Journal of Experimental Criminology
https://doi.org/10.1007/s11292-024-09656-3

Beyond conventional metrics: the elusive impact of the Pilares program on crime in Mexico City

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Accepted: 23 November 2024

Abstract

Objectives The aim of this study is to evaluate the impact of the Pilares community program on crime rates and crime harm in Mexico City during the period from 2019 to 2023.

Methods Employing a staggered difference-in-differences methodology, we examined the effects of the Pilares program on three crime metrics—Crime Rate (CR), Crime Harm per Resident (CHIP), and Crime Harm per Victim (CHIV)—within 10-block and 20-block areas surrounding the Pilares centers.

Results The analysis did not detect statistically significant changes in the CR, CHIP, or CHIV that could be attributed to the Pilares program. Unexpectedly, a slight increase in the CR was observed in 2023 within the 20-block areas surrounding the program sites.

Conclusions The results of our analysis suggest that the Pilares program did not impact crime rates or related harm within the evaluated timeframe. This finding underscores the complexities involved in assessing community-based interventions in high-crime vulnerable areas.

Keywords Crime outcomes · Impact evaluation · Crime harm · Community centers · Collective efficacy

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Published online: 09 January 2025

Introduction

In the academic literature, there has been a growing interest in the impact of community collective efficacy (CE) programs on crime in recent years. These programs are based on the idea that fostering CE can be effective for preventing crime, which represents a departure from previous perspectives focused more on other concepts of crime prevention such as the Crime Prevention Through Environmental Design (CPTED) perspective (Kim et al., 2019; Lee et al., 2016; Montoya et al., 2016) or police interventions such as hot-spots policing (Braga et al., 2012; Weisburd & Eck, 2004) or community policing (Bland et al., 2021; Gill et al., 2014).

The effectiveness of CE programs in reducing crime has recently started to be evaluated. The findings are largely diverse, differing by location and type of crime (Fabusuyi, 2018; Heinze et al., 2018; Iyer et al., 2020; Nubani et al., 2023; Ramey & Shrider, 2014; Stokes, 2020; Telep & Hibdon, 2018; Weisburd et al., 2021). These programs are becoming increasingly popular in various regions, including Latin America. For instance, the Pilares program in Mexico City, established in 2019, has significantly grown to 303 community centers across the city between then and 2023. This program was initiated with the aim of revitalizing the social structure of vulnerable communities in Mexico City, with targeting crime and violence prevention as one of its objectives (Gobierno de la Ciudad de Mexico, 2018).

In this study, we evaluated the impact on crime between 2019 and 2023 in the surrounding areas where the Pilares centers were located. Three outcome measures were examined: the overall Crime rate (CR), the Crime harm index per Resident (CHIP), and the Crime harm index per Victim (CHIV). It is noteworthy that these crime metrics experienced a significant decline from 2019 to 2020 due to the COVID-19 pandemic. However, while the CR has steadily increased since 2021, the CHIP and CHIV have steadily decreased (see Tables A1 and A2 in the Appendix).

While the decline in crime during the COVID-19 pandemic has been attributed to changes in routine activities (Estévez-Soto, 2021; Vilalta et al., 2022a, b), the reasons for the differences in trends warrant further investigation. Notably, it remains unclear whether the Pilares program has contributed to the decreases in crime harm. While we acknowledge that CE initiatives such as the Pilares program have demonstrated effectiveness in reducing certain types of interpersonal crimes through enhanced social cohesion and collective action, their influence on broader crime metrics such as crime rates and harm that encompass crimes less directly related to CE still invite empirical examination.

We utilized a staggered difference-in-differences (DiD) analysis to account for the phased rollout of the Pilares program centers in Mexico City over time. This method, combined with the three previous outcome measures, enables us to separate the evolving effects of the program as it has progressed. By aligning this approach with multiple measures, we gain a more comprehensive understanding of how Pilares' impact may not only vary over time but also across different aspects of crime. In this sense, the chosen title for this study summarizes the challenges inherent in interpreting the effects of community-based initiatives on crime, emphasizing the need for a multiple outcomes to capture the different aspects of CE programs (Shadish & Cook, 1998).

This study is divided into five major sections. In the first section, we describe the Pilares program in Mexico City. In the second section, we review a number of previous evaluations of CE programs and their impacts on crime. In the third section, we present the data and methods utilized in this study. The fourth section presents the results of the data analyses. In the fifth and final section, we discuss our findings, the study's limitations, and conclude with some suggestions for future studies.

The Pilares program

The Pilares program is a Mexico City policy program that aims to empower communities through the provision of educational opportunities, sports activities, cultural workshops, and vocational training.[1] The courses are designed to create educational and economic opportunities for individual empowerment. Additionally, Pilares community centers provide free access to computer facilities with internet connectivity. All services are provided at no cost, and participants receive financial assistance based on their different roles such as educators, workshop leaders, community monitors, or cultural and sports promoters.[2]

This program has been well received. In 2021, the Pilares program was awarded the UNESCO Prize for Promoting Equality.[3] With the 2023 Reform to the Mexico City Education Law, the Pilares centers are now integrated into the Community Education Subsystem of Mexico City, with their courses recognized as extracurricular activities.[4]

The Pilares program is based on the principles of collective efficacy, aiming to foster community engagement, education, emotional well-being, and social networking to promote social cohesion and shared norms—factors that can help regulate behavior and prevent crime.

One of the aims of the Pilares program is "to contribute to the reduction of crime and violence,"[5] which is why the community centers are located based on four criteria: places with low levels of social development, high population densities, high numbers of young individuals between 15 to 29 years old, and existing issues related to violence.[6] Their location criteria in high crime locations is supported by substantial research indicating that crime tends to be concentrated in specific "hotspots" and efforts should be focused there (Chainey et al., 2019; L. W. Sherman, 2007; Weisburd, 2018).

[1] Pilares serves as the acronym for *Puntos de Innovación, Libertad, Arte, Educación y Saberes* (i.e., Points of Innovation, Freedom, Art, Education and Knowledge).

[2] See: https://www.evalua.cdmx.gob.mx/storage/app/media/evaluacion20/evaluacionext/pilares/Informe%20Final%20Pilares.pdf

[3] See: https://informedegobierno.cdmx.gob.mx/acciones/educacion-3/

[4] Ley de Educacion de la Ciudad de Mexico, article 10, fraction XII.

[5] Ley de Educacion de la Ciudad de Mexico, article 52, fraction X. Visit: https://www.congresocdmx.gob.mx/media/documentos/16dfcd254ec727792d543b38a89c689bbfe7f3b4.pdf

[6] See: https://gobierno.cdmx.gob.mx/acciones/pilares/

Two previous studies report that Pilares community centers face significant challenges in fostering social capital and trust due to their locations in high-crime areas (Chavez Lopez, 2022; González & Varela, 2021). It is reported that the Pilares centers in the city center have struggled to build a sense of community amid settings with heavy traffic, businesses, and employment (González & Varela, 2021). Similarly, centers outside the city core have encountered distinct obstacles, with one in a high-traffic area with elevated property crime, and another in a socioeconomically disadvantaged region with high domestic violence rates (González & Varela, 2021). One conclusion is that the location of Pilares centers in areas with high violence, crime, and low socioeconomic development have hindered their ability to effectively promote inclusivity and community engagement (Chavez Lopez, 2022). Despite the program's goals of enhancing CE and reducing crime, the scarce existing literature indicates that these location-based challenges may undermine these objectives, not to say that the lack of comprehensive assessments on the program's impact on crime and violence rates leaves its overall effectiveness in question, suggesting a need for more targeted evaluations to understand and address these implementation barriers.

Crime prevention programs may have unintended effects (Hohl et al., 2019). Factors like high social vulnerability and residential mobility can hinder the program's ability to build collective efficacy (Leverentz et al., 2018; Sampson, 2012), limiting its impact. The choice of crime metric used to assess the program's success can also influence the evaluation findings. Next, we will examine evaluations of other collective efficacy programs and their findings.

Previous evaluations of collective efficacy programs

Collective efficacy (CE), that is, social cohesion and trust among neighbors combined with their willingness to intervene on behalf of the common good, has been found associated with lower levels of crime and violence (Becker, 2019; Burchfield & Silver, 2013; Hipp & Wickes, 2017; Lindblad et al., 2013; Morenoff et al., 2001; Sampson et al., 1998).

The premise of CE community programs is that it helps prevent crime (Beck et al., 2012; Cantora et al., 2016). Collective efficacy can be seen as a proxy for social crime controls (Weisburd et al., 2015). Within the social disorganization literature, informal social control has been conceptualized in primarily two ways: informal surveillance (i.e., guardianship) and direct intervention (Ohmer et al., 2010).

Creating place-based collective efficacy poses a challenge (Hipp & Wickes, 2018; Mennis et al., 2013). Methods for fostering collective efficacy have encompassed forming connections, educating bystanders, promoting restorative justice, reaching consensus through organizing efforts, implementing greening initiatives, and establishing neighborhood watch programs (Beck et al., 2012; Heinze et al., 2018; Maxwell, 2018; Ohmer et al., 2010; Stokes, 2020; Triplett, 2007). Nevertheless, how to develop collective efficacy for crime prevention remains an unresolved issue in research (Ohmer et al., 2016).

