Cityscape

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Guest Editor's Introduction

Ronald E. Wilson
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Introduction

The increasing role of geographical analysis in solving social problems is not just a practical response by government agencies. Illustrated in this issue of *Cityscape* is the incorporation of geographic methods and techniques toward understanding issues of crime and disorder, two major negative influences on the quality of life in urban America. The primary emphasis in the use of this new approach is on the delivery of programs and services to people through place as a means to increase the impact of federal, state, and local investments on the quality of life in urban neighborhoods.

Urban Geography, Place, and Crime

Crime changes with urban development patterns. Opportunities for criminal activity emerge, disappear, or move as geography changes across the urban landscape. Patterns emerge, dissipate, or persist based on changes in economic, ecological, and demographic conditions. Future crimes are far more predictable by place of occurrence than by a particular offender (Sherman and Weisburd, 1995; Weisburd et al., 2004). The greater predictability arises because places are relatively rigid; land use, infrastructure, and even demography change slowly. Places are resistant to change in the absence of major investments of time and money to make change occur. Public policy, especially local public policy, usually drives such investments.

The environmental criminology subdiscipline began with the 1975 paper, "Residential Burglary and Urban Form," (Brantingham and Brantingham, 1975, 1981). As one of the first empirical studies to establish the interaction between criminals and geography, the Brantinghams examined the geographic patterns of criminal offending within and between places. Environmental criminology fused geographical principles with criminological theory, providing opportunities to test empirically interactions between crime and place. The resulting research applied and tested new theories of crime rooted in urban development, including crime pattern theory (Brantingham and Brantingham, 1975), routine activities (Cohen and Felson, 1979), journey to crime (Phillips, 1980; Rengert, 1992), and geographic profiling (Rossmo, 2000). Other longstanding theories, such as social disorganization (Shaw and McKay, 1942), rational choice (Cornish and Clarke, 1986), territoriality (Taylor, 1988), and deviant places (Stark, 1987) were modified from this research to include a geographic aspect. Geographic theories strengthen criminological theories by providing a place-based foundation for where offenders live, why incidences occur where they do, and how offenders move within a particular geography. Geographic theories also offer insight into the development and change of urban form (spatial organization) and into the interactions between places that form from those changes (spatial interaction).

The development of Geographic Information System (GIS) software and spatial statistics has significantly affected the ability of law enforcement to combat crime and criminal justice to deliver services (Wilson, 2007). Because crimes have a spatial structure and form cohesive patterns, place-based approaches can make public policy more efficient. Actions from public policy simultaneously affect multiple people within the same target area. Crime types have a spatial structure based on urban geography. Residential burglaries happen only in residential areas. Commercial robberies, likewise, transpire only in commercial districts. Auto thefts more frequently happen in places with large amounts of parking that are difficult to monitor. Homicide tends to occur across larger areas where poverty, inequality, physical deterioration, and economic decline have long been established. Because places are interconnected, the benefits from targeted places can diffuse outward to adjacent places and upward to larger geographic areas to strengthen the whole. This diffusion compounds the positive effects of such programs while adding little additional cost.

Places are not isolated or detached from the surrounding geography. Social, economic, or political interactions occur within and between places in which places that are closer together are more related and share similar conditions. This phenomenon is known as the first law of geography (Miller, 2004; Tobler, 1970). Distance decay, a core idea by which spatial interactions and relationships between places are analyzed, measures the first law of geography. What occurs in one place diffuses to adjacent places, and from adjacent places, upward to larger geographies. The outward spillover of crime into adjacent neighborhoods leads to several places becoming unattractive; this, in turn, can lead to an entire set of neighborhoods becoming afflicted with a host of new social ills (Barr and Pease, 1990; Galster, 2005; Hakim and Rengert, 1981; Hesseling, 1994; Hipp, Tita, and Greenbaum, 2009). These places sometimes become failed neighborhoods. A failed neighborhood upwardly supplies an area with lower educational attainment, higher unemployment, unhealthy conditions, dilapidated buildings, and a wrecked infrastructure. Disproportionate amounts of human services, public safety, maintenance projects, and like resources are spent on these places, with little positive contribution in return from these places.[1] Tax revenue shrinks, assets are sold, capital improvement is suspended, businesses move out, jobs are shed, and residents who can leave do so. The legacy of place (Eberts, Erickcek, and Kleinhenz, 2006) may undermine the potential to solve social, economic, or political problems because these problems become entrenched.

Articles in This Symposium

Urban crime policy crosscuts a broad area of governmental actions toward solving problems. Change can be instilled through creating programs, enhancing laws, establishing regulations,

[1] Researchers at the Spatial Information Design Lab at Columbia University and the Justice Mapping Center appropriately described these places as Million Dollar Blocks (MDBs). The primary aspect of the MDB project was to research the costs of incarceration whereby offenders were continuously cycling in and out of prison back to and from the same neighborhoods that offered little opportunity for them to succeed. More information is available at http://www.spatialinformationdesignlab.org/projects.php?id=16.

improving the environment, or redirecting resources that alter place or behavior in place. The symposium in this issue of *Cityscape* features a range of articles that demonstrate the interplay of crime patterns and urban geography.

The first two articles illustrate the effect of place-based polices on particular segments of the population in which geographical analysis played a key role in uncovering the effects. In "Sex Offenders, Residence Restrictions, Housing, and Urban Morphology: A Review and Synthesis," Tony H. Grubesic, Alan T. Murray, and Elizabeth A. Mack demonstrate the human and geographic consequences that arise for offenders, residents, and the government in finding suitable places for offenders to live. The authors summarize recent research findings on housing availability problems sex offenders face after residency restriction laws are implemented. Highlighted are problems that arise when place is not taken into account when making policy. "The Coaction of Neighborhood and Individual Effects on Juvenile Recidivism" is an excellent example of the interaction between individuals, neighborhoods, and rehabilitation programs. Philip W. Harris, Jeremy Mennis, Zoran Obradovic, Alan J. Izenman, and Heidi E. Grunwald uncover effects of historical characteristics of place on the variation of juvenile reoffending and the effect on the types of crimes committed. The authors make an argument for crafting place-based rehabilitation programs designed to help juveniles refrain from reoffending based on the type of neighborhood in which they live.

The third article illustrates the spatial interaction between places and their characteristics that exemplify the first law of geography. In "Mapping the Spatial Influence of Crime Correlates: A Comparison of Operationalization Schemes and Implications for Crime Analysis and Criminal Justice Practice," Joel M. Caplan examines the geographic correlates of crime that spatially influence nearby crimes. This article demonstrates two particular aspects of using place to understand crime. The first is the geographic dynamic of spillover and diffusion effects between adjacent places with shared characteristics. The second is the demonstration of local characteristics of a place that affects an offender's probability of committing crimes.

The fourth and fifth articles demonstrate the use of spatial analysis methods to evaluate the effectiveness of place-based programs. Roderick W. Jones and Derek J. Paulsen's "HOPE VI Resident Displacement: Using HOPE VI Program Goals To Evaluate Neighborhood Outcomes" and Meagan Cahill's "Using the Weighted Displacement Quotient To Explore Crime Displacement From Public Housing Redevelopment Sites" look at the effects of HUD's HOPE VI Program on residents and the places they live and to which they move. Both articles examine the displacement effect from programs that alter the built environment in three different cities. Jones and Paulsen examined changes in neighborhoods in a small city and found that residents from HOPE VI sites moved to neighborhoods that were of higher poverty and had more crime. Conversely, Cahill examined displacement of crime in two medium-sized cities and found a diffusion of benefit from HOPE VI, combined with local redevelopment, in the sites and surrounding areas. Crime was reduced and living conditions for residents improved. The mixed results suggest a better understanding is required of how people affect place when programs temporarily move participants.

Similarly, the sixth article also demonstrates the effect on place from people moving but, more specifically, through a program that allows participants to choose their neighborhood. In "Do Vouchers Help Low-Income Households Live in Safer Neighborhoods? Evidence on the Housing Choice

Voucher Program," Michael C. Lens, Ingrid Gould Ellen, and Katherine O'Regan examine whether Housing Choice Voucher (HCV) participants move to safer neighborhoods. An overall goal of the HCV Program is to give low-income families the option of moving to neighborhoods with better employment opportunities, improved education for their children, and, most importantly, a safer environment free of crime. This article demonstrates the partial progress of participants finding safe places to live and discusses the characteristics associated with those places.

In the final article, "Modeling Criminal Distance Decay," Mike O'Leary shows how urban geography can be mathematically modeled to understand how urban structure affects criminal decision behavior. The results show how offenders operate and adjust to the geographic structure as they move through a metropolitan area. His work is intended to highlight how research can more realistically simulate target selection based on how offenders exploit their choice of targets within a geographic context.

The international commentaries from Canada, Colombia, and South Africa bring this symposium full circle regarding crime and the structure of urban geographies. Even though various historical circumstances, policies, and cultural aspects have shaped the urban patterns in these countries, place is still a consistent framework in which to measure and understand the variation of crime. These commentaries exemplify the urban development differences between the United States and other countries, yet they show how places with low qualities of life can systemically lead to many social problems, of which crime is a major catalyst.

The articles in this symposium are only a small sample of the many works highlighting the interaction of crime and the urban environment. Readers interested in pursuing other recent literature should consult the following special issues from other journals:

- "Crime in the City." 2008. *Built Environment* 34 (1).
- "Crime Mapping." 2007. *Social Science Computing Review* 25 (2).
- "Geographic Aspects of Sex Offender Residency Restrictions." 2009. *Criminal Justice Policy Review* 20 (1).
- "Bayesian Journey to Crime Modeling." 2009. *Journal of Investigative Psychology and Offender Profiling* 6 (3).
- "Empirical Evidence on the Relevance of Place in Criminology." 2010. *Journal of Quantitative Criminology* 26 (1).

Enhanced Policymaking and Practice

Governmental actions can alter the fate and trajectory of places, because public policy solutions to crime are often about *where*. This dynamic between people and place can no longer be ignored. It must be appreciated that when policy shapes place, the changes in those places in turn affect people, and the resulting reactions by people ultimately come back to help reshape policy. Preventing or intervening in crime by targeting place allows neighborhoods to flourish through building or sustaining a higher quality of life. As GIS and other spatial analysis tools become more prominent and more research supports their effectiveness, governments will likely craft more comprehensive policies that give full consideration to how geography can help meet the goals of policy actions. The utility of more complex geographic analysis for policymakers confronting crime has yet to be established, and our goal in this symposium is to show what that utility might be. The Department of Housing and Urban Development, for its part, is making significant investments in all aspects of geographical analysis to support the many different community needs at the intersection with the Department's mission and programs. Crime prevention is a persistent need of many communities, and it is hoped these articles will give researchers, practitioners, and policymakers new ideas to pursue so they can better meet that need, with geography as a foundation.

Sex Offenders, Residence Restrictions, Housing, and Urban Morphology: A Review and Synthesis

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Abstract

Although residence restrictions for convicted sex offenders are widely enforced in the United States, these policies remain controversial. Most restrictions are defined geographically, prohibiting convicted offenders from establishing a permanent residence within a prescribed distance from sensitive facilities like schools, parks, and bus stops. Proponents argue that residence restrictions protect families and children from sexual violence, but others argue that these policies can produce a variety of unintended social, economic, and geographic outcomes, such as reducing available housing, forcing offenders to cluster in socially disenfranchised neighborhoods, limiting access to rehabilitation facilities, and generating spillover effects to nearby communities. This article provides an overview of sex offender laws in the United States and synthesizes the literature pertaining to sex offender policies and their geographic implications for housing availability and affordability. This article also addresses the effects of urban morphology on sex offender policies and outcomes, and it ends with an agenda for future research.

Introduction

The United States is home to a broad spectrum of sex offender policies. From community notification laws to residence restrictions, federal, state, and local legislation conceived for managing convicted offenders is both dynamic and controversial (Yung, 2010).[1] One of the more contentious legislative approaches for controlling offender whereabouts at the local and state levels, is the establishment of residence restriction zones around sensitive facilities, such as schools, daycare centers, parks, bus stops, and other locations where children congregate. These spatial restriction zones (SRZs) are defined by a distance criterion, typically ranging from 500 to 3,500 feet from a sensitive facility, within which a convicted offender may *not* establish a permanent residence. The goal of these restrictions is to minimize the potential for interaction between offenders and children, thereby reducing the risk of recidivism and enhancing public safety (Grubesic and Murray, 2010). Although this type of legislation is popular, little empirical evidence exists on the effectiveness, or lack thereof, of the legislation in achieving its intended goals and objectives (Tewksbury and Levenson, 2007). Nevertheless, the general public strongly supports these laws, further motivating continued implementation and enforcement of policies for managing convicted offenders (Mancini et al., 2010).

The effects of residence restrictions on both offenders and communities are the subject of intense scrutiny. Tewksbury (2005) suggested social or cultural implications, or "collateral consequences," are associated with such restrictions. For example, residence restrictions are thought to create difficulties in reintegrating offenders into communities, causing social isolation and limiting offenders' access to rehabilitation services (Burchfield and Mingus, 2008; Levenson, 2008; Levenson and Cotter, 2005; Zevitz and Farkas, 2000).

Similarly, significant effort recently has been dedicated to exploring the effects of residence restrictions on the availability and affordability of housing in communities. Much of this literature has suggested that larger SRZs decrease housing availability for sex offenders (Barnes et al., 2009; Chajewski and Mercado, 2009; Zandbergen and Hart, 2006; Zgoba, Levenson, and McKee, 2009). Although these observations are not particularly surprising, they provide the impetus for pursuing more nuanced and relevant matters associated with housing that may be the result of residency restriction laws. For example, residence restrictions not only limit housing availability, but recent work identifies potential effects of these policies on local housing values (Linden and Rockoff, 2008; Pope, 2008), affordability (Grubesic, Matisziw, and Murray, 2010; Grubesic, Murray, and Mack, 2008), and the emergence of sex offender clusters (Grubesic, 2010).

The purpose of this article is to provide an overview of how sex offender residency laws interact with local geography and urban morphology to generate both intended and unintended outcomes. We begin with a general review of sex offender laws at federal, state, and local levels. This review is followed by a brief historic overview of how local legislation is used to control the spatial distribution of undesirable facilities and populations in the United States. The next three sections explore the specific geographic manifestations of sex offender policies and also highlight how poor cross-jurisdictional coordination of offender laws can influence housing options and affordability and create geographic concentrations of offenders. We also review strategic options for communities

[1] For a thorough review of community notification laws, see Bedarf (1995), Hughes and Kadleck (2008), and Logan (2003).

dealing with unique local distributions of sensitive facilities, populations, and convicted offenders. We conclude by discussing the policy implications for sex offender laws and housing, highlighting the importance of urban morphology.

Sex Offender Laws

Numerous sex offender laws exist in the United States. Although many of these laws do not have an obvious link to housing issues for convicted offenders, a variety of externalities are associated with these policies that can affect housing availability and affordability. In an effort to better understand how such legislation is structured across political jurisdictions and the housing effects associated with these laws, this section reviews sex offender legislation at federal, state, and local levels.

Federal Laws

Perhaps the most widely recognized approach to managing sex offenders is community notification laws. These laws are instituted to monitor the whereabouts of convicted offenders once they have served their prison sentence and are released into the community. At the federal level, these laws were initially enacted in 1994 as the Jacob Wetterling Crimes Against Children and Sexually Violent Offender Registration Act[2] (Wetterling Act). The Wetterling Act mandated that each state implement a sex offender registry. Megan's Law[3] amended this act in 1996, requiring states to establish a community notification system to alert residents when a sex offender moves into their community. Communities are given significant leeway in the approach used for notification; methods include phone calls, going door-to-door, or using some type of publicly accessible Internet database. The Lynchner Act[4] (1996) also amends the Wetterling Act, requiring lifetime registration for recidivists and offenders that commit aggravated sexual offenses. The Lynchner Act, however, is largely subsumed by the more recent Adam Walsh Child Protection and Safety Act of 2006[5] (Walsh Act). The Walsh Act organizes sex offenders into three tiers and mandates that the most serious offenders (Tier 3) update their whereabouts every 3 months for their lifetimes. Tier 2 offenders are required to update their information every 6 months for 25 years and Tier 1 offenders must update their information annually for 15 years.

Although community notification laws were initially developed to protect children from predatory sex offenders (Levenson, 2003), opponents of these laws argue that most sexual assaults committed against children are by acquaintances known to the victim (Catalano, 2006). They claim that this method of managing offenders is largely ineffective, and that it is a drain on human and financial resources for local law enforcement agencies (Zevitz and Farkas, 2000). The human resources required to maintain accurate offender information are substantial because these databases are relatively dynamic and quickly outdated. In part, this is because offenders are a highly mobile

[2] Jacob Wetterling Crimes Against Children and Sexually Violent Offender Registration Act. 1994. Violent Crime Control and Law Enforcement Act of 1994, H.R. 3355 C.F.R. § 170101.

[3] Megan's Law, Public Law 104–145 C.F.R. § 170101 (d) of the Violent Crime Control and Law Enforcement Act of 1994.

[4] Lychner Sexual Offender Tracking and Identification Act. 1996. Public Law 104–236 C.F.R.

[5] Adam Walsh Child Protection and Safety Act of 2006. Public Law 109–248.

population, changing residences within and between jurisdictions (for example, county to county, state to state) frequently (Murray et al., in press; Turley and Hutzel, 2001). Further, many offenders are simply noncompliant, failing to register, re-register, or de-register after they have moved. Therefore, it is common for law enforcement officials to lose track of an offender's whereabouts, leading to inaccurate and outdated registry databases (Cohen and Jeglic, 2007; Davey, 2006; Mack and Grubesic, 2010).

State Laws

Sex offender laws at the state level consist of a more varied mix of strategies for managing convicted offenders.[6] First, registration requirements vary substantially between states. Although all offenders are required to register, as mandated by the Walsh Act, the information that is collected during the registration process differs. For example, in the state of Missouri, officials collect an assortment of personal information, including a DNA sample, but the state of Idaho does not mandate DNA collection. These same state-level differences also manifest in sex offender residence restrictions. These restrictions are designed to control the spatial distribution of convicted offenders, effectively limiting potential exposure to children by forcing offenders to establish a permanent residence beyond a prespecified distance from a sensitive facility. Because no consistent definition exists among states, restriction distances and the types of facilities deemed sensitive (schools, daycare centers, parks, and bus stops) vary considerably across states. This variability generates a haphazard landscape of restrictions for convicted offenders. Approximately 30 states maintain some type of residence restriction with little consistency among them. For example, Florida and Ohio mandate that offenders live outside a 1,000-foot SRZ from schools and daycare facilities; Mississippi stipulates a 1,500-foot SRZ; Illinois, 500 feet; and California, 2,000 feet. Amendments to the laws further complicate matters. For example, Georgia recently amended its sex offender laws with House Bill 571.[7] Depending on when the offender was convicted, he or she may or may not have any residence and employment restrictions.[8]

Other state-level efforts designed to manage offenders include state-funded efforts to apprehend and prosecute offenders in violation of registration laws. Although these efforts are not generally classified as sex offender "laws," they are indicative of state-level efforts to monitor this population. For example, both Arizona and Wisconsin have implemented state-funded task forces to determine the whereabouts of absconded offenders and prosecute them (Groves, 2005; Rubiano, 2005).

Local Laws

Most of the local sex offender laws in the United States are largely derived from state-level policies. In particular, residence restrictions are often adjusted at the local level in an effort to reflect more conservative community standards and preferences regarding sex offenders. For example, Florida has nearly 130 different local residence restrictions in place. These restrictions range from the

[6] Global Positioning Systems and lifetime supervision policies are also used in many states (Cohen and Jeglic, 2007).

[7] Georgia General Assembly House Bill 571. 2010.

[8] For a thorough summary of these amendments, see http://www.gachaplains.org/pdf/HB_571_Summary.pdf.

state-level minimum distance of 1,000 feet, up to 3,000 feet locally (Killian, 2008). Although the structure of the Florida residence restrictions is fairly standard, many other communities are developing and implementing alternative strategies for managing the spatial distribution of convicted offenders. For example, one alternative approach seeks to control the spatial density of convicted offenders. This approach uses laws that are designed to reduce the interaction between offenders and the exposure of communities to these potentially problematic populations (Grubesic and Murray, 2008). Specifically, in Brookhaven Town, New York, it is illegal for more than two registered offenders to live in the same single-family home (Whittle, 2008). The locality levies fines against both the offenders and the landlord in this case. Similarly, a senate bill in Arizona that did not pass attempted to limit the number of offenders in multiunit apartment complexes to at most 10 percent of the units.[9] Further, a different bill in Arizona sought to prohibit convicted sex offenders from living in the same residential structure and no closer than 1,320 feet of each other.[10] This type of dispersion strategy is increasingly popular, with similar approaches enacted in California (Eakins, 2008; Mazza, 2008; Sahagun, 2008), New York (Whittle, 2008), and Wisconsin (Boyd, 2008).

Typological Summary

The simple federal, state, and local typological framework of sex offender laws detailed above leads to the following four summary points pertaining to housing. First, residence restrictions can limit housing availability for convicted offenders (for example, Barnes et al., 2009; Chajewski and Mercado, 2009; Zandbergen and Hart, 2006). Although this fact is rather obvious, SRZs, by design, are meant to keep offenders from establishing a permanent residence near a school or other sensitive facility. As a result, the SRZs make large areas of potential housing in communities off limits. Second, after local jurisdictions begin to modify existing offender policies (for example, extending or contracting an SRZ based on distance) or develop new sex offender residence restrictions (for example, saturation statutes and dispersion ordinances), estimating the actual effects on housing availability within a community becomes challenging. Specifically, because housing availability is now codependent on the distribution of sensitive facilities and on offender distributions, expected outcomes are neither obvious nor intuitive. Third, this matrix of local restrictions can be complicated further by the influence of geographically proximate communities and their associated residence restrictions, particularly if no effort is made to coordinate policies across jurisdictions. For example, if SRZs spill over into adjacent communities, some offenders may be considered noncompliant by one community but compliant by the other. In a similar vein, repercussions are likely to emerge when one community is aggressively enforcing offender residency restrictions and their neighboring communities are not. This situation can result in an emergence of offender clusters. Finally, the affordability of available housing must be considered in communities that have enacted sex offender laws. As noted previously, all communities have unique morphological characteristics and have varied spatial distributions of sensitive facilities and available housing. Therefore, the ways in which these characteristics interact are important to consider when evaluating housing availability and affordability associated with sex offender laws.

[9] Arizona State Senate Bill 1338. 2005.

[10] Arizona State Senate. Amendment to H.B. 2332. 2005.

Geographical Regulations

This section provides a brief review of the geographic characteristics of sex offender laws in the United States. More importantly, these spatial approaches to sex offender management are set within the historical context of related socially unacceptable practices.

Socially Unacceptable Practices

The United States has a long history of legislative approaches to regulating the spatial distribution of undesirable facilities, socially unacceptable practices, and their negative externalities. Moreover, the use of such laws and restrictions are by no means limited to convicted sex offender residency issues. For example, Ryder (2004) noted that adult entertainment or "vice" districts exist in virtually every major city in the United States, from San Francisco (for example, the Tenderloin), to Philadelphia (for example, South Columbus Boulevard.), to Portland, Oregon (for example, Lower Burnside). These districts are often home to businesses that sell pornographic materials and provide topless entertainment (Papayanis, 2000). In many of these districts, drug dealing and prostitution are not uncommon (Cameron, 2004; Ryder, 2004). In other instances, adult-oriented districts may give way to smaller urban locales/nodes that serve a specific social purpose but are often deemed socially undesirable. For example, group rehabilitation homes for recovering drug addicts or sex offenders can be viewed as objectionable facilities within a community.

Although these undesirable districts and facilities may, in some cases, be transient, the approaches used to regulate their distributions are fairly standard. In fact, the strategies employed are nearly identical to the residence restriction ordinances implemented in many communities for sex offenders. Seattle, for example, had zoning laws that prohibited group homes from being located within 1,320 feet of each other (Mac Donald, 1994). In effect, this is a dispersion ordinance that seeks to maintain a prespecified distance between facilities. Moreover, regardless of the population being served (for example, drug addicts, victims of domestic abuse), this type of approach is undeniably a geographic-based management tool. In a slightly different context, there has been a relatively long history of communities attempting to control the operation and location of adult video stores, strip clubs, and pornographic movie theaters. Again, these laws often ban the operation of these businesses from within a prespecified distance of schools and churches (Cameron, 2004; Papayanis, 2000). In effect, these ordinances demarcate SRZs, much like those used to manage sex offender populations throughout the United States.

The constitutionality of these types of spatial restrictions on undesirable facilities was upheld by the Supreme Court in 1976 (Papayanis, 2000). The legislation in question was the city of Detroit's "Anti-Skid Row Ordinance," which was developed to deter the local, negative externalities generated by the concentration of adult bookstores and movie theaters. As Finkelman (2006: 1808) notes:

> [e]stablishments exhibiting material depicting specific sexual activities or 'anatomical areas' as outlined by the ordinances could not be located within 500 feet of a residential area or 1,000 feet of two other regulated uses that included such business as bars, pawnshops, pool halls and shoeshine parlors.

The written opinion by the Supreme Court found that Detroit's Anti-Skid Row Ordinance and its associated spatial restrictions were acceptable land use tools for managing the spatial distributions of these businesses and preserving the quality of Detroit's residential neighborhoods (Finkelman, 2006).

The historical use and application of geographic regulations across a range of social contexts is significant for sex offender residency laws for several reasons. First, it effectively set a precedence for spatially separating problematic establishments and practices from residential areas and each other. Second, these types of management approaches are community specific. In other words, after the constitutionality of these approaches was established, local community standards could be used to determine how rigorous the geographic restrictions could be. For example, while Detroit determined that 500 feet from residential areas and 1,000 feet from other regulated business was sufficient for restrictions, other communities could stipulate larger (or smaller) distances if necessary. These two elements of geographic regulation play an important role in residence restrictions for sex offenders, the specifics of which are detailed in the subsections that follow.

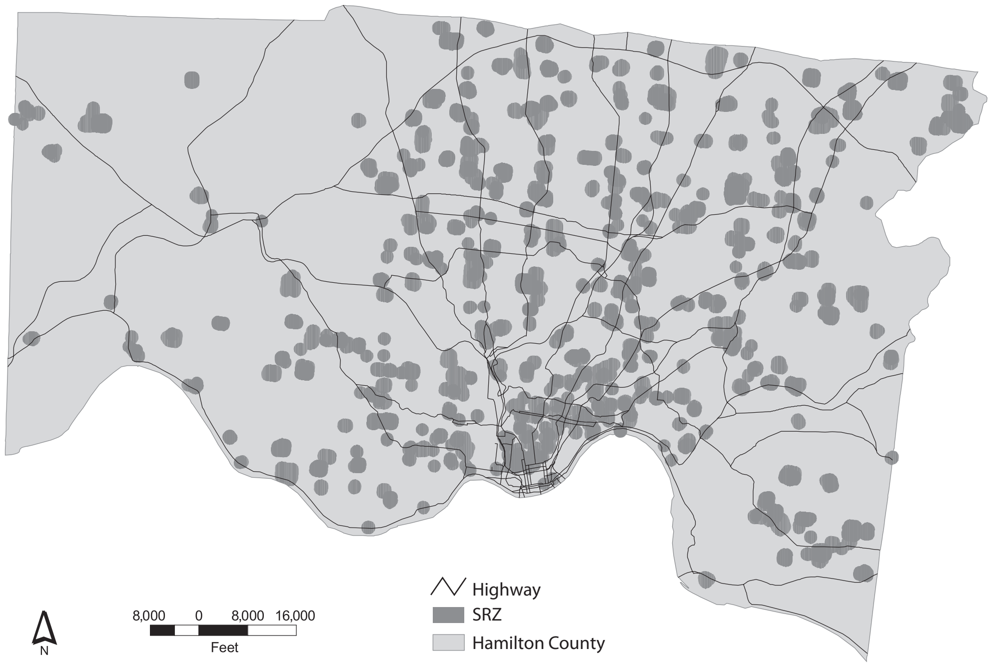
Sex Offender Residence Restrictions

As noted in the introduction, convicted sex offender residence restrictions vary substantially among states. Residence restrictions for sex offenders are very similar to the ordinances detailed in the Socially Unacceptable Practices section for geographically regulating establishments providing socially unacceptable practices. In essence, both types of restrictions seek to physically separate potentially problematic individuals or activities from sensitive facilities or areas within a community. Further, depending on community standards, the severity of these restrictions can vary. For example, California requires that offenders establish a permanent residence at least 2,000 feet away from schools or parks, whereas convicted offenders in Ohio must establish a residence at least 1,000 feet away from schools or daycare centers.

Although both geographic and contextual differences exist, the manifestation of SRZs in communities throughout the United States is quite similar. For example, consider the 1,000-foot restriction in Hamilton County, Ohio (exhibit 1). Each SRZ is based on a single parcel, or group of parcels, that correspond to school-owned property in Hamilton County. This includes both public and private schools for the county. As noted by Grubesic, Murray, and Mack (2007), the use of parcel data is critical for establishing SRZs. Specifically, if schools are represented as a single point for establishing SRZs, one would effectively ignore the presence of parking lots, athletic fields, and other school-affiliated grounds where sensitive populations (for example, children) congregate. As a result, parcel data are critical for both establishing SRZs and estimating their effects in a community. The interpretation of exhibit 1 is relatively simple: according to Ohio state law, areas shaded in dark gray are effectively off limits to offenders for establishing a permanent residence. Exhibit 2 provides a larger scale snapshot of how SRZs are structured locally. In this case, residential parcels colored dark gray are still available to offenders, but those colored light gray are not because some, or all, of the parcel is within 1,000 feet of one or more of the three school parcels, highlighted in black. As noted by Murray and Grubesic (in press), there are alternative approaches for delineating the specific geometries associated with SRZs and the parcels identified as off limits. For example, instead of using an intersection rule for identifying parcels, one might denote restricted parcels based on centroids within an SRZ, a parcel's furthest edge, or some combination of geographic

Exhibit 1

Regional Effects of SRZs: Hamilton County, Ohio (SRZ = 1,000 ft.)



SRZ = spatial restriction zone.

criteria. Regardless, exhibit 2 illustrates how SRZs manifest in most urban areas. Clearly, available housing is reduced, but as noted by Grubesic, Murray, and Mack (2007), more than 236,000 housing units, or roughly 63 percent of the total, remained available when the 1,000-foot SRZ is imposed in Hamilton County. This study also found that approximately 50 percent of all available rental units in Hamilton County are located outside the defined SRZs. Again, housing availability is diminished, but substantial housing options remain in Hamilton County for convicted offenders.

The residence restrictions detailed in this section represent the simplest strategy for geographically managing convicted offenders. In the next section, more punitive hybrid strategies for managing offenders are reviewed. Although similarities exist between hybrid approaches, SRZs, and the geographic management of socially unacceptable practices, a new layer of geographic complexity is introduced when dealing with hybrid restrictions.

Hybrid Residence Restrictions and SRZs: A Codependency

As discussed in the Local Laws section, hybrid residence restrictions implemented at the local level in the United States are growing in popularity. Hybrid restrictions typically make use of standard SRZs (for example, 1,000 feet from a sensitive facility), but also include some other geographic criteria to help manage offender distributions. For example, dispersion ordinances require that offenders establish a permanent residence outside of the standard SRZ, but also require that offenders maintain a prespecified distance between each other (for example, 1,320 feet). This type

Exhibit 2

Local Geographic Effects of SRZs

SRZ = spatial restriction zone.

of strategy is designed to minimize offender clustering within a community. Saturation statutes are structured in a similar fashion. Standard SRZs remain in effect, but the density and/or proportion of offenders are included as a secondary criterion. For example, a saturation statute may dictate that only 10 percent of residential units within a multifamily complex can be inhabited by offenders. Or, as structured in Brookhaven Town, New York, no more than two offenders may live in a single-family residence.

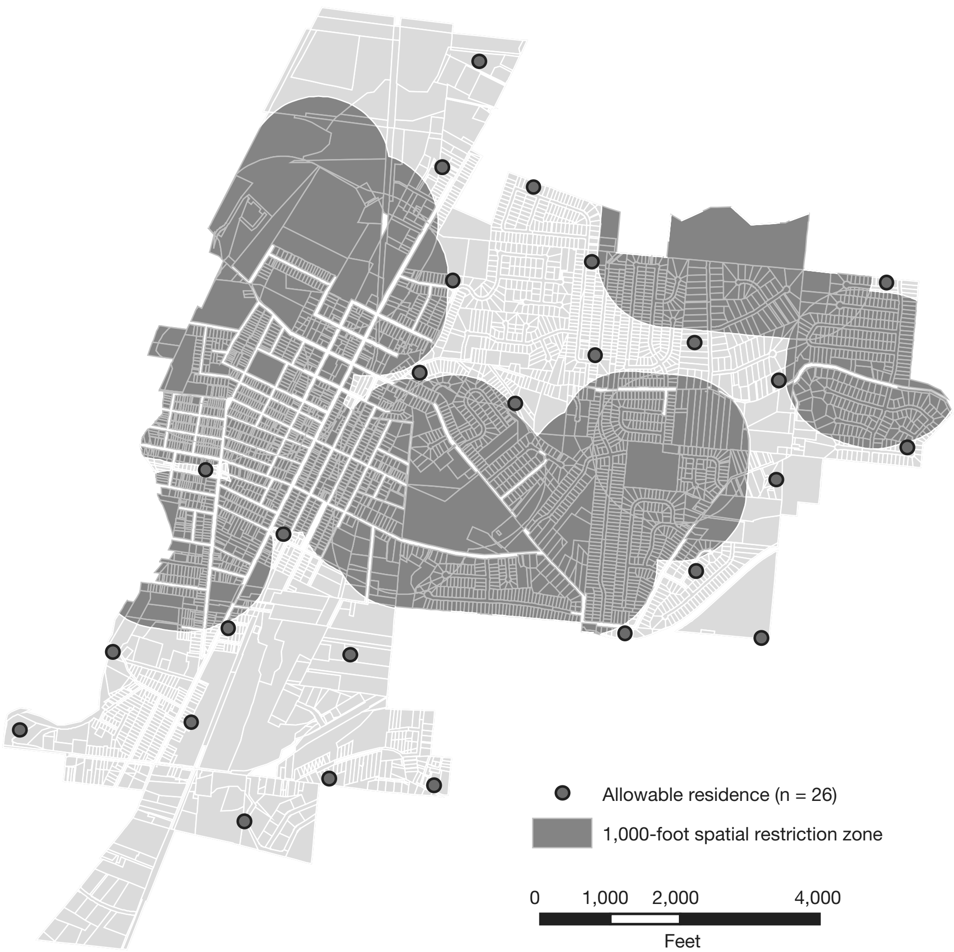
The effects of these hybrid residence restrictions are significantly more challenging to estimate because housing availability, as an example, is suddenly codependent on the distribution of sensitive facilities and on offenders. Consider the example drawn from Grubesic and Murray (2008) for Reading, Ohio. The goal of the Reading case study was to determine how the state-level 1,000-foot residence restrictions would interact with a supplemental dispersion ordinance of 1,320 feet between offenders. Specifically, Grubesic and Murray designed a mathematical programming model to determine how many sex offenders could reside in Reading while maintaining the stipulated spatial restrictions between offenders.[11] The results suggested that Reading could accommodate 26 offenders while

[11] See appendix for a full description of this model.

maintaining the criteria outlined by the hybrid strategy (exhibit 3).[12] Such an approach provides a benchmark to evaluate contingencies associated with implementing hybrid restriction strategies; one that can be used to compare existing distributions of offenders with other possible arrangement. This case study also highlights the awkward codependency between SRZs and hybrid strategies and their joint impacts on housing availability for offenders. Not only are offenders required to maintain an awareness of what housing stock is available outside the SRZ, they must also be cognizant of where other offenders have established a permanent residence in an effort to adhere to the hybrid restriction(s) that may be in place. Clearly, without advanced analytical and modeling approaches combined with detailed spatial information, the contingencies of these hybrid strategies are difficult to identify, especially for offenders, landlords, law enforcement agencies, and corrections officials.

