



Measuring Change in Social Cohesion, Collective Efficacy and Public Safety Outcomes during MAP Implementation in NYC

FEBRUARY 2021

A report submitted to the John Jay College of Research and Evaluation Center and the NYC Mayor's Office of Criminal Justice

AUTHORS:
Erik Scherpf, PhD
John K. Roman, PhD

 **NORC** at the
University of
Chicago

Table of Contents

Executive Summary	1
The Project in Brief: The Mayor’s Action Plan	3
The Survey Instrument and Data Collection	4
Survey Items and Measures	4
Sampling Frame	5
Data Collection	5
Literature Review	6
Analytic Approach	7
Data Analysis	9
Empirical Model	9
Dependent Variables	11
MAP Variable	11
Development Crime Trends and Collective Efficacy	11
Results	12
Effects of MAP on Crime, controlling for latent attitudes	12
Table 1: Random Intercept Poisson Models of Seven Major Felonies	13
Table 2: Random Intercept Poisson Models of Non-Seven Major Felonies	15
Table 3: Random Intercept Poisson Models of Misdemeanors	16
Effects of Latent Attitudes on Crime, Controlling for MAP	17
Table 4: Relationship between Social Cohesion and Long-term Reported Crime Rates	17
Conclusion	17
References	19

Executive Summary

The NYC Mayor's Action Plan (MAP) is a comprehensive neighborhood-based strategy to increase safety through coordinated crime reduction efforts in 17 New York City Housing Development Authority (NYCHA) communities across New York City (NYC). The general goal of the MAP evaluation is to link MAP intervention activities to place-based outcomes, measured as aggregated individual outcomes and development-level outcomes. What distinguishes the MAP intervention from other place-based public safety interventions is the priority placed on motivating positive changes in community engagement (including positive changes in social cohesion, legitimacy, and collective action) and in community well-being (including public health, economic development, and education) in addition to changes in crime incidence and prevalence and overall perception of public safety.

The goal of the MAP evaluation, conducted by John Jay Research and Evaluation Center (JohnJayREC) was to measure changes in these three measures of resident outcomes, measured one year apart, using data from two cross-sectional survey data collections and on resident

attitudes and with administrative data on reported crime. In our companion research note, **Measuring Change in Residents Attitudes and Beliefs during MAP Implementation**, we report the results of analyses examining the relationship between MAP participation and changes in resident attitudes about community engagement and community well-being, and observed changes in criminal incidence.



This paper is one of a series of reports describing research on the NYC Mayor's Action Plan. The MAP research is a partnership between John Jay Research and Evaluation Center at John Jay College of Criminal Justice (JohnJayREC), the Mayor's Office of Criminal Justice (MOCJ) in New York City, and NORC at the University of Chicago. MAP is an ambitious effort to integrate human service and violence reduction programs in communities managed by the New York City Housing Authority (NYCHA) with a history of higher than average violence and public safety challenges. The goal of this research is to better understand the effects of human services interventions designed to improve public safety in nontraditional ways, through increases in trust between government and residents, trust among residents, changes in readiness for collective action, and improvements in the perceived legitimacy of government actions. The three products from the MAP research are:

- [John Jay Research and Evaluation Center project updates](#). The JohnJayREC research update series describes the evaluation plan, MAP implementation, and interim findings.
- **Resident Self-Reported Change in Community Engagement and Well-Being in MAP Neighborhoods**. In this brief, NORC describes the results of a difference in differences analysis of changes in MAP and non-MAP residents' perceptions of social cohesion and collective efficacy over one year of MAP implementation.
- **Measuring Change in Social Cohesion, Collective Efficacy, and Public Safety Outcomes during MAP Implementation in NYC**. In this brief, NORC describes the results of an analysis testing whether changes in MAP resident attitudes and beliefs affect reported crime.

The challenge with this research is that these two outcomes can be expected to be inversely correlated. In practice, that means that when community well-being and community engagement increase, prior research predicts that criminal incidence will decline. When criminal incidence increases, prior research predicts that community engagement and community well-being will decline. The timing of this effect is not well understood. A change in one outcome might affect the other in the short-term, or the effect may occur over a longer time horizon. As a result, one key hypothesis to be tested is the timing of any observed change—whether changes in resident attitudes have a short- or long-lag before affecting criminal incidence and public safety.

It is important to note that there is also an element of reverse causality such that if the research tests the effect of MAP on crime, controlling for resident attitudes, that the level of crime may have simultaneously changed resident attitudes. To solve this problem, the study uses an iterative design, where the outcome (crime) is tested for one period and the predictors (MAP and resident attitudes are tested for a prior period). When resident attitudes are tested as the key measure, MAP and crime are measured for the prior period.

In situations where simultaneity and reverse causality are present, it is not appropriate to pose causal questions. That is, if more crime causes there to be more pessimistic resident attitudes, it is not reasonable to conclude that pessimistic attitudes cause higher crime incidence. Thus, we consider this analysis to be exploratory, rather than causal and investigate the effect of MAP on criminal incidence controlling for prior resident attitudes about well-being and engagement, and the effect of MAP on resident attitudes, controlling for the prior crime.

Despite these limitations, this study can offer important insights for MAP and its partners, and for other place-based interventions with goals about community building that go beyond crime reduction. Those types of programs are proliferating due in part to a growing consensus in the research literature that improvements in community building have important consequences for residents that go beyond a narrow goal of increasing informal social control to reduce crime.