Several evaluation studies show variations in results with some indicating decreases in violent crime and offenses against individuals, assaults, rape, burglary and other property crimes, as well as juvenile arrests (Fabusuyi, 2018; Heinze et al., 2018; Iyer et al., 2020; Nubani et al., 2023; Ramey & Shrider, 2014; Stokes, 2020; Telep & Hibdon, 2018; Weisburd et al., 2021) (see Table 1). In certain contexts, there was no change observed in crimes such as robbery or overall criminal activity (Iyer et al., 2020; Stokes, 2020). Additionally, some settings reported no changes in property crimes or drug violations; however, there were reports of shootings and homicides (Iyer et al., 2020; John et al., 2020; Stokes, 2020). There is no evidence of spatial displacement of crime and disorder (Telep & Hibdon, 2018); nevertheless, evidence suggests an increase in crime reporting and police calls rising (Weisburd et al., 2021).

Under this logic, increases in official crime counts or rates at the intervention sites do not necessarily indicate a deterioration of the crime problem. Enhanced cooperation between law enforcement and the community could result in more individuals reporting crimes (Hipple & Saunders, 2020; Weisburd et al., 2021). Moreover, a program that reports an increase in drug violations during an opioid epidemic should not be deemed a failure without considering what might have occurred if it had not been implemented (John et al., 2020). These issues underscore the importance of utilizing alternative measures in policy evaluations such as the crime harm index.

Table 1 Outcomes of place-based collective efficacy interventions

Authors	Time frame	Place	Focus	Outcomes/Trends
Nubani et al. (2023)	2017–2019	Three small cities in Michigan, USA	Neighborhood	Perception of Crime (↑)
Weisburd et al. (2021)	2015–2016	Brooklyn Park, USA	Crime Hotspots	Crime Reporting (↑) Crime Incidence (↓)
Iyer et al. (2020)	2015–2016	Baltimore, USA	Crime Hotspots	Juvenile Arrests (↓) Crime (↔) Shootings & Homicides (↑)
Stokes (2020)	2010–2104	Philadelphia, USA	Crime Hotspots	Assault (↓) Burglary (↓) Homicide (↑) Rape (↓) Robbery (↔) General (↓)
John et al. (2020)	2013–2016	Dayton, USA	Neighborhood	Property Crimes (↑) Drug Violations (↑)
Fabusui (2018)	2008–2011	Pittsburgh, USA	Crime Hotspots	Property Crimes (↓) Against Persons (↓)
Heinze et al. (2018)	2009–2013	Flint, USA	Vacant Lots	Assault (↓) Total Crime (↓)
Telep and Hibdon (2018)	2011–2014	Seattle, USA	Crime Hotspots	Disorder (↓) Drug crimes (↓) All Crimes (↓)
Ramey and Shrider (2014)	1993–2007	Seattle, USA	Neighborhoods	Violent Crime (↓)

Overall, these studies collectively contribute to a nuanced understanding of collective efficacy theory and its implications for crime prevention and control. They underscore the significance of community-level responses, social cohesion, and informal social control in shaping crime dynamics and policy interventions. Additionally, studies have underscored the importance of community engagement for Crime Prevention through Environmental Design (CPTED) in addressing crime prevention strategies, emphasizing the role of collective efficacy in these approaches (Nubani et al., 2023).

It is important to acknowledge that CE programs are not expected to equally impact all types of criminal activity. While CE has been associated with reductions in public and interpersonal crimes, crimes such as fraud or identity theft are less likely to be influenced by community cohesion. Accordingly, the crime metrics examined in this study, including the general CR, CHIP, and CHIV, encompass a broader range of crime types, including property crimes, domestic incidents, and other offenses that may not be as directly responsive to CE programs like the Pilares. In this sense, our decision to include different metrics such as the crime rate and crime harm indexes was made to provide a general assessment of the Pilares program's potential impact on crime. While these outcomes encompass offenses not directly associated with CE, they offer insights into how CE-driven initiatives such as the Pilares program may influence overall safety and crime severity.

We now turn to explain the data and methods used in this study to further contextualize our approach and findings.

Data and methods

Data and measures

We utilized three different crime measures as outcomes: the Crime Victimization rate (CR), the Crime Harm Index (CHI), and the Crime Harm Index per Victim (CHIv). Data on crime victimization were gathered from Mexico City's Open Data official website, encompassing information on 1,137,760 crime victims between 2019 and 2023.[7] For this study, we used 1,107,889 (97.3%) of these cases due to their inclusion of the geographic coordinates where the incident took event. Our analysis was conducted at a geospatial level with census blocks as the unit of analysis ($N=66{,}318$). We used the 2020 polygon data shapefiles of census blocks provided by the Mexican National Institute of Statistics. Crime victims were aggregated either to their respective or nearest census block and then divided by the resident population from the 2020 Census, in order to calculate the general CR per year for each block ($\times 1000$).

Crime harm was estimated following the Cambridge Criminal Harm Index (CCHI) (L. Sherman et al., 2016; L. W. Sherman & Cambridge University associates, 2020). First, the minimum prison sentence length (measured in months) specified in Mexico City's Penal Code is applied to each crime incident. For instance,

[7] The database contains information on the type of crime, sex, and age of the victim.

the sentence for homicide ranges from 8 to 20 years. If the lowest sentence length is 8 years, then the harm caused by the crime based on this minimum sentence is multiplied by 12 months. This yields an individual CHI score of 96-month units for this crime. The sum of weighted crimes within each census block is then totaled to obtain an aggregated CHI score at the block level. The block CHI score provides a measure of the overall level of harm caused by crimes in each block, taking into account both the severity and frequency of crimes committed. The block CHIV was estimated by dividing the census block CHI by its respective number of victims. In this sense, the CHIV score is a relative measure of harm in each block that indicates which blocks are more harming for victims, providing us a more detailed measure of the crime problem (see Tables A1 and A2 in the Appendix). Finally, the CHIP was estimated by dividing the block CHI by its respective number of residents. The CHIP is a measure of the per capita crime harm in each block, reflecting the average harm experienced by residents due to crime. It allows for comparison of crime harm across blocks of different population sizes, showing blocks where residents are disproportionately affected by crime relative to their population.

Notice that these metrics enable the exploration of potential effects of CE-based interventions, such as the Pilares program, that could extend beyond crime categories typically linked to CE. Consequently, it is crucial to interpret the results cautiously, acknowledging that the observed outcomes may reflect a combination of influences from different crime types.

Empirical strategy

The Pilares community centers have been gradually set up, with the addition of new centers each year from 2019 to 2023. Our analysis begins by examining trends by contrasting the treated and not treated areas within each yearly cohort, reminding the reader that new Pilares centers were implemented on a yearly basis where new centers were incorporated into the program. This part of the analysis is centered on their CR, CHIP, and CHIV levels over time.

To estimate the effects of the Pilares' centers, we created areas of influence of 10 and 20 blocks around the census block where the Pilares centers had been located. We then estimated the mean of the CR, CHIP, and CHIV for these areas of influence so that we could compare two groups of interest, namely the treated and not treated areas on a yearly basis. The mean distance between nearest census blocks in Mexico City is 71.4 m. On average, a 10-block area of influence around a Pilares center covers an area of approximately 700 m, while a 20-block area covers around 1.4 km. We calculated out crime metrics within these areas annually to test for significant changes in our crime metrics inside the areas of influence.[8]

[8] There were between 2390 to 2501 blocks every year with zero residents and yet more than one victim (e.g., public plazas, parks, etc.). Since these blocks lacked population data, we could not calculate the CR or CHIP. To address this, we assigned the citywide average CR and CHIP for each year to these blocks, enabling us to calculate the mean values within the areas of influence around each block.

To make areas of influence comparable, we used coarsened exact matching (CEM) due to its effectiveness in reducing imbalance in covariates between treated and control groups (Blackwell et al., 2009; Iacus et al., 2012). As mentioned earlier, the Pilares program located its community centers in places with lower levels of social development, high population densities, a large number of young individuals aged 15 to 29, and existing concerns related to violence. Accordingly, we used four covariates for the CEM procedure. The social development index (SDI) developed by the Mexico City Evaluation Council,[9] served as an indicator of social development, and was available at both the census block level of analysis. Population density was calculated by dividing the total population in each census block by its area in square kilometers, and then multiplying it by 1000 to indicate thousands per square kilometer.[10] To represent the younger demographic, we utilized the 15–24-year-old population per census block, as the 15–29-year-old data is not publicly accessible in the 2020 census. Violence was represented by the total number of victims in 2019 per census block in order to give all areas of influence the same baseline. For the 10-block areas, the CEM method matched 270,164 blocks as controls (out of 331,590 over the 5-year period) with the 1524 treated units (i.e., out of 1530 block units over the 5-year period). For the 20-block areas, CEM matched 214,454 blocks as controls with 1517 treated units. The results of the CEM procedure can be seen in Fig. A1 in the Appendix.

Next, we utilized a difference-in-differences (DID) impact evaluation design. Since, the gradual implementation of the Pilares program presents a challenge for the standard two-way fixed effects DiD approach due to varying effects within treated area cohorts over time (Goodman-Bacon, 2021; Sun & Abraham, 2021), we employed the staggered DID setup proposed by Callaway and Sant'Anna (2021a). This framework enables us to assess both yearly and cumulative impacts of Pilares community centers within cohorts of treated areas of influence. Essentially, our goal is to calculate the average treatment effect among the treated (ATT) separately for each cohort (i.e., never-treated and treated) and time using the never-treated group as control or counterfactual. We then combine these group-time ATTs into a weighted ATT that takes into account these variations in intervention effects over time.