Exhibit 3

Maximal Residency Distribution, Reading, Ohio



Source: Grubesic and Murray (2008)

[12] At the time of the analysis, Reading was home to 12 convicted sex offenders.

Given the number of potential variations for residence restrictions and their geographic ramifications, issues associated with policy coordination become more important. In particular, while residence restrictions are contingent upon local community standards, communities do not exist in isolation. As a result, locales with strikingly different approaches to managing sex offenders that are geographically proximal to each other may create some unexpected outcomes, particularly where the spatial distribution of offenders is concerned. These issues are explored in the next section.

Cross-Jurisdictional Coordination

Perhaps the greatest challenge in developing and implementing sex offender residence restrictions is coordinating ordinances and statutes between political jurisdictions. As noted earlier, although many states have established residence restrictions, these laws largely function as a minimum requirement. For example, Florida mandates that convicted offenders cannot establish a permanent residence within 1,000 feet of a school, playground, park, daycare center, designated school bus stop, or other places children regularly congregate, but counties and municipalities throughout the state have passed more restrictive legislation. Volusia County, Florida, provides an excellent example (exhibit 4). As of 2007, Volusia County (which has a population of 496,575) completely contained the Deltona–Daytona Beach–Ormond Beach metropolitan area, the 101st largest by population in the United States (Census, 2007). Volusia County has 16 incorporated cities and towns and nearly 70 unincorporated areas. Within the county, 8 different incorporated cities and towns have residence restrictions of 2,500 feet.[13] Oak Hill, Florida, maintains a 1,500-foot restriction. Matters are further complicated by DeBary, Flagler Beach, Orange City, and Ormond Beach, all of which added libraries and churches to the list of sensitive facilities. Finally, Holly Hill, Florida, also stipulates that the restricted area is enforceable outside its city limits.

This patchwork of sex offender laws has significant implications. Consider, for example, how these laws manifest geographically in Volusia County. In a recent report, Longa (2009) noted that 748 convicted offenders had established a permanent residence in the county. Clearly, the complex mesh of restriction distances and sensitive facilities within the county create challenges for offenders in locating suitable housing that is not in violation of local laws. To better illustrate the complexities associated with the various regulations in place in Volusia County, a parcel-level analysis was conducted.

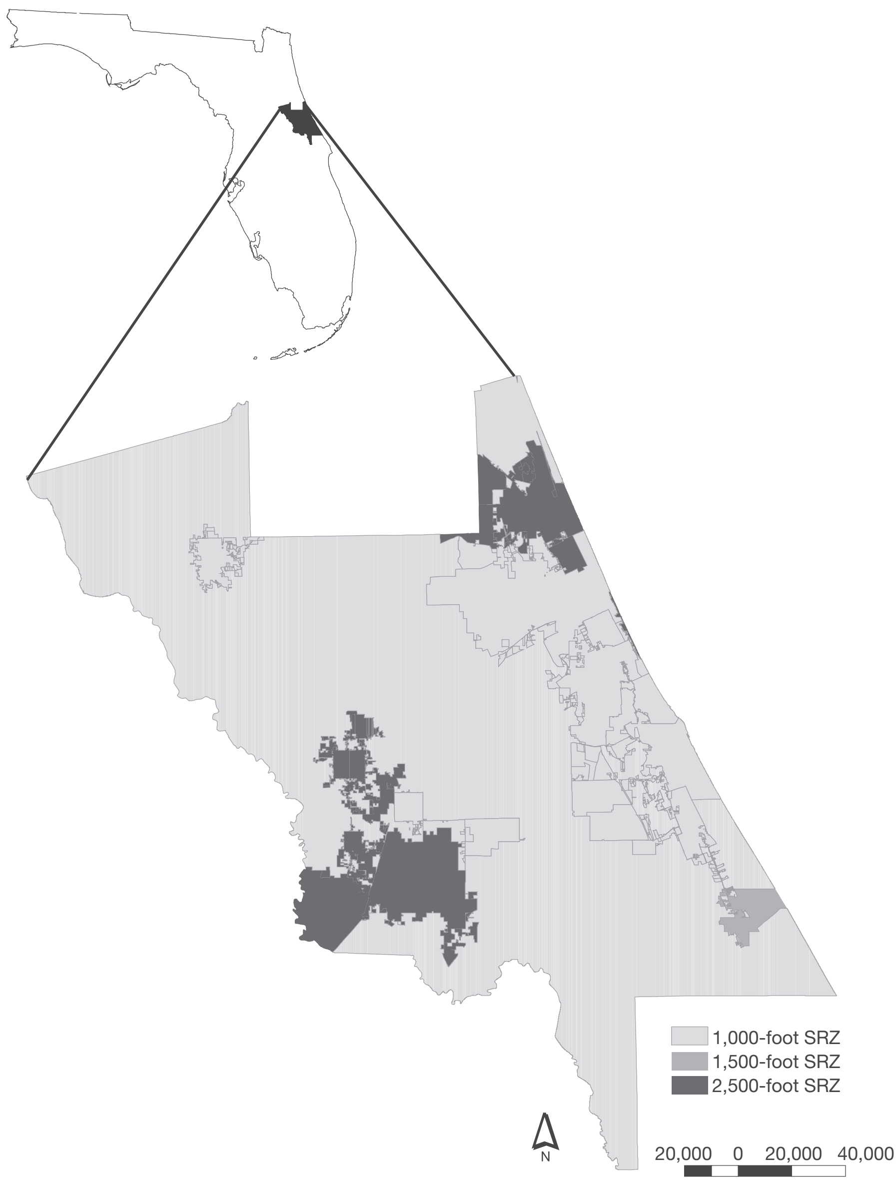
Parcel data for all schools, daycare facilities, and parks were acquired for analysis (Volusia, 2010). Parcels that correspond to libraries and churches were also acquired for communities that list these as sensitive facilities for residence restrictions. SRZs were generated for each parcel to provide a generalized map of areas designated as off limits for convicted offenders.[14] The results strongly suggest that cross-jurisdictional coordination is a concern in Volusia County. For example, exhibit 5 displays the three different residence restrictions and the associated SRZs in effect for the county. Three major points need to be made here. First, large portions of Volusia County are off limits to

[13] Daytona Beach Shores, DeBary, DeLand, Deltona, Flagler Beach, Holly Hill, Orange City, and Ormond Beach maintain a 2,500-foot SRZ.

[14] This analysis is not completely representative of areas that are off limits to offenders. School bus stops and community centers were not included in the analysis.

Exhibit 4

Volusia County, Florida, and Associated Community Residence Restrictions

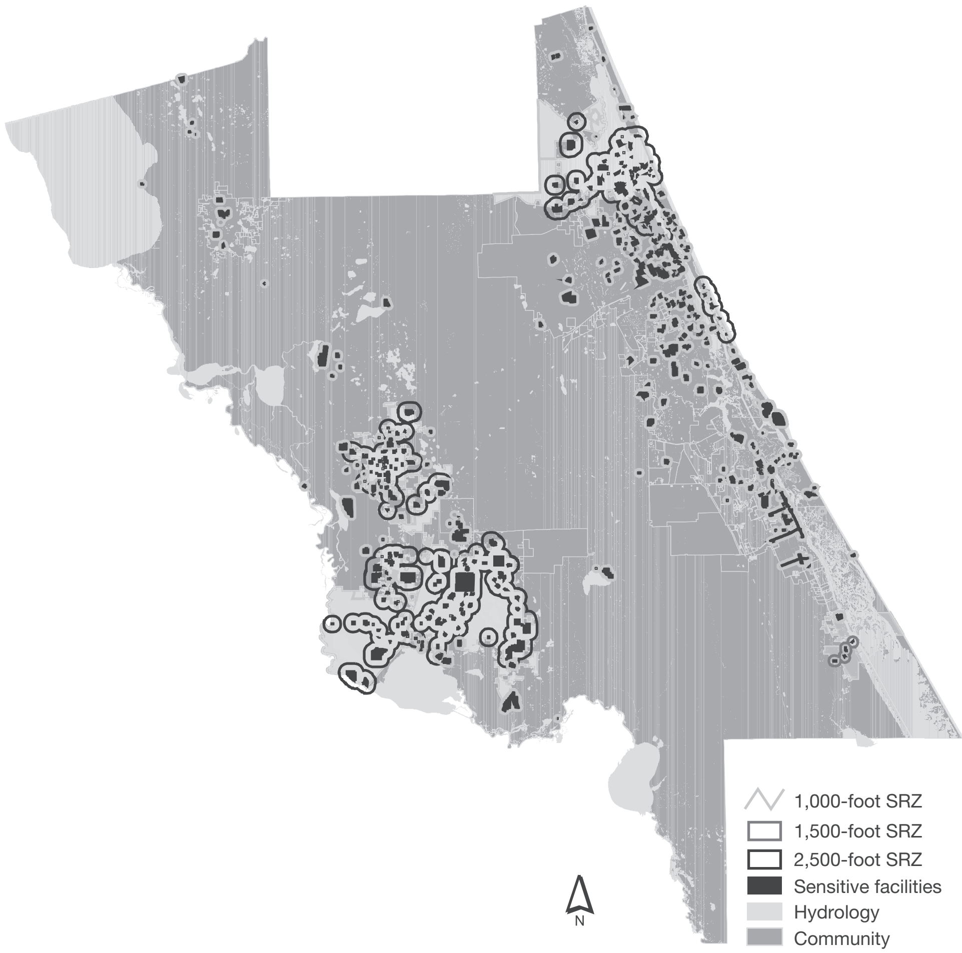


SRZ = spatial restriction zone.

convicted sex offenders. Many of the areas that are not off limits are primarily agricultural areas or protected wetlands and lakes. Second, when examining the SRZs for Holly Hill (2,500 feet), the community that stipulates its SRZs are enforceable beyond its municipal boundaries, it becomes increasingly clear that both housing selection for convicted offenders and the implementation of

Exhibit 5

Geographic Manifestation of SRZs in Volusia County, Florida



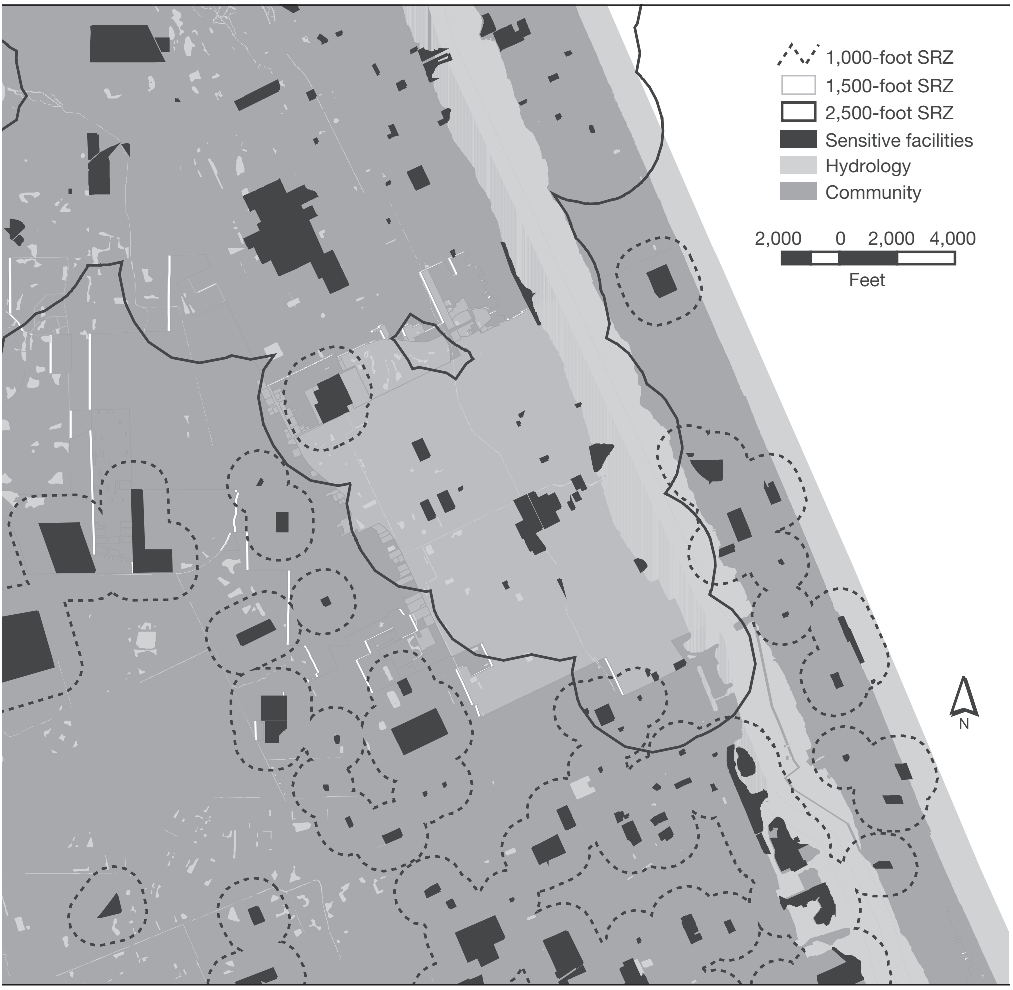
SRZ = spatial restriction zone.

residence restrictions for law enforcement agencies are exceedingly difficult (exhibit 6). Not only do Holly Hill's SRZs clearly spill over into neighboring communities, but neighboring communities that adhere to the baseline SRZ implemented by Florida (1,000 feet) are now subject to Holly Hill residence restrictions. Third, only small portions of Holly Hill that are without sensitive facilities are available for sex offenders to establish a permanent residence. Only a fraction of this area, however, is zoned residential. Of course, this patchwork of restrictions is associated with a single county in Florida. Considering that the state has nearly 130 unique residence restrictions implemented by counties and municipalities (Killian, 2008), understanding effects and implications is not easy.

Clearly, the lack of cross-jurisdictional coordination can be problematic both locally and regionally. The inability to unambiguously demarcate what housing units are available or unavailable to convicted offenders is one issue. Moreover, poor communication between communities also

Exhibit 6

Local Manifestation of Spatial Restriction Zones in Volusia County, Florida



SRZ = spatial restriction zone.

jeopardizes the ability for law enforcement agencies and corrections officials to monitor offenders. In the next section, we illustrate one significant outcome associated with the patchwork of offender restrictions and poor cross-jurisdictional coordination—sex offender clusters.

Offender Clusters

One of the collateral consequences of the seemingly haphazard landscape of residence restrictions is the emergence of sex offender clusters. Although much of the existing discourse regarding offender clusters is largely anecdotal (Gonnerman, 2007; Maloney, 2006), the general consensus is that communities with a higher geographic concentration of convicted sex offenders may be exposed to an inordinate share of recidivistic risk. Such clusters are, in many cases, the byproduct of varied local laws. Grubesic (2010) provided a methodological framework for statistically evaluating offender concentrations, identifying several significant clusters of convicted offenders in Illinois. One important component to this analysis that directly relates to the problems with cross-jurisdictional coordination highlighted in the Volusia County case study is the movement of offenders from communities with rigorous sex offender laws into unincorporated or politically weak jurisdictions that do not have the ability to pass more stringent sex offender laws or do not have the ability to use human resources (for example, law enforcement) to manage offender populations effectively. As noted by Grubesic (2010), the Palace Mobile Home Park in the unincorporated community of Lealman, Florida (Pinellas County), is an example of this problem. Because it is located 2,100 feet away from the nearest school and has not passed more stringent restrictions than the state of Florida (1,000 feet), it exhibits a very high concentration of offenders. In fact, nearly 50 percent of its 200 residents are convicted offenders (Raghunathan, 2007). A similar situation existed underneath the Julia Tuttle Causeway in Miami, where severe residence restrictions in Dade County forced many convicted offenders to establish a tent community (Zarrella and Oppmann, 2007).

One final aspect of sex offender clusters relates to the locations of sex offender rehabilitation programs in a community. In many states, the social and psychological services that paroled offenders are required to receive are found in a very limited number of locales. For example, in Ohio, there are only three designated halfway homes for convicted offenders: one in Cincinnati, one in Mansfield, and one in Lebanon (Handwerk and Ali, 2009). Although a handful of other options are available in special circumstances, these alternative facilities review offenders on a case-by-case basis and have the right to reject offender participation.

Given a relatively limited distribution of rehabilitation facilities in Ohio and elsewhere, it is hardly surprising that many offenders concentrate in areas near rehabilitation services. As noted by Grubesic (2010), the Humboldt Park neighborhood in Chicago was identified as an offender cluster, but it is also home to the largest sex offender counseling service and rehabilitation facility in the state of Illinois. Simply put, one driving force behind this cluster of offenders appears to be related to access of court-mandated rehabilitation programs.

Given the results illustrated in the Geographical Regulations section and the Cross-Jurisdictional Coordination section, it is clear that residence restrictions for convicted offenders and housing availability in communities are closely intertwined. Many intricacies are associated with residence restrictions and hybrids that need to be considered when evaluating their potential social, economic, and geographic effects. Housing is a major concern, but so are issues associated with cross-jurisdictional planning for the geographic outcomes associated with sex offender laws and access to state, metropolitan area, or local community services. In the next section, we pull together all of these threads and illustrate how sex offender laws, urban morphology, and housing interact. Although the interactions are both complex and community specific, the next section further illustrates why spatial analysis is critical to better understanding the ramifications of sex offender laws and related public policies.

Urban Morphology and Housing Availability and Affordability

One final aspect of sex offender laws and the effect of their geographic manifestations concerns the morphological structure of communities where residence restrictions are imposed. Broadly defined, urban morphology refers to the "study of the city as human habitat" (Moudon, 1997: 3). Because communities are spatially and temporally dynamic, with their buildings, streets, parks, and monuments changing through time, communities represent an accumulation of many individual and collective actions; all of which are governed by social, economic, political, and geographic forces. As a result, housing availability and affordability in a community reflect a long history of urban development and governance, influenced by a wide variety of geopolitical and geoeconomic forces.

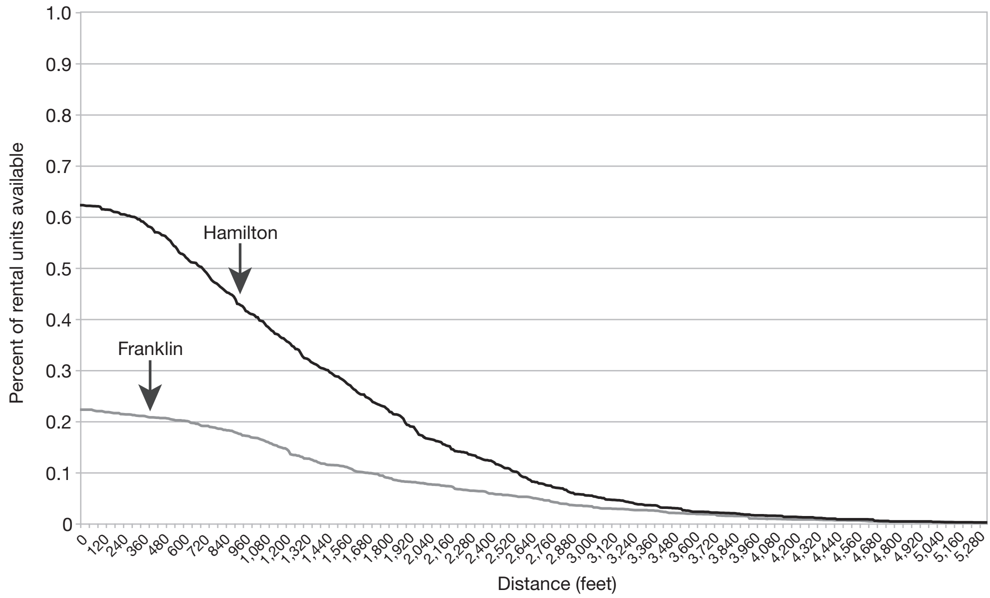
With this history in mind, the somewhat generic and arbitrary residence restrictions for convicted sex offenders, which state legislatures ratify, may be problematic. As noted previously, restriction distances range from 500 feet in Illinois to 2,000 feet in California. What remains unclear is why these particular distance restrictions are imposed. Are these restriction distances based on the morphological structures of these communities? If so, how is the distribution of sensitive facilities and populations different in Illinois when compared with California, which has more aggressive statewide restrictions? These questions have no obvious answers, but better ways of framing these policy changes exist. First, a positive aspect of uniform restriction distances is that they provide law enforcement agencies and corrections departments a regularized framework for managing convicted sex offenders. Second, by reducing variations in residence restrictions, uniformity provides offenders with an easily understood target restriction distance during their search for permanent housing. A weakness of this approach is that the one-size-fits-all strategy can create spatial inequities. Because each community has a unique distribution of housing, rents, and sensitive facilities, generic residence restrictions may predispose certain communities to a disproportionately higher number of convicted sex offenders (Grubesic and Murray, 2008) establishing a permanent residence. As noted earlier in this article, the formation of sex offender clusters is fueled by a combination of generic policies and poor cross-jurisdictional coordination.

A comparative analysis of Franklin and Hamilton Counties in Ohio reveals the effects of urban morphology on housing availability and affordability (Grubesic, Matisziw, and Murray, 2010) and demonstrates the need for considering the unique morphology of places when implementing various spatial restriction zones in communities. Using a Geographic Information System-based (GIS-based) approach for evaluating the geographic implications of different restriction distances for sensitive facilities across a suite of rental cost thresholds produced a number of interesting results.[15] For example, exhibits 7a through 7d highlight variations in the availability and affordability of housing across four average monthly rent thresholds for each county. In this instance, the percentage of rental units potentially available (0 to 100 percent) within the county is summarized on the *y*-axis, and the variations in restriction distances (0 to 5,280 feet, in 10-foot increments) is summarized on the *x*-axis. Exhibit 7a suggests that, with rent levels at $500 or less, Hamilton

[15] In Franklin and Hamilton Counties, 98.5 percent of all elementary and secondary schools were used in this analysis. Data were missing largely because of incorrect addresses in the Ohio State Department of Education databases or indeterminate errors associated with the geographic base files used for analysis.

Exhibit 7a

Housing Availability at Different Contract Median Rent Levels With Varying Restriction Distances in Franklin and Hamilton, Ohio: $500 and Below



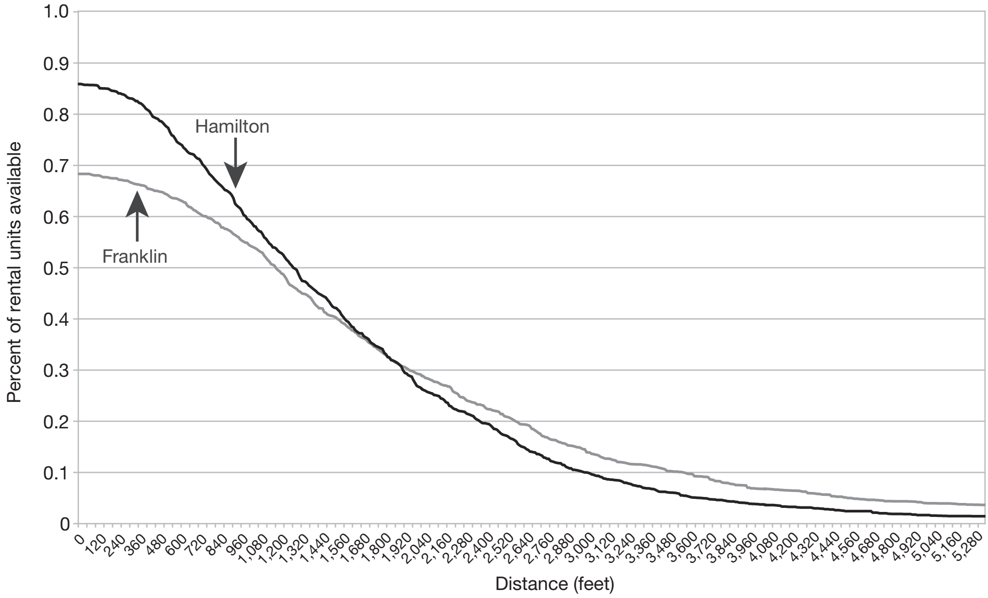
Source: Grubesic, Matisziw, and Murray (2010)

County always displays a higher percentage of housing availability than Franklin County, regardless of the restriction distances used. When the average rent threshold is set to $650 or less, however, Hamilton County has a higher percentage of units available up to 1,900 feet from sensitive facilities. Beyond this restriction distance, Franklin County has a higher percentage of its housing available.

These results are important for several reasons. First, a one-size-fits-all strategy to restrict the residency of convicted offenders ignores the community-specific impacts of these policies. In fact, the effects of residency restrictions are highly variable because of the heterogeneous nature of community morphologies (for example, distributions of sensitive facilities, rental housing, and average rents). Franklin and Hamilton Counties provide an example of this variability; each county displays a different level of housing availability across average rent thresholds and restriction distances. Second, these results suggest that the ability to balance residence restriction parameters with the goal of ensuring the availability of affordable housing for convicted sex offenders requires significant analytical exploration. Specifically, if communities are too aggressive in defining residence restrictions, all housing options for offenders may be eliminated and encourage offenders to abscond or live in violation of local regulations. If communities are too lenient, they may increase the recidivistic risk for sensitive populations. Therefore, although a generic, state-mandated SRZ is convenient, restriction ordinances tailored to community characteristics and needs will likely be more effective. To achieve the delicate balance of protecting vulnerable populations while ensuring the availability of suitable housing for offenders, these policies require empirical evaluation before

Exhibit 7b

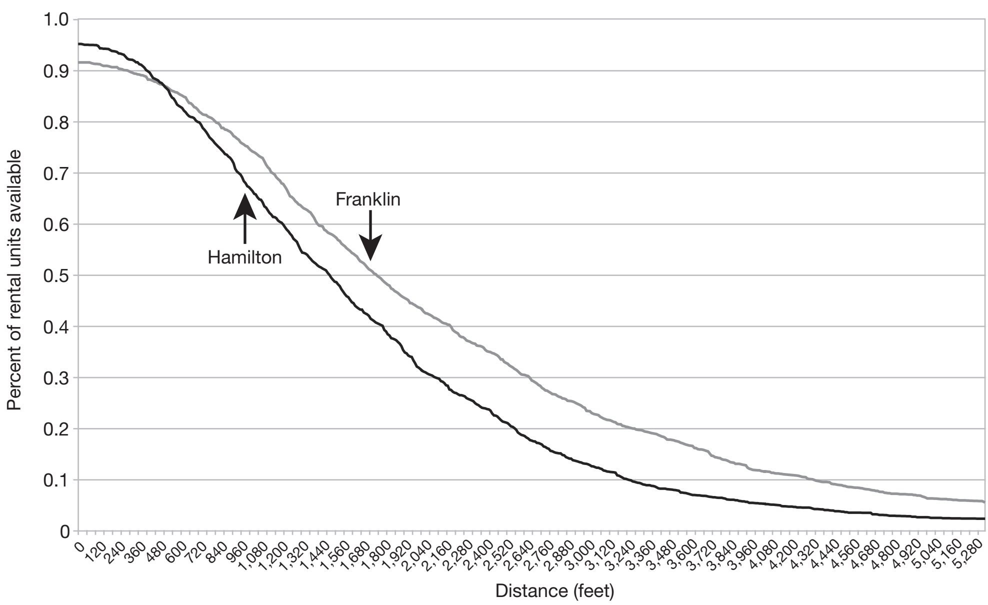
Housing Availability at Different Contract Median Rent Levels With Varying Restriction Distances in Franklin and Hamilton, Ohio: $650 and Below



Source: Grubesic, Matisziw, and Murray (2010)

Exhibit 7c

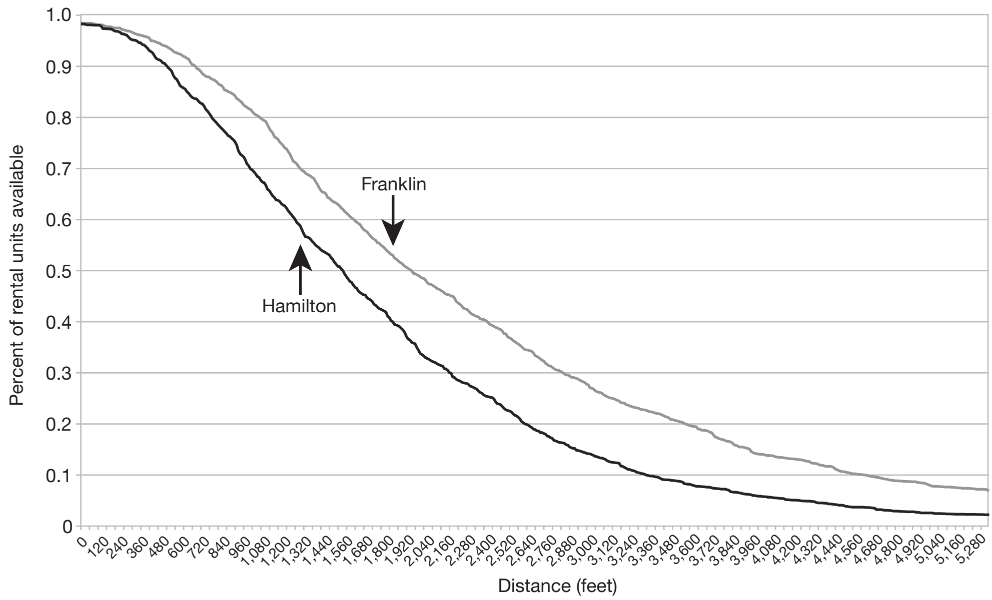
Housing Availability at Different Contract Median Rent Levels With Varying Restriction Distances in Franklin and Hamilton, Ohio: $800 and Below



Source: Grubesic, Matisziw, and Murray (2010)

Exhibit 7d

Housing Availability at Different Contract Median Rent Levels With Varying Restriction Distances in Franklin and Hamilton, Ohio: $1,000 and Below



Source: Grubesic, Matisziw, and Murray (2010)

their implementation. Research on this topic thus far clearly suggests that objective evaluations of these policies are an important first-step in developing reasonable and actionable public policies for managing convicted offenders.

Discussion and Conclusion

Given the variation in sex offender laws in the United States, regulating offenders will continue to challenge federal, state, and local officials for many years to come. This article provided a review of community notification laws, the modern genesis of sex offender management, and the history of regulation of socially unacceptable practices. The review of sex offender laws and regulations highlighted both the geographical implications and the jurisdictional issues confronting policymakers and law enforcement officials now and in the future. The discussion of the effect of urban morphology on housing availability and affordability for offenders clearly illustrated the need for place-specific policies and the need for objective evaluations of policies before their implementation.

This review also suggested three major themes worthy of further discussion. First, implementing residence restrictions is unlikely to abate in the United States, regardless of their controversial nature and likely inefficacy. Currently, these laws receive too much public and legislative support in state and local communities to make their removal realistic (Mancini et al., 2010; Schiavone and

Jeglic, 2008). In fact, not only are these restrictions more popular than ever, recent evidence suggests that these laws are becoming increasingly punitive (Mack and Grubesic, 2010), often morphing into hybrid restrictions such as dispersion ordinances and saturation statutes (Grubesic, 2010).

Second, although residence restrictions and their associated SRZs are relatively simple in structure, they are implemented in highly complex community systems. As a result, the outcomes of sex offender laws, both locally and regionally, can be unexpected and challenging to predict without detailed analysis. For example, the haphazard landscape of residence restrictions and poor cross-jurisdictional coordination in Florida has created a highly confusing environment for both law enforcement officials and convicted sex offenders. It is extremely difficult to determine where one set of residence restrictions ends and another begins. In addition, a number of precarious housing outcomes result from these applications of sex offender policies, including the unintended development of sex offender clusters in unincorporated areas or along the margins of SRZs in urban areas. These types of outcomes can be avoided, but a significant amount of spatial analytical work is required to help evaluate the contingencies associated with these public policies before their implementation.

A third important point is that the one-size-fits-all management approach employed by many states is likely problematic and may not be consistent with local needs and objectives. It has already been established that communities and regions that deviate from this approach, including Florida, create a chaotic landscape of housing availability for convicted offenders. Almost no effort is made, however, to coordinate variations in local residence restrictions between jurisdictions. Further, because the morphology of each community is different, empirically based decisionmaking should be more widely used when modifying state-mandated SRZs to better fit local community standards.