Overall, the study finds an association between the highest awareness of the MAP initiative) and reductions in serious crime (i.e., changes in the seven major felonies traditionally recorded by the FBI and misdemeanors. MAP dosage is defined as developments where the highest percentage of resident's self-report knowledge of MAP programs and activities were assigned as high MAP awareness. Developments with the fewest residents were aware of MAP programs and activities were assigned a low MAP awareness. However, in all developments, MAP awareness is relatively low, and thus the measure of MAP dosage is imprecise. The effect is moderate, as seen in an estimated reduction in the incidence rate ranging from 37 to 43 percent for serious crimes and a reduction in the incidence rate of misdemeanors of between 13 and 20 percent, though neither effect is statistically significant. Findings are promising but should be interpreted cautiously because the measure is only an indirect measure of MAP dosage, which would be a more reliable predictor of changes in attitudes and beliefs.

The study also finds that there is little effect of crime rates and development-level perceptions of community engagement and community well-being in the study period. This aligns with the results of the companion study which finds little effect of MAP on these attitudes. Taken together, the results suggest that attitudes toward community engagement and community well-being are stable over time, due to structural conditions of concentrated poverty intertwined with criminal justice factors, which limits the extent to which programs can affect those measures. The single exception is social cohesion, which is associated with an inverse relationship with changes in crime—declines in crime are associated with an increase in social cohesion, which is an expected relationship.

The Project in Brief: The Mayor’s Action Plan

Launched in 2014, the Mayor’s Action Plan for Neighborhood Safety (MAP) is led by the New York City (NYC) Mayor’s Office of Criminal Justice (MOCJ). MAP is a comprehensive neighborhood-based strategy to increase safety through coordinated crime reduction efforts at 15 NYCHA developments across New York City. The MAP approach enlists residents, City agencies, and community-based partners to help move beyond enforcement and address the factors underlying safety – providing opportunities for work and play, health and well-being, and youth development; promoting activated, well-maintained spaces through community and human-centered design; and improving trust between neighbors with a responsive and just government. The stated mission of MAP is: “To improve community safety in places impacted by historic disinvestment by creating opportunities for residents to identify key issues underlying crime and participate in the decision-making to address these priorities.”

MAP outcomes focus on reductions in crime and victimization as well as broad improvements in social determinants, including health, employment, and community building. As a critical component of community building, MAP seeks to increase social capital through improvements in safety and opportunity for community connectedness. Outcomes are measured both by reductions in crime and public safety, and improvements in perceptions of public safety, as well as improved perceptions of public agency legitimacy (or procedural justice), social cohesion, and trust.

The John Jay College of Criminal Justice Research and Evaluation Center (JohnJayREC) serves as the lead research institution for the MAP evaluation. NORC partnered with JohnJayREC to develop and administer a two-wave cross-sectional resident survey. The resident survey included a baseline and a follow-up survey administered one year apart, in early 2019 and early 2020. The survey collects data on respondent perceptions of public safety and the quality of relationships among residents and between residents and the government. The survey was a random household survey targeting 40 completed responses from residents of 17 MAP

developments and a matched (random) sample of residents from 17 NYCHA developments that also experience well above average rates of violence as compared to other NYCHA properties.

The Survey Instrument and Data Collection

Survey Items and Measures

The foundations for the items used in the survey instrument were developed from social disorganization theory that posits that community social organization regulates and maintains effective informal social control. Effective strategies for preventing behavioral and health problems within a target community focus on the risk factors that lead to problems, and the protective factors that prevent them. While both risk and strength (protective factors) play a substantial role in determining community health, much more is known about risk factors—and thus, the survey focuses on measuring changes in risk that result from the MAP intervention.

To create items that address the breadth of the MAP Program, key constructs in various kinds of literature were reviewed, including social capital: social cohesion, perceptions of safety, informal social control, and collective efficacy; perceptions of domestic violence; awareness of the availability of government services; procedural justice; and interactions with and trust in government figures and institutions. Literature and scales from various fields were reviewed, including the social sciences, criminal justice, and health and medicine. Internet searches were conducted using Google©, Google Scholar©, and ProQuest© for the key constructs. Searches included the following keywords: social capital, safety and opportunity for community connectedness, perceptions of public safety, public agency legitimacy, perceptions of procedural justice, social cohesion, and trust, all with and without pairing the following words in the searches: survey, questionnaire, and scale.

Much of the survey research on the effect of social service-based interventions on public safety and social welfare in neighborhoods with concentrated disadvantage are derived directly from the Project on Human Development in Chicago Neighborhoods (PHDCN). PHDCN is a major interdisciplinary study aimed at deepening society's understanding of the causes and pathways of juvenile delinquency, adult crime, substance abuse, and violence (Earls, Brooks-Gunn, Raudenbush and Sampson, 1999). PHDCN measured social capital as collective efficacy by examining the causes and pathways of juvenile delinquency, adult crime, substance abuse, and violence, using surveys, interviews, observations, and administrative data. Combining two studies into a single, integrated design, the first study examined community, social, economic, organizational, political, and cultural structures, and the dynamic changes that take place within these systems; and the second study followed randomly selected adolescents and young adults (N=7,000), which examined the changing circumstances of their lives as well as the personal characteristics that may lead them to choose or reject a variety of antisocial behaviors. PHDCN questions and scales inform many of the measures used in this instrument.