In this setup, the ATT is a cohort or group-time average treatment effect is denoted by (Callaway & Sant'Anna, 2021a):

$$ATT(g,t) = \mathbb{E}\left[Y_t(g) - Y_t(0) | G_g = 1\right]$$

where Y is the dependent variable, Gg indicates when an area of influence first received a Pilares community center, and t is the time point.

In this setup, the ATT(g,t) does not impose limitations on the variation of treatment effects among groups or over time. By holding a specific cohort or group constant (e.g., g) and changing the time factor (e.g., t), it is possible to estimate

9 See. https://evalua.cdmx.gob.mx/

10 The mean area of a census block in Mexico City in 2020 was 9.2 thousand meters, that is, a 0.92% of a square kilometer.

average treatment effects over time within specific cohorts as they were incorporated into the program. Furthermore, according to Callaway and Sant'Anna (2021b), this setup can be expanded to create other causal parameters of interest in our study, such as assessing whether the ATTs of the Pilares program differed across treated cohorts, examining if ATTs varied based on length of exposure to the program, and the time-cumulative ATTs.

We utilized linear regression to estimate the ATT(g,t). The equation used for estimation was the following (Callaway & Sant'Anna, 2021a):

$$Y = \alpha_1^{g,t} + \alpha_2^{g,t} \times G_g + \alpha_3^{g,t} \times 1\{T = t\} + \beta^{g,t} \times \left(G_g \times 1\{T = t\}\right) + \epsilon^{g,t}$$

Here, a_1 is a constant term specific to a particular group g in time period t, a_2 is the coefficient for variable G_g which is a binary variable indicating group membership, a_3 is the coefficient for the time period that equals 1 when $T = t$, b is the ATT estimate capturing the estimated effect of the Pilares community centers, and e is the error term representing compositional unobserved factors. The pre-treatment parallel trends assumption is tested conditional on observed confounders after the CEM procedure. We utilized the conditional moments test, following the methodologies outlined by Callaway and Sant'Anna (2021a), in addition to the p values for pre-tests of parallel trends assumption included in every estimation by default.

We initiate our analysis by visually examining trends. We create plots of the mean values of CR, CHIP, and CHIV from 2019 to 2023, with a 95% margin of error incorporated. A comparison is carried out between the treated and not treated cohorts and each cohort categorized by the year they were first treated under the Pilares Program. Following this, we calculate four distinct causal parameters that cover different aspects of treatment variation in our DiD approach (Callaway & Sant'Anna, 2021a, 2021b):

- Group-time average treatment effects (GTATT): These determine the ATTs for each group at specific time periods, reflecting the annual influence of the Pilares program on areas of influence within a particular group or cohort at different time points. These are used to evaluate the credibility of the parallel trends assumption by looking for consistency among them prior to treatment. The DiD setup involves conducting a Pre-test on parallel lines for each crime outcome measure.
- Dynamic effects (DATT): The fluctuating impact of the treatment over different time periods can be estimated by aggregating the GTATTs across the various lengths of exposure to the program. This method entails evaluating ATTs across diverse durations of exposure, with an overall DATT providing a comprehensive assessment of the program's influence over varying time periods.
- Group-specific effects (GATT): GTATTs can also be combined to evaluate whether the effects of the Pilares program differed among groups or cohorts of treated areas around the Pilares centers.
- Calendar-time effects (CATT): Finally, we assess whether the effect of the Pilares program varied over different years. The GTATTs are utilized to summarize the impact of engaging in the intervention during specific time periods for all treated units up to that time.

Since minor changes in the number of crime victimizations occurring in less populated census blocks can lead to substantial fluctuations in the crime rates (CR) and crime harm per capita (CHIP), introducing potential bias into the estimates, we weighted our staggered DiD models by census block population size. To address potential serial correlation, heteroskedasticity, and complex clustering within the data, a bootstrapping approach was utilized to estimate the standard errors for the staggered DiD models.

Weighted averages of the group-time average treatment effects parameters are outlined in the following section, and specific GTATTs are detailed in the Appendix. Plots illustrating the results for other causal parameters are provided. A significance level of 0.05 was employed for statistical analysis. Data analyses were conducted in the R software with the *did* package (v. 2.1.2) (Callaway & Sant'Anna, 2021b), *MatchIt* (v. 4.5.5) (Ho et al., 2018), *cobalt* (v. 4.5.4) (Greifer, 2020), and *ggplot2* (v. 3.5.0) (Wickham, 2016). We used the *Jenny.AI* large language model to correct English grammar and syntax, not for generating content. The authenticity, intellectual value, and errors are solely attributable to the authors.

Results

Crime trends in *Mexico* City

Figure A1 shows the trends for census blocks that were not treated by the Pilares Program and those that were treated, categorized by the year they first received treatment and according to their area of influence, that is, 10 blocks or 20 blocks around them. We observe that the rates of crime victimization (CR) and levels of crime harm per resident person and victim (CHIP and CHIV) decreased from 2019 to 2020 due to the COVID-19 pandemic and associated lockdown measures. What is interesting is that they have stayed consistent since for both groups with and without a Pilares community center—changes between 2020 and 2023 are within the margin of error.[11]

One trend among the treated areas of influence is that, on average, those that began treatment in 2023, had lower levels of CR and CHIP, yet similar levels of CHIV, within an area of 10 blocks from their location, as compared to their preceding cohorts. While the intervals of confidence overlap, it appears that latter treated areas were places with lower levels of crime on average than the early treated areas. On the other hand, treated areas showed to have higher levels of CR and crime harm in the 20-block area of influence between 2019 and 2023, on average, as compared with the not treated areas. These findings suggest that the Pilares program was purposefully implemented in areas exhibiting higher levels of crime, and subsequently expanded to areas with lower crime rates. The increased crime victimization and

[11] Crime data introduces uncertainty due to the dark figure problem. Hence, we present these trends with a $1/-1$ standard error interval from the mean for meaningful comparisons between treated and not treated groups of census blocks and their areas of influence over time.

crime harm observed within the 20-block radius of treated areas, compared to not treated areas, between 2019 and 2023, suggests that the program targeted areas facing more pressing crime-related challenges.

Another pattern is that the CR trend saw a modest rise after 2020 for the not treated areas, while the CHIP per person and CHIV underwent consistent declines starting that year. In contrast, the trends for the treated areas remained relatively stable across the CR and CHIP metrics throughout the entire period, although the CHIV rapidly decreased as well, indicating that the latter metric declined at a faster pace than the other two metrics. This implies a shift in the distribution of crimes from more severe to less severe offenses for the entire city. Further research is needed to investigate this observed shift, which remains an open empirical question.[12]

In the following section, we present the findings of the staggered difference-in-differences analyses, which will validate several of the observed trends.

Impacts of the Pilares program on the CR, CHI, and the CHIv metrics

Table 2 shows the weighted average of the GTATT effect for each outcome measure, examining the 10-block and 20-block areas of influence surrounding the Pilares program areas. These weighted averages provide a concise overview of the findings. The 95% confidence intervals for the GTATT weighted averages suggest uncertainty regarding the true impact of the Pilares program on all crime metrics. While the positive GTATT values across the metrics cautiously imply a potential increase in crime in the treated areas, these findings are not statistically significant. For instance, the GTATT value of 5.7 for the crime rate in the 10-block area indicates an average increase of 5.7 victims per 1000 residents around the Pilares centers compared to untreated areas, but the confidence intervals include both positive and negative values, leaving this increase non-significant. Overall, the analysis does not provide statistically significant evidence of the Pilares centers impacting crime rates and crime harm within the 10-block and 20-block areas of influence.

The parallel trends assumption was not met, indicating pre-existing differences in crime trends and levels between treated and control areas.[13] While CEM improved group comparability, disparities remained. We acknowledge this limitation and urge caution in interpreting our findings.

The use of DATTs allows us to analyze the effect of the Pilares program based on the length of exposure. In Fig. 1, a zero length of exposure represents the immediate (same year) impact of participating in the program, while a -1 length corresponds to the year before areas were first treated, and a 1 length corresponds to the first year after being treated (Callaway & Sant'Anna, 2021a). Among treated

[12] Between 2019 and 2023, Mexico City has experienced a significant decrease in homicide crimes and increasing number of victims of domestic violence and fraud. We found no previous studies explaining these trends.

[13] Tables A4, A5 and A6 in the Appendix presents the GTATT for every group and time period in the analysis for each crime metric, in addition to the respective P-values of the Pre-tests of parallel trends.

