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When Crime Moves Where Does It Go? Analyzing the Spatial Correlates of Robbery Incidents When Crime Moves Where Does It Go? Analyzing the Spatial Correlates of Robbery Incidents Displaced by a Place-based Policing InterventionDisplaced by a Place-based Policing Intervention

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Abstract
Objective:
Examine the place-based correlates of robbery incidents displaced by a foot-patrol intervention in Newark, NJ. We use constructs from Crime Pattern and Social Disorganization theories to test hypotheses concerned with associations between the structure of the environment and the displacement of crime.
Method:
Robbery incidents were spatially joined to street segments to study micro-level displacement processes. Predictor variables were operationalized using data from the Newark Police Department and Infogroup USA. Generalized Linear models tested associations between the characteristics of street segments and displaced robbery in the target area as compared to a control.
Results:
Environmental structure is important to understanding the settings of displacement, though this varied between spatial and temporal displacement. Relationships between displaced crime and model covariates did not always appear in expected directions. For example, bus stops predicted increased spatial displacement while corner stores predicted decreased levels of temporal displacement.
Conclusions:
While testing for displacement has become commonplace in place-based policing interventions, less attention has been paid to the micro-level factors that may facilitate the displacement of crime events. Both bus stops and corner stores show consistent associations with displaced crime, but the directions of these relationships suggest more complex processes requiring further examination.

Keywords:
Spatial displacement, Temporal displacement, Crime generators and attractors, Social Disorganization; Robbery

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INTRODUCTION

Amongst police practitioners, there is a well-documented belief that, despite their best efforts, crime will simply move to another area in response to targeted crime prevention interventions (Guerette & Bowers, 2009; Weisburd, Wyckoff, Ready, Eck, Hinkle, & Gajewski, 2006). Despite this oft-held belief, much empirical research reports that crime displacement is rare (Barr and Pease, 1990; Clarke & Weisburd, 1994; Eck, 1993; Gabor, 1990; Guerette & Bowers, 2009; Hesseling, 1994). However, a number of other studies indicate the absence of displacement is far from guaranteed (Andresen & Malleson, 2014; Andresen, & Shen, 2019; Choo, Choi, & Sung, 2011; Lawton, Taylor, & Luongo, 2005; Piza & O'Hara, 2014; Piza, Wheeler, Connealy, & Feng, 2020; Ratcliffe, Taniguchi, Groff, & Wood, 2011, Waples, Gill, & Fisher, 2009).

Complicating the study of displacement, a recent meta-analysis of hot spots policing evaluations found that only 40% of all studies included reporting displacement analysis results (Braga, Turchan, Papachristos, & Hureau, 2019). Similarly, Guerette & Bowers's (2009) review of situational crime prevention evaluations found potential spatial and temporal displacement was only measured in 47% and 5% of cases, respectively. In total, 26% reported displacement effects of some kind (Guerette & Bowers, 2009), a sizable minority. This lack of reporting, when combined with a publication bias towards successful policing interventions (Bowers, Johnson, Guerette, Summers, & Poynton, 2011) suggests a dark figure of displacement findings and has limited our capacity to examine the crime displacement phenomenon. More importantly, outside of the seminal spatial displacement and diffusion of crime study in Jersey City, NJ (Weisburd, Wyckoff, Ready, Eck, Hinkle, & Gajewski, 2006) there has been limited empirical analysis with the sole focus on examining the mechanistic or contextual influences that may help explain crime displacement.

There have been notable examples within the place-based policing evaluation literature, among them a cohort of foot-patrol centric interventions, where disaggregated crime categories exhibited spatial and/or temporal displacement (see Hodgkinson, Saville, & Andresen, 2020; Lawton, Taylor, & Luongo, 2005; Piza & O'Hara, 2014; Ratcliffe, Taniguchi, Groff, & Wood, 2011). Of particular relevance to the current study, Piza & O'Hara's (2014) evaluation of Operation Impact in Newark, NJ found evidence of significant spatial and temporal displacement. Piza & O'Hara's (2014) displacement findings stand out within the overall place-based policing literature and provide an ideal test case for examining the etiology of spatial and temporal crime displacement.

The current study builds upon Piza & O'Hara (2014) through an analysis of the micro-places comprising the Operation Impact target area, control area, and catchment zone (used to measure spatial displacement). In doing so, we test the argument of Piza & O'Hara (2014) that the place-based characteristics of the target area and catchment zone likely facilitated displacement. To test this proposition, we measured the presence of both features of the built environment informed by crime pattern theory and household-level measures of common variables related to social disorganization (poverty, residential, mobility, and home ownership). Measures were aggregated to the street-segment level, which builds upon previous measurement strategies that rely on larger aggregations (e.g., block groups or census tracts), and interpolate down to the street segment. Findings suggest that the spatial composition of micro-places is an important contextual factor in understanding the settings of displacement, though our models suggest a nuanced relationship between characteristics of the environmental backcloth, social disorganization, and the occurrence of displacement.

REVIEW OF RELEVANT LITERATURE

Place-based Policing and Crime Displacement

While there are many potential forms of crime displacement (Eck, 1993; Repetto, 1976), most empirical research stems from place-based police intervention evaluations and focuses on spatial and temporal displacement (Johnson, Guerette, & Bowers, 2014). Spatial and temporal displacement occurs when, because of police intervention, offenders change the location or time at which they normally offend, respectively (Eck, 1993). Place-based policing studies have observed that displacement effects are reportedly bounded in space and time, in that offending opportunities are less likely to be realized the farther from the original target in space and time (Bowers & Johnson, 2003; Eck, 1993). Displacement effects have been found to be short-term (Sorg, Haberman, Ratcliffe, & Groff, 2013).

Crime displacement is often explained through a combination of rational choice (Cornish & Clarke, 1987) and routine activity (Cohen & Felson, 1979) theories of offender decision-making. In the place-based policing literature, displacement is thought to be the result of the actions by practitioners through intervention to change the perceivable risk of certain types of opportunities in specific places and how offenders react to said change (Bowers, Johnson, Guerette, Summers, & Poynton, 2011; Guerette & Bowers, 2009). As such, spatial displacement occurs when offenders are blocked from opportunities and choose to exploit opportunities found in alternate places, often nearby (Bowers & Johnson, 2003; Eck, 1993) where the perceived risk of apprehension is lower. Temporal displacement occurs by a similar dynamic, but instead of traveling to new places, offenders are aware of the temporal boundaries of the intervention and merely wait for an opportunity that would have previously been outside their normal offending time frame. It has been suggested that because crime opportunities are not universal, it is more likely that the initial blockage combined with a lack of consistent perceivable opportunity to offend limits the likelihood of displacement (Bowers, Johnson, Guerette, Summers, & Poynton, 2011; Telep, Mitchell, & Weisburd, 2014).

Much of what we know about crime displacement stems from the place-based policing literature where the analysis of displacement is considered tertiary to the main treatment effect. A noteworthy exception is the randomized controlled trail conducted by Weisburd, Wykoff, Ready, Eck, Hinkle, & Gajewski, (2006). In this study, researchers in partnership with Jersey City, New Jersey Police Department examined the response by offenders to geographically focused police interventions aimed at reducing prostitution and drug-related crimes at two hot spots. Findings from ethnographic observations and arrestee interviews confirmed a rational choice deliberation of criminal opportunities whereby the opportunity cost of moving to another area to exploit new opportunities outweighed the benefits.

Given crime only occurs in a minority of micro-places and is spatially concentrated (Weisburd, 2015), the criminogenic characteristics of high-crime places are less likely to exist elsewhere (Telep, Mitchell, & Weisburd, 2014; Weisburd & Telep, 2012). Considering this fact, Eck (1993) contends that crime displacement rarely rises to a level that offsets the achieved crime reductions in the area targeted by police interventions. Such total displacement is only possible in circumstances where crime is caused by deterministic forces (Eck, 1993). Deterministic forces are structural in nature and act upon individuals. For example, income mobility levels, the capacity for an individual to advance to a higher income class than the previous generation, has been found to be largely inherited from previous generations and directly affected by neighborhood characteristics (Chetty & Hendren, 2018). Additionally, should potential displacement areas and times contain similar levels of opportunities and place-based characteristics, it follows that displacement would be more likely (Short, Brantingham, Bertozzi, & Tita, 2011). The nature and dosage of place-based policing interventions is also important to consider as well given that enforcement actions, like quality of life stops and field interrogations, have been associated with increased violent crime levels in subsequent time periods (Piza & Gilchrist, 2018).