The survey instrument was assessed by two focus groups with twelve residents of MAP research sites (including residents of both treatment and comparison communities). Each participant was asked to complete the draft MAP Resident Survey and participate in a one-hour focus group regarding feedback on the survey questions. The objective of the focus group session was to assess the respondents' comprehension of the questionnaire items, including question intent and the meaning of specific words and phrases in the survey item. Residents also described issues with sensitive questions. The resident feedback from the focus groups was incorporated into the final survey instrument.

Sampling Frame

The survey was administered over five weeks in the late winter of 2019 and again in the late winter of 2019. NORC implemented an address-based sample (ABS) multimode approach to complete approximately 1,360 interviews in each of the two cross-sectional waves. The sample was drawn from residents living in New York Housing Authority developments, both those receiving the intervention and those not receiving the intervention.¹ For the baseline (and the follow-up wave), NORC sought to conduct about 680 interviews in the 17 NYCHA developments receiving the MAP intervention and about 680 in 17 NYCHA developments that did not receive the MAP intervention.

The starting sample for each wave of the survey included 15,000 households. Adults (age 18 and over) residing in sampled households were randomly selected for the survey. The survey was conducted in English, Spanish, Cantonese, and Mandarin. Cognitive interviews verified the survey was approximately 20 minutes in length. Randomly selected participants received a \$2 pre-incentive in the mail along with an explanation of the survey goals and process, as well as directions to access the web-based instrument. Respondents received \$15 upon completion of the survey with a \$10 bonus for completing within two weeks of the beginning of the survey period. Sample response was continuously measured throughout the time the survey was in the field, as was data from survey respondents. Outbound telephone calls were scheduled to begin in week 5 for survey non-respondents but were initiated after three weeks due to unexpectedly high production and only in the six communities where the neighborhood target had not been achieved.

Data Collection

Residents of the 34 MAP and matched non-MAP developments received a letter inviting them to participate in the web survey via a mailing addressed to the resident with a request that an adult in the household access and complete the web survey. Data collection for the MAP Resident

¹ While 15 developments are receiving the intervention, three of the developments have two separately managed developments and are thus treated as independent observations in the survey data collection. These 17 developments are matched with 17 distinct non-treated developments in the control group.

Survey began February 9, 2019, with the mailing of the web invitation letter. This letter provided a link to the web survey and the respondent's unique login credentials. During the first 7 days of data collection, 1,429 completed surveys were received online, far exceeding expectations. NORC also received hundreds of calls to the study's toll-free line. These calls were returned, and the survey was completed by telephone, per the respondent's request. An identical process was completed again beginning February 7, 2020. For the baseline survey, data collection ended four weeks ahead of the planned ten-week period, with 1,941 completed surveys. For the follow-up survey, data collection was again completed four weeks ahead of schedule with a total of 1,563 completed surveys.

Literature Review

This study uses repeated cross-sectional data from the two waves of the NYCHA MAP survey, together with time-series data on development-level crime to investigate the relationship between changes in neighborhood crime and MAP interventions in NYCHA developments, controlling for development latent variables, such as collective efficacy and social cohesion. Prior research on collective efficacy and social cohesion was generally followed in this study in constructing both the latent variables and in developing the hypotheses to be tested.

A seminal article by Sampson et al. (1997), informed by data collected as part of the PHDCN, sparked interest in the relationship between collective efficacy and an array of outcomes that included crime, well-being, and education. One consistent finding emerging from these studies is that a neighborhood's collective efficacy is strongly tied to its socio-demographic characteristics. In particular, concentrated disadvantage evinces a strong negative relationship with collective efficacy. Nearly all prior studies of collective efficacy (and related latent constructs) rely on cross-sectional data, hence providing only a single snapshot in time.

Sampson et al. (1997) used individual-level responses to ten questions from a PHDCN survey to construct two scales labeled "informal social control" and "social cohesion." These two scales were then combined at the neighborhood level using an item-response model to produce a single measure labeled "collective efficacy." Collective efficacy is a measure that Sampson and colleagues posited captured the degree of linkage between a neighborhood's mutual trust and its willingness to intervene for the common good. The authors asserted that the "collective efficacy of residents is a critical means by which urban neighborhoods inhibit the occurrence of interpersonal violence."

The study employed three measures of violence, two of which were based on responses from the survey itself. The first was a scale based on five questions about respondents' perceptions of violence in their neighborhood in the past six months. The second was a (binary) measure based on whether they or anyone in their family had experienced violent victimization.

The authors also hypothesized that neighborhood-level collective efficacy reduces the direct effects of a neighborhood's social composition on violent behavior. In other words, collective efficacy mediates the effect of other neighborhood attributes on violence. The authors test this hypothesis by estimating models of the effect of concentrated disadvantage, immigrant concentration, and residential stability on violent behavior with and without a measure of collective efficacy. They found that community violence is less frequent where neighbors' willingness to intervene is higher. Subsequently, many other studies have provided evidence that collective efficacy can partially explain the variation in violence across neighborhoods.

Neighborhood-level social processes are not easy to study. A growing number of studies have turned to original survey-based approaches to assess neighborhood-level social ties and associations. Taylor et al. (1984) constructed block-level measures of the proportion of respondents in 63 Baltimore neighborhoods who belonged to a neighborhood organization and the proportion who felt responsible for what happened in the area surrounding their home. Both measures were significantly and negatively related to rates of violence, exclusive of other ecological factors. Simcha-Fagan and Schwartz (1986), who studied 553 residents in 12 NYC neighborhoods during the mid-1980s, found a significant negative relationship between the rate of self-reported delinquency and rates of organizational participation and residents. Using survey data from Great Britain, Sampson and Groves (1989) found the density of local friendship networks was associated with lower robbery rates.