Table 2 Weighted averages of group-time average treatment effects (GTATT) of the Pilares program on the CR, CHIP, and the CHIV outcomes

	Area of influence: 10 blocks				Area of influence: 20 blocks			
	GTATT	SE	[95% CI]		GTATT	SE	[95% CI]	
Crime rate (CR)	5.720	5.345	−4.756	16.196	7.269	4.382	−1.319	15.859
Crime harm per capita (CHIP)	0.847	0.212	−0.331	0.500	0.073	0.122	−0.167	0.313
Crime harm per victim (CHIV)	2.783	2.325	−1.773	7.340	1.299	0.811	−0.290	2.888

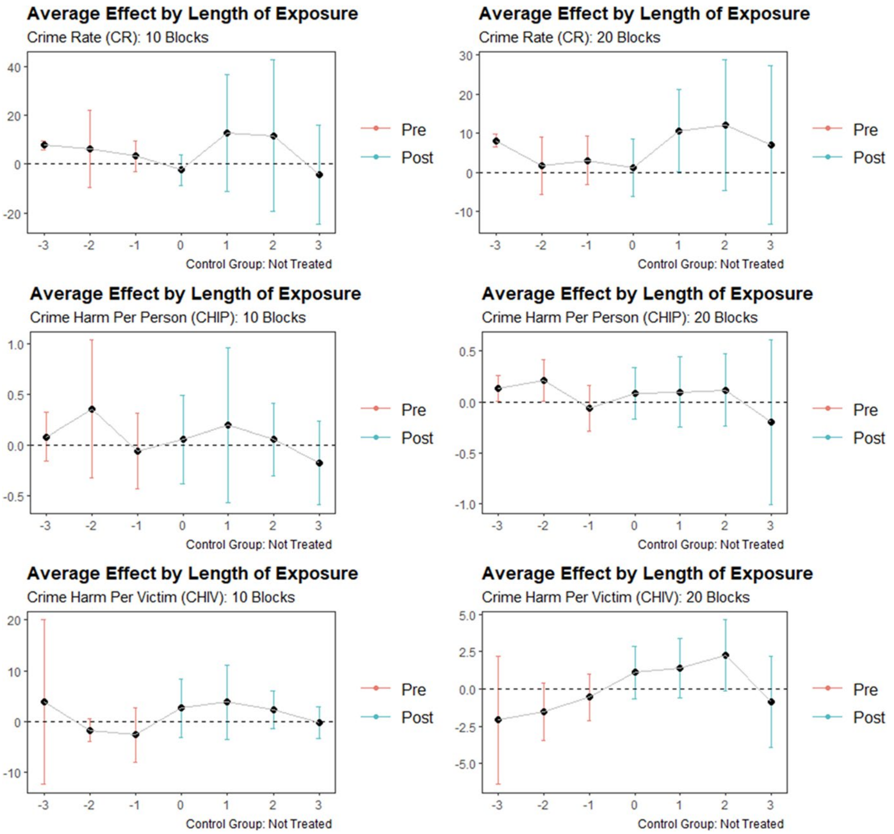

Fig. 1 Effects of the Pilares program on the CR, CHIP, and the CHIV measures by length of exposure (DATT)

areas, there appears to be significantly higher CR three years prior to implementing the Pilares program (approximately 7.7 more victims per 1000 residents above those never treated in the 10-block area of influence and 8 more victims per 1000

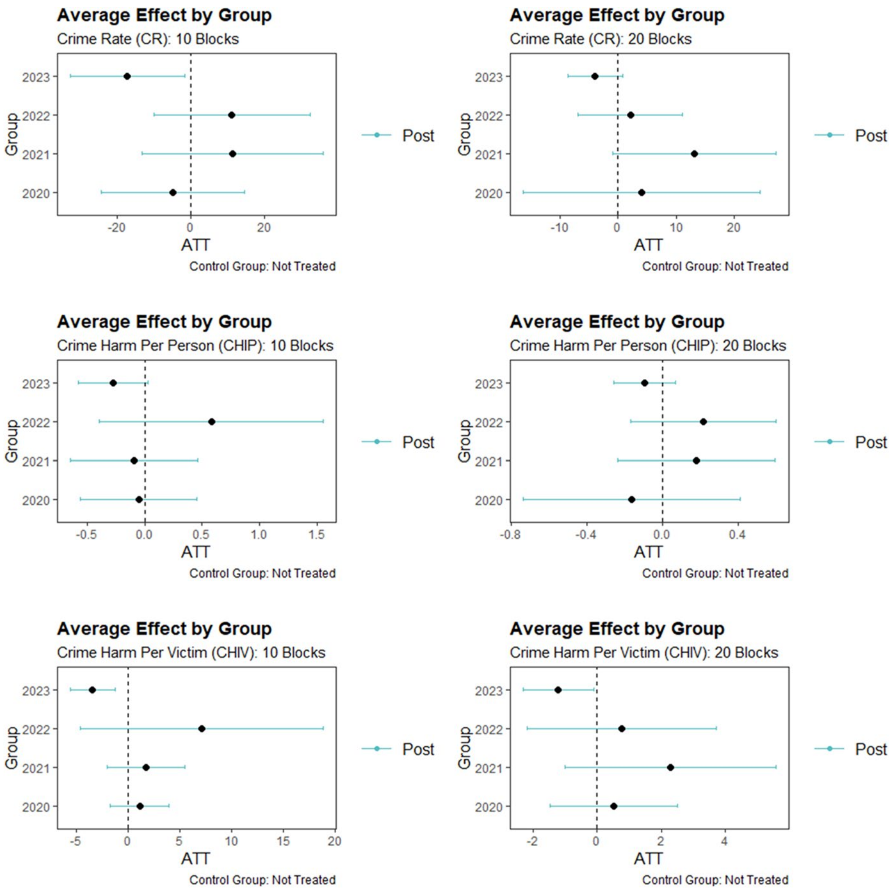

Fig. 2 Effects of the Pilares program on the CR, CHIP, and the CHIV measures by Group/Cohort of treated neighborhoods (GATT)

residents in the 20-block area of influence compared to the not treated group). As for the CHIP and CHIV outcomes, there is no statistically significant evidence of the Pilares program reducing crime harm at any point between three years before or after implementation.[14]

Next, we evaluated whether the effect of the Pilares program varied among groups/cohorts of treated areas via the group-specific effects (GATT) estimations. Figure 2 presents evidence of a statistically lower levels of CR and CHIV among the 2023-treated areas, confirming our previous finding that latter treated areas by the Pilares program were places with lower levels of crime, on average, than early

[14] There are some instances of the CHIP being significantly higher in the treated areas on and 2 years before treatment (see Fig. A2 and Tables A5 and A6).

treated areas. Conversely, there is no indication of a significant impact on the CR, CHIP, and CHIV within any group or cohort of treated areas, at any radii or area of influence.

Finally, we seem to detect evidence of significant calendar-time effects (CATT) of the Pilares Program solely for the CR and only in 2023 (see Fig. 3). However, not in the desired direction. We find that the Pilares Program, contrary to our expectations, is associated with an increase in crime victimization rates (CR) within the 20-block areas surrounding the Pilares centers in 2023. Specifically, there are approximately 11 more crime victims per 1000 residents on average compared to areas without Pilares centers. This finding suggests that the program may not be effectively reducing crime in its areas of influence or that other factors

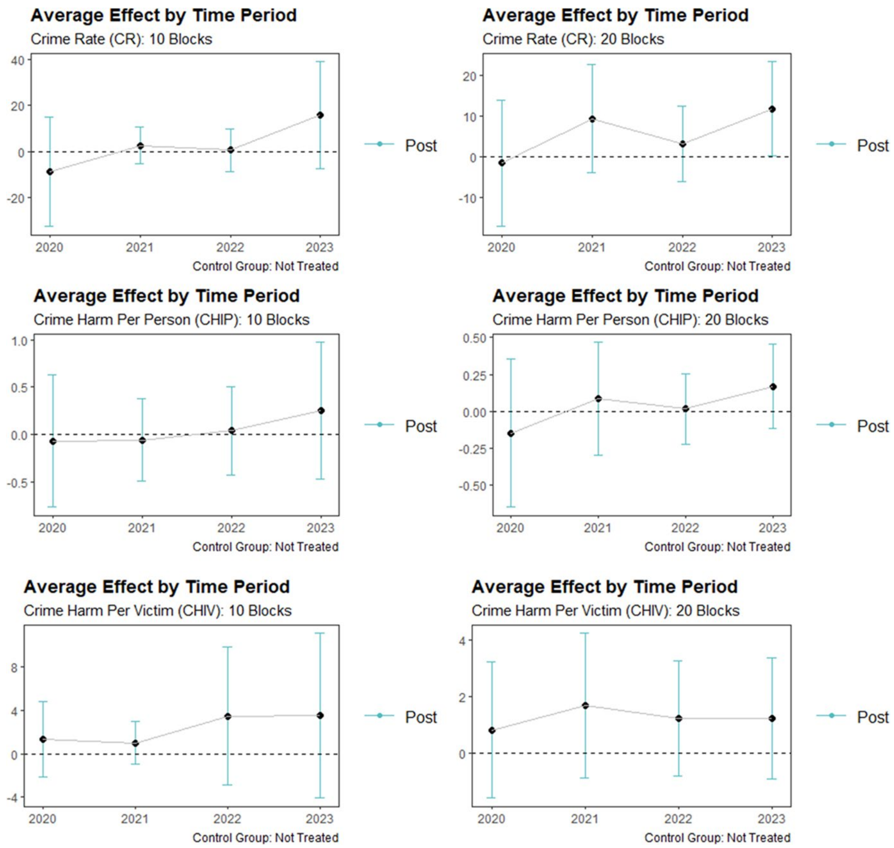

Fig. 3 Effects of the Pilares program on the CR, CHIP, and the CHIV measures by time period (CATT)

are increasing crime rates. We find no significant differences regarding the CHIP and CHIV outcomes.

In sum, our analysis did not find statistically significant evidence that the Pilares program impacted crime rates or harm within the 10-block and 20-block areas of influence around the Pilares locations. The group-time average treatment (GTATT) effects were uncertain, with positive values suggesting potential increases, but the estimates were not statistically significant. The dynamic treatment effects estimates (DATT) showed significantly higher CR in treated areas 3 years before the program, but no significant evidence of the program reducing crime harm per resident or victim over time. Group-specific estimates (GATT) indicated lower initial crime in areas treated in 2023, but no significant program impacts on crime across previously selected areas for treatment. Somewhat unexpectedly, a significant calendar-time effect (CATT) in 2023 suggested the program was associated with an increase of about 11 more crime victims per 1000 residents in the 20-block areas around the Pilares centers. This raises questions about the program's effectiveness or other external factors contributing to rising crime in the last year under evaluation. We will now discuss these findings in the following section.

