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January 2015
Research Brief 2015-01

RESEARCH BRIEF

Effectiveness of the Cure Violence Model in New York City

INTRODUCTION

In 2012, the New York City Council launched the Crisis Management System (CMS), a violence reduction program based in part on the **Cure Violence** model. The **CMS** program is designed to reduce gun violence with comprehensive and community-based prevention efforts, including the Cure Violence strategy and additional wrap-around services. Wrap-around services are optional supports offered to program participants based on their individual circumstances. Supportive services often focus on employment, education, health, mental health, and legal assistance.

The CMS began as a recommendation of the City Council's **Task Force** to Combat Gun Violence. After reviewing a wide range of information about gun violence across the City, the Task Force recommended the implementation of Cure Violence and the CMS in every borough of New York City. Provider agencies were instructed to include Cure Violence as a core component.

The Cure Violence model was developed by Gary Slutkin, a Chicago physician and epidemiologist who turned to violence prevention after spending more than a decade fighting epidemics in Africa. The model is premised on the idea that violence spreads like an epidemic, and that it can be treated using the methods employed to combat and control disease. The model posits that people learn violent behavior through everyday interactions with friends and family members, especially those they admire the most.

Research suggests that Cure Violence is a promising practice model. A study by **Johns Hopkins University** suggested that gun violence fell in three of four Baltimore neighborhoods after the introduction of Cure Violence. In one area, homicides decreased 56 percent, and all four neighborhoods experienced declines in at least one of the study's two violent indicators.

In another study, New York's **Center for Court Innovation** compared violence trends in several Brooklyn neighborhoods with and without Cure Violence and concluded that the presence of the program was associated with an overall decline in violence.

KEY COMPONENTS OF CURE VIOLENCE

1. **DETECT AND INTERRUPT** violent conflicts and violent retaliations (analogous to stopping epidemics).
2. **IDENTIFY AND TREAT** the people most at risk of violence by helping them to change behavior, leave gangs, learn conflict resolution skills, and get assistance with employment, etc.
3. **MOBILIZE** community to shift social norms to non-violence and support the individual-level changes made by Cure Violence participants.

METHODS

The New York City Council and the Robert Wood Johnson Foundation provided funding for the Research & Evaluation Center at John Jay College to assess the effectiveness of Cure Violence in New York City. As part of the Center's larger **program** of research on violence reduction efforts, a team of researchers began tracking crime outcomes in the City. The first important task was to create an effective comparison strategy. Even if violent crime appeared to drop in neighborhoods after implementing Cure Violence, it would not be appropriate simply to attribute the change to Cure Violence.

In recent years, of course, it has become commonplace for public officials to over-attribute the effects of crime policy. When crime goes down following the launch of any new program, those in favor of the new program are anxious to call it a success. But, what if crime goes down nearly everywhere at the same time? How can one isolate the effects of just that program? Evaluators address this problem by using a comparison strategy.

Researchers worked with analysts at the New York Police Department (NYPD) to assemble information about violence in all New York City neighborhoods and to compare areas with and without Cure Violence programs. The analysis focused on Cure Violence programs in three areas: two neighborhoods in Brooklyn (East New York and Crown Heights) and one neighborhood in Manhattan (West Harlem). All three areas were operating Cure Violence programs as of 2010.

Matching Comparison Areas

As shown in the accompanying tables and graphics, the analysis began by comparing homicide rates in the three Cure Violence neighborhoods with all other areas of New York City. It was immediately clear that a simple comparison with all other neighborhoods was unacceptable from an evaluation perspective. It was also clear that additional modeling would be required to identify the general direction of change while accounting for variation between census tracts.

Together, the three Cure Violence areas encompassed 13 U.S. Census Tracts. These areas were by definition more disadvantaged and more at-risk for violence. The study needed to identify 13 other census tracts with similar population characteristics and similar rates of serious violence in 2009, just before the launch of the City Council's Crisis Management System and the implementation of new Cure Violence programs.

The study identified comparison areas using propensity scoring (see Apel and Sweeten 2010; Ho, Imai, King and Stuart 2007; Ho, Imai, King and Stuart 2013; Rubin 1974; Heckman and Robb 1985; Rosenbaum 2002; and Stuart 2004).

Researchers first used a logistic regression model to predict the chances that any particular census tract in New York City would be in an area with a Cure Violence program. The model relied on a range of variables, including the number of shootings, the total population of the tract as of 2010, and various population characteristics such as basic demographics, the percentage of residents in poverty, and levels of unemployment (Glenn 2014). The regression model was then used to identify 13 suitable comparison tracts.

