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Measuring the effect heterogeneity of police enforcement actions across spatial contexts

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ABSTRACT

Purpose: This study tests whether the effect of police actions is influenced by similar crime generators and attractors (CGAs) that influence crime. Said differently, in recognition that the presence of CGAs presents higher risk of crime at certain places, we test whether CGAs similarly create a situation where specific police enforcement actions are more effective at certain types of places than others.

Methods: Using longitudinal logistic regression models incorporating panel data, we measure the effect of various police enforcement actions on gun violence in Newark, NJ. Risk Terrain Modeling (RTM) was further used to test whether the effect of the enforcement activities vary across spatial contexts.

Results: When considered on their own, police enforcement actions were associated with increased likelihood of gun violence. However, certain types of enforcement actions conducted where CGAs highly co-locate, as identified through RTM, were associated with decreased likelihood of gun violence.

Conclusions: Findings suggest that where officers conduct enforcement activities may be as important as what precise enforcement activities they enact. This has implications for the place-based policing tactics. Understanding the spatial context of high-crime areas can help police design strategies in a manner that maximizes their crime prevention utility.

1. Introduction

Criminology has seen increased interest in the relationship between crime and place over the previous three decades. Perhaps the most replicated finding from this body of literature is that crime does not occur evenly across the urban landscape, but rather clusters within distinct hot spots (Lee, Eck, SooHyun, & Martinez, 2017; Sherman, Gartin, & Buerger, 1989; Weisburd, 2015). The observed concentration of crime has significant implications for police practice, with rigorous quasi-experimental and experimental evaluations consistently finding that hot spots policing generates significant reductions in crime (Braga, Papachristos, & Hureau, 2014; Weisburd & Eck, 2004). Hot spots policing tactics have recently been complimented by a range of analytical techniques broadly referred to as predictive policing (Perry, McInnis, Price, Smith, & Hollywood, 2013). Such predictive methods are assumed to help police in working more proactively with limited resources, specifically by assisting in prioritizing targets for intervention. Many common predictive policing techniques pay particular attention to features of the urban landscape in an attempt to measure how specific environmental features generate crime. One such spatial analysis technique is Risk Terrain Modeling (RTM), which aims to diagnose the spatial risk factors of criminal behavior, emphasizing micro places where multiple significant risk factors co-locate (Caplan & Kennedy, 2016; Caplan, Kennedy, & Miller, 2011).

The current study seeks to help fill a gap in the literature relating to an important area of overlap between hot spots policing and geospatial predictive policing research. Hot spots policing has taken several forms, involving a range of different police actions (Braga et al., 2014). Thus, it is surprising to note that we do not have a clear idea of what types of police tactics seem to work best within hot spots themselves (Haberman, 2016). In addition, it is still largely unknown whether certain police enforcement actions are influenced by similar crime generators and crime attractors that influence crime itself. In light of the research evidence, it is possible that police actions do not uniformly impact crime at places, but rather exhibit a heterogeneous effect depending on the composition of the surrounding environment. Said differently, if crime generators and attractors present higher risk of crime at certain places within the landscape, they may also create a situation where specific police enforcement actions may be more effective at certain types of places than others.

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The current study emerged from a partnership with the Newark, NJ Police Department (NPD) during a time when dwindling resources led to a reconfiguration of their place-based enforcement strategies and a desire of leadership to better understand the context in which the effect of police activity can be maximized. Building upon the approach of Kennedy, Caplan, and Piza (2011), we began the analysis by using RTM to identify micro-places throughout the city hosting multiple spatial risk factors for gun violence. Following this analysis, we measured the effect of various street-level enforcement activities conducted by NPD officers on the occurrence of gun violence within micro-places. We concluded by statistically measuring whether the effect of the aforementioned police enforcement actions differed across spatial contexts. We found that the effect of specific enforcement actions significantly differed depending upon the level which significant crime generators and attractors co-locate. These results suggest that where enforcement actions occur may be as important to crime reduction as what kind of enforcement actions are enacted.

2. Environmental criminology, crime concentration, and hot spots policing

The geographic concentration of crime, as well as place-based policing strategies, is informed by the Environmental Criminology perspective. Environmental Criminology is a family of theories concerned with criminal events and the immediate circumstances in which they occur (Wortley & Mazerolle, 2008): Routine Activities (Cohen & Felson, 1979), Rational Choice (Cornish & Clarke, 1986), and Crime Pattern Theory (Brantingham & Brantingham, 1993a,b). Routine Activities considers crime as the outcome of the spatial and temporal convergence of a likely offender and a suitable target in the absence of a capable guardian. Rational Choice considers crime as the outcome of an appraisal process in which the potential offender considers the risks and rewards inherent in a given crime opportunity. Crime Pattern Theory is typically credited with connecting the tenets of Routine Activities and Rational Choice, explicitly operationalizing them to space (Andresen, 2014: 8).

Crime Pattern Theory posits that offenders, who are inherently rational actors (see Cornish & Clarke, 1986), will make calculations on when and where to offend based on specific geographic locations, and specific characteristics of suitable targets within those areas. These offenders, then, are not randomly choosing targets in time and space, but rather choose targets within an area's “environmental backcloth” when and where situational factors are conductive to offending (Brantingham & Brantingham, 1993a). Brantingham and Brantingham (1993b) described the environmental backcloth as the physical characteristics of places and their subsequent influence on human behavior within the area. The environmental backcloth is comprised of three types of activity spaces: nodes (places where people spend extended amount of time, such as home, work, and places of recreation), paths (travel routes between nodes), and edges (boundaries between different areas) (Brantingham & Brantingham, 1993b). Activity spaces, and by extension their encompassing environmental backcloth, can be made criminogenic by the presence of crime generators and crime attractors. *Crime generators* are places where large groups of people congregate for reasons unrelated to criminality (Brantingham & Brantingham, 1993a). Generators may become criminogenic because the presence of large groups of people may provide criminal opportunities to would-be offenders (Bernasco & Block, 2011; Brantingham & Brantingham, 1993a, 1995). Conversely, *crime attractors* are places that provide specific opportunities for crime events to occur, bringing together motivated offenders for the express purpose of committing certain types of crimes (Brantingham & Brantingham, 1993a,b). As discussed by Clarke and Eck (2005: step 17), common examples of crime generators include shopping areas, transportation hubs, festivals, and sporting events while crime attractors include places such as prostitution strolls and drug markets. However, Clarke and Eck (2005) additionally note that as the reputation of a crime generator spreads, increasing numbers of offenders that are drawn to the area, it can transition into a crime attractor. This shows that the relationship between activity spaces and crime is fluid in nature, able to take various forms over time.

As Brantingham and Brantingham (1999) note, the combination of these different layers in the environment overlaid within the environmental backcloth theoretically produces concentration of crime hot spots. While no common definition of hot spots exists (Eck, Chainey, Cameron, Leitner, & Wilson, 2005), the common conceptualization used by researchers and practitioners refer to micro-places located at specific buildings and addresses, street segments, or clusters of street blocks where crime concentrates (Weisburd, 2008). In their seminal piece, Sherman et al. (1989) found that 3.3% of addresses in Minneapolis accounted for just over 50% of calls-for-service over a 12-month period. Subsequent studies have found similar clustering for an array of crime types, as demonstrated in a recent systematic review of crime concentration at places (Lee et al., 2017). Research incorporating longitudinal methods have further demonstrated that hot spots persist over rather extensive time periods. Scholars have observed high levels of crime concentration over a decade or longer in cities such as Seattle (Weisburd, Bushway, Lum, & Yang, 2004; Weisburd, Groff, & Yang, 2012), Boston (Braga, Hureau, & Papachristos, 2011; Braga, Papachristos, & Hureau, 2010), Vancouver (Curman, Andresen, & Brantingham, 2015), Chicago (Schnell, Braga, & Piza, 2016), Albany (Wheeler, Worden, & McLean, 2016), and The Hague (Steenbeek & Weisburd, 2016).

