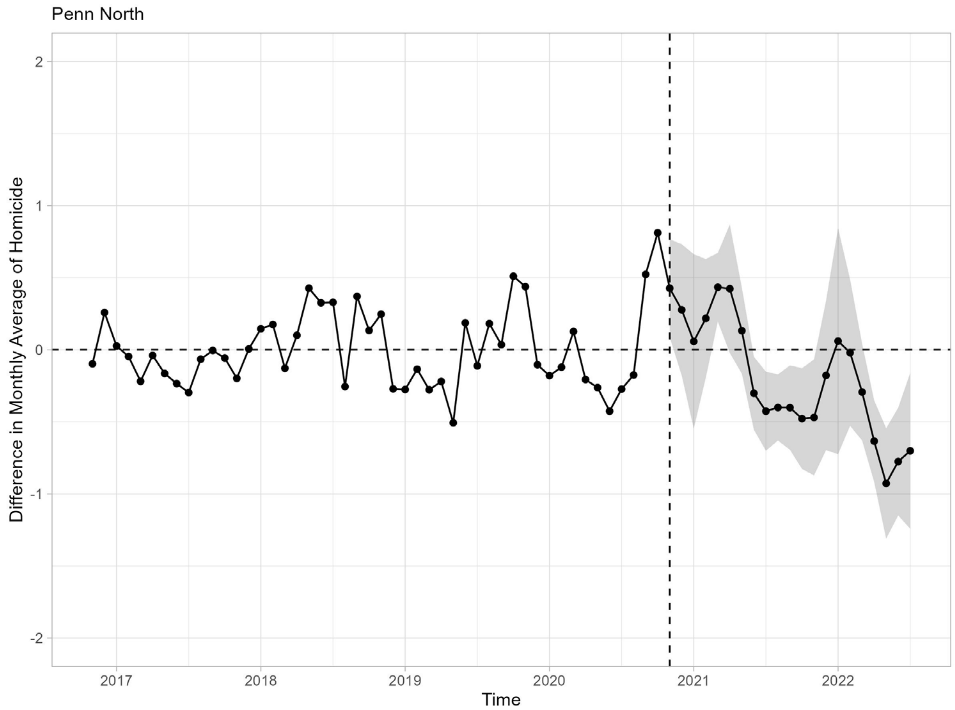

Figure 8A. Difference between Woodbourne-McCabe's augmented synthetic control for homicides and a 3-month moving average for homicides in Woodbourne-McCabe.

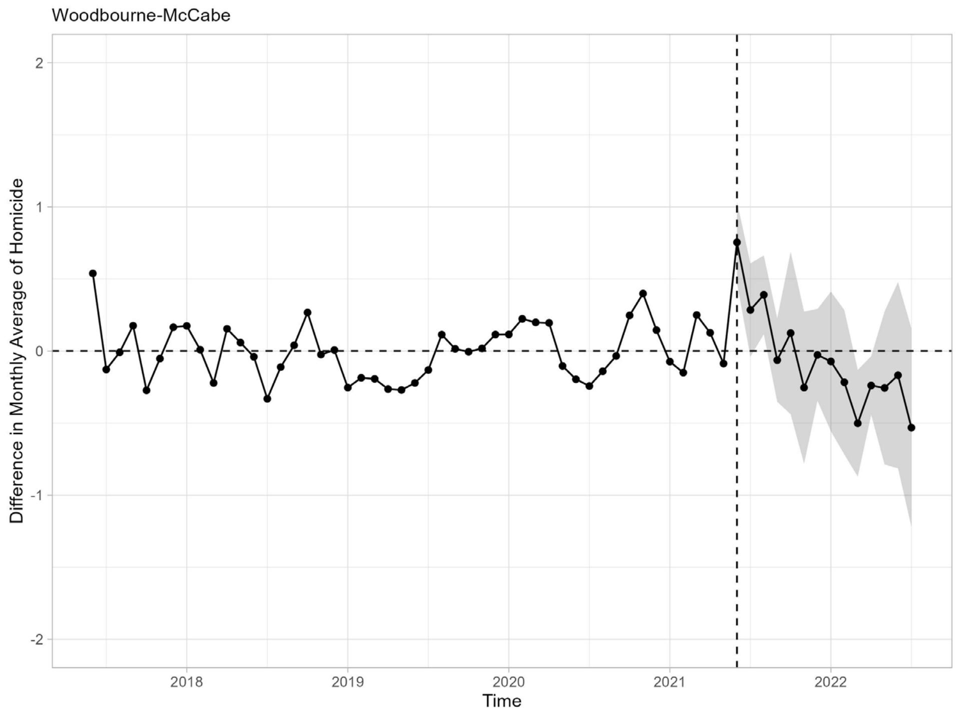

Figure 9A. Difference between Franklin Square's augmented synthetic control for homicides and a 3-month moving average for homicides in Franklin Square.

