

# The Variable Impacts of Public Housing Community Proximity on Nearby Street Robberies

Cory P. Haberman<sup>1</sup>,  
Elizabeth R. Groff<sup>1</sup>, and Ralph B. Taylor<sup>1</sup>

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## Abstract

**Objectives:** Use crime pattern theory to investigate the proximity effects of public housing communities on robbery crime while taking into account the presence of nearby nonresidential facilities. **Method:** The study uses data describing 41 Philadelphia public housing communities and their surrounds. Surrounds are defined using two increments of street block-sized buffers. Multilevel models (buffer areas nested around public housing communities) allowing the proximity effect to vary across communities and predicting its shape with public housing level predictors are estimated. **Results:** The multilevel models show that the shape of proximity effects varies across public housing communities and depends on community size, even after factoring in presence of nonresidential facilities. Spatially, multiple

<sup>1</sup> Department of Criminal Justice, Temple University, Philadelphia, PA, USA

## Corresponding Author:

Cory P. Haberman, 515 Gladfelter Hall, 1115 W. Polett Walk, Philadelphia, PA, 19122, USA.  
Email: cory.haberman@temple.edu

public housing communities close to one another have more intense robbery patterns. **Conclusions:** Labeling all public housing communities as equally criminogenic robbery exporters is unwarranted. In fact, some communities have lower robbery counts than the areas surrounding them. Consequently, effectively addressing robbery in and around public housing communities will require careful consideration of where the problem is located. Locating public housing communities more than two blocks apart may reduce robbery.

### **Keywords**

public housing, proximity, distance, crime pattern theory, multilevel modeling

Public housing is a prominent feature of the urban cores of most American cities (Holzman 1996). Originally conceptualized as a job creation plan and temporary housing for families hoping to rebound in the post-Depression era, American public housing policy has slowly transitioned to long-term housing for the perpetually disadvantaged (Huth 1981). Today, television and print news stories as well as quantitative (Holzman, Hyatt, and Kudrick 2005; Roncek, Bell, and Francik 1981)<sup>1</sup> and qualitative social science research (Kotlowitz 1992; Venkatesh 2002; Venkatesh 2008) have made public housing virtually synonymous with poverty and crime (Farley 1982; Roncek et al. 1981).

The association of public housing with poverty and crime has created a “not in my back yard attitude” among nearby market-value residents. Political reaction to communities’ fear of crime spillover (Santiago, Galster, and Pettit 2003) has led to the geographic concentration of public housing communities and in turn exacerbated social problems associated with economic disadvantage (Massey and Kanaiaupuni 1993). Federal programs, such as the U.S. Department of Housing and Urban Development’s (HUD) HOPE VI are based on the premise that relocating and rebuilding public housing communities at lower densities will improve public housing residents’ standards of living. These programs are proceeding, however, without a solid understanding of public housing proximity effects. Simply stated, policy-makers need to know whether public housing increases crime in the surrounding area and if so, the size and geographic extent of those proximity effects.

The current research embeds an investigation of micro-level proximity effects within an environmental criminological crime pattern theory

framework to address two specific research questions. First, after controlling for the presence of other potentially criminogenic facilities, something not done in previous works, do public housing communities affect street crime levels nearby? Second, if proximity effects are present then are public housing proximity effects variable depending on the characteristics of individual public housing communities?

## Theoretical Perspective

Environmental criminology explains the geographic and temporal patterning of crime by understanding how human interaction creates criminal opportunities (Wortley and Mazerolle 2008). The urban landscape is viewed as a collection of places or nodes which are connected to one another by a street network or other transportation modes (i.e., pathways; Brantingham and Brantingham [1981] 1991, 1993, 1995). At the same time, people have activity spaces which consist of the places they visit on a routine basis and the routes (i.e., paths) they take among those places (Horton and Reynolds 1971). The distribution of a city's land uses and particular facilities influences where and how people will travel to use the city each day (Groff, Weisburd, and Morris 2009; Horton and Reynolds 1971; Kinney et al. 2008). Recognizing the importance of routine activities theory's idea that crime events stem from the convergence of motivated offenders with suitable targets lacking adequate guardianship (Cohen and Felson 1979), crime pattern theory predicts that crime will cluster along the most commonly traveled pathways and around particular nodes which create the greatest number of offender-target convergences (Brantingham and Brantingham 1993).

Further, some facilities will generate crime by attracting many people and other facilities by attracting many criminals (Brantingham and Brantingham 1995). Subsequent research has empirically linked numerous types of facilities with higher levels of crime in the surrounding area: high schools (Roman 2005; Roncek and LoBosco 1983; Roncek and Faggiani 1985), bars and taverns (Roncek and Maier 1991), convenience stores (Schweitzer, Kim, and Mackin 1999), public transportation stations (Block and Block 2000; Block and Davis 1996), check-cashing stores (McCord and Ratcliffe 2007), liquor stores, halfway houses, and homeless shelters (McCord and Ratcliffe 2007; Rengert, Ratcliffe, and Chakravorty 2005). Because public housing communities are themselves a people concentrating node within the urban landscape, it is likely that crime will also cluster around public housing communities.

## **Crime around Public Housing Communities**

Two studies have compared crime rates within public housing communities to crime rates within adjoining buffer areas or beyond. Fagan and Davies (2000) compared crime levels within 82 public housing communities in the Bronx, NY, to three buffer zones extending on in 100 yard increments. Violence rates were lowest in the 100 to 200 yard buffers and highest within the 0 to 100 yard buffers, with the communities' rates falling in between. Additional results from two-stage least squares regression models suggested that crime was diffusing outward from the public housing communities and the authors suggested that public housing communities may serve as the epicenter of social exchanges in areas that lack social control.

Holzman et al. (2005) results varied by crime type: robbery and property crime was higher in a 300-meter (984.25 feet) buffer around the public communities and assault was higher within the community than in adjoining buffers. The authors suggested commercial facilities in the buffer zones provided more attractive robbery targets than the residential public housing communities where high unemployment rates translated into high levels of guardianship. At the same time, unemployed individuals probably contributed to higher rates of violence within the communities since they spent more time at home where they could become involved in violent events, especially domestic violence.

Three other studies investigated broader scale distance effects of public housing communities. Crime rates within census blocks were considered as a function of distance from public housing communities by Roncek et al. (1981). In Cleveland, an indicator of public housing communities' proximity linked to higher census block violent crime rates but not higher property crime rates. Further, census blocks adjacent to public housing communities experienced two more violent crimes per year than nonadjacent blocks, even after controlling for citywide public housing community influence on each census block.

In Atlanta, McNulty and Holloway (2000) explored whether the census block group level race-crime relationship could be explained by the geographic anchoring of impoverished minority populations in public housing communities. They found that an interaction between a block group's percentage of Black residents and distance to public housing was inversely associated with murder, rape, assault, and public order crimes (but not robbery and property crimes), but simple slope analyses showed that the relationship between percentage African American and the dependent variables became negligible for block groups a mile or more from the nearest public

housing community. The authors concluded that the neighborhood-level race–crime relationship is related to the geographic distribution of public housing because that distribution spatially concentrates poverty.