Interest in micro-level opportunity structures and their influence on hot spot formation has also spurred increased attention on how police can effectively control crime at micro places (Braga & Weisburd, 2010). Moving from randomized patrols (Kelling, Pate, Dieckman, & Brown, 1974) to more focused techniques at crime hot spots, police departments have seen success in curbing crime problems in cities (Braga et al., 2014). However, while there is general consensus on the effectiveness of hot spots policing, much less is known regarding the precise actions police officers should take when engaged in such practices (Haberman, 2016). Studies included in Braga et al.'s (2014) systematic review incorporated a diverse set of tactics including situational crime prevention (Braga & Bond, 2008), proactive traffic stops (Sherman & Rogan, 1995a), raids on drug houses (Sherman & Rogan, 1995b), directed motor vehicle patrol (Taylor, Koper, & Woods, 2011), and foot patrol (Ratcliffe, Taniguchi, Groff, & Wood, 2011), among other tactics. In addition, street-level actions enacted by police officers can exhibit a great deal of variability even within single interventions. Enforcement actions are often not situationally dictated, with officers enjoying a great deal of latitude when choosing how to address incidents of concern (Famega, 2005). Hence, a number of appropriate enforcement decisions are available to officers in most instances (Schafer, Carter, Katz-Bannister, & Wells, 2006).

Better understanding the influence of precise police officer actions, and not just overarching strategies (e.g. hot spots policing), can have great benefit in contemporary policing. Despite the emergence of hot spots policing, as well as other evidence-based strategies such as problem-oriented policing, routine patrol remains the primary activity of police (Mastrofski & Willis, 2011). Therefore, even in cities committed to evidence-based strategies, a bulk of patrol officers will be dedicated to the delivery of standard patrol and response services. In light of this fact, understanding the effect of street-level enforcement actions is key, as all patrol officers can engage in such activity, regardless if deployed at hot spots or in a general patrol function.

3. Police enforcement actions, environmental context, and effect heterogeneity

In revisiting the tenets of Environmental Criminology, it is important to acknowledge Brantingham and Brantingham's (1993b) basic description of the environmental backcloth as a dynamic entity in which people and features of the urban landscape interact in a manner that influences behavior patterns. While this "person-environment nexus" (Moreto, Piza, & Caplan, 2014: 1104) has predominately been analyzed through the manifestation of criminal behavior and observed crime levels, Brantingham and Brantingham (1993b) did not conceptualize the environmental backcloth as inherently criminogenic. Rather, the environmental backcloth also houses non-criminal activities, and can possibly serve a protective function against crime in certain contexts. In light of this observation, an exclusive focus on potential offenders and their criminal behavior overlooks the role of capable guardians and their protective actions within the environmental backcloth. Said differently, research has yet to explore the possibility that the effect of police actions on crime may be contingent upon the characteristics of the encompassing environment.

In a certain respect, the hot spots policing literature provides some level of evidence that the effect of policing tactics is at least somewhat contingent on the environment in which they occur. The main premise behind the inaugural hot spots policing experiment (Sherman & Weisburd, 1995) was that the deterrent effect of patrol could be heightened if focused within micro geographic units rather than spread across larger areas, such as patrol beats or neighborhoods. The numerous replications of this original finding confirm the influence of geographic hot spots on policing tactics (Braga et al., 2014). The emergence of analytical frameworks able to readily contextualize hot spot geographies, specifically by identifying and diagnosing crime generators and attractors, offers the opportunity to further classify micro geographies according to their environmental composition. Such analytical techniques allow for the testing of potential interaction effects between police activity and environmental composition. As an example, Piza, Caplan, and Kennedy (2014) measured the influence of a series of micro-level environmental features on the crime control effect of individual CCTV camera sites, finding that specific environmental features were associated with the reduction of certain crimes and the increase of others. The presence of bars, for example, within a camera's environmental backcloth was associated with decreases in overall violent crime and robbery, while the presence of corner stores was associated with increases in thefts from auto. A similar study by Lim and Wilcox (2017) examined the effects of CCTV cameras on various crime types in different spatial contexts within Cincinnati. Lim and Wilcox (2017) found that CCTV cameras produced significant reductions in crime, but only in some location types. For instance, the effect of cameras on assaults, robberies, and burglaries was significantly reduced only in residential areas, whereas auto thefts and thefts from autos did not experience significant reductions, regardless of location type.

The findings of Piza et al. (2014) and Lim and Wilcox (2017) support a call for research on the influence of spatial context on the effect of police practices. These studies found evidence that the effect of a place-based intervention (i.e. CCTV) was not homogeneous, but rather conditional on the composition of the immediate surrounding environment. While this research measured this phenomenon in regards to a single strategy we believe that the field would benefit from rigorous testing of whether individual police actions (e.g. arrests, citations, etc.) exhibit similar effect heterogeneity across space. We feel that such research would have particular importance in contemporary policing, as both scholars and practitioners have prioritized further development of a portfolio of effective police practices.

Caplan and Kennedy (2016) argue that the consistent finding that crime generators and attractors allow crime hot spots to emerge and persist over time suggests that police should re-conceptualize their place-based interventions to more readily, and directly, target crime generators and attractors responsible for hot spot formation. To diagnose the spatial context of high crime areas, Caplan and Kennedy (2016) emphasize the use of RTM in the problem analysis stage of intervention development. As described by Caplan, Kennedy and Miller (2011: 365), RTM involves statistically identifying spatial risk factors related to an outcome event (i.e. crime) of interest and then combining said risk factors into a "composite map" that assigns a risk value at every micro-unit within a given study area. It is this notion of the "composite map" representing the co-location of multiple spatial risk factors that separates RTM from other place-based analytical methods, which have typically considered the influence of crime generators and attractors individually.

To build upon the process of risk factor selection, Kennedy et al. (2011) introduced a technique to select individual crime generators and attractors for the final composite map based upon their observed relationship to the crime of interest. This technique is helpful in situations where police agencies maintain large amounts of GIS data, which precludes simply incorporating all available data into an RTM. It also assists in analysts' selection of the best combination of data layers. Kennedy et al.'s (2011) approach of risk factor selection has since been further developed and automated via the Risk Terrain Modeling Diagnostics Utility (RTMDx) (Caplan & Kennedy, 2013). RTMDx has been used to analyze a variety of crime types, including aggravated assault (Drawve & Barnum, 2017; Kennedy, Caplan, Piza, & Buccine-Schraeder, 2016), burglary (Caplan, Kennedy, Barnum, & Piza, 2015), carjacking (Lersch, 2017), motor vehicle theft and recovery (Piza, Feng, Kennedy, & Caplan, 2016), robbery (Barnum, Caplan, Kennedy, & Piza, 2017), battery against police officers (Caplan, Marotta, Piza, & Kennedy, 2014), and street-level drug selling (Barnum, Campbell, Trocchio, Caplan, & Kennedy, 2016).

4. The current study

In light of the research evidence, it is possible that police actions do not uniformly impact crime, but rather exhibit a heterogeneous effect depending on the composition of the environmental backcloth. Given that the presence of crime generators and attractors presents higher risk of crime at certain places within the landscape, it is possible that such features of the environment create a situation where certain police enforcement actions may be more effective at certain types of places than others. It is with this in mind that we designed the current study.

The current study contributes to the literature in a number of ways. First, we build upon Kennedy et al. (2011) to identify significant spatial risk factors of gun violence in Newark, NJ. Following this analysis, we measure the effect of various street-level enforcement activities conducted by Newark Police officers on the occurrence of gun violence within micro-places. We conclude by measuring whether the effect of the police enforcement actions differed across spatial contexts, as identified through RTM.

5. Data

Newark is the largest city in New Jersey, spanning over twenty-six square miles with a population of nearly 280,000 persons according to the last decennial census. The percentage of residents living below the poverty level (29.7%) is nearly three times that of NJ as a whole (10.8%). Ethnic minorities largely comprise Newark's population with 52.4% of the population Black and 33.8% of residents identifying themselves as Hispanic or Latino (U.S. Census Bureau, 2010). The city has historically struggled with issues of gun violence (Tuttle, 2009), with internal police department data indicating that from 2007 to 2010 over 84% of murders resulted from a gunshot while roughly half of all robberies involved a firearm (Piza & O'Hara, 2014, p. 698).[1]

[1] In the current study, we excluded the portion of Newark comprised by Newark Liberty Airport and the shipping Port of Newark, which are outside of the NPD's jurisdiction, from the study area. While technically within NPD jurisdiction, the vicinity immediately surrounding the airport and port were also excluded from the final study area because the NPD does not typically deploy any patrol units in this area due to it being exclusively comprised of highways and vacant land. This study area conceptualization reflects the approach of prior geospatial analyses of crime in Newark (see Moreto et al., 2014; Piza et al., 2014).