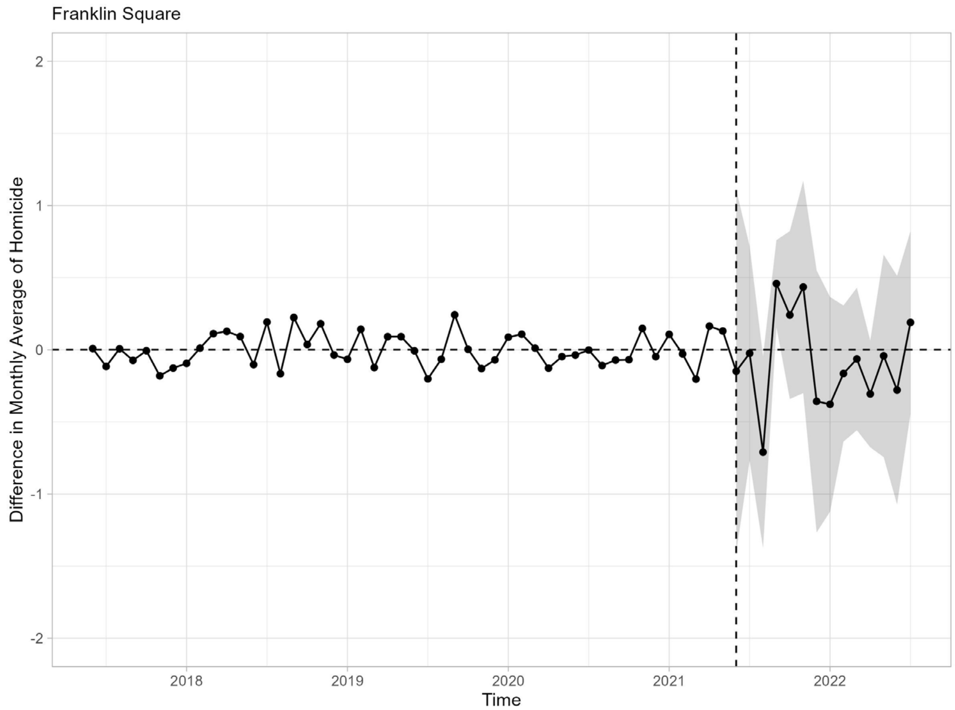

Figure 10A. Difference between Brooklyn's augmented synthetic control for homicides and a 3-month moving average for homicides in Brooklyn.

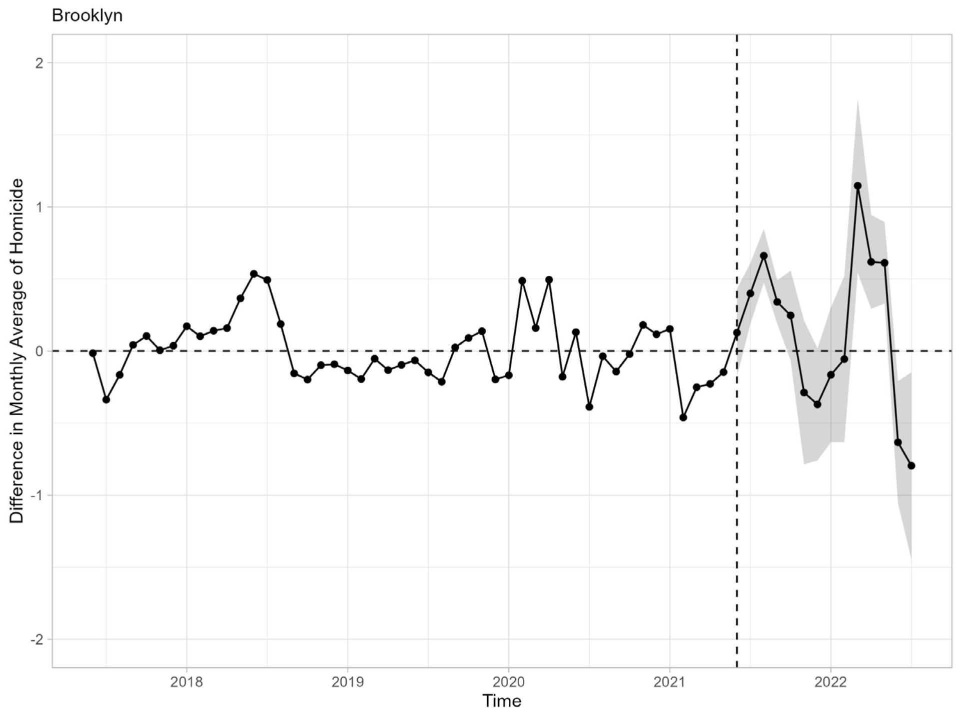

Figure 11A. Difference between Belvedere's augmented synthetic control for homicides and a 3-month moving average for homicides in Belvedere.

