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Communities as Neighborhood Guardians: A Spatio-Temporal Analysis of Community Policing in Nairobi's Suburbs

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Abstract The efficacy of citizens to participate in neighborhood-watch activities and report signs of trouble is important for safeguarding communities against crime. Community policing is a key policing strategy for utilizing the capability of residents to solve local crime-related problems. However, variability in social cohesion among communities profoundly affects the contribution of individuals towards policing. After 7 years of a community policing intervention in suburban Nairobi, Kenya, this study assesses the program as a state-initiated and community-sustained security venture. We compare micro-scaled concentrations of different property and violent crimes to identify geographic variations over time using kernel density estimates and spatio-temporal scan statistics. Multi-level regression models assess the direct and conditioned perceptions of individuals and their neighbors, and how these perceptions influenced crime variation during the pre- and post-intervention periods of community policing. Both the density estimates and the scan statistics pinpoint a disproportionate crime reduction across neighborhoods. The research findings also depict an interaction between the communal willingness to participate in neighborhood-watch activities and the relative crime decline. In particular, those communities that have good relations with the police are more inclined to involve themselves in community policing. The findings of this study are discussed in terms of their implications for policy.

Keywords Community policing · Kernel density estimation · Space-time scan statistic · Multi-level regression · Nairobi (Kenya)

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Introduction

Past and recent sociological evidence has demonstrated a profound influence of community characteristics over the crime patterning in the geographic space (Sampson et al. 1997; Braga et al. 2014). Thus, community policing (CP) programs are established based on the ability of citizens to notify the police about crime and disorder (Reisig 2010). However, it is a demanding task to facilitate a voluntary police-community contact, and to inspire citizens to participate in CP programs. Police officers encounter differences in levels of cooperation from the communities, differences that arise from the motivation for setting up such programs, and how their implementation is approached (Wisler and Onwudiwe 2008; Cordner 2014; Gill et al. 2014). While in developed cities police departments have traditionally acquired government resources for implementing CP programs and encouraging citizen participation (see, e.g., Connell et al. 2008, Leverentz 2014, Pinto and de Garay 2014), in developing country cities, such as discussed in this study, the policing resources are usually insufficient. Security intervention programs are hence characterized by inconsistent funding (Olima 2013; Bull 2014). Additionally, CP programs in developing countries are usually state-centered (Wisler and Onwudiwe 2008; Nalla and Newman 2013; Bull 2014). As such, instances of misguided management, underfunding, corruption and state absenteeism often result in communities unilaterally sustaining informal social control and neighborhood security (Wisler and Onwudiwe 2008). Contextual characteristics of individuals and communities hence essentially determine the nature of police-community collaboration.

The implementation of CP yielded various outcomes in the past, based on the measurements of program parameters, such as police effectiveness, citizen satisfaction and the perceived fear of crime (Lord et al. 2009; Weisburd et al. 2012; Gill et al. 2014; Stein and Griffith 2015). The exploration of offending patterns after the implementation of CP programs has also revealed different levels of success of the intervention (MacDonald 2002; Duncan et al. 2003; Connell et al. 2008; Weisburd et al. 2010; Koper et al. 2010). However, far less is known about the interrelationship between community efficacy for participating in the intervention programs and the subsequent changes in reported neighborhood crime. Citizen perceptions about crime and their levels of satisfaction with the police provide valid clues about safety, but more insight can be gained if these clues are validated using outcomes of crime incidents in a reliable statistical framework. Also problematic to the existing knowledge is that the literature has sometimes applied measurements of CP program parameters that are highly generalized. For example, past studies have aggregated outcomes of CP intervention to entire police beats and entire cities (MacDonald 2002; Connell et al. 2008). This generalization generates a biased inference, because CP initiatives are designed to address local causes and effects of crime incidence at a small spatial scale. Lord et al. (2009) and Feigl et al. (2015) both illustrate that the spatial context influences CP practices, and that significant effects which are particular to the neighborhoods become excluded when outcomes are observed over large areas. Finally, in contrast with the unique contribution of the analysis presented in this paper, research on CP experiences has mainly reported findings from large US, UK and Australian cities (Gill et al. 2014). Knowledge from the literature is one-sided because administrative practices, socio-structural aspects of neighborhoods and levels of police-community reciprocity vary greatly within the African small-town settings.

In order to address the above-mentioned issues, this research assesses the geospatial outcomes of a CP initiative in Kenya's Nairobi suburbs. We employ multiple datasets and spatial statistical analyses to compare the policing efficacy of communities with changes in crime frequency over time. The CP initiative that this study evaluates has two noteworthy features: Firstly, even though the program is state-initiated, it is controlled by the suburban communities and their local police without supplementary funding from the government. Secondly, the program involves communities of diverse socio-economic backgrounds. We, thus, take into account contextual differences that result from varying spatial and spatio-temporal characteristics to answer the question: "*Has community policing altered delinquency and the fear of crime in Eastern Nairobi?*" The following sections provide a brief review of CP and introduce the case study. After introducing the methodology and the study data, we present the major results and discuss the implications for policymakers.

Literature Review

Neighborhood Influence on Policing Behavior

CP programs are designed to cultivate mutual respect in police-community interaction, encouraging in turn a crime-preventive collaboration of communities with law enforcement (Lord et al. 2009; Nalla and Newman 2013; Cordner 2014). CP programs began in Anglo-America with these goals, and the practice has rapidly become global (Reisig 2010). Brogden and Nijhar (2013) provide a comprehensive overview of CP experiences across different countries. While the authors identify variations in how CP is practiced, they generally acknowledge that such intervention programs are aimed at encouraging citizens to take charge of security-related problems. Literature has shown, however, that the ability of individuals and communities to cooperate in crime prevention relates strongly with the density of community ties (Sampson et al. 1997). Mutual trust among neighbors increases the willingness of individuals to intercede for the common good, and members of close-knit communities feel more inclined to call the police when trouble is spotted and to assist crime victims. In contrast, when cohesion is low and rules are unclear among neighbors, mechanisms for informal crime prevention become ineffective. Past studies have identified demographic factors, such as the stratification along socio-economic and tribal lines, and residential instability, as the key detriments to cohesive communities (Sampson et al. 1997; Lord et al. 2009; Law and Chan 2012). These conditions disrupt the social relationships among neighbors because they prevent the generation of resources, friendship and trust. For example, it is hypothesized that high residential turnover weakens the communal capability to regulate behavior and renders individuals unable or unwilling to get involved in policing activities (Sampson et al. 1997). Studies have also found out that residents who exhibit fear and mistrust due to some form of segregation often withdraw into social clusters along common attributes, such as age, gender or ethnicity (Duncan et al. 2003; Lord et al. 2009; Stein and Griffith 2015). Brunson (2007) as well as Stein and Griffith (2015) add to this knowledge the discovery that young African-American males who experienced negative contact with the police were less likely to cooperate in CP activities. Stein and Griffith (2015) further discovered that police responsiveness influenced the willingness of communities to participate in crime prevention. This finding highlights the fact that police actions can crucially influence the success of CP programs.