An unresolved (theoretical and empirical) issue pertains to the timing, and causal order, of crime and latent scale measurement. One view is that changes in collective efficacy bring about changes in neighborhood crime rather quickly (i.e., in a matter of weeks or months) and that, in turn, changes in violence can translate in short order to changes in collective efficacy. An alternative view holds that movements in neighborhood collective efficacy are reflected in movements in crime with a more substantial lag, in terms of years instead of weeks or months (Hipp and Wickes, 2017).

Analytic Approach

The first research task is to adjust the available data to test the hypothesis that MAP interventions in NYCHA developments affect neighborhood crime, controlling for development latent variables, such as collective efficacy and social cohesion. Without any empirical adjustments, the data available for this study is not well suited to directly establishing the temporal order needed for a clear causal effect running from collective efficacy (or another latent variable) to reported neighborhood crime. The second wave of the NYCHA MAP survey was completed in March 2020, while the most recently available administrative crime data terminates at the end of the second quarter of 2020. Due to the onset of the covid-19 pandemic in NYC in March 2020—an event that profoundly affected reported crime incidents, including the second quarter crime data—it is reasonable to exclude this data point from the analysis. Also, COVID-19 induced

change in crime is likely to have started in March 2020, and thus partially affects first quarter 2020 data. Thus, there is insufficient post-survey data to measure a change in crime resulting from a change in collective efficacy and other latent constructs.

Another limitation of the data available for this study is the relatively close temporal proximity (one year) of the two survey waves. Our previous report established no statistically or practically significant changes in any of the ten scale variables constructed from the survey items. This suggests that—over one year—these latent measures are rather stable. However, this stability means that there is little variation in collective efficacy between the two survey waves with which to identify an effect on crime.

Because of these data limitations, the goal of this study is not to establish a causal effect of collective efficacy (or other latent variables) on crime.² Rather, the focus of this report is the effect of the MAP intervention that occurred between the survey waves on changes in crime. In this framework, latent variables serve as a control or mediating, variables in a model where the explanatory variables of primary interest are those estimating the effect of the MAP treatment on development crime. Hence, although the coefficients on the scale scores may suffer from simultaneity bias—due to the limitations discussed above—this does *not* bias the coefficients on the MAP variables of interest. Omitting the (imperfect) latent variables from the model would likely bias our estimates of the MAP effect on crime (so long as those latent variables indeed belong in the model).

One approach to the simultaneity problem proposed by Hipp and Wickes (2017) is to use the lagged values of collective efficacy and crime as instrumental values for their respective contemporaneous values. For example, given two periods of data on crime incidents and items measuring collective efficacy, the period 1 measure of crime would instrument for the period 2 measure of crime. The relationship between current and lagged measures of collective efficacy is less clear, given the relatively nascent status of the research literature. It is not as clear that the lagged value of collective efficacy affects crime only through the contemporaneous value of collective efficacy, and not directly.

Despite these difficulties, interest also lies in the role of development level crime on NYCHA residents' perceptions and attitudes about their development. Our approach here is not to address this question in a simultaneous equations framework, but rather to estimate the second set of models that establishes a clearer temporal ordering of our measures of development crime and collective efficacy.³ In this approach, the question of interest becomes the relationship between

² Indeed, in terms of establishing the appropriate temporal order, our data are better suited to analyzing the effect of crime on collective efficacy.

³ Identification in a simultaneous equations model hinges on a plausible exclusion restriction. Apart from the one suggested by Hipp and Wickes (2017), we were not able to such a variable.

relative (i.e., cross-sectional) differences between long-run development crime trends and the scale scores that reflect the latent development variables.

Data Analysis

In this report, we estimate the relationship between development-level MAP participation and crime. To investigate this question we merged administrative criminal offense incident data, drawn from the NYC data portal, to the two waves of the NYCHA MAP survey. We focus on three broad offense categories as dependent variables: the so-called seven major felonies, non-seven major felonies, and misdemeanors. For each of these three offense categories, we estimated ten separate regression models. Each model includes variables capturing the average demographic characteristics of survey respondents in each development and the full interaction of an indicator for development-level MAP participation with an indicator for the post-MAP intervention period (i.e., wave 2 of the survey).

We also measure the mediating effect of residents’ perception and attitudes by including as explanatory variables latent scale scores constructed from the survey data. These scales measure residents’ perceptions of a range of latent constructs, including development social cohesion, collective efficacy, government engagement, and procedural justice. We examine the mediating effect of each of the ten latent scale variables individually, rather than including them all in a single model. In other words, for each of the three dependent variables, we estimate ten separate regressions—one for each scale score. Estimating the effect of one scale variable at a time isolates the mediating effect of each and mitigates the multi-collinearity (and resulting imprecision) that would result from including all of the scale scores in a single model.