Our analysis covers the calendar year of 2010. This year marked a significant shift in place-based policing for the NPD, due to the termination of 13% of the agency's officers in response to the city's fiscal crisis (The Star Ledger, 2010). This loss of officers, most of whom were early career officers assigned to patrol functions, led the agency to phase-out their large-scale hot spots policing projects that dedicated large numbers of officers to high crime places on a continual basis (see, for example, Piza & O'Hara, 2014: 713). In light of this loss of personnel and shift in strategy, the agency increasingly tasked officers with taking proactive enforcement actions against street-level incidents of concern during their course of normal duty, which largely involved general patrol activities and responses to reported calls for service. NPD officials believed that such strategies would allow for the real-time disruption of situational factors that can generate crime, specifically incidents of gun violence that were the primary focus on NPD's crime prevention mission (Jenkins & DeCarlo, 2015; Piza & O'Hara, 2014).

Data were obtained from a variety of sources at the NPD. Crime incident data were collected from the NPD's Records Management System (RMS). While Kennedy et al. (2011) incorporated shootings as their dependent variable, we expanded our operational definition to reflect overall gun violence: all homicides, aggravated assaults, and robberies committed with a firearm. In our discussion with NPD officials at the time, we learned that the agency commonly considered such incidents alongside shootings in order to gain a holistic view of the gun violence problem, and identify target areas for directed patrols.

NPD's RMS also provided arrest data. We were interested in street-level arrests conducted in response to real time situational factors, which the NPD considered one of their primary crime control enforcement tactics, rather than retroactive arrests conducted by investigative units. Thus, all arrests conducted by investigative units, who arrest suspects for crimes committed in the past as determined by retrospective investigations, were excluded from the analysis. We were interested in the effect of various types of enforcement actions, so we categorized arrests into 4 types: warrant arrests (resulting from patrol officers making proactive contact with a suspect), narcotics arrests, gun arrests, and social disorder arrests. These arrest types were identified based upon their relation to gun violence occurrence, both according to the beliefs of NPD command staff and as reflected in the empirical literature. In situations where suspects were charged with multiple offenses, we used the "top charge" in our classification schema.[2]

Data on field interrogations and quality-of-life summonses were collected from the NPD's CompStat portal, an internal database that captures performance measures of interest for NPD command staff. Field interrogations refer to situations in which an officer approaches a citizen due to reasonable suspicion of crime activity, as per the standards established by Terry v. Ohio (1968). Quality of life summonses are citations issued for behaviors commonly referred to as social disorder in the literature, such as drinking in public, gambling in public, and aggressive panhandling (Kelling & Coles, 1996). Along with proactive arrests, Newark police leadership considered these enforcement actions as the primary street-level tactics of the agency at the time (Jenkins & DeCarlo, 2015; Piza & O'Hara, 2014). It should be noted that field interrogations and quality of life summonses that resulted in the on-site arrest of a suspect (through the discovery of an open warrant, for example) were considered as an arrest for the analysis. In other words, police enforcement actions were not double-counted. All data were geocoded by NPD analysts to street centerlines, with the geocoding rate for gun violence (99.3%), arrests (99.2%), field interrogations (99.3%), and quality of life summonses (99.4%) all well above the minimum geocoding rate of 85% suggested by Ratcliffe (2004).[3]

In order to contextualize micro-places throughout the study area, we collected data pertaining to various environmental features of interest. Our selection of environmental features was informed by the approach of Kennedy et al. (2011).[4] In total, we included eight environmental features in the analysis: bars, liquor stores, corner stores, take out restaurants, at-risk housing, gang territory, narcotics-related calls for service and social-disorder related calls for service. Bars and liquor stores were included due to their status as "crime attractors" in prior crime-and-place research (Bernasco & Block, 2011; Kennedy et al., 2011; Ratcliffe, 2012; see also Roncek & Maier, 1991). Corner stores and take-out restaurants are particularly criminogenic in the context of Newark. Corner stores often serve as anchors of illicit drug markets, while the high foot traffic and late hours of operation that often characterize take-out restaurants make it difficult for police to distinguish legitimate customers from those loitering for unlawful purposes (Kennedy et al., 2011). Lists of bars, liquor stores, and take-out eateries were obtained from the City of Newark licensing unit, with each data set geocoded with a match rate of 100%. Corner stores were operationalized from a list of grocery stores obtained from InfoGroup, a leading provider of residential and commercial data for reference, research, and marketing purposes.[5] The InfoGroup layer included 251 total stores, with the lead author driving to each location to identify the mom-and-pop type businesses that are colloquially referred to as "bodegas," which were of interest to the current study. Like the other facility types, corner stores were geocoded in their entirety.

At-risk housing captures the city parcels containing public housing and privately-owned complexes similar in scope to public housing complexes, in recognition that such complexes can contribute to crime in a similar manner as public housing in Newark (Kennedy et al., 2011). The file was created through a partnership between the NPD, the Newark Housing Authority, and various City of Newark Departments, and has been used previously in geospatial analyses of crime in Newark (Kennedy et al., 2011; Miller, Caplan & Ostermann, 2016; Moreto et al., 2014; Piza et al., 2014). The gang territory layer was created by Braga, Grossman, and Piza (2011) during a series of focus groups lasting between 1 and 2 h with investigators from various units of the NPD. Following the approach of prior research using qualitative police intelligence to identify criminogenic geographies, particularly in support of focused deterrence strategies (Dalton, 2003; Kennedy, Braga, & Piehl, 1997; McGarrell & Chermak, 2003; McGloin, 2005), researchers asked officers to identify the locations of prevalent gang territories by drawing on a large map. Officers provided criminal intelligence regarding the nature and scope of the gang activity to support their

[2] The hierarchy of arrest charges used in this study was as follows: gun possession, narcotics, social disorder, and warrant. Warrant was considered the lowest level because it is indicative of prior infractions by the suspect rather than immediately observable criminal behavior.

[3] We calculated geocoding rates by identifying all incidents in the shapefiles with

(*footnote continued*)
assigned XY coordinates, meaning that NPD analysts were able to find an appropriate match for the listed address.

[4] Our operationalization differed from Kennedy et al. (2011) in a few ways. First, Kennedy, Caplan, and Piza used officer contacts with known gang members as a proxy measure for gang territory. Given that we had access to the actual gang territory boundaries as defined by the NPD (Braga, Grossman, and Piza, 2011), we felt that using this layer provided a more valid measure of gang territory. Second, Kennedy, Caplan, and Piza used drug arrests as a proxy measure of drug markets. Given that arrests were part of our independent variables, we instead used calls for service data to identify the markets. Lastly, while Kennedy, Caplan, and Piza merged corner stores and liquor establishments into a single "risky facilities" layer, we opted to look at these layers separately to acknowledge their potential differing effect on gun violence.

[5] InfoGroup uses a multi-pronged approach in collecting and ensuring the accuracy of their business data, incorporating business record information from thousands of sources (see: http://www.infogroupdatalicensing.com/why-infogroup-data-licensing/what-we-do). InfoGroup's data research specialists manually verify the accuracy of data, making over 100,000 calls a day to ensure listed business are in operation (see: http://www.infogroupdatalicensing.com/why-infogroup-data-licensing/how-we-do-it). The data files we obtained included all businesses verified during our study period of 2010. A number of crime-and-place studies have incorporated data from InfoGroup (e.g. Caplan et al., 2015; Kennedy et al., 2016; Miller et al., 2016) as well as other commercial providers that provide similar information (e.g. Bernasco & Block, 2011). InfoGroup data is also used in the Business Location platforms of ESRI, developer of the ArcGIS software suite and the recognized industry leader in GIS technology (ESRI, 2015).

answers with considerable agreement existing among the police officers in attendance at the focus groups.