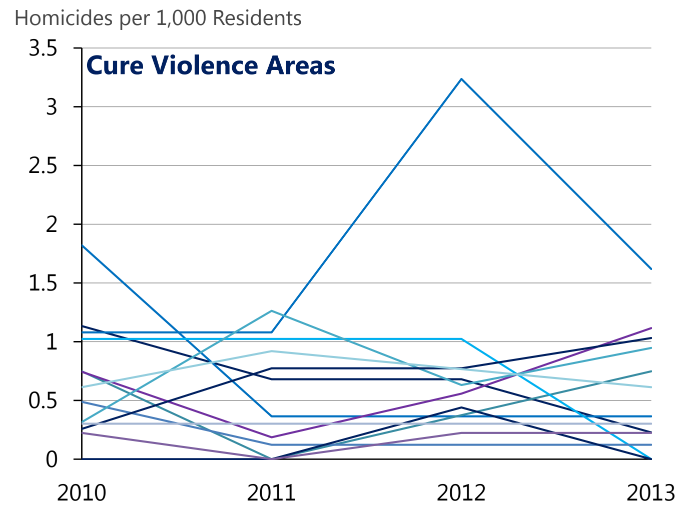
The research team next examined the levels of homicide in each census tract in both treatment and comparison areas. Homicide rates were relatively low and varied considerably from year to year.

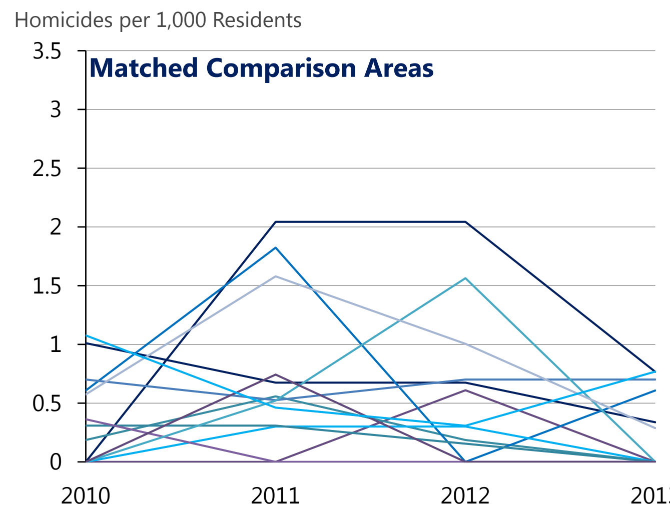
Because it was not possible to see clear data patterns at the level of individual census tracts, the study turned to a series of hierarchical growth curve models in order to assess homicide trends in Cure Violence areas compared with matched areas.

Matched Neighborhoods Are More Similar to Neighborhoods with Cure Violence Programs

		Comparisons Areas	
Area Characteristics	Cure Violence	Matched Areas	All Other NYC Areas
Average Population	4094	3894	3875
Avg. Shootings in 2009	1.4	1.6	0.5
Percent Poor Residents	26	24	16
Percent Unemployment Among Young Males	48	48	40

Homicide Rates in Individual Census Tracts Vary Too Much to be Informative





Note: Each graphic shows the per capita rates of homicide in 13 neighborhoods (U.S. Census Tracts) between 2010 and 2013. "Cure Violence Areas" are the 13 census tracts where new Cure Violence programs were implemented in 2010. "Matched Comparison Areas" are 13 other New York census tracts that did not have Cure Violence programs and were matched to the Cure Violence tracts using propensity scores that incorporated population size, racial and ethnic demographics, poverty, unemployment, and violent crime in 2009.

RESULTS

The homicide trends depicted here are drawn from the results of a series of linear growth curve models. Growth curve modeling —originally adapted from hierarchical linear modeling techniques designed to analyze cross-sectional data— is an effective approach for assessing the variability in data trends among different populations or places (Raudenbush and Bryk 2002).