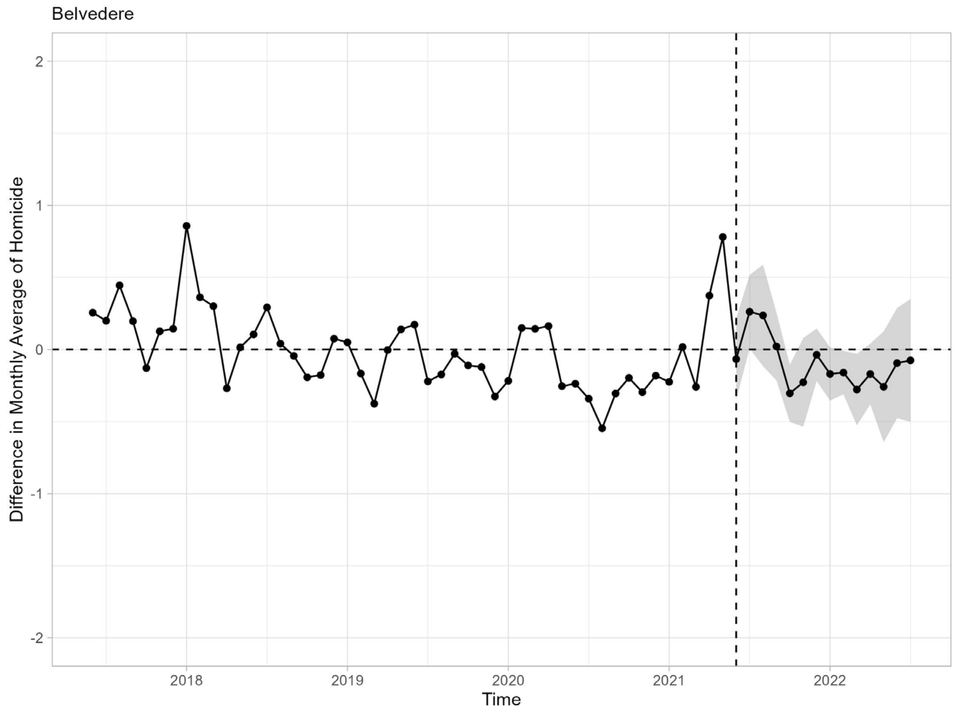

Figure 12A. Difference between McElderry Park's augmented synthetic control for nonfatal shootings and a 3-month moving average for nonfatal shootings in McElderry Park.