Where does this leave sex offender policies? Certainly, the interaction between urban morphology and housing is very complicated and highly variable. Also, the collateral consequences associated with these policies clearly call for a more balanced approach to ensuring community safety while also ensuring a socially supportive environment for offenders, where housing and rehabilitation needs are met. Although the historical approach of proposing laws and regulations without fully understanding and exploring their implications is problematic, the evaluation of their implications is also no easy task. Given these challenges, there exists a clear need to explore new analytical methods including GIS, statistical tests, and mathematical models in the evaluation stages of these policies. More detailed spatial information for use in these analyses is also needed, so that more effective policies can be formulated in the future.

Appendix

In the model used for Reading, Ohio, geographic requirements stipulated areas where convicted sex offenders were not permitted to reside (that is, residence restrictions) and minimal separation between offenders (that is, dispersion). The model produced ensured that no violations of the separation requirements occur, providing important information to corrections officials and policymakers for benchmarking the number of offenders that could potentially reside in a region, under the proposed restrictions. This model is structured as follows:

k = index of potential residences for convicted sex offenders.

$\boldsymbol{\Gamma}$ = minimum geographic separation between offender residences.

$\boldsymbol{\Phi}_k$ = potential residences within stipulated separation $\boldsymbol{\Gamma}$ of residence k.

$$Z_k = \begin{cases} 1 \text{ if a convicted sex offender resides at } k \\ 0 \text{ otherwise} \end{cases}$$

Maximize $$\sum_k Z_k \qquad (2)$$

Subject to $$Z_k + Z_l \leq 1 \qquad \forall k, l \in \Phi_k \qquad (3)$$

$$Z_k = \{0,1\} \qquad \forall k \qquad (4)$$

Again, this model can be used to benchmark the number of convicted offenders that could potentially reside in a region, as well as where they could reside, while simultaneously ensuring that separation restrictions are maintained. The objective (2) maximizes the number of offenders residing in a region. Constraints (3) ensure that no two selected residences are within the separation requirement. This is based on $\boldsymbol{\Gamma}$ that defines the set $\boldsymbol{\Phi}_k$, and is established by a community or local law enforcement agency. Integer restrictions are imposed in constraints (4).

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The Coaction of Neighborhood and Individual Effects on Juvenile Recidivism

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Abstract

Ecological approaches to explaining juvenile delinquency emphasize the importance of spatial influences on patterns of delinquency. Studies of recidivism among juvenile offenders, on the other hand, have rarely taken neighborhood influences into account. Moreover, conventional statistical approaches adapted for investigating spatial neighborhood effects, such as hierarchical linear modeling (HLM), are typically subject to assumptions regarding the nature of the spatial relationships under investigation that may, in fact, mask relevant neighborhood influences on individual outcomes. The study discussed in this article applied geographic analysis to the analysis of adjudicated juvenile delinquents assigned to court-ordered programs by the Family Court of Philadelphia, Pennsylvania. We examined the simultaneous effects of neighborhood and individual (including family) characteristics on juvenile recidivism using local spatial clustering of probabilities of re-offending. Geographic Information Systems provided the technology to integrate diverse spatial data sets, quantify spatial relationships, and visualize the results of spatial analysis. In the context of juvenile recidivism, this approach provided new insights on how and why recidivism rates vary from place to place. We found not only that recidivism was concentrated in specific areas of the city, but also that types of recidivism offenses were spatially concentrated. Importantly, the findings also show that predictors of reoffense vary from place to place.

Introduction

Criminologists, sociologists, geographers, and psychologists have long known that the environment in which an individual lives shapes behavior patterns, attitudes and preferences, and interpretations of the behaviors of others. On a macrosocial scale, Shaw and McKay (1942) found that spatial patterns of crime were associated with neighborhoods occupied by recent immigrants. They theorized that families and individuals that had recently arrived in Chicago were disconnected socially, and that social disorganization prevented informal social controls from curbing antisocial behavior. More recent research supports the conclusion that opportunities to engage in delinquency are greater in neighborhoods with weak social organization and little in the way of social controls (Sampson and Groves, 1989).

Bronfenbrenner's ecological systems theory (1981) also underscored the value of the external social and physical habitat in which an individual lives. His theory outlines four nested systems that surround individuals, beginning with the most proximate, the microsystem (for example, the family), and ranging out to the macrosystem, or the larger social and cultural context of our immediate environs. Sampson (2001, 1997) argues that social disorganization is not only an attribute of macrosystems, such as cities, but also is a way of looking at microsystems. Certain characteristics of microsystems, such as families and neighborhoods characterized by frayed relationships, lack the means to inhibit deviant behavior.

A competing theoretical perspective, differential association, rests on the work of Sutherland and Cressey (1992). This perspective attributes involvement in delinquency to the influences of norms, values, and expectations of people most intimately involved in an individual's life. To the extent that the values, norms, and behavioral expectations communicated by intimates support certain deviant behaviors, the individual will adopt patterns of delinquent behavior that are not considered morally wrong. Akers (1998) extended this theory by adding a social learning component that explains the process by which deviant values and behaviors are embraced. The concept of peer contagion is another expression of this theory, but is one that has primarily evolved to explain how residential programs designed to reduce delinquency can produce adverse effects (Dishion and Dodge, 2005), although recent evidence also suggests cross-neighborhood peer contagion effects in delinquency and recidivism (Mennis et al., 2011).

Although these spatial perspectives speak to the environments in which individuals reside or in which they carry on routine activities, none of them speak to the concept of place. Place-based analyses regard places as distinct entities that tell their own stories. Visual representations and spatial clustering of target variables across a geographically defined area can produce information not otherwise observable and facilitate the development of complex and useful research questions. These questions can then be tested with both qualitative and quantitative social science methods.

It is also worth noting that examinations of recidivism differ in a critical way from research on delinquency. When studying delinquency, researchers begin with the general population of youths and predict which youths will become delinquent. Studies of recidivism, such as this one, begin with known delinquents and seek to differentiate persistent from short-term delinquents. Many of the factors known to predict delinquency may have already been accounted for in the selection of this offender population; thus, correlates of delinquency may not be relevant to predicting further offending among known delinquents.

A number of studies have identified individual-level predictors of recidivism. These factors include criminal history, age at first arrest, substance abuse, and education (Elliot, Huizinga, and Ageton, 1985; Farrington and Hawkins, 1991; Frederick, 1999; Snyder and Sickmund, 2006; Yoshikawa, 1994). In addition, current age, negative peer relations, family problems, emotional distress, and previous treatment facility placement have been identified as individual-level attributes that increase the risk of juvenile recidivism (Baird, 1984; Marczyk et al., 2003; Snyder and Sickmund, 2006; Wiebush et al., 1995).

Studies examining the effects of neighborhood-level variables on rates of juvenile recidivism, however, are less common. Kubrin and Stewart (2006: 167) noted that "we know very little about how the ecological characteristics of communities influence the recidivism rates of this population." Previous research on recidivism is largely framed in terms of program evaluation, a literature that rarely acknowledges neighborhood context. Several meta-analyses of juvenile treatment programs have determined that the level of success and effective components of juvenile treatment differ between institutional and noninstitutional programs (Lipsey, 1999; Lipsey and Wilson, 1998). Lipsey and Wilson (1998), in their meta-analysis of 200 programs for serious and violent juvenile offenders, concluded that community-based programs garnered larger effects than did institutional programs.

The purpose of this study is to address this gap in the literature regarding neighborhood effects on juvenile recidivism. We examine this effect using a variety of methods that each contribute to a more complex and useful understanding of how place and individual characteristics interact to produce continued involvement in delinquency.

Philadelphia

Philadelphia is bounded on the east by the Delaware River and bisected by the Schuylkill River in its western environs. At the approximate time of the data collection used in this study, the city's population of approximately 1.44 million was 45 percent White, 43 percent African American, 8.5 percent Hispanic, and 4.5 percent Asian.

Philadelphia neighborhoods, even those characterized by poverty, social isolation, and crime, differ in their ability to protect their young residents from making contact with the juvenile justice system. Evidence of these differences is found in a study conducted by Jones et al. (2001), which reported that ZIP Code best predicted which first-time offenders who were expected to become chronic offenders actually went on to become chronic offenders (accruing three or more arrests). Using the Program Development and Evaluation System (ProDES) database (described in the Data section), the authors developed a risk instrument identifying the characteristics of chronic offenders at the time of their first contact with the juvenile court. Of the youths who had chronic-prone characteristics, none of the youths living in the 19144 ZIP Code (Germantown) went on to become chronic offenders. On the other hand, more youths in the 19143 (Kingsessing) ZIP Code became chronic offenders than were predicted. The authors concluded that these extreme differences were likely a result of differential access to neighborhood resources.

Fader (2003), in her study of youths in juvenile aftercare, used the ProDES data and an inventory of community-based youth serving programs. Although she found no systematic neighborhood effects, she did identify a neighborhood (North Philadelphia East–19133) in which aftercare clients were at a very high risk for unsuccessful transition back into the neighborhood. A second related finding, because it involves the same general area, is that aftercare programs were not producing the same degree of positive results for Hispanic clients as for youths of other racial groups. The youths in this study were concentrated in a specific area of the city.

Our study follows a similar line of inquiry. The two questions addressed in this article are (1) Why is recidivism more common in some neighborhoods than others? and (2) Why are certain types of reoffending (offense type) more common in some neighborhoods than others?

We employ a place-based perspective that can yield hypotheses about causes of recidivism likely overlooked in past research.

Data

Data on juvenile delinquents were acquired from the ProDES database, which was developed by the Crime and Justice Research Institute at Temple University under a contract with the city of Philadelphia. The ProDES database tracks juveniles assigned to court-ordered programs by the Family Court of Philadelphia. It was designed to evaluate all programs used by the city of Philadelphia for its delinquent youths, monitoring program outcomes from 1994 to 2004. ProDES collected data at four points in time: (1) at the point of commitment to a program, (2) at program intake, (3) at discharge from the program, and (4) 6 months after program discharge (charges for new offenses, including adult charges).

Youths were ordered to attend 1 of 26 community-based programs scattered throughout Philadelphia at the discretion of the judge. These programs include after-school programs, alternative schools, and mentoring programs that youths attend while living at home. Of the 26 programs, 14 were after-school programs that combined tutoring, group counseling, and recreational services; 3 were alternative schools; 2 combined alternative schooling with after-school activities; and 4 were classified as mentoring programs. Of these programs, 3 also provided after-school group counseling. Finally, 2 programs were classified as counseling programs; these programs, which specialized in services to sex offenders or youths with substance-abuse problems, engaged youths in individual and group therapy 3 to 5 hours a week.

The records in ProDES were geocoded based on the home address given at the point of program commitment. Of those records, we eliminated records of females from the analysis, because the literature and our own preliminary analyses suggested that the causes of female juvenile recidivism differ from those of male juvenile recidivism. We also eliminated from our analysis any period of commitment to a residential treatment program (which would thus render environmental characteristics of the juvenile's residence location moot). Youths in aftercare programs, however, were included. The data set used for the present analysis included 7,166 case records, where each record comprises a youth's characteristics and offense history at the point of adjudication as well as data on the first subsequent offense (recidivism offense), if any.

The Philadelphia Police Department also provided data for this study. These data included type and location of all crime in the city of Philadelphia from 2000 to 2002, excluding rape, and contain 321,785 crime events occurring during that 2-year period. The data were divided into eight crime types: homicide, robbery, assault, burglary, theft, vehicle theft, weapon violation, and drug crime. Of the 321,785 crime events in the police data, 299,855 were successfully geocoded, for a success rate of more than 93 percent—well above the 85-percent minimum success rate for geocoding crime data set forth by Ratcliffe (2004).

The neighborhood-level data included 2000 Census data. In addition, we used the neighborhood boundaries delineated by the Philadelphia Health Management Corporation (PHMC), which exhaustively partitions the city into 45 neighborhood polygons. The PHMC biannually surveys a sample of Philadelphia residents within each of the 45 neighborhoods and includes items related to neighborhood safety and perceptions.

We considered several outcome variables based on different recidivating offense types: drug offenses, person (violent) offenses, and property offenses. Recidivism was defined as the filing of a petition in Family Court for a new offense. Tracking of recidivism started at the point of disposition for the instant offense and ended 6 months after program discharge. Each of the three outcomes is dichotomous—whether the juvenile reoffended with an offense of that type. Of the 7,166 juveniles in the data set, 1,030 (14 percent) recidivated with a drug offense (selling or possession), 725 (10 percent) recidivated with a person offense, and 794 (11 percent) recidivated with a property offense. Recidivism with other offense types (for example, sex offenses, weapons offenses) was less common. The number of juveniles recidivating with any offense type was 2,881 (40 percent).

Four types of explanatory variables are used in this study to address the theoretical mechanisms described in the literature review: (1) background characteristics of the individual juvenile, (2) the initial offense that the juvenile committed upon entry to the Family Court system (referred to as the "instant offense"), (3) social disorganization in the neighborhood within which the juvenile resides, and (4) indicators of overall delinquency and recidivism nearby the juvenile's residence (referred to as "contagion" variables). Exhibits 1 and 2 report descriptive statistics for all the categorical and continuous predictor variables used in this study, respectively.

In keeping with the theme of this issue of *Cityscape*, this article focuses primarily on findings related to predictors of recidivism that have to do with place characteristics, as opposed to predictors related to the individual juvenile.

Exhibit 1

Descriptive Statistics for Categorical Variables (N = 7,166)

Predictor Variable	N	Percent
Race		
White	818	11
African American	5,252	73
Hispanic	943	13
Other	153	3
Public assistance	2,271	32
Parental crime	1,149	16
Prior institutional living arrangement	2,553	36
Out-of-home placement ever	545	8
Instant drug offense	1,691	24
Instant person offense	2,571	36
Instant property offense	2,280	32

Exhibit 2

Descriptive Statistics for Continuous Variables (N = 7,166)

Predictor Variable	Mean	Standard Deviation
Age (years)	15.7	1.7
Number of prior arrests	0.8	1.3
Drug sale density (per km^2)	214	316
Percent female head of household with children	20%	8%
Percent vacant housing	15%	10%
Percent high school graduate	59%	14%
Area juvenile count	183	100
Area any recidivism rate	0.40	0.68
Area drug recidivism rate	0.15	0.54
Area person recidivism rate	0.10	0.34
Area property recidivism rate	0.11	0.36

Methods

In this section, we focus on findings produced by applying hot spot analysis, hierarchical linear modeling (HLM) (Raudenbush and Bryk, 2002), logistic regression, and mapping of results, with an emphasis on the usefulness of mapping. GIS was used to integrate the individual and spatial data sets, conduct hot spot analyses, and visualize the results of logistic regression analyses that included neighborhood attributes. We conducted hot spot analysis using the locations of the residences of each youth in the sample. By differentiating youths in terms of recidivism, we revealed concentrations of recidivists. This analysis aided in the development of our research questions. HLM is form of regression analysis that is used when some data are nested in other data, such as individuals who reside in the same neighborhood. Because we can assume neighborhood characteristics affect recidivism of all the delinquent youths in the neighborhood in the same way, we need to account for these factors independently of characteristics of the individuals.

In a subsequent analysis, logistic regression was used with neighborhood and local deviant influences, measured at the individual level as a function of distance from each youth's place of residence. To aid in the interpretation of the statistical results, we also investigated local spatial clustering of probabilities using the G_i^* statistic (Getis and Ord, 1992; Ord and Getis, 1995), which measures the degree to which the observations within a specific distance from a geographic point (for example, 1 kilometer from each youth's place of residence) have values distinctly similar to, or different from, the mean for all persons in the sample.[1]

[1] Consider the spatial weights matrix $\{w_{ij(d)}\}$ such that $w_{ij(d)} = 1$ if location i is within distance d of location j, and $w_{ij(d)} = 0$ if it is not. In this study, d = 1 km, chosen as a compromise between minimizing the distance over which we hypothesize peer contagion to occur while also allowing for a sufficient number of observations to be collected for calculation of G_i^*. If $W_i^* = \sum_j w_{ij}(d)$ and $S^*_{1i} = \sum_j w_{ij}(d)$, and if $\bar{z}$ and s^2 denote the sample mean and variance, respectively, then

$$G_i^*(d) = \frac{\sum_j w_{ij}(d) z_j - w_i^* \bar{z}}{s\{[(nS^*_{1i}) - W_i^{*2}]/(n-1)\}^{1/2}}$$

Findings

Philadelphia is a city of distinct neighborhoods, although the boundaries of these neighborhoods are ambiguously defined. We can characterize these neighborhoods in a number of ways, but because we refer to the PHMC definitions in this study, the map in exhibit 3 shows these 45 neighborhoods along with their commonly used names. We use these labels in the discussions that follow.

Philadelphia is also widely known to be racially and ethnically segregated. Exhibit 4, which shows maps created by the city's Planning Commission, clearly shows that the Hispanic population is concentrated in an area within and surrounding the neighborhood of Hunting Park-Fairhill. Many of the north-center and southwestern neighborhoods have largely African-American populations. Neighborhoods with largely White populations are concentrated in the far northeast and far northwest, along the east border, and spanning two neighborhoods in South Philadelphia: Grey's Ferry-Passyunk and Eastwick-Elm. These racially and ethnically demarcated areas emerged as central to our conclusions regarding the nature of juvenile recidivism.

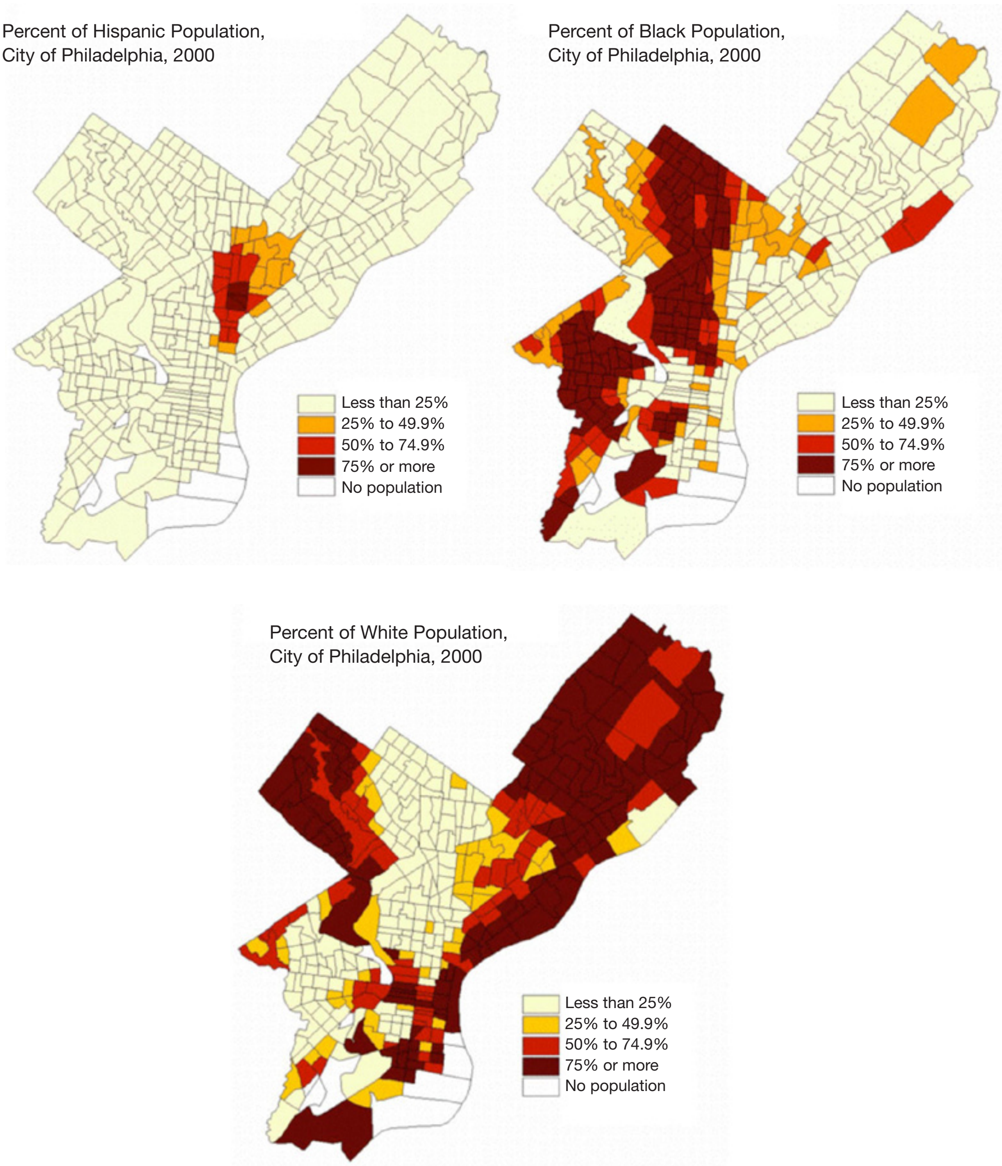
Exhibit 3

Philadelphia's Neighborhoods

Source: Philadelphia Health Management Corporation

Exhibit 4

Racial and Ethnic Segregation of Philadelphia’s Population by Census Tract



Source: Philadelphia City Planning Commission at www.philaplanning.org

As indicated by the locations of points in exhibit 5, which maps z-scores of the G_i* applied to juvenile recidivism rates, the residences of juvenile offenders are clustered geographically, with 10 percent of the total from Hunting Park, 6 percent from Paschall/Kingsessing, and about 5 percent each from Mill Creek, Nicetown/Tioga, Olney, Overbrook, and Strawberry Mansion (see exhibit 3). Furthermore, exhibit 5 shows that recidivism is also highly concentrated. For example, among delinquent youths living in the adjacent neighborhoods of Hunting Park-Fairhill, Juniata Park-Harrowgate, and Upper Kensington, recidivism rates are more than double the rate for the city as a whole.

We found the PHMC-defined neighborhoods, which were useful descriptively, to be too large to capture with sufficient granularity differences among the places where these delinquent youths were living. Consequently, much of the analysis involved tracts or local spatial clustering with the G_i* statistic, a method we used to capture the characteristics of other delinquents within a defined distance from each youth's place of residence.

In addition, we found that when recidivism was examined in terms of type of recidivism offense (person, property, or drug), patterns of recidivism were markedly more place specific. Exhibit 6 shows final models from the logistic regression analyses of individual and census tract data. Previous behavior is a strong predictor of future behavior, so the effect of number of previous arrests on recidivism was expected. Similarly, we find a positive relationship between previous institutional placement and any recidivism.

Exhibit 5

Juvenile Recidivism Hot Spots

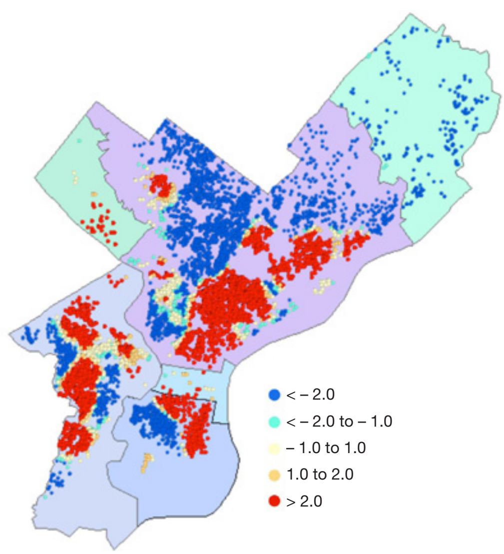


Exhibit 6

Stepwise-Forward Logistic Regression of Offense-Specific Recidivism: Final Models (N = 7,166) (1 of 2)

Predictor Variables	Recidivism	Drug Offense	Person Offense	Property Offense
Individual				
Age	—	1.13*** (24.05) C.I. 1.08–1.19	0.93*** (8.66) C.I. 0.89–0.98	—
White	0.88 (2.24) C.I. 0.74–1.04	0.66*** (8.35) C.I. 0.50–0.88	—	1.00 (0.00) C.I. 0.80–1.26
Hispanic	0.98 (0.07) C.I. 0.84–1.14	1.20 (3.35) C.I. 0.99–1.45	0.74* (5.17) C.I. 0.56–0.96	—
Public assistance	1.09 (2.34) C.I. 0.98–1.21	—	—	
Parental crime	1.17* (5.27) C.I. 1.02–1.33	—	1.37*** (9.80) C.I. 1.12–1.66	—
Number of prior arrests	1.22*** (90.67) 1.17–1.27	1.09*** (10.34) C.I. 1.03–1.14	1.13*** (17.27) C.I. 1.06–1.19	1.17*** (39.57) C.I. 1.12–1.23
Prior institutional placement	1.50 *** (58.99) C.I. 1.36–1.67	1.59*** (38.79) C.I. 1.38–1.84	—	—
Instant Offense Type				
Drug offense	1.29*** (15.78) C.I. 1.14–1.47	2.11*** (97.95) C.I. 1.82–2.44	—	0.67*** (12.56) C.I. 0.54–0.84
Person offense	—	—	1.30*** (9.44) C.I. 1.10–1.53	—
Property offense	1.20*** (9.01) C.I. 1.06–1.34	—	—	1.49*** (21.85) C.I. 1.26–1.76
Neighborhood Social Disorganization				
Area drug sale density (ln)	—	—	—	—
Area percent female household with children (ln)	1.01 (0.05) C.I. 0.91–1.13	—	—	—
Area percent vacant housing (ln)	—	0.98 (0.08) C.I. 0.87–1.11	—	—
Area percent high school graduate (ln)	—	—	—	—
Contagion Effects				
Area juvenile count (ln)	—	—	—	—
Area any recidivism rate (ln)	4.01*** (67.84) C.I. 2.88–5.59	—	—	—
Area drug recidivism rate (ln)	—	2.57*** (70.34) C.I. 2.06–3.21	—	—
Area person recidivism rate (ln)	—	—	3.07*** (74.65) C.I. 2.38–3.96	—
Area property recidivism rate (ln)	—		—	3.30*** (74.26) C.I. 2.51–4.33
Constant	1.49 (2.40)	0.10*** (21.84)	3.67** (7.28)	1.43 (1.33)

Exhibit 6

Stepwise-Forward Logistic Regression of Offense-Specific Recidivism: Final Models (N = 7,166) (2 of 2)

Predictor Variables	Recidivism	Drug Offense	Person Offense	Property Offense
Nagelkerke R2	0.08	0.12	0.04	0.06
Area under ROC curve	0.64*** C.I. 0.63–0.66	0.71*** C.I. 0.69–0.72	0.63*** C.I. 0.61–0.65	0.65*** C.I. 0.63–0.67

ln = natural log of the variable; ROC = receiver operating characteristic

**p < 0.05. **p < 0.01. ***p < 0.005.*

Notes: A dash (—) indicates a variable that was allowed to enter that model but was not included by the stepwise procedure. Cell values indicate odds ratios. Wald statistic shown in parentheses. C.I. indicates confidence interval at 95 percent confidence.

The pattern for the other three offense types presents us with some indication that the type of offense matters. Our finding that delinquent youths tend to specialize in the types of offenses they commit is consistent with previous research (Armstrong, 2008; Blumstein et al., 1988; Piquero et al., 1999). For each offense type, some degree of specialization was found. This tendency, however, is far stronger for those who committed drug offenses. A previous drug offense more than doubles the probability of a drug reoffense. These findings suggest that the causal mechanisms underlying drug offending differ from those influencing other types of offending.

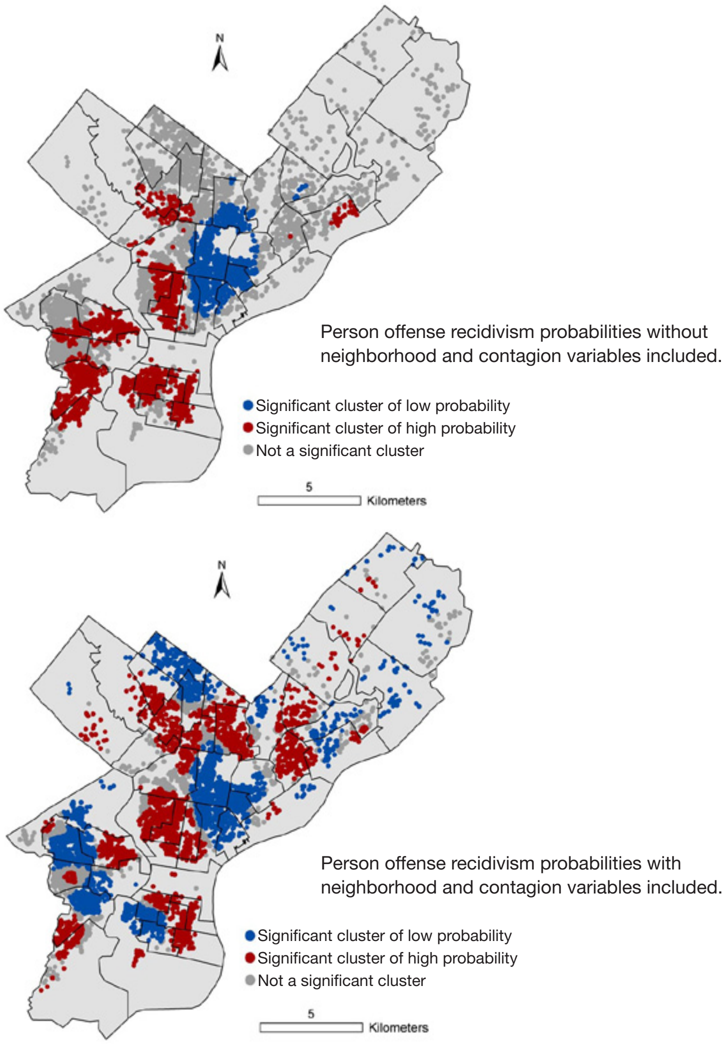
Looking at environmental effects, we find that our measure of neighborhood disorganization was not influential after accounting for other predictors, but that high rates of juvenile recidivism in the neighborhood surrounding individual youths greatly increased the likelihood of recidivism in individual offenders. This finding suggests a spatial contagion effect that is consistent with the effect of delinquent peers as a factor mediating the effect of neighborhood structural factors and parental behavior (Cattarello, 2000; Chung and Steinberg, 2006). To further investigate the influence of the contagion variables, we compared maps of the local spatial clustering of probability of recidivism from models that include individual level data only and models that include individual and census tract variables for each outcome variable. In keeping with the theme of this issue of *Cityscape*, we focus this discussion on just two of the outcomes: drug offense recidivism and person offense recidivism. These results were the most interesting of all modeled offense types.

Exhibit 7 shows two maps of juvenile delinquents, where each point in the maps represents the home location of an individual juvenile and the color of the point indicates significant local spatial clustering of the probability of person offense recidivism. These maps were created from the probabilities generated by the analysis of two different models of person offense recidivism using the variables shown in exhibit 6, where the map on the top excludes the neighborhood and contagion effect variables and the map on the bottom includes them. Using the resulting probability data, the G_i^* statistic was calculated for each juvenile location, using a bandwidth of 1 kilometer. Significant local clusters of high and low probability of recidivism are shaded light and dark, respectively. (See the color version of this map in the online version of *Cityscape* at www.huduser.org.)

These clusters of high and low probability of recidivism stand in stark contrast to the locations of programs that serve these youths. Exhibit 8 shows program locations and relative program sizes,

Exhibit 7

Spatial Clustering of Modeled Person Offense Recidivism Probabilities for Models Without (top) and With (bottom) Neighborhood and Contagion Variables

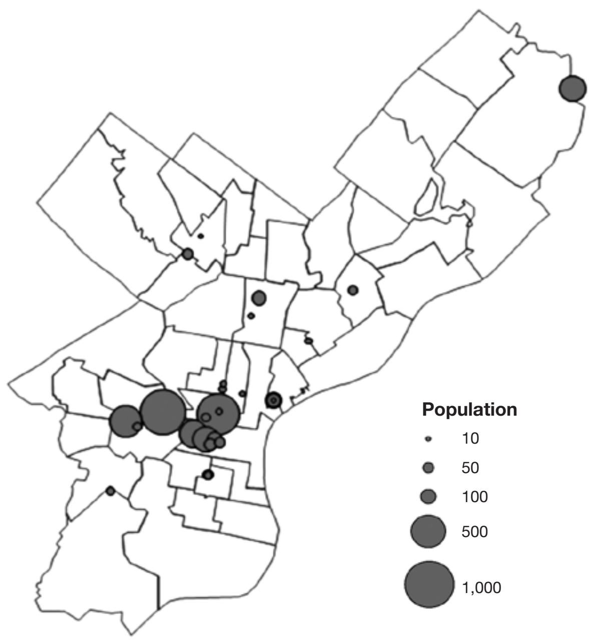


measured in terms of numbers of clients. As this map indicates, most programs are located in the center city business district; one program is situated on the far northeast border of the city.

The maps in exhibit 7 on the top and bottom are markedly different, with the map on the top showing low predicted probability of person offense recidivism for the neighborhood of Hunting Park-Fairhill and vicinity (exhibit 3), with high probabilities in several African-American neighborhoods in North and West Philadelphia. In contrast, the map on the bottom shows that including the neighborhood and contagion variables in the model allows for low predicted probability in several other neighborhoods, as well as other high-probability neighborhoods in areas of Northwest Philadelphia and lower

Exhibit 8

Locations and Population Size of Community-Based Programs



Northeast Philadelphia with predominantly White populations (see exhibit 4). These results suggest the interaction of spatial contagion with race in producing person offense recidivism outcomes.

Analogous maps of modeled probabilities of drug offense recidivism demonstrate further evidence of the interaction of contagion characteristics with race (Mennis and Harris, 2011). In this case, a single cluster of high probability of drug offense recidivism is located in the Hunting Park-Fairhill and Juniata Park-Harrowgate neighborhoods, extending down into the Poplar-Temple and Lower Kensington neighborhoods. This cluster of drug offense recidivism overlaps neatly with the area of Philadelphia with the highest concentration of Hispanic residents (exhibit 4), and, without including neighborhood and contagion variables, Hispanic race at the individual level is a highly influential factor in the likelihood of drug offense recidivism. Without the inclusion of spatial variables, one could easily conclude that drug selling is an Hispanic phenomenon. Exhibit 6 shows that the inclusion of neighborhood and contagion variables renders Hispanic identity nonsignificant, suggesting a mediating causal pathway where neighborhood and contagion effects can be seen to operate through race.

What is additionally remarkable from comparing the maps in exhibit 7 with analogous maps of drug offense recidivism is the clear physical separation of drug and person offense recidivism in Philadelphia. Each spatial pattern is also distinct from spatial patterns of the recidivism rate for all types of offenses (exhibit 5). The drug-offending neighborhood of Hunting Park-Fairhill referenced previously is also a cluster of very low levels of person offending. Similarly, in the areas surrounding this drug-offending area, we find clusters of person offending but little in the way of drug offending.