Empirical Model

To estimate the effect of MAP on development crime rates, conditional on development socio-demographic characteristics and latent characteristics such as collective efficacy, we propose Poisson Random Intercept Models. Specifically, *CRIME*—the number of events or incidents reported in time period t —is assumed to follow a Poisson distribution:

$$\Pr(CRIME_{kt}|\mu) = \frac{\exp(-\mu_{kt}) \mu_{kt}^{CRIME_{kt}}}{CRIME_{kt}!}$$

Here μ is the expectation of *CRIME* in development k and time t , and is given by $\mu = \lambda POP$, where λ represents the incidence rate and POP denotes the development population.

$$\ln(\mu_{kt}) = \ln(POP_k) + \beta_0 + \beta_1 MAP_k + \beta_2 POST_t + \beta_3 MAP_k x POST_t + \beta_4 SCALE_{kt} + DEMO_{kt}\Gamma + \alpha_k \tag{1}$$

In equation (1) above, μ_{kt} denotes the logarithm of the expected number of incidents for one of the three offense categories (seven majors, non-seven majors, and misdemeanors) in development k at time t . MAP_k is an indicator variable equal to one if development k participated in MAP, and $POST_t$ is an indicator variable for the second, post-intervention, wave of the survey, while $MAP_k \times POST_t$ denotes the interaction of these two binary variables.⁴ $SCALE_{kt}$ denotes the scale score in development k at time t . $DEMO_{kt}$ is a vector of average demographic characteristics of residents in development k at time t . These characteristics were collected from respondents in each survey round and include gender, age, race/ethnicity, education, household size, employment status, and tenure in NYCHA. $\ln(POP_k)$ is the natural logarithm of the development population.⁵ Note that this represents the exposure term and enters the model with a coefficient constrained to equal unity.⁶ The term α_k represents a development-specific intercept. In the Poisson random intercept models we estimate, this term follows a gamma distribution.⁷

Given that each dependent variable is a count variable, equation (1) is estimated as a Poisson random intercept model. Note that to estimate equation (1), the left-hand side of the equation is the count of incidents for a given offense category, while the development-level population enters the model as the offset (or exposure) term. Prior research has shown that Poisson specification performs better than negative binomial specification when using fixed effects (Wooldridge, 1999).⁸ Moreover, for random effects models, the inclusion of a random intercept mitigates concerns about overdispersion that typically apply to Poisson models. As a robustness check, we also estimated negative binomial regressions and these yielded similar results.

The development-level control variables were constructed by averaging reported demographic characteristics by development. The validity of these variables as development-level controls hinges on the representativeness of the survey sample in each development.⁹ Similarly, the scale score variables represent the development average scores for a given scale. For each dependent

⁴ Note that the value of MAP_k is constant across the two waves of the survey (but varies across developments), whereas $POST_t$ will equal one for all developments in wave 2 (and equal zero for all developments in wave 1).

⁵ Data on development-specific populations were only available as of 2019, so this variable does not vary by time. Since the survey waves are so temporally proximate, and because we do not expect large fluctuations in development populations over this period, we do not believe this poses an important drawback.

⁶ This exposure term accounts for the fact that the denominator of the incidence rate for each development (i.e., their respective populations) differ.

⁷ In addition to random intercept models, we also estimate, but do not present here, fixed effect models. In the fixed effects framework, α_k are no longer random variables but rather fixed parameters. The results from the fixed effects models were similar to the random effects specifications and did not alter our conclusions.

⁸ In addition to the random-effects Poisson models presented below, we also estimated fixed-effects Poisson models to check the robustness of our results, though we do not present those results in this report. The results from the fixed-effects Poisson specifications were qualitatively similar to the random-effects models. In particular, we did not detect any significant MAP effects.

⁹ Ideally, we would like to draw on census data, but until the 2020 data is made available this data source has the drawback of being rather dated. Alternatively, small-area estimates from the American Community Survey (ACS) are five-year averages and would enter the model as a time-invariant development-level characteristic that would not be identified in the difference-in-difference framework.

variable, the models differ by the scale variable included on the right-hand side. Our approach of including only one scale variable at a time aims to isolate the impact of each scale variable and mitigate the multi-collinearity that would result from trying to estimate the effect of all of the scales in a single model.

Dependent Variables

We estimated models for three different offense categories: those that fall under the seven major felonies (murder, rape, robbery, felony assault, burglary, grand larceny, and grand larceny of a motor vehicle), other major felony offenses, and misdemeanors. Reported incidents falling under each of these categories were aggregated over three months. The aim was to aggregate the crime data over the three months most proximate to the survey interviews, which occurred in February and March of 2019 and 2020. However, because the Covid-19 pandemic appeared to dramatically affect reported crime statistics in March 2020, we opted to aggregate from December to February. For the pre-MAP intervention period, crime is measured between December 2018 and February 2019, and for the post-period, crime is measured between December 2019 and February 2020. It should be noted that in each wave most interviews occurred in February (the first month of survey data collection for both waves).

MAP Variable

As described in our previous report, 17 developments were selected for “treatment” in MAP. Another 17 developments were assigned to a comparison group that did not receive a MAP intervention. This comparison group was constructed via a propensity score matching procedure. We measured the MAP treatment in two ways. First, we considered a simple binary treatment, distinguishing between those developments that received any MAP intervention and those that received none (i.e., the comparison group). We also go beyond the binary treatment measure by drawing on information in wave 2 of the NYCHA MAP survey on residents’ awareness of specific MAP activities in their development. Based on this information, JohnJayREC ranked NYCHA MAP developments from those with the greatest MAP involvement to those with the least. Using this ranking, we categorized the lowest six development as “low MAP”, the middle six as “mid MAP”, and the top five as “high MAP.” This more granular definition of the MAP treatment allows us to measure dose responses and may better capture the heterogeneous nature of the MAP treatment across NYCHA developments.