Discussion and conclusion

This study examined the impact of the Pilares program on crime in Mexico City using three measures: the overall Crime rate (CR), the Crime harm per resident (CHIP), and the Crime harm per victim (CHIV). The Cambridge Criminal Harm Index (CHI) was used to calculate the crime harm, which considers both the severity and frequency of crimes. The CR provides a general measure of criminal activity, while the CHIP indicates the average harm experienced by residents, and the CHIV reflects the intensity of harm inflicted on victims, regardless of their residency status. These measures can help identify areas where victims experience more severe offenses, even if the overall CR is low.

The Pilares program has operated since 2019. The Pilares program aims to empower Mexico City communities through educational, recreational, and vocational activities. It follows the principles of collective efficacy (CE), with objectives of community engagement, crime and violence prevention, and social networking. The centers have to be located in areas with low social development, high population densities, many young residents, and existing violence issues.

While we acknowledge that the crime metrics used in the study may not directly capture the effects of the Pilares program's focus on CE, this case study provides an opportunity to evaluate the broader impact of such community-based interventions on crime and harm in large cities. By examining the Pilares program through these crime metrics, we can assess whether initiatives aimed at enhancing CE have a measurable impact on reducing crime rates and harm, even for crimes not traditionally associated with the former. This contributes to a greater understanding of the potential of community-based interventions to improve public safety and informs policymakers on the effectiveness and limitations of implementing similar programs in different contexts.

We utilized a staggered difference-in-differences (DiD) method for impact evaluation (Callaway & Sant'Anna, 2021b). This method was applied to our three metrics, diverging from the conventional practice of using the standard pre-post DiD method on a single crime metric such as crime incidence or total arrests (see Table 1). We opted for this methodology because it allowed us to evaluate the impact of the Pilares program across various dimensions of crime over different periods and exposure durations. The number of Pilares community centers has been increasing every year.

The staggered DiD method allows to calculate four types of impact estimates (Callaway & Sant'Anna, 2021b): Group-Time Average Treatment Effects (GTATT), Dynamic Effects (DATT), Group-Specific Effects (GATT), and Calendar-Time Effects (CATT). GTATT effects estimate the treatment effects for the treated group at specific time periods, helping to assess the parallel trends assumption by checking for consistency before treatment. By aggregating GTATTs over different lengths of exposure, DATT effects capture how the impact of the treatment changes over time. GATT effects evaluate whether the program's effects differ among various cohorts of treated areas. Lastly, CATT effects assess whether the program's impact varies across different years by summarizing GTATTs over calendar periods.

Our GTATT estimates do not provide statistical evidence that the Pilares program has impacted crime rates or harm within the 10-block and 20-block areas surrounding the Pilares locations. The DATT effects estimates revealed significantly higher CR in the treated areas 3 years prior to the program's implementation, but no significant evidence that the program reduced CHIP or CHIV over time. Additionally, the GATT effects estimates indicated lower initial CR in areas treated by a Pilares center in 2023, yet no significant impacts on crime outcomes across areas selected for treatment between 2019 and 2022. Furthermore, CATT estimate for 2023 suggested the program was associated with an increase in the CR within the 20-block areas of influence around the Pilares centers, which raises questions about the program's effectiveness or the potential influence of other external factors contributing to rising crime in the final year under evaluation.

Despite the inability to meet the parallel trends assumption, the available evidence suggests that the Pilares program has thus far been ineffective in demonstrating any statistically significant impact on crime prevalence or criminal harm within the 10-block and 20-block areas surrounding its locations. The program's impact on crime thus remains inconclusive from a statistical perspective.

This absence of evidence underscores the complexities in designing and evaluating community interventions. Policymakers should consider program duration, location-specific factors, and baseline crime levels when assessing impact. The use of diverse metrics can yield varying, and at times, inconclusive results. Precisely, the lack of statistical significance does not equate to program ineffectiveness, as it may reflect limitations such as insufficient time for effects to materialize (Wo et al., 2016), measurement limitations, or unaccounted external factors like the COVID-19 pandemic. Consequently, policymakers must exercise prudence in interpreting these results and avoid hastily concluding ineffectiveness, as the program's impact may be more subtle than the metrics capture.

This study has several limitations. The staggered DiD models did not meet the parallel trends assumption, likely due to inherent differences in pre-treatment crime trajectories between treated and control areas. The use of broad crime metrics may have missed changes in specific crime types influenced by the program's objectives. As said above, perhaps the relatively short 5-year evaluation period may have been too brief to capture long-term effects (Wo et al., 2016). The COVID-19 pandemic significantly altered crime trends, and the study did not account for potential spillover effects between areas or variations in program implementation across locations. Future evaluations should address these limitations to provide a detailed understanding of the Pilares program's impact.

To conclude, this study presents three key findings. First, the Pilares program did not significantly reduce CR, CHIP, or CHIV in the surrounding areas during the evaluation period. In some cases, there were unexpected increases in CR, suggesting the program may not effectively address crime or that other external factors were at play. Second, the lack of significant findings does not necessarily mean the program was ineffective, but rather reflects the complexities of measuring the impact of community interventions in areas with substantial existing disparities. Third, the findings highlight the need for robust evaluation strategies when assessing community-oriented programs like Pilares. Rather than viewing the lack of immediate statistical evidence as a definitive judgment on the program's effectiveness, it should motivate developing deeper strategies to enhance the program's impact on public safety.

Appendix

Table A1 Yearly Means, Standard Errors, and Confidence Intervals for CR, CHIP, and CHIV in 10-Block Areas of Influence by Group* (Unmatched Groups)

	Year	Mean	SE	95% CI
Crime Rate (CR):				
Not Treated	2019	73.1	1.3	[70.6–75.5]
Treated	2019	84.4	34.6	[16.6–152.1]
Not Treated	2020	52.9	0.8	[51.2–54.5]
Treated	2020	64.9	14.2	[37.1–92.8]
Not Treated	2021	59.0	1.0	[57.1–60.9]
Treated	2021	86.9	21.5	[44.8–129.0]
Not Treated	2022	61.1	1.1	[59.0–63.3]
Treated	2022	87.5	20.4	[47.6–127.4]
Not Treated	2023	62.3	1.1	[60.2–64.5]
Treated	2023	92.4	22.2	[48.9–136.0]
Crime Harm Per Person (CHIP):				
Not Treated	2019	1.7	0.0	[1.7–1.8]
Treated	2019	1.9	0.7	[0.6–3.3]
Not Treated	2020	1.2	0.0	[1.2–1.3]
Treated	2020	1.5	0.3	[0.8–2.2]
Not Treated	2021	1.1	0.0	[1.1–1.2]
Treated	2021	1.9	0.6	[0.8–3.0]
Not Treated	2022	1.1	0.0	[1.1–1.2]
Treated	2022	1.6	0.3	[0.9–2.2]
Not Treated	2023	1.1	0.0	[1.0–1.1]
Treated	2023	1.6	0.4	[0.8–2.3]
Crime Harm Per Victim (CHIV):				
Not Treated	2019	14.7	0.0	[14.6–14.7]
Treated	2019	18.9	1.2	[16.5–21.3]
Not Treated	2020	13.9	0.0	[13.8–14.0]
Treated	2020	16.6	0.8	[15.1–18.1]
Not Treated	2021	12.7	0.0	[12.7–12.8]
Treated	2021	15.5	0.5	[14.5–16.5]
Not Treated	2022	12.4	0.0	[12.4–12.5]
Treated	2022	15.2	0.4	[14.3–16.0]
Not Treated	2023	10.8	0.0	[10.8–10.9]
Treated	2023	12.6	0.3	[11.9–13.3]

*The number of Pilares centers established each year was the following: 52 in 2019, 63 in 2020, 126 in 2021, 52 in 2022, and 7 in 2023, for a total of 303

Table A2 Yearly Means, Standard Errors, and Confidence Intervals for CR, CHI, and CHIv in 20-Block Areas of Influence by Group* (Unmatched Groups)

	Year	Mean	SE	95% CI
Crime Rate (CR):				
Not Treated	2019	76.7	1.0	[74.7–78.6]
Treated	2019	94.6	40.0	[16.2–173.0]
Not Treated	2020	55.2	0.6	[53.9–56.4]
Treated	2020	59.9	11.2	[38.0–81.8]
Not Treated	2021	62.5	0.8	[60.9–64.0]
Treated	2021	72.9	12.5	[48.3–97.4]
Not Treated	2022	64.6	0.9	[62.8–66.3]
Treated	2022	75.2	12.9	[49.8–100.5]
Not Treated	2023	65.7	0.9	[64.0–67.5]
Treated	2023	78.6	12.9	[53.2–103.9]
Crime Harm Per Person (CHIP):				
Not Treated	2019	1.8	0.0	[1.8–1.8]
Treated	2019	2.1	0.7	[0.7–3.6]
Not Treated	2020	1.3	0.0	[1.2–1.3]
Treated	2020	1.5	0.3	[0.9–2.1]
Not Treated	2021	1.2	0.0	[1.2–1.2]
Treated	2021	1.6	0.3	[1.0–2.2]
Not Treated	2022	1.2	0.0	[1.2–1.2]
Treated	2022	1.4	0.2	[1.0–1.8]
Not Treated	2023	1.1	0.0	[1.1–1.1]
Treated	2023	1.4	0.2	[0.9–1.8]
Crime Harm Per Victim (CHIV):				
Not Treated	2019	14.8	0.0	[14.7–14.8]
Treated	2019	17.8	1.1	[15.7–19.9]
Not Treated	2020	14.0	0.0	[13.9–14.1]
Treated	2020	16.4	0.6	[15.1–17.6]
Not Treated	2021	12.8	0.0	[12.7–12.8]
Treated	2021	15.3	0.4	[14.5–16.0]
Not Treated	2022	12.5	0.0	[12.5–12.6]
Treated	2022	15.1	0.4	[14.4–15.9]
Not Treated	2023	10.9	0.0	[10.9–10.9]
Treated	2023	12.8	0.3	[12.2–13.3]