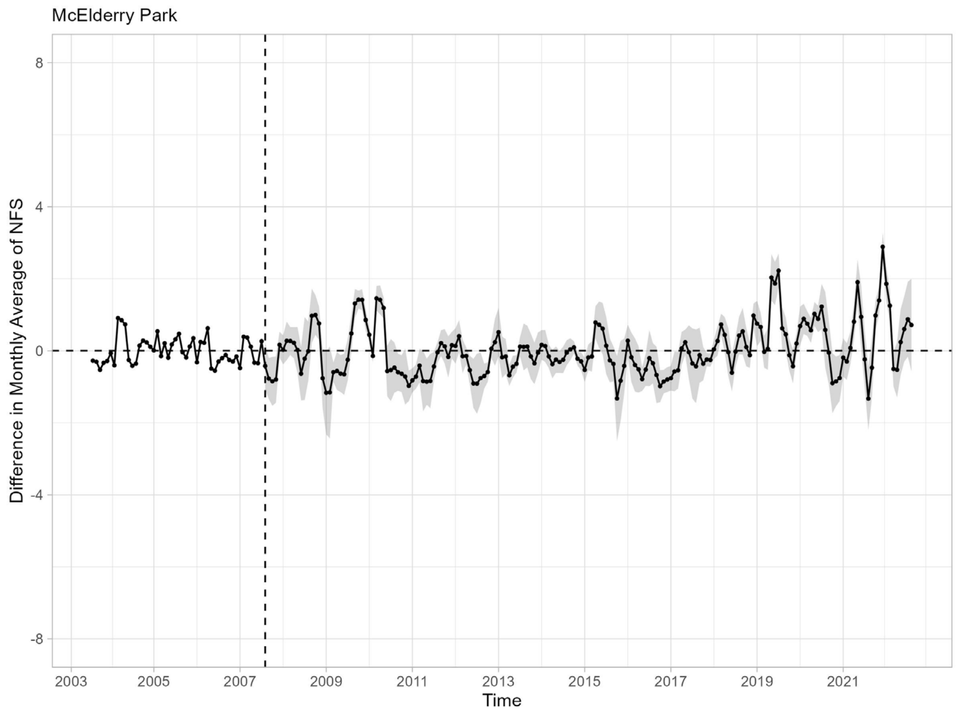

Figure 13A. Difference between Cherry Hill's augmented synthetic control for nonfatal shootings and a 3-month moving average for nonfatal shootings in Cherry Hill.

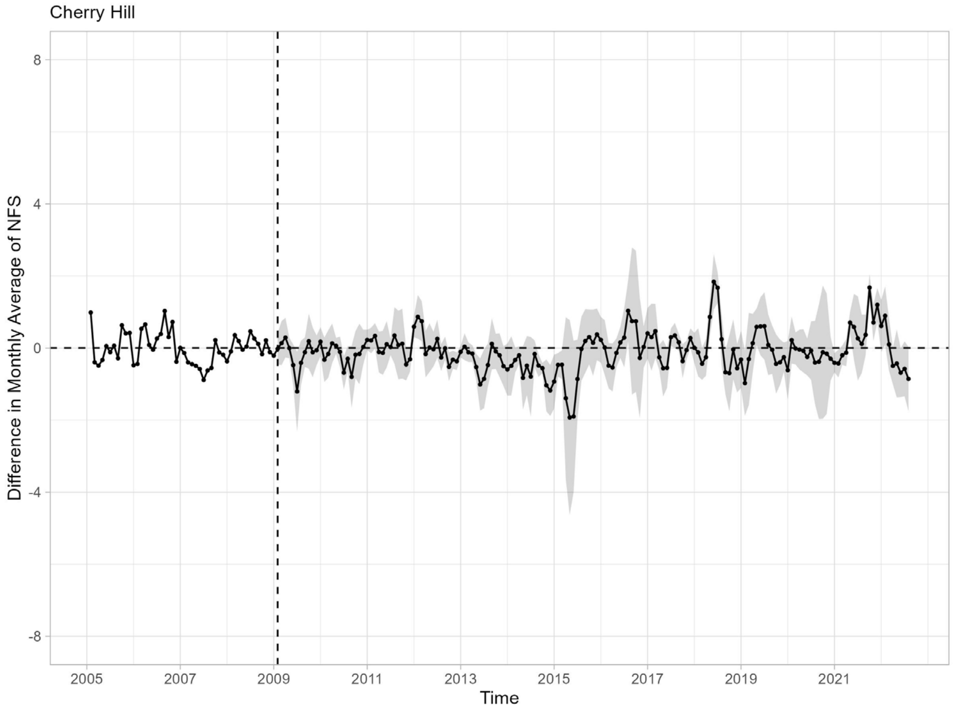

Figure 14A. Difference between Lower Park Heights' augmented synthetic control for nonfatal shootings and a 3-month moving average for nonfatal shootings in Lower Park Heights.