Characteristics of the natural and built environments also affect the societal capability to deal with crime (Kenya 2010; Groff & Lockwood 2014). There is evidence, for example, that less crime occurs in those low-income US neighborhoods that are well-connected through the street network (Ward et al. 2014). Well-designed road networks facilitate a rapid police response and the increased likeliness of apprehension discourages potential offenders from committing crimes. In contrast, unpleasant structures and environment, such as the littering in neighborhoods, breed a ground ripe for crime perpetration (Sampson et al. 1997). That being said, a complete depiction of the crime risk needs to control for relevant socio-economic aspects, as well as the amount of neighborhood exposure to criminogenic facilities.

Large police departments of the developed world have on the one hand devised strategies to boost amicable relationships among neighbors and to encourage citizen participation in CP programs. Well-known examples include permanent deployment of policing officers into the neighborhoods (Nalla and Newman 2013). and community-participatory initiatives, such as the Seattle Neighborhood Matching Fund (Leverentz 2014) and the Mexico National Crime Prevention Program (Pinto and de Garay 2014). On the other hand, government institutions in developing countries often initiate intervention programs that they do not actively manage or sustain (Wisler and Onwudiwe 2008; Baker 2010; Bull 2014). The efficacy of policing in such countries hence varies profoundly across communities as influenced by other structural determinants. Wisler and Onwudiwe (2008, p. 427) have described policing in African neighborhoods as “a community in search of a state.” Kenya is a case in point of where communities oversee security by liaising actively with selected security representatives and the police (Wisler and Onwudiwe 2008; Olima 2013). Carr (2005) has described this model of CP as *neo-parochialism*. Carr reports having successfully used the model among Chicago neighborhoods. The crime risk was reduced through the establishment of collaborative partnerships among private institutions (i.e., family, friends), parochial institutions (neighbors and neighborhood institutions) and administrative levels of control.

Crime rates in Nairobi are accelerated by criminals who live in low-income neighborhoods and illegally possess arms (K’Akumu and Olima 2007; Ruteere et al. 2013). A survey of Nairobi’s citizens revealed that at least 37 % of those surveyed had been victims of robbery, 22 % of theft victimization, and 18 % of physical assault (Stavrou 2002). With limited government resources for law enforcement and poor road conditions in many neighborhoods, help can be hours away, particularly in unfavorable weather (LeBas 2013; Tranchant 2013). Communities living near informal settlements experience crime in equal measure because offenders often target higher-income neighborhoods (Ruteere et al. 2013). But a major source of high crime risk is the low neighbor cohesion that originates from two elements: The first is high resident turnover, particularly among renters who compose a large majority of Nairobi’s population. Rapid city expansion, nonbinding housing contracts and high availability of manpower for moving contribute to the residential instability of Nairobi’s communities and to the difficulty of nurturing long-term relationships (Thuo 2013). The second crime-aggravating factor stems from Kenya’s multi-ethnic nature. Ethnic wrangles due to the stratification and political marginalization of certain communities cause hostility and rivalry among different groups (Roberts 2012). The informal social control breaks down, creating opportunities for crime, and citizens are increasingly obliged to make private security arrangements (Baker 2010; Rasmussen 2012; Parks 2013).

Community Policing Intervention in Nairobi's Suburbs

To subdue the high crime risk, the Kenyan government initiated a CP program in 2004 under the police reforms for transparency and accountability (Ruteere 2011). The intervention began with two pilot sites—the Kibera informal settlements located west of Nairobi, and Isiolo town located in north-eastern Kenya - before being implemented throughout the country (Lidén 2012). However, undesirable aspects of the CP program, such as its state-centeredness, direct adaptation of western practice, a corrupt and misguided administration, and poor funding, all caused delays in community acceptance (Ruteere and Pommerolle 2003; Gituai 2010). The program began to take root in 2009 following waves of post-election violence that caused a cultural stratification and distrust in communities (Roberts 2012). Crime rates rose rapidly, making it necessary for the government to increase citizen education on safety issues and neighborhood-watch activities (Finnegan et al. 2008; Gituai 2010; Amnesty 2013; Ruteere et al. 2013). The police force was strategically reformed thereafter to increase their response efficiency and to revise their perception of citizens as crime suspects and aggrieved victims (Kenya 2010). Although the CP program is now recognized as a pillar of police performance in Kenya, its funding is not prioritized by the government and no police jurisdiction has restructured the program's organizational components to make it a dominant policing model. The level of police-community reciprocity is hence irregular, and this affects how the communities guard their neighborhoods.

Similar to the neo-parochial intervention model of Carr (2005). CP in Nairobi involves communities of different socio-economic backgrounds collaborating with administrative controls to fight crime (Mohamed 2013). On the one hand, communities of middle-to-high income pool the resources required for engaging the resident welfare associations and neighborhood-watch groups that arbitrate resident-police efforts to address crime (Olima 2013). On the other hand, residents of low-income neighborhoods have adopted Tanzania's so-called *Nyumba Kumi* (ten houses) model of CP, where the residents elect representatives to facilitate police-community interactions and identify security solutions among small groups of households (Olima 2013; Mutanu 2014). Thus, while both models depend on the level of reciprocity between the community and police, the latter model has its success further hinged on the capacity of security representatives to regulate individual behavior.

Data and Methods

Study Area

The study observes CP outcomes over the residential housing estates of Eastern Nairobi. These estates are located approximately 13 kilometers from the central trading hub. They were constructed in timed phases, resulting in small groups of houses similar in structure, which constitute the neighborhoods shown in Fig. 1a. Additionally, the study area has three informal settlements (slums), characterized with populous makeshift residential structures. These slums grow rapidly as the city grows, bringing in its wake waves of individuals in search for employment. The city's rubbish dump is another source of disorder in Eastern Nairobi. In addition to the disturbance caused by trucks that are driven into the area to dump the city's waste, the rubbish dump also conceals delinquent activities. How and whether to relocate this dump is a major bone of contention among legislators (National National Assembly 2010).