While crime opportunity has been found to be discontinuous (Bowers, Johnson, Guerette, Summers, & Poynton, 2011) there has yet to be an examination of what kind of places or social phenomena drive the creation of opportunities that become displaced crimes. This is despite the overwhelming amount of research evidence confirming the importance of place characteristics in the distribution of risk, and clustering of crime incidents in space and time (Bernasco & Block, 2011; Caplan, Kennedy, & Miller, 2011; Kennedy, Caplan, & Piza , 2011; McCord, Ratcliffe, Garcia, & Taylor, 2007; Weisburd, 2008). In considering the overall crime-and-place literature, Crime Pattern Theory and Social Disorganization perspectives can help us consider the environmental factors that can make displacement more likely. Crime Pattern Theory (Brantingham & Brantingham, 1993a; 1995) is the marriage of rational choice (Cornish & Clarke, 1987) and routine activity (Cohen & Felson, 1979) perspectives explicitly operationalized to place (Andresen, 2014). When combined with the insights and constructs from Social Disorganization research we create a cohesive representation of urban social phenomena that may influence the displacement of crime. Crime Pattern Theory and Social Disorganization perspectives have provided researchers with validated measurable constructs that allow researchers to consider the characteristics of place that allow for such an examination. We employ these perspectives to underpin our current analysis.

Crime Pattern Theory and the Anticipation of Displacement

Crime Pattern Theory contends that characteristics of places drive crime activity, specifically the existence of constructs known as crime generators and crime attractors (Brantingham & Brantingham, 1995). Crime generators offer increased opportunities because of the opportunities created by the sheer volume of people passing through them, both offenders and targets (Bernasco & Block, 2011; Brantingham & Brantingham, 1995). Crime attractors are micro-unit places with well-known opportunities for criminal activity that are easily perceivable and therefore attract offenders. However, crime generators may evolve into crime attractors over time, as motivated offenders learn of the criminal opportunities afforded by these places (Clarke & Eck, 2005). These micro-places drive crime rates for larger area units and make up part of what is known as the "environmental backcloth" that underpins all human activity for a given area (Brantingham & Brantingham, 1993a). In addition to explaining the spatial patterning of crime, this environmental backcloth has implications for police activity as well and may influence the manner by which police activity affects micro-level crime patterns (Piza & Gilchrist, 2018).

Several environmental features have been found to operate as crime generators and/or attractors within the environmental backcloth. Relevant to the current study, bus stops acting as public transportation nodes have been reported to increase risk of street robbery (Liu, Lan, Eck, & Kang., 2020) and this increased risk is stable throughout and across years (Szkola, Piza, & Drawve., 2021). Such transportation nodes have been theorized to increase offender awareness through greater accessibility to areas while also increasing ability of offenders to successfully exit areas and avoid detection by law enforcement (Brantingham & Brantingham, 1993b). Similarly, corner stores or convenience stores are more likely to be found among robbery hot spots (Connealy, 2020a), and in one study was found to consistently increase the risk of robbery across three cities (Connealy, 2020b). The combination of such small retail outlets and vacant or blighted properties in the area have been found to increase the risk of violence (Valasik & Martinez, 2019). It then follows that the combination of corner stores with area disadvantage creates opportunities for criminal offending by being a simple meeting place of both offenders and suitable targets.

Another aspect of the environmental backcloth pertinent to the current study is presence of at-risk and public housing. Haberman, Groff, & Taylor (2013) report that clusters of public housing have been observed to increase risk of robbery and that spacing such complexes farther apart may reduce the intensity of robbery crime patterns. Prior research in Newark, NJ has found at-risk housing, a combination of public housing and privately-owned complexes similar in scope to their public housing counterparts, to be significantly associated with heighted crime levels (Kennedy, Caplan, & Piza, 2011; Moreto, Piza, & Caplan, 2014). This body of research has two important implications for the current study. First, when at-risk housing is associated with drug markets, as is the case in the target area of Operation Impact, this is characteristic of areas where the environmental backcloth is conducive to crime. Second, that the greater the degree the target and catchment areas overlap with at-risk housing, the greater the intensity of crime patterns due to the large influx of individuals oriented towards criminal offending.

Inter-related with public housing is the role of gang activity in explaining crime rates. Gangs represent some of the most highly active and criminally oriented groups within a given city (Braga, 2003), with gang membership associated with heighted risk of violence at both the individual (Papachristos, Braga, Piza, & Grossman, 2015) and geographic (Kennedy, Caplan, & Piza, 2011) levels in Newark. Large numbers of offenders are commonly present within gang territory; this helps explain high-crime levels as offenders are less likely to exploit opportunities the farther they travel from their homes (Bernasco & van Dijke, 2020). Gang territory has also been found to co-locate with drug markets which are also known to drive crime activity in urban areas (Braga, 2003). Thus, police interventions may displace crime if neighboring street segments outside the intervention area are within the same gang territory, as they represent a decaying but viable opportunity field.

Further research confirms the importance of accounting for the interplay between land use, street networks, and crime activity (Frith & Johnson 2017; Summers & Johnson, 2017; Rosser, Davies, Bowers, Johnson, & Cheng, 2017). Highly accessible activity nodes will increase foot traffic like at public transportation sites (Gerell, 2018) and the use of non-local roads within these connected street networks have been found to facilitate crime (Brantingham & Brantingham, 2003). Non-local (e.g., arterial) roadways offer pathways to channel criminal activity to and from nodes or where known criminal opportunities can be exploited. Thus, non-local roads may facilitate the displacement of crime from one node to another in the face of a police intervention blocking offending opportunities at the original node (Brantingham & Brantingham, 2003).

Social Disorganization and Micro-Unit Crime Analysis

Brantingham & Brantingham (2003) further posit that crime displacement is likely the result of a more dynamic process including the socio-economic status (SES) of the offenders and their neighborhoods they inhabit or choose to move their offending activity. For example, Bernasco & Block, (2009) state that age differences and access to capital (like vehicles), create differences in possible offending opportunities and this has implications for the spatial patterning of crime. The socio-economic status of micro-places along with the proportion of owner-occupied homes has also been observed to have a direct effect on crime rates (Jones &

Pridemore, 2019). Furthermore, Jones & Pridemore (2019) found models that included both crime generators and social disorganization measures at the street segment level were found to out-perform (in terms of predictive power) models with only social disorganization or crime pattern theory-informed constructs in explaining street segment-level crime rates. Combining environmental criminology and social disorganization perspectives allow for more holistic measures of the environmental backcloth that has previously explained where crime concentrates (Braga & Clarke, 2014; Jones & Pridemore, 2019), and, moving forward, may help explain crime displacement effects.

Social disorganization is thought to result from a range of neighborhood factors that inhibit the development of social cohesion (Shaw & McKay, 1942). Rapid population turnover, or residential mobility, contributes to social disorganization by preventing the establishment of informal social controls through shared values of the community (Kornhauser, 1978). Poverty has also been highly correlated with mediating constructs like collective efficacy that have been found to be inversely related to crime levels (Sampson, Raudenbush, & Earls, 1997). The lack of owner-occupied homes and a corresponding transient population with few social ties are unlikely to exert place management for the properties that are drivers of crime activity due to lack of investment in the community (Eck, 2015). Furthermore, the existence of a high proportion of renter's on a given block will be entirely dependent on the level of parochial control routinely exercised by landlords to guard against crime activity (Bursik & Grasmick, 1993; Smith, Frazee, & Davison, 2000).