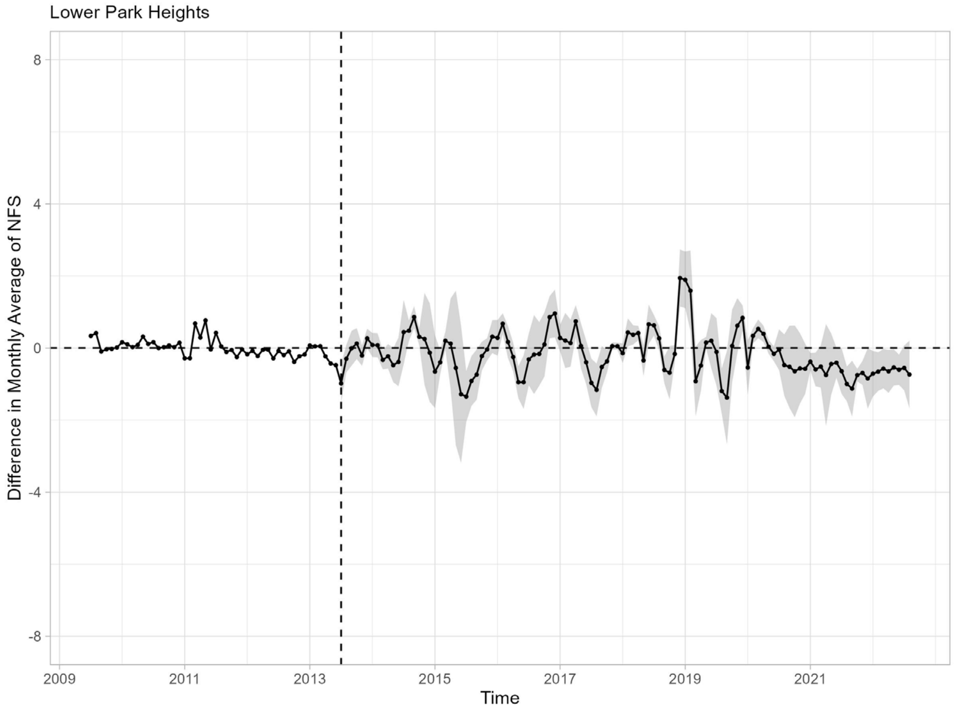

Figure 15A. Difference between Sandtown-Winchester's augmented synthetic control for nonfatal shootings and a 3-month moving average for nonfatal shootings in Sandtown-Winchester.

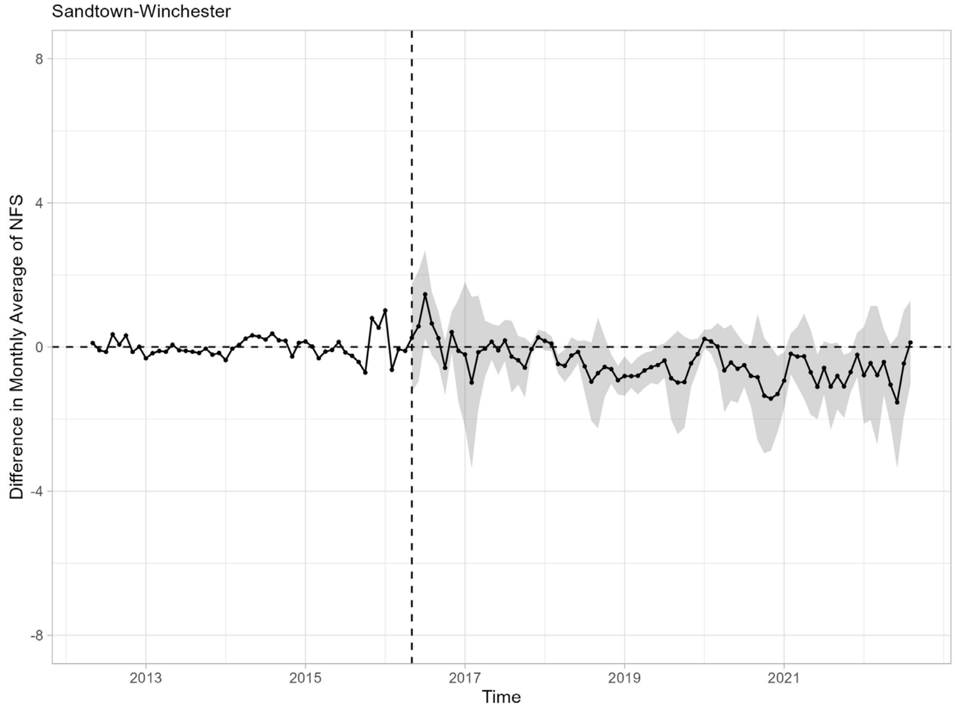

Figure 16A. Difference between Mondawmin's augmented synthetic control for nonfatal shootings and a 3-month moving average for nonfatal shootings in Mondawmin.