Data

Police Crime Reports

The study outcomes include crime incidents that occurred throughout the 52 neighborhoods between January 2009 and December 2012. The police in Buruburu, Nairobi recorded the incidents (n=12,939), which comprise property crimes (theft, burglary, robbery, drug peddling) and violent crimes (rape, mugging). These crimes were selected for the analysis because they are the most likely to be influenced by an intervention strategy involving the communities. Crime locations were geocoded using global positioning system (GPS) devices and topographic maps. However, in addition to underreporting, several issues affect the crime data. First, about 6 % of the incidents were recorded with insufficient location information, and were thus irrelevant for the analysis. Second, crimes perpetrated by multiple individuals were sometimes recorded repeatedly, an inconsistency that was observed in about 2.6 % of the data. Nevertheless, this incidence data constitutes the most accurate information about the neighborhoods' crime outcomes. Fig. 1b depicts a disproportional offending trend across

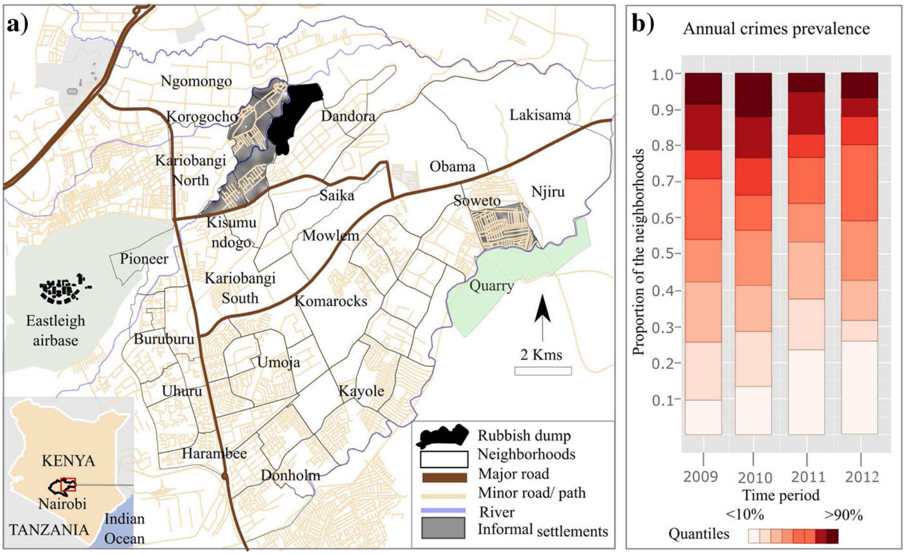

Fig. 1 Geographic locations of neighborhoods (**a**), and the statistics of neighborhood crime between 2009 and 2012 (**b**)

neighborhoods, particularly when the lower and upper levels are examined. But more conspicuous is the reduction of neighborhood crime rates in the post-intervention period (2011–2012), compared to the previous years.

Participants Survey

The survey data was collected after a series of face-to-face interviews with individuals sampled independently across the neighborhoods. The survey was conducted between July and August of 2011, approximately six months after the beginning of active CP practice, and this allowed the participants to remember the important changes. Researchers worked with police officers stationed across the neighborhoods to oversee a secure and formal process. 583 subjects (11 representatives per estate, S.D. = ±4) offered their opinion about different security aspects and their level of participation in the CP program. 65 % of the participants were interviewed on weekends near their homes, 13.5 % were met at bus stops, and the rest were met at pubs, markets and other social places. Interviews offered a convenient communication strategy, particularly for the non-English speakers and individuals who could not fill out a questionnaire. Individuals received monetary rewards for completing the survey. Monetary incentives can potentially yield responses that are highly optimistic, but previous experiments have also shown that motivated respondents increase the response quality (Singer and Kulka 2002). In this study, for example, the monetary rewards considerably reduced the item-missing data. After excluding three erroneous and incomplete response units, the items had complete information across all the scales of measurement. Another design strategy was the requirement for participants to present their national identification cards. This approach is prone to bias because the survey data only represents the papered nationals. However, the identification requirement offered an effective means to avoid the same individual to participate more than once in the survey. It further made possible the ascertainment that each participant was a legal resident of the neighborhoods.

Variables

Four dependent variables were generated from the survey data and the police crime reports. The first (Model 1) is a categorical variable that includes eight survey items to express the efficacy of residents for CP. Neighborhood representatives responded along four categories ("1- never, 2- once, 3- two to five times, or 4- many times") about how often they had (i) attended neighborhood-watch meetings, (ii) participated actively in the neighborhood-watch activities, (iii) contributed resources for neighborhood watch, (iv) involved themselves in activities within the CP framework, such as cleaning sections of the neighborhood, intervening to stop fight outbreaks, or alerting their neighbors when crime was spotted. Participants additionally expressed the likelihood between 1 ("certainly not") and 4 ("certainly would"), that they would (i) support victims of a crime, and (ii) alert the police about crime in their neighborhood. Since we suspected an interrelationship between the individuals' willingness to participate in the intervention program and the density of community ties, individuals were further asked to express in the same manner the likelihood that their neighbors could be counted upon to support crime victims or alert the police of suspicious activity. Together, the eight items had a high internal consistency (Cronbach's α=0.85), and thus, they constructed a measurement scale labeled *Policing efficacy*, i.e., the capacity of individuals to collaborate in the CP program.

The second independent is *Perceived crime* (Models 2, 5), a survey scale that quantifies how individuals experienced crime during the post-intervention period of CP. Residents responded according to four categories ("I have: 1- never, 2- once or twice, 3- three to five times, 4- many times"), about (i) how many times they had fallen victim to crime, and (ii) how many times they had witnessed or heard about crimes happening in their neighborhood. Opinion was sought with respect to the time frame "*since the beginning of this year*". The third variable, *Property crime* (Models 3, 6), depicts the rate of property crime incidents per 10,000 residents. Finally, *Violent crime* (Models 4, 7) similarly records the rate of violence incidents per 10,000 residents.

Several independent variables were analyzed at the individual and neighborhood levels. At the individual level, variables comprised the individual's age in years, and gender (with 0=male, 1=female), and two perception measurements. The first perception measurement captures the nature of police-community relations which has theoretically been linked with the individual's willingness to cooperate in crime prevention (Stein and Griffith 2015). Participants responded along five categories ("Would you: 1- completely disagree, 2- agree, 3- neither agree nor disagree, 4- disagree, 5- completely disagree"), about their perception that the police (i) provided helpful service, (ii) dealt successfully with most crimes, (iii) were friendly to citizens, (iv) responded efficiently to emergency. Together, the four items adequately represented the latent measurement labeled *Satisfaction* (α=0.76). The second perception measurement, *Prior perceived crime*, characterizes the crime experience during the pre-intervention period. Individuals responded in the same manner as with the dependent variable, *Perceived crime*, about (i) having fallen victim to crime, and (ii) having witnessed crime during the months before the beginning of the year. This scale was also reasonably consistent (α= 0.68).

Four independent variables were constructed at the neighborhood level.[1] The first three employ data from the 2009 census.[2] Low socio-economic status, *Low-SES*, describes the proportion of households i) without electricity, ii) living in a house constructed using iron sheets, grass or tin, and iii) using firewood or charcoal for cooking. A principal component analysis identified the largest eigenvector/eigenvalue pair (α=0.82) to define *Low-SES*. The second variable, *Homeownership*, denotes the proportion of households that are owner-occupied. *Ethnic heterogeneity* measures the proportion, p, of individual membership to each of the seven ethnic clusters: Kikuyu, Luo, Luhya, Kamba, Kisii, Kalenjin and other. Squared proportions from each ethnic cluster, i, were summed up, and their difference from unity (i.e., $1-\sum p_i^2$, Blau 1977), generated a probability score ranging between 0 (absolute homogeneity) and 1 (absolute heterogeneity). Finally, owing to evidence that criminogenic facilities influence crime and the community behavior (Groff & Lockwood 2014), the analysis considers the amount of neighborhood exposure to the city's rubbish dump. The variable, *Dump*

[1] Other potential variables not highly significant for the estimation were excluded to increase the model statistical power. A bivariate correlation analysis and the assessment of variance inflation factors (VIF) showed no evidence of multicollinearity among the remaining independent variables.