Lastly, narcotics- and disorder-related calls for service were extracted from the NPD's computer-aided dispatch system. These layers were used as proxy measures for street-level markets of illicit drug activity and disorderly behavior, respectively. Narcotics activity included calls for service reporting drug activity reported via the anonymous tip line, street-level drug activity, and unverified drug activity (meaning the complainant did not directly witness the drug transaction, but has ample reason to believe a drug transaction occurred). Social disorder calls included disorderly persons, drinking in public, noise complaint, obstruction of public passage, panhandling, prostitution, and urinating in public. Calls for service were provided by the NPD in spreadsheet format. The research team then geocoded the data to street centerlines (to match NPD's internal geocoding method) achieving match rates of approximately 99% for both narcotics and social disorder. To protect against duplicate cases due to multiple citizens calling about the same incident (Klinger & Bridges, 1997), we deleted duplicate events (identified by their police-assigned event numbers) via the "Delete Identical" tool in ArcGIS, 10.3.

6. Analytical approach

We began our analysis by conducting an RTM for gun violence in Newark. The RTM tested the 8 aforementioned spatial risk factors: At-risk housing, Bars, Corner stores, Liquor stores, Social disorder calls for service, Gang territory, Narcotics calls for service, and Take-out restaurants. We used the RTMDx Utility (Caplan & Kennedy, 2013) to conduct the analysis. RTMDx identifies the optimal spatial influence and operationalization[6] for each risk factor as well as a Relative Risk Value (RRV). The RRV is calculated by exponentiating risk factor coefficients provided by the RTM, and can be considered as a weighting value used to compare the effect of risk factors with one another.

For the analysis, Newark was modeled as a set of contiguous grids of equally sized 226 ft. by 226 ft. cells (N = 9129), representing approximately one-half of the average block length in the city, as measured within ArcGIS. RTMDx tests risk factor influence through a penalized regression model with crime counts (in this case, gun violence) as the dependent variable. Various operationalizations of the aforementioned risk factors are independent variables, with RTMDx measuring whether each raster cell is within a certain distance of the risk factor (i.e. proximity) or in an area of high concentration of the risk factor (i.e. density). Each risk factor was tested at half-block increments out to 3 blocks (1356 ft.). Through this method, the eight risk factors generated 72 independent variables that were tested for significance. Incorporating 72 covariates in a single model may present problems with multiple comparisons, in that we may detect spurious correlation simply due to the number of variables tested. The penalized regression method used by RTMDx alleviates potential problems with spurious correlation due to multiple comparisons by reducing the large set of variables to a smaller set of variables with non-zero coefficients. This is accomplished through an elastic net method that forms five stratified folds from the raster cells, balancing crime counts between the folds. This balancing process is done to ensure that there is some variance across the folds to aid in the numeric stability of the modeling process. For each covariate, RTMDx then builds five simultaneous models for each fold to rigorously test the influence of each independent variable on the crime outcome, and identify a set of variables with useful predictive value (i.e. with non-zero coefficients).

For the current study, RTMDx selected 30 variables as potentially useful. These variables were then utilized in a bidirectional step-wise regression process to determine the final model type. Following a null model with no model factors, RTMDx adds each variable to the null model and re-measures the Bayesian Information Criteria (BIC) score to identify the most parsimonious combination of variables. After each iteration, the model with the lowest BIC score is selected as the new candidate model (the model to surpass). RTMDx repeats the process, adding and removing variables one step at a time, until no variable addition/removal surpasses the previous BIC score. RTMDx repeats this process with two stepwise regression models: one Poisson and one negative binomial, selecting the best model with the lowest BIC score. RTMDx also produces a relative risk value (RRV) that can be interpreted as the weight of the individual risk factor, and therefore may be used for comparison across all risk factors (for more information on the statistical procedure of RTMDx, see Heffner, 2013).

Following the RTM analysis, we conducted longitudinal logistic regression models to test the effect of police enforcement actions on the occurrence of gun violence. We incorporated Thiessen polygons as units of analysis in the regression models, following the approach of recent crime-and-place studies (Haberman, 2017; Ratcliffe et al., 2011). Thiessen polygons create a Voronoi network that uses lines to divide a plane into areas closest to a set of points (see Chainey & Ratcliffe, 2005). We used street intersection points to create the polygons in ArcGIS, 10.3. In the current study, each space within an intersection's encompassing Thiessen polygon was closer to that intersection than any other intersection in the study area (see Fig. 1).[7]

Within ArcGIS, monthly panel data was spatially joined to each Thiessen polygon in the study area. The dependent variable is a binary measure denoting whether an incident of gun violence occurred during the month in question ("1") or not ("0"). A series of independent variables were also joined to the polygons. To reflect the spatial context of the surrounding environment, we included a series of binary measures to reflect the spatial context of each polygon, as determined via RTM. Following the identification of significant risk factors and calculation of their respective RRV, RTMDx calculates the relative risk score (RRS) for each grid cell throughout the study area. In calculating each cell's RRS, RTMDx uses map algebra to sum the RRV of each significant risk factor whose spatial influence overlaps the given grid cell.

Our RTM models found that, on average, micro-places in Newark have a RRS of 3.68 with a standard deviation of 5.1. Therefore, we categorized each unit's risk value into one of three categories: mean to + 1 standard deviation, + 1 standard deviation to + 2 standard deviations, and greater than + 2 standard deviations.[8] These categories represent different concentrations of spatial risk factors, with micro-places exhibiting higher risk scores experiencing greater co-location of crime generators and attractors than micro-places with lower risk scores.

To measure police officer activity, we included monthly counts of the six aforementioned enforcement actions of interest: field

[6] The notion of spatial influence operationalization is key, as prior research suggests that different criminogenic features exert different types of influence on crime. Research in Philadelphia, for example, found that violence is highly clustered within 85 ft of bars then dissipates rapidly (Ratcliffe, 2012), while the effect of schools, halfway houses, and drug treatment centers varies substantially by distance and crime type (Groff & Lockwood, 2014). RTMDx identifies the precise distance at which the effect of the spatial risk factor on crime is maximized.

[7] Thiessen polygons were used to account for the inherent ambiguity of spatial crime data. In particular, police officers oftentimes report a crime location as the nearest street intersection (e.g. "Main St. and Central Ave.") rather than the precise address of occurrence (e.g. "100 Main St.") (Braga, Hureau, and Papachristos, 2011: 15). Such crimes occurring at intersections do not fall within a single street segment, but rather overlap with all street segments that comprise the intersection. While prior research has simultaneously used street segments and street intersections as units of analysis to avoid this issue (e.g. Braga et al., 2010; Braga, Hureau, and Papachristos, 2011) 6 of the 8 spatial risk factors used in this study (all except the narcotics and disorder calls) were mapped to precise street addresses (meaning that street intersections would not house a single spatial risk factor). Therefore, we determined that Thiessen polygons best maximized the internal validity of our measures.

[8] We originally planned on including an additional category of places with risk scores below the mean of 3.68. However, interaction terms created with this binary measure presented issues of collinearity, causing many variables of interest to be excluded. Therefore, we decided to not include this category in the final analysis.