Development Crime Trends and Collective Efficacy

The second question of interest that can be addressed with the combined survey and administrative crime data is whether long-term trends in crime affect latent development characteristics such as collective efficacy and social cohesion. To this end, we estimate an OLS regression of development level scale scores on long-term trends in each offense category. The long-term crime trends are defined as the average rates per 1000 population in each development

from 2010 to 2018. Measurement in this way, these trends pre-date the first wave of the NYCHA MAP survey so that, unlike the contemporaneous crime measures used in the previous set of models, the pre-survey crime trend variables are not simultaneously determined with the latent outcome variables. This allows for a clearer assignment of the direction of causality. However, this type of specification still falls short of telling a convincing causal story. Most importantly, with this type of model, the study is no longer exploiting the repeated cross-section aspect of the survey data. As a result, the model does not control for time-invariant development-level factors. To capture development-level heterogeneity that might be confounding the measured impact of development-level crime, the regression model includes other observable development level characteristics, such as average monthly rents, the percentage of fixed income households, and development density, as well as average development demographic characteristics and a MAP participation indicator.

Results

Effects of MAP on Crime, controlling for latent attitudes

Table 1 presents the results from estimating the Poisson random-intercept difference-in-difference model displayed in equation (1) for crime incidents classified as one of the seven majors. Each model in table 1 differs only by the mediating variable included in the model. The results are broadly similar across these models. Coefficients are reported as incidence rate ratios (IRR). The coefficients of interest are those on the three interaction terms; namely, each of the three MAP treatment levels interacted with the post-intervention (i.e., wave 2) indicator. None of the indicator variables is significantly different from zero. The coefficient on the interaction of POST with the high MAP treatment is consistently negative (i.e., below unity) and of substantial magnitude (an estimated reduction in the incidence rate ranging from 37 to 43 percent).¹⁰ However, these effects are not precisely estimated.

In each model, we look in turn at whether the inclusion of individual latent development characteristics as control variables alters our conclusion about the effect of MAP on crime incidents. Each column reports parameter estimates, given the addition of one of the latent development characteristics. These models also test whether the latent development characteristics are significantly associated with crime incidents. The results suggest that the inclusion of these variables does not change the qualitative conclusions from each model. Neither the direction nor magnitude of the MAP effects materially change in any specifications.

¹⁰ The coefficients on POST were consistently negative and significant across models, suggesting lower incidence rates for seven major felonies in the post period. Moreover, the coefficients on the HIGH MAP are consistently positive and significant across models, suggesting higher initial incidence rates in high MAP treatment developments relative to developments in the comparison group.

Table 1: Random Intercept Poisson Models of Seven Major Felonies

	CE (binary)	CE	Govt Engage	Percept Safety	NYCHA PJ	NYPD PJ	Social Cohesion
POST	0.728*	0.703*	0.740*	0.729*	0.721*	0.725*	0.714*
	(0.107)	(0.105)	(0.112)	(0.108)	(0.109)	(0.109)	(0.109)
Low_MAP	0.877	0.888	0.833	0.828	0.828	0.824	0.843
	(0.200)	(0.202)	(0.183)	(0.184)	(0.184)	(0.185)	(0.189)
Mid_MAP	1.237	1.273	1.298	1.283	1.301	1.269	1.243
	(0.261)	(0.269)	(0.272)	(0.268)	(0.276)	(0.269)	(0.269)
High_MAP	1.779*	1.865*	1.725*	1.743*	1.759*	1.752*	1.774*
	(0.431)	(0.463)	(0.419)	(0.423)	(0.430)	(0.426)	(0.435)
Low_MAPxPOST	1.073	1.134	1.191	1.200	1.214	1.206	1.159
	(0.330)	(0.334)	(0.348)	(0.355)	(0.360)	(0.357)	(0.344)
Mid_MAPxPOST	1.160	1.210	1.147	1.167	1.159	1.171	1.191
	(0.312)	(0.328)	(0.308)	(0.320)	(0.310)	(0.319)	(0.325)
High_MAPxPOST	0.627	0.568	0.580	0.574	0.570	0.578	0.583
	(0.227)	(0.203)	(0.205)	(0.203)	(0.201)	(0.205)	(0.208)
Collective Efficacy (Binary)	0.888						
	(0.0946)						
Collective Efficacy		0.866					
		(0.0793)					
Govt Engagement			1.164				
			(0.384)				
Perception of Safety				1.009			
				(0.0707)			
NYCHA Proc Justice					1.016		
					(0.0408)		
NYPD Proc Justice						0.991	
						(0.0397)	
Social Cohesion							0.978
							(0.0377)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep Var Min	1	10	3	12	20	22	33
Dep Var Max	5	13	4	17	29	30	43
Observations	68	68	68	68	68	68	68

Exponentiated coefficients; Standard errors in parentheses

= * p<0.05 ** p<0.01 *** p<0.001

Table 2 displays the results from the same models in **Table 1** for non-seven major felonies. Here again, none of the interaction terms are significant.¹¹ We observe two significant coefficients on latent neighborhood characteristics: collective efficacy and perceptions of safety. Both of these coefficients imply an inverse relationship with the incidence rate of non-seven major felonies; e.g., an increase in collective efficacy is associated with a decrease in the rate of non-seven major felonies. Similarly, an increase in perceptions of safety is associated with a lower rate of non-seven major felonies. Of course, perception of safety has likely been influenced by prior trends in development crime so this result cannot be given a causal interpretation.