[2] Specific details about the census are available at http://statistics.knbs.or.ke/nada/index.php/catalog/55/related_materials.

proximity, was operationalized as the proximity of each neighborhood to the rubbish dump along the road network. An origin–destination matrix was computed to reflect the nearest distances from the neighborhoods' centroids to the border of the dump.

Research Design

The analysis investigates spatial and space-time crime patterns, and subsequently correlates the crime trends with the efficacy of participation in CP in a three-step process that is described in this section.

Kernel Density Estimation

Since crimes do not occur uniformly across neighborhoods (Sampson et al. 1997). their spatial distribution can be mapped more efficiently through geographical methods. Kernel density estimation (KDE) is a popular exploratory analysis strategy for quantifying spatial crime patterns over time (Weisburd et al. 1993; Kennedy et al. 2011). KDE interpolates point locations into area-wide representations of crime intensity to identify "hotspot" areas for a security intervention. Centering a kernel function (e.g., Gaussian) of a pre-specified or dynamic bandwidth over each data point yields estimates of intensity that are spatially smoothed (Leitner and Helbich 2011; Davies et al. 2014). As the appropriate bandwidth is usually not known a priori, we applied an adaptive bandwidth scheme for this analysis. The bandwidth varies depending on the underlying crime distribution: smaller bandwidths are applied in those locations that exhibit a high point density, while larger bandwidths are allocated where incidents are more sparse. This dynamic adjustment reflects the "true" variation in the crime distribution and reduces the probability for biased outcomes. However, the KDE does not reflect sequential variation of crime over time. Thus, the next step assesses the efficacy of the CP intervention by means of spatio-temporal scan statistics.

Space-Time Scan Statistic

The likelihood that a crime will occur at a certain location depends largely on whether crimes have previously been reported for the same location (Reisig 2010). The space-time permutation scan statistic (STPSS) is particularly useful for conducting a sequential examination of the event data to detect space-time hotspots of crime (Helbich and Leitner 2012; Jones and Kulldorff 2012). The STPSS applies a three-dimensional window of varying dimensions to search each crime location and time period continuously against the next ones in order to detect clusters. The radius and the height of the scanning window respectively define the spatial and temporal dimensions (Leitner and Helbich 2011). The expected numbers of crime incidents and times are estimated based on the observed counts using a spatio-temporal permutation model, while assuming a constant crime risk. The statistical significance of each cluster is then computed through a Monte Carlo simulation approach. Estimates include the primary cluster, i.e., the cluster of the highest likelihood, and secondary clusters, which are statistically less significant than the primary cluster.

Multilevel Regression Analysis

To examine the level at which crime rates are deviant upon the policing efficacy of neighbors, statistical models regressed the four dependent variables (i.e., *Policing efficacy*, *Perceived crime*, *Property crime*, and *Violent crime*) against two individual-level covariates and four neighborhood-level variables. As described in prior work (see Raudenbush and Sampsojn 1999; Stein 2010; Holmes et al. 2015). multilevel models defined the hierarchical structure of the study data and the interaction across the hierarchy levels. First, neighborhood policing efficacy was assessed by fitting a logistic regression model for ordinal outcomes (Christensen 2015) to the eight-item scale with values ranging from 1 to 4 for each item. The response was reverse-coded, and the fourth (lowest-rated) category formed the reference for realizing a chain of cumulative probabilities, $Pr\{\gamma_{ijk} \le m\} = \pi_1,..,\pi_{m.}$ These probabilities represent the likelihood that a certain response will fall into, or below a certain category, m ($m=1, \ldots 4$), rather than above it. Since $Pr\{\gamma_{ijk} \le 4\}$ must equal unity, there exist only three unique probabilities. The model, thus, collapsed the response data into dichotomized threshold values for a pair-wise comparison between the ordered categories. Item responses were modeled at the level 1 (among-individuals) in the following manner:

$$Level\,1: \; Y_{ijk} = \pi_{jk} + \sum_{m=1}^{M-1} \alpha_m D_{mijk} + e_{ijk}, \; m = 1, \ldots, 3, \;\; i = 1, \ldots, 8, \;\; e_{ijk} \sim N\left(0, \sigma^2\right) \qquad (1)$$

where Y_{ijk} denotes the i^{th} ordinal outcome of the j^{th} resident of the k^{th} neighborhood, and α_m is the m^{th} threshold parameter denoting the (log) odds of the response falling within a certain category or below. The value of D_{mijk} equals unity if the response corresponds to the m^{th} value, and equals zero otherwise. Measurement errors, e_{ijk}, are independently distributed within each individual. The parameter π_{jk} indicates the "true score" of each individual. The level 2 model (individuals within neighborhoods) adjusts this score to account for the influence of covariates:

$$Level\,2: \;\; \pi_{jk} = \eta_k + \beta_1 (Age)_{jk} + \beta_2 (Gender)_{jk} + r_{jk}, \;\; r_{jk} \sim N(0, \tau_\pi) \qquad (2)$$

where β_1 and β_2 and account for the partial effects of the individual-level covariates, and r_{jk} accounts for the random effect, i.e., the difference between an individual's true score, π_{jk}, and the neighborhood mean, η_k. Random effects are independently distributed with variance τ_π (the variance within neighborhoods). At the third level (between-neighborhoods), the neighborhood mean score is adjusted to control for the influence of four neighborhood-level covariates:

$$\begin{aligned} Level\;\; 3: \;\; \eta_k &= y_0 + y_1 (LowSES)_k + y_2 (Hom.own.)_k + y_3 (Eth.het.)_k \\ &+ y_4 (Dum.prox.)_k + u_k, \;\; u_k \sim N\left(0, \tau_\eta\right) \end{aligned} \qquad (3)$$

where γ_0 is the overall mean between neighborhoods, and u_k is a random effect distributed uniformly between neighborhoods with variance τ_η.

The model of perceived crime was set up in a similar manner to the policing efficacy model. Ecometric properties of the survey measurement scales (*Policing efficacy*, *Satisfaction*, *Perceived crime* and *Prior perceived crime*) were examined before including the influence of individual- and neighborhood-level covariates. The examination included assessing the correlation properties and measuring the level of agreement among individuals via the intra-neighborhood correlation coefficient (ICC). The ICC is a ratio of the between-neighborhoods variance to the sum of between- and within-neighborhood variances (Raudenbush and Sampsojn 1999). Higher values indicate a greater agreement between the residents of a neighborhood. Furthermore, reliability estimates of the neighborhood measurements were calculated based on the 3-level model. The reliability of the neighborhood-level mean, η_k, is a function of the ICC and of the number of participants in each neighborhood, n_{jk}. It is the ratio of the estimated variance to the variance observed in neighborhoods, and higher values indicate greater differences among the neighborhood means.