*The number of Pilares centers established each year was the following: 52 in 2019, 63 in 2020, 126 in 2021, 52 in 2022, and 7 in 2023, for a total of 303

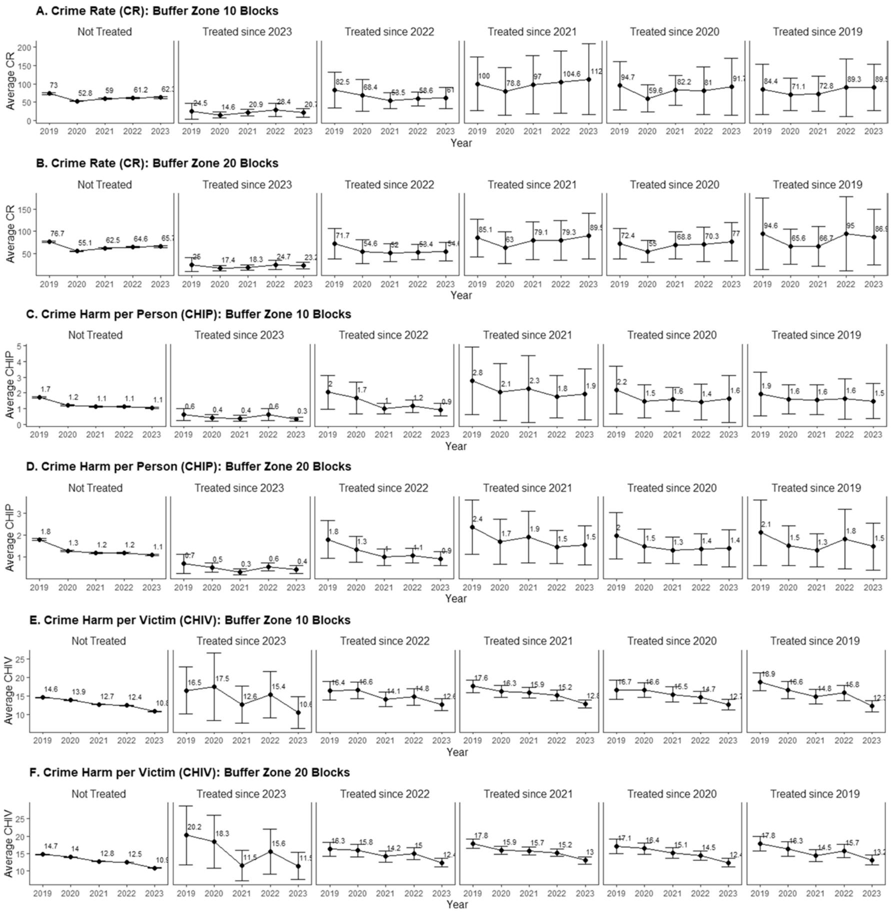

Fig. A1 Trends in CR, CHIP, and CHIV by Pilares center years of treatment

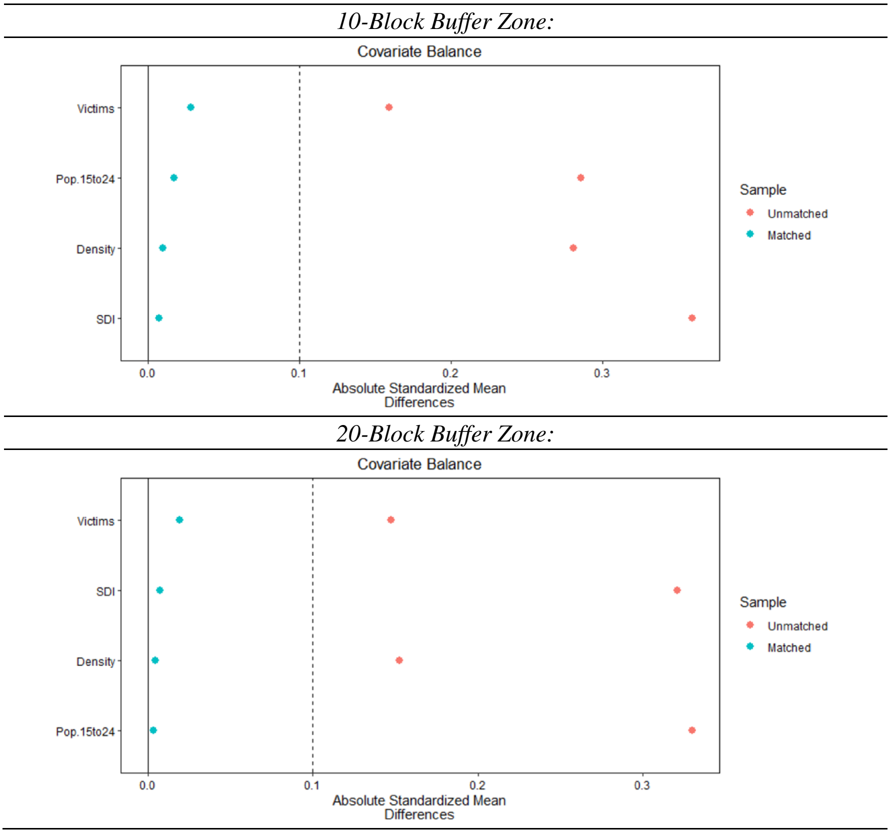

Fig. A2 Standardized Mean Differences of Covariates Pre- and Post-CEM Matching in the 10-Block and 20-Block Areas of Influence

Table A3 Yearly Means, Standard Errors, and Confidence Intervals for the Control Variables in 10-Block and 20-Block Areas of Influence by Group* (Unmatched Groups)

	Mean	SE	95% CI
10-Block Buffer Zone:			
Social Development Index (SDI):			
Not Treated:	0.81	0.00	[0.81–0.81]
Treated:	0.78	0.00	[0.77–0.78]
Population Density:			
Not Treated:	0.06	0.00	[0.06–0.06]
Treated:	0.05	0.00	[0.04–0.05]
Population 15–29 years old:			
Not Treated:	18.4	0.0	[18.3–18.4]
Treated:	22.3	0.4	[21.5–23.1]
20-Block Buffer Zone:			
Social Development Index (SDI)			
Not Treated:	0.81	0.00	[0.81–0.81]
Treated:	0.79	0.00	[0.78–0.79]
Population Density:			
Not Treated:	0.06	0.00	[0.06–0.06]
Treated:	0.05	0.00	[0.05–0.05]
Population 15–29 years old:			
Not Treated:	18.8	0.0	[18.7–18.8]
Treated:	22.9	0.4	[22.1–23.7]

Our rationale for utilizing various outcome measures is rooted in the possibility that CE programs may have diverse effects on different aspects of crime. For example, while crime rates offer an evaluation of the occurrence of criminal incidents, integrating crime harm indexes enable us to grasp the qualitative and severity dimensions of crime events. By examining different crime outcomes concurrently, we can provide a more thorough assessment that not only measures the frequency of crimes but also differentiates between varying levels of harm caused.

Table A4 CR: Group-Time Average Treatment Effects in 10-Block and 20-Block Areas of Influence

		Area of Influence: 10-Block			Area of Influence: 20-Block		
Group	Time	ATT(g,t)	Std. Error	95% CI	ATT(g,t)	Std. Error	95% CI
2020	2020	-8.755	11.854	[-36.378, 18.868]	-1.543	8.162	[-18.937, 15.853]
2020	2021	-0.533	9.978	[-23.784, 22.719]	7.667	15.933	[-26.293, 41.626]
2020	2022	-5.790	8.661	[-25.973, 14.393]	3.110	13.491	[-25.644, 31.865]
2020	2023	-4.247	10.456	[-28.613, 20.119]	6.922	10.262	[-14.949, 28.794]
2021	2020	0.288	3.669	[-8.262, 8.838]	0.423	3.611	[-7.274, 8.120]
2021	2021	4.353	2.934	[-2.485, 11.191]	10.461	6.563	[-3.528, 24.450]
2021	2022	8.355	11.234	[-17.825, 34.535]	11.961	6.720	[-2.360, 26.283]
2021	2023	21.727	23.744	[-33.604, 77.058]	17.002	10.709	[-5.822, 39.826]
2022	2020	6.525	8.032	[-12.193, 25.243]	1.681	4.207	[-7.287, 10.648]
2022	2021	5.916	4.640	[-4.896, 16.727]	5.806	4.048	[-2.821, 14.434]
2022	2022	-4.071	1.457	[-7.466, -0.676]	-6.889	2.223	[-11.627, -2.152]
2022	2023	26.569	22.720	[-26.376, 79.513]	11.091	11.217	[-12.817, 35.000]
2023	2020	**7.776**	**0.778**	**[5.964, 9.588]**	**8.051**	**0.825**	**[6.293, 9.809]**
2023	2021	4.464	5.048	[-7.300, 16.228]	1.006	2.015	[-3.288, 5.300]
2023	2022	**11.022**	**4.124**	**[1.412, 20.632]**	**4.971**	**1.904**	**[0.913, 9.029]**
2023	2023	-17.323	8.788	[-37.801, 3.155]	-3.967	2.485	[-9.264, 1.330]
P-value of Parallel Trends pre-test:				< 0.000			< 0.000