Table 3 presents the same set of results for misdemeanors. Once again, we do not find any significant MAP effects on the incidence rate of misdemeanors. Though not statistically significant, the coefficient on the interaction term involving high MAP treatment developments is consistently negative and implies a reduction in the incidence rate of misdemeanors of between 13 and 20 percent. The coefficients on each of the latent development characteristics are all near unity and insignificant.

¹¹ The sign of the coefficients on the interaction terms differs somewhat from the previous models of seven major felonies. Most notably, low MAP treatment developments are associated with rather large, but statistically insignificant, reductions in incidence rates.

Table 2: Random Intercept Poisson Models of Non-Seven Major Felonies

	CE (binary)	CE	Govt Engage	Percept Safety	NYCHA PJ	NYPD PJ	Social Cohesion
POST	0.915 (0.232)	0.797 (0.207)	0.909 (0.235)	0.877 (0.225)	0.969 (0.249)	0.906 (0.235)	0.835 (0.223)
Low_MAP	0.814 (0.280)	0.855 (0.291)	0.784 (0.264)	0.832 (0.279)	0.785 (0.265)	0.770 (0.264)	0.798 (0.269)
Mid_MAP	1.020 (0.306)	1.071 (0.321)	1.024 (0.310)	1.036 (0.312)	1.011 (0.299)	1.028 (0.307)	0.970 (0.295)
High_MAP	1.660 (0.564)	1.903 (0.647)	1.644 (0.556)	1.766 (0.594)	1.563 (0.530)	1.656 (0.566)	1.687 (0.568)
Low_MAPxPOST	0.569 (0.292)	0.552 (0.276)	0.607 (0.302)	0.566 (0.281)	0.557 (0.278)	0.621 (0.314)	0.562 (0.280)
Mid_MAPxPOST	1.048 (0.445)	1.071 (0.460)	1.057 (0.450)	0.856 (0.381)	1.009 (0.432)	1.066 (0.456)	1.118 (0.482)
High_MAPxPOST	0.970 (0.515)	1.018 (0.531)	0.908 (0.467)	0.989 (0.512)	1.014 (0.526)	0.935 (0.486)	1.057 (0.560)
Collective Efficacy (Binary)	0.931 (0.145)						
Collective Efficacy		0.703* (0.0965)					
Govt. Engagement			0.871 (0.445)				
Perception of Safety				0.801* (0.0838)			
NYCHA Proc Justice					0.915 (0.0560)		
NYPD Proc Justice						0.981 (0.0596)	
Social Cohesion							0.935 (0.0532)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep Var Min	1	10	3	12	20	22	33
Dep Var Max	5	13	4	17	29	30	43
Observations	68	68	68	68	68	68	68

Exponentiated coefficients; Standard errors in parentheses

=* p<0.05 ** p<0.01 *** p<0.001

Table 3: Random Intercept Poisson Models of Misdemeanors

	CE (binary)	CE	Govt Engage	Percept Safety	NYCHA PJ	NYPD PJ	Social Cohes
POST	1.104 (0.0829)	1.088 (0.0860)	1.110 (0.0855)	1.108 (0.0836)	1.117 (0.0858)	1.112 (0.0882)	1.086 (0.0864)
Low_MAP	0.946 (0.177)	0.928 (0.172)	0.924 (0.177)	0.934 (0.177)	0.919 (0.175)	0.927 (0.179)	0.927 (0.172)
Mid_MAP	1.124 (0.204)	1.144 (0.207)	1.153 (0.217)	1.122 (0.208)	1.122 (0.213)	1.157 (0.220)	1.124 (0.206)
High_MAP	1.478* (0.279)	1.493* (0.283)	1.479* (0.289)	1.461* (0.280)	1.472* (0.286)	1.482* (0.289)	1.490* (0.282)
Low_MAP x POST	1.224 (0.214)	1.296 (0.211)	1.320 (0.215)	1.263 (0.212)	1.284 (0.216)	1.314 (0.215)	1.278 (0.213)
Mid_MAP x POST	1.057 (0.164)	1.080 (0.169)	1.060 (0.167)	1.027 (0.164)	1.069 (0.167)	1.056 (0.170)	1.087 (0.172)
High_MAP x POST	0.868 (0.167)	0.816 (0.147)	0.801 (0.145)	0.804 (0.144)	0.805 (0.144)	0.795 (0.144)	0.821 (0.149)
Collective Efficacy (Binary)	0.919 (0.0689)						
Collective Efficacy		0.955 (0.0593)					
Govt. Engagement			1.027 (0.229)				
Perception of Safety				0.946 (0.0509)			
NYCHA Proc Justice					0.984 (0.0269)		
NYPD Proc Justice						1.004 (0.0239)	
Social Cohesion							0.981 (0.0255)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep Var Min	1	10	3	12	20	22	33
Dep Var Max	5	13	4	17	29	30	43
Observations	68	68	68	68	68	68	68

Exponentiated coefficients; Standard errors in parentheses

="* p<0.05 ** p<0.01 *** p<0.001"

Effects of Latent Attitudes on Crime, Controlling for MAP

Finally, we examine the relationship between long-term incident rates for each of the three offense categories considered in this report and latent development variables. We estimated this model for each of the ten scales constructed from the NYCHA MAP survey; however, we obtained significant results for only one scale: social cohesion. We therefore only present the results for the models estimating the relationship between social cohesion and each of the three offense categories (see table 4). The average rate of all three offense categories (per 1000 population), measured between 2010 and 2018, was negatively related to reported social cohesion in early 2019. These relationships were statistically significant for seven major felonies and misdemeanors.