Unlike the ordinal outcomes of resident perceptions, the continuous outcomes corresponding to observed crime rates were modeled at the neighborhood level using linear fixed effects regression models. The outcome in the k^{th} neighborhood is estimated as $Y_k = \beta_0 + \sum \beta_i X_{ik} + \varepsilon_k$, where β_i is the i^{th} partial effect of neighborhood-level covariates, X_k (i=1,…, 4), and ε_k are uniformly distributed residuals.

Results

Spatial and Spatio-Temporal Distributions of Crime Events

A linear observation of the crime incidents depicts a distinct temporal trend for property crimes (Fig. 2). High magnitude and fluctuation characterize incidents in the pre-intervention period of CP, but the offending frequency was reduced after three months

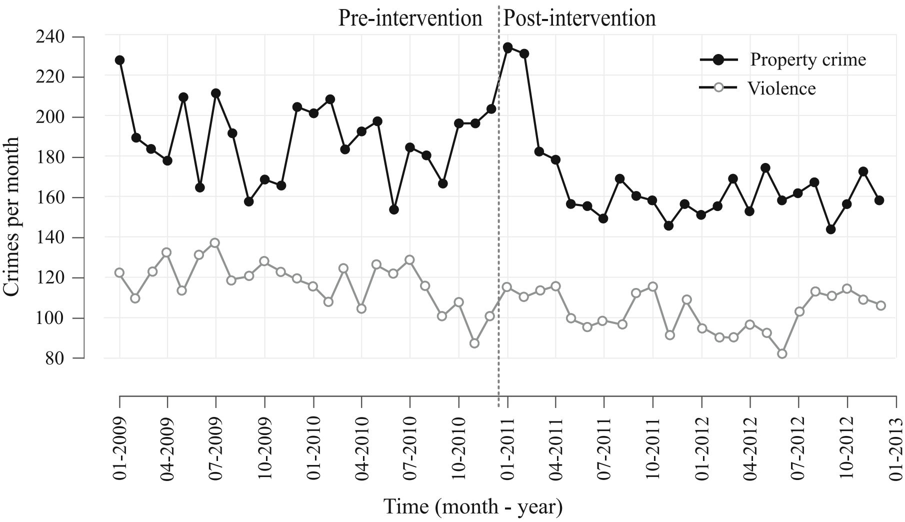

Fig. 2 Temporal trends of neighborhood property and violent crimes (2009–2012)

of the intervention. The trend was also relatively stable in this second period, with no particular peaks and declines. The offending pattern was, nevertheless, unstable for neighborhood violence during both periods. Less property and violent crime incidents were recorded during the post-intervention period, but the crime risk appeared to be more subdued for property crimes. During this period, 32 % fewer incidents were registered compared to the pre-intervention period. Offending variance was high overall, ranging from 124 to 238 incidents for property crime, and from 83 to 137 incidents for violent crime.

The assessment of spatial patterns using KDEs uncovered a distinct trend in the micro-scaled crime distribution. As hypothesized, the likelihood of property crimes and violence occurring in the neighborhoods was reduced for the most part (Fig. 3b, d). While a clear reduction of the property crime risk occurred near the informal settlements and the rubbish dump, no reduction of violence was apparent in these areas. This observation, and the observation of unclear temporal patterns for violence, necessitated further investigation into the event data to detect potential spatio-temporal clusters.

Similar to the KDE outcomes, spatio-temporal statistics uncovered significant clusters of property and violent crimes ($p<0.01$), based on 9999 Monte Carlo permutations. Table 1 lists the 18 most significant hotspots, and Fig. 4 maps their occurrence in the geographic space. Crime incidents showed a distinct spatio-temporal distribution. In particular, property crimes were predominant in the month of December, while violence was more prevalent in July. However, the hotspots detected after the CP intervention were not endemic to a particular month. This observation highlights the possibility that a spatio-temporal process influencing the occurrence of crime in the pre-intervention period was interrupted in part by an increased active neighborhood guardianship. The geographic influence was also clear. As expected based on the KDE output, property and violent crimes occurred mostly near the informal settlements and the rubbish dump. Although neighborhoods around this area observed no significant crime reduction, the once-prominent hotspots that were detected further south were significantly decreased after CP implementation. This observation is important for policing, because the most significant cluster of property crimes ($p<0.001$) occurred south-west of the study area shortly before the CP intervention. While the spatio-temporal statistics pinpointed a general decline in offending, there is much stronger evidence that the trend of property crimes changed as a result of the intervention. Crime clusters observed during the post-intervention period contained fewer incidents and spanned a shorter time duration than the clusters of the previous period.

Assessing Citizen Experience of Community Policing

Results from the KDE and the STPSS showing a crime decrease might be due to a targeted police presence more than to police-community relations, and the observed crime rate variation may well have coincided with the onset of the intervention program. Thus, the study examined the community participation in and the perception of the CP program to control for confounding effects. Bivariate correlation tests of the four survey measurement scales showed positive and negative correlations and a moderate capability for convergence. *Policing efficacy* was related positively with *Satisfaction* (0.712), and was negatively correlated with both *Perceived crime* (−0.464) and *Prior perceived crime* (−0.246). The latter two scales were also somewhat negatively correlated (−0.13), as were *Satisfaction* and *Prior perceived crime* (−0.25).