In contrast, although drug offending and person offending are somewhat separated in the Cobbs Creek and Haddington-Overbrook neighborhoods (see exhibit 3), evidence suggests that violence and drug offending are more likely to be colocated in these southwestern neighborhoods than in the drug-offending area to the north.

Discussions with the Criminal Intelligence Unit of the Philadelphia Police Department have added more to this picture. According to the chief of this unit, drug selling in the Hunting Park-Fairhill and Juniata Park-Harrowgate neighborhoods of the city is highly structured under one or very few large drug-selling organizations. Individuals are employed by this organization to work regular hours at a specific hourly rate. Given that this area is largely Hispanic, highly segregated, and economically depressed, employment options for adolescents and young adults are limited. In contrast, drug selling in the areas of Cobbs Creek and Haddington-Overbrook is associated with turf gangs that use violence to protect their markets. The population of these economically depressed neighborhoods is largely African American, although the larger area is racially diverse.

The interaction of race, neighborhood characteristics such as concentrated disadvantage, and spatial/peer contagion in producing recidivism outcomes for various offense types can be interpreted within the framework of urban settlement patterns of Philadelphia. Like many industrial cities in the Northeast and Midwest United States, Philadelphia has seen substantial population decline since the 1950s as many manufacturing industries that provided substantial employment in Philadelphia have either shut down or moved out of the city. Population decline has been associated with "White flight," where many of the White residents who worked in manufacturing left the inner city for the suburbs, leaving behind an aging and increasingly dilapidated housing stock around the old industrial core of the city. Consequently, African Americans, and later Hispanics (primarily from Puerto Rico until relatively recently), moved into these more affordable neighborhoods. As jobs and commercial development fled these neighborhoods over the ensuing decades, however, housing values stagnated and concentrated poverty became entrenched.

The intense pattern of racial segregation observed in exhibit 4 is a vestige of this economic and residential history of the city and has been aided by historical redlining and other discriminatory practices that encouraged residential segregation. As shown in exhibit 4, the African-American population is strongly concentrated in the poor, inner-city neighborhoods of North Philadelphia and parts of West Philadelphia and South Philadelphia. Outside of Center City and University City, which serve as the primary business and university districts, the White population is concentrated most heavily in relatively affluent Northwest Philadelphia and in middle- and working-class Northeast Philadelphia. Some White working-class neighborhoods in the inner city remain from the manufacturing past, in neighborhoods in the lower northeast, from Frankford to Port Richmond, in Manayunk and Roxborough, and in parts of South Philadelphia.

As Massey and Denton (1993) pointed out, the intense residential segregation that can be observed in Philadelphia acts to reinforce concentrated disadvantage by limiting access to resources and opportunities for advancement out of poverty. For juveniles, we note that the combination of concentrated poverty and high levels of segregation may act to enhance peer contagion of learned criminal behavior while limiting contact with nondelinquent peers. Thus, neighborhood- and race-specific affiliation with certain offense types among juveniles may be in part a product of the spatial clustering of concentrated disadvantage and segregation that typify the spatial expression of Philadelphia neighborhoods. The structural economic and discriminatory forces that have produced these highly segregated patterns of residential settlement may thus be seen as a primary mechanism in a chain of causation that produces social norms and practices in which juvenile offense specialization is allowed to develop and flourish. These patterns of offense specialization can then be detected at the neighborhood level as spatial clustering in offense type. In addition, we have found evidence that such neighborhood-level expertise in offending can then be exported to adjacent neighborhoods through the process of peer contagion based on proximity (Mennis et al., 2011).

Limitations

A major challenge to spatial and place-based analyses is the definition of spatial unit. As Sampson, Morenoff, and Gannon-Rowley (2002) and others have noted, the term "neighborhood" can mean many things. Researchers often use census tracts, block groups, or administratively defined areas such as police districts. In this article, we use more than one method of defining spaces for different analyses, but we make clear for each set of findings reported whether we are using PHMC-defined neighborhoods, census tracts, or a fixed distance from each youth's home location. We used both census tracts and point-level data in this study, but we recognize that the ways people interact daily with their environments shapes their perceptions of what is normal, permissible, and unacceptable.

Secondly, our followup period for tracking recidivism—6 months following program termination—may be regarded as too short. On average, these youths were at risk in the community for 13 months following disposition by the court, which is clearly sufficient time to be influenced by local forces. We note that more than 40 percent of the youths in this study recidivated during this period of time. Certainly, more youths recidivated after more than 6 months, but it is unlikely that the absence of these data biased our results.

We note, too, that an important social disorganization concept, collective efficacy, was missing even though we had access to this measure from the PHMC data. We chose to use a finer level of spatial aggregation than the 45 neighborhoods that improved on the overall predictive power of the data, sacrificing this important factor in the process. Thus, although we suggest at several points that social disorganization is not supported by our findings, we have not fully tested social disorganization theory. Other competing explanations for our findings are consistent with social disorganization theory; we have not ruled these out.

A fourth limitation has to do with offense specialization. Recent studies of offense specialization have employed longitudinal analyses, examining several offense transitions over time. We have analyzed only one offense transition; thus, we have not included previous offense transitions that may challenge our conclusion about offense specialization. Moreover, we have not examined changes in offending patterns with age or experience.

Conclusions

Juvenile offender recidivism plays an important role in policymaking and program evaluation. Nationally, juvenile reoffending rates have been found to be as high as 66 percent when measuring recidivism by rearrest and as low as 33 percent when measuring reoffending by reconvictions within a few years of release (Mears and Travis, 2004). In fact, policymakers in juvenile justice are now implementing standards for measuring recidivism that do, in fact, acknowledge that program outcomes are spatially heterogeneous (Harris, Lockwood, and Mengers, 2009). Missing from this discussion, however, is a sense of how place determines not only whether recidivism rates are high or low, but also what kinds of offenses are committed and why youths are pulled back into further involvement in crime.

We draw four broad conclusions from the findings reported above:

1. Delinquent reoffending is spatially dependent rather than spatially diverse. This finding is strongest for drug offending, leading us to conclude that effective research on juvenile drug offending should incorporate neighborhood context.

2. For some types of offending, especially drug selling, juveniles are likely to specialize. This specialization is likely to be influenced by opportunities, constraints, and pressures present in the youth's neighborhood.

3. Recidivism offense type is spatially dependent. Residing in a high spatial concentration of any particular type of reoffending increases the chance that a delinquent youth will recidivate with that type of offense.

4. Geographically defined places provide influences that can increase and decrease the likelihood of recidivism, but the nature of these risk and protective factors vary widely from neighborhood to neighborhood.

We have found evidence that delinquent youths tend to specialize in committing offenses of a particular type, but that specialization is far more likely among drug offenders than youths committing nondrug offenses. Moreover, we contend that specialization is influenced by peer contagion. That is, youths tend to specialize in offenses in which other juveniles in their neighborhood specialize. This finding of spatially dependent specialization suggests that there are neighborhood dynamics at play that we do not fully understand. The association between ethnicity and drug offending is particularly strong, and we note the effect of historical patterns of segregated Hispanic communities on drug selling discussed elsewhere (see, for example, Bourgois, 2003). Other studies have found that peer influence plays a critical proximal role in decisions by youths to sell drugs. Their perceptions of the acceptability and profitability of drug dealing are influenced most directly by peers and young adults within their communities (Li and Feigelman, 1994; Ricardo, 1994; Whitehead, Peterson, and Kaljee, 1994). The spatial concentrations of drug selling are particularly strong, suggesting that youths in those areas are under significant pressure to participate in a business common to adult and juvenile neighbors. Their perceptions that "everyone is doing it" may be quite accurate in some of the neighborhoods we identify.

The predictors of person offense specialization, on the other hand, although also spatially dependent, are less clear. Family disruption (referring to Sampson and Groves, 1989), in the form of parental criminality, did affect person reoffending, but we do not know if family disruption is more likely in neighborhoods with high levels of person offending. On the other hand, parental criminality suggests an environment in which antisocial behavior can be learned. We know that aggression is a learned behavior (Bandura, 1969), suggesting support for a social learning explanation for the pattern we see.

Our findings, not all of which are reported in this article, suggest that neighborhood is a significant predictor of juvenile recidivism when offense type is ignored and when examining only drug offense recidivism. Economic disadvantage alone, however, does not play a significant role in juvenile recidivism once the individual characteristics of juveniles are accounted for. It should be noted, of course, that strong relationships exist between indicators of neighborhood social disorganization, such as crime and socioeconomic disadvantage, and indicators we captured at the individual level, such as race and public assistance. Moreover, we have not tested all of the elements of social disorganization noted in the literature.

Philadelphia is a city where historical patterns of industrial development, residential settlement, and suburbanization have created a deeply segregated residential pattern with concentrated poverty in inner-city minority neighborhoods. We note that some previous studies that ascribe a causal effect to neighborhood social disorganization used only spatially aggregated data (for example, Sampson and Groves, 1989; Veysey and Messner, 1999), thus making it difficult to distinguish the effect of those characteristics of social disorganization that may be measured at an individual level (for example, race) from those that are perhaps more characteristic of a neighborhood as a whole (for example, vacant housing rate—although no individual lives in a vacant house, the rate of vacant housing in a neighborhood is indicative of its character).

Our findings are inconsistent with those of Little and Steinberg (2006) who concluded that "adolescents who sold the most drugs were more likely to live in contexts characterized by high physical and social disorder…" (Little and Steinberg, 2006: 378). In addition, they found that drug activity increases violence within neighborhoods, net of their measures of social disorganization. Their conclusion that "traditional dimensions of social disorganization predict drug activity which, in turn, leads to higher levels of criminal violence," serves to tie drug and violent offending together in disadvantaged neighborhoods (Martínez, Rosenfeld, and Mares, 2008: 866). We find, instead, that areas with high concentrations of drug recidivism, where adult drug arrests are also concentrated, are not always the same as those areas where violence is concentrated. It would appear that in the area of Philadelphia where drug selling is most concentrated—an area that is isolated by economic disadvantage and ethnicity—is not an area where violence is prevalent. We did note an area in the southeastern section of Philadelphia where drug selling and violence are colocated. Again, spatial distinctions like these will facilitate improved prediction and program.

It is likely that under conditions of specialization, different offense types require different causal explanations. If a single causal model were all that was needed, we would not expect to find spatial dependency of offense types. Instead, we find areas of Philadelphia in which juvenile recidivists are exhibiting specialization of a particular offense type. This pattern of specialization not only implies different causal models, but also suggests that neighborhood attributes must be part of the causal picture.

A number of our analyses produced findings that demonstrate that drug offending, as a form of recidivism, is different from person or property offending. Exhibit 6 indicates that drug offenders, compared with youths committing person and property reoffenses, were more likely to have committed a previous drug offense, to have had a previous institutional placement, and to have resided in a neighborhood with a high juvenile drug recidivism rate. In a separate analysis using HLM (not shown), we found that drug offenders were older than the mean at the time of their first arrest.

Our interpretation of these results is that juveniles who offend earlier in their lives are more likely to recidivate with person and property offenses, whereas drug offenders come to the attention of the justice system at a later age and are likely to continue selling drugs even after a period of residential placement. These findings suggest that the causal mechanisms underlying drug offending differ from those influencing other types of offending.

The extent of specialization among drug offenders, relative to other offender types, indicates a relatively organized neighborhood structure that supports involvement in this type of delinquency. That is, opportunities to gain access to drugs must be present, and reinforcement of the behavior must be likely. At the same time, the combination of poverty, Hispanic culture, and high rates of adult drug selling and specialization imply that opportunities to engage in legitimate employment are less available in Hispanic neighborhoods in Philadelphia. These findings are consistent with the argument raised by Baumer and Gustafson (2007), in reference to drug selling, regarding "the crime generating effect of a high level of commitment to monetary success goals combined with a low level of commitment to legitimate means for pursuing such goals" (p. 651). Our findings on the Hispanic neighborhoods add to this perspective by highlighting the potential for cultural responses to economic deprivation. Several studies conclude that the primary attraction of illicit drug selling is the potential income that is rarely attainable for youth in economically depressed neighborhoods (Reuter et al., 1990).

Implications for Theory

Different theories may be needed to explain place-based patterns of juvenile recidivism and to serve as foundations for program design. High levels of involvement in instrumental crimes that are prevalent among adults and juveniles in an economically disadvantaged neighborhood are indicative of norms and values consistent with those crimes and social learning mechanisms that pull youths into participation in those specific criminal activities. Our findings with respect to drug selling in particular suggest that a differential association/social learning theory such as that proposed by Akers (1998) best fits places where drug selling is embedded in the culture and normative behavior of a neighborhood.

Because high levels of violent offending are more ubiquitous than drug selling and are associated with poverty, it is more likely that violent offending occurs where social disorganization is greatest. The spatial separation of drug selling recidivism and an absence of social connectedness and informal social controls likely permit conflicts to escalate to violence and norms of toughness to dominate life on the street. Similarly, where violence and drug selling coexist, such as in the southwestern part of Philadelphia, research on gang involvement becomes relevant. In particular, Gordon et al. (2004) found that youths that joined gangs were already involved in delinquency and that their involvement in drug selling increased greatly upon joining a gang. In this case, social disorganization may explain the existence of gangs and the attraction to gangs, but involvement in drug selling may be facilitated by organization.

Implications for Policy

If different offense types require different causal explanations and if reoffense type is spatially dependent, then juvenile justice programs should be designed around the causal mechanisms involved and be created with specific neighborhoods in mind. This place-based perspective implies small, neighborhood-based programs, and, in the case of an Hispanic neighborhood, culturally specific in design. Undoubtedly, recidivism among delinquent youths is tied to other social problems in the same neighborhoods. Because these problems go beyond delinquency, policy changes are needed that include local public health, educational, recreational, cultural, and business organizations.

What we find in Philadelphia, however, is that community programs cluster in center city (exhibit 8), often far from their young clients, and that several of these programs are quite large and draw juveniles from many diverse parts of the city. These services tend to be divorced from the neighborhoods in which their clients reside. The place-based perspective suggested by this study implies that these programs should be decentralized, located where their clients reside, tailored to the characteristics of these local environments, and linked to other youth- and family-serving agencies in these same neighborhoods.

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Mapping the Spatial Influence of Crime Correlates: A Comparison of Operationalization Schemes and Implications for Crime Analysis and Criminal Justice Practice

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Abstract

Decades of criminological research have identified a variety of independent variables that correlate significantly with particular crime outcomes. Less is understood about how these correlates, or factors, of crime can be operationalized to maps in ways that best represent their spatial influences on the emergence of nearby crime events. A geographic information system (GIS) enables the exploration of spatial influence, which refers to the way in which features of a landscape affect places throughout the landscape. For example, empirical knowledge that bars correlate with locations of violent crimes can be mapped in several ways to show more or less crime-prone places, such as places with bars, places within certain distances from bars, or places with higher concentrations of bars. Rather than just a feature's presence, its influence on space is important because context affects criminal behavior. GIS enables analysts to move beyond just creating maps of points that coexist with crime to creating visual narratives of how settings become conducive to crime. With growing use of spatial risk assessments and predictive modeling in the criminal justice community, operationalizing crime correlates to geographic units across a landscape is an important task that requires careful consideration. This article presents (1) a detailed discussion of the theoretical framework relevant to risk analysis and spatial influence and (2) three primary methods for operationalizing criminogenic features to a geographic map. One of these maps is included in a risk terrain model (RTM) along with three other spatially operationalized maps of different criminogenic features to produce a composite map of criminogenic

Abstract (continued)

contexts for shootings in Irvington, New Jersey. The RTM is then deconstructed to show how each spatially operationalized map layer adds to the overall predictive validity. Finally, the article demonstrates how producing an RTM of theoretically grounded operationalizations of spatial influence from many risk factors can be used as a control measure of environmental context when evaluating the spatial effect of place-based interventions on future crime events. Tending to the detail of mapping the spatial influence of crime correlates is particularly important and necessary for maximizing the reliability and validity of assessments of the likelihood of crime to occur at certain places within a study area.

Introduction

Imagine an unfamiliar visitor to an American city. As she stands on the sidewalk, she calls a local friend on the cell phone to meet; he asks where she is. No street signs are nearby. As she walks to the street corner to figure out the specifics of her location, she nonchalantly describes the area as the "bar district" to break the silence over the phone and in hopes that her friend knows where she is talking about. She is not in a bar and may not even be directly in front of a bar. Why, then, would she describe this part of the city as the bar district? The simple answer, perhaps, is because she observed a high concentration of bars within the area and defined that quality of the landscape to be a bar district. From a criminological perspective, bars and other liquor establishments are known to correlate with robberies (for example, Tilley et al., 2005; Wright and Decker, 1997). The person might be at even greater risk of being robbed if she is within one block from a bar (Smith, Frazee, and Davison, 2000) as opposed to farther away. Therefore, it could be argued with empirical support that she is at greater risk of robbery where she stands talking on the phone compared with other places in the city with a lower concentration of bars and she would not be near any of them. Kennedy and Van Brunschot (2009: 4) define risk as "a consideration of the probabilities of particular outcomes." In the previous example, the visitor's risk of robbery is not only a function of the criminogenic features (that is, bars) themselves, but also the distribution of those features throughout the landscape, her proximity to them, and the distal limits of the influences those features have—both individually and combined—on the attraction of potential offenders, suitable victims, and crime (Cohen and Felson, 1979).

Location matters when assessing the likelihood of crime because crimes cluster at certain locations (Eck et al., 2005; Harries, 1999; Ratcliffe, 2006; Sherman, 1995; Sherman, Gartin, and Buerger, 1989; Weisburd, 2008; Weisburd and Braga, 2006). Environmental characteristics of these locations influence and enable the seriousness and longevity of crime problems and ensuing "hotspots" (Mastrofski, Weisburd, and Braga, 2010; Sherman, 1995). Criminal activity concentrates at specific, select spots—a trend that is well supported by research and comports with the daily experiences of analysts in law enforcement agencies around the world. The identification of crime hotspots informs researchers where illegal behavior is clustered, however, not necessarily why it is clustered at a particular location. Understanding the spatial interaction effects of certain correlates, or factors, of crime is key to assessing and valuing criminogenic place-based risk (Caplan, Kennedy, and Miller, 2011; Weisburd, 2008).

For many decades, criminologists have identified factors at (or features of) places that help explain occurrences and distributions of criminal behavior and reported crime incidents. Yet, it is not the mere presence or absence of the factors that attracts or generates crime (Brantingham and Brantingham, 1995). It is the spatial influence of these criminogenic factors on their environments that enables motivated offenders and increases the likelihood of illegal activity at certain places. For example, as presented previously, the spatial influence of bars as a risk factor for robbery could be described as "being within a certain distance from a single bar heightens a person's risk of victimization"; or, "being at a place with a nearby high concentration of bars heightens a person's risk of victimization." Both of these situations could be true at the same time, or only one or neither, depending on the location within the city (Basta, Richmond, and Wiebe, 2010). Notice, though, that at the microlevel unit of "the place where a person is standing," the risk of being robbed could vary according to the spatial influences that bars have on the urban landscape.

With the growing use of spatial risk assessments and predictive analytics in the criminal justice community (Rubin, 2010; Weisburd, 2008; Weisburd et al., 2001), operationalizing the spatial influence of crime factors to geographic units throughout a landscape is an important task that requires special consideration and tools (Raines, Sawatzky, and Bonham-Carter, 2010; Tomlin, 1994). In particular, a geographic information system (GIS) enables analysts to create visual narratives of how environmental settings become conducive to crime. GIS enables the exploration of spatial influence, which refers to the way in which features of a landscape affect places throughout the landscape. This concept can apply to many types of environments, including small and large extents (for example, local or global) and rural, suburban, and urban areas. This article explores ways in which correlates of crime can be operationalized to maps, using GIS, to represent the correlates' effects on the environments in which the crimes occur. Tending to this detailed level of mapmaking is particularly important and necessary for maximizing the reliability and validity of assessments of the likelihood of crime to occur at certain places within a study area, and it is something that has been neglected in much of the work that attempts to make such assessments. Following an expanded discussion of the theoretical framework relevant to risk analysis and spatial influence, this article presents three primary methods for operationalizing criminogenic features to a geographic map: (1) presence of the features, (2) concentration of the features, and (3) distance from the features. One of these maps is included in a risk terrain model (RTM)—a framework that Caplan, Kennedy, and Miller (2011) proposed to assess spatial crime risks, along with three other spatially operationalized maps of different criminogenic features. After testing the predictive validity of the RTM for shootings in Irvington, New Jersey[1], the article presents the deconstruction of the model to show how each spatially operationalized map layer adds to the overall predictive validity—primarily because each individual operationalization of spatial influence is statistically valid by itself; when combined, they are more precise. Finally, the article shows how producing an RTM

[1] The New Jersey State Police provided shooting data through the Regional Operations Intelligence Center.

of theoretically grounded operationalizations of spatial influence from many risk factors yields a value of risk that can be used as a control measure of "environmental context" when evaluating the spatial effect of place-based interventions on future crime events.

Conceptual and Theoretical Framework: The Case for Operationalizing Spatial Influences

Routine activities—a popular theory in the criminal justice sciences—states that crime is likely to occur when motivated offenders converge, suitable targets exist, and capable guardians are lacking (Cohen and Felson, 1979). What is more likely to occur is that motivated offenders will commit crime against suitable targets at certain places according to the environmental characteristics of those places that make it easier to complete the crime successfully and reap the rewards without punishment (for example, not getting caught; Clarke and Felson, 1993). Routine activities theory is event focused. To apply the theory to practice, police need to focus on future events by anticipating and controlling the behavior of individuals no matter where they are or where they are traveling. This endeavor is very difficult. What is more manageable for police agencies is to allocate resources to places that are most attractive to motivated offenders and to places where crime is most likely to occur given certain environmental characteristics (Weisburd, 2008). These places have the greatest crime risk. In the long-standing debate in criminology concerning what promotes crime, it is not enough to say that crime risk increases when the number of criminals increases. What is more likely is that the crime risk at places that have criminogenic attributes is higher than at other places because these locations attract motivated offenders (or more likely concentrate them in close locations) and are conducive to allowing certain events to occur. This assessment is different from saying that crime concentrates at highly dense hotspots. It suggests, instead, that individuals at greater risk to commit crime will congregate at locations that are best suited for perpetrating it. This statement does not imply that more or better targets of crime exist (because there may be less to steal and fewer rewards from robbing individuals), but rather that the conditions for criminal behavior (for example, lower risk of apprehension or retaliation) are better at these places than at others.

Paul and Patricia Brantingham provided important conceptual tools for understanding relationships between places and crimes. They referred to the "environmental backcloth" that emerges from the confluence of routine activities and physical structures overlaying areas (Brantingham and Brantingham, 1981). This backcloth is dynamic and can be influenced by the forces of "crime attractors" and "crime generators" which contribute to the existence of crime hotspots (Brantingham and Brantingham, 1995). Attractors are those specific things that attract offenders to places to commit crime. Generators refer to the greater opportunities for crime that emerge from increased volume of interaction occurring at these areas. The concentration of crime at specific places or hotspots is consistent with the idea of an environmental backcloth, is well supported by research (for example, Eck, 2001; Eck et al., 2005; Harries, 1999; Sherman, Gartin, and Buerger, 1989), and comports with the daily findings of crime analysts in law enforcement agencies around the world (Weisburd, 2008). Crime hotspots indicate where behavior is clustered. Connecting criminal behavior to precursory environmental context is more challenging, but important for comprehensive crime analysis and forecasting efforts. As Abbott (1997: 1152) states about the central tenets of the human ecologists who were the first to systematically study crime in space, "the Chicago School thought that no social fact makes any sense abstracted from its context in social (and often geographic) space and social time. …Every social fact is situated, surrounded by other contextual facts and brought into being by a process relating it to past contexts." Ecologists ranging from Burgess (1928) to Shaw and McKay (1969) sought out ways to extract social indexes from data on communities for use in their explanations of crime occurrence and distribution.

Operationalizing the spatial influence of a crime factor tells a story about how that landscape feature affects behaviors and attracts or enables crime occurrence at places near to and far from the feature itself (Freundschuh and Egenhofer, 1997). When certain motivated offenders interact with suitable targets, the risk of crime and victimization conceivably increases. When motivated offenders interact with suitable targets at certain criminogenic places, however, the risk of criminal victimization is even higher. Similarly, when certain motivated offenders interact with suitable targets at places that are not conducive to crime, victimization risk is lowered. GIS can produce maps that visually articulate these environmental contexts in which certain crimes are more or less likely to occur as a result of the combined influence of one or more criminogenic features affecting the same place (Caplan, Kennedy, and Miller, 2011). In this way, criminal behavior is modeled as less deterministic and more functional of a dynamic interaction that occurs at specified places.

Risks of Crime at Places

Opportunities for crime are not equally distributed across places, or "small micro units of analysis" (Weisburd, 2008: 2), and so the analytical approach to studying criminogenic places plays a critical role in the reliability and validity of efforts to assess vulnerabilities and future crime hotspots. Opportunity theorists (for example, Cohen, Kluegel, and Land, 1981; Simon, 1975) have suggested that variations in crime are explained by opportunities to commit crime at locations that are accessible to the offender. Although well developed theoretically, research has been constrained in its ability to operationalize "opportunity" and to develop a metric for assessing it. Cohen and Felson (1979: 595) admitted that, although crime can be more easily facilitated if motivated offenders converge, suitable targets for victimization exist, and an absence of capable guardians occurs, "the risk of criminal victimization varies dramatically among the circumstances and locations in which people place themselves and their property." Cohen, Kluegel, and Land (1981) refashioned the routine activities theory, renaming it "opportunity" theory, to include concepts of exposure, proximity, guardianship, and target attractiveness as variables that increase victimization risk. A common thread among opportunity theorists and related scholarly thinkers is that the unit of analysis for "opportunity" is a place, and that the dynamic nature of that place constitutes opportunities for crime. For example, Eck (2001, 2002), Lee and Alshalan (2005), Mears, Scott, and Bhati (2007), Basta, Richmond, and Wiebe (2010), and Brantingham and Brantingham (1995) all directly state or imply the place-based nature of criminogenic opportunities. Crime control and prevention activities must consider not only who is involved in the criminal events, "but also the nature of the environments in which these activities take place" (Kennedy and Van Brunschot, 2009: 129) because opportunity for crime is an attribute of all places. As an attribute of places, opportunity is not an absolute value, a dichotomous variable, or a static quotient. It is rarely or never zero. Opportunity varies in degrees and changes over space and time as public perceptions about environments evolve, as new crimes occur, as police intervene, or as motivated offenders and suitable targets travel. Assessing spatial criminogenic opportunity requires a conceptual framework that is attuned to incorporating multiple dynamic factors and producing intelligence that serves strategic decisionmaking and tactical action. This intelligence production can be achieved through risk assessment.

Kennedy and Van Brunschot (2009: 4) define risk assessment as "a consideration of the probabilities of particular outcomes." The concept of risk is not new or unique to the criminal justice community (Andrews, 1989; Burgess, 1928; Glueck and Glueck, 1950; Gottfredson and Moriarty, 2006), and risk assessment has a long history of being used to identify, prevent, or control crime (Kennedy and Van Brunschot, 2009). Risk models provide tools for identifying hazards and vulnerabilities that can lead to crime outcomes. Kennedy and Van Brunschot (2009: 11) surmised that risk provides a metric that can help tie different parts of the crime problem together and offers a probabilistic interpretation to crime analysis that enables one to suggest that certain things are likely to happen and others are preventable, based on risk assessments. When "opportunity for crime" is thought of in terms of "risk of crime," places can be evaluated in terms of varying degrees of criminogenic risk relative to certain nearby or far away criminogenic features of the environment.

Although risk assessment provides an efficient way to analyze crime opportunities, challenges appear in the operationalization of crime opportunity in a GIS. The way that criminogenic features have been modeled in a GIS is often contrary to how people experience and conceptualize their environments (Couclelis, 1992; Frank and Mark, 1991). Geographers suggest that regions, such as cities, are learned by humans piecemeal over time, an assertion that is grounded in the view from psychology that "perceptions of space, spatial cognition, and spatial behavior are scale-dependent and experience-based," explained Freundschuh and Egenhofer (1997: 362). (See also Montello, 1993.) So, when assessing the risk of crime to occur at conceivably any location throughout a city, the use of vector points, lines, and polygons in a GIS are poor representations of criminogenic features on a map because they bear no particular relationship to the dynamic surrounding environment. (Couclelis, 1992). "There are difficulties with this view of the world," explained Couclelis (1992: 66), "mainly that points, lines, and polygons that define vector objects do not have naturally occurring counterparts in the real world." The vector objects are approximations of environmental features, but lack any theoretical or empirical link to their geographies (Freundschuh and Egenhofer, 1997). Broad inattention to different spatial conceptualizations of criminogenic features has led to misrepresentations of these urban, suburban, and rural features in GIS and resulting maps (Freundschuh and Egenhofer, 1997). The way people (for example, motivated offenders and suitable victims) conceptualize and operate in space is an important consideration for the mapping of crime risk throughout landscapes. Cartographically modeling these conceptualizations and the spatial influence of criminogenic features using a GIS in a way that reflects the actors' views is an important part of what Freundschuh and Egenhofer (1997: 363) describe as "*Naive Geography*, a set of theories of how people intuitively or spontaneously conceptualize geographic space and time" (see also Egenhofer and Mark, 1995), and can yield more meaningful and actionable spatial intelligence for use by public safety professionals (Frank, 1993; Freundschuh and Egenhofer, 1997; Mark, 1993).

Understanding these crime-prone places, however, requires more than just a snapshot of how offenders and victims interact at a point in space. As shown in the following sections, the best way to map these factors for the articulation of criminogenic "backcloths" (Brantingham and

Brantingham, 1981) is to operationalize the spatial influence of each factor throughout a common landscape rather than atheoretically mapping the factors as points, lines, or polygons in a manner that keeps them disconnected from their broader social and environmental contexts. To succeed at this task, information needs to be incorporated about these places with expected increased crime risks. Fortunately, decades of criminological research have identified a variety of independent variables to be significantly correlated with a variety of crime outcomes that can be used to inform expectations. For example, Caplan, Kennedy, and Miller (2011) studied gang-related shootings and operationalized the spatial influence of known gang members' residences as "areas with greater concentrations of gang members residing will increase the risk of those places having shootings" and depicted this risk factor as a density map created in a GIS from known addresses of gang members' residences. Kennedy, Caplan, and Piza (2010) operationalized the spatial influence of several known correlates of shooting events in Newark, New Jersey, such as public housing. The spatial influence of public housing was mapped to show all places within two blocks from public housing to be at higher than normal risk of shootings compared with all other places throughout the city (for example, Eck, 1994; HUD, 2000; Newman, 1972; Poyner, 2006; Roncek and Francik, 1981). Operationalizing the spatial influence of crime risk factors addresses various theoretical and methodological issues concerning the use of GIS for crime forecasting and assessing place-based victimization risk (Freundschuh and Egenhofer, 1997). The most basic utility of this innovation is that it maximizes the validity of cartographic models and empirical measures used for statistical tests. The next section demonstrates these effects to crime analysis when the same crime correlate is modeled in a GIS according to a variety of spatial influences types.

Operationalizing the Spatial Influence of Criminogenic Features

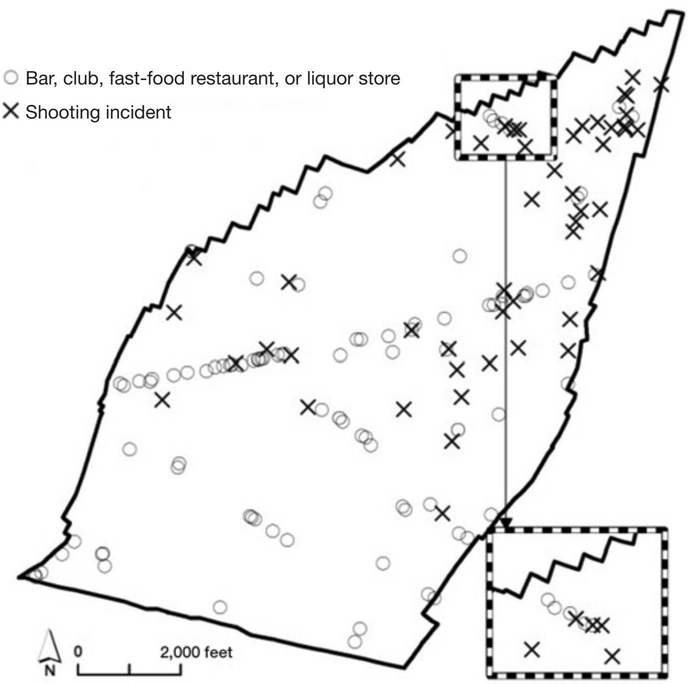
Three primary ways to operationalize the spatial influence of criminogenic features are (1) presence or absence of features, (2) density of features, or (3) distance from features. Each approach is demonstrated in turn. Two general lessons to be learned from the forthcoming discussion: First, it is reasonable to rely on theory and empirical research to identify crime correlates and to operationalize their spatial influence; second, many ways exist to operationalize the spatial influence of crime correlates about their environments, but some methods are more appropriate and efficacious than others. These insights reinforce the notion that approaches to crime analysis, spatial risk assessment, and crime forecasting cannot be atheoretical and must be evidence based. The approaches must be grounded in ways that account for the dynamic interaction of all criminogenic features throughout a landscape.

Presence or Absence of Features

Crime analysis can yield different results when the same crime correlate is modeled in a GIS according to a variety of empirically justified spatial influences. Exhibit 1 shows point symbols representing the locations of shooting incidents (the crime) and bars, clubs, fast-food restaurants, and liquor stores (the crime risk factors) in Irvington. These crime risk factors, or criminogenic features of the landscape, are correlated with shooting incidents in several empirical research studies, both in Irvington and other settings (for example, Block and Block, 1995; Brantingham and Brantingham, 1995; Caplan, Kennedy, and Miller, 2011; Clarke and Eck, 2005; Eck, Clarke, and Guerette, 2007; Kennedy, Caplan, and Piza, 2010). Represented on the map in exhibit 1 are 97 features and 58 shooting incidents. Visual inspection of the map suggests that shooting incidents occur near criminogenic features. Only one shooting incident was at the exact same address as a fast-food restaurant, however, as shown in the extent rectangle at the bottom right of the map. Given the state of knowledge from existing empirical research, it might be said that Irvington as a whole is at greater risk for shootings compared with other municipalities because it has higher numbers of criminogenic features. Short of revoking business licenses and forcibly closing all or some of the most problematic establishments, however, this fact would be less than useful for Irvington's public safety practitioners who must operate at microlevel places within their municipality to suppress and prevent shootings and other violence. Accepting that their city is empirically more crime-prone compared with other cities and doing nothing about it is not an option.