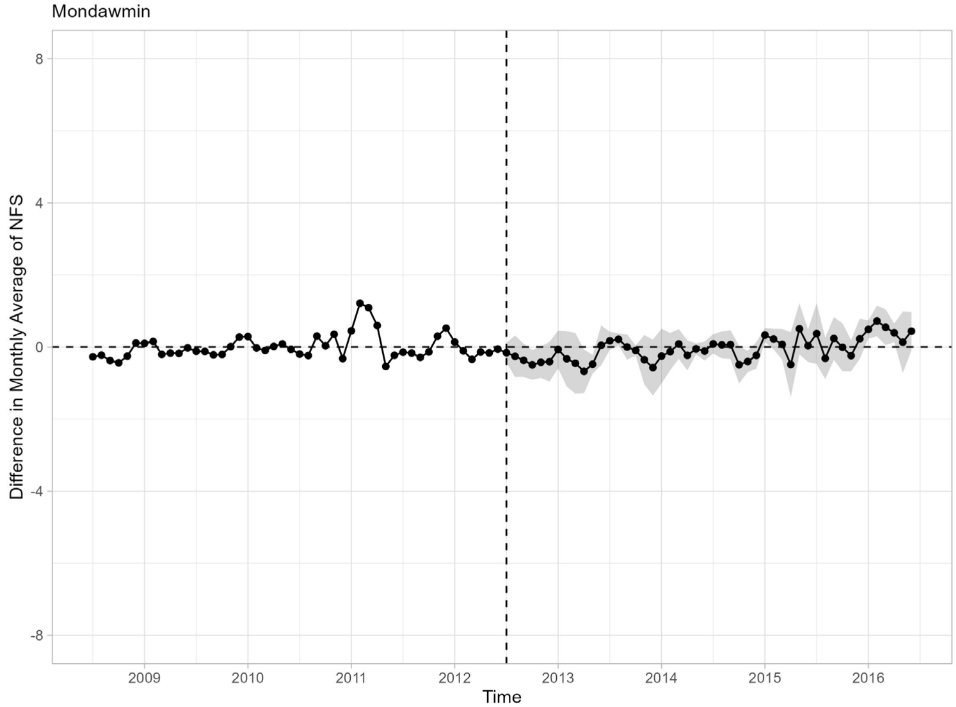

Figure 17A. Difference between Belair-Edison's augmented synthetic control for nonfatal shootings and a 3-month moving average for nonfatal shootings in Belair-Edison.

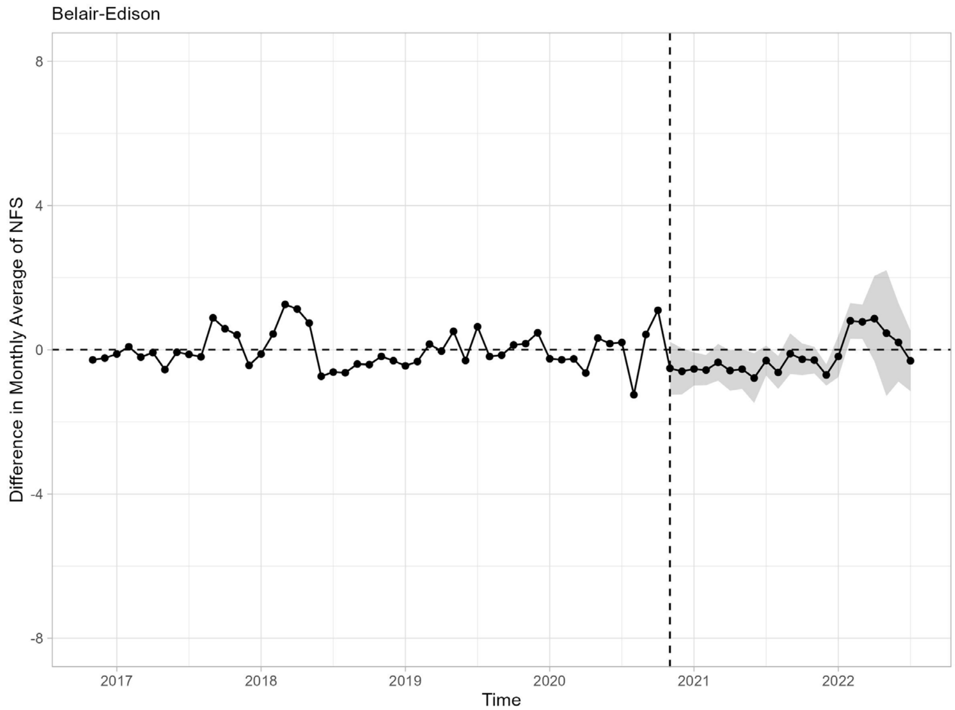

Figure 18A. Difference between Penn North's augmented synthetic control for nonfatal shootings and a 3-month moving average for nonfatal shootings in Penn North.