Holloway and McNulty (2003) reframed the relationship between block group distance to public housing and violent crime by arguing that this effect would vary depending on a community’s physical design and immediate context. When estimating separate models for each of the forty-two different public housing communities in Atlanta, and using block group distance from public housing as a predictor, they found the public housing distance–violent crime link varied. Distance was a significant predictor in the expected negative direction in models for twenty public housing communities, a significant positive predictor in the models for five others, and an insignificant predictor for the remaining seventeen. Proximity impacts were stronger for public housing communities with more housing units and high-rise family developments. The authors concluded that public housing communities are not homogenous and stereotyping all public housing communities as equally criminogenic is unwarranted.

### *Extending Past Studies*

In sum, prior studies show public housing communities adversely affect crime in their surrounds. Crime generally decreased as distance from public housing increased. These studies, however, suffer from three shortcomings addressed here. First, prior works have failed to control for compositional differences in facility patterns in the surrounding areas. As noted above, many studies have linked the presence of certain facilities to higher levels of crime. Failing to model the impact of other facilities may have led to less robust models in earlier work. Second, existing studies, *excluding* Holloway and McNulty (2003), implicitly assume that all public housing communities impact crime in the surrounding areas uniformly. The crime pattern theory framework adopted here anticipates proximity effects will vary depending on the characteristics of the public housing communities themselves. For example, communities with more total residents may have proximity effects which “drop-off” faster as distance increases because more populous communities may create more spatially dense offender–victim encounters within the community. Similarly, a faster drop-off in the proximity effect might be expected moving farther away from family communities as compared to elderly communities because members of family communities may lead more active lifestyles and thereby increase the likelihood of victim–offender encounters within the community as socializing occurs (Kotlowitz

1992; Venkatesh 2002; Venkatesh 2008). Third, extant research relies on census delineated geographic units and measures proximity across large distances. In keeping with recent research suggesting high-traffic facilities impact nearby areas over relatively short distances (Groff 2011; Ratcliffe In press), the varying proximity effects examined here are measured at the micro level of street blocks. Overall, more micro-scale distances are used while allowing proximity effects to vary while controlling for compositional differences in facilities, a factor which has been insufficiently integrated into works to date (Brantingham and Brantingham [1981] 1991, 1995).

## **Data and Method**

Because buffers at different distances from the public housing communities are nested by the public housing communities themselves, multilevel models (MLMs) are used (Raudenbush and Bryk 2002).

### *Level-Two Units: Public Housing Communities*

The level-two units in this analysis are public housing communities in Philadelphia, PA, USA. The Philadelphia Public Housing Authority (PHA), serving over 81,000 Philadelphians, is the fourth largest in the country. The Philadelphia Police Department (PPD) and HUD provided data describing public housing communities in Philadelphia.

The PPD supplied geographic data in the form of an ArcGIS shapefile containing the boundary of each public housing community (PPD, 2011). These outlines were used to construct the buffer areas discussed in the following sections of the article. The Philadelphia PHA operated 41 public housing developments in 2007; however, only 40 level-two units are analyzed in this study. Two developments were aggregated into one community due to their geographic proximity.<sup>2</sup> These two communities are separated by only a shared residential street and were deemed analytically indistinguishable.

The HUD (2009) data set provided community level measures for the 40 public housing communities in the geographic data from the PPD. These data were collected between July 2007 and December 2008 by local PHAs and landlords operating federally subsidized housing using official HUD forms, HUD-50058 and HUD-50059. Roughly 88 percent of occupied units returned a completed self-reporting form in Philadelphia, but the only level-two variable that would have been impacted by a low response

rate used in the present analysis, residential population, was obtained from the Philadelphia PHA's inventory database and therefore is a 100 percent count.

### *Level-Two Independent Variables*

Level-two independent variables, characteristics of public housing communities, were derived from the HUD (2009) data set. The size of each public housing community was provided as the total number of residents in each community. The resident type of each public housing community was measured using two dummy variables: family communities and senior communities, with a reference category representing communities with mixed, family, and senior, populations. Descriptive statistics for all variables are shown in Table 1.

### *Level-One Units: Buffer Areas*

The level-one units in this analysis are buffer areas surrounding individual public housing communities. Each public housing community was buffered at 50 feet, 450 feet, and 850 feet. The 50 feet buffer includes the actual public housing development, representing the community itself and the streets running adjacent to the public housing development. This was done because geocoding is a slightly imprecise process (Chainey and Ratcliffe 2005:60-63). Crimes that occurred within the community would actually be geocoded on the street running along its border. Street crimes in Philadelphia are also sometimes geocoded to intersections when their precise locations are unclear. Therefore, the 50 feet buffer would correctly attribute all crimes occurring within the community and geocoded to the street in front of the community to the community itself. The average length of a Philadelphia street block is 400 hundred feet (McCord and Ratcliffe 2009; Ratcliffe and Rengert 2008), so the second and third buffers represent the area surrounding the public housing community at distances of one and two blocks out, respectively. This distance was used to reflect research that has found that the effects of criminogenic facilities only extend a relatively short distance from a facility (Groff 2011; Ratcliffe In press).

After the 50, 450, and 850 feet buffers were created for each public housing complex, parts of the buffers of 18 public housing communities overlapped.<sup>3</sup> In order to retain statistical independence and avoid double counting crime incidents in the overlapped buffers, each overlapping buffer area was assigned to just one community using the following systematic process. First, the buffers were decomposed into 212 independent buffer

**Table 1.** Descriptive Statistics of Dependent and Independent Variables.

Variable	N	Min	Max	M	SD	Skewness
Dependent variables						
Street robberies	120	0	26	6.26	6.04	1.67
Exposure variable						
Area square miles	120	0.003	0.133	0.06	0.04	0.28
Level-two independent variables						
Total residents	40	17	1,696	430.40	412.03	1.30
Building resident type <sup>a</sup>						
Family	19	—	—	—	—	—
Senior	12	—	—	—	—	—
Family and Senior	9	—	—	—	—	—
Level-one independent variables						
Buffer distance						
50 feet buffer	40	—	—	—	—	—
50-450 feet buffer	40	—	—	—	—	—
450-850 feet buffer	40	—	—	—	—	—
Buffer intersections	120	0	4	0.63	1.04	1.82
Beer establishments	120	0	1	0.08	0.26	3.27
Check-cashing businesses	120	0	2	0.08	0.32	4.66
Drug treatment centers	120	0	2	0.12	0.41	3.70
Halfway houses	120	0	2	0.08	0.31	3.91
High schools	120	0	2	0.24	0.50	2.00
Homeless shelters	120	0	3	0.09	0.39	5.23
Parks	120	0	3	0.44	0.67	1.40
Pawn brokers	120	0	1	0.03	0.18	5.27
Subway stations	120	0	2	0.04	0.24	6.36

Source: Department of Housing and Urban Development (2009); Philadelphia Liquor Control Board (2009); Philadelphia Police Department (2007); Philadelphia Police Department (2008) Level-two units public housing communities ( $n = 40$ ). Level-one units buffer areas ( $n = 120$ ).