Estimates with no zero in their 95% CI are significant and thus should be presented in bold. Control Group: Never Treated

Table A5 CHIP: Group-Time Average Treatment Effects in 10-Block and 20-Block Areas of Influence

		Area of Influence: 10-Block			Area of Influence: 20-Block		
Group	Time	ATT(g,t)	Std. Error	95% CI	ATT(g,t)	Std. Error	95% CI
2020	2020	-0.071	0.365	[-0.813, 0.670]	-0.149	0.252	[-0.695, 0.397]
2020	2021	0.088	0.313	[-0.546, 0.722]	-0.137	0.227	[-0.629, 0.356]
2020	2022	-0.040	0.182	[-0.409, 0.330]	-0.168	0.301	[-0.821, 0.485]
2020	2023	-0.179	0.216	[-0.618, 0.259]	-0.203	0.373	[-1.012, 0.606]
2021	2020	0.073	0.271	[-0.477, 0.624]	-0.024	0.192	[-0.441, 0.394]
2021	2021	-0.147	0.317	[-0.790, 0.496]	0.210	0.276	[-0.389, 0.808]
2021	2022	-0.238	0.369	[-0.988, 0.511]	0.039	0.219	[-0.436, 0.513]
2021	2023	0.113	0.289	[-0.474, 0.700]	0.280	0.205	[-0.165, 0.726]
2022	2020	0.405	0.366	[-0.338, 1.148]	**0.234**	**0.094**	**[0.031, 0.437]**
2022	2021	-0.252	0.243	[-0.746, 0.242]	-0.148	0.080	[-0.322, 0.026]
2022	2022	0.406	0.364	[-0.333, 1.146]	0.114	0.115	[-0.135, 0.363]
2022	2023	0.758	0.655	[-0.572, 2.087]	0.318	0.281	[-0.291, 0.928]
2023	2020	0.082	0.135	[-0.193, 0.356]	**0.133**	**0.055**	**[0.013, 0.253]**
2023	2021	-0.043	0.061	[-0.167, 0.082]	0.015	0.043	[-0.079, 0.108]
2023	2022	**0.348**	**0.092**	**[0.162, 0.534]**	**0.200**	**0.056**	**[0.079, 0.322]**
2023	2023	-0.272	0.148	[-0.573, 0.028]	-0.096	0.085	[-0.281, 0.090]
P-value of Parallel Trends Pre-test:				< 0.000			< 0.000

Estimates with no zero in their 95% CI are significant and thus should be presented in bold. Control Group: Never Treated

Table A6 CHIV: Group-Time Average Treatment Effects in 10-Block and 20-Block Areas of Influence

		Area of Influence: 10-Block			Area of Influence: 20-Block		
Group	Time	ATT(g,t)	Std. Error	95% CI	ATT(g,t)	Std. Error	95% CI
2020	2020	1.332	1.502	[-2.043, 4.706]	0.826	1.155	[-1.667, 3.318]
2020	2021	1.238	1.747	[-2.687, 5.163]	1.260	1.257	[-1.453, 3.973]
2020	2022	2.104	1.487	[-1.237, 5.445]	0.876	0.897	[-1.061, 2.813]
2020	2023	-0.178	1.581	[-3.729, 3.372]	-0.853	1.433	[-3.945, 2.240]
2021	2020	-1.018	1.941	[-5.378, 3.343]	-0.832	1.140	[-3.294, 1.629]
2021	2021	0.865	1.190	[-1.808, 3.539]	1.926	1.752	[-1.856, 5.708]
2021	2022	1.787	1.989	[-2.681, 6.255]	1.939	1.978	[-2.331, 6.209]
2021	2023	2.533	2.657	[-3.436, 8.502]	3.005	1.540	[-0.318, 6.328]
2022	2020	-0.807	1.494	[-4.163, 2.550]	-1.045	1.328	[-3.911, 1.821]
2022	2021	-5.187	3.921	[-13.995, 3.620]	-0.774	0.975	[-2.878, 1.330]
2022	2022	6.351	5.448	[-5.887, 18.590]	0.664	1.174	[-1.869, 3.197]
2022	2023	7.922	6.805	[-7.365, 23.209]	0.860	1.923	[-3.290, 5.009]
2023	2020	3.847	5.149	[-7.719, 15.412]	-2.090	2.041	[-6.495, 2.314]
2023	2021	-8.385	4.930	[-19.461, 2.690]	-5.242	4.487	[-14.925, 4.442]
2023	2022	**4.080**	**1.538**	**[0.625, 7.535]**	**3.941**	**0.853**	**[2.101, 5.782]**
2023	2023	-3.411	1.150	[-5.995, -0.827]	-1.209	0.604	[-2.512, 0.095]
P-value of Parallel Trends Pre-test:				< 0.000			< 0.000

Estimates with no zero in their 95% CI are significant and thus should be presented in bold. Control Group: Never Treated

Declarations

Competing interests The authors declare no competing interests.

References

Beck, E., Ohmer, M., & Warner, B. (2012). Strategies for preventing neighborhood violence: Toward bringing collective efficacy into social work practice. *Journal of Community Practice, 20*(3), 225–240. https://doi.org/10.1080/10705422.2012.700278

Becker, J. H. (2019). Within-neighborhood dynamics: Disadvantage, collective efficacy, and homicide rates in Chicago. *Social Problems, 66*(3), 428–447. https://doi.org/10.1093/socpro/spy013

Blackwell, M., Iacus, S., King, G., & Porro, G. (2009). Cem: Coarsened exact matching in stata. *The Stata Journal: Promoting Communications on Statistics and Stata, 9*(4), 524–546. https://doi.org/10.1177/1536867X0900900402

Bland, N., Calder, A., Fyfe, N. R., Anderson, S., Mitchell, J., & Reid, S. (2021). Public policy reform and police prevention practice: A journey upstream? *Policing: A Journal of Policy and Practice*, *15*(3), 1882–1893. https://doi.org/10.1093/police/paab008

Braga, A., Papachristos, A., & Hureau, D. (2012). Hot spots policing effects on crime. *Campbell Systematic Reviews, 8*(1), 1–96. https://doi.org/10.4073/csr.2012.8

Burchfield, K. B., & Silver, E. (2013). Collective efficacy and crime in Los Angeles neighborhoods: Implications for the Latino Paradox*. *Sociological Inquiry, 83*(1), 154–176. https://doi.org/10.1111/j.1475-682X.2012.00429.x

Callaway, B., & Sant'Anna, P. (2021a). Difference-in-differences with multiple time periods. *Journal of Econometrics, 225*(2), 200–230. https://doi.org/10.1016/j.jeconom.2020.12.001. Accessed 5 Dec 2023.

Callaway, B., & Sant'Anna, P. H. C. (2021b). did: Difference in Differences (Version 2.1.2) [Computer software]. https://bcallaway11.github.io/did/

Cantora, A., Iyer, S., & Restivo, L. (2016). Understanding drivers of crime in East Baltimore: Resident perceptions of why crime persists. *American Journal of Criminal Justice, 41*(4), 686–709. https://doi.org/10.1007/s12103-015-9314-6

Chainey, S. P., Pezzuchi, G., Guerrero Rojas, N. O., Hernandez Ramirez, J. L., Monteiro, J., & Rosas Valdez, E. (2019). Crime concentration at micro-places in Latin America. *Crime Science, 8*, 1–5.

Chavez Lopez, J. L. (2022). *Los PILARES y su estrategia para la transformación y la cohesión social* [Bachelor of Sociology, Universidad Autonoma Metropolitana (UAM), Unidad Xochimilco]. https://repositorio.xoc.uam.mx/jspui/handle/123456789/27314. Accessed 6 Dec 2023.

Estévez-Soto, P. R. (2021). Crime and COVID-19: Effect of changes in routine activities in Mexico City. *Crime Science, 10*(1), 15. https://doi.org/10.1186/s40163-021-00151-y

Fabusuyi, T. (2018). Is crime a real estate problem? A case study of the neighborhood of East Liberty, Pittsburgh. *Pennsylvania. European Journal of Operational Research, 268*(3), 1050–1061.

Gill, C., Weisburd, D., Telep, C. W., Vitter, Z., & Bennett, T. (2014). Community-oriented policing to reduce crime, disorder and fear and increase satisfaction and legitimacy among citizens: A systematic review. *Journal of Experimental Criminology, 10*(4), 399–428. https://doi.org/10.1007/s11292-014-9210-y

Gobierno de la Ciudad de Mexico. (2018). *Programa de Gobierno de la Ciudad de México 2019–2024*. Gobierno de la Ciudad de México. https://plazapublica.cdmx.gob.mx/processes/programa-de-gobierno-cdmx/f/1/?locale=es. Accessed 5 Dec 2023.

González, R. P., & Varela, A. V. (2021). Territorialidad urbana y seguridad. Una agenda en materia de capital social para el programa Pilares de la Ciudad de México. *Revista CIFE: Lecturas de Economía Social, 23*(39). https://revistas.usantotomas.edu.co/index.php/cife/article/view/7157. Accessed 5 Dec 2023.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics, 225*(2), 254–277.