Traditionally, social disorganization research has focused on the neighborhood-level (Bursik & Grasmick, 1993; Kornhauser, 1978; Kubrin & Weitzer, 2003; Sampson, Raudenbush, & Earls, F., 1997). However, researchers have called for a renewal of social disorganization research that is alternatively focused on street segments (Weisburd, Groff, & Yang, 2012, 2014a, 2014b). A re-focusing of social disorganization to micro-units, such as street segments, allows for better integration with environmental criminology perspectives (Braga & Clarke, 2014) given the level to which street segments have become privileged in crime-and-place research (Schnell, Braga, & Piza, 2017). Street segments are suggested to have their own unique "behavior settings." Non-conforming or criminal activities may be less acceptable on one street than another as each street segment represents a new micro-community (Taylor, 1997). Weisburd, Groff, & Yang (2012) provide further support for the existence of such micro-communities with their observation that the level of social disorganization-informed constructs varies drastically across street segments.

A primary challenge relates to the level of measurement at which social disorganization measures are available. Social disorganization constructs are typically measured at meso-level units, such as census tracts or block groups. This presents challenges in using micro-level units in social disorganization research. Previously, studies have attempted to assign values from a larger aggregation level (e.g., census tracts) to street segments, assuming uniformity across the component micro-places (Piza, Feng, Kennedy, & Caplan, 2017). More sophisticated techniques have recently been advanced to interpolate measures from meso- to micro-level units of analysis to better capture the heterogeneity of socio-demographic characteristics across micro-places (Kim, 2018). Finally, proxy measures have also been used. For example, socioeconomic status and residential stability have been estimated from property records (Jones & Pridemore, 2019) and consistent voter registration have been operationalized as a measure of collective efficacy (Weisburd, Bushway, Lum, & Yang, 2004).

CURRENT STUDY

SCOPE OF CURRENT STUDY

To examine the association between place and displaced robbery activity we have compiled data from several sources and employed geospatial techniques to shape the data into the appropriate form for analysis. We have measured our primary social disorganization predictors at the household-level and aggregated these data to the street segment along with crime pattern theory, robbery activity, and enforcement activity measures. This allows for a more granular measure of social disorganization that what has been possible in prior research. In the following sections, we begin by providing an in-depth description of the study site, including historical crime trends and observable place-based characteristics. We then describe the sourcing and operationalization of our place-based measures along with our rationale examining associations at the micro-unit of analysis. Finally, we regress our micro-unit constructs onto displaced robbery activity and contextualize the results of the analysis.

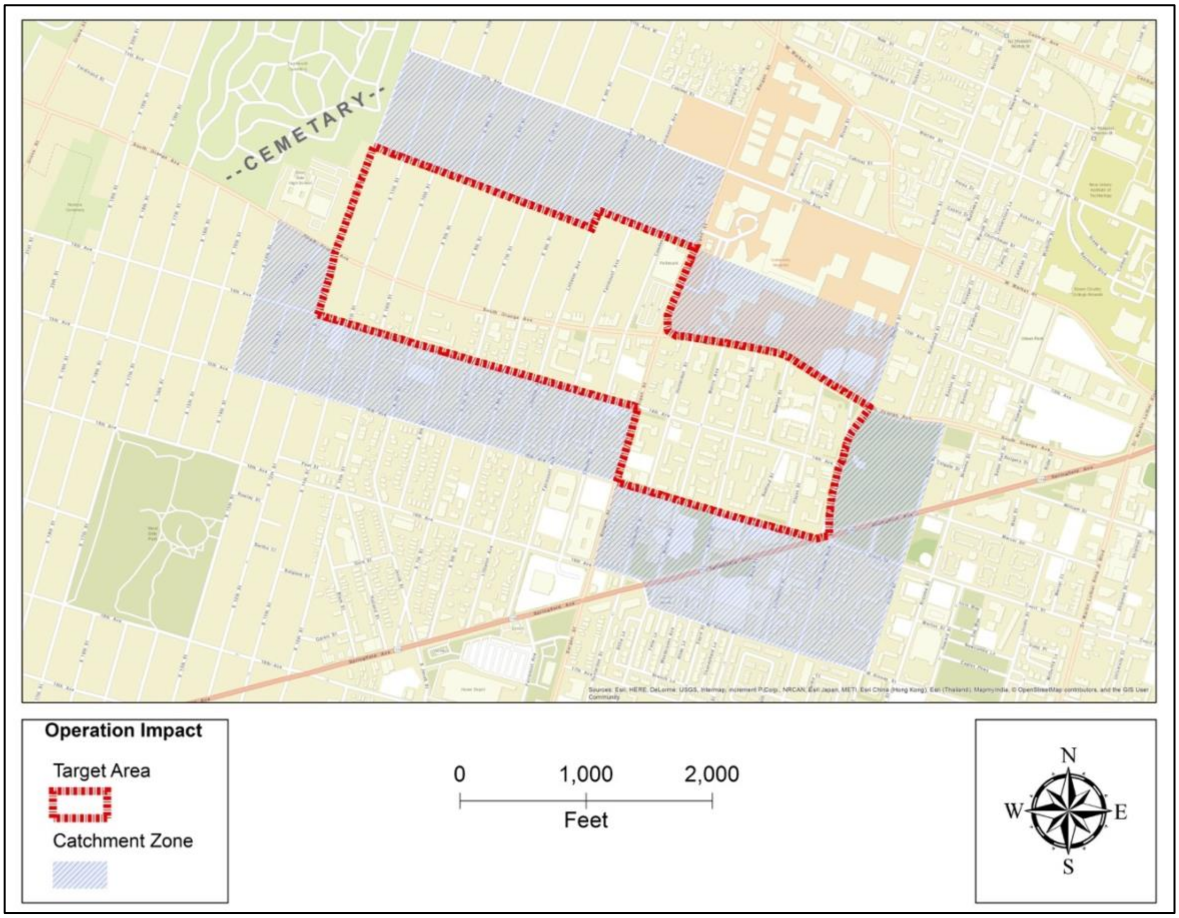
STUDY SETTING

Our study is based in Newark, NJ, the administrative seat of Essex County and the largest city in New Jersey both in terms of area (26^2 miles) and population (estimated 277,000 residents)[1]. From 2007 to 2010 over 84% of murders occurred as a result of a gunshot wound and almost 50% of robberies involved a firearm, largely attributed to illegal drug markets (Piza & O'Hara, 2014).

In June of 2008, the Newark, NJ Police Department (NPD) launched Operation Impact, a place-based foot patrol intervention targeting one of the most violent areas of the city. Newark police officials anticipated that the foot patrol officers would prevent crime by disrupting street-level quality-of-life issues and the illicit narcotics trade, in reflection of the mission of the agency at the time (Jenkins & DeCarlo, 2015; Piza & O'Hara, 2014). This intervention was modeled after a New York City Police Department program of the same name, assigning select officers to a foot patrol beat within the Operation Impact target area upon graduation from the police academy.

The geographic focus of the current study is based on the subset of Newark, NJ that was the site of Operation Impact. The Operation Impact target area falls within NPD's 4th Precinct and is bisected by a wide thoroughfare that features many small businesses and retail storefronts. New Community Homes, a large public housing complex, sat to the southeast of the target area and is known to be a high-violence drug trafficking area (for more description see Piza & O'Hara, 2014). Additional foot patrol officers were directed to the treatment area starting in 4 June 2008 and ending in 3 June 2009. Officers conducted foot patrols 7 days a week between the hours of 6pm and 2am to coincide with times during which violence peaked. To measure the treatment effect, Piza & O'Hara (2014) designated two areas as controls in their evaluation to compare crime rates. The catchment area of a one-block radius immediately adjacent to and surrounding the target area was used to test for spatial displacement (see Figure 1).

Figure 1. Operation Impact Target Area and Catchment Zone



The control street segments are found in two areas. The largest control area consists of the entirety of the 4th precinct excluding the treatment and catchment areas. In the control area standard law enforcement methods were applied such as routine patrol, retrospective investigations, and ad hoc narcotics operations (Piza & O'Hara, 2014). The second, smaller control area is known in the original study as Zone B and falls within NPD's 5th Precinct. Zone B contains large high-rise apartment buildings and several retail storefronts, much like the target area, that makes it a near-equivalent comparison site in terms of geography. NPD had designated the Zone B a "Narcotic Hot-Spot Zone" and dedicated increased motorized and plain-clothes patrol emphasizing proactive enforcement activity to reduce crime. However, the intensity and dosage of the additional proactive enforcement was much less in Zone B than that of the treatment area[2].