<sup>a</sup> Building resident type consists of 2 dummy variables. For the family variable, communities with only family units were coded as 1 and all other buildings were encompassed by the reference category. For the senior variable, communities housing only elderly residents were coded as 1 and all other building types were included in the reference category.

slivers covering a total of 6.82 square miles. Of the 212 total buffer slivers, 129 slivers covering 6.25 square miles, or 91 percent of total area under study, were associated with only one community from the start. The remaining eighty-nine slivers were areas where the buffers of two or more communities overlapped. These eighty-nine slivers contained only 0.57 square miles or roughly 9 percent of the total area under study. For all overlapping buffers, there was never an instance where the entire buffer of a community was completely subsumed by the buffer of another community.

Allocation rules were then established to assign each of the eighty-nine overlapped buffer slivers to only one public housing community. First, an attempt was made to assign the overlapped buffer areas to the most proximate public housing community. For example, if the 450 feet buffer of development X overlapped with the 850 feet buffer of development Y, then the area would be designated to development X's 450 feet buffer area. A total of sixty-one overlapped buffer slivers were assigned using this first rule. The remaining twenty-eight overlapping slivers were then allocated through random assignment. In other words, these overlapping buffer slivers were theoretically attributed to the "wrong" community in roughly half of the allocations and made finding a statistical relationship more difficult. After each overlapped area was assigned to only one community, the slivers were reaggregated to create a single buffer at each of the three distances for each community. In total, 120 level-one public housing buffer areas were created; one buffer at each of the three distances for each of the forty communities.

### *Level-One Independent Variables*

Level-one variables include measures of the individual buffer areas. First, because the area of the level-one buffer areas varies across public housing communities, an exposure variable of area in square miles was used in our models to control for those differences. The first predictor at level-one is the proximity effect. The proximity effect variable was coded with the first 50 feet buffer, including the public housing community, as 0, the next 450 feet buffer away as 1, and the second 450 feet buffer as 2. The second predictor controls for the buffer overlap among different communities.<sup>4</sup> This variable is simply a count of the number of different community buffers a buffer intersected with. Third, counts of nine different nodes within each buffer were entered at level one as well. The relationship between alcohol serving establishments and crime is well established (Roncek and Maier 1991 among many others). Other studies have found a positive relationship between check-cashing businesses (McCord and Ratcliffe 2007), drug treatment centers (Taniguchi and Salvatore in press), halfway houses (Rengert et al. 2005), high schools (Roman 2005; Roncek and Faggiani 1985; Roncek and LoBosco 1983), homeless shelters (McCord and Ratcliffe 2007), parks (Groff and McCord In press), pawn brokers (McCord and Ratcliffe 2007), and subway stations (Block and Block 2000; Block and Davis 1996; McCord and Ratcliffe 2009)<sup>5</sup>. All data except beer establishments were provided by the PPD's crime analysis unit (PPD 2008). Beer

establishments were extracted from Philadelphia Liquor Control Board's (PLCB) liquor license database using license classifications for small markets, delis, sandwich shops, and taverns permitted to sell alcohol for on-site and off-site consumption.

Researchers have recently questioned whether certain types of facilities need to be present or is it just simply that "busy places," a mix of nonresidential facilities, create crime opportunities and determine spatial crime patterns (Wilcox and Eck 2011). Here we do not distinguish between facilities which increase criminal opportunity at a place and those that simply increase the number of people; both are consistent with crime pattern theory. In other words, from the former perspective, our facility variables account for the crime opportunities that specific types of facilities might create. From the latter perspective, they serve as a proxy for foot traffic density in the buffer areas. Observational counts of pedestrian traffic and nonresidential land uses at the street block level have found that pedestrian counts load strongly on a nonresidential versus residential street block composition component (see Taylor, Shumaker, and Gottfredson 1985). Such a pattern suggests pedestrian counts are indistinguishable at the street block level from nonresidential land use patterns.

### *Dependent Variable*

The dependent variable in the present analysis is the number of street robberies occurring in each individual buffer area during calendar year 2007.<sup>6</sup> Incident level data for street robbery were obtained from the PPD. A single type of violent crime, street robbery, is used in order to reduce the heterogeneity inherent in aggregate crime categories (Clarke 2008; Smith, Frazee, and Davison 2000). Moreover, the violent nature and frequency of street robbery makes it a major concern in Philadelphia (Ramsey 2008). In 2007, the robbery rate in Philadelphia reached 714.58 robberies per 100,000 citizens compared to the national robbery rate of 147.6 robberies per 100,000 residents (Federal Bureau of Investigation 2007). Additionally, because Americans rightly perceive the likelihood of robbery victimization is much greater than most other crimes (Ferraro 1995:47), understanding the dynamics of street robbery might lead to policies that impact a wider range of Americans. Finally, street robbery matches the theoretical foundation of the present analysis as robbery is the quintessential predatory crime, and ethnographic research with active robbers has demonstrated that opportunity concentrating places figure prominently in robbers' searches for suitable targets (St. Jean 2007; Wright and Decker 1997). The mean of the

dependent variable is 6.26 with a variance of 36.48, indicating a Poisson distribution with over dispersion (Long and Freese 2006:350).

## Results

The series of multilevel count models estimated included an initial null model confirming significant ( $p < .001$ ) variation in expected robbery counts across public housing communities; an analysis of covariance MLM examining the fixed effect of buffer proximity while controlling for nearby facilities (first half of Table 2) and confirming significant robbery differences between communities remained ( $p < .001$ ) even after controlling for facility differences across buffers; and a full model where a significantly varying proximity impact ( $p < .05$ ) was predicted using public housing community features (second half of Table 2). The level two total residents' variable in the full model was grand mean centered.

### *Analysis of Covariance (ANCOVA) Model*

The ANCOVA model shows expected robbery counts decrease 43 percent for each additional buffer farther from a public housing community, holding the presence of other nonresidential facilities constant.<sup>7</sup> This finding agrees with previous work (Fagan and Davies 2000; Holzman et al. 2005; Roncek et al. 1981), but extends it in two important ways: proximity effects appear even when using short distances and controlling for variation across the buffers in nonresidential facilities. Additionally, the ANCOVA model shows that certain facilities are associated with increases in robbery counts and others with decreases. Specifically, the presence of a high school increases the expected robbery count in a buffer by 50 percent compared to 63 percent for a homeless shelter, 55 percent for a pawn broker, and 30 percent for a subway station. On the other hand, the presence of a drug treatment center or halfway house decreases the expected robbery count by 24 percent and 29 percent, respectively.