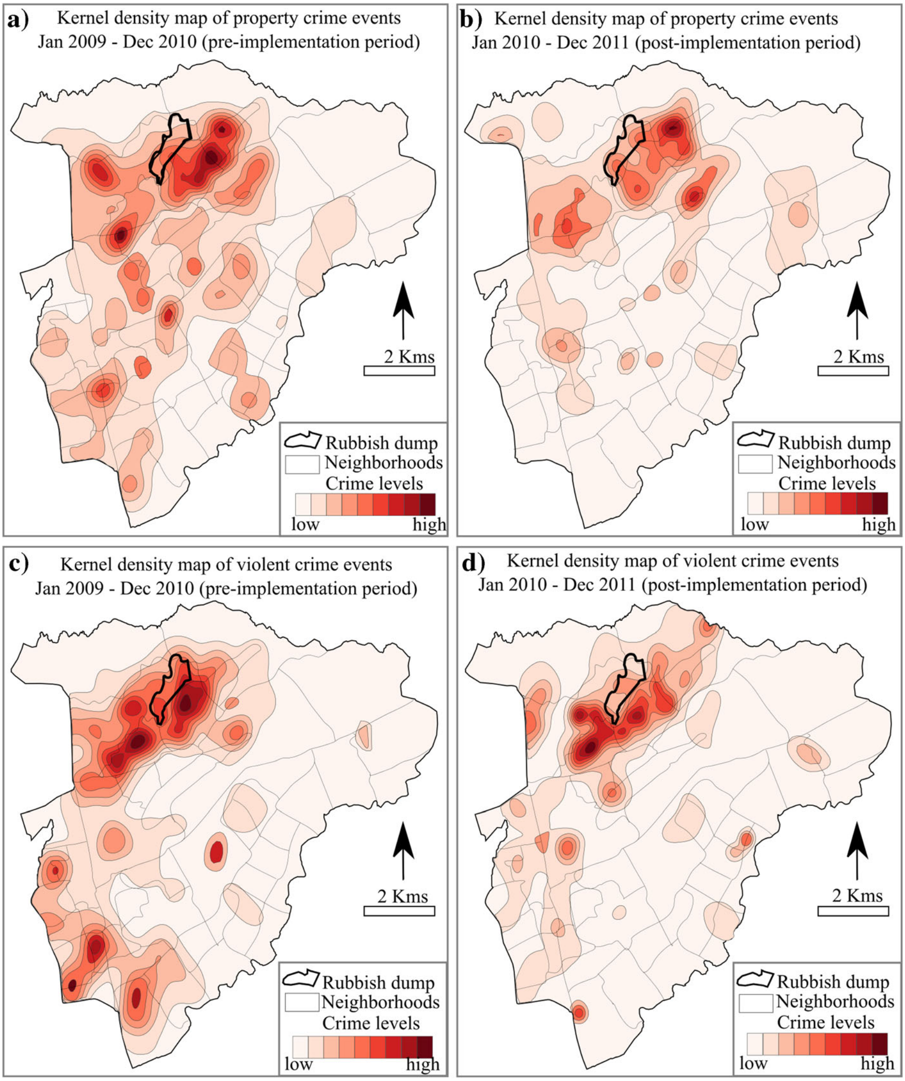

Fig. 3 Spatial clusters of property and violent crime incidents during the pre-intervention (2009–2010) and post-intervention (2011–2012) of neighborhood watch

The ecometric properties of the four scales are presented in Table 2. Generally, variance was low within neighborhoods and high between neighborhoods, suggesting that perception was more homogenous within than between neighborhoods. Neighborhood reliability was high for most of the scales, and ranged from 0.73 to 0.89.

Estimating Community Policing Efficacy

Probabilities measuring policing efficacy between neighborhoods were 8 %, 33 %, 44 % and 15 % respectively for the item categories 1, 2, 3 and 4, indicating more response homogeneity around the middle scale points. This first model determined none of the

Table 1 Clusters of property crime incidents (n=8154) and violence incidents (n=4785) recorded between 2009 and 2012

Crime type	Cluster ID$_a$	Outbreak date	Duration (days)	Observed cases	Expected cases	Relative risk	Test statistic
Property crimes	1	Thu, 30.12.2010	25	50	5.5	9.1	79.85***
	2	Fri, 05.06.2009	10	8	1.8	4.4	15.2***
	3	Fri, 11.12.2009	19	12	2.3	5.2	17.46***
	4	Sun, 02.05.2010	21	26	6.2	4.2	15.28***
	5	Sat, 10.07.2010	6	10	1.25	8.1	14.25***
	6	Tue, 24.08.2010	15	24	3.5	6.9	12.6***
	7	Sun 12.12.2010	12	89	19.3	4.6	37.56***
	8	Sun 26.12.2010	23	26	4.3	6.1	66.49***
	9	Sat, 02.04.2011	20	27	6.2	4.4	26.33***
	10	Thu, 30.08.2012	16	21	8.2	2.6	16.16***
Violent crimes	1	Sun 22.01.2011	23	15	2.4	6.3	43.07***
	2	Sun, 19.04.2009	12	8	1.3	6.1	13.28***
	3	Wed 22.07.2009	19	26	4.8	5.4	40.59***
	4	Sat 15.05.2010	25	22	3.4	6.4	16.45***
	5	Wed 14.07.2010	17	12	2.1	5.7	17.84***
	6	Sun, 06.11.2011	11	16	4.2	3.8	6.19**
	7	Wed 11.07.2012	15	22	5.1	4.3	15.04***
	8	Thu, 04.10.2012	21	19	5.5	3.5	9.01***

Notes: *p<0.05; **p<0.01; ***p<0.001

[a] Cluster 1 refers to the primary clusters while the remaining ones are of second order listed in a temporal sequence

individual level covariates to have significant influence on the efficacy of individuals to take part in the CP program (Table 3), but older residents exhibited a higher efficacy than their younger counterparts. On the one hand, homeownership was found to be a neighborhood stabilizer that raised the likeliness of neighborhood intervention. High ethnic heterogeneity of communities and increased exposure to the rubbish dump were found to be, on the other hand, obstacles to neighbor cohesion. These two factors decreased the likeliness of program participation in a significant manner.

Relating Guardianship with Neighborhood Crime

Table 4 depicts estimates of the perceived crime risk (Model 2a, 2b), and the estimates of property (Model 3a, 3b) and violent crimes (Model 4a, 4b) using data from the post-intervention period. The *Policing efficacy* variable is included in one of each pair of the models to controls for the influence of CP participation on crime perception and crime incidence. Random effects of the policing efficacy model, u_k (Eq. 3) compose this variable, excluding the effects of the four neighborhood-level predictors (Sampson et al. 1997; Holmes et al. 2015). The *Satisfaction* variable characterizing police perception was built in a similar manner. As expected, good police-community relations and an increased effectiveness for solving security problems influenced lower crime rates, but

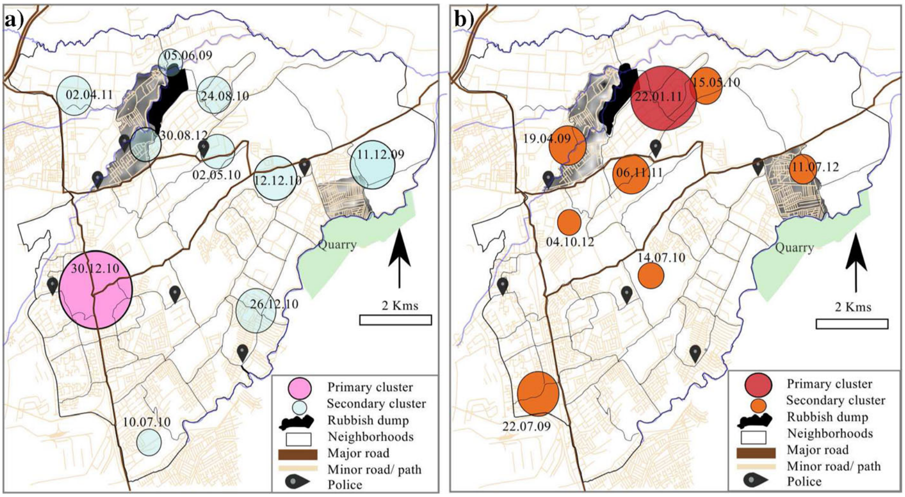

Fig. 4 Outbreaks of property crime (**a**) and violence (**b**) estimated from police-recorded crime data (2009–2012)

this influence was surpassed by the policing efficacy. The *Policing efficacy* variable explained more of the variability in crime risk than any other predictor. Adding this variable to the model of perceived crime (Model 2b) resulted in a better model fit, judging from the significant reduction in residual deviance from 1387 to 1341. Similarly, including *Policing efficacy* into the linear models effected a minimized residual sum of squares (RSS) both for the model of property crimes ($RSS_{Model\ 3b}$= $RSS_{Model\ 3a}$ - 16 %) and for that of violence ($RSS_{Model\ 4b}$=$RSS_{Model\ 4a}$ - 14 %).