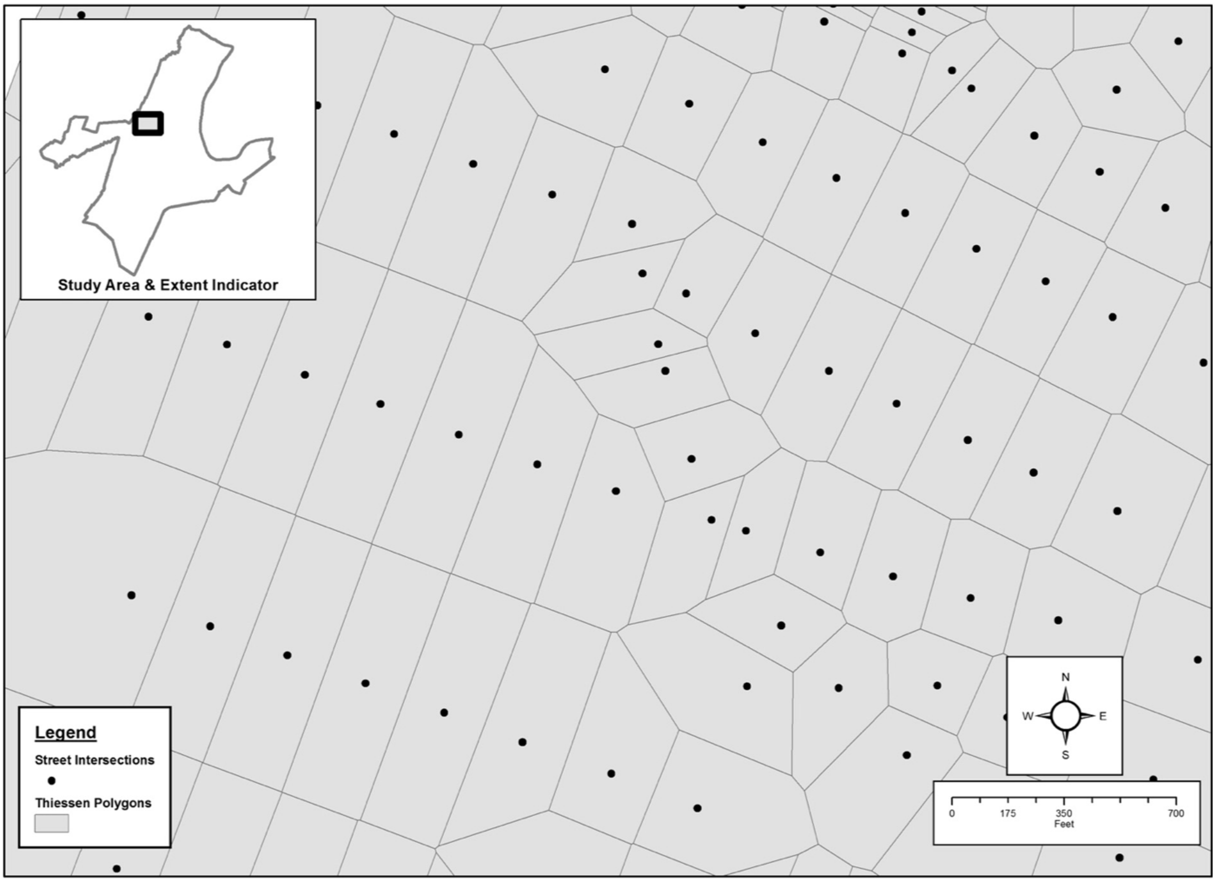

Fig. 1. Thiessen polygons.

interrogations, quality of life summonses, warrant arrests, narcotics arrests, gun arrests, and social disorder arrests. The models included interaction terms to identify the number of enforcement actions occurring at places belonging to each of the 3 aforementioned spatial contexts, as designated by RTM. For each RTM designation category, interaction terms were calculated by multiplying each enforcement action with the binary variable denoting the particular RTM designation. To better determine the causal effects on gun violence, each enforcement variable and interaction term was lagged (t-1) to represent the prior month.

In addition to the independent and interaction variables of interest, our models include 13 control variables to account for factors that may influence gun violence occurrence. First, a spatial lag was created within the GeoDa spatial analysis software to control for the observed presence of spatial autocorrelation.[9] To control for the differing sizes of Thiessen polygons, the area (square miles) was calculated for each observation. Two variables were included to control for socio-demographic characteristics of each polygon's surrounding census block group: concentrated disadvantage (Morenoff, Sampson, & Raudenbush, 2001; Sampson, Raudenbush, & Earls, 1997) and racial heterogeneity (Berg, Stewart, Brunson, & Simons, 2012). Concentrated disadvantage was a standardized index composed of the percentage of residents receiving public assistance, the percentage of families living below the poverty line, the percentage of female-headed households with children under the age of 18, and the percentage of unemployed residents.[10] Racial heterogeneity measures the probability of members of different ethnicities living in the same neighborhood, with high probabilities suggesting the coexistence of conflicting and competing values regarding the appropriateness of illicit conduct (Berg et al., 2012: 412).[11] The number of days in the month was used to account for potential exposure to gun violence, as longer months may have more daily opportunities to experience crime. A continuous variable measuring the progression of the monthly time periods (e.g. January = 1, February = 2, etc.) was included to account for the temporal trends in the data, following the approach of prior crime-and-place research incorporating longitudinal models (e.g. Braga et al., 2011, 2012; Braga et al., 2010; Carter & Piza, 2017). A lagged (t-1) binary variable measured the number of gun violence incidents occurring in the preceding month. To measure the amount of people potentially present within each polygon, we measured the ambient population, which represents the "on-street" population of an area, measuring the number of persons who frequent an area for work, school, or recreation (Andresen, 2011: 195). The ambient population was calculated using the Oak Ridge National Laboratory's LandScan database, which provides a 24-hour estimate of the expected population present at a spatial scale of about 1km^2. Each Thiessen polygon was assigned the ambient population of its surrounding grid.

In recognition of the fact that places falling within different police precincts may be susceptible to different organizational forces, we identified which of NPD's four police precincts the unit fell within. Newark's 3rd precinct, the smallest in the city, was used as the reference category in our models.[12] In recognition of the effect seasonality can

[9] Moran's I = 0.42 (p = 0.001). First order Queen Continuity was used in the creation of the spatial lag variable.

[10] While prior measures of social disadvantage have also included percentage of Black residents, racial composition was addressed via the separate racial heterogeneity variable, following the approach of recent crime-and-place research (Carter & Piza, 2017; Piza et al., 2016; Weisburd et al., 2012), as discussed subsequently.

[11] Racial heterogeneity was calculated via the following formula: [(%White, non-Hispanic * % non-white, non-Hispanic) + (%black, non-Hispanic * % non-black, non-Hispanic) + (%Hispanic * %non-Hispanic)]/3 (Weisburd et al., 2012).

Table 1
Descriptive statistics (panel data).

Dependent variable	Mean (std. dev.)	Min. (Max.)	1-Year total
Gun violence	0.04 (0.20)	0 (3)	1312
RTM designation	**No (%)**	**Yes (%)**	
Below mean (1–3.67)	27,192 (73.40)	9852 (26.60)	
Mean to + 1 SD (3.68–8.70)	21,528 (58.11)	15,516 (41.89)	
+ 1 SD to + 2 SD (8.71–13.73)	31,656 (85.46)	5388 (14.54)	
Greater than + 2 SD (13.74–58.74)	30,768 (83.06)	6276 (16.94)	
Independent variables	**Mean (std. dev.)**	**Min. (Max.)**	**1-Year total**
Quality-of-life summonses	0.56 (2.27)	0 (96)	20,771
Field interrogations	1.10 (3.76)	0 (166)	40,920
Warrant arrests	0.37 (1.42)	0 (47)	13,656
Violent crime arrests	0.03 (0.24)	0 (13)	954
Narcotics arrests	0.14 (0.84)	0 (34)	5330
Gun arrests	0.01 (0.17)	0 (15)	430
Social disorder arrests	0.01 (0.18)	0 (15)	449
Control variables (continuous)	**Mean (std. dev.)**	**Min. (Max.)**	
Spatial lag	0.43 (0.47)	0 (3.20)	
Area (square miles)	0.01 (0.00)	0 (0.08)	
Concentrated disadvantage	0.07 (3.89)	− 4.93 (13.52)	
Racial heterogeneity	0.09 (0.04)	0.01 (0.17)	
Ambient population	4892.1 (2729.9)	395.5 (16,715)	
Control variables (categorical)	**N (%)**		
1st	9261 (25.0%)		
2nd	9261 (25.0%)		
3rd	9261 (25.0%)		
4th	9261 (25.0%)		

exhibit on gun violence, we identified the quarter of the year each monthly unit fell within. Quarter 1 (January – March) was used as the reference category in our models (See Table 1 for descriptive statistics of the variables discussed in this section).