### *Full Model: Average and Varying Proximity Effects*

In the full-model allowing proximity impacts to vary by public housing community, each additional 400 feet traveled from a public housing community, on average, results in a significant 34 percent decrease in expected robbery counts when all other variables in the model are held constant, an impact about a quarter smaller than seen in the ANCOVA model. Again,

**Table 2.** Multilevel Model Results for Robbery Count Dependent Variable.

	ANCOVA Model				Full Model			
	Beta Coefficient	SE	Event Rate Ratio	t-ratio	Beta Coefficient	SE	Event Rate Ratio	t-Ratio
Intercept	5.31	0.16	202.95	33.61***	4.92	0.32	136.35	15.50***
Total residents	—	—	—	—	0.0007	0.0004	1.0007	1.84*
Family community	—	—	—	—	0.17	0.33	1.19	0.53
Senior community	—	—	—	—	0.52	0.46	1.68	1.12
Buffer distance	-0.55	0.06	0.57	-8.63***	-0.42	0.15	0.66	-2.90**
Total residents	—	—	—	—	-0.0005	0.0002	0.999	-2.91**
Family community	—	—	—	—	-0.23	0.15	0.80	-1.51
Senior community	—	—	—	—	-0.22	0.20	0.80	-1.08
Buffer intersections	-0.05	0.13	0.95	-0.41	0.11	0.06	1.12	1.74*
Beer establishments	0.38	0.26	1.47	1.50	0.54	0.19	1.71	2.83***
Check-cashing businesses	0.22	0.15	1.25	1.51	-0.09	0.13	0.92	-0.67
Drug treatment centers	-0.27	0.11	0.76	-2.43**	-0.08	0.12	0.93	-0.62
Halfway houses	-0.34	0.12	0.71	-2.94**	-0.55	0.16	0.57	-3.45***
High schools	0.41	0.09	1.50	4.56***	0.42	0.13	1.52	3.328***
Homeless shelters	0.49	0.08	1.63	5.84***	0.54	0.06	1.71	8.48**
Parks	0.007	0.09	1.01	0.074	0.05	0.10	1.06	0.60
Pawn brokers	0.44	0.23	1.55	1.93*	0.64	0.26	1.90	2.44**
Subway stations	0.26	0.16	1.30	1.70*	0.36	0.13	1.44	2.71***
Random effect	Variance Component	Chi-square	df		Variance Component	Chi-square	df	
Intercept	0.73	122.65***	39	—	0.83	116.81***	36	—
Buffer distance	—	—	—	—	0.13	54.03**	36	—

Note: Level-two units are public housing communities ( $n = 40$ ). Level-one units are buffer areas ( $n = 120$ ). Dependent variable specified as a Poisson distribution with overdispersion and an exposure variable of area (square miles). The distance variable is a fixed effect in the ANCOVA model and specified with a random slope in the full model. Level-two variable total residents is grand mean centered.

\* $p < .1$ .

\*\* $p < .05$ .

\*\*\* $p < .01$ .

public housing proximity effects are found using short distances and while controlling for potentially criminogenic facilities.

On the other hand, there is significant variation ( $p < .05$ ) around this average proximity impact in Philadelphia. Even at this micro level, all public housing communities were *not* equally criminogenic for their surrounding communities. This finding both confirms and extends earlier work. Holloway and McNulty's (2003) differential proximity impact is extended because said impact appears even though much shorter distances are used and the variation in nearby facilities is taken into account. Thus, the findings from this more micro-level study offers additional evidence countering the stereotyped notion that all public housing communities are equally criminogenic.

The variation in proximity effects aligns as hypothesized by crime pattern theory with a community feature. More total residents in the public housing community linked negatively to the proximity slope, in other words, each additional 100 residents in a public housing community over the average-sized community made the proximity impact 1 percent steeper. This differential impact fits within a crime pattern theory framework; more populated communities, as compared to less populated ones, will create more convergences of motivated offenders and suitable targets within the community.

Examining the local context of Philadelphia suggests community size-linked design features might have contributed to variations in proximity effects. Only six communities had above-average populations. Three consisted of vast campuses of mid-rise apartment buildings, two were campuses with multiple high-rise buildings, and the remaining community was an extensive neighborhood of row homes. In short, Philadelphia's more populated communities are also the communities with designs that would facilitate robbery in the community (see Newman 1973; Newman and Franck 1982). They have designs that allow robbers to escape quickly (St. Jean 2007) or "get lost" in the labyrinth of buildings (Merry 1981).

### ***Full Model: Community-Level Predictors of Average Expected Robbery Counts***

The results of the full model indicate the total number of residents within individual public housing communities explains a portion of the variance in the intercept (average expected robbery count) across public housing communities (Table 2). The average expected robbery count within the buffer areas around a community increases by 7 percent for each additional 100

residents above the average-sized community. One explanation for this finding might be that larger communities are embedded in a more disadvantaged ecological context. Political resistance to public housing construction has often meant that public housing has been built in disadvantaged areas (Massey and Kanaiaupuni 1993). Therefore, it is not unreasonable to infer that larger public housing communities receive the greatest resistance and are most often built in the most disadvantaged neighborhoods. Similarly, the construction of a larger community could have led to further decline in an area as residents might have moved after it was built (Bursik 1989). Because crime rates are higher in more disadvantaged neighborhoods (Peterson and Krivo 2010), the buffers around larger communities would then, on average, have greater expected robbery counts than smaller communities located in more advantaged areas. Further research is needed to better understand the differences between the areas around larger versus smaller public housing communities.

### *Full Model: Level-One (Buffer-Level) Predictors*

Recall that we noted the number of times a buffer from one community intersected the buffer of another to explore any multiplier effect of being close to more than one public housing community. In the ANCOVA model, the effect of the buffer intersection variable was insignificant. After freeing the slope of the distance variable, the full model predicts a 12 percent increase in expected robbery counts each time the buffer of one public housing community intersects with another community's buffer. This difference occurs simply because in the latter model the intersection variable impact is conditional on the random effect of the distance variable (Everitt and Hothorn 2010:236). Nonetheless, this result suggests geographic clustering of public housing communities, a factor that policymakers can control, creates a greater concentration of offender–victim convergences, and facilitates street robbery opportunities.

Our model also shows that the theoretically relevant facility variables missing in previous studies are important for understanding street robbery around public housing communities. Five facilities significantly increase expected robbery counts within the buffer areas: (1) beer establishments, (2) homeless shelters, (3) subway stations, (4) pawn brokers, and (5) public high schools.

In line with other published research and crime pattern theory, the presence of each additional beer establishment in a buffer increases expected robbery counts by 71 percent. These facilities generate a flow of people

coming and going, some of whom may be inebriated, and therefore provide an anchor point that concentrates victims and offenders. Because beer establishments serve as a popular hangout in urban neighborhoods, it is difficult to know who is innocently hanging around and who is waiting around for an opportunity to commit a robbery.