Greifer, N. (2020). cobalt: Covariate balance tables and plots. *R Package Version*, *4*(0).

Heinze, J. E., Krusky-Morey, A., Vagi, K. J., Reischl, T. M., Franzen, S., Pruett, N. K., Cunningham, R. M., & Zimmerman, M. A. (2018). Busy streets theory: The effects of community-engaged greening on violence. *American Journal of Community Psychology, 62*(1–2), 101–109. https://doi.org/10.1002/ajcp.12270

Hipp, J. R., & Wickes, R. (2018). Problems, perceptions and actions: An interdependent process for generating informal social control. *Social Science Research, 73*, 107–125. https://doi.org/10.1016/j.ssresearch.2018.03.015

Hipp, J. R., & Wickes, R. (2017). Violence in urban neighborhoods: A longitudinal study of collective efficacy and violent crime. *Journal of Quantitative Criminology*, *33*(4), Article 4. https://doi.org/10.1007/s10940-016-9311-z

Hipple, N. K., & Saunders, J. (2020). Evaluation of the innovations in community-based crime reduction (CBCR) program: Executive summary and final report. *Annotation*. https://www.ojp.gov/library/publications/evaluation-innovations-community-based-crime-reduction-cbcr-program-executive. Accessed 6 Dec 2023.

Hohl, B. C., Kondo, M. C., Kajeepeta, S., MacDonald, J. M., Theall, K. P., Zimmerman, M. A., & Branas, C. C. (2019). Creating safe and healthy neighborhoods with place-based violence interventions. *Health Affairs, 38*(10), 1687–1694. https://doi.org/10.1377/hlthaff.2019.00707

Ho, D., Imai, K., King, G., Stuart, E., & Whitworth, A. (2018). Package 'MatchIt.' *Version.[Google Scholar]*. https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=8f825371cc962f4d36bf18dfcb36783a00279bd5. Accessed 6 Dec 2023.

Iacus, S. M., King, G., & Porro, G. (2012). Causal inference without balance checking: Coarsened exact matching. *Political Analysis, 20*(1), 1–24.

Iyer, S., Knott, C., & Cantora, A. (2020). Community-based empowerment, collective efficacy, and collaborative data-sharing: Key elements for crime reduction planning in Baltimore. In R. J. Stokes & C. Gill (Eds.), *Innovations in Community-Based Crime Prevention* (pp. 23–43). Springer International Publishing. https://doi.org/10.1007/978-3-030-43635-3_2

John, B., Arrington, A., LePore-Jentelson, J., & Stock, R. (2020). A community-based response to the opioid-epidemic-linked crime in Dayton, Ohio. In R. J. Stokes & C. Gill (Eds.), *Innovations in Community-Based Crime Prevention* (pp. 45–64). Springer International Publishing. https://doi.org/10.1007/978-3-030-43635-3_3

Kim, D., Hong, S.-W., & Jeong, Y. (2019). Crime prevention effect of the second generation crime prevention through environmental design project in South Korea: An analysis. *Social Sciences, 8*(6), 187.

Lee, J. S., Park, S., & Jung, S. (2016). Effect of crime prevention through environmental design (CPTED) measures on active living and fear of crime. *Sustainability, 8*(9), 872.

Leverentz, A., Pittman, A., & Skinnon, J. (2018). Place and perception: Constructions of community and safety across neighborhoods and residents. *City & Community, 17*(4), 972–995. https://doi.org/10.1111/cico.12350

Lindblad, M. R., Manturuk, K. R., & Quercia, R. G. (2013). Sense of community and informal social control among lower income households: The role of homeownership and collective efficacy in reducing subjective neighborhood crime and disorder. *American Journal of Community Psychology, 51*(1–2), 123–139. https://doi.org/10.1007/s10464-012-9507-9

Maxwell, C. D. (2018). Collective efficacy and crime. In *The Blackwell Encyclopedia of Sociology* (pp. 1–2). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781405165518.wbeosc064.pub2

Mennis, J., Dayanim, S. L., & Grunwald, H. (2013). Neighborhood collective efficacy and dimensions of diversity: A multilevel analysis. *Environment and Planning a: Economy and Space, 45*(9), 2176–2193. https://doi.org/10.1068/a45428

Montoya, L., Junger, M., & Ongena, Y. (2016). The relation between residential property and its surroundings and day- and night-time residential burglary. *Environment and Behavior, 48*(4), 4. https://doi.org/10.1177/0013916514551047

Morenoff, J. D., Sampson, R. J., & Raudenbush, S. W. (2001). Neighborhood inequality, collective efficacy, and the spatial dynamics of urban violence*. *Criminology, 39*(3), 3. https://doi.org/10.1111/j.1745-9125.2001.tb00932.x

Nubani, L., Fierke-Gmazel, H., Madill, H., & De Biasi, A. (2023). Community engagement in crime reduction strategies: A tale of three cities. *Journal of Participatory Research Methods*, *4*(1). https://jprm.scholasticahq.com/article/57526. Accessed 7 Dec 2023.

Ohmer, M. L., Warner, B. D., & Beck, E. (2010). Preventing violence in low-income communities: Facilitating residents' ability to intervene in neighborhood problems. *J. Soc. & Soc. Welfare, 37*, 161.

Ohmer, M. L., Teixeira, S., Booth, J., Zuberi, A., & Kolke, D. (2016). Preventing violence in disadvantaged communities: Strategies for building collective efficacy and improving community health. *Journal of Human Behavior in the Social Environment, 26*(7–8), 608–621. https://doi.org/10.1080/10911359.2016.1238804

Ramey, D. M., & Shrider, E. A. (2014). New parochialism, sources of community investment, and the control of street crime. *Criminology & Public Policy, 13*(2), 193–216. https://doi.org/10.1111/1745-9133.12074

Sampson, R. J. (2012). Great American City: Chicago and the Enduring Neighborhood Effect. University of Chicago Press.

Sampson, R. J., Raudenbush, S. W., & Earls, F. (1998). Neighborhood collective efficacy: Does it help reduce violence? US Department of Justice, Office of Justice Programs, National Institute of ….

Shadish, W. R., & Cook, T. D. (1998). Donald Campbell and Evaluation Theory. *American Journal of Evaluation, 19*(3), 417–422. https://doi.org/10.1177/109821409801900318

Sherman, L., Neyroud, P. W., & Neyroud, E (2016). The Cambridge Crime Harm Index: Measuring total harm from crime based on sentencing guidelines. *Policing: A Journal of Policy and Practice*, *10*(3):171–183. https://doi.org/10.1093/police/paw003

Sherman, L. W. (2007). The power few: Experimental criminology and the reduction of harm. *Journal of Experimental Criminology, 3*(4), 299–321. https://doi.org/10.1007/s11292-007-9044-y

Sherman, L. W. & Cambridge University associates. (2020). How to count crime: The Cambridge Harm Index Consensus. *Cambridge Journal of Evidence-Based Policing, 4*(1–2), 1–14. https://doi.org/10.1007/s41887-020-00043-2

Stokes, R. J. (2020). Improving community governance to reduce crime: The case of the Philadelphia's Mantua BCJI Program. In R. J. Stokes & C. Gill (Eds.), *Innovations in Community-Based Crime Prevention* (pp. 65–89). Springer International Publishing. https://doi.org/10.1007/978-3-030-43635-3_4

Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics, 225*(2), 175–199.

Telep, C. W., & Hibdon, J. (2018). Community crime prevention in high–crime areas: The Seattle neighborhood group hot spots project. *City & Community, 17*(4), 1143–1167. https://doi.org/10.1111/cico.12342

Triplett, R. (2007). *Collective efficacy and crime*. John Wiley & Sons, Ltd. https://doi.org/10.1002/9781405165518.wbeosc064

Vilalta, C., Fondevila, G., & Massa, R. (2022a). The impact of anti-COVID-19 measures on Mexico City criminal reports.*Deviant Behavior*, *0*(0), 1–15. https://doi.org/10.1080/01639625.2022.2092431

Vilalta, C., Fondevila, G., & Massa, R. (2022b). Virus containment measures and homicide in Mexico: An assessment of community strain theory. *Journal of Criminal Justice, 82*, 101992. https://doi.org/10.1016/j.jcrimjus.2022.101992

Weisburd, D. (2018). Hot spots of crime and place-based prevention: Vollmer award. *Criminology & Public Policy, 17*(1), 5–25. https://doi.org/10.1111/1745-9133.12350

Weisburd, D., & Eck, J. E. (2004). What can police do to reduce crime, disorder, and fear? *The ANNALS of the American Academy of Political and Social Science, 593*(1), 42–65. https://doi.org/10.1177/0002716203262548

Weisburd, D., Hinkle, J. C., Braga, A. A., & Wooditch, A. (2015). Understanding the mechanisms underlying broken windows policing: The need for evaluation evidence. *Journal of Research in Crime and Delinquency, 52*(4), 4.

Weisburd, D., Gill, C., Wooditch, A., Barritt, W., & Murphy, J. (2021). Building collective action at crime hot spots: Findings from a randomized field experiment. *Journal of Experimental Criminology, 17*(2), 161–191. https://doi.org/10.1007/s11292-019-09401-1

Wickham, H. (2016). ggplot2: Elegant graphics for data analysis. Springer-Verlag.

Wo, J. C., Hipp, J. R., & Boessen, A. (2016). Voluntary Organizations and Neighborhood Crime: A Dynamic Perspective. *Criminology, 54*(2), 212–241. https://doi.org/10.1111/1745-9125.12101

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