The original evaluation of Operation Impact (Piza & O'Hara, 2014) found that overall crime levels in the treatment area reduced at a greater rate than controls, though to a lesser extent when compared to Zone B alone[3]. When violent crime categories were assessed individually, Piza & O'Hara (2014) observed uneven crime control effects. Robbery crimes increased 73% during the intervention's non-operational period (2am-6pm), compared to a reduction of 34% during operational hours (6pm-2am), indicating the presence of temporal displacement. Weighted displacement quotients (Bowers & Johnson, 2004) demonstrated noteworthy spatial displacement of overall violence occurring during both the intervention's operational period and the 24-hour temporal period. Furthermore, weighted displacement quotients indicated that more crimes were displaced than prevented (i.e., total displacement), a rare occurrence in the place-based policing literature. A review of raw crime counts showed robbery to be primarily responsible for the spatial displacement, with a robbery increase of 58% in the catchment area. When robbery was removed from the calculation, overall violence crime decreased from 18 to 17 in the catchment area. In consideration of the prominence of robbery in Piza & O'Hara's (2014) findings, we focus on robbery in our analysis.

DATA & UNIT OF ANALYSIS

Our study period covers the Operation Impact 1-year pre-implementation period (4 June 2007 through 3 June 2008) through the 1-year implementation period (4 June 2008 through 3 June 2009). Street segments were incorporated as the unit of analysis. We generated street segments using a street centerline file that was converted into individual street segments using ESRI's ArcGIS software. Given our independent variables are measured at the address-level we chose to aggregate our data to the street segment due to the known coding errors associated with relying on addresses while keeping the unit of analysis small enough to not smooth over crime trends (Braga, Papachristos, & Hureau, 2010). Previous foot patrol evaluations provide support for examining crime at the micro-unit of analysis. Novak, Fox, Carr, & Spade (2016) found that violent crime and robberies decreased when assessing at micro places (Novak, Fox, Carr, & Spade, 2016) while Andresen & Hodgkinson (2018) found crime drops at larger units of analysis could be attributed to just a few micro-places.

DEPENDENT VARIABLES

The NPD provided robbery data at the incident level. Robbery incidents were geocoded and spatially joined to street segments. The use of street segments presents challenges pertaining to the treatment of crimes occurring at street intersections, which overlap with multiple individual street segments. Some prior crime-and-place studies have excluded crime occurring at street intersections since they do not fall within any single unit. However, we opted against excluding crimes falling on street intersections as to not unintentionally bias our results.

We followed the approach used by Kim (2018) and Hipp & Kim (2017) by evenly distributing crime points across the overlapping street segments (e.g., if there are 4 intersecting streets, each segment is assigned 0.25 of a crime). We apportioned crimes occurring at intersections because our main predictor variables were measured at the household level and had specific addresses that did not map to street intersections. This fact made it inappropriate to use intersections as our unit of analysis or to combine separate street segments and intersections into "street units" as has been done previously (Braga, Hureau, & Papachristos, 2011; Piza, Wheeler, Connealy, & Feng, 2020). Given that fractions of events were assigned to street segments, our resulting dependent variable is a continuous measure of robbery activity rather than discrete counts of robbery incidents.

To create the dependent variables for our separate models, robbery crime incidents were categorized based on whether they fell into treatment, catchment, or control areas. Following that process, crimes were further categorized temporally into whether they occurred during the "operational" period (6pm-2am) or "non-operational" period (2am-6pm)[4]. Table 1 presents descriptive statistics of robbery activity across these distinct times periods and intervention zones.

Table 1. Robbery Activity Across Time Periods and Intervention Zones

Robbery Activity Post-Intervention (by Time Period and Zone)							
Zone	**Time Period**	**Obs.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Sum**
Treatment	24-HR	109	0.34	0.67	0.00	3.25	36.92
	Non-Op (2am-6pm)	109	0.18	0.43	0.00	2.25	19.33
	Operational (6pm-2am)	109	0.16	0.40	0.00	2.00	17.58
Catchment	24-HR	114	0.40	0.75	0.00	4.00	45.83
	Non-Op (2am-6pm)	114	0.24	0.54	0.00	3.00	27.08
	Operational (6pm-2am)	114	0.16	0.39	0.00	2.00	18.75
Control	24-HR	1,147	0.19	0.48	0.00	5.00	218.08
	Non-Op (2am-6pm)	1,147	0.10	0.32	0.00	4.00	114.50
	Operational (6pm-2am)	1,147	0.09	0.33	0.00	2.33	103.58

INDEPENDENT VARIABLES

Independent variables are comprised of two subgroups depending on their theoretical underpinning including Crime Pattern Theory (6) and Social Disorganization (3). In addition to the robbery data, the NPD provided GIS data layers depicting at-risk housing complexes, bus stops, and known gang territory. The remaining Crime Pattern Theory and Social Disorganization constructs were developed using data from InfoGroup Business and Consumer data. InfoGroup data has been increasingly used and validated in crime and place research[4] (e.g., Caplan, Kennedy, Barnum, & Piza, 2017; Piza & Gilchrist, 2018; Connealy & Piza, 2019).

All measures under-pinned by Crime Pattern Theory are dichotomous and signify whether the street segment contains the feature[5]. Crime Pattern Theory measures are considered to increase the criminogenic nature of the environmental backcloth: bus stops, corners stores, known gang territory, and at-risk housing. Gang territory boundaries were previously developed during focus groups consisting of NPD detectives and Braga, Grossman, and Piza (2011)[6]. At-risk housing boundaries are comprised of City of Newark land parcels that are the site of public housing and similar privately owned apartment complexes, as such buildings have been previously found to influence crime patterns similarly (Kennedy, Caplan, Piza, 2011; Piza & Gilchrist, 2018)[7]. We also created a dichotomous variable designating street segments as non-local roads (=1), based on the street centerline file designation. Finally, we include a standardized continuous measure of accessibility representing the number of street segments connected to the unit in question.

Social disorganization variables were measured at the household level with the InfoGroup residential dataset and covers every parcel in the study area. The household-level measures were aggregated to the street segment as proportions then standardized as z-scores (see Table 2). This contrasts with previous operationalizations of social disorganization constructs that have interpolated census data onto street segments (Smith, Frazee, & Davison, 2000; Kim, 2018) or used proxy measures (Weisburd, Groff, & Yang, 2012) and are thus less susceptible to the error in measurement associated with the "ecological fallacy" (Robinson, 1950). Our first measure, residential mobility, measures the proportion of residents reporting living at the address for less than one year (Bruce, Roscigno, & McCall, 1998). We then standardized the measure to normalize the data for regression analysis. Our second social disorganization measure, poverty, was defined as income less than the established poverty-line for a three-person household threshold[8]. Homeownership was defined as those households wherein the respondent indicated they were the homeowner. Separate interaction measures were also included for each of the 3 social disorganization variables in the same manner as described in the previous section, for a total of 9 variables.