A 71 percent increase in expected robbery counts is associated with the presence of each additional homeless shelter within the buffer areas. Homeless shelter patrons may be victims and/or offenders. If public resistance to homeless shelters led to their construction in more disadvantaged and crime prone areas, then the clientele and staff may be victimized as they travel to and from the facilities. Alternatively, homeless shelters concentrate financially disadvantaged individuals who may commit robberies in the nearby area. Rengert et al. (2005) found that homeless shelters were associated with an increase in drug offenses in the nearby area. One interpretation of this finding is that some homeless shelter patrons may also be drug users who possess the financial motivation to commit robberies in the nearby area. Although the connection between drug use and crime is a clear one (Adamson and Sellman 1998; Kinner et al. 2009; Nurco, Hanlon, and Kinlock 1991), further research is needed to make any definitive statements about the processes driving the impact of homeless shelters on crime.

Consistent with past research (Block and Block 2000; Block and Davis 1996; McCord and Ratcliffe 2009), a 44 percent increase in the expected robbery count is associated with the presence of each subway station within a buffer area. Because subway stations provide a frequent influx of people, potential offenders and victims, there are increased opportunities for robberies in the areas surrounding subway stations.

The expected robbery count increases by 90 percent for each additional pawn broker in a public housing buffer. This can likely be credited to the fact that patrons leaving pawn brokers with newly acquired funds provide attractive robbery targets in the nearby area. Again, this analysis does not provide any means to distinguish whether a robbery is the function of a particular facility or busy places (see Wilcox and Eck 2011).

Similar to findings of past studies (Roman 2005; Roncek and Faggiani 1985; Roncek and LoBosco 1983), each additional high school in a public housing buffer area increased the expected robbery count by 52 percent. High schools are anchor places in the routine activity spaces of students and school employees. Therefore, they provide a pool of potential offenders and victims who may become involved in a robbery event while traveling to and from school. Also, a high school campus with benches, steps, and even an outdoor basketball court, provides an accommodating staging area for

nearby residents (Anderson 1999). This ancillary social dynamic, again, may facilitate robbery opportunities in the surrounding area.

Contrary to our hypothesis, the expected robbery count decreases by 43 percent for each halfway house present in a public housing buffer.<sup>8</sup> This finding is inconsistent with the common perception that halfway houses increase crime in the surrounding area because they, by definition, concentrate “known criminals.” It is probable, however, that in order to ensure the success of their clients, halfway house staff members act as place managers and provide guardianship around the facilities (Eck 1994; for empirical examinations of the effectiveness of place managers see Green Mazerolle, Kadleck, and Roehl 1998; Madensen and Eck 2008).

## Discussion

Using crime pattern theory and relying on recent advances in software and data availability, this study explored public housing proximity effects over short distances while allowing those effects to vary across communities and controlling for nearby facilities. The empirical results indicate proximity effects are variable across public housing communities, and this variation links to public housing community population as expected by crime pattern theory. Additionally, a concentration effect was observed; multiple public housing communities close to one another have more intense robbery patterns.

The varying impact of proximity showed that not all public housing communities contributed comparably to higher robbery counts relative to the immediate surround. For communities that followed the average trend, the expected robbery count decreased with each additional buffer. For other communities, robbery counts were lower inside the community and on the adjacent block but higher in the surrounding area. Finally, other communities exhibited low robbery counts within the community and the adjacent block, showed a spike in robbery counts in the areas about a block away, and then a decrease in robbery counts in the areas about 2 blocks away.

This finding is in agreement with previous studies which have suggested that crime levels vary within public housing communities in the same city (Fagan and Davies 2000; Farley 1982; Holzman et al. 2001) and unsurprising considering how much the characteristics of individual public housing communities can vary across a city (Holzman 1996). Most importantly, this finding demonstrates that painting all public housing communities with the same brush, as comparably powerful generators of robbery for spaces in and immediately around them, is misleading. It follows that addressing robbery

in and around public housing communities will require careful consideration of where the problem is actually located. The implementation of a robbery reduction or prevention initiative will need to critically think about how the local context shapes human activities and facilitates convergences of motivated offenders and suitable targets. Implementing a robbery reduction initiative focused on robberies in the area surrounding a public housing community might be politically attractive to nearby market-value residents but also might do little to address the real problem if the latter is located within the public housing community. At the same time, the significant proximity effect was found across a short distance and should allow law enforcement and other city agencies to concentrate their efforts in a much smaller area.

Our findings related to the robbery-linked roles of other facilities in the buffers cast additional doubts on crime spillover stereotypes about public housing communities. In this study, we included both public housing communities and nonresidential facilities because these places facilitate the convergence of motivated offenders and suitable targets (Brantingham and Brantingham 1993; 1995). Although the current data do not make it possible to distinguish whether a crime is associated with a particular facility, our models do suggest that, on average, buffers with more facilities experienced higher expected robbery counts than those with fewer facilities. Viewing that finding in the context of Wilcox and Eck's (2011) argument that crime events may simply be a function of the human interaction and convergence that busy places create rather than the presence of a particular type of node and the work of Eck, Clarke, and Guerette (2007) that found not all facilities within a homogenous population are equally criminogenic suggests researchers should use caution before labeling a particular facility type as criminogenic. Public housing communities may only be one facility contributing to a local crime problem.

From a policy standpoint, current findings, if verified in future works in other locales, suggest insights about locating and administering public housing communities in ways that may reduce robberies. First, the micro scale of our research and concentration effect found suggests public housing communities should be located more than two blocks apart. In addition, the increase in expected robbery counts associated with larger population public housing communities offers evidence in support of public housing communities with fewer residents. Third, our findings show that when non-residential facilities such as beer establishments, halfway houses, high schools, homeless shelters, pawn brokers and subway stations are located within about two blocks of public housing, there are more street robberies.

Strategic urban planning and zoning revisions could be used to avoid such mixing. Because of the small spatial scale used, the separation suggested by the current work is so short that it could still satisfy local public housing residents' commercial and social needs while providing them with a safer surround.

Of course, gaps about our understanding of public housing and crime dynamics remain. Future studies should include more details about the physical/design attributes (such as levels of natural and mechanical surveillance, access to the homes, or signs of resident territoriality), community demographics, and measures of the social processes within public housing communities (see Sampson 2002). The surrounding urban backcloth also deserves more complete description (Sampson and Wooldredge 1987). In short, a multilevel perspective that includes measures describing the community, resident population, and urban backcloth, will provide a more robust understanding of the link between public housing and crime (Taylor 2010)<sup>9</sup> The application of this methodology to public housing in additional cities will help determine whether these findings from Philadelphia are representative of all cities, or whether they only hold for other large cities in the United States.