Exhibit 1

Irvington, NJ, 2007: Correlation of Environmental Features Represented as Vector Points

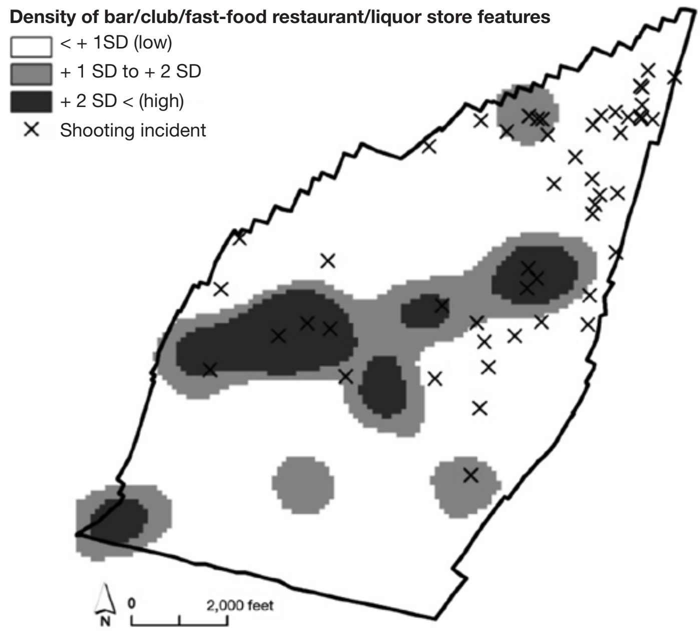


Density of Features

Bars, clubs, fast-food restaurants, and liquor stores are often not the exact locations where associated crimes happen. Rather, shootings occur at places that are in some way defined or influenced by them. As shown in exhibit 2, the spatial influence of these features on shooting incidents is related to their concentration at places throughout the municipality and was operationalized as a raster density map. Shooting incidents are cartographically modeled as more likely to happen at places

Exhibit 2

Irvington, NJ, 2007: Correlation of Environmental Features Represented as Density of Points



SD = standard deviation.

where bars, clubs, fast-food restaurants, and liquor stores are most concentrated. "Places" are defined in the raster map as cells sized 100 feet by 100 feet and the distal limits of nearby features (that is, search radius) used to define the density of each place was set at 1,480 feet. Technically, cell sizes determine how coarse or smooth the raster map will appear: the smaller the cell size, the smoother the map will be (imagine pixels on a television screen). Conceptually, raster cells are the microlevel places for which risk is being assessed and their size should be meaningful for operational purposes. For example, Kennedy, Caplan, and Piza (2010) used a cell size of 145 feet by 145 feet for risk terrain modeling in Newark because that was one-half the median block length in the city. They reasoned that about one block was a meaningful area for crime events to happen within and was small enough for targeted police interventions should risk in these areas be found to be high.[2] In this study, the 100-foot cell (that is, place) size was selected based on the average block length in Irvington (370 feet) so that the microlevel places depicted on the map in exhibit 2

[2] As extreme examples, a cell size of 2 inches would be unreasonable because a person cannot fit in that space and a cell size of 10 miles would not be meaningful for operational policing given the vast area within each cell. Exceptionally large cell sizes could also create problems regarding the phenomenon of "edge effects." Ultimately, the cell size is a subjective decision that should be based on how precise the risk assessment needs to be—the smaller the cell size the better the precision (as long as the risk factor data—for example, point-level data—are also precise). The general rule of thumb is to select a cell size that will enable actionable interpretations of risk terrain maps.

distinguish the spatial influence of criminogenic features as precisely as one corner or the middle of a street block. The 1,480-foot search radius for the density calculation was selected because it equaled approximately four blocks (that is, 370 feet by four blocks), a meaningful sphere of influence for these criminogenic features as attributes of places within the radius. In real terms, and to continue with the example from the introduction section, a person might describe the place where she is standing as the bar district because she observed many bars within a four-block radius.

The density map in exhibit 2 is symbolized according to standard deviational breaks, with all places colored in darker gray having density values greater than +2 standard deviations from the mean density value—which statistically puts these places in the top 5 percent of the most densely populated with criminogenic features. The lighter gray represents places with density values between +1 and +2 standard deviations; white places have density values below +1 standard deviation. As shown on the map, places with greater concentrations of criminogenic features appear to be more frequented by shootings than the bars, clubs, fast-food restaurants, and liquor stores themselves (when compared with exhibit 1). In fact, 20 out of 58 (34 percent) shootings during 2007 occurred at places with density values above +1 standard deviations. It is realized that this result is arguably due to simply identifying a larger "catchment" area to which shootings are aggregated—compared with the feature points themselves. Such an argument is valid and needs to be addressed for statistical tests, as will be done in later sections of this article. For now, however, the intention is to demonstrate operationalizing the spatial influence of criminogenic features in different ways.

Given the state of knowledge from existing empirical literature and the spatial influence of criminogenic features to be operationalized as the concentration of these features throughout the environment, it might be said that places in Irvington with higher concentrations of bars, clubs, fast-food restaurants, and liquor stores are at greater risk for shootings compared with all other places within the municipality. This fact might encourage Irvington police to prioritize and allocate resources to the densest places. In this way, police could preemptively target a few high-density areas of criminogenic features rather than allocating resources to every individual feature in an effort to control and prevent shootings.

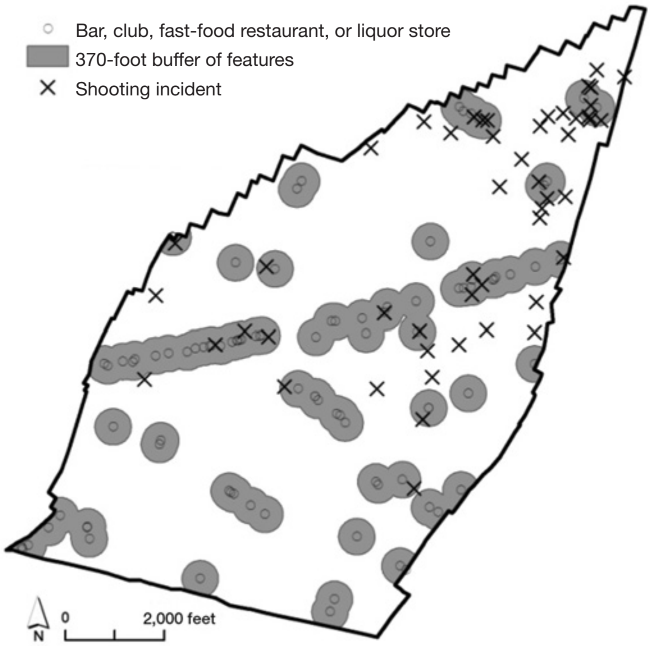
Distance From Features

Bars, clubs, fast-food restaurants, and liquor stores may be considered attractors or generators of shootings (Brantingham and Brantingham, 1995). Perhaps they are the venues where most suitable victims hang out or where the most likely and motivated offenders visit, become intoxicated, or lose self-control (Clarke and Felson, 1993). Due to increased police presence or other capable guardians such as bouncers, witnesses, or closed-circuit television cameras, however, offenders do not shoot their victims inside or directly outside of such facilities. Rather, shootings are more likely to occur at certain distances away. Thought of in this way, the spatial influence of bars, clubs, fast-food restaurants, and liquor stores on shootings is more a function of distance from the closest criminogenic feature rather than the presence or absence of the feature at the shooting incident location. Exhibit 3 shows a map that operationalizes this distal spatial influence with a 370-foot buffer (about 1 block) around all features.

Although only 1 shooting out of 58 during 2007 happened exactly at or in a bar, club, fast-food restaurant, or liquor store, and 20 happened at places defined by high concentrations of these

Exhibit 3

Irvington, NJ, 2007: Correlation of Environmental Features Represented as Distance From Points



criminogenic features, 31 shootings occurred within one block from these features. In fact, 15 out of the 20 shootings that happened at places with high-density values occurred within one block from a criminogenic feature. The average nearest distance of a bar, club, fast-food restaurant, or liquor store to a shooting incident was 424 feet, with a standard deviational distance of 342 feet. Statistically, therefore, about 66 percent of all shooting incidents in Irvington during 2007 could have been expected to occur within +1 standard deviation, or 766 feet, from these criminogenic features. The operationalized spatial influence of the highest risk created by these features to be all places within about one block, or 370 feet—a definition that was grounded in theory and empirical research, identified places with more than one-half (53 percent) of all shooting incident locations.

It is realized that this result is arguably due to identifying a larger catchment area to which shootings are aggregated. Compared with feature points themselves, this argument is true. The coverage area of places with density values above +1 standard deviations (as shown in exhibit 2) is 0.806 square miles, however, and the coverage area of places within one block of a criminogenic feature (as shown in exhibit 3) is 0.725 square miles, which equals about 0.25 percent of Irvington's total area. More shootings occurred in a smaller area that was deemed affected by nearby criminogenic features in a conceptually meaningful way. Although empirical research suggests that bars, clubs, fast-food restaurants, and liquor stores are correlated with shootings, the most meaningful cartographic model of places that are at the greatest risk of shootings is one that operationalizes the spatial influence of these features on shooting incidents to be up to a certain distance away. This cartographic model of the spatial influence of bars, clubs, fast-food restaurants, and liquor stores might not be the case in other jurisdictions or for other crime types, but it is corroborated by existing research (for example, Smith, Frazee, and Davison, 2000; Tilley et al., 2005; Wright and Decker, 1997), and it reinforces the importance of modeling these criminogenic features in commensurate ways on a map.

Modeling the Interaction of Crime Risks Throughout an Urban Landscape

Now consider the role that the interaction of spatial influences of criminogenic features has on increasing the risks that crime will take place. Caplan, Kennedy, and Miller (2011) and Kennedy, Caplan, and Piza (2010) measured the place-based interaction of several criminogenic features using a technique called risk terrain modeling. Risk terrain modeling is an approach to risk assessment whereby separate map layers representing the influence and intensity of each risk factor at every place throughout a landscape is created in a GIS. Then all risk map layers are combined to produce a composite risk terrain map with values that account for all risk factors at every place throughout the landscape. Risk terrain modeling builds on principles of hotspot mapping, environmental criminology, and problem-oriented policing to produce maps that show where conditions are ideal or conducive for crimes to occur in the future, given the existing environmental contexts. Further, it offers a new and statistically valid way to articulate and communicate crime-prone areas at the microlevel according to the spatial influence of criminogenic features.

Risk terrain modeling comprises three concepts. Risk suggests the likelihood of an event occurring given what is known about the correlates of that event, and it can be quantified with positive, negative, low, or high ordinal values. The measures are ordinal because it is not necessarily known whether a risk value of 10 is twice as risky as a value of 5, but it is higher. Using risk as a metric, it is possible to model how risk evolves spatially and temporally, accounting for the different stages of a crime event (Kennedy and Van Brunschot, 2009). A terrain is a grid of the study area made up of equally sized cells that represent a continuous landscape of places where values of risk exist. Raster maps are used to represent terrains in risk terrain modeling because of their ability to model continuous landscapes. Places are defined in raster maps by cells of size x^2 (for example, 100 feet by 100 feet). Modeling broadly refers to the abstraction of the real world at certain places. Specifically within the context of risk terrain modeling, modeling refers to the process of attributing qualities of the real world to places within a terrain, and combining multiple terrains together to produce a single composite map in which the newly derived value of each place represents the compounded criminogenic risk of that place.

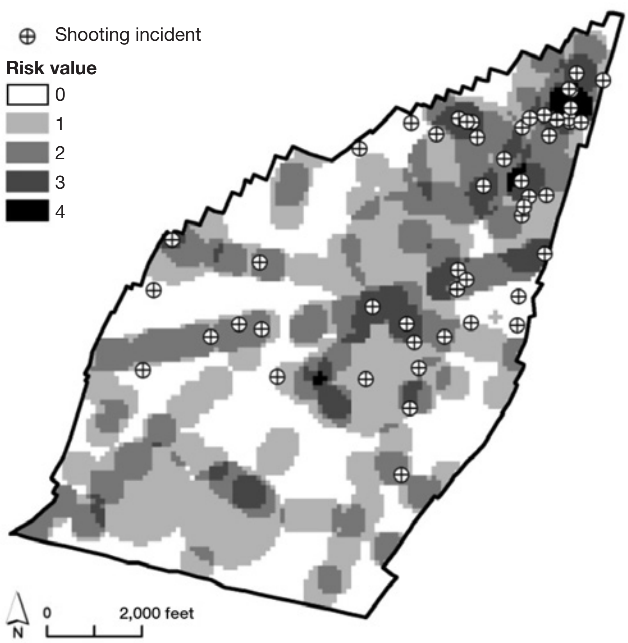
Crime explanations can be accounted for in an RTM by different factors that tie different components of risk together to explain individual, group, and institutional influences and effects on crime events. Risk terrain maps paint a picture, so to speak, of the combined effects of spatial influences of different factors at every place throughout a landscape. Clustering of illegal activity in particular areas is explained in an RTM by the unique combination of criminogenic factors that make these areas opportune locations for crime. This clustering occurs where the potential for, or risk of, crime comes as a result of all the attributes found at these places.

Qualities of places themselves do not create crime. They simply point to locations where, if the conditions are right, the risk of crime or victimization will be high. Risk terrain modeling assumes a step that is basic to the development of GIS in assuming that certain locations can acquire attributes that when combined in prescribed ways can create contexts in which certain outcomes are made more likely. For example, the attributes of open space, presence of children, and proximity to schools may indicate a playground. These attributes combined can be used to anticipate the types of behavior that would be expected in a playground—reducing the uncertainty that forecasts about what would transpire at a playground are wrong. In this way, risk terrain modeling uses the spatial influence of environmental features as a means of assigning likelihood (or risk) that certain events will happen at particular places. Outcomes may be benign (for example, children playing) or they may take on a more sinister character in which a combination of certain types of factors related to crime creates a context in which the risk of crime events can occur.

A key component of risk terrain modeling is to operationalize the spatial influence of crime risk factors, as discussed in the previous section. The objective, explain Caplan and Kennedy (2010), is to create separate maps of the study area, each representing the influence of a risk factor throughout the landscape. At least one raster map is created for each risk factor to represent the intensity of its criminogenic influence at every microlevel place throughout the study area. The resulting raster map shows where crime is most likely to occur as a result of particular conditions within the urban form. Cells within a raster map are the unit of analysis for risk terrain modeling. Exhibit 4 presents a risk terrain map for shootings in Irvington. It was produced according to the steps outlined by Caplan and Kennedy (2010) and includes four risk factors that previous empirical research found

Exhibit 4

Irvington, NJ, 2007: Risk Terrain and Shooting Incidents



to be correlated with shooting incidents: Gang members (Kennedy, Piehl, and Braga, 1996; Topalli, Wright, and Fornango, 2002); bus stops (Loukaitou-Sideris, 1999); schools (Roncek and Faggiani, 1985; Roncek and Lobosco, 1983); and facilities of bars, clubs, fast-food restaurants, and liquor stores (Block and Block, 1995; Brantingham and Brantingham, 1995; Clarke and Eck, 2005; Eck, Clarke and Guerette, 2007; Kennedy, Caplan, and Piza, 2010). Data on gang members were composed of addresses of all known gang members' residences,[3] and was operationalized as a density map because the spatial influence of these features was understood as areas with greater concentrations of gang members residing will increase the risk of those places having shootings. Addresses of all public bus stops were obtained from NJ TRANSIT (New Jersey's public transportation corporation) and operationalized as a distance map up to 555 feet away because the spatial influence of these features was understood as up to one and one-half blocks away from bus stops—transportation resources that motivated offenders and targeted victims frequent and use regularly—are at greater risk for shootings because targeted victims are most vulnerable when they arrive at or leave these destinations (Loukaitou-Sideris, 1999). Addresses of all public and private school buildings were obtained from the New Jersey Department of Education through the New Jersey Geographic Information Network and operationalized as "distances up to three blocks (up to 1,110 feet) are at the greatest risk for shootings" (Xu, Kennedy, and Caplan, 2010). Bars, clubs, fast-food restaurants, and liquor establishments were operationalized in a distance map in accordance with exhibit 3 and the previous related discussion.

The RTM (exhibit 4) of places in Irvington that share the locations and spatial influences of all aforementioned shooting risk factors has high predictive validity. Logistic regression results presented in exhibit 5 suggest that for every increased unit of risk, the likelihood of a shooting more than doubles (Exp(B) = 2.43, $p < 0.01$). Stated another way, the likelihood of a shooting happening at particular 100-foot-by-100-foot places in Irvington during 2007 increases by 143 percent as each additional risk factor affects that place.

Looked at in a different way, as shown in exhibit 6, more than 42 percent of all shooting incidents occurred in the top 10 percent of the highest risk places during calendar year 2007 (Pearson chi square = 55.897; df = 1; $p < 0.01$). The highest risk places were designated as such with a first-tier sorting of the risk values of all cells (N = 3,975) in descending order and then a second-tier sorting

Exhibit 5

Logistic Regressions for Period 1 Risk Value on Period 2 Shooting

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for Exp(B)	
							Lower	Upper
Risk value	0.888	0.145	37.606	1	< 0.001	2.431	1.830	3.230

B = Beta. C.I. = Confidence Interval. df = degrees of freedom. S.E. = standard error. Sig. = significance. Wald = Wald coefficient.

Nagelkerke R Square = 0.081.

[3] The New Jersey State Police provided data through the Regional Operations Intelligence Center and the many data sets they maintain, validate, and update regularly to support internal crime analysis and police investigations.

Exhibit 6

Shootings in Highest Risk Cells

Place Designated as Top 10% of Highest Risk? (N = 3,975)	Any Shootings Present During 2007 (Yes %, N = 47)
No	57.4
Yes	42.6

Pearson Chi-Square = 55.897; df = 1; p < 0.01.

by random number to randomize the sorting of cells with the same risk values.[4] Then the first 398 cells were designated as "highest risk" and all other cells were designated as "not highest risk."

In sum, this risk terrain map produced with thoughtfully operationalized criminogenic features yielded a valid and reliable forecasting model that was empirically and theoretically grounded. The criminogenic features were selected according to findings from previous empirical research, and they were included in the model in a manner that accounted for their spatial influence at all nearby and faraway places throughout the landscape. The resulting risk terrain map articulates environmental contexts of places that are most likely to attract, enable, and generate criminal shooting incidents as a function of the combined influences of criminogenic features within Irvington. This RTM is deconstructed in the next section to explain why it is valid, and to elucidate the key role that operationalizing the spatial influence of criminogenic features had on its predictive validity.

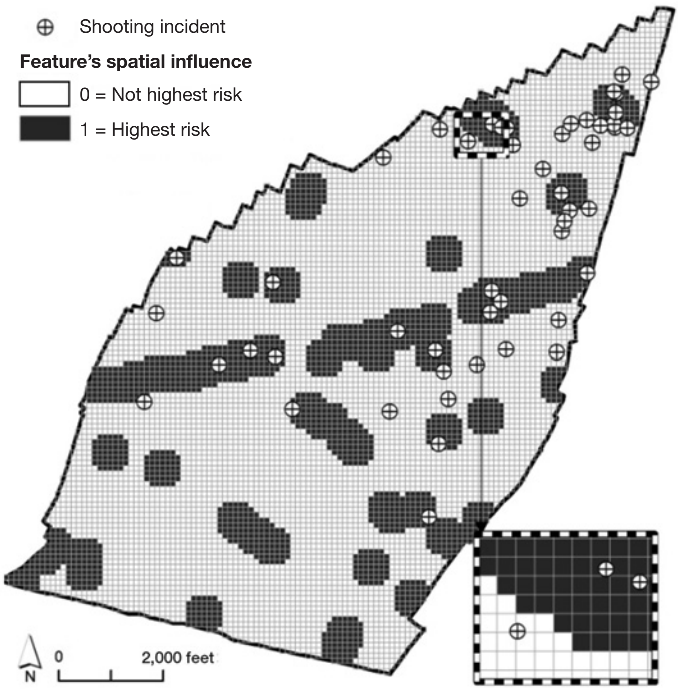
Valid Operationalizations of Spatial Influence Make Risk Terrain Modeling Work

A shooting or other crime incident could conceivably occur at any location in Irvington. That is, criminals do not generally offend with regard to census tract or other geographic units of aggregation. A victim who was shot at 123 Main Street could just as likely been shot at 115 Main Street if he stopped to tie his shoe, walked slower, or was delayed for any number of other reasons. Raster mapping in GIS, specifically developed to model continuous landscapes (Tomlin, 1994, 1991), captures this reality of how people populate, operate within, and travel through a landscape and models how crime can occur at microlevel places better than vector maps (Caplan, Kennedy, and Miller, 2011; Groff and La Vigne, 2002). Cells within a raster map are the standard unit of analysis for statistical testing across individual map layers and the final risk terrain map. For each map layer in the RTM discussed in the previous section, each cell (that is, place) has attributes that account for whether or not it is affected by a criminogenic feature, respectively. For example, exhibit 7 shows the map layer of "spatial influence of bars, clubs, fast-food restaurants, and liquor stores"; all places within one block from any of these features were operationalized as highest risk for shootings to occur. Cells that were located within the spatial influence of these features were given a value of "1"; all other cells were given a value of "0." A second attribute was also assigned to each cell noting the presence ("1") or absence ("0") of one or more shooting incidents during 2007. This

[4] The random number ensured that every cell had an equal chance of being sorted above or below the 10-percent cut point. For example, if 11 out of 100 cells had a risk value of 4, and they were sorted in descending order, the top 10 percent of cells to be designated as "high risk" would all have risk values of 4. The 11-percent cell, however, would be excluded due to a rather arbitrary standard sorting algorithm.

Exhibit 7

Irvington, NJ: Spatial Influence of Bars, Clubs, Fast-Food Restaurants, and Liquor Stores; Operationalized as 370 Feet From Features Is Highest Risk



procedure was repeated for all four map layers of criminogenic features included in the RTM so that the statistical validity of the operationalized spatial influence of each feature could be assessed with 2-by-2 cross tabulation tables and chi-square tests.

As shown in exhibit 8, all four cartographic representations of the spatial influence of criminogenic features in Irvington were statistically significant at $p < 0.05$. Of all shootings that occurred during 2007, 68 percent happened at places defined by their influence from bus stops; 55 percent happened at places defined by their influence from bars, clubs, fast-food restaurants, or liquor stores; 53 percent

Exhibit 8

Statistical Validity of Operationalized Spatial Influence

Criminogenic Feature	Operationalized Spatial Influence of Highest Risk	Any Shootings Present During 2007 (Yes %)	Pearson Chi-Square Value
Schools*	Within 3 blocks	53.2	5.363
Bus stops**	Within 1 block	68.1	7.707
Bars, clubs, fast-food restaurants, and liquor stores**	Within 1 block	55.3	19.318
Known gang members' residences**	Density value greater than +2 standard deviations	38.3	37.813

** p < 0.05. ** p < 0.01.*

happened at places defined by their influence from schools; and 38 percent happened at places defined by their influence from known gang members' residences. Again, "places" are cells sized 100 feet by 100 feet.

Combining the four maps of the spatial influence of criminogenic features into a single composite risk terrain map shows how compounded risk is distributed throughout Irvington and becomes a better predictor of shooting locations. As shown in column 3 of exhibit 9, the compounded risk of shootings gets larger in more confined areas of Irvington with each additional unit value of risk. When the four maps are combined with risk terrain modeling, 74 percent (43 out of 58) of shootings happened at places that were affected by two or more criminogenic features (that is, risk values were 2, 3, or 4). Of the shootings, 48 percent (28 out of 58) happened at places affected by three or more criminogenic features. Only 46 out of 3,975 places (cells) had risk values of 4 and were considered places where shootings could occur.[5] Of all shootings, 14 percent happened at these high-risk places representing barely more than 1 percent of the area of Irvington. Exhibit 4 shows that places with risk values of 4 were quite coalesced into relatively few clusters. Police commanders and other community partners could prioritize these areas (followed by areas with values of 3, 2, and 1, respectively) for targeted evidence-based interventions to prevent shootings with a high level of confidence in the efficaciousness of their resource allocation strategy.

It would appear from column 1 of exhibit 9 that bus stops are the most important feature to affect crime because 68 percent of all shootings happened nearby. Many bus stops are located in Irvington, however, and nearly one-half (48 percent) of the places in the township are cartographically modeled

Exhibit 9

Relative Spatial Influence of Criminogenic Features

Spatial Influence Map of...	Column 1: % of Shootings Present	Column 2: % of Irvington's Area[a]	Column 3: Shootings (Counts) per Square Mile[b]
Bus stops	68	48	57.35
Bars, clubs, fast-food restaurants, and liquor stores	55	27	82.86
Schools	53	37	58.82
Gang members' residences	38	11	146.66
Composite risk value of 2, 3, or 4	74	38	79.63
Composite risk value of 3 or 4	48	10.5	186.66
Composite risk value of 4	14	1	470.59

[a] Calculated by the number of cells having the attribute of the spatial influence of the criminogenic feature or the risk value, respectively. For example, 3,975 cells were included in the statistical analyses. So, if 46 cells had a risk value of "4," then the area would be 46/3975 = 0.011 or 1.1 percent.

[b] Square mile is based on the number of cells having the attribute of the spatial influence of the criminogenic feature or the risk value, respectively. Cells are 100 feet by 100 feet, or 10,000 square feet. So, if 418 cells had a risk value of either 3 or 4, then (418 cells x 10,000 square feet = 4,180,000 square feet) / (5,280 feet per mile x 5,280 = 27,878,400) = 0.15 square mile. 28 shootings in these respective cells / 0.15 square mile = 186.66 shootings per square mile.

[5] Shootings could be tracked only to street segments because the address level data were geocoded to street segments. So, the number 3,975 represents the number of cells that intersect with a street centerline segment.

as being located within the spatial influence of risk posed by the bus stops. This fact that 'more ground encompasses more shootings' relates to the modifiable area unit problem and requires that relative shooting counts be calculated to control for the square area of features' influences. As shown in column 3 of exhibit 9, places influenced by gang members' residences actually have the most shooting incidents per area and could be a principal feature of the landscape that attracts shootings. To assert that places where gang members reside are definitely places where shootings will happen, however, is like saying the presence of motivated offenders, suitable victims, and no capable guardians always results in crime (that is not true; Cohen and Felson, 1979). What is more accurate, and what risk terrain maps articulate visually, is that places affected by gang members' residences and one or more additional criminogenic features have the greatest likelihood of shootings to occur. As shown in column 3 of exhibit 9, places influenced by all four criminogenic features hosted meaningfully more shooting incidents per square area compared with all other places. Several criminogenic features may influence smaller numbers of places, but as a whole, these places have a very high relative frequency of shootings. Operationalizing the spatial influence of criminogenic features to maps is an important task for maximizing the construct validity of the effect these features have on crimes. Combining these maps with an RTM gives such cartographic modeling practical utility for policing operations by articulating a continuous landscape of compounded risk at all places; resulting maps can be used to efficiently allocate resources and target interventions.

Evaluate Place-Based Interventions While Controlling for Environmental Context

Hindsight is 20/20, as the saying goes. At this point, after analyzing old data, it may seem a bit unfair to say that interventions to suppress and prevent shootings could have been strategically targeted in Irvington to maximize benefits. Police agencies operating in Irvington, however, did in fact have a targeted strategy to suppress and deter shootings. Now with risk terrain modeling and the understanding of the spatial influence of criminogenic features, a spatial analytic method is used for evaluating the shooting suppression strategy. The township of Irvington is relatively small (about 2.9 square miles), sandwiched between a slightly bigger suburban township and the larger city of Newark. Its murder rates for 2007, however, were 38.7 per 100,000 people compared with the national average of 4.9 for similar sized cities across the country (FBI, 2008). Primarily for this reason, Irvington drew a considerable amount of attention from political leaders and law enforcement officials, who set up a special task force to assist the smaller municipal police force with policing this jurisdiction. During 2007, the task force consisted of uniformed state troopers who patrolled targeted areas in both a highly visible saturation capacity and in aggressive undercover operations. Drug arrests at these targeted areas were the task force's principal intervention method; the purpose was to incapacitate likely shooters and likely victims (because shootings were mostly gang and drug related) by means of arrest, conviction, and incarceration. Although this strategy yielded an overall reduction of violence[6] in Irvington since before the task forces' inception and the number of shootings has remained fairly constant since (about 25 biannually), its effect on the spatial distribution of new shootings remained unknown.

[6] According to the New Jersey State Police Uniform Crime Reports, the violent crime rate in 2006—before the task force—was 22.4 per 1,000, with a murder count of 21. In 2009, the violent crime rate was 18.2 per 1,000, with a murder count of 17. The total number of violent crimes in 2006 was 1,321 and in 2009 was 1,024.

Knowing that certain criminogenic features attract and enable shootings above and beyond the routine activities of offenders, victims, or police, Irvington's contextual landscape must be controlled for when evaluating geographically targeted interventions such as the task force's aforementioned drug arrests. A validated RTM of Irvington's fixed criminogenic contexts is especially useful for such an evaluation. The risk terrain map in exhibit 4 was "fixed" because it was produced from criminogenic features that did not change during the year. For example, the count and locations of school buildings did not change during 2007. In Irvington, (probably like many other jurisdictions), schools, bus stops, bars, and so on are not demolished or erected on a regular basis. Therefore, the aforementioned RTM with predictive validity (exhibit 4) articulates the fixed criminogenic contexts for shootings at microlevel places throughout Irvington. Risk terrain modeling has not yet been used to create a contextual control measure of environmental crime risks for the purpose of evaluating police interventions at places, but it could. The fixed context risk terrain map can be used as a base map—a backcloth, so to speak (Brantingham and Brantingham, 1981)—to evaluate the spatial effect of the task force's targeted drug arrests during the first half of 2007 on subsequent shooting locations during the second half of 2007. A reasonable time frame to measure this effect is 6 months because the New Jersey State Police routinely report 6-month crime trends to the public (for example, www.njsp.org/info/stats.html#cit) and revise policing operations and strategies accordingly.

The first step to evaluate the spatial effect of targeted drug arrests on shooting incident locations is to operationalize the intended spatial influence of drug arrests and produce a respective map layer to be added to the fixed context RTM. The basic information sought from evaluating this intervention is whether it was successful, defined by an overall reduction of shooting incidents without displacement or reemergence. This spatial evaluation seeks to answer: What effect did targeted drug arrests during January through June 2007 (Period 1) have on the locations of shooting incidents during July through December 2007 (Period 2)?

Shootings occurred in 32 known locations during Period 1 and 26 locations during Period 2, which was a slight reduction. As shown in exhibit 10, the spatial distribution of shootings during the two time periods changed, with more incidents clustered in northeastern Irvington during Period 2 than had occurred there during Period 1. It is hypothesized that places with higher concentrations of targeted drug arrests had a mitigating effect on the criminogenic contexts at these places and, therefore, shootings would have been less likely to occur. Drug arrest locations were geocoded to street centerline shapefiles and then used to produce the density map in exhibit 11, showing the places with density values greater than +2 standard deviations from the mean drug arrest density value throughout Irvington. These "highest density" places were reclassified with a value of "1" and all other places were assigned a value of "0." Parameters for this map were similar to map layers already included in the fixed context risk terrain map, described previously: "places" were defined by a cell size of 100 feet and density was calculated with a search radius of 1,110 feet, about three blocks.

To test the hypothesis that places with higher drug arrest concentrations deterred future shootings, the drug-density map was subtracted from the fixed context risk terrain map to produce a new risk terrain map with values ranging from -1 to +4. As shown in exhibit 12, this new RTM (hereafter called the "Hypothesis RTM") is statistically significant, although not as much as the original fixed-context RTM. The Nagelkerke R Square of the Hypothesis RTM was 0.032; the fixed-context RTM was 0.081. The Nagelkerke R Square provides a measure of how well future outcomes are likely to

Exhibit 10

Irvington, NJ: Biannual Spatial Distribution of Shooting Incidents

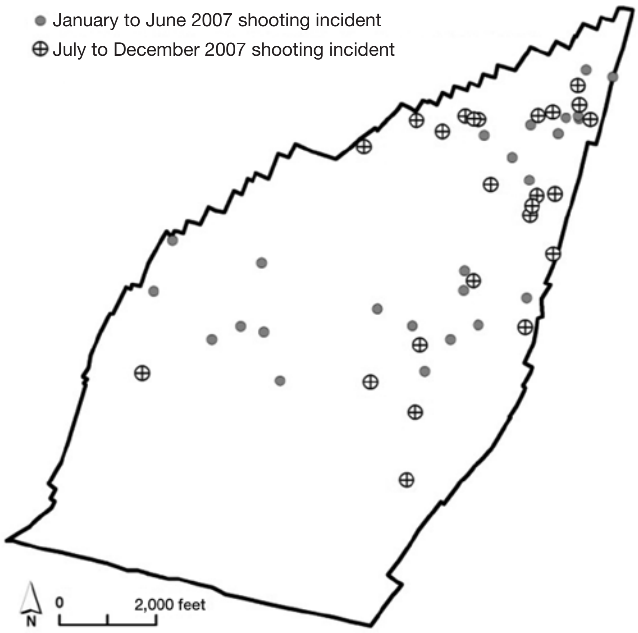
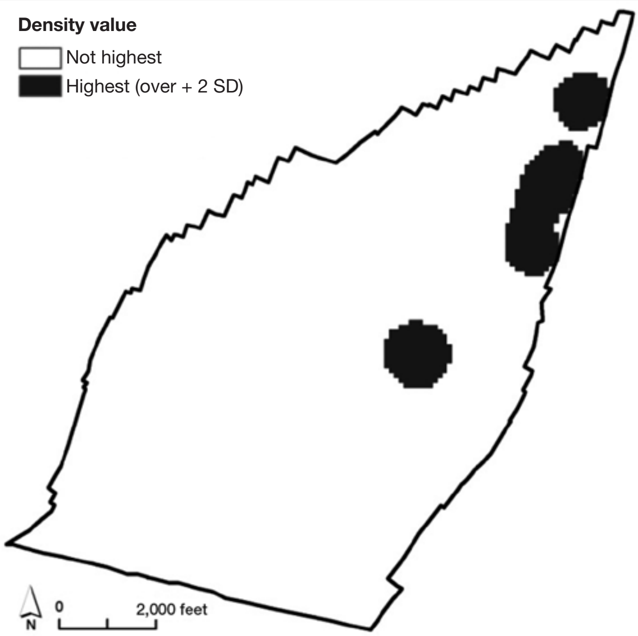


Exhibit 11

Irvington, NJ: January–June 2007, Highest Density Drug Arrest Places



SD = standard deviation.

be predicted by the model. Values of Nagelkerke R Square mean that the Hypothesis RTM only explains about 3 percent of the variance in future shooting locations compared with about 8 percent explained by the fixed-context RTM.