Table 2. Independent Variable Descriptive Statistics

	Catchment				Target				Control			
Variable	**Count**	**Min.**	**Max.**	**Mean.**	**Count**	**Min.**	**Max.**	**Mean**	**Count**	**Min.**	**Max.**	**Mean**
Gang Territory	36	0	2	0.33	64	0	2	0.68	504	0	3	0.52
Bus Stop	16	0	3	0.22	16	0	4	0.27	119	0	6	0.18
Corner Store	8	0	2	0.08	5	0	1	0.05	45	0	2	0.04
At-Risk Housing	28	0	3	0.34	30	0	2	0.30	132	0	3	0.12
Non-local Road	29	-	-	-	40	-	-	-	343	-	-	-
Residential Mobility (Percent)	-	0	75	12.30	-	0	100	17.44	-	0	100	14.18
Below Poverty (Percent)	-	0	100	42.02	-	0	100	55.29	-	0	100	38.67
Homeownership (Percent)	-	0	100	12.05	-	0	100	9.65	-	0	100	24.34
Accessibility (avg. no. nodes)	-	0	9	2.25	-	0	9	2.46	-	0	15	2.01
Enforcement Activity	-	-0.79	16.07	0.25	-	-0.79	14.59	1.10	-	-0.79	66.81	0.21
Pre-Intervention Robbery	-	0	1	0.12	-	0	4	0.28	-	0	3	0.12
Spatial Lag (Robbery - Non-op)	-	-0.28	1.84	0.27	-	-0.28	2.54	0.23	-	-0.28	2.55	-0.01
Spatial Lag (Robbery – All Periods)	-	-0.38	1.55	0.27	-	-0.38	2.25	.34	-	-0.38	2.54	-0.01
Street Segment Length	-	25.44	1316.57	399.64	-	19.91	1243.70	376.75	-	0.03	2144.44	361.80

Notes: Enforcement Activity and Spatial Lag measures are standardized. Street segment length is in feet

INTERACTION TERMS

For each independent variable, we created interaction terms to measure the effect on robbery levels in our specific geography of interest. For each independent variable, we created interaction terms to measure the effect of robbery levels in our specific geography of interest. For the spatial displacement (Model 1) and spatial/temporal displacement (Model 2) analyses, we interact the independent variables with a dichotomous measure identifying the street segments as falling within the catchment zone (1) or not (0). For the temporal displacement analysis (Model 3), we interact the independent variables with a dichotomous measure identifying the street segments as falling within the Operation Impact target area (1) or not (0).

Whereas the standard independent variables measure the effect of the various measures on crime throughout the study setting the interaction terms measure how the effect of each variable differs across different categories of a modifier (Karaca-Mandic, Norton, & Dowd, 2004); in the current study, modifiers are the different intervention areas of interest. For example, the standard bus stop measure tests the effect of bus stops on robbery in street segments throughout the cumulative study setting. In Model 1, the bus stop interaction term tests the effect of bus stops on robbery *within the catchment zone*. In Model 2, the bus stop interaction term tests the effect of bus stops on robbery *within the catchment zone* and *during the intervention non-operational period*. In Model 3, the bus stop interaction term tests the effect of bus stops on robbery *within the target area* and *during the intervention non-operational period.* The same rationale applies to all interaction terms in our analysis.

CONTROL VARIABLES

Finally, we included four control variables that account for different types of exposure. First, we controlled for the intensity of police activity in the study area using geocoded enforcement action data provided by NPD. Enforcement actions are standardized continuous variables and include arrests, quality of life stops and field investigations. Interaction measures, as discussed earlier, were also created for enforcement actions. Second, we controlled for the length of the street segment as a standardized continuous measure, as longer street segments may offer more crime opportunities relative to shorter street segments[9]. Third, we included a continuous measure of pre-intervention robbery activity to control for historical crime levels, each corresponding to the same time period as the dependent variable. Additionally, we included spatial lag variables to account for the degree to which robbery activity in a given street segment is correlated to robbery activity in adjacent street segments. Dichotomous variables were included designate whether the street segment was part of the target (=1), control zone (=1), and catchment (=1).

ANALYTICAL APPROACH

We employ a series of generalized linear regression models with a gaussian specification to accommodate the continuous dependent variable. Generalized linear regression is more robust to normality assumptions than ordinary least squares regression. The use of linear models provides further benefits given the inclusion of interaction terms in our models. Linear models allow for straight-forward interpretation of interaction terms, while non-linear models present challenges in the calculation and interpretation of interaction terms (Karaca-Mandic, Norton, & Dowd, 2004). Such challenges have led some scholars to recommend against the use of interaction terms in models with categorical dependent variables (Mustillo, Lizardo, & McVeigh, 2018). Therefore, given the heavy reliance on the interaction terms in our analysis, we opted for generalized linear models over the type of count regression models included in a number of prior crime-and-place studies.

We conducted the statistical analysis using the *glm* command in STATA v.15. The models employed have the following general form:

$$E(Robbery\ Activity) = \beta_0 + \beta_1 X_i + \beta_2 X_i + \beta_n X_i \ \ldots\ldots + \in$$

Where $E(Robbery\ Activity)$ is the expected level of robbery activity (which varies based on the area of interest), β_0 is the model intercept, $\beta_1 X_i$ is the estimated parameter value for the first explanatory variable and coefficient (holding all other variables constant) and $\in$ is the random error term. As an example, to examine spatial displacement, we regress our measures that represent the structure of the environment consisting of crime pattern theory and social disorganization constructs, while controlling for historical crime trends and policing activity on to observed displaced robbery activity in the catchment areas.

The following analysis employs three different models. Model 1 focuses on spatial displacement and regresses our independent variables onto post-intervention robbery activity in the catchment areas for all time periods. Model 2 is focused on examining the correlates to both spatially and temporally displaced crimes where we regress our predictor variables onto post-intervention robbery activity in the catchment area for only the non-operational period. Model 3 solely examines temporal displacement, and we regress our predictor variables onto post-intervention robbery activity in the target area during the non-operational time-period. We report results as exponential coefficients, which communicate the effect of covariates in terms of percentage increase in the dependent variable.

RESULTS

Model 1 represents our examination of contextual correlates to displaced robbery activity via spatial displacement (see Table 3). Holding all other variables constant, robbery activity increased 35% within catchment area street segments containing a bus stop, as indicated by the interaction term (exp(b) =1.35). This contrasts with the effect of bus stops in the study setting generally, with the presence of bus stops associated with a 15% decrease in robbery activity (exp(*b*) = 0.85). The role of non-local roads is consistent across the entire study setting and within the catchment-area specifically as indicated by the standard measure (exp(*b*) = 1.09) and interaction term (exp(*b*) = 1.25). The standard measures further found corner stores (exp(*b*) = 1.26) and poverty (exp(*b*) = 1.04) to be associated with heightened levels of robbery activity. Model 1 found no other significant associations among the interaction term measures.

Table 3 – Spatial Displacement (Model 1) Results

Model 1	**DV – Robbery Activity - All Time Periods**				
Interaction Terms	**exp(b)**	**Std. Err.**	**Z**	**P<**	**95% C.I.**
Gang Territory	0.91	0.11	-0.85	0.40	0.72 - 1.14
Bus Stop*	1.35	0.20	2.12	0.03	1.02 - 1.80
Corner Store	1.34	0.28	1.39	0.17	0.89 – 2.02
At-Risk Housing	1.14	0.14	1.08	0.28	0.90 - 1.45
Non-local Road*	1.25	0.14	1.95	0.05	1.00 - 1.56
Accessibility	0.95	0.06	-0.85	0.40	0.83 - 1.08
Below Poverty	1.02	0.06	0.34	0.73	0.91 - 1.14
Residential Mobility	1.08	0.06	1.43	0.15	0.97 - 1.19
Homeownership	0.96	0.06	-0.8	0.42	0.87 - 1.06
Enforcement Activity	0.98	0.02	-0.98	0.33	0.93 - 1.02
Standard Measures					
Gang Territory	0.99	0.03	-0.38	0.71	0.93 - 1.05
Bus Stop***	0.85	0.04	-3.39	0.00	0.78 - 0.93
Corner Store**	1.26	0.09	3.11	0.00	1.09 - 1.46
At-Risk Housing	1.00	0.04	-0.06	0.95	0.91 - 1.09
Non-local Road*	1.09	0.04	2.52	0.01	1.02 - 1.16
Accessibility	1.02	0.02	0.99	0.32	0.98 - 1.07
Below Poverty*	1.04	0.02	2.54	0.01	1.01 - 1.07
Residential Mobility	1.02	0.01	1.35	0.18	0.99 - 1.04
Homeownership	0.98	0.01	-1.63	0.10	0.97 - 1.00
Catchment Zone	1.02	0.08	0.21	0.83	0.88 - 1.18
Control Measures					
Pre-intervention Robbery***	1.10	0.03	3.59	0.00	1.04 - 1.16
Enforcement Activity**	1.02	0.00	3.25	0.00	1.01 - 1.03
Spatial Lag	1.03	0.03	0.82	0.41	0.96 – 1.10
Segment Length***	1.00	0.00	5.66	0.00	1.00 - 1.00
Constant	1.02	0.03	0.61	0.54	0.96 - 1.08
	n	1,253		**AIC**	1.360254
	LL	-827.199		**BIC**	-8484.96