Finally, an improved understanding of public housing proximity effects will require the utilization of different methodologies. Ethnographic research that questions offenders about how they decide where to commit street robberies may be useful (see St. Jean 2007; Wright and Decker 1997). Merry's (1981) study was a first step in this direction, but because she interviewed juveniles who were only robbing within a public housing community, her finding cannot shed light on the initial decision of where to conduct robberies. Alternatively, researchers with access to data about crime locations and both offenders' and victims' home addresses might use mobility triangles to better understand offending and victimization patterns among public housing community residents (Griffiths and Tita 2009; Tita and Griffiths 2005). Overall, research that sheds more light on how facilities contribute to crime problems will help researchers build more parsimonious theories and practitioners design better prevention plans.

In conclusion, the current work extends previous studies of public housing proximity or distance effects on violent crime using a crime pattern theory perspective to demonstrate that public housing proximity effects vary among communities within the same city, are shaped by public housing communities population, and remain even after using short distances and controlling for micro-level compositional differences in facilities close to public housing communities.

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## Notes

1. Farley (1982) and Weatherburn, Lind, and Simon (1999) did not find support for the hypothesis that crime rates are higher in public housing communities than the city as a whole.
2. The aggregated communities included a family and senior row home community of 1,251 residents and a small senior apartment building with 55 residents (Housing and Urban Development 2009).
3. These 18 communities make up five distinct geographic clusters. One cluster consists of two below-average-sized family buildings, albeit one community is nearly double the size of the other. Another two-community cluster is comprised of an average-size family community and a smaller senior community. The third cluster contains three above-average-sized family communities. The fourth cluster consists of three senior communities situated along the same busy thoroughfare and a large family community not far south of the middle-senior community. The last cluster contains seven communities. Two family senior mixed buildings and two above-average-sized family communities that make up a diamond with a small elderly community directly in the center. The two remaining communities in the cluster consist of a small family community and a small senior community that both tangentially overlap on opposite sides of community at the bottom tip of the diamond.
4. Given the proximity of some communities, Tobler's (1970) first law of geography, and the potential for spatial dependency to influence the parameters of multilevel models (Savitz and Raudenbush 2009), we tested for spatial dependence using a distance-based Global Moran's *I*s (Anselin, Syabri, and Kho 2006). Significant spatial autocorrelation was not found for either the robbery count or robbery rate per 1,000 residents. Details available from authors upon request.
5. The total number of each facility present in all level-one public housing buffers is check-cashing businesses ( $n = 9$ ), drug treatment centers ( $n = 14$ ), halfway houses ( $n = 10$ ), high schools ( $n = 29$ ), homeless shelters ( $n = 11$ ), parks ( $n = 53$ ), pawn brokers ( $n = 4$ ), and subway stations ( $n = 5$ ).

6. Street robbery events were identified using standard UCR reporting codes (i.e., 300 to 308) and geocoded at a 99 percent hit rate. The 2007 data were used because the HUD data were collected for 18 months starting in July 2007 and the local PHA opened three new communities during the 2008 calendar year that were not represented within the PPD or HUD data. Therefore, it was inferred that the available data best represented the state of Philadelphia's public housing for calendar year 2007.
7. The percentage effect of the proximity effect variable was obtained by subtracting the event rate ratio for the proximity effect from 1. Numbers below 1 represent negative effects and can be interpreted like a percentage decrease much like an odds ratio (Raudenbush and Bryk 2002).
8. In the analysis of covariance (ANCOVA) model the drug treatment centers were also significantly inversely related to public housing buffer expected robbery counts but became insignificant once the proximity effect was allowed to vary between communities. We recognize this negative effect is in the opposite direction as hypothesized. All correlations between level-one variables were 0.58 or less and multicollinearity was ruled out after examining the results of different linear and hierarchical regression models. Since drug treatment centers and half-way houses have a somewhat similar function, we would have suggested the place manager interpretation also explains the negative effect of drug treatment centers. Similarly, the check-cashing effect is also in the unexpected negative direction. In our diagnostic models, the check-cashing variable essentially "washed out" by adding combinations of other facilities. In short, our results do not suggest that check-cashing businesses will never be criminogenic; they just are not in the context of the present study and analysis; short distances away from public housing communities where other facilities are also located and proximity effects vary by locale. The fact that the effect of the check-cashing variable changed from positive in the ANCOVA model to negative in the full model is due to the fact that "how" we are modeling distance (fixed vs. random effect) changed in the two models, making parameters in the latter model contingent on that random effect (Everitt and Hothorn 2010:236).
9. We are grateful to an anonymous reviewer for raising the importance of thinking about differences between types of facilities, their ecological context, and the differences between individuals who use a particular facility.

## References

- Adamson, S. J., and J. D. Sellman. 1998. "The Pattern of Intravenous Drug Use and Associated Criminal Activity in Patients on a Methadone Treatment Waiting List." *Drug and Alcohol Review* 17:159-66.

- Anderson, E. 1999. *Code of the Street: Decency, Violence, and the Moral Life the Inner City*. New York, NY: W. W. Norton.
- Anselin, L., I. Syabri, and Y. Kho. 2006. "Geoda: An Introduction to Spatial Data Analysis." *Geographic Analysis* 38:5-22.
- Block, R. L. and C. B. Block. 2000. "The Bronx and Chicago: Street Robbery in the Environs of Rapid Transit Stations." Pp. 121-35 in *Analyzing Crime Patterns: Frontiers of Practice*, edited by V. Goldsmith, P. McGuire, J. Mollenkopf, and T. Ross. Thousand Oaks, CA: SAGE.
- Block, R. L. and S. Davis. 1996. "The Environs of Rapid Transit Stations: A Focus for Street Crime or Just Another Risky Place?" Pp. 145-84 in *Crime and Place*, edited by R. V. Clark. Monsey, NY: Criminal Justice Press.
- Brantingham, P. and P. Brantingham. [1981] 1991. "Notes on the Geometry of Crime." Pp. 27-54 in *Environmental Criminology*, edited by P. Brantingham and P. Brantingham. Prospect Heights, IL: Waveland.
- Brantingham, P. L. and P. J. Brantingham. 1993. "Environment, Routine, and Situation: Toward a Pattern Theory of Crime". Pp. 259-94 in *Routine Activity and Rational Choice*, edited by R. V. Clarke and M. Felson. New Brunswick, NJ: Transaction Publications.
- Brantingham, P. L. and P. J. Brantingham. 1995. "Criminality of Place: Crime Generators and Crime Attractors." *European Journal of Criminal Policy and Research* 3:1-26.
- Bursik, R. J. J. 1989. "Political Decisionmaking and Ecological Models of Delinquency: Conflict and Consensus". Pp. 105-17 in *Theoretical Integration in the Study of Deviance and Crime: Problems and Prospects*, edited by S. F. Messner and M. D. Krohn. Albany: SUNY.
- Chainey, S. and J. H. Ratcliffe. 2005. *GIS and Crime Mapping*. London, England: Wiley.
- Clarke, R. V. 2008. "Situational Crime Prevention." Pp. 178-94 in *Environmental Criminology and Crime Analysis*, edited by R. Wortley and L. Mazerolle. Portland: Willan.
- Cohen, L. E. and M. Felson. 1979. Social Change and Crime Rate Trends: A Routine Activity Approach. *American Sociological Review* 44:588-608.
- Eck, J. E. 1994. "Drug Markets and Drug Places. A case control study of the spatial structure of illicit drug dealing." University of Maryland, College Park, MD. Unpublished doctoral dissertation.
- Eck, J. E., R. V. Clarke, and R. Guerette. 2007. "Risky Facilities: Crime Concentration in Homogeneous Sets of Facilities." *Crime Prevention Studies* 21:225-264.
- Everitt, B. S. and T. Hothorn. 2010. *A Handbook of Statistical Analyses Using R*. 2nd ed. Boca Raton: Chapman & Hall/CRC Press.