After further reflection, it is apparent that comparing the Hypothesis RTM to the fixed-context RTM is like comparing apples to oranges. As with any other statistical tests, one must consider only the results of the hypothesized model against the alternative, or null, hypothesis. The null hypothesis for the task force's intervention is that places with higher drug arrest concentrations attract future shootings. To adjust to this null hypothesis, the drug-density map was added to the original fixed-context risk terrain map to create a "Null Hypothesis RTM" with values ranging from 0 to 5. As shown in exhibit 12, the Null Hypothesis RTM has statistically significant predictive validity, with a Nagelkerke R Square value of 0.073.

Compared with the Hypothesis RTM, the Null Hypothesis RTM explains the variance of shooting locations much better. Targeted drug arrests at certain areas appear to have actually attracted new shooting incidents to these same places. This result seems counterintuitive and many explanations are likely for this happenstance. Methodologically, a limitation of the RTM is that it does not account for very small increments of time, so it is possible that shootings were deterred when police were in an area, but then ensued shortly after they left. Or perhaps many targeted drug arrests created new open turf that other drug dealers fought to control. Targeted drug arrests may simply not be an appropriate response to gun shooting crimes. Recall that the RTM with the best predictive validity and most explained variance of future shooting locations was the fixed context RTM, which did not include any risk factors directly related to drug arrests. Yet police sought to suppress and deter shootings with targeted drug arrests. A more effective intervention might have been to use evidence-based practices to mitigate one or more of the criminogenic risk factors that were included in the fixed context RTM, thereby reducing the availability of places that are conducive to shootings. Such an intervention might include increasing shooters' apprehension risks through strategic interventions at places within one block from bus stops, bars, clubs, fast-food restaurants, and liquor stores; increasing police patrols along travel routes to and from schools, especially within the immediate three-block areas; or taking civil actions to shut down the most historically problematic bars—giving priority to establishments within places having risk values of 4.

Exhibit 12

Logistic Regressions for Period 1 Hypothesis RTM on Period 2 Shootings

						Risk Value 95% C.I. for Exp(B)	
	B	S.E.	Wald	Sig.	Exp(B)	Lower	Upper
Hypothesis RTM: Drug arrests as mitigating factor[a]	0.645	0.222	8.465	0.004	1.906	1.234	2.942
Null hypothesis RTM: Drug arrests as aggravating factor[b]	0.715	0.154	21.608	< 0.001	2.045	1.512	2.764

B = Beta. C.I. = Confidence Interval. df = degrees of freedom. S.E. = standard error. Sig. = significance. Wald = Wald coefficient.

[a] Nagelkerke R square = 0.032; df = 1.

[b] Nagelkerke R square = 0.073; df = 1.

A case was presented for measuring and mapping criminogenic features not as points, lines, or polygons, but as qualities of space throughout a landscape. Thinking about crime correlates not as finite objects, but rather as centers of radiating criminogenic influence across the urban landscape enables cartographically modeling environments in terms of microlevel place-based risks that are more enduring than just the characteristics of the people who frequent these places. Cartographic models of spatial influence are consistent with ideas that were popular among ecologists (for example, Holland, 1998), repeated by environmental criminologists when Brantingham and Brantingham (1995) talked about environmental backcloths, expressed in the key elements of problem-oriented policing (Center for Problem-Oriented Policing, 2010), and are now appearing in terms of risk terrains or opportunity structures (Caplan, Kennedy, and Miller, 2011; Groff and La Vigne, 2002). Individual risk factors are important, such as those owned by motivated offenders or potential victims (Cohen and Felson, 1979), but environmental contexts relative to certain criminogenic features are also very important in assessing crime-prone places. Many places probably abound daily with motivated offenders, suitable victims, and no capable guardians, but crimes do not always occur there. Why? Because these elements must simultaneously exist at enabling places to yield criminal events.

A few researchers have connected environmental factors to crime through simulation models, including recent work by Brantingham and Tita (2008), Tita and Griffiths (2005), and Groff (2007a, b), suggesting that the criminal justice community may be closer in its ability to show not just that certain factors are important in creating criminogenesis, but also to explain how these factors interact to produce the crime outcomes that appear. This article advances these efforts to measure environmental context as an element of criminal events by proposing a technique for operationalizing crime risk factors in cartographic form so that their otherwise intangible influences on places can be statistically tested, used to better inform resource allocation, and controlled for when evaluating place-based interventions. Three operationalizations of spatial influence of criminogenic features within a landscape were presented: presence of features, concentration of features, and distance from features. All are shaped by the urban form or physical layout and design of a city, which is the structural setting for people to interact and commit crimes. The most appropriate operationalization can differ by crime type and research setting, but it should always be derived from theory and expert knowledge.

Cartographically modeling the likelihood of crime at all places throughout a landscape according to the spatial influences that certain criminogenic features have on those places is a more realistic depiction of criminal opportunity (Couclelis, 1992; Frank and Mark, 1991; Freundschuh and Egenhofer, 1997). Operationalizing the spatial influence of criminogenic features considers criminal behaviors as less deterministic and more as a function of a dynamic interaction that occurs at places. Qualities of space themselves do not create crime; they simply point to locations where, if the conditions are right, the risk of crime or victimization will go up. It cannot be assumed, although, that because one or more criminogenic features affect a location that crime will definitely happen. What is more likely is that the likelihood of crime at places that have several criminogenic attributes is higher than at other places because these locations attract motivated offenders (or more likely concentrate them in close locations) and are conducive to allowing certain events to occur. Although physical structure and public activities can have an effect on the ways in which crime occurs (Basta, Richmond, and Wiebe, 2010; Groff 2007a, b), it has been difficult to show empirically how the connection works because of data problems and the complexity of the issue. Measuring and modeling criminogenic features according to their spatial influences addresses the empirical difficulty. Operationalizing spatial influence also lends itself to multilevel modeling in GIS with techniques such as risk terrain modeling, which models the combined influences of criminogenic features at places. When risk terrain modeling is performed with fixed criminogenic features, it can serve as an environmental control measure for evaluating spatial effects from place-based interventions.

The allure of mapping spatial influences of criminogenic features is that doing so can closely tie information to strategic planning. In addition, it provides a means by which police and other community leaders can evaluate interventions. It comports with the idea that the public has anxieties that translate into demands for prevention strategies to reduce crime risks (and crime fears). It also addresses the idea that certain areas can be more dangerous than other areas, even if criminogenic features are not present, and, therefore, that those places justifiably demand greater attention. Combined with risk terrain modeling, it also provides an evaluation approach that can determine a program's effectiveness and efficacy, or wastefulness of certain resource types used.

Author

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HOPE VI Resident Displacement: Using HOPE VI Program Goals To Evaluate Neighborhood Outcomes

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Abstract

This study evaluates the neighborhoods selected by HOPE VI residents in Lexington, Kentucky, following the demolition of the Charlotte Court housing project. HOPE VI is a public policy program designed to address problems associated with severely distressed public housing. A central routine of HOPE VI is demolishing housing projects and redeveloping the original site into new mixed-use housing. Demolition displaces a large percentage of residents to other neighborhoods, using Section 8 vouchers. In this study, using the goals of HOPE VI as a conceptual framework, we developed measures to determine if HOPE VI residents improved their circumstances at the neighborhood level following their displacement. We found no significant difference between the original Charlotte Court neighborhood and the new neighborhoods that residents selected. Using negative binomial regression, the results of the study show that crime and the percent of the population that is African American are significant predictors of the number of displaced households within a neighborhood selected by displaced residents. The study concludes with a discussion of policy implications and an offering of potential solutions to the many problems associated with HOPE VI resident displacement.

Introduction

HOPE VI is a public policy program designed to address problems associated with severely distressed public housing. A central HOPE VI routine is the demolition of existing housing projects and redevelopment of new mixed-use housing on the original site. Research on HOPE VI has shown that demolition displaces a large percentage of residents to other neighborhoods through the use of Section 8 vouchers (Abt, 1996; Comey, 2007; Goetz, 2010; Kingsley, Johnson, and Pettit, 2003; Popkin et al., 2002). Many HOPE VI residents report that their new neighborhoods are improvements; however, many also report that their quality of life is only moderately enhanced (Abt, 1996; Goetz, 2010; Popkin et al., 2002). HOPE VI objectives center on improving housing quality on the original site and decreasing the concentration of crime, poverty, unemployment, and racial segregation (HUD 2008; Popkin et al., 2004; Popkin et al., 2000). HOPE VI research has yielded disparate findings in study sites across the nation. This article adds to the HOPE VI literature by examining the HOPE VI redevelopment of the Charlotte Court housing project in Lexington, Kentucky. Kingsley, Johnson, and Pettit (2003) identified Lexington as having among the most concentrated distribution of displaced residents when compared with 73 redevelopment projects in 48 cities. This study is designed to gauge the efficacy of HOPE VI in Lexington by evaluating measures that are consistent with goals and objectives identified from the U.S. Department of Housing and Urban Development (HUD) documentation and past studies evaluating HOPE VI.

The study examined whether HOPE VI residents selected their new home because it offered an opportunity to improve their lives, or because it was the next best available housing. A key of any examination of HOPE VI is that nearly any location outside of the most severely distressed public housing is likely to be an improvement for the residents (Abt, 1996). Determining the efficacy of HOPE VI is difficult, because a clear set of measures for program outcomes is neither clearly stated, nor openly available. The study therefore identifies several factors believed to be adequate measures of HOPE VI goals and objectives. One hypothesis is that neighborhoods that HOPE VI residents selected in Lexington were better in overall neighborhood conditions such as crime, poverty, unemployment, and racial segregation. A second hypothesis is that, despite the improvement, the number of relocated residents in a neighborhood is significantly associated with measures of reported crime, poverty, unemployment, and racial segregation. If these hypotheses are supported, some weight can be given to the argument that HOPE VI has qualitatively achieved its goals, but simultaneously failed, because new neighborhoods are still significantly associated with the measures identified as problematic in the HOPE VI literature.

HOPE VI Goals and Objectives

The goals and objectives of HOPE VI have been notoriously opaque. The National Housing Law Project (2002) mentioned that one key problem with HOPE VI is its uncertain objectives. The goals and objectives from past studies associated with neighborhood quality generally pertain to improving the quality of public housing; decreasing the concentration of crime, poverty, unemployment, and racial segregation; and building local partnerships with community organizations

(HUD, 2010; Wexler, 2001). The goals are unlikely to capture the full range of initiatives set forth by HOPE VI; however, the goals do represent key factors associated with the social and economic improvements expected for HOPE VI residents.

The first identified HOPE VI goal is to improve living conditions of severely distressed public housing through demolition and renewal projects (Gilderbloom, 2008; HUD, 2010; Popkin et al., 2004). The construction and design methods vary across the nation, where some cities have rebuilt public housing on old sites, and others have used the old public housing sites as land for building new mixed-use or affordable housing. In many instances the demolition of public housing sites has left many former residents with few housing options. As a result, many residents turned to Section 8 vouchers or were forced to move to other housing projects (Buron et al., 2002). The present study reveals similar relocation patterns as residents either moved to a different public housing location or to private apartment housing in a different neighborhood.

The second goal of HOPE VI is to revitalize communities in an effort to reduce the concentration of poverty. This effort often includes limiting the capacity of the public housing rebuilt at the original site and, subsequently, relocating residents to various neighborhoods through Section 8 vouchers (Popkin et al., 2004; Wexler, 2001). America's housing projects are home to the most economically and socially disadvantaged population (Schill and Wachter, 1995). High-poverty neighborhoods have multiple layers of problems, ranging from health-related issues to high rates of homicide. Because of these problems, HOPE VI has aimed to reduce the spatial concentration of poverty by dispersing residents to areas with lower poverty levels. If this goal is achieved, new neighborhoods will have significantly lower poverty levels.

The third goal of HOPE VI is to create opportunities for residents to become self-sufficient through the use of services that provide various types of job training and employment. These services include computer training, daycare, after-school programs, and job referrals (Popkin et al., 2004). If this goal is achieved, neighborhoods selected by displaced residents would not have high unemployment levels. When new neighborhoods selected by displaced residents have insignificant unemployment levels, available jobs, and job training, HOPE VI can be considered successful in moving residents to neighborhoods that, at the very least, expose residents to more employment opportunities.

The fourth goal of HOPE VI is to reduce public housing residents' exposure to incidents of crime (Gilderbloom, 2008; HUD, 2010; Popkin et al., 2004). Several studies identified problems with crime as a key concern of many residents (Popkin et al., 2002; Smith, 2002). It is well known that housing projects have become havens for drug dealing, robbery, and homicide—a central focus of HOPE VI was to eliminate these problems from the lives of public housing residents. If this goal is achieved, the new neighborhood that a displaced resident selected should have lower crime levels than the old neighborhood.

A final goal of HOPE VI identified in the literature is to reduce the amount of racial segregation. Housing projects in the United States traditionally have high rates of African-American residents (Brooks et al., 2005; Fischer, 1999; Kingsley, Johnson, and Pettit, 2003). Mendenhall, DeLuca, and Duncan (2005) found that women who were relocated to neighborhoods with lower percentages of African Americans were able to find and hold on to jobs for a longer period of time and were less likely to accept welfare benefits. Peterson and Krivo (1993) found that racial segregation leads to higher levels of homicide among black residents. If this goal is achieved, the new neighborhoods that displaced residents select should have low levels of African-American population.

The goals of HOPE VI are important, because they identify objectives the program is designed to achieve. Highlighting program objectives provides a way of measuring the efficacy of the program's outcomes. This study uses HOPE VI goals as a conceptual framework for selecting explanatory variables used in the final analysis. The goals identify several key themes used to study the overall effect that HOPE VI has had on displaced residents' living conditions.

Outcomes for HOPE VI Residents

A fairly consistent finding of HOPE VI research is that residents tend to move to locations with substantially fewer problems when compared with the original housing site (Goetz, 2010). Studies have also indicated, however, that outcomes for residents are generally mixed (National Housing Law Project, 2002). A key finding in this study is that, despite the many improvements observed in past studies, the residents affected by HOPE VI continue to struggle in their everyday lives. The findings presented in the following sections indicate that new neighborhoods have only slight improvements over the original HOPE VI neighborhood. Results also indicate, however, that the new neighborhoods may still be areas that are troubled by crime, poverty, unemployment, and racial segregation. Admittedly, other outcomes for neighborhoods, aside from crime, poverty, unemployment, and racial segregation, have been identified in the literature. For example, Goetz (2010) identified other problem areas such as children's school and social experience, health and behavior outcomes, housing neighborhood characteristics, and social networks. Currently, no existing reliable measures of these other factors can be analyzed at the census block group level. Despite this limitation, poverty, crime, unemployment, and racial segregation are excellent proxies for the goals previously outlined.

Crime

Many studies on HOPE VI have shown that a key concern of HOPE VI residents is their exposure to crime (Barbrey, 2004; Buron et al., 2004; Gilderbloom, 2005; Popkin, 2003; Popkin et al., 2000). Popkin (2003) found that residents of inner city public housing complexes are likely to be offenders and victims of violent crime. Buron et al. (2002) reported that many HOPE VI residents wanted their new neighborhoods to have less drug trafficking and violent crime. Research on HOPE VI has generally found that residents have reported increases in perceived safety levels within their new neighborhoods (Buron, 2004; Buron et al., 2002; Goetz, 2010; Popkin and Cove, 2007; Popkin et al., 2004). Ludwig, Duncan, and Hirschfield (2001) found that moving out of public housing reduces the risk for children to engage in juvenile crime. Most studies that explore crime in HOPE VI neighborhoods have used survey measures to determine how residents perceive safety in their new neighborhood. Few studies have examined the association between displaced HOPE VI residents and neighborhood crime levels. One exception to this gap in the literature is Gilderbloom's (2005) study of a HOPE VI redevelopment in Newport, Kentucky. He found a 19-percent drop in crime at the original site over a 7-year period. This finding was expected because of the large drop in population through resident displacement. Gilderbloom did not describe crime levels in the displaced residents' new neighborhoods. Barbrey (2004) also evaluated crime at the original public housing location in Knoxville, Tennessee, but found that HOPE VI had little effect on overall crime levels, suggesting that HOPE VI did not substantially improve safety levels for residents.

Poverty

Studies show that poverty levels in new neighborhoods are lower than in the original neighborhood (Boston, 2005; Buron, Levy, and Gallagher, 2007; Buron et al., 2002; Clampet-Lundquist, 2004; Fischer, 1999; Goetz, 2010; Kingsley, Johnson and Pettit, 2003; Popkin et al., 2004). Buron et al. (2002) showed that nearly 40 percent of relocated residents moved to areas that were classified as low poverty. The same study also showed, however, that 40 percent of residents moved to high-poverty areas. Kingsley, Johnson, and Pettit (2003) showed that residents who used Section 8 vouchers moved from neighborhoods with 61-percent poverty rates to neighborhoods with average poverty rates of 27 percent. Despite the improvement in overall neighborhood economic circumstances, research has shown that many residents are unable to take advantage of the economic improvement. Clampet-Lundquist (2004) showed that residents who moved to lower poverty neighborhoods were unable to benefit from their new circumstance because they were unable to connect to local social and communal networks. Overall, it appears that poverty in new neighborhoods is substantially lower when compared with the original neighborhood, but it is not clear if this change means a direct improvement for displaced residents. Residents continue to live impoverished lives, and continue to have many of the same economic problems that were present in their original neighborhoods.

Unemployment

Research on unemployment and HOPE VI generally indicates that residents do not improve their employment circumstances (Barrett, Geisel, and Johnston, 2006; Clampet-Lundquist, 2004; Goetz, 2010; Levy and Woolley, 2007). Clampet-Lundquist (2004) showed that the residents displaced by using Section 8 vouchers reported few opportunities for employment in their new neighborhoods. Levy and Woolley (2007) also reported that residents who relocated have been unable to improve their employment circumstances largely because of health problems. Barrett, Geisel, and Johnston (2006) showed that issues with transportation and childcare limited opportunities for employment among HOPE VI residents. Buron et al. (2002) found that many residents were employed. Residents who were not employed, however, reported barriers such as lack of job training and few opportunities for employment. The authors also reported that many residents who moved using Section 8 vouchers had trouble paying rent or other bills in the new private-market housing because of lack of income from unemployment and higher bill payments required in the private housing market. Thus, the research on HOPE VI and employment indicates that residents continue to struggle to find work after moving to homes in new neighborhoods.

Racial Segregation

Racial segregation is a well known aspect of public housing in the United States, and is defined as a high percentage of residents within a neighborhood being from a minority population. Research indicates that HOPE VI neighborhoods have high percentages of African-American residents (Brooks et al., 2005; Buron et al., 2002; Fischer, 1999; Kingsley, Johnson and Pettit, 2003; Popkin et al., 2002). Fischer (1999) concluded that HOPE VI residents who relocate using Section 8 vouchers end up in neighborhoods that are racially segregated. Kingsley, Johnson, and Pettit (2003) conducted a nationwide study and found that HOPE VI has generally failed to decrease the amount of racial segregation that displaced residents experienced. Buron et al. (2002) found that change in racial segregation for most residents' neighborhoods was minimal. In general, it appears that neighborhoods where HOPE VI residents move continue to be racially segregated, despite HOPE VI objectives.

HOPE VI in Lexington, Kentucky

HOPE VI relocations from the Charlotte Court Housing Project in Lexington are especially unique when compared with most other cities across the country. Kingsley, Johnson, and Pettit (2003) showed that Lexington had the second highest average (4.8) of Section 8 relocations per census tract. Their finding that displaced residents are tightly clustered is confirmed by our data mapped at the block group level (see exhibit 1). The average number of Section 8 households per census tract across the country was only two households per tract. In addition, Lexington was 1 of only 4 cities, out of 48 total, where more than 40 percent of the relocatees moved to census tracts with large clusters of other relocated residents. This finding suggests that a small number of census

Exhibit 1

Relocation Counts per Block Group in Lexington, Kentucky

tracts in Lexington have absorbed a large percentage the HOPE VI residents. Research has shown that high concentrations of displaced residents will likely affect housing stock, crime, and social disorder in the clustered areas (Coulton and Pandey, 1992; Crane, 1991; Kingsley, Johnson, and Pettit, 2003). Therefore, Lexington provides a unique opportunity to study the neighborhoods of displaced HOPE VI residents.

Another reason Lexington is ideal for studying HOPE VI is that the relocations in Lexington occurred at the end of 1999, approximately the same time period that the 2000 Decennial Census was conducted. This timing means that the 2000 Census provides data about the neighborhoods at approximately the same point in time as the Charlotte Court HOPE VI redevelopment. The cross-sectional nature of this study is an advantage because it provides a look at the neighborhoods that residents selected at the same time as their initial relocation. The typical neighborhood types that residents moved to directly after being displaced from the original public housing site can, thus, be determined.

Summary and Hypotheses

The quality of neighborhoods chosen by displaced residents is an important determinant of whether or not HOPE VI goals have been achieved. The goals provide language that can be used to identify variables that measure HOPE VI efficacy. Among many HOPE VI objectives, key aims are to decrease the exposure of residents to crime, decrease the concentration of poverty, improve opportunities for employment, and reduce racial segregation. Research on the outcomes of HOPE VI residents has been inconclusive, but has generally found that new neighborhoods are an improvement for residents (Goetz, 2010). Nearly all potential housing available outside of severely distressed housing projects will be an improvement for HOPE VI residents. It is likely, however, that neighborhoods that HOPE VI residents selected have similar problems to those found in the original HOPE VI redevelopment neighborhood. Lexington, Kentucky, was selected as the research site because of data availability, the unique characteristics of relocations within the city, and the time association between the relocations and the 2000 Decennial Census. Neighborhoods that displaced HOPE VI residents selected are likely to be significantly different from the original neighborhood.

Hypotheses

Based on the goals previously listed, a series of hypotheses were developed to test whether displaced HOPE VI residents moved to better neighborhoods. First, the neighborhoods that displaced HOPE VI residents selected are expected to be significantly lower on measures of crime, poverty, unemployment, and racial segregation than the original Charlotte Court neighborhood. If the new neighborhoods' levels are significantly lower than Charlotte Court's, then it could be argued that HOPE VI achieved its goals.

Second, it is expected that, despite the improvement in neighborhood conditions when compared with the Charlotte Court neighborhood, the neighborhoods that displaced HOPE VI residents select will continue to be positively and significantly associated with rates of crime, poverty, unemployment, and racial segregation net of controls that might predict high rates of households using Section 8 vouchers. If supported, the results would indicate that neighborhoods that displaced HOPE VI residents select continue to be plagued by the same problems that HOPE VI is designed to alleviate.

This article proceeds with the understanding that HOPE VI redevelopments are highly contextual, and using one example to generalize to all HOPE VI sites would be inappropriate. Studies that incorporate redevelopment sites not previously researched, however, provide opportunities for researchers to consider how HOPE VI has affected different cities at different times. HOPE VI goals are to improve the lives of individuals who live in public housing; therefore, evaluations should consider HOPE VI goals and objectives when evaluating how the program has affected residents' lives. This study extends the current body of research by employing official police data, framing the hypotheses based on the program goals, and using a study site that has a unique distribution of relocated residents.

Data

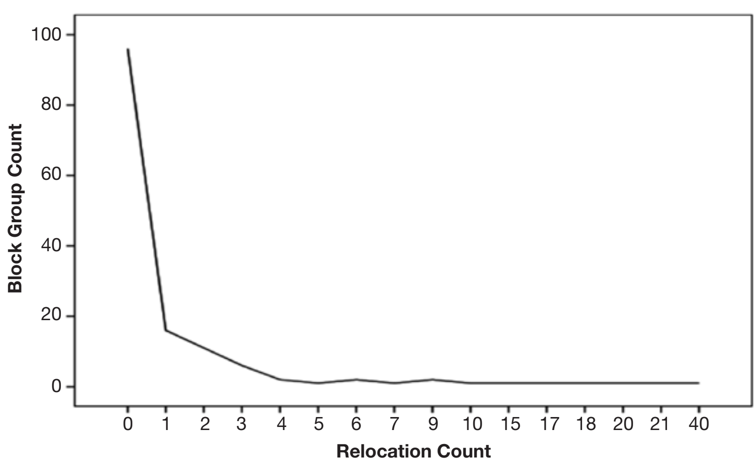
The data for this project were collected for a sample of 148 block groups in Lexington, Kentucky. Lexington is located in central Kentucky and in 2000 had a population of 260,512, making it the 64th largest city in the United States. The data used for analysis were obtained from three sources: Lexington Housing Authority, the United States Census Bureau, and the Lexington Police Department. The study's variables are described in the next section.

Dependent Variable

The dependent variable for this study is a count of the number of displaced residents per census block group. The data were obtained from the Lexington Housing Authority. The data included 260 addresses that were geocoded using Cartographica's Bing Geocoder and achieved a 98-percent match rate. The addresses that did not match were either incorrectly recorded, or were located within another city. Consistent with Kingsley, Johnson, and Pettit (2003), displaced residents were highly concentrated in a small number of city block groups. Exhibit 2 illustrates the positively skewed relocation distribution and the large number of block groups that received zero relocations.

Exhibit 2

Distribution of Dependent Variable



Independent Variables

The main independent variables in this study are reported crimes, poverty, unemployment, and African-American population. The crime data were obtained from the Lexington Police Department for the year 1999. The reported crimes were provided at the address level and included assaults, auto theft, burglary, robbery, and disorderly conduct. The data were geocoded using Cartographica's Bing Geocoder and achieved a 94-percent match rate. Data from 1999 were used because they match the temporal timeframe of the census data used for the other independent variables. Poverty rates were measured by the 2000 Census and were defined as the percentage of the population living below the poverty line. Unemployment was also measured by the census and was defined as the percentage of the population over age 16 who are unemployed. The final independent variable collected from the 2000 Census was the percentage of the population that was African American. Racial segregation has been shown to be a continuing problem for HOPE VI and, therefore, it is assumed that neighborhoods with high percentages of African-American population may be more likely to have displaced HOPE VI residents move there.

Control Variables

The control variables used in this study are necessary because it is likely that displaced residents selected neighborhoods based on housing availability (Smith, 2002). A central argument of this article is that, although improvements may exist for residents, it is likely that difficulties still exist at the neighborhood level because residents' housing choices are limited. That is, residents are most likely to choose places to live that are willing to take on residents using Section 8 housing vouchers or that provide other forms of public housing. Therefore, controls were used for the rental vacancy rate, which is defined as the amount of vacant and available rental housing. Another important control is the percentage of the population that receives public assistance; because HOPE VI is a form of public assistance, a control was used to account for the tendency of displaced residents to move to locations where other residents receive some form of public assistance. The variables used to measure HOPE VI and the controls for housing availability are described in exhibit 3.

Exhibit 3

Neighborhood Condition Descriptive Statistics

Variable	Mean	Standard Deviation
Relocations	1.72	4.69
Reported crimes	28.61	28.18
Percent poverty	14.77	13.40
Percent unemployment	3.33	5.26
Percent African American	14.57	19.60
Percent public assistance	2.49	3.99
Rental vacancy rate	3.22	3.57

Spatial Autocorrelation

Because of the spatial nature of the distribution of HOPE VI residents, it was prudent to test for spatial autocorrelation. Spatial autocorrelation is based on the idea that spatial events are arranged in a random or nonrandom manner due to factors associated with geographic location. Spatial autocorrelation causes biased estimates because the assumption of independence required by most statistics is violated. In the current study, it is likely that residents selected homes in specific areas because of the availability of rental housing that was eligible for rent using Section 8 vouchers. Thus, it is logical that characteristics of specific places might affect the distribution of the displaced residents. GeoDa was used to test spatial autocorrelation. Results indicate that the Moran's I statistic was not significant (Moran's I = 0.12, p = 0.11), which leads to the conclusion that spatial autocorrelation is not any more present in the spatial distribution of displaced residents than what would be expected by random chance. As a result, the data were modeled with a nonlinear count model rather than a spatial-dependence model.

Methods

The analysis process for this study proceeded in two steps. To test the first hypothesis, the study compared the original Charlotte Court neighborhood with the new neighborhoods that displaced residents selected. We used rates of crime, poverty, unemployment, and racial segregation to compare the neighborhoods. We expected to find that the new neighborhoods that displaced residents selected would be significantly lower on each of the measures listed above. Next, to test the second hypothesis, the study used regression analysis to determine if crime, poverty, unemployment, and racial segregation could significantly predict counts of displaced residents net of controls that could explain the presence of households using Section 8 vouchers. We discuss special problems with the regression models in the next section.

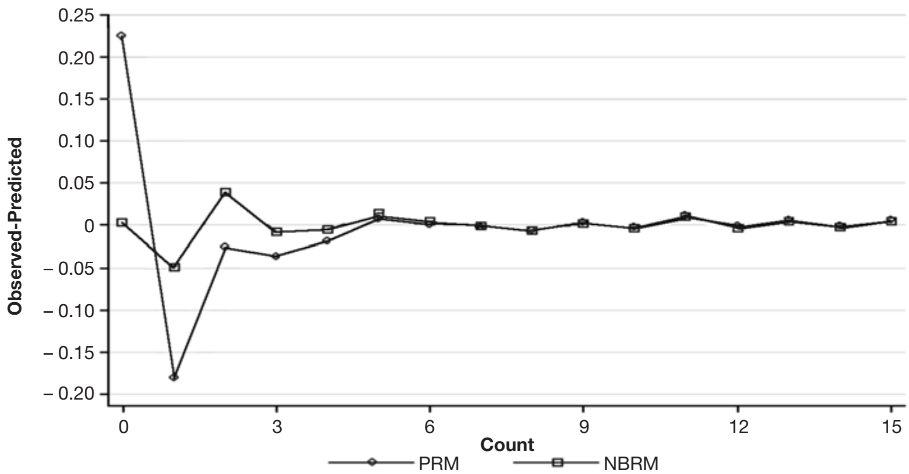
Poisson and Negative Binomial Regression Models

The dependent variable in this study is a count of the number of displaced HOPE VI residents per census block group. Standard linear regression models, in general, are inappropriate for count data due to overdispersion. The Poisson regression model better estimates data that are counts by assuming a nonlinear distribution. It is typical for count variables to be overdispersed, however, due to the presence of a high number of zero counts. Overdispersion describes the situation in which the variance of the dependent variable exceeds the mean (Long, 1997; Osgood, 2000). A key assumption of the Poisson regression model is that the variance must equal the mean for the model to accurately predict the dependent variable. In the social sciences it is rare for the Poisson regression model to fit the data distribution of a count variable. When data are overdispersed, the Poisson regression model underestimates zero counts, which is the case in the present study. To formally test for overdispersion, a likelihood ratio test was conducted comparing the Poisson model with the negative binomial model. There is significant evidence of overdispersion ($G^2 = 152.17$, $p < 0.01$); therefore, the negative binomial regression model is more appropriate for the analysis than the Poisson model.

Exhibit 4 compares the fit of Poisson regression model with that of the negative binomial regression model. Points greater than zero indicate that the model underpredicts the observed values, and

Exhibit 4

Comparing Poisson and Negative Binomial Regression Models



NBRM = Negative Binomial Regression Model. PRM = Poisson Regression Model.

points less than zero indicate that the model overpredicts the observed values of the dependent variable. Notice that the Poisson model drastically underpredicts zero counts for the dependent variable. To account for this problem, the negative binomial regression model includes a parameter that enables the variance of the dependent variable to exceed the mean. Exhibit 4 shows a much stronger fit for the negative binomial regression, especially when the number of relocations within a block group is zero.

Findings

The following sections describe the results of a t-test for neighborhood comparisons and the negative binomial regression analysis examining proxy variables for HOPE VI goals and controls for neighborhood choice among displaced residents.

Comparing Charlotte Court With Selected Neighborhoods

To examine the first hypothesis, the Charlotte Court neighborhood was compared with the rest of the neighborhoods that HOPE VI residents selected. A t-test was used to examine the mean differences between the selected neighborhoods and the Charlotte Court neighborhood. The number of neighborhoods that received at least one displaced resident was 48. Exhibit 5 shows the findings. Overall, the average levels of crime, poverty, and racial segregation were lower, and unemployment was higher, in the new neighborhoods. The differences were not significant, however. These findings do not support the initial hypothesis that neighborhoods selected by displaced residents would be significantly better than Charlotte Court, which leads to the conclusion that the neighborhoods that residents selected were not substantial improvements when compared with the conditions in their original neighborhood.

Exhibit 5

Comparing Charlotte Court With Selected Neighborhoods (n = 48)

	Charlotte Court	Selected Neighborhoods (n = 48)	Significance
Reported crime	49.0	44.0	0.87
Percent poverty	44.0	30.0	0.70
Percent unemployment	3.4	4.3	0.86
Percent African American	28.0	23.0	0.60

Because of the wide distribution of displaced residents around the city (see exhibit 1), the study included a secondary analysis, conducted between Charlotte Court and the neighborhoods that received a large number of displaced residents. A cutoff was selected for neighborhoods that received 10 or more displaced households. Neighborhoods that received 10 or more households were selected because they were public housing sites or places that were likely to accept Section 8 vouchers. Of the sample, 8 neighborhoods received more than 10 displaced residents, and, overall, these 8 neighborhoods accounted for 147 relocations—nearly 60 percent of the total displaced residential households. Exhibit 6 shows that the 8 neighborhoods had higher (but not statistically significant) levels of crime, poverty, unemployment, and African-American population than the Charlotte Court neighborhood.