Notes: Interaction terms reflect covariate effect on robbery within the catchment zone
*p<.05, **p<.01, ***p<.001

Model 2 is also focused on robbery in the catchment area but further focuses on non-operational time periods, amounting to a simultaneous test of spatial and temporal displacement (see Table 4). Like the results of Model 1, the role of bus stops changes when considering catchment-interacted and standard measures. Holding all other variables constant, robbery activity increased 24% during non-operational time periods within catchment area street segments that contain a bus stop (exp(*b*) = 1.24). When considering the standard measure that considers the cumulative study area, the relationship between the presence of a bus stop on a street segment and robbery activity flips to a significant 9% decrease (exp(*b*) = 0.91). A heterogeneous effect across the cumulative study setting and the catchment area was also observed for residential mobility. During non-operational time periods, residential mobility was associated with an 8% robbery increase in catchment area street segments (exp(*b*) = 1.08) with no significant effects reflected for the cumulative study setting (i.e., the residential mobility standard measure). No other significant associations were identified among the interaction term measures. Model 2 estimated the presence of a corner store was associated with a 14% increase in robbery within the cumulative study area (exp(*b*) = 1.14). Additionally, for every 1-unit increase in poverty there was significant 3% increase (exp(*b*) = 1.03) in robbery activity at street segments throughout the study area.

Table 4 –Spatial/Temporal Displacement (Model 2) Results

Model 2	DV - Robbery Activity- Non-Operational Period				
Interaction Terms	**exp(b)**	**Std. Err.**	**Z**	**P<**	**95% C.I.**
Gang Territory	1.00	0.08	-0.02	0.99	0.85 - 1.17
Bus Stop*	1.24	0.12	2.15	0.03	1.02 - 1.51
Corner Store	1.24	0.18	1.50	0.14	0.93 - 1.66
At-Risk Housing	1.03	0.09	0.32	0.75	0.87 - 1.21
Non-local Road	1.12	0.09	1.46	0.14	0.96 - 1.33
Accessibility	0.97	0.04	-0.58	0.56	0.89 - 1.07
Below Poverty	0.96	0.04	-1.17	0.24	0.88 - 1.03
Residential Mobility*	1.08	0.04	2.03	0.04	1.00 - 1.15
Homeownership	0.97	0.03	-0.93	0.35	0.90 - 1.04
Enforcement Activity	1.00	0.02	0.22	0.82	0.97 - 1.04
Standard Measures					
Gang Territory	0.99	0.02	-0.37	0.71	0.95 - 1.03
Bus Stop**	0.91	0.03	-2.68	0.01	0.86 - 0.98
Corner Store**	1.14	0.06	2.46	0.01	1.03 - 1.26
At-Risk Housing	0.99	0.02	-0.24	0.81	0.93 - 1.06
Non-local Road	1.04	0.02	1.56	0.12	0.99 - 1.09
Accessibility	1.02	0.02	1.27	0.20	0.99 - 1.05
Below Poverty**	1.03	0.02	2.85	0.00	1.01 - 1.05
Residential Mobility	1.00	0.01	-0.57	0.57	0.98 - 1.01
Homeownership	0.99	0.01	-1.63	0.10	0.98 - 1.00
Catchment Zone	1.04	0.06	0.70	0.49	0.93 - 1.15
Control Measures					
Pre-intervention Robbery	1.06	0.03	1.89	0.06	1.00 - 1.12
Enforcement Activity***	1.01	0.00	3.61	0.00	1.01 - 1.02
Spatial Lag	1.00	0.02	0.15	0.88	0.95 – 1.03
Segment Length***	1.00	0.00	4.62	0.00	1 .00– 1.00
Constant	1.02	0.02	0.91	0.36	0.98 - 1.06
	n	1,253		**AIC**	0.642119
	LL	-377.28		**BIC**	-8625.72

Notes: Interaction terms reflect covariate effect on robbery during the non-operational hours (2am-6pm) within the catchment zone.
*p<.05, **p<.01, ***p<.001

Our test of temporal displacement, Model 3, identified two interaction measures that were significantly associated with robbery activity (see Table 5). Holding all other variables constant, robbery activity decreases 28% (exp(b) = 0.72) during non-operational time periods within the target area. Within the target area, police enforcement activity was associated with a significant 4% increase (exp(b) = 1.04) in robbery during non-operational time periods. Enforcement activity's relationship to temporally displaced robbery activity holds when considering the cumulative study area. For every one-unit increase in enforcement activity there is a significant 1% increase (exp(b) = 1.01) in robbery activity in street segments throughout the cumulative study area during non-operational time periods. Standard measures of corner stores estimate a 14% increase (exp(b) = 1.14) in robbery activity in street segments throughout the cumulative study area during non-operational time periods. In addition, for every one-unit increase in poverty, there is a corresponding 3% increase (exp(b) = 1.03) in robbery activity in street segments throughout the cumulative study area during non-operational time periods.

Table 5 – Temporal Displacement (Model 3) Results

Model 3	**DV – Robbery Activity Non-Operational Period**				
Interaction Terms	**exp(b)**	**Std. Err.**	**Z**	**P<**	**95% C.I.**
Gang Territory	1.12	0.08	1.67	0.10	0.98 - 1.28
Bus Stop	0.89	0.08	-1.19	0.23	0.74 - 1.08
Corner Store*	0.72	0.12	-2.00	0.05	0.52- 0.99
At-Risk Housing	1.10	0.09	1.16	0.25	0.94 - 1.28
Non-local Road	1.04	0.08	0.59	0.56	0.90 - 1.20
Accessibility	1.03	0.05	0.67	0.50	0.94 - 1.13
Below Poverty	1.01	0.03	0.42	0.67	0.95 - 1.08
Residential Mobility	0.98	0.03	-0.78	0.44	0.92 - 1.04
Homeownership	1.01	0.03	0.18	0.86	0.94 - 1.07
Enforcement Activity**	1.04	0.01	2.59	0.01	1.01 - 1.06
Standard Measures					
Gang Territory	0.99	0.02	-0.36	0.72	0.96 - 1.03
Bus Stop**	0.92	0.03	-2.79	0.01	0.86 - 0.97
Corner Store**	1.14	0.06	2.69	0.01	1.04 - 1.26
At-Risk Housing	1.00	0.03	-0.16	0.87	0.94 - 1.05
Non-local Road	1.04	0.02	1.76	0.08	1.00 - 1.09
Accessibility	1.02	0.01	1.48	0.14	0.99 - 1.05
Below Poverty***	1.03	0.01	3.23	0.00	1.01 - 1.05
Residential Mobility	1.00	0.01	-0.59	0.56	0.98 - 1.01
Homeownership	0.99	0.01	-1.77	0.08	0.98 - 1.00
Operation Impact Target Area	0.93	0.06	-1.23	0.22	0.82 - 1.05
Control Measures					
Pre-intervention Robbery	1.03	0.03	1.11	0.27	0.98 - 1.09
Enforcement Activity***	1.01	0.00	3.86	0.00	1.01 - 1.02
Spatial Lag	0.99	0.02	-0.52	0.61	0.95 – 1.03
Segment Length***	1.00	0.00	4.47	0.00	1.00 - 1.00
Constant	1.02	0.02	1.17	0.24	0.99 - 1.06
	n	1,250		**AIC**	0.540791
	LL	-312.994		**BIC**	-8614.59

Notes: Interaction terms reflect covariate effect on robbery during the non-operational hours (2am-6pm) within the Operation Impact Target area.
*p<.05, **p<.01, ***p<.001

DISCUSSION AND CONCLUSION

Our study found support for place-based characteristics being associated with displaced robbery activity. Across all three examinations of spatial, spatial/temporal, and temporal displacement we observed a few unique relationships, but a remarkable amount of agreement. For example, when considering the standard measures for bus stops corner stores, enforcement activity, and the role of poverty, all three models found associations with robbery activity in the same direction. For each type and combination of spatial or temporal displacement, standard measures of bus stops were found to decrease robbery activity. However, given the opposite relationship was found among interaction measures, specifically our catchment-interacted variables, our findings support the notion that specific features of the environmental backcloth can influence the occurrence of displacement, even if they do not influence the occurrence of crime more generally. In addition, there are some noteworthy differences in terms of associations between spatial and temporal displacement, suggesting that there are different dynamics at work.