7. Findings

Table 2 displays the findings of the RTM analysis. Six of the eight risk factors were found to be significantly related to the occurrence of gun violence: social disorder calls for service, corner stores, narcotics calls for service, gang territory, liquor stores, and take out restaurants. Social disorder calls exhibited the largest RRV (3.17), suggesting that places within a half-block blocks of this risk factor were > 3 times more likely to experience gun violence than places absent the spatial influence of any risk factors. Corner stores (RRV = 2.23) and narcotics calls (RRV = 2.14) both generated risks for gun violence within a half-block that were over two-times higher than places absent risk factors while gang territory (RRV = 1.93) was associated with a nearly two-times greater likelihood of gun violence within 2-blocks. Liquor stores (RRV = 1.43) and take out restaurants (RRV = 1.41) exhibited the weakest effects on gun violence, but still heighted risk of crime occurrence by 43% at places within 2.5 blocks and by 41% at places within 3 blocks, respectively, as compared to places absent these risk factors. At-risk housing and bars were not found to be significantly related to gun violence and were thus excluded from the final RTM.

Fig. 2 displays a map of the final RTM. Using map algebra (Tomlin, 1994), RTMDx sums the cumulative RRVs measuring the spatial influence exerted within each micro-place throughout the jurisdiction. The mean risk score was 3.68 with a standard deviation of 5.1. Places with high risk scores are defined by their exposure to high co-location of the significant risk factors: social disorder-calls, corner stores, narcotics-calls, gang territory, liquor stores, and take out restaurants.

Table 2
Risk factor testing.

Risk factor	N	Op.	S.I.	Coef.	RRV
In the final RTM					
Social disorder calls for service	18,999	Dens.	Half block	1.15	3.17
Corner stores	227	Dens.	Half block	0.80	2.23
Narcotics calls for service	8738	Dens.	Half block	0.76	2.14
Gang territory	3187	Prox.	2 blocks	0.66	1.93
Liquor stores	1130	Prox.	2.5 blocks	0.35	1.43
Take out restaurants	244	Prox.	3 blocks	0.34	1.41
Intercept (rate)	–	–	–	− 3.29	–
Intercept (overdispersion)	–	–	–	− 1.12	–
Tested but not in the final RTM					
At-risk housing	2692	–	–	–	–
Bars	246	–	–	–	–

Abbreviations: Op., Operationalization; Dens., Density; Prox., Proximity; S.I., Spatial Influence; Coef., Coefficient, RRV, Relative Risk Value.
Note: RTMDx only accepts point files as inputs. At-Risk Housing and Gang Territory were provided as polygons and converted to polygons prior to the analysis. To conduct the conversion, researchers first converted the perimeter of each polygon to a series of points placed about one half block (i.e. 226 ft.) from each other. To convert the interior of the polygon, the vector was first converted to a raster grid with cell size of 226 ft. The raster was then converted to a point file, with each raster cell centroid represented as a single point. The N values in Table 1 are the number of points input into RTMDx. The points were created from the following number of polygon features: 137 at-risk housing complexes, and 73 gang territories.

Table 3 displays the findings of the first two longitudinal logistic regression models.[13] Models were run in a step-wise fashion, with the enforcement actions appearing alone in model 1. The relevant RTM interaction terms were then added in subsequent models. To account for their different scales and ranges, enforcement actions were standardized (i.e. converted to z-scores) to allow for easier interpretation and comparison of findings (Carter & Piza, 2017).

In model 1, four of the enforcement actions achieved statistical significance, each associated with an increased likelihood of gun violence. One-unit increases in quality of life summonses were associated with an 8% increased likelihood of gun violence occurring within the subsequent month (OR = 1.08). Warrant arrests and narcotics arrests were both associated with a 7% increased likelihood of gun violence (OR = 1.07). One-unit increases in field interrogations were associated with a 6% increased likelihood of gun violence (OR = 1.06).

Model 2 includes the interaction terms measuring enforcement actions occurring at micro-places with risk scores between the mean (3.68) and + 1 standard deviation above the mean (8.70). While spatial risk factors commonly appear in the environmental backcloth of these places, the concentration of such features is not considerably high in comparison to most areas of Newark. All four of the enforcement actions that achieved statistical significance in model 1 maintained their significance in model 2, each exhibiting a similar positive relationship with gun violence. Conversely, only 2 of the 6 interaction terms achieved statistical significance. Both quality of life summonses and gun arrests were both associated with increased likelihood of gun violence when conducted within places with about average risk scores. Given that similar positive relationships were exhibited in model 1, we can conclude that the effect of enforcement actions enacted within this

[12] We originally planned on calculating robust standard errors for each of the four clusters of police precincts. However, several models failed to converge when we used this technique. Thus, we included precincts as control variables in the model to account for the potentially differing organizational forces.

[13] To measure the presence of multicollinearity, we calculated the variance inflation factor (VIF) and associated tolerance (1/VIF) for each of the explanatory variables (Hamilton, 2013: 203). Tolerance values were above 0.1 in each instance, demonstrating an absence of multicollinearity. Owing to space constraints, VIF results are not presented in text but are available from the lead author upon request.

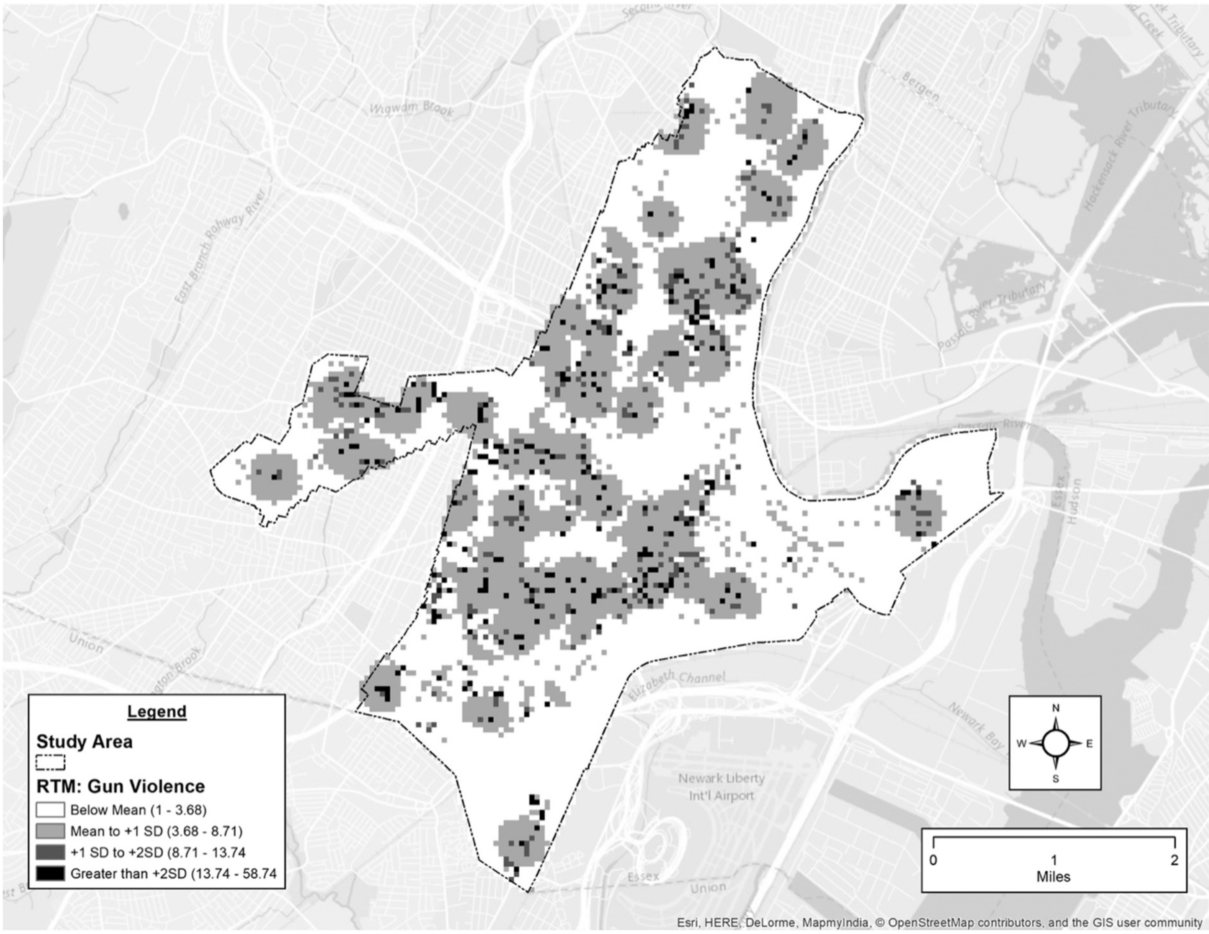

Fig. 2. Risk terrain map for gun violence in Newark.

spatial context do not differ substantially from their general application.