Exhibit 6

Comparing Charlotte Court With Selected Neighborhoods (n = 8)

	Charlotte Court	Selected Neighborhoods (n = 8)	Significance
Reported crime	49.0	81.0	0.47
Percent poverty	44.0	47.0	0.91
Percent unemployment	3.4	3.9	0.72
Percent African American	28.0	31.0	0.89

Negative Binomial Regression Results

The first baseline model included only the control variables. Model 1 in exhibit 7 shows the results from the negative binomial regression analysis. HOPE VI resident presence in new neighborhoods was significantly associated with public assistance levels present in the neighborhood and with the amount of housing that was for rent and vacant. For every one unit increase in public assistance, the expected count of displaced residents increases by 15.8 percent ($z = 2.415$, $p < 0.01$). For every one-unit increase in rental vacancy, the expected number of displaced residents increases by 33.7 percent ($z = 4.09$, $p < 0.001$).

Model 2 in exhibit 7 shows the influence of the main explanatory variables. The number of reported crimes and amount of racial segregation were significant. For every one unit increase in reported crime, the expected count of displaced residents increases by 3.5 percent ($z = 4.65$, $p < 0.001$). For every one unit increase in African-American population, the count of displaced residents is expected to increase by 4.2 percent. Poverty and unemployment were not significantly associated with the number of displaced households within a neighborhood net of the other explanatory variables.

Model 3, in exhibit 7 includes both the explanatory and control variables. Reported crime and the African-American percentage of the population were significant indicators when holding all other variables constant. The percent changes in crime and African-American population were almost identical to the results from Model 2. The effect for poverty became negative when all of the variables are included; however, this effect is small and insignificant. Interestingly, the control variables, which were significant in Model 1, lose significance in Model 3. Consistent with past research, Model 1 appears to show that the amount of public assistance and vacant rental housing within a neighborhood affects residents' decisions in their move. Despite the effects that these factors had on residents' decisions, however, it appears that neighborhoods that residents selected were still significantly associated with reported crime and with the percentage of African Americans in the neighborhood population.

Many explanatory and control variables are correlated. Exhibit 8 shows the variables correlation matrix. Although none of the variables have very strong associations, many are significantly associated with one another. To account for the collinearity of the explanatory variables, each variable was evaluated independently with the control variables to remove any possibility of multicollinearity disrupting the results.

Model 4 in exhibit 9 shows that crime continues to be significantly associated ($z = 4.61$, $p < 0.001$) with displaced HOPE VI households and continues to have a similar expected percent change. Model 5 indicates that poverty is significant when considered independent of other explanatory

Exhibit 7

Negative Binomial Regression Results

Variables	Model 1				Model 2				Model 3			
	❑	SE	p	%Cg.	❑	SE	p	%Cg.	❑	SE	p	%Cg.
Reported crimes					0.034	0.007	0.000	3.5	0.033	0.007	0.000	3.4
Poverty					0.004	0.015	0.786	0.4	– 0.013	0.189	0.491	– 1.3
Unemployment					0.018	0.029	0.533	1.9	0.022	0.030	0.472	2.2
African American					0.040	0.010	0.000	4.2	0.034	0.009	0.015	3.5
Public assistance	0.146	0.060	0.016	15.8					0.064	0.043	0.140	6.6
Rental vacancy	0.290	0.070	0.000	33.7					0.085	0.052	0.107	8.9
Model x^2(*df*)	34.48(2)				73.90(4)				78.34(6)			

%Cg. = percent change. p = p-value. SE = standard error.

Exhibit 8

Variable Correlations

	Relo-cations	Reported Crimes	Poverty	Unemploy-ment	African American	Public Assistance	Rental Vacancy
Relocations	1						
Reported crimes	0.49*	1					
Poverty	0.43*	0.39*	1				
Unemployment	0.07*	0.23*	0.31*	1			
African American	0.55*	0.37*	0.55*	0.14	1		
Public assistance	0.41*	0.22*	0.57*	0.09	0.57*	1	
Rental vacancy	0.52*	0.41*	0.44*	0.08	0.40*	0.23*	1

**0.05 significance level*

Exhibit 9

Negative Binomial Regression Coefficients

Variable	Model 4				Model 5			
	❑	SE	p	%Cg.	❑	SE	p	%Cg.
Reported crimes	0.036	0.007	0.000	3.7				
Poverty					0.051	0.021	0.016	5.2
Unemployment								
African American								
Public assistance	0.127	0.046	0.000	13.6	0.082	0.065	0.208	8.6
Rental vacancy	0.131	0.057	0.023	14.0	0.230	0.069	0.001	26.0
Model x^2(*df*)	62.80(3)				40.83(3)			
Variable	**Model 6**				**Model 7**			
	❑	SE	p	%Cg.	❑	SE	p	%Cg.
Reported crimes								
Poverty								
Unemployment	0.049	0.051	0.332	5.1				
African American					0.046	0.012	0.000	4.8
Public assistance	0.144	0.060	0.017	15.5	0.039	0.044	0.373	4.0
Rental vacancy	0.258	0.071	0.000	33.0	0.195	0.339	0.000	21.6
Model x^2(*df*)	35.64(3)				54.65(3)			

%Cg. = percent change. p = p-value. SE = standard error.

variables. In addition, Model 3 showed that when all of the variables were considered simultaneously, the effect of poverty on relocation was negative. Model 5 indicates that, after controlling for the public assistance level and the percent of rental vacancies, poverty is a significant factor present in new neighborhoods. The fact that poverty is no longer significant when the other explanatory variables are included indicates that, while poverty continues to be a factor in new neighborhoods, crime and percent African American are stronger predictors of displaced residents in the neighborhoods. Model 6 indicates similar results as previous analyses. Neighborhoods that HOPE VI residents selected do not have significant problems associated with unemployment. Model 7 indicates that the percentage of population that is African American continues to be significant when considered independent of the other explanatory variables.

Summary and Implications

The findings presented in this study suggest that displaced HOPE VI residents in Lexington, Kentucky, chose to move to areas where crime and racial segregation are significant problems. The reason behind these choices is unclear, but indications from past research on HOPE VI displacement suggest that housing choice is highly dependent on the housing market at the time of the relocation (Kingsley, Johnson, and Pettit, 2003; Popkin et al., 2002; Smith, 2002). The findings from this study are consistent with those previous studies. Displaced residents chose neighborhoods that had high levels of public assistance available and that had a high number of vacant rental units. These findings suggest that residents moved to neighborhoods that were the next best available housing beyond the most severely distressed public housing.

Two important considerations must be understood before determining the effects of HOPE VI redevelopments. The first consideration is that project site evaluation results have little value in describing the outcomes of the original residents unless a high percentage of them returned to the redeveloped housing. In the present study, no previous residents returned to the original site. Thus, to gain the best understanding of the outcomes for the residents, it is important to focus attention on the types of places where HOPE VI residents move. The second consideration that must be made is that determining the level of improvement for HOPE VI residents is very difficult. Within practically any examination of HOPE VI, it will be difficult for researchers to argue that relocation housing is not at least somewhat better than the original public housing. It seems inevitable that a program designed to identify and redevelop the most severely distressed public housing would have high levels of residents reporting better living circumstances. Two questions remain: Are the new housing and neighborhoods areas that can sustain social cohesion? Were the areas that absorbed hundreds of displaced residents prepared to do so?

The purpose of this article is not to indicate that these neighborhoods were troubled because of the residents, but instead that the residents moved to neighborhoods with preexisting problems, and combining these preexisting problems with an already struggling population may be the recipe for future failure. This study's main finding is that crime levels and racial segregation in a city block group significantly predict the number of displaced residents after controlling for neighborhood choice factors. These findings raise serious questions for the city of Lexington about how effective the implementation of the Charlotte Court HOPE VI project was and if better planning would have positively affected the outcomes of residents involved in the relocation process.

This study's methodology is an example of how readily available data can be used to inform and guide public policy decisionmaking. Local police departments, local housing agencies, and a number of federal agencies have data available for analysis, which can greatly aid in predicting governmental program outcomes. A logical relocation method would be to provide residents with housing services in neighborhoods with lower crime and racial segregation levels.

One HOPE VI goal, to create local partnerships that can provide additional funding and services for the residents, was not analyzed in this study. A good use of HOPE VI funds would be to promote relationships between Section 8 voucher users and local property owners that are located in areas with better schools, lower crime, lower racial segregation, and, in general, more opportunities for success. This service would enable the city to provide a safeguard from increasing problems in neighborhoods on the brink of becoming troubled and would provide more economic and social opportunities to residents.

Another good use of local partnerships would be to develop design initiatives that are conducive to returning residents to the original neighborhood. Many original resident households do not have enough money to move back into mixed-use, affordable housing typical of HOPE VI redevelopments. Local partnerships should work with designers to develop new housing that is designed for the original residents. Designs should include considerations for social cohesion and crime prevention as well as for social and physical sustainability. Designing HOPE VI redevelopments for the original residents does more to attack the problems that most concern the individuals whom HOPE VI is supposed to help. In addition, working to return original residents to the HOPE VI sites eliminates problems associated with resident displacement. Neighborhoods selected by displaced residents in this study were already struggling with issues related to crime, poverty, unemployment, and racial segregation. Thus, working to help residents avoid these areas is mutually beneficial for both the displaced residents and the potential new neighborhoods. By promoting partnerships in the local housing market, the concentration of displaced residents in already struggling neighborhoods can be reduced and more can be done to return residents to their original neighborhoods where more social capital is available.

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Using the Weighted Displacement Quotient To Explore Crime Displacement From Public Housing Redevelopment Sites

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Abstract

HOPE VI, a federal funding initiative begun in 1992, is designed to eradicate severely distressed public housing. The program implicitly recognized the importance of geography to its efforts, also aiming to improve conditions in areas surrounding sites targeted for improvement under HOPE VI. This article considers changes effected by HOPE VI redevelopment from the perspective of geography, examining the spatial movement of crime in and around five public housing sites in Milwaukee, Wisconsin and Washington, D.C., throughout their redevelopment, using the Weighted Displacement Quotient (WDQ). The results from Milwaukee were mixed, with evidence of crime displacement provided by some of the WDQs. In Milwaukee, the redevelopment's reduction effects on crime grew with time and were stronger later in the study period. The results from Washington, D.C.'s Capitol Gateway and Capper/Carrollsburg sites were much more consistent than those from Milwaukee, because the WDQs for different areas and time periods produced similar results, indicating a diffusion of benefits. Because of its simplicity, the WDQ should be attractive to practitioners who are studying the effects of this type of redevelopment, as long as the method is used with the understanding that the results are descriptive.

Introduction

Since 1992, HOPE VI has been the largest and perhaps the most visible federal effort to improve—or rebuild altogether—the nation's most decayed public housing and most dire living conditions. At its inception, HOPE VI represented a radical change in housing policy, with the idea that the worst public housing developments needed extreme changes: most HOPE VI sites are demolished and replaced with new, redesigned housing. The program also aims to reduce the concentration of extreme poverty that is typical in targeted public housing developments by creating mixed-income and mixed-use spaces, and by mixing renters and owners.

The reauthorization of HOPE VI in 1998 cited six main goals of the program, three of which were improving the living conditions and lives of public housing residents, deconcentrating poverty and low-income families, and making those changes sustainable. A fourth goal, "contributing to the improvement of the surrounding neighborhood,"[1] explicitly recognized that redevelopment plans could not ignore what was going on around each site, and that improving the surrounding area was key to sustaining changes brought about by redevelopment. Geography, therefore, was understood to be an important element of HOPE VI efforts. This article considers changes effected by HOPE VI redevelopment from the perspective of geography, examining the spatial movement of crime in and around five public housing sites throughout their redevelopment.

Although many studies have considered the effects of HOPE VI on both residents and neighborhoods (for example, see Castells, 2010; Popkin et al., 2004, 2002; Turbov and Piper, 2005; Zielenbach and Voith, 2010), few have considered the effects of redevelopment under this federal program on crime levels in the neighborhoods surrounding the sites, and fewer still have specifically tied changes in crime levels to a site's redevelopment timeline and physical changes.

The current research aims to remedy that deficiency through an examination of crime displacement and/or potential diffusion of benefits in and around five public housing developments undergoing redevelopment in Milwaukee, Wisconsin, and Washington, D.C. This article reports on the results from one part of a larger research project that statistically analyzed crime displacement using three different methodologies; this article focuses on the results of the Weighted Displacement Quotient (WDQ) (Bowers and Johnson, 2003).[2]

The WDQ is a descriptive measure based on simple arithmetic, making it easy to implement and very accessible, even to those without a background in statistics. One big attraction of the quotient is the ease of changing its parameters, which allows a researcher to compare results for different areas and across different time periods in short order. Interpreting the results is straightforward.

The WDQ should be attractive to practitioners who are studying the effects of large-scale public housing redevelopment, as long as the method is used with the understanding that the results are descriptive. Policymakers want to know what works immediately or soon after an intervention is implemented, and this short-term thinking often precludes researchers from using mores statistically rigorous designs. This desire for very timely results makes the WDQ valuable. One of this article's aims is to demonstrate that limited resources or statistical skills should not limit the ability of practitioners to consider possible displacement or diffusion of benefits in the area around the redevelopment site.

[1] U.S. Housing Act of 1937, Section 24(a). Public Law 93–383 (42 U.S.C. 1437v) as amended by Section 535 of the Quality Housing and Work Responsibility Act of 1998. Public Law 105–276, October 21, 1998.

[2] Contact the author for information on the full report that contains analysis using all three methodologies.

Public housing is being renovated under this federal program nationwide, with the expectation that quality of life in the immediate and surrounding areas will be improved greatly. The program's ability to affect community crime rates, however, is still unclear, and the research for this article sought to address that question.

Background

This article first reviews the relevant literature in two main topic areas on which the current research is founded. A significant amount of previous work has been conducted on levels of crime in public housing and the elements of public housing that might contribute to higher crime rates. Less work, however, has focused on displacement following crime prevention and intervention efforts, and even less has focused on displacement from public housing. This work thus expands the body of evidence on both the effects of crime on public housing redevelopment and the likelihood that crime will be displaced to other areas after such efforts are implemented. Finally, this section details the data and methodology used in this research.

Crime and Public Housing

Two main schools of thought inform our research: (1) crime and space approaches, which include ideas from the Crime Prevention Through Environmental Design school and defensible space theory and (2) social disorganization theory. These approaches have a common focus: the importance of informal social control, manifested, in this case, as public housing residents' ability to control criminal behaviors. Both of these approaches also focus at least in part on the physical nature of the neighborhood—in this case, a public housing site—and its effects on crime and social control.

These perspectives have guided the investigation of public housing and crime over the past several decades, and it is commonly recognized that the residents of the kinds of severely distressed public housing sites targeted by HOPE VI are disproportionately affected by crime (DeFrances and Smith, 1998; HUD, 2000). Pyle (1976) suggested that areas with public housing tended to attract a substantial number of offenders from surrounding areas, while more recent research by Fagan and Davies (2000) found that violent crime tended to be associated with public housing units. Likewise, Dunworth and Saiger (1994) found higher rates for drug arrests and violent crime in areas with public housing compared with similar neighborhoods.

This relationship between public housing and crime is supported by further evidence that the environment of many public housing complexes attracts drug trafficking and violence (Fosburg, Popkin, and Locke, 1996; Popkin et al., 2002). Newman's (1996, 1972) foundational work on defensible space suggested that the physical design of public housing was key in preventing crime there. Likewise, Popkin et al.'s (2004) review of HOPE VI tied the often extremely unsafe conditions that existed in HOPE VI sites before redevelopment to poor physical design of the buildings themselves.

Although the studies mentioned previously analyzed crime in and around public housing, few studies have focused on assessing the effect of large-scale changes to public housing environments (Jones, 2002; Turbov and Piper, 2005). Turbov and Piper (2005) considered changes in crime levels surrounding HOPE VI sites; while they simply reported crime levels before and after redevelopment, their work did find that crime levels dropped dramatically in HOPE VI neighborhoods.

Crime Displacement

Although numerous types of displacement might occur after implementing an anticrime initiative, this article focuses solely on spatial displacement, or the movement of crime from a targeted area to nearby areas. Previous research in this area has largely focused on displacement that occurs as the result of a focused police enforcement effort or police intervention. These interventions are typically focused on small hot spots of crime—several square blocks at most—and have distinct periods of implementation.

Determining how to predict and test for possible spatial crime displacement following an intervention is one that has been the focus of environmental criminologists for at least the past three decades (Brantingham and Brantingham, 1993; Cornish and Clarke, 1987; Gabor, 1990, 1981; Repetto, 1976; Sherman, Gartin, and Buerger, 1990). The literature on these efforts is limited, and those studies that have considered displacement have shown mixed results (Barclay et al., 1996; Braga and Bond, 2008; Braga et al., 1999; Fritsch, Caeti, and Taylor, 1999; Lawton, Taylor, and Luongo, 2005; Weisburd et al., 2006). Essentially, no clear or consistent finding exists in the literature regarding the likelihood that displacement will occur or the expected magnitude of any displacement that might occur. Although displacement does not appear to be a given after police enforcement efforts, researchers do not know if those conclusions can be applied to other, more long-term events, like the redevelopment of public housing. Nevertheless, this information on whether such displacement may occur is imperative for practitioners planning large-scale redevelopment efforts.

We theorize that crime can be displaced from public housing redevelopment sites in two main ways. Displacement can occur when public housing residents move to new locations and crime moves with those individuals to their new residences. Crime displaced in this manner would be expected particularly in the case where large numbers of residents are moved *en masse* to a new location. Alternatively, crime itself may move out of the redevelopment site to nearby locations. In this case, the perpetrators of crime (for example, drug dealers) might attempt to maintain their criminal activities in the same general area, but are forced out of the redevelopment site itself (for example, by construction or increased enforcement). Or, the criminal opportunities in the redevelopment site might be reduced, but nearby areas may still offer criminal opportunities and thus absorb the crime that would have otherwise been occurring in the redevelopment site itself.

At the outset of our research, our assumption was that crime would move via either or both modes of displacement: with relocated residents moving to their new neighborhoods, or to other nearby areas offering similar criminal opportunities. Because of limitations in the data collected for this study, however, our ability to study explicitly the first mode of spatial displacement was limited. In neither Milwaukee nor Washington, D.C., were we able to obtain information on the locations of individual residents during and after the redevelopment process. These limitations were tempered somewhat, especially in Milwaukee, by one important factor: the housing authority there made a significant effort to keep residents within the redevelopment neighborhood and moved residents around among available units as construction took place elsewhere within the site. Therefore, although we did not have information on Milwaukee residents' new addresses, we had good reason to believe that many, if not most, remained on site, and were therefore able to test for both types of spatial displacement simultaneously.

In Washington, D.C., we learned from interviews with housing authority staff that residents were moved to any available public housing unit or given Section 8 vouchers. Those interviewed did not feel that critical masses of residents had all moved to the same areas but rather that residents were scattered to various locations throughout the city. The lack of data on residents and the scattering of residents throughout the city made testing the first type of spatial displacement—where crime moves with residents to their new neighborhoods—both impossible and, arguably, irrelevant. The second mode of displacement, however, was fully testable in both Milwaukee and Washington, D.C.

Data

The research team conducted interviews with staff members of the Housing Authority of the City of Milwaukee (HACM) and the District of Columbia Housing Authority (DCHA) to gather information used to determine the redevelopment timelines and define pre-, during-, and post-intervention periods for use in the analyses.

The research team collected address-level incident data for the city of Milwaukee from the Milwaukee Police Department for the January 2002-to-February 2010 period.[3] Incident data included all 'Group A' offenses as classified under the National Incident-Based Reporting System. We then geocoded addresses using a streetfile provided by the City of Milwaukee with a 100-percent match rate. Finally, the team classified offenses into personal (violent) and property offenses. Personal offenses included homicide, sexual offenses, assault offenses, and kidnapping. Offenses were aggregated into monthly counts, giving project staff 110 months of data with which to conduct statistical analyses.

The research team also collected address-level incident data for Washington, D.C., from the Metropolitan Police Department (MPD) for the January 2000-to-September 2009 period. Incident data included all Part I offenses as classified under the Uniform Crime Report system run by the Federal Bureau of Investigation. MPD provided the research team with the geographic coordinates of all incident locations, so no geocoding was necessary. As in Milwaukee, researchers classified data into personal and property offenses, following the same scheme used for the Milwaukee data.

Methods

Before analysis began, the research team had to (1) identify the overall timeline of redevelopment for each site in the study; (2) determine the 'intervention' point(s) so that we could identify displacement periods, during which we would expect to see displacement; (3) define the boundaries

[3] Note that the police department in Milwaukee changed data systems in early 2005. This shift in systems created two data issues: one was that data for the last 3 months of 2004 were missing. Monthly totals for those months were imputed using data before and after the missing months. The second issue was that arrest data from before 2005 were missing; we thus were unable to analyze arrest data as initially planned.

of the site from which crime displacement might occur; (4) define the displacement areas (those sites to which crime might be displaced); and (5) identify comparison areas. Low-income housing redevelopment under HOPE VI typically takes place over a long period of time, and the redevelopment sites often have poorly defined, vague, or overlapping geographic boundaries. This was the case in Milwaukee, especially, which made site definition very difficult. Site definition in Washington, D.C., however, was relatively straightforward.

Crime displacement is most often studied by choosing an area to which crime will most likely be displaced—referred to as the "displacement zone"—and comparing levels of crime in that area with the target area (area where the intervention took place). The displacement zone most commonly surrounds the target area; this particular design is sometimes described as a "buffer zone." This buffer zone can be concentric, reaching a set distance in all directions from the target area, or it can be contiguous to the target area but extending only in limited directions (Hamilton-Smith, 2002). Most research thus far has looked for immediate spatial displacement in areas contiguous to the target area (Braga, 2001). The size of the zone varies in the literature as well, and Bowers and Johnson (2003) suggested that there is a displacement gradient that describes displacement as decreasing with increasing distance from the target area; they suggested using multiple displacement zones that increase in distance from the target area for comparison purposes.

The displacement areas for both the Milwaukee and Washington, D.C. sites were drawn as concentric rings (buffer zones) around the target area. We tested two zones for displacement in each site: one ring that was 1,000 feet from each site and one that was 2,000 feet from each site. The two buffer areas were mutually exclusive; the area contained in the 2,000-foot buffer did not include the 1,000-foot buffer. This method allowed us to determine whether displacement or diffusion of benefits occurred only within areas very close to the site, or if either had a wider reach.

In the selected study sites, comparison areas were selected based on recommendations from both HACM and DCHA. Comparison sites were other public housing developments that were similar to the redeveloped sites before their redevelopment. In Milwaukee, because the target area selected was so large, we included the area in a 3,000-foot buffer surrounding the comparable public housing development as the comparison area. In Washington, D.C., only the actual area of the comparison public housing site was used.

For each site, the research team also established an "intervention" period, during which time redevelopment was occurring in earnest. We searched for displacement during and after this period. The selected intervention points are discussed in more depth in the following section.

Weighted Displacement Quotient

Bowers and Johnson (2003) developed the WDQ method to assist displacement research where lengthy time series pre- and post-intervention are not available. They developed the WDQ to identify the possible presence of displacement or diffusion, not the absolute size of any displacement or diffusion that might have occurred. The WDQ considers levels of crime in three areas: target (A), displacement (B), and comparison or control (C) areas.

The quotient has two parts: the *displacement measure*, which measures the change in crime in the displacement area relative to the change in crime in the control area over the same period, and is the numerator shown in equation 1; and the *success measure*, which measures the success of an intervention—the reduction (or slowed increase) of crime in the target area relative to a comparison area—and is the denominator in equation 1. The displacement measure is divided by the success measure to calculate the final WDQ. The full formula is provided below.

$$WDQ = \frac{B_{t1}/C_{t1} - B_{t0}/C_{t0}}{A_{t1}/C_{t1} - A_{t0}/C_{t0}} \qquad (1)$$

where A_{t0} and A_{t1} are crime levels in the target area at times 0 and 1; B_{t0} and B_{t1} are crime levels in the displacement area at times 0 and 1; and C_{t0} and C_{t1} are crime levels in the control area at times 0 and 1.

Interpretation of WDQ results is straightforward. The value of the WDQ is often within or near the range of -1 to 1. Larger values (positive or negative) indicate greater effects. The measure produces a positive score when a diffusion of benefits to the buffer area exists and crime levels have gone down. Positive values that are less than 1 indicate diffusion, or a positive effect on crime levels in the displacement area, that is smaller than the effect of the intervention in the target area. Values greater than 1 indicate that the positive effects on crime levels were greater in the displacement area than in the target area. A negative score indicates displacement of crime; values between 0 and -1 indicate that displacement did occur, but that the negative effect in the displacement area was less than the positive effect of the intervention in the target area. Values less than -1 indicate that the negative effects (increased crime) to the displacement area were actually greater than the positive effects in the target area.

Research Sites

Five redevelopment sites were included in this research: three in Milwaukee and two in Washington, D.C.

Milwaukee, Wisconsin

The three Milwaukee sites are located in the city's North Side. Violence in the area combined with declining housing stock made the area ripe for redevelopment and it was targeted by HACM for improvement in the early 2000s. HACM received $19 million for redevelopment of the old Highland Park site (known as Highland Gardens/Highland Homes after redevelopment) in 2002 and another $19.5 million in 2003 for redevelopment of scattered public housing sites ("scattered sites") in the city's Midtown neighborhood. A third site, Cherry Court, located within several blocks of the Highland Park site, was redeveloped as well, but not with HOPE VI funds. Cherry Court was ultimately included in the analysis because its redevelopment likely would not have taken place at the time it did were it not for the co-occurring, nearby HOPE VI activities; it was redeveloped following the same design principles as used in HOPE VI sites; it served as a base for service provision to residents in the scattered sites redeveloped under HOPE VI; and it was located very close to the Highland Park site and surrounded by the scattered sites, so it was reasonable to expect that changes at Cherry Court could have affected crime and violence occurring at Highland Park and among the scattered sites. The three Milwaukee sites were analyzed together because of their close geographic proximity to each other.

HACM staff said they made every effort possible to both keep the number of moves for any resident at two (once to move out of older housing and once to move back in to newer housing) and to keep residents in the same neighborhood if they desired. This strategy was feasible in Milwaukee because a number of units in the immediate vicinity of the HOPE VI sites were vacant when the HOPE VI awards were made, and because the redevelopment projects moved very quickly.

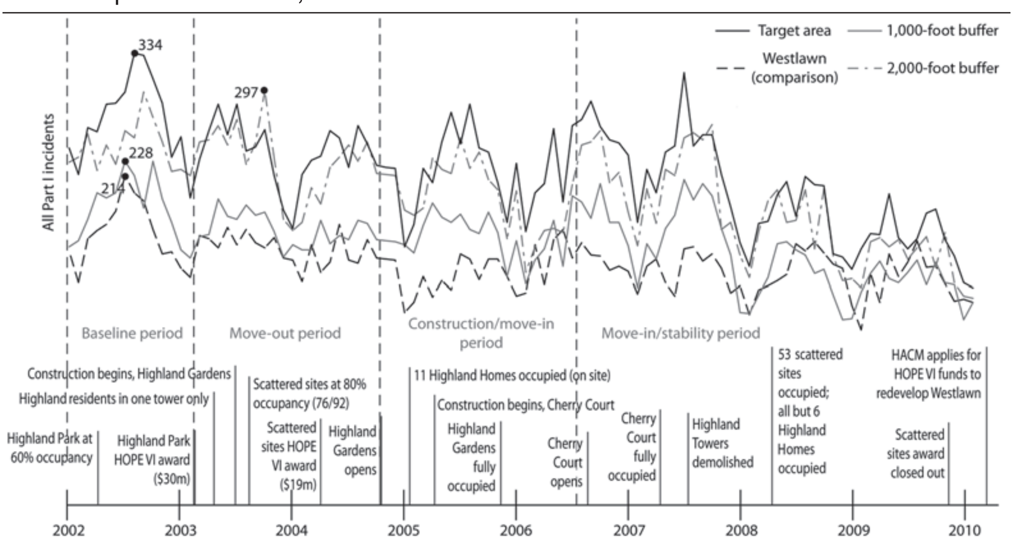
Exhibit 1 displays a timeline of events associated with the redevelopment of the Milwaukee sites. The Highland Park development was a superblock public housing development composed of two highrise towers and, on the same lot, 56 family units in barracks-style multifamily buildings. The new site contains a new midrise building named Highland Gardens, newly constructed single-family homes on the few blocks surrounding Highland Gardens called Highland Homes, and a newly built Cherry Court.

Because the three redevelopment projects in the study neighborhood (Highland Gardens, Highland Homes, and Cherry Court) were located very close to each other, the research team decided to draw the target area boundary around all scattered sites, including Cherry Court and Highland Park. The selected site boundaries contained most of the units among which residents were shuffled during the redevelopment process. In Milwaukee, therefore, we were still able to test for both modes of displacement—with residents to their new addresses or to areas near the site itself—together.

Exhibit 2 is a map of the Milwaukee sites included in this study, including the comparison area, Westlawn. The comparison area was chosen based on recommendations from the HACM and its socioeconomic characteristics.

Exhibit 1

Redevelopment Timeline, Milwaukee



HACM = Housing Authority of the City of Milwaukee.

Exhibit 2

Milwaukee Redevelopment and Comparison Sites

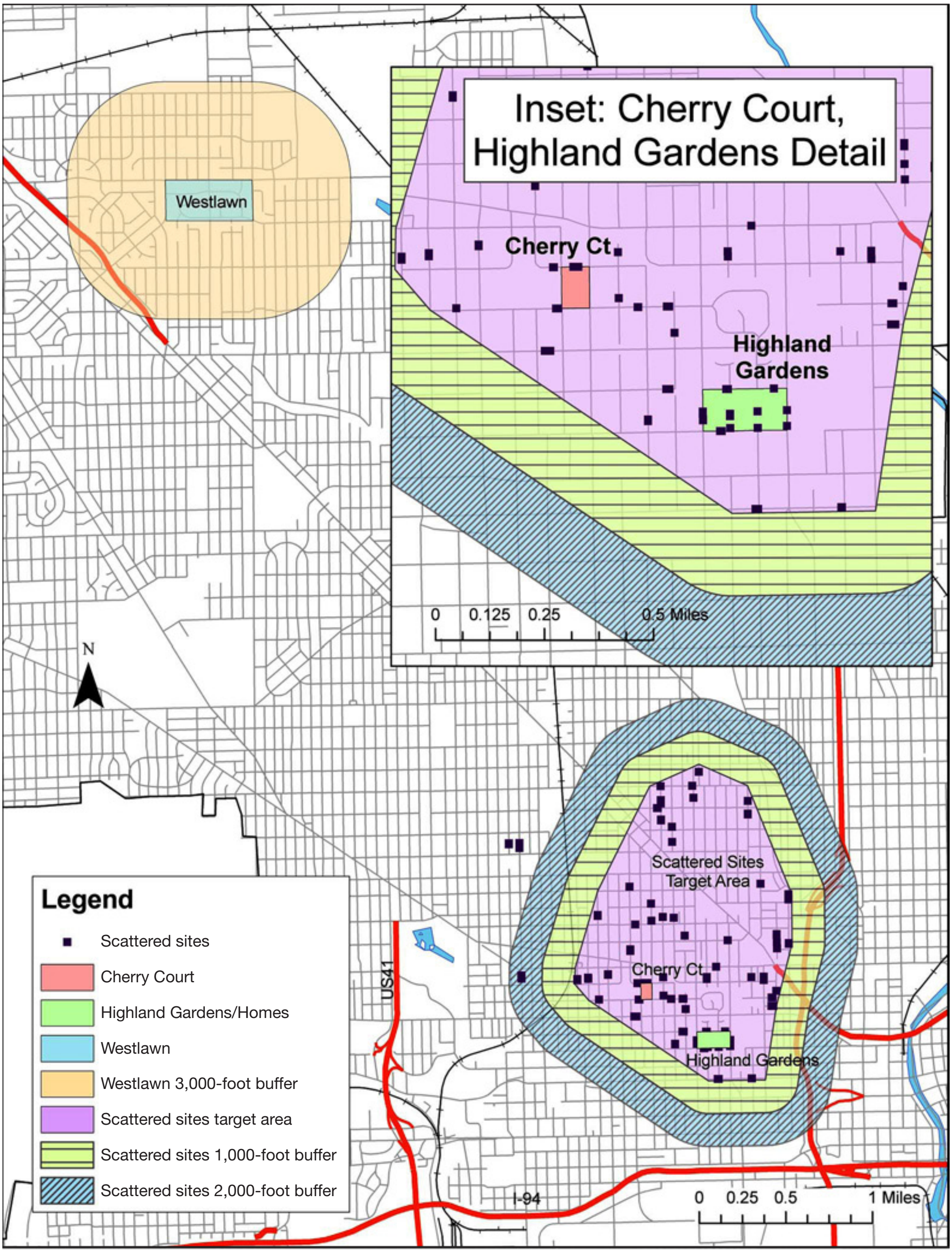


Exhibit 3 provides selected socioeconomic measures for 2000 for the area containing most of the scattered sites; for Highland Gardens, Highland Homes, and Cherry Court; and for the comparison site.[4]

According to HACM staff, before redevelopment took place, loitering was common and youth were involved in delinquent behaviors, but staff reported limited narcotics activity at the Highland site. In the scattered sites area, break-ins were the major complaint of residents. At the Cherry Court site, narcotics were more prevalent and the Cherry Street Mob, a local narcotics gang, was involved in much of the criminal activity in the area. Prostitution was also noted in the site before redevelopment. Following redevelopment, staff reported a significant decline in crime and safety issues in an around the site. The city as a whole, however, also experienced significant declines in crime at the end of the study period. These citywide decreases were accounted for in the displacement analyses through the use of the comparison area.