Corner stores were routinely estimated to increase crime. Street segments throughout the study area that contain more households where the residents are living below poverty also can expect increases in robbery activity due to displacement. This reflects the link between poverty and crime whereby residents are unlikely to stay long in places that exhibit the features of poverty and do not create the social ties necessary to respond informally to changes in crime patterns. Lastly, enforcement activity may be a driver of temporal displacement activity, finding support for the influence of police activities and crime (Groff, Ratcliffe, Haberman, Joyce, & Taylor, 2015; Sorg, Wood, Groff, & Ratcliffe, 2014; Telep, Mitchell, & Weisburd, 2014) but given the small effect sizes the increases in enforcement activity would have to be substantial to see a significant difference in displaced crime activity.

When considering spatial displacement (see Model 1 and 2), there was a positive relationship between catchment area interacted bus stops and displaced robbery activity. This finding reflects the research literature that proposes bus stops and similar transit hubs act as crime generators (Bernasco & Block, 2011; Gerell, 2018). Conversely, measures generally representing the overall study area reported a negative relationship, suggesting a more general dampening effect of such places on robbery activity. This finding highlights the importance of the place-based characteristics of catchment areas and role of opportunity in facilitating spatial displacement. Specifically, we see that due to the spatial allocation of bus stops throughout target and catchment areas, the built environment is either providing a continuous opportunity field for offenders to take advantage of or acting to connect offenders to new opportunities in the immediate vicinity.

One finding of note is the role of non-local roads where significant associations were found for spatial displacement but not for the combined spatial and temporal displacement model. Brantingham & Brantingham (2003) theorize the role of non-local roads as important to displacement and we find support for its role in spatially displacing crime. The lack of association with the combined spatial and temporal displacement analysis (Model 2) shows the need for nuance in addressing displacement, as spatial and temporal displacement are likely similar but not operating by identical dynamics. Furthermore, non-local roads are likely frequented more often during the non-operational hours of the study by both suitable targets *and* capable guardians that can provide "eyes on the street" (Jacobs, 1961) during more normative activity hours.

Another layer of nuance is the solitary finding in Model 2 whereby there was a significant association between robbery activity and the level of residential mobility on street segments within the catchment area. As residential mobility increases it represents an area where residents do not live for long and do not build social ties that allow for the creation of informal social control capacity. It is likely that during the non-operational hours the catchment area will be filled with individuals who, after observing the increase in police presence in the previous time period, decide to go outside as the intervention subsides. However, as they are less familiar with the area this may drive robbery activity as they are unwittingly joining motivated offenders in the same place and time.

Temporal displacement of robbery activity to the non-operational period (Model 3) appears to be driven by enforcement activity in the target area during operational hours. Furthermore, interaction measures report a dampening effect of corner stores on robbery activity in the non-operational period. This may be because of previous enforcement activities in the target area, the lack of available opportunities as corner stores may be closed for a portion of the non-operational period, or because of the intervention itself. Oftentimes foot patrols direct officers to known crime generators or attractors within hot spots (e.g., corner stores) and that deterrence effect may last longer than the intervention period.

While there are many forms of crime displacement (Eck, 1993; Repetto, 1976), we focus entirely on spatial and temporal displacement due to the availability of the data and design of the evaluation conducted by Piza & O'Hara (2014). Likely, there are additional forms of displacement that we are unable to examine due to the nature of the intervention. For example, such crime hot spots are likely to also contain prostitution that is known to move indoors because of crackdowns (Weisburd, Wykoff, Ready, Eck, Hinkle, & Gajewski, 2006; Choo, Choi, & Sung, 2010). Data on prostitution, as well as other incidents not considered Part 1 crimes, was unavailable to us. In addition, considering overall violence decreasing while robbery increased, some level of crime switch displacement may have been operating. However, the scope of the current study did not allow for testing this displacement type.

We had statistical limitations due to the small study area limiting the number of street segments included in the analysis. However, such a spatially specific intervention is ideal for effective crime control and is likely a contributing factor to the overall success of the intervention. Previous studies of displacement also recommend the use of concentric rings (Bowers, Johnson, & Hirschfield, 2004) or examine how crime may spatially shift because of the intervention (Andresen & Shen, 2019). Future analysis of displacement could use these techniques to examine spatial or temporal displacement that is more distal relative to the target of the intervention, as recommended by Johnson, Guerette, & Bowers (2014).

In addition to statistical limitations, we were unable to measure an important aspect of social disorganization, ethnic heterogeneity. However, given the increasing concentration of race in place (Denton & Massey, 1993), street segments within census tracts with homogenous populations are likely to exhibit similar characteristics. Readers familiar with the crime-and-place literature likely noticed certain types of facilities commonly incorporated in this type of research, inclusive of liquor establishments, schools, and take-out eateries, were not included in our analysis. That is because of their sparse presence in the current study area, given its relatively small size and the mixed residential-commercial nature of the land usage. For example, only 1 bar, 1 school, and 2 take-out eateries were present within the catchment area. Research using a larger sample of street segments could measure the effect of such additional Crime Pattern Theory measures on crime displacement. Similarly, we lacked data and measures that capture the physical description of the Crime Pattern Theory measures. The risk of displaced crimes we found to be associated with bus stops and corner stores may not be uniform across all stores within the study areas and that there may be “risky facilities” (Eck & Clarke, 2007) that lack security measures and perceivable guardianship that make them criminogenic. However, the lack of nuance among categories of crime generators and attractors is a regular limitation of many studies that employ crime pattern theory constructs, making this area potentially fruitful for further research into the concentration of crime at places. While the “Iron Law of Troublesome Places” as proposed by Wilcox & Eck, (2011) suggests that only a few risky facilities with chronic crime problems are driving the relationships observed, it was infeasible to discern differences within facility types as in Steinman, Drawve, Datta, Harris, & Thomas (2020). Specifically, due to the small study area and the correspondingly low numbers of facilities, we did not have sufficient variance across features to identify the those 20% of facilities that are “risky”.

Despite these limitations, this study positively contributes to the crime-and-place literature. Within the place-based policing literature, this study provides important nuance to the role that the built environment and opportunity plays in the movement of crime resulting from police intervention. More generally, this study suggests further support for the continued measurement of social disorganization and crime pattern theory-informed constructs at the micro-level and the contention that street segments may have unique behavior settings that is related to the level of crime experienced at micro-places. Future studies should continue exploring the theoretical overlap between social disorganization and crime pattern theories.

NOTE

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[1] US Census Bureau, 2010 ACS Estimates

[2] Operation Impact deployed 12 officers and three supervisors within the quarter-mile target area on a nightly basis. Place-based enforcement did not occur as rigorously within Zone B, with focused patrol and street-level narcotics operations occurring on an intermittent basis. The patrol officers assigned to Zone B's encompassing sector remained the only officers with daily responsibilities in the area.

[3] We calculated Weighted Displacement Difference (WDD) (Wheeler & Ratcliffe, 2018) statistics for each crime type to verify results. Our WDD analysis confirmed the original results of Piza & O'Hara (2014). Full results and discussion on the WDD analysis available on request.

[4] See: http://www. infogroupdatalicensing.com/why-infogroup-data-licensing/how-we-do-it

[5] We considered using continuous measures rather than binary measures for the Crime Pattern Theory variables. Unfortunately, doing so resulted in several of our interaction variables being removed from the regression models due to collinearity. This was likely due to the small number of street segments containing multiple features (see Table 2).

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

[7] At-risk housing data 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, Caplan, Piza, 2011; Miller, Caplan & Ostermann, 2016; Moreto, Piza, & Caplan, 2014; Piza & O'Hara, 2014).