Table 4 displays the results of model 3 and model 4, which measure the effect of enforcement occurring in areas with risk scores between + 1 and + 2 standard deviations above the mean (8.71–13.73) and risk values greater than + 2 standard deviations above the mean (13.74–58.74), respectively. The same four enforcement actions significant in the previous models maintained their significance and relation to the dependent variable in model 3. The interaction terms odds ratios, however, differed in direction and significance from the prior models. In particular, narcotics arrests conducted at places with risk values between + 1 and + 2 standard deviations above the mean exhibited crime prevention effects, with every 1 unit increase associated with an 8% decreased likelihood of gun violence (OR = 0.92). This is in contrast to the standard application of narcotics arrests, which was associated with an increased likelihood of gun violence. This finding suggests a potential influence of spatial context, with places exhibiting risk scores between + 1 and + 2 standard deviations above the mean being more receptive to the crime prevention effects of narcotics arrests than other places in Newark.

In model 4, three enforcement actions maintained their statistically significant relationship to gun violence: warrant arrests (OR = 1.19), quality of life summonses (OR = 1.15), and field interrogations (OR = 1.08). Narcotics arrests, positively related to gun violence in all prior models, failed to achieve statistical significance. Two of the interaction terms achieved statistical significance. Within places with risk scores greater than + 2 standard deviations above the mean, 1-unit increases in quality of life summonses (OR = 0.91) and warrant arrests (OR = 0.88) were associated with 9% and 12% reduced likelihood of gun violence, respectively. Along with the findings of model 3, these findings further suggest the importance of spatial context in place-based policing. In particular, at places with the highest concentration of crime generators and attractors, quality of life summonses and warrant arrests significantly reduce future levels of gun violence. This is despite the fact that the general application of these enforcement actions was positively related to the dependent variable. Overall, the interaction term findings across our models highlight the influence of spatial context on the crime prevention effect of police enforcement actions.[14]

8. Discussion and conclusion

Findings from the current study provide numerous insights for the crime-and-place literature. First, it contributes to research on RTM by identifying significant spatial risk factors of gun violence in Newark. The findings of the RTM reflect important themes from the criminological literature. While the relationship between disorder and crime has been hotly debated (see Sousa & Kelling, 2006; Taylor, 2006), a recent review of research found that, overall, the empirical literature

[14] Interestingly, concentrated disadvantage and racial heterogeneity, two common measures of social disorganization, did not achieve statistical significance in any model. The reader may find this curious in light of the extensive literature linking social disorganization with crime occurrence. The lack of statistical significance may be at least in part due to the panel structure of the database. To review, the officer enforcement and crime data were measured at monthly intervals given the dynamic nature of this data. Conversely, the social disorganization measures were only available for one point in time (as measured by the census), meaning that each unit had identical values across all time periods. Therefore, sufficient variance may not have been present for a significant effect to be generated.

Table 3
Longitudinal logistic regression findings (Model 1 and Model 2).

Covariates	Model 1 (enforcement only)		Model 2 (RTM: Mean to + 1 SD)	
	Odds ratio	S.E.	Odds ratio	S.E.
Independent variables				
Quality-of-life summonses	1.08	0.02**	1.06	0.02**
Field interrogations	1.06	0.02*	1.06	0.03*
Warrant arrests	1.07	0.03*	1.07	0.03*
Narcotics arrests	1.07	0.02**	1.07	0.02**
Gun arrests	0.99	0.02	0.99	0.02
Social disorder arrests	0.98	0.03	0.98	0.03
RTM designation	–	–	0.76	0.06**
Interaction terms (x RTM designation)				
Quality-of-life summonses	–	–	1.05	0.01*
Field interrogations	–	–	1.03	0.03
Warrant arrests	–	–	0.98	0.04
Narcotics arrests	–	–	0.99	0.03
Gun arrests	–	–	1.05	0.02*
Social disorder arrests	–	–	0.96	0.05
Control variables				
Spatial lag	0.93	0.17	0.93	0.17
Area (square miles)	1.11	0.04**	1.11	0.03**
Concentrated disadvantage	1.02	0.01	1.01	0.01
Racial heterogeneity	0.59	0.52	0.55	0.48
Days in month	1.18	0.05**	1.18	0.05**
Month sequence	1.13	0.04**	1.13	0.05**
Lagged gun violence	1.34	0.15*	1.34	0.16*
Ambient population	0.99	0.00	0.99	0.00
Quarter of the year				
2nd	0.93	0.13	0.93	0.14
3rd	0.73	0.18	0.74	0.18
4th	0.61	0.22	0.62	0.22
Precinct				
2nd	2.58	0.32**	2.64	0.32**
4th	2.74	0.35**	2.84	0.36**
5th	2.42	0.32**	2.47	0.33**
Model				
Log	− 4729.41		− 4718.02	
Wald	X^2 (20) = 310.97		X^2 (27) = 336.50	

NOTE: Quarter 1 (January–March) used as the reference category for each of the Quarter variables. 3rd precinct used as the reference category for each of the Precinct variables. N = 33,957.
* $p < 0.05$.
** $p < 0.01$.

Table 4
Longitudinal logistic regression findings (Model 3 and Model 4).

Covariates	Model 3 (RTM: + 1 SD to + 2SD)		Model 4 (RTM: greater than + 2 SD)	
	Odds ratio	S.E.	Odds ratio	S.E.
Independent variables				
Quality-of-life summonses	1.07	0.02**	1.15	0.05**
Field interrogations	1.07	0.03*	1.08	0.04*
Warrant arrests	1.07	0.03*	1.19	0.07**
Narcotics arrests	1.09	0.03**	0.98	0.05
Gun arrests	0.99	0.02	0.96	0.04
Social disorder arrests	0.99	0.03	0.88	0.08
RTM designation	1.32	0.13**	2.27	0.19**
Interaction terms (x RTM designation)				
Quality-of-life summonses	1.02	0.02	0.91	0.04*
Field interrogations	1.00	0.03	0.97	0.04
Warrant arrests	1.03	0.03	0.88	0.05*
Narcotics arrests	0.92	0.02*	1.08	0.05
Gun arrests	0.99	0.03	1.03	0.04
Social disorder arrests	0.97	0.05	1.10	0.08
Control variables				
Spatial lag	0.98	0.18	0.98	0.18
Area (square miles)	1.11	0.04**	1.12	0.03**
Concentrated disadvantage	1.01	0.01	1.01	0.00
Racial heterogeneity	0.61	0.53	0.70	0.60
Days in month	1.18	0.05**	1.18	0.05**
Month sequence	1.13	0.04**	1.13	0.04**
Lagged gun violence	1.34	0.15*	1.32	0.15*
Ambient population	0.99	0.00	0.99	0.00
Quarter of the year				
2nd	0.93	0.14	0.94	0.14
3rd	0.73	0.18	0.74	0.18
4th	0.62	0.22	0.63	0.22
Precinct				
2nd	2.50	0.31**	2.45	0.30**
4th	2.70	0.34**	2.53	0.32**
5th	2.43	0.32**	2.18	0.29**
Model				
Log	− 4721.77		− 4679.61	
Wald	X^2 (27) = 327.06		X^2 (27) = 426.00	

NOTE: Quarter 1 (January – March) used as the reference category for each of the Quarter variables. 3rd precinct used as the reference category for each of the Precinct variables. N = 33,957.
* $p < 0.05$.
** $p < 0.01$.

demonstrates that disorder significantly stimulates crime (Skogan, 2015). Gang membership is well established as a risk factor for violence victimization (Ozer & Engel, 2012; Papachristos, Braga, Piza, & Grossman, 2015) with geographies claimed as gang territory typically experiencing heightened amounts of gun violence (Kennedy et al., 1997; Zeoli, Pizarro, Grady, & Melde, 2014). A similar relationship has been demonstrated between drug markets and violence (Corsaro, Hunt, Hipple, & McGarrell, 2012). These findings suggest that markets of illicit activity, and the human behaviors that occur within them, may create an opportune situation for gun violence. Conversely, the remaining significant risk factors (corner stores, liquor stores, and take out restaurants) reflect recent research finding that features of the built environment can help generate and sustain crime hot spots (Bernasco & Block, 2011; Caplan et al., 2011; Caplan & Kennedy, 2016; Kennedy et al., 2011; Kennedy et al., 2016).