Exhibit 3

Milwaukee Socioeconomic Indicators, 2000

Socioeconomic Indicators	Area	
	HOPE VI Site	Westlawn
Area (square miles)	1.62	1.96
Residential population	21,323	19,796
Percent of population ages 12–17	13.0	12.3
Percent of population ages 18–24	16.1	9.2
Percent of population male	47.6	45.1
Percent of population Hispanic	4.0	2.7
Percent of population Black	71.5	59.7
Percent of housing units vacant	11.8	4.1
Percent of population high school graduates (> 25)	57.9	71.2
Percent of population in labor force (> 16)	56.0	64.0
Percent of households receiving public assistance	12.4	5.9
Percent of population below poverty level	42.3	23.2
All Part I crimes, 2002*	3,331	1,943
Violent crimes, 2002*	664	418
Property crimes, 2002*	2,023	1,158

** Crime counts are reported for the scattered sites target area and the comparison area (Westlawn plus its 3,000-foot buffer) only, not for larger census blocks used for reporting socioeconomic data.*

Source of socioeconomic data: U.S. Census Bureau, 2000

Source of crime data: Milwaukee Police Department

Washington, D.C.

Two HOPE VI sites in Washington, D.C., were selected for this research: the Capitol Gateway site (formerly East Capitol Dwellings and Capitol View Plaza I and II)[5] and the Arthur Capper/Carrollsburg site.[6] In Washington, D.C., site definition was straightforward—the sites had clearly

[4] The comparison site actually comprises a 3,000-foot buffer around Westlawn to accommodate the fact that the scattered sites are spread out, making the target area relatively large.

[5] Although this site was renamed as part of the development, this report will refer to the site both pre- and post-development as Capitol Gateway (its post-development name) to reduce confusion among readers.

[6] Although the full name of this site is Arthur Capper, in the text it will simply be referred to as Capper.

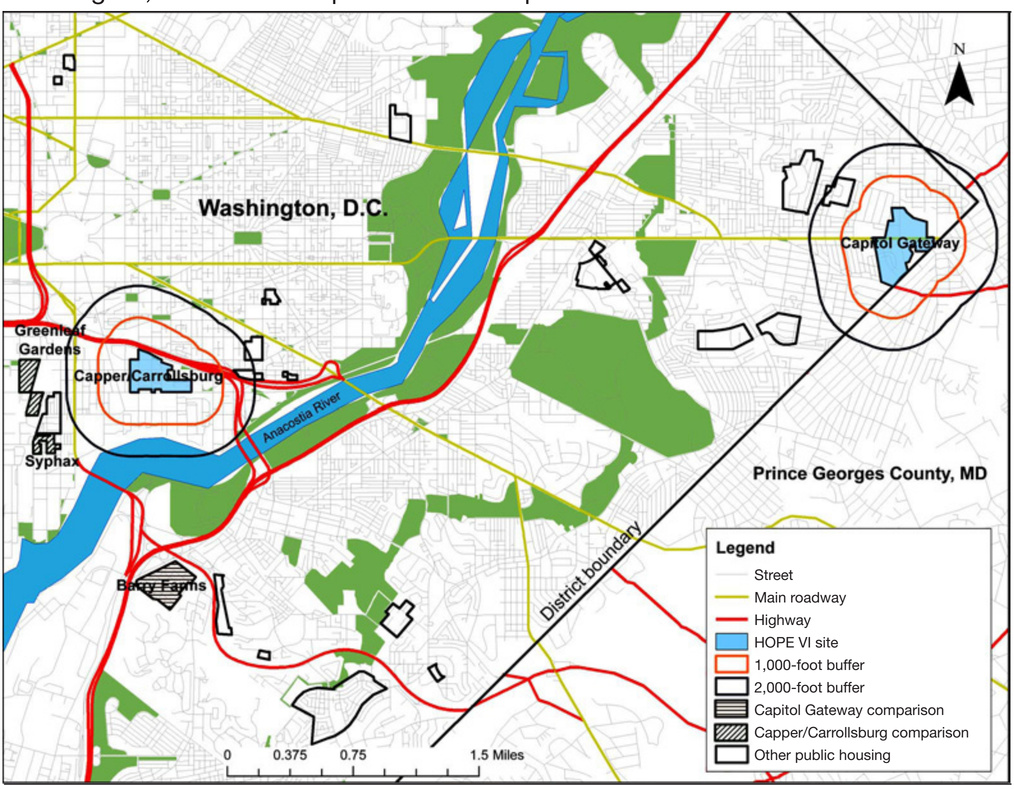
defined boundaries that were used in the current research. The boundaries included the immediate area under redevelopment. Such clearly defined and compact public housing developments resulted in sites that were much smaller than the Milwaukee site. Exhibit 4 provides a map of the two sites selected for this study and their comparison areas.

Two main differences distinguished the Washington, D.C. HOPE VI experience from the Milwaukee experience. First, the redevelopment timeline in Washington, D.C., was much longer—it took longer from the time of the award until newly built units were available for move-in than it did in Milwaukee. The long timeline meant that significant changes in individual family structure took place while redevelopment was progressing: children might grow up and no longer live with the family; adults may become parents and have more family members to house. These changes meant that the available redeveloped units might have been too large or too small for former residents' needs, so they would opt out of returning.

Second, residents were scattered into other available units in the city—while many received vouchers for other housing, including nonpublic housing, because of the tight rental market at the time in Washington, D.C., many residents were forced to move into other public housing (Popkin et al., 2002). The limited availability of nearby rental housing meant that residents were moved to different areas of the city. These relocated residents often formed close ties to their new neighborhoods and chose not to be uprooted a second time, long after their initial move out of the redevelopment site.

Exhibit 4

Washington, D.C. Redevelopment and Comparison Sites



Finally, particularly at the Capper/Carrollsburg site, the character of the neighborhood underwent extreme change over the course of the redevelopment period. The neighborhood change stemmed not just from HOPE VI, but also from other development in the area. For instance, many small businesses closed and were replaced by chain stores or higher end stores than were previously there, and a new baseball stadium and a number of high-end condominiums were built.

Because we did not obtain information on where residents were relocated, the research team was unable to identify possible displacement zones that were noncontiguous to the HOPE VI sites but that housed a large number of displaced HOPE VI residents. The long timeline meant that many residents had already established themselves in the new neighborhoods and had lived there for several years by the time new units were available. By the end of the redevelopment timeline, many did not want to move back to their previous neighborhoods even though they had been redeveloped. In Washington, D.C., then, fewer residents of the new housing were residents of the sites before redevelopment.

Capitol Gateway

In August 2000, DCHA received $30.8 million to redevelop the East Capitol Dwellings/Capitol View Plaza site, which is located on the border of the northeast and southeast quadrants. The site sits on East Capitol Street, a major thoroughfare into Washington, D.C., from Prince George's County, Maryland, and it is adjacent to a Metro bus stop. The 577-unit barracks-style housing was built in 1955 and was 30 percent vacant at the time of the HOPE VI application in 2000 (DCHA, 2000). The adjacent Capitol Plaza site consisted of two highrise buildings, with units in one building reserved for seniors. In addition to the deteriorating physical conditions of the building, the layout of the site contributed to public safety problems: buildings were isolated from the rest of the neighborhood, and winding streets and open spaces created locations on the interior of the site that were hard to police and provided convenient escape routes for criminals (DCHA, 2000). Drug use was also rampant (Popkin et al., 2002). Although homicides in public housing were dropping throughout Washington, D.C., in the late 1990s, homicides at East Capitol actually increased in 1998, contributing to the site's reputation as one of Washington, D.C.'s most dangerous.

Exhibit 5 displays the timeline of redevelopment events for the Capitol Gateway site starting with the HOPE VI award in 2000. Resident relocation at Capitol Gateway began shortly after the award to DCHA was made and continued for approximately 2 years. The building reserved for senior residents was constructed first, with move-in starting in February 2005. Family units, made up largely of townhouses, were open for occupancy beginning in September 2006. The new sites were designed to have no unit access through common areas—all access to units was from the outside. In addition, extensive lighting was installed, a small toddler playground was built, and the site did *not* include large outdoor areas for residents to congregate, such as a basketball court, to discourage loitering.

Exhibit 6 provides socioeconomic indicators for the two Washington, D.C. sites and their comparison areas. The Capitol Gateway comparison site, Barry Farms, was selected based on input from the DCHA and socioeconomic characteristics to match the former East Capitol site.

Exhibit 5

Redevelopment Timeline, Capitol Gateway, Washington, D.C.

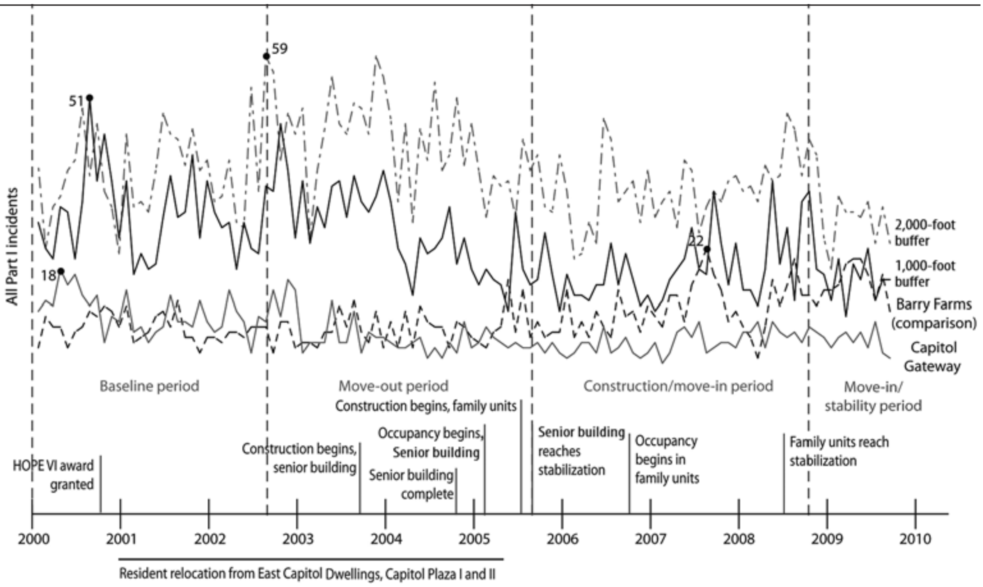


Exhibit 6

Washington, D.C. Socioeconomic Indicators, 2000

Socioeconomic Indicators	Area			
	Capitol Gateway	Barry Farms	Capper/ Carrollsburg	Syphax/ Greenleaf Gardens
Area (square miles)	0.1	0.05	0.06	0.04
Residential population	3,839	1,796	1,853	1,958
Percent of population ages 12–17	10.6	15.3	10.9	7.6
Percent of population ages 18–24	8.6	14.0	9.8	8.3
Percent of population male	45.3	42.3	45.6	39.7
Percent of population Hispanic	0.6	1.1	0.0	1.2
Percent of population Black	97.0	97.1	97.1	94.4
Percent of housing units vacant	32.6	5.1	6.7	6.4
Percent of population high school graduates (> 25)	44.9	49.2	59.1	57.7
Percent of population in labor force (> 16)	45.0	38.0	35.0	37.0
Percent of households receiving public assistance	18.5	38.8	12.9	16.9
Percent of population below poverty level	41.7	73.5	61.8	53.4
All Part I crimes, 2000*	141	89	98	127
Violent crimes, 2000*	58	48	45	62
Property crimes, 2000*	83	41	53	65

** Crimes counts are reported for the target and comparison areas only, not for larger census blocks used for reporting socioeconomic data.*

Source of socioeconomic data: U.S. Census Bureau, 2000
Source of crime data: Metropolitan Police Department (Washington, D.C.)

Capper/Carrollsburg

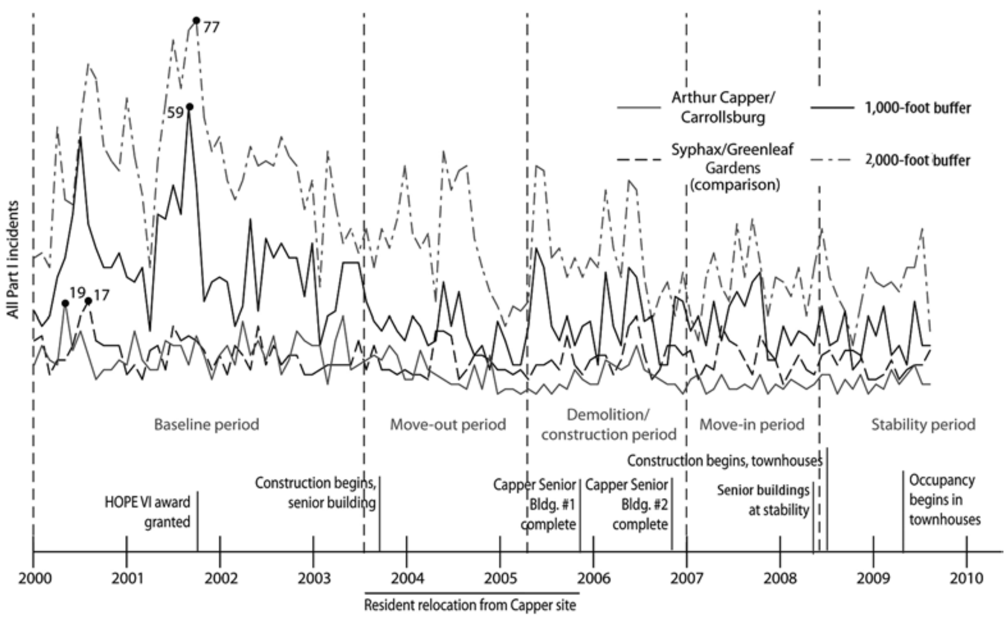
The Arthur Capper/Carrollsburg site, part of which dates to 1958, was located in the city's southeast quadrant (Dupree, 2007). The site is separated from the rest of the city by the Southeast Freeway, which runs near the northern part of the site and on the other side of which is the economically better-off Capitol Hill section of the city. The site consisted of barracks-style housing and a highrise for seniors. The site became a haven for drugs and crime, and efforts to renovate it in the 1970s did not solve the crime problem. In 2000, the neighborhood that was home to Capper/Carrollsburg had one of the lowest median income levels in the city (Wilgoren, 2003).

In 2001, DCHA was awarded $34.9 million to redevelop the Arthur Capper/Carrollsburg site, and the city planned a one-to-one replacement of public housing units. At that point, city officials and developers had already started to direct redevelopment funds and plans toward the so-called "Near Southeast" but little redevelopment had begun. Three years later, the Washington Nationals decided to locate their new baseball stadium in the neighborhood, and new federal buildings had already been constructed in the area. The HOPE VI redevelopment was just one part of a larger revitalization of the neighborhood.

Exhibit 7 displays the timeline of redevelopment events for the Capper/Carrollsburg site starting with the HOPE VI award.[7] Redeveloping the Capper/Carrollsburg site took the longest of the

Exhibit 7

Redevelopment Timeline, Capper/Carrollsburg, Washington, D.C.



[7] Note that much of the information collected about the Capper/Carrollsburg site and timeline came from www.jdland.com. That website is maintained by a resident of the area who has been documenting the changes in the Near Southeast since 2003 and who is well known by the DCHA. In fact, some DCHA staff members recommended that project staff visit the site for more detailed information about the changes that had taken place since the HOPE VI awards.

five study sites. Phase I of resident move-out of the barracks-style units started in 2003. The site was demolished piece by piece, as new units were built and began to be occupied. The new site contained a number of different elements, including townhouses and two midrise buildings for seniors. The buildings for seniors were the first to be finished and occupied; construction on the townhomes followed. At the end of the study period (end of 2009), occupancy had begun at the townhomes but units were still available for sale.

DCHA staff reported that at Capper/Carrollsburg, drug offenses in particular stayed local even during the redevelopment process. The perception of staff familiar with the area was that drug dealers simply moved a few blocks away from the redevelopment site to maintain their existing drug markets. This makes sense in light of the fact that the site is located next to a highway, providing potential drug customers with an easy entry/exit point to drug markets and dealers in the area. This phenomenon supports the idea of looking for immediate displacement around the site and, although this phenomenon was not identified specifically in Milwaukee or for Capitol Gateway, the likelihood is strong that any drug markets in those two sites followed similar patterns—both are located near major thoroughfares or highways that would contribute to keeping drug markets in the same vicinity as the sites themselves.

Exhibit 6 provides socioeconomic indicators for the neighborhoods of the Capper/Carrollsburg site and its comparison area, Syphax/Greenleaf Gardens. The comparison site was selected based on recommendations from DCHA staff, and the two sites were very similar on the selected measures shown here in 2000, prior to the HOPE VI award.

Results: Milwaukee

The first step in analyzing the HOPE VI redevelopment sites for displacement or diffusion was to examine the change in crime levels before and after the redevelopment efforts. Exhibit 1 includes line graphs of all crime in the four main study areas (the site, two displacement buffers, and comparison area—Westlawn and its 3,000-foot buffer). The timeline suggests that crime in the site and two displacement areas dropped throughout the study period, from 2002 through 2010. Crime in the comparison area remained relatively stable over the same period.

The timeline demonstrates the long nature of the intervention period—the period during which the site was redeveloped. It also illustrates that it is hard to identify a specific date on which the intervention started or ended. The analyses thus use varying lengths of pre- and post-intervention periods. The intervention periods, however, generally center around September 2003 through November 2004, roughly the period of construction on Highland Gardens. Although significant construction on Cherry Court and the scattered sites homes continued after Highland Gardens was finished, this period was chosen based on the idea that once one project within the larger target area was finished and occupants returned, the influence of that redevelopment would start to be felt throughout the site, as residents became more aware and convinced of the changes that were taking place in their neighborhood.

Exhibit 8 provides crime density maps for 4 selected years in the study period: 2003, 2005, 2007, and 2009. The density maps were created using data covering a 1-mile radius around the site to

Exhibit 8

Density of Crime Over Time, Milwaukee (1 of 2)

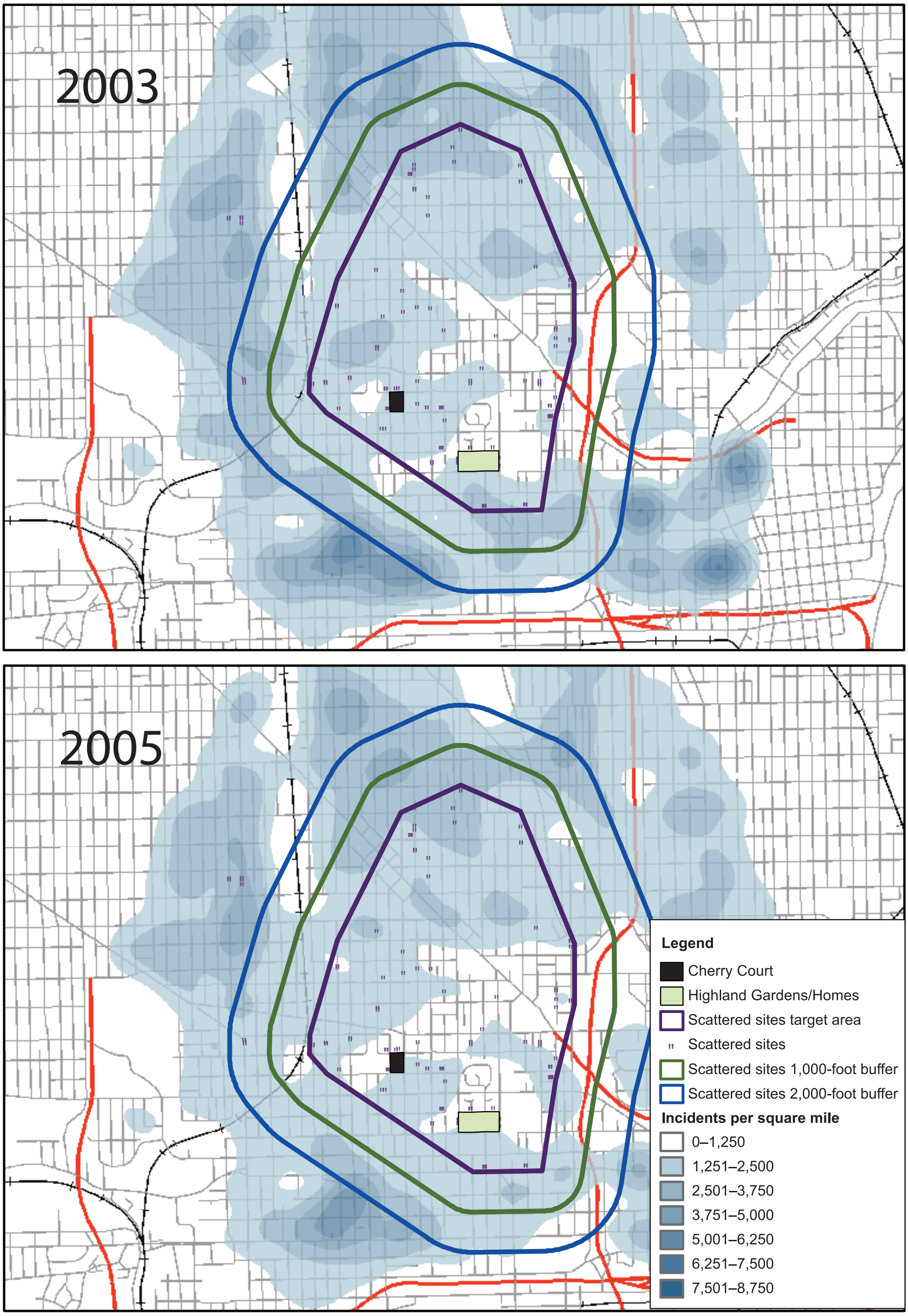
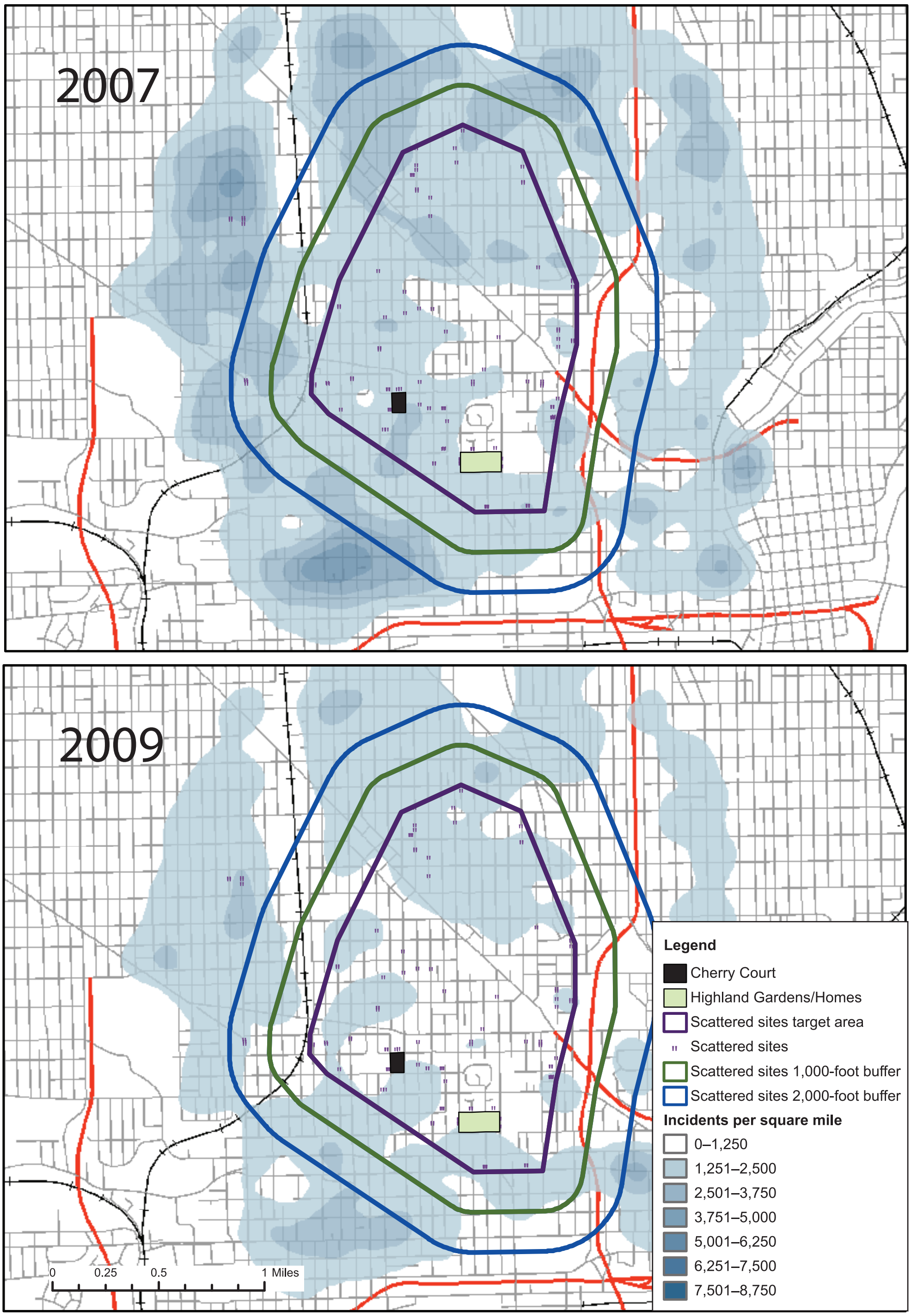


Exhibit 8

Density of Crime Over Time, Milwaukee (2 of 2)



capture any hot spots that might be occurring nearby but just outside the site boundaries. These maps were used purely for descriptive purposes, and they reveal that the density of crime inside the site appears to lessen with time. Hot spots outside the site boundaries, especially to the south, do remain, but they do decrease somewhat with time as well.

We calculated the WDQ using several different sets of pre- and post-intervention periods and looked for displacement during the intervention as well. The intervention period used was September 2003 through November 2004. The WDQ is restrictive in its need for pre- and during-/post-intervention periods to be of the same length. Therefore, the timing of the intervention relative to the start of the period covered by the data can affect the length of the periods examined for displacement. In Milwaukee, the intervention began in September 2003, only 20 months after the start of our period of data coverage (January 2002). Therefore, we could not calculate the WDQ using pre- or post-intervention periods longer than 20 months. We calculated the WDQ for four different time periods, specified in exhibit 9. The WDQ was also calculated for all crime, personal crime, and property crime.

Exhibit 9 provides the WDQ for each of the time periods and buffers considered. The exhibit also provides the success measure, or the denominator of the WDQ. If the success measure was positive, crime increased over the period and a search for displacement or diffusion was not warranted. The WDQ was thus not reported for those periods/areas for which the success measure was positive. The exhibit highlights those periods/areas where we found displacement or diffusion to be larger than the direct effects in the target area (that is, they were greater than 1 or less than -1).

In the all crimes category, the success measure was negative, indicating a drop in crime in the target area over the time period of interest, for only one set of time periods studied—the 15-month pre-intervention period and the 15-month intervention period. In that period in the 1,000-foot buffer, the WDQ was positive but less than 1, indicating that diffusion did take place, but it was less than

Exhibit 9

Weighted Displacement Quotient Results, Milwaukee

Pre/Post Length	t_0 (Pre-Intervention Period)	t_1 (Intervention or Post-Intervention Period)	Type of Crime	Success Measure	WDQ 1,000-Foot Buffer	WDQ 2,000-Foot Buffer
12 months	September 2002–August 2003	December 2004–November 2005	All	0.203	—	—
			Personal	0.012	—	—
			Property	– 0.189	0.308	1.331
15 months	May 2002–August 2003	December 2004–March 2006	All	0.222	—	—
			Personal	– 0.044	– 0.396	– 1.423
			Property	– 0.129	0.288	1.549
15 months*	May 2002–August 2003	September 2003–November 2004	All	– 0.048	0.124	– 0.680
			Personal	0.036	—	—
			Property	– 0.126	0.090	0.160
18 months	March 2002–August 2003	December 2004–May 2006	All	0.171	—	—
			Personal	– 0.059	0.105	– 0.018
			Property	– 0.167	0.535	1.647

WDQ = Weighted Displacement Quotient.

**Searched for displacement during intervention period.*

Note: The intervention period was September 2003 through November 2004.

the effect in the redevelopment site. In the 2,000-foot buffer during that time period, however, the WDQ was negative but greater than -1, indicating that a small amount of displacement may have occurred. All success measures for the all crimes category (whether positive or negative) were close to 0, indicating very small changes in crime over the period.

For personal crimes, the success measure was positive in two of the time periods searched. For the 15-month pre- and post-intervention periods, the WDQ was negative in both buffer areas. For the 2,000-foot buffer, it was less than -1, indicating that displacement did occur, and that the increase in personal crime in the 2,000-foot buffer was greater than the decrease in the target area itself. For the 18-month pre- and post-intervention periods, both WDQs were close to 0, indicating that little to no change occurred in either buffer area.

For property crime, the WDQ indicated that a diffusion of benefits from the redevelopment site to the area within 2,000-foot of the site took place, and those benefits were about equal to the direct effects of the redevelopment in the site itself. This finding was true for all but one set of time periods studied: the 15-month pre-intervention period and the 15-month intervention period, for which the WDQ was near 0, indicating little to no change in crime occurred in the buffer area.

To summarize, the WDQ effort in Milwaukee had mixed results, with all crimes and personal crimes showing either no change or some signs of minimal crime displacement. For property crimes, however, this methodology suggested a diffusion of benefits. For all crime types and all sets of time periods analyzed, the results were strongest in the 2,000-foot buffer.

Results: Capitol Gateway, Washington, D.C.

Exhibit 5 includes line graphs of all crime in the four main study areas for the Capitol Gateway site; dotted lines delineate the different study periods. Crime in the site appeared to drop significantly beginning in 2003, and crime in the two buffer zones also decreased, although not to the same degree as in the target area. Crime in the comparison area remained relatively stable until 2007, at which point monthly crime levels started rising.

Exhibit 10 provides crime density maps for 4 selected years in the study period: 2002, 2004, 2006, and 2008. The density maps were created using data covering a 0.5-mile radius around the site and they reveal that the density of crime inside the site appeared to lessen with time. Most of the hot spots disappeared by 2006, but the 2008 map showed a slight resurgence in the crime densities, especially in the 2,000-foot buffer on the Washington, D.C. side. After 2002, however, the target area itself had a very low density of crime.

The initial intervention period that we used was October 2002 through July 2006, which was roughly the period of construction of the senior building and the family units. We calculated the WDQ using several different sets of pre- and post-intervention periods, and looked for displacement during the intervention as well. Exhibit 11 provides the WDQ for each of the time periods and buffers considered. The exhibit also provides the success measure, or the denominator, of the WDQ.

The WDQ results for Capitol Gateway across all types of crime and time periods were more consistent than they were for Milwaukee. All but one success measure was negative, indicating that for the most part, both property and personal crimes decreased in the redevelopment site over the study

Exhibit 10

Density of Crime Over Time, Capitol Gateway, Washington, D.C. (1 of 2)

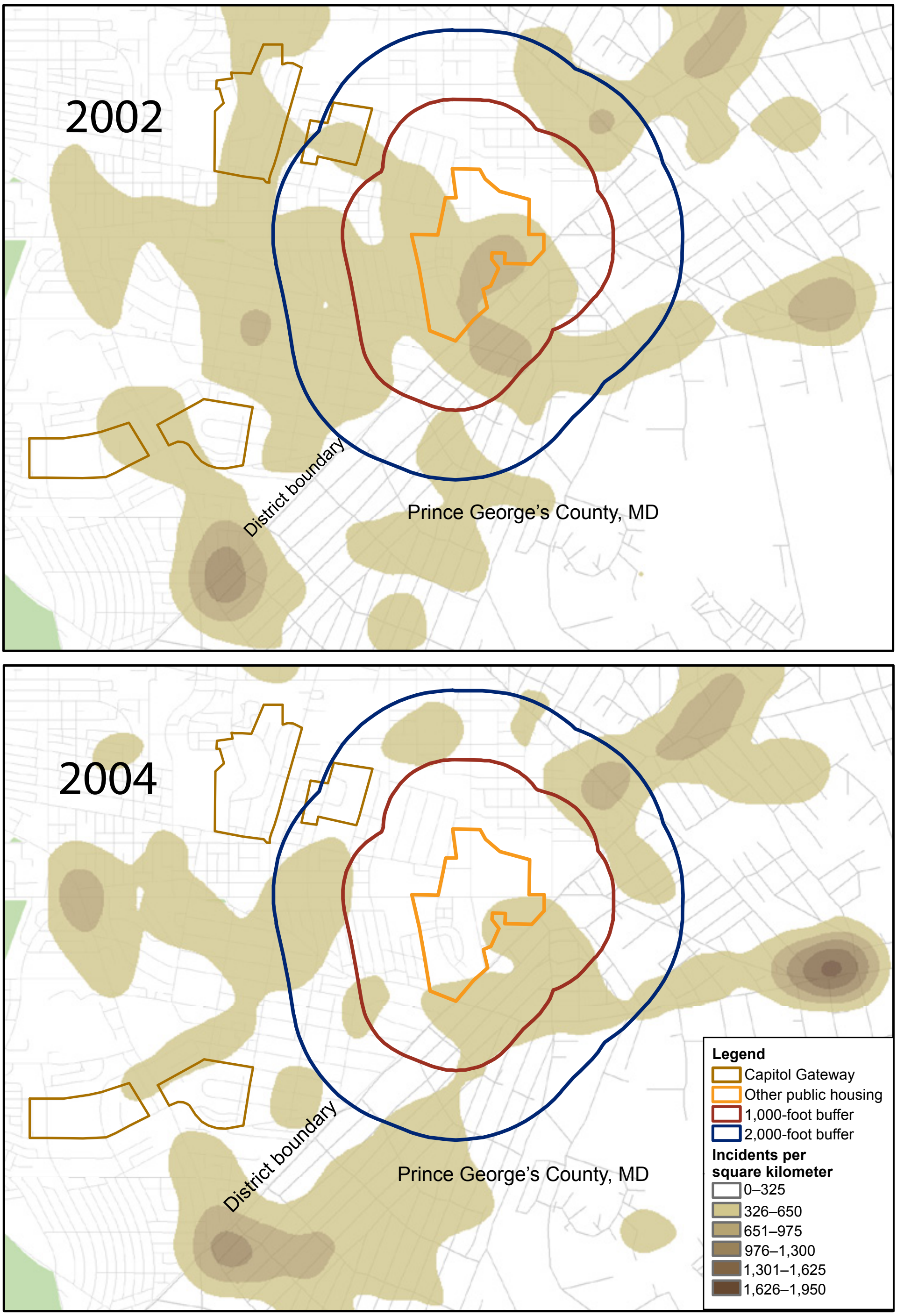


Exhibit 10

Density of Crime Over Time, Capitol Gateway, Washington, D.C. (2 of 2)