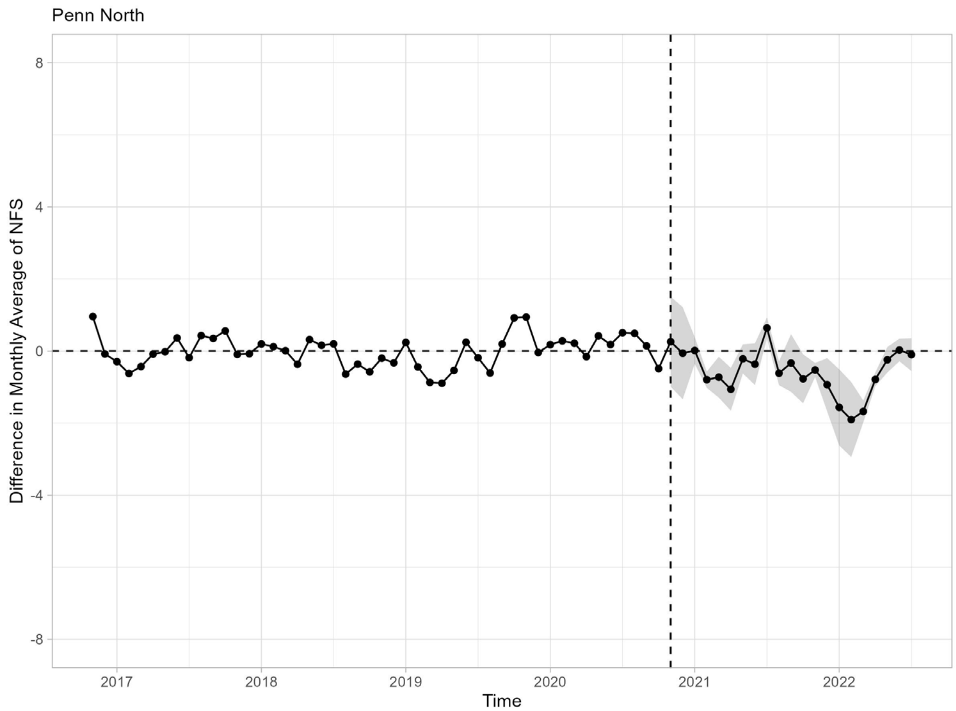

Figure 19A. Difference between Woodbourne-McCabe's augmented synthetic control for nonfatal shootings and a 3-month moving average for nonfatal shootings in Woodbourne-McCabe.

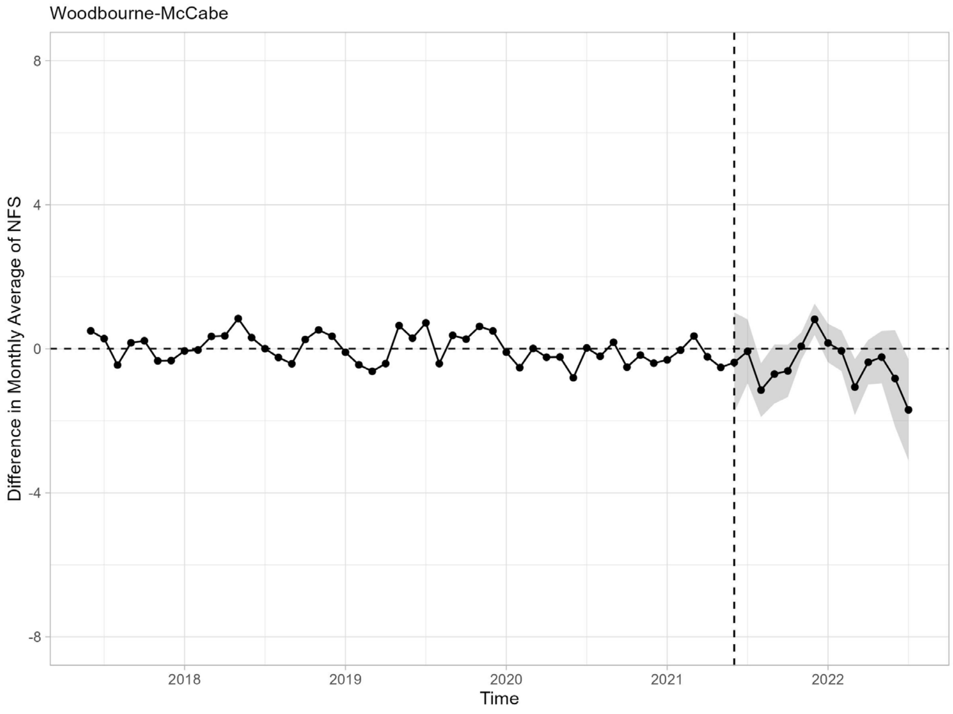

Figure 20A. Difference between Franklin Square's augmented synthetic control for nonfatal shootings and a 3-month moving average for nonfatal shootings in Franklin Square.