Table 4: Relationship between Social Cohesion and Long-term Reported Crime Rates

Dependent Variable: Social Cohesion	Seven Majors (1)	Non-Seven Majors (2)	Misdemeanors (3)
MAP	-0.343 (0.488)	-0.145 (0.834)	-0.585* (0.282)
Seven Majors/1000	-0.158* (0.0696)		
Non-seven major/1000		-0.203 (0.255)	
Misdemeanors/1000			-0.0352*** (0.00636)
Demographic Controls	Yes	Yes	Yes
Observations	34	34	34

Standard errors in parentheses

=* p<0.05 ** p<0.01 *** p<0.001

Conclusion

The study finds some evidence that a greater awareness of the MAP program was associated with some decrease in observed crime in treatment developments. The models find little evidence that the latent variables describing resident attitudes toward community engagement and community well-being have a significant effect on observed crime, nor do they have an effect on the MAP association with crime. These effects of greater awareness of MAP occur in two of the three measures of criminal offending in NYCHA neighborhoods—the incidence of serious crimes as measured by the sum of all seven ‘major’ crime types and the incidence of misdemeanors. There is no effect of MAP on other felonies.

The effect is moderate, with an estimated reduction in the incidence rate of serious crimes between 37 and 43 percent and a reduction in the incidence rate of misdemeanors of between 13 and 20 percent, though neither effect is statistically significant. One plausible explanation for the weak statistical effect is that the measure of MAP ‘dosage’ is in itself relatively weak.

Developments where the highest percentage of resident’s self-report knowledge of MAP programs and activities were assigned as high MAP dosage. Developments, where the fewest residents were aware of MAP programs and activities, were assigned a low MAP ‘dosage’. However, in all developments, MAP awareness is relatively low, and thus the measure of MAP dosage is imprecise. As a result, the confidence intervals around those measures of MAP dosage are relatively broad. When measures are imprecise, the results are at risk of a TYPE II error, where a false null is rejected. Put another way, the risk of a false negative increase. The result is, however, encouraging.

On the theoretical question of whether changes in crime affect development-level attitudes about community engagement and community well-being, the results are more straightforward, and there is little evidence of an effect. The one caveat is that long-term crime trends are negatively correlated with social cohesion (community trust), meaning that the decrease in crime was significantly correlated to an increase in social cohesion. This association was observed for both serious crimes (the seven ‘majors’) and misdemeanors. This suggests that resident attitudes are relatively stable with respect to changes in crime, due to conditions of concentrated poverty intertwined with criminal justice factors, replicating the finding from the prior study of MAP effects. The result suggests that even an effective program with similar attributes to MAP would be unlikely to substantially change these latent measures.

References

Browning CR (2002) The Span of Collective Efficacy: Extending Social Disorganization Theory to Partner Violence. *Journal of Marriage and Family* 64(4). Wiley Online Library: 833–850.

Browning CR, Dietz RD and Feinberg SL (2004) The Paradox of Social Organization: Networks, Collective Efficacy, and Violent Crime in Urban Neighborhoods. *Social forces; a scientific medium of social study and interpretation* 83(2). Oxford Academic: 503–534.

Bursik RJ Jr, Grasmick HG, Bursik, et al. (1999) *Neighborhoods & Crime*. Lexington Books.

Gibson CL, Zhao J, Lovrich NP, et al. (2002) Social integration, individual perceptions of collective efficacy, and fear of crime in three cities. *Justice Quarterly: JQ / Academy of Criminal Justice Sciences* 19(3). Routledge: 537–564.

Hipp, JR and Wickes R (2017) Violence in Urban Neighborhoods: A Longitudinal Study of Collective Efficacy and Violent Crime. *Journal of Quantitative Criminology* 33(4): 783-808.

Maxwell CD, Garner JH and Skogan WG (2018) Collective Efficacy and Violence in Chicago Neighborhoods: A Reproduction. *Journal of contemporary criminal justice* 34(3). SAGE Publications Inc: 245–265.

Osgood DW (2000) Poisson-Based Regression Analysis of Aggregate Crime Rates. *Journal of quantitative criminology* 16(1). Springer: 21–43.

Raudenbush SW and Bryk AS (2002) *Hierarchical Linear Models: Applications and Data Analysis Methods*. SAGE.

Ross CE and Jang SJ (2000) Neighborhood disorder, fear, and mistrust: the buffering role of social ties with neighbors. *American journal of community psychology* 28(4). Springer: 401–420.

Sampson RJ (1997) Collective Regulation of Adolescent Misbehavior: Validation Results from Eighty Chicago Neighborhoods. *Journal of adolescent research* 12(2). SAGE Publications Inc: 227–244.

Sampson RJ and Raudenbush SW (2004) Seeing Disorder: Neighborhood Stigma and the Social Construction of ‘Broken Windows’. *Social psychology quarterly* 67(4). SAGE Publications Inc: 319–342.

Sampson RJ, Raudenbush SW, and Earls F (1997) Neighborhoods and violent crime: a multilevel study of collective efficacy. *Science* 277(5328): 918–924.

Wooldridge, JM (1999) Distribution-free estimation of some nonlinear panel data models. *Journal of Econometrics*, 90(1): 77-97.