The second contribution of this study involves the effect of various police enforcement actions. It is interesting that the street-level enforcement actions were not associated with crime reductions, but rather enhanced the likelihood of gun violence in several instances. In interpreting this finding, it is important to remember that the enforcement actions in this study were administered in an unfocused manner, predominantly during general patrol activities. This is an important consideration, as the policing literature largely finds that highly focused policing strategies exhibit the largest evidence of effect (Lum, Koper, & Telep, 2011; Weisburd & Eck, 2004). In this sense, the fact that the enforcement actions included in this study did not generate crime reductions is perhaps unsurprising. However, this begs the question of why certain actions were associated with increased likelihood of gun violence. In one sense, police enforcement may have created an unstable situation that contributed to gun violence. For example, narcotics arrests could theoretically disrupt drug markets by creating a "replacement effect" in which drug dealers (violently) compete to fill the void left by the arrested dealer (Blumstein, 2006). However, it may again be important to consider the unfocused nature of officer activity during the study period. In light of the police layoffs and restructuring of the NPD's place-based strategies, police officers were expected to take proactive actions against street-level incidents of concern during the course of their normal deployment. Given the fact that officers may have been directed to specific areas when responding to citizen calls for service, officers may have found themselves at places with pre-existing gun violence problems. In this sense, enforcement actions may not have generated violence as much as they reflected the ongoing state of affairs. This observation is supported by that fact that lagged shootings achieved statistical significance in the logistic regression models, showing prior levels of gun violence to be a key predictor of future events.

In light of the unfocused nature of the enforcement activity, the findings pertaining to the RTM interaction terms are very informative. In particular, despite their unfocused delivery, narcotics arrests were associated with gun violence reductions at places with risk scores between + 1 and + 2 standard deviations above the mean. In addition, at places with the highest concentration of crime generators and attractors (i.e. risk values greater than + 2 standard deviations above the mean), quality of life summonses and warrant arrests effectively prevented future gun violence incidents. These findings suggest that understanding the spatial context of high-crime areas can help police design strategies in a manner that maximizes their crime prevention utility.

This observation supports recent research in policing emphasizing the statistical diagnosis of high crime areas (Caplan & Kennedy, 2016; Lum & Koper, 2012; Tate, Neale, Lum, & Koper, 2013). The current study builds upon this body of research by suggesting a new approach to target area selection. Currently, place-based policing efforts predominately select target areas based upon their observed levels of crime (e.g. presence of crime hot spots). The current study suggests that, in addition to crime levels, analysts should consider the spatial composition of hot spot areas in the final selection of target areas. This can help to tailor interventions so that targeted places have maximum likelihood of benefitting from the planned police activity. Conversely, such strategies could be diverted from places with a different spatial composition.

Our findings also suggest future avenues of research to inform place-based policing efforts. First, scholars can test the influence that different methodologies of classifying criminogenic environments have on findings. In particular, while we used RTM to identify micro-places defined by the co-location of all spatial risk factors, an alternate method would be to identify places housing different combinations of risk factors. Using the current study as an example, the co-location all risk factors (i.e. social disorder calls, corner stores, narcotics calls, gang territory, liquor stores, take out restaurants) may differentially affect crime than various possible combinations of risk factors (e.g. gang territory, corner stores, and liquor stores; gang territory, narcotics calls, and disorder calls; disorder calls and corner stores; etc.). Recent research has incorporated conjunctive analysis of case configurations (CACC) to identify micro-level “behavior settings” defined by unique combinations of activity nodes and land-use areas (Caplan, Kennedy, Barnum, & Piza, 2017; Hart & Miethe, 2015). While outside of the scope of the current study (particularly due to the large number of potential behavior settings observed in the study setting), future research can use such an approach to interact police enforcement actions with environments of interest.

Future research can also expand the scope of enforcement actions included in the statistical analysis. We included traditional enforcement measures due to their daily collection by the NPD, central role in the NPD's gun violence prevention mission during the study period, and easy accessibly in NPD databases. However, recent research suggests that police enforcement may not always be necessary to generate crime reductions. For example, Piza (2018) found that minimally invasive guardian actions (i.e. business checks, citizen contacts, bus checks, and taxi inspections) had a greater crime prevention effect than traditional police enforcement actions (i.e. arrests, quality of life summonses and field interrogations). Other studies suggest that police can generate crime reduction via conspicuous presence and more informal community engagement in lieu of traditional enforcement (Ariel, Weinborn, & Sherman, 2016; Nagin, Solow, & Lum, 2015). Including such less-punitive actions in future research may provide a more holistic view of contemporary policing activities. In addition, from a policy perspective, emphasizing less punitive police officer actions may be particularly appealing in light of recent events in American policing. The constitutionality of traditional enforcement actions, in particular pedestrian stops and terry pats (i.e. stop question and frisk), has come under legal scrutiny. Indeed, the NPD entered into a consent decree with the U.S. Department of Justice in 2016, due to DOJ investigators finding that police officers routinely failed to articulate reasonable suspicion to justify pedestrian stops, in violation of 4th Amendment standards (US Department of Justice Civil Rights Division, 2014).[15] Therefore, understanding the effect of a wider range of enforcement actions may help curtail such practices. It should also be noted that findings of the current study can also help towards this end, specifically by allowing police to enact specific enforcement actions only in the micro-places conducive to their effect, and deemphasizing such tactics in all other places within the jurisdiction. In such a case, punitive enforcement actions would be restricted to only the situations in which they are the most appropriate course of action, which may minimize the potential for civil rights issues to arise.

Despite these implications, the current study, like most research, suffers from some limitations that should be mentioned. For one, the scope of our data was limited by what was contained within accessible databases. We alluded to this issue with the enforcement data in the prior paragraph, but similar limitations were present in the RTM analysis. While we made every effort to include an exhaustive set of risk factors in the analysis, informed by the research of Kennedy et al. (2011), we were limited to what was obtainable via available data sources. It is possible that pertinent, and informative, spatial risk factors were excluded. We should also note limitations inherent in our dependent variable, as prior research has noted that official crime data are biased by the absence of crimes not reported to and/or recorded by the police (Black, 1970). Given the serious nature of the crimes included in our gun violence measure, we believe that underreporting is likely less of an issue in the current study than in research focusing on other crime types. Nonetheless, we acknowledge the commonly referenced limitations of Part 1 crime data. In addition, the results of our analysis may have been impacted by the specific time frame incorporated. While we organized our panel data into 1-month time periods, prior research suggests that the prevention effect of street-level police enforcement actions may dissipate within a shorter period of time (see, for example, Wyant, Taylor, Ratcliffe, & Wood, 2012). It should be noted that we first attempted to conduct our analysis using 1-week time intervals, but that these models led to the exclusion of many independent variables and interaction terms of interest due to collinearity. The structure of our data necessitated a larger temporal period. We recommend that researchers interested in replicating this study incorporate shorter time frames if their data allow.

References

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[15] While the consent decree and DOJ investigation both fall outside of the study period, it is certainly possible that an undisclosed number of the field interrogations (i.e. pedestrian stops) included in the current study lacked constitutional support. In such a case, our findings may not be generalizable to other justifications where police enact enforcement actions in full compliance with the constitution. However, it should be noted that the current study would not be the first instance of researches evaluating a questionable police tactic. For example, Weisburd, Wooditch, Weisburd, and Yang (2016) evaluated the deterrence effects of New York City's Stop, Question, and Frisk (SQF) program during a time period when the US Federal Court found that the practice routinely violated the 4th and 14th Amendments of the constitution (Floyd et al. v. City of New York, 2013). While analyzing a potentially unconstitutional practice may seem counterproductive, Sweeten (2016) noted that such evaluations have value specifically because such practices may be applied in other jurisdictions, either in complete legal compliance or with a currently unknown level of unconstitutionality. In light of these observations, we believe our findings have important implications for place-based policing, regardless of the nature of the field interrogations included in our study.

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