[8] US Census Bureau, 2010 ACS Estimates

[9] An alternate way to control for crime opportunity is to measure the number of households per street segment. Results of models incorporating number of households in lieu of street segment length do not substantially differ from the original analysis. Results of these sensitivity tests are presented in an appendix available as online supplemental material.

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APPENDIX

Table A1. Household Count Sensitivity Analysis – Model 1

Model 1	**DV – Robbery Activity - All Time Periods**				
Interaction Terms	**exp(b)**	**Std. Err.**	**Z**	**P<**	**95% C.I.**
Gang Territory	0.89	0.10	-1.02	0.31	0.71 - 1.12
Bus Stop*	1.35	0.19	2.05	0.04	1.01 - 1.79
Corner Store	1.31	0.28	1.26	0.21	0.86 - 1.98
At-Risk Housing	1.13	0.14	1.01	0.31	0.86 - 1.44
Non-local Road*	1.32	0.15	2.39	0.02	1.05 - 1.65
Accessibility	0.95	0.06	-0.72	0.47	0.84 - 1.09
Below Poverty	1.00	0.06	-0.02	0.99	0.89 - 1.12
Residential Mobility	1.09	0.06	1.67	0.10	0.98 - 1.21
Homeownership	0.96	0.05	-0.82	0.41	0.87 - 1.06
Enforcement Activity	0.97	0.02	-1.15	0.25	0.93 - 1.02
Standard Measures					
Gang Territory	1.00	0.03	0.12	0.90	0.95 - 1.06
Bus Stop***	0.86	0.04	-3.12	0.00	0.78 - 0.95
Corner Store***	1.26	0.10	3.10	0.00	1.09 - 1.47
At-Risk Housing	1.03	0.05	0.56	0.57	0.94 - 1.12
Non-local Road**	1.09	0.04	2.53	0.01	1.02 - 1.16
Accessibility*	1.05	0.02	2.18	0.03	1.00 - 1.09
Below Poverty*	1.04	0.02	2.37	0.02	1.01 - 1.07
Residential Mobility	1.02	0.01	1.72	0.09	1.00 - 1.04
Homeownership	0.99	0.01	-0.75	0.46	0.97 - 1.01
Catchment Zone	1.02	0.08	0.21	0.84	0.87 - 1.18
Control Measures					
Pre-intervention Robbery***	1.12	0.03	4.06	0.00	1.06 - 1.18
Enforcement Activity**	1.01	0.01	2.48	0.01	1.00 - 1.02
Spatial Lag	1.03	0.03	0.95	0.34	0.97 – 1.10
Household Count***	1.00	0.00	3.60	0.00	1.00 - 1.01
Constant***	1.10	0.03	3.65	0.00	1.04 - 1.15
	n	1,253		**AIC**	1.375528
	LL	-836.768581		**BIC**	-8480.734

Notes: Interaction terms reflect covariate effect on robbery within the catchment zone
*p<.05, **p<.01, ***p<.001

Table A2. Household Count Sensitivity Analysis – Model 2

Model 2	DV – Robbery Activity - Non-Operational Period				
Interaction Terms	**exp(b)**	**Std. Err.**	**Z**	**P<**	**95% C.I.**
Gang Territory	0.99	0.08	-0.13	0.90	0.84 - 1.16
Bus Stop*	1.23	0.12	2.09	0.04	1.01 - 1.5
Corner Store	1.23	0.18	1.40	0.16	0.92 - 1.64
At-Risk Housing	1.02	0.09	0.25	0.80	0.86 - 1.21
Non-local Road	1.16	0.09	1.81	0.07	0.99 - 1.35
Accessibility	0.98	0.05	-0.45	0.65	0.89 - 1.07
Below Poverty	0.94	0.04	-1.44	0.15	0.87 - 1.02
Residential Mobility*	1.08	0.04	2.21	0.03	1.01 - 1.16
Homeownership	0.97	0.03	-0.93	0.35	0.9 - 1.04
Enforcement Activity	1.00	0.02	0.07	0.95	0.97 - 1.04
Standard Measures					
Gang Territory	1.00	0.02	0.02	0.98	0.96 - 1.04
Bus Stop*	0.92	0.03	-2.45	0.01	0.86 - 0.98
Corner Store*	1.14	0.06	2.42	0.02	1.02 - 1.26
At-Risk Housing	1.01	0.03	0.27	0.79	0.95 - 1.07
Non-local Road	1.04	0.02	1.56	0.12	0.99 - 1.09
Accessibility*	1.03	0.02	2.29	0.02	1 - 1.06
Below Poverty**	1.03	0.01	2.78	0.01	1.01 - 1.05
Residential Mobility	1.00	0.01	-0.27	0.79	0.98 - 1.01
Homeownership	0.99	0.01	-0.91	0.36	0.98 - 1.01
Catchment Zone	1.04	0.06	0.71	0.48	0.93 - 1.16
Control Measures					
Pre-intervention Robbery*	1.07	0.03	2.43	0.02	1.01 - 1.14
Enforcement Activity***	1.01	0.00	3.08	0.00	1.00 - 1.02
Spatial Lag	1.01	0.02	0.26	0.79	0.96 - 1.05
Household Count**	1.00	0.00	2.61	0.01	1 .00– 1.00
Constant***	1.06	0.02	3.46	0.00	1.03 - 1.10
	n	1,253		**AIC**	0.6538265
	LL	-384.6222862		**BIC**	-8624.137

Notes: Interaction terms reflect covariate effect on robbery during the non-operational hours (2am-6pm) within the catchment zone.
*p<.05, **p<.01, ***p<.001

Table A3. Household Count Sensitivity Analysis – Model 3

Model 3	**DV – Robbery Activity Non-Operational Period**				
Interaction Terms	**exp(b)**	**Std. Err.**	**Z**	**P<**	**95% C.I.**
Gang Territory	1.10	0.08	1.44	0.15	0.96 - 1.26
Bus Stop	0.88	0.08	-1.33	0.18	0.73 - 1.06
Corner Store*	0.72	0.12	-1.94	0.05	0.52 - 1
At-Risk Housing	1.08	0.09	0.92	0.36	0.92 - 1.26
Non-local Road	1.06	0.08	0.79	0.43	0.92 - 1.22
Accessibility	1.02	0.05	0.38	0.70	0.93 - 1.11
Below Poverty	1.02	0.03	0.49	0.62	0.95 - 1.09
Residential Mobility	0.98	0.03	-0.73	0.47	0.92 - 1.04
Homeownership	1.01	0.03	0.22	0.83	0.94 - 1.08
Enforcement Activity**	1.03	0.01	2.43	0.02	1.01 - 1.06
Standard Measures					
Gang Territory	1.00	0.02	0.00	1.00	0.96 - 1.04
Bus Stop*	0.92	0.03	-2.53	0.01	0.87 - 0.98
Corner Store*	1.14	0.06	2.61	0.01	1.03 - 1.26
At-Risk Housing	1.01	0.03	0.36	0.72	0.95 - 1.07
Non-local Road	1.04	0.02	1.72	0.09	0.99 - 1.09
Accessibility*	1.04	0.01	2.53	0.01	1.01 - 1.06
Below Poverty***	1.03	0.01	3.40	0.00	1.01 - 1.06
Residential Mobility	1.00	0.01	-0.34	0.74	0.98 - 1.01
Homeownership	0.99	0.01	-1.06	0.29	0.98 - 1.01
Operation Impact Target Area	0.92	0.06	-1.31	0.19	0.81 - 1.04
Control Measures					
Pre-intervention Robbery	1.05	0.03	1.70	0.09	0.99 - 1.11
Enforcement Activity***	1.01	0.00	3.60	0.00	1.01 - 1.02
Spatial Lag	0.99	0.02	-0.44	0.66	0.95 - 1.03
Household Count	1.00	0.00	1.94	0.05	1.00 - 1.00
Constant***	1.06	0.02	3.79	0.00	1.03 - 1.10
	n	1,250		**AIC**	0.5538746
	LL	-321.1716357		**BIC**	-8613.00

Notes: Interaction terms reflect covariate effect on robbery during the non-operational hours (2am-6pm) within the Operation Impact Target area.
*p<.05, **p<.01, ***p<.00