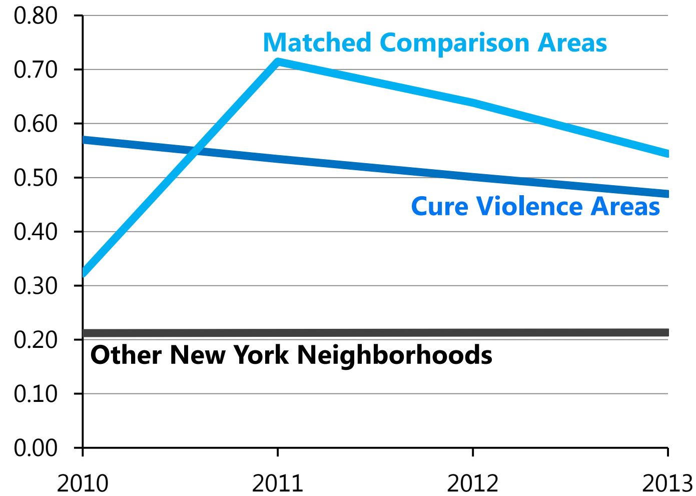
Given the small number of time periods in the current analysis, and the fact that the treatment variable (i.e. Cure Violence versus no Cure Violence) is time-invariant, a growth curve model is a suitable choice for determining whether violence trends in Cure Violence areas differ significantly from trends in other parts of the city (Phillips and Greenberg 2008). This approach has been used by Kubrin and Herting (2003) to study trends in homicide across neighborhoods in St. Louis. Rosenfeld and colleagues (2007) used similar methods to assess the impact of order maintenance arrests on precinct-level robbery and homicide trends in New York City. Coupled with the propensity score matching technique, this approach allowed the study to compare temporal crime trends in Cure Violence areas relative to other areas which were similar in terms of demographic and economic conditions as well as previous levels of violence.

The top figure illustrates average homicide rates for all 13 Cure Violence neighborhoods and the 13 matched neighborhoods, as well as all other census tracts in the City that experienced at least one homicide. The use of propensity score matching, coupled with growth curve modeling, allowed the analysis to discern general trends in homicide and to assess whether trends in Cure Violence sites differed significantly from other areas in the city.

Of course, part of the overall decline in homicides —even within Cure Violence areas— was due to the general crime decline seen throughout the United States in recent years. After spiking upward in 2011, homicide rates in matched comparison areas declined at roughly the same pace seen in Cure Violence neighborhoods. Overall, however, the average homicide rate in matched neighborhoods ended up 69 percent higher in 2013 than it had been in 2010. In Cure Violence neighborhoods, on the other hand, the average homicide rate fell 18 percent.

These results suggest that observed changes in homicide were not simply a reflection of the general violent crime drop. Nor would it be accurate to attribute the declining homicide rates to varying levels of enforcement. The study analyzed other growth curve models to estimate trends in arrests and "complaints" (i.e. crimes reported to NYPD) for crimes such as robbery, aggravated assault, and possession of dangerous weapons. In these models, the differences between Cure Violence areas and other areas of New York City were much smaller. Thus, the changes in homicide were not completely aligned with changes in overall crime rates or rates of arrest.

Homicides Declined in Cure Violence Areas While Increasing Overall in Other Areas Between 2010 and 2013



Year Reported	Rates Shown in Graphic (Homicides per 1,000 Residents) Cure Violence	Matched Areas	All Other NYC Areas
2010	0.570	0.322	0.212
2011	0.534	0.715	0.213
2012	0.501	0.639	0.213
2013	0.470	0.544	0.213
Pct. Change 2010-2013	–18%	+69%	+1%

Rates of "Complaints" (i.e. Reported Crimes) and Arrests Varied Much Less Between Areas

	Percent Change in Rates (per 1,000 Residents) Cure Violence	Matched Areas	All Other NYC Areas
Homicide	–18%	+69%	+1%
Violent "Complaints"	–3%	–2%	+3%
Violent Arrests	–8%	–18%	–10%

Note: Graphics and tables shows results from a series of growth curve models. "Cure Violence Areas" include 13 census tracts where Cure Violence programs were implemented as of 2010. "Matched Comparison Areas" are 13 different census tracts in New York City that did not have Cure Violence programs during this time period and were matched to the Cure Violence tracts using propensity score matching techniques. Other New York City areas include any U.S. Census Tract with at least one homicide between 2003 and 2013. Models of arrests and "complaints" (or reported crimes) included violent crimes such as robbery, aggravated assault, and weapons possession.

CONCLUSION

This analysis of crime data from New York City neighborhoods over a four-year period is not definitive evidence for the effectiveness of the Cure Violence model. However, the results suggest that the model may be effective in reducing rates of homicide. When compared with similarly situated neighborhoods not served by Cure Violence, areas of New York City that implemented Cure Violence programs in 2010 tended to experience greater declines in homicide by 2013.

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ACKNOWLEDGEMENTS

Funding support for this research brief was provided by the **Robert Wood Johnson Foundation** and the **New York City Council**. The authors are grateful for the cooperation and support of the **New York Police Department** in providing and documenting the law enforcement data used in this brief. The crime data used in this report were provided by and continue to belong to the New York City Police Department. Further use of the data must be approved by the New York City Police Department. Points of view or opinions contained within this document are those of the authors and do not necessarily represent the official position or policies of the New York City Police Department.