- Fagan, J. and G. Davies. 2000. "Crime in Public Housing: Two-way Diffusion Effects in Surrounding Neighborhoods." Pp. 121-35 in *Analyzing Crime Patterns: Frontiers of Practice*, edited by V. Goldsmith, P. McGuire, J. Mollenkopf, and T. Ross. Thousand Oaks, CA: SAGE.
- Farley, J. E. 1982. "Has Public Housing Gotten a Bum Rap? The Incidence of Crime in St. Louis Public Housing Developments." *Environment and Behavior* 14:443-77.
- Federal Bureau of Investigation. 2007. *Uniform Crime Report*. Washington, DC: United States Department of Justice.
- Ferraro, K. F. 1995. *Fear of Crime: Interpreting Victimization Risk*. Albany, NY: State University of New York Press.
- Green Mazerolle, L., C. Kadleck, and J. Roehl. 1998. "Controlling Drug and Disorder Problems: The Role of Place Managers." *Criminology* 36:371-433.
- Griffiths, E. and G. Tita. 2009. Homicide in an Around Public Housing: Is Public Housing a Hotbed, a Magnet, or a Generator of Violence for the Surrounding Area? *Social Problems* 56:474-93.
- Groff, E. R. 2011. Exploring 'Near': Characterizing the spatial extent of drinking place influence on crime. *Australian and New Zealand Journal of Criminology* 44:156-179.
- Groff, E. R. and E. S. McCord. 2012. "The Role of Neighborhood Parks as Crime Generators." *Security Journal* 25:1-24.
- Groff, E. R., D. Weisburd, and N. A. Morris. 2009. "Where the Action is at Places: Examining Spatio-Temporal Patterns of Juvenile Crime at Places Using Trajectory Analysis in GIS." Pp. 61-86 in *Putting Crime in its Place*, edited by D. Weisburd, W. Bernasco, and G. J. N. Bruinsma. New York, NY: Springer.
- Holloway, S. R. and T. L. McNulty. 2003. "Contingent Urban Geographies of Violent Crime: Racial Segregation and the Impact of Public Housing in Atlanta." *Urban Geography* 24:187-211.
- Holzman, H. R. 1996. "Criminological Research on Public Housing: Toward a Better Understanding of People, Places, and Spaces. *Crime & Delinquency* 42:361-78.
- Holzman, H. R., R. A. Hyatt, and T. R. Kudrick. 2005. "Measuring Crime in and Around Public Housing Using GIS." Pp. 311-329 in *Geographic Information Systems and Crime Analysis*, edited by F. Wang. Hershey, PA: Idea Group.
- Horton, F. E. and D. R. Reynolds. 1971. "Action Space Differentials in Cities." Pp. 83-102 in *Perspectives in Geography: Models of Spatial Interaction*, edited by H. McConnell and D. Yaseen. DeKalb, IL: Northern Illinois University Press.
- Housing and Urban Development. 2009. *A Picture of Subsidized Housing*. Retrieved February 25, 2010 (<http://www.huduser.org/portal/picture2008/index.html>).

- Huth, M. J. 1981. "An Examination of Public Housing in the United States After Forty Years." *Journal of Sociology* 8:471-88.
- Kinner, S. A., J. George, G. Campbell, and L. Degenhardt. 2009. "Crime, Drugs and Distress: Patterns of Drug Use and Harm Among Criminally Involved Injecting Drug Users in Australia." *Australian and New Zealand Journal of Public Health* 33:223-27.
- Kinney, J. B., P. L. Brantingham, K. Wuschke, M. G. Kirk, and P. J. Brantingham. 2008. Crime Attractors, Generators and Detractors: Land Use and Urban Crime Opportunities. *Built Environment* 34:62-74.
- Kotlowitz, A. 1992. *There are no Children Here: The Story Of Two Boys Growing Up in the Other America*. New York: Knopf Doubleday.
- Long, S. J., and J. Freese. 2006. *Regression Models for Categorical Dependent Variables Using Stata*. 2nd ed. College Station, TX: State Corp.
- Madensen, T. D. and J. E. Eck. 2008. "Violence in Bars: Exploring the Impact of Place Manage Decision-making." *Crime Prevention and Community Safety* 10:111-125.
- Massey, D. S., and S. M. Kanaiaupuni. 1993. "Public Housing and the Concentration of Poverty." *Social Science Quarterly* 74:109-22.
- McCord, E. S. and J. H. Ratcliffe. 2007. "A Micro-spatial Analysis of the Demographic and Criminogenic Environment of Drug Markets in Philadelphia." *The Australian and New Zealand Journal of Criminology* 40:43-63.
- McCord, E. S. and J. H. Ratcliffe. 2009. "Intensity Value Analysis and the Criminogenic Effects of Land Use Features on Local Crime Patterns." *Crime Patterns and Analysis* 2:17-30.
- McNulty, T. L. and S. R. Holloway. 2000. "Race, Crime, and Public Housing in Atlanta: Testing a Conditional Effect Hypothesis." *Social Forces* 79:707-29.
- Merry, S. E. 1981. *Urban Dangers: Life in a Neighborhood of Strangers*. Philadelphia, PA: Temple University Press.
- Newman, O. 1972. *Defensible Space*. New York, NY: Macmillan.
- Newman, O. and K. A. Franck. 1982. "The Effects of Building Size on Personal Crime and Fear of Crime." *Population and Environment* 5:203-20.
- Nurco, D. N., T. E. Hanlon, and T. W. Kinlock. 1991. "Recent Research on the Relationship Between Illicit Drug Use and Crime." *Behavioral Sciences & the Law* 9:221-42.
- Peterson, R. D. and L. J. Krivo. 2010. *Divergent Social Worlds: Neighborhood Crime and the Racial-spatial Divide*. New York, NY: Russell Sage.
- Philadelphia Liquor Control Board. 2009. *Pennsylvania Liquor Control Board Licensee Database*. Harrisburg, PA: Pennsylvania Liquor Control Board.
- Philadelphia Police Department. 2007. *Crime incident data*. Philadelphia, PA: City of Philadelphia.