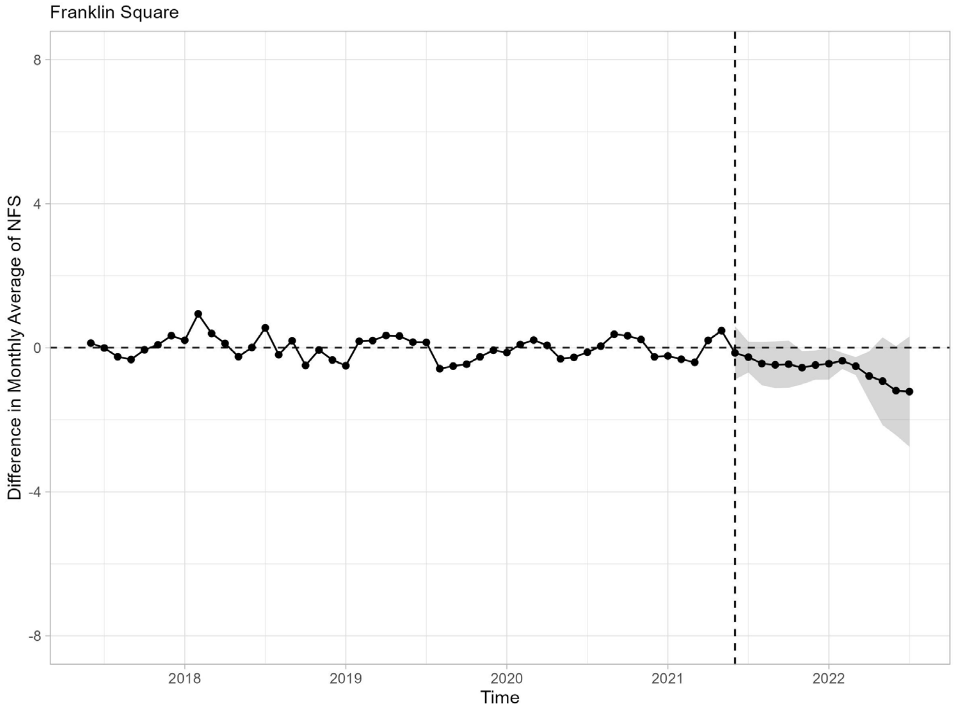

Figure 21A. Difference between Brooklyn's augmented synthetic control for nonfatal shootings and a 3-month moving average for nonfatal shootings in Brooklyn.

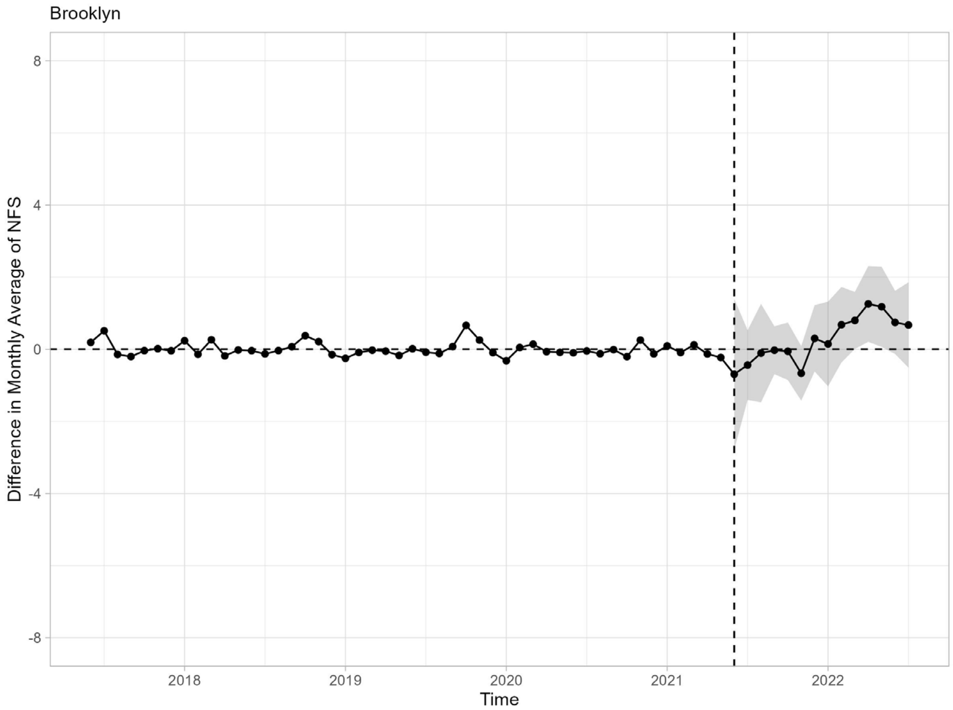

Figure 22A. Difference between Belvedere's augmented synthetic control for nonfatal shootings and a 3-month moving average for nonfatal shootings in Belvedere.