High ethnic stratification increased the crime risk significantly, particularly with respect to violence (Model 4). This influence was, however, mitigated by *Policing efficacy* (Model 4b). The *Dump proximity* variable impacted positively on the crime risk, and unlike the former variable, the effect of the dump was still significant even after controlling for the policing efficacy. Exposure to this criminogenic facility appears to have heightened the social disorganization of places and decreased the impact of security intervention efforts.

Accounting for Neighborhood Crime in the Pre-Intervention Period

The three models in Table 4 were modified in the subsequent step to assess the validity of the outcomes observed during the post-intervention period of the CP program.

Table 2 Variance components and reliability estimates of the survey data (n=583 participants, 52 neighborhoods)

Parameter	Policing efficacy	Satisfaction	Perceived crime	Prior perceived crime
Within-individual variance	0.682	0.235	0.331	0.443
Within-neighborhood variance	0.471	0.493	0.167	0.484
Between-neighborhood variance	0.292	0.677	0.411	0.151
Intra-neighborhood correlation	0.384	0.581	0.703	0.238
Neighborhood reliability	0.886	0.865	0.762	0.732

Table 3 Model 1 - Results from an ordinal logistic regression model for policing efficacy (n=583 participants, 52 neighborhoods)

Variable	Estimate	SE	t-value
Intercept	−1.263**	0.385	−3.281
Individual-level predictors			
Age	0.005	0.003	1.667
Female	0.004	0.061	0.032
Neighborhood-level predictors			
Low-SES	−2.465**	0.850	−2.901
Homeownership	3.425***	0.773	4.431
Ethnic heterogeneity	−2.245***	0.502	−4.472
Dump proximity	−0.911**	0.291	−3.131
Deviance	1467		
Explained variance (%)	0.741		

Note: *p<0.05; **p<0.01; ***p<0.001

Confounding outcomes were controlled for using three variables that characterized the pre-intervention crime experience. As expected, the partial effect of *Policing efficacy* was negative, and it remained statistically significant, even after controlling for the prior crime experience (Table 5). The high crime rate experienced during the pre-intervention period was negatively correlated with crime incidence after the intervention, but none of the partial effects associated with the prior crime experience was statistically significant. Model coefficients were generally unaffected when controlling for the prior experience. Consistent with the previous observation (Table 4), the *Satisfaction* variable was negatively correlated with all outcomes, and more significantly with crime perception (Model 5). In contrast, exposure to the rubbish dump continued to influence an increased crime risk. The control for prior crime experience facilitated increased model fitness. All the models had reduced errors in comparison with models without prior crime control, and the combined explanatory power of these models was also increased. Nevertheless, it can be concluded that prior crime experience had a limited influence on the crime perception and its incidence during the CP post-intervention period.

Discussion and Conclusion

This research sought to answer how a CP initiative has altered the offending rate in Eastern Nairobi. The study constitutes a unique contribution to the statistical analysis of a policing experience among suburban communities, and it tackles the need to examine the product of a security policy intervention.

The irregular crime decrease that has been observed across neighborhoods after CP implementation has been linked with variation in policing efficacy between neighborhoods. The datasets and tools that were used to analyze the impact of CP have largely yielded consistent observations. The results also show that analysis outcomes are more

Table 4 Model 2 - Results from an ordinal logistic regression model of perceived crime (n=583), Model 3 - Results from a linear regression model of neighborhood property crime (n= 52), Model 4 - Results from a linear regression model of neighborhood violent crimes (n= 52)

Model 2. *Perceived crime*$_b$	a) Without *Policing efficacy*			b) With *Policing efficacy*		
Variable	Estimate	SE	t-value	Estimate	SE	t-value
Intercept	1.187***	0.126	9.421	0.911***	0.173	5.266
Low-SES	0.438*	0.217	2.018	0.183	0.109	1.679
Homeownership	−1.156**	0.373	−3.099	−1.002	0.404	−0.108
Ethnic heterogeneity	0.953*	0.422	2.258	0.701	0.501	1.399
Dump proximity	0.159*	0.065	2.446	0.123*	0.051	2.412
Satisfaction	−0.995***	0.169	−5.888	−0.667**	0.165	−4.042
Policing efficacy	–	–	–	−0.425***	0.044	−9.659
Deviance	1387			1341		
Explained variance (%)	70.002			75.146		
Model 3. *Property crime*$_c$	a) Without *Policing efficacy*			b) With *Policing efficacy*		
Variable	Estimate	SE	t-value	Estimate	SE	t-value
Intercept	1.038*	0.350	2.974	0.813**	0.281	2.893
Low-SES	0.512*	0.222	2.187	0.439	0.265	1.657
Homeownership	−0.270	0.643	−0.430	−0.276	0.302	−0.914
Ethnic heterogeneity	0.154	0.201	0.718	0.118	0.204	0.578
Dump proximity	0.147*	0.073	2.002	0.103	0.092	1.120
Satisfaction	−0.575**	0.145	−3.206	−0.467	0.309	−1.512
Policing efficacy	–	–	–	−0.681***	0.141	−4.830
Residual sum of squares	309.404			259.103		
Explained variance (%)	62.466			66.301		
Model 4. *Violent crime*	a) Without *Policing efficacy*			b) With *Policing efficacy*		
Variable	Estimate	SE	t-value	Estimate	SE	t-value
Intercept	0.901**	0.307	2.935	0.802	0.655	1.224
Low-SES	0.111	0.084	1.321	0.117	0.101	1.158
Homeownership	−0.263	0.300	−0.877	−0.195	0.219	−0.891
Ethnic heterogeneity	0.614**	0.151	4.066	0.836	0.430	1.944
Dump proximity	0.806***	0.209	3.856	0.755*	0.301	2.508
Satisfaction	−0.455	0.233	−1.953	−0.116	0.073	−1.589
Policing efficacy	–	–	–	−0.790***	0.134	−5.896
Residual sum of squares	71.041			61.388		
Explained variance (%)	51.302			63.107		

Notes: *p<0.05; **p<0.01; ***p<0.001

[b] The model of perceived crime adjusts for gender and age of individuals (n=583). Satisfaction and Policing efficacy are modes of neighborhood level random effects after adjusting for individual level covariates

[c] The models of property and violent crimes are estimated at the neighborhood level

distinct and reliable when the effects of a policing initiative are examined across small spatial units, such as neighborhoods. While the literature in which outcomes have been aggregated over large areas has reported of the CP practice being inconsequential to

Table 5 Model 5 - Results from an ordinal logistic regression model for perceived crime (n=583 participants), Model 6 - Results from a linear regression model for neighborhood property crime (n= 52), Model 7 - Results from a linear regression model for violent crime (n= 52)[d]

	Model 5 - Perceived crime[e]			Model 6 - Property crimes			Model 7 - Violent crimes		
Variables	Estimate	SE	t-value	Estimate	SE	t-value	Estimate	SE	t-value
Intercept	0.897***	0.172	5.215	0.822**	0.271	3.033	0.801	0.655	1.223
Low-SES	0.181	0.103	1.757	0.456	0.264	1.727	0.114	0.104	1.097
Homeownership	−1.017	0.907	−1.121	−0.254	0.291	−0.873	−0.196	0.223	−0.879
Ethnic heterogeneity	0.804*	0.504	1.595	0.116	0.210	0.552	0.844*	0.431	1.958
Dump proximity	0.127*	0.058	2.190	0.112	0.093	1.204	0.740*	0.303	2.442
Satisfaction[f]	−0.653**	0.170	−3.841	−0.483	0.303	−1.595	−0.115	0.072	−1.597
Policing efficacy	−0.424***	0.032	−11.778	−0.670**	0.139	−4.821	−0.792***	0.133	−5.955
Prior perceived crime	−0.436	0.225	−1.938	–	–	–	–	–	–
Prior property crime	–	–	–	−0.343	0.175	−1.961	–	–	–
Prior violent crime	–	–	–	–	–	–	−0.119	0.101	−1.178
Deviance	1332			–			–		
Residual SSE	–			261.455			52.199		
Explained variance (%)	77.002			66.126			64.217		

Notes: *p<0.05; **p<0.01; ***p<0.001

[d] All models control for the crime experience during the pre-intervention period

[e] The model of perceived crime controls for gender and age of individuals (n=583)

[f] Satisfaction, Policing efficacy and prior perceived crime are modes of neighborhood-level random effects after adjusting for the influence of gender and age between individuals

crime reduction (e.g., MacDonald 2002; Connell et al. 2008), the spatial generalization caused neighborhood-level influences to remain undetected. Nevertheless, the unsettled definition of CP, and the differences between Nairobi and other cities, make difficult a comparison of the current research results with findings that have been reported elsewhere. Notwithstanding these differences, our findings of the conditional decrease in neighborhood crime rates relate to previous literature (Carr 2005; Connell et al. 2008; Koper et al. 2010). These findings support the notion that parochial units and the police can indeed control neighborhood crime. We also discovered that those effects which negatively influence the likelihood of citizens to contribute to security efforts also increase crime prevalence. For example, the rubbish dump was a significant detriment to policing efficacy and neighborhood safety. Even after controlling for the crime experience in the pre-intervention period, we observed that the dump was related to a high crime risk. Neighborhood factors, such as deprivation and ethnic heterogeneity, also abetted the crime risk. Duncan et al. (2003) and Stein and Griffith (2015) report similar results for US and London neighborhoods. These authors also demonstrate that the amount of citizen contribution towards safety counterbalances the effects of the crime generators. Similarly, our observation that police satisfaction influenced the policing efficacy and lowered crime rates is consistent with the results obtained for US neighborhoods (Lord et al. 2009; Stein and Griffith 2015). However, contrary to previous findings (e.g., Sampson et al. 1997, Duncan et al. 2003), personal characteristics of individuals influenced neither the communal policing efficacy nor the crime experience. The implication of this observation, and one that is important for strategic policing, is that communal goals in Eastern Nairobi can easily prevail over individual-level attributes.

Altogether, our observations provide scientific evidence that a properly executed intervention strategy can overcome the social disorganization and contribute to crime risk reduction. The crime rate decrease observed in December was particularly unexpected, given that citywide, crime is usually high during this holiday month (Momanyi 2011; Mutanu 2014). It appears that this temporally delineated phenomenon was known and could be acted upon if parochial and administrative units collaborated. That being said, the disproportionate crime incidence observed in this study has three implications. First, while there is much stronger evidence of the property crime trend changing as a result of the intervention, the unclear temporal patterns of violence incidents over the two observation periods make it impossible to conclude with certainty that the CP program caused a reduction in violence risk. This limitation points out the need for comparison group designs in policy interventions. Second, in relation to this observation are the differences in community capacity for actualizing the security intervention. As Olima (2013) observed, residents of affluent neighborhoods in Nairobi are able to contribute resources towards neighborhood security, but the neighborhoods associated with low income exhibit resource insufficiency and are unable to sustain partnerships between the public and parochial controls. Furthermore, low-income neighborhoods in Eastern Nairobi are located near the city's rubbish dump, and exposure to this disorganization clearly limited the capability of the communities to effectively regulate individual behavior. This observation pinpoints that communities in the dump's vicinity require prioritization for a security initiative. Thus, the study results transcend the initial intention of measuring the community efficacy for policing and also identify the areas requiring targeted police presence. Third, the CP program in Nairobi differs from programs that were implemented elsewhere, in the sense that no considerable government funding was invested towards a uniform program sustenance. The evidence of CP effectiveness, despite resource constraints, is encouraging. Given the significance of CP outcomes that are reported in this study, police could benefit from CP by encouraging citizen participation and engraining the program further into the main fabric of the policing framework.

The research presented in this paper has several limitations. First, and owing to the need for extensive geocoding of observations, the study has observed CP outcomes in a relatively small area. For more reliable outcomes, future research is necessary to assess intervention outcomes over different cities or throughout the country. In relation to this problem is the evidence that hotspots or coldspots need to be examined over long periods of time before they can be determined as stable (Sherman et al. 1989). The patterns of high and low crime rates observed in this study could have stemmed from a pooling of the observations, rather than from the systematic crime accumulation or dispersion following a CP intervention. Second, aggregating crime counts at the neighborhood level made the inference prone to the modifiable areal unit problem (MAUP; Openshaw and Taylor 1979). This was further convoluted by the dissimilarity of the observation units' size. Additionally, the respondent data that was used to assess perception was sparsely sampled. Although a reasonable balance of responses was achieved across the residents and neighborhoods, and while the multilevel structure further increased the reliability of the analysis outcomes, more skepticism can be avoided when a larger number of neighborhood representatives are considered. Finally, the practice of CP unfolded alongside national elections and enforced traditional policing. It was hence difficult to extract specific long-term influences of CP. It is pertinent, therefore, that repeated measurements be undertaken over time to increase the validity of future assessments. Furthermore, the MAUP problem can be addressed through future measures, adopting natural aggregation areas of crime (e.g., street segments, see Groff and Lockwood 2014), weighting observations by their observed distances, and employing consistent spatial units (e.g., Kennedy et al. 2011). Initiatives such as the South African Project for Statistics on Living Standards and Development (PSLSD) are striving to capture socio-economic data at the household level and make possible such forms of analysis (Gradín 2013). Lastly, future analysis should ascertain that the CP initiative did not simply displace crimes to the neighboring areas unobserved in this research. These limitations notwithstanding, however, the observations revealed by this study demonstrate a considerable efficacy in implementing an alternative policing strategy in Nairobi's neighborhoods.

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