- Philadelphia Police Department. 2008. *Geographic Locations of Nonresidential Facilities*. Philadelphia, PA: City of Philadelphia.
- Philadelphia Police Department. 2011. *Geographic locations of Public Housing Communities*. Philadelphia, PA: City of Philadelphia.
- Ramsey. C. H. 2008. *Crime Fighting Strategy*. Presented to Mayor Michael A. Nutter. Philadelphia, PA: City of Philadelphia.
- Ratcliffe, J. H. 2011. "How Near is Near? Quantifying the Spatial Influence of Crime Attractors and Generators." *Patterns, Prevention, and Geometry of Crime*, edited by M. A. Andresen and J. B. Kinney. London: Routledge.
- Ratcliffe, J. H. and G. F. Rengert. 2008. Near Repeat patterns in Philadelphia shootings." *Security Journal* 21:58-76.
- Raudenbush, S. W. and A. S. Bryk. 2002. *Hierarchical Linear Models: Applications and Data Analysis Methods*. 2nd ed. Thousand Oaks, CA: SAGE.
- Rengert, G. F., J. H. Ratcliffe, and S. Chakravorty. 2005. *Policing Illegal Drug Markets: Geographic Approaches to Crime Reduction*. Monsey, NY: Criminal Justice Press.
- Roman, C. G. 2005. "Routine Activities of Youth and Neighborhood Violence: Spatial Modeling of Place, Time, and Crime." Pp. 293-310 in *Geographic Information Systems and Crime Analysis*, edited by F. Wang. Hershey, PA: Idea Group.
- Roncek, D. and D. Faggiani. 1985. "High Schools and Crime: A Replication." *The Sociological Quarterly* 26:491-505.
- Roncek, D., R. Bell, and J. M. Francik. 1981. "Housing Developments and Crime: Testing a Proximity Hypothesis." *Social Problems* 29:151-66.
- Roncek, D. W. and A. LoBosco. 1983. "The Effect of High Schools on Crime in their Neighborhood." *Social Science Quarterly* 64:598-613.
- Roncek, D. W., and P. A. Maier. 1991. "Bars, Blocks, and Crime Revisited: Linking the Theory of Routine Activities to the Empiricism of 'Hot Spots'." *Criminology* 29:725-53.
- Sampson, R. J. 2002. "Transcending Tradition: New Directions in Community Research, Chicago Style." *Criminology* 40:213-30.
- Sampson, R. J. and J. Wooldredge. 1987. "Linking Micro and Macro Dimensions of Victimization Models." *Journal of Quantitative Criminology* 3:371-93.
- Santiago, A. M., G. C. Galster, and K. L. Pettit. 2003. "Neighborhood Crime and Scattered-site Public Housing." *Urban Studies* 40:2147-163.
- Savitz, N. V. and S. W. Raudenbush. 2009. Exploiting Spatial Dependence to Improve Measurement of Neighborhood Social Processes." *Sociological Methodology* 39:151-83.
- Schweitzer, J. H., J. W. Kim, and J. R. Mackin. 1999. "The Impact of the Built Environment on Crime and Fear of Crime in Urban Neighborhoods." *Journal of Urban Technology* 6:59-73.

- Smith, W. R., S. G. Frazee, and E. L. Davison. 2000. "Furthering the Integration of Routine Activity and Social Disorganization Theories: Small Units of Analysis and the Study of Street Robbery as a Diffusion Process." *Criminology* 38:489-523.
- St. Jean, P. K. B. 2007. *Pockets of Crime: Broken Windows, Collective Efficacy, and the Criminal Point of View*. Chicago, IL: Chicago University Press.
- Taniguchi, T. A. and C. Salvatore. In Press. The Criminogenic Impact of Drug and Alcohol Treatment Facilities on Violent and Property Crime: A Socio-economic Contingent Relationship. *Security Journal*.
- Taylor, R. B. 2010. "Communities, Crime, and Reactions to Crime Multilevel Models: Accomplishments and Meta-challenges." *Journal of Quantitative Criminology* 26:455-66.
- Taylor, R. B., S. A. Shumaker, and S. D. Gottfredson. 1985. Neighborhood-level Links Between Physical Features and Local Sentiments: Deterioration, Fear of Crime, and Confidence." *Journal of Architectural Planning and Research* 2:261-75.
- Tita, G. and E. Griffiths. 2005. "Traveling to Violence: The Case for a Mobility-based Spatial Typology of Homicide." *Journal of Research in Crime and Delinquency* 42:275-308.
- Tobler, W. R. 1970. "A Computer Movie Simulating Urban Growth in the Detroit region." *Economic Geography* 46:234-40.
- Venkatesh, S. A. 2002. *American Development: The Rise and Fall of a Modern Ghetto*. Cambridge, MA: Harvard University Press.
- Venkatesh, S. A. 2008. *Gang Leader for a Day: A Rogue Sociologist Takes to the Streets*. New York, NY: Penguin Books.
- Weatherburn, D., B. Lind, and K. Simon. 1999. "Hotbeds of Crime? Crime and Public Housing in Urban Sydney." *Crime & Delinquency* 45:256-71.
- Wilcox, P., and J. E. Eck. 2011. Criminology of the Unpopular: Implications for Policy Aimed at Payday Lending Facilities. *Criminology & Public Policy* 10:473-482.
- Wortley, R. and L. Mazerolle. 2008. "Environmental Criminology and Crime Analysis: Situating the Theory, Analytic Approach and Application". Pp. 1-18 in *Environmental Criminology and Crime Analysis*, edited by R. Wortley & L. Mazerolle. Portland OR: Willan.
- Wright, R. T. and S. H. Decker. 1997. *Armed Robbers in Action: Stickups and Street Culture*. Boston, MA: Northeastern University Press.

## Author Biographies

**Cory P. Haberman** is a graduate student in the Department of Criminal Justice at Temple University. His research interests include the geography of crime and

policing. He currently serves as a research assistant to Professors Jerry Ratcliffe and Elizabeth Groff on the Philadelphia SMART Policing Initiative.

**Elizabeth R. Groff** is an assistant professor in the Department of Criminal Justice at Temple University. Her research interests include place-based criminology; modeling geographical influences on human activity; role of technology in police organizations; and the development of innovative methodologies using geographic information systems, agent-based simulation models, and randomized experiments.

**Ralph B. Taylor** is a professor of criminal justice and (courtesy appointment) geography and Urban Studies at Temple University. Publications can be found online at [www.rbtaylor.net/pubs.htm](http://www.rbtaylor.net/pubs.htm). Current projects include municipality-level crime forecasting in a metropolitan area (with Liz Groff), short- and long-term crime risk surface prediction in Philadelphia (with Jerry Ratcliffe), and communities and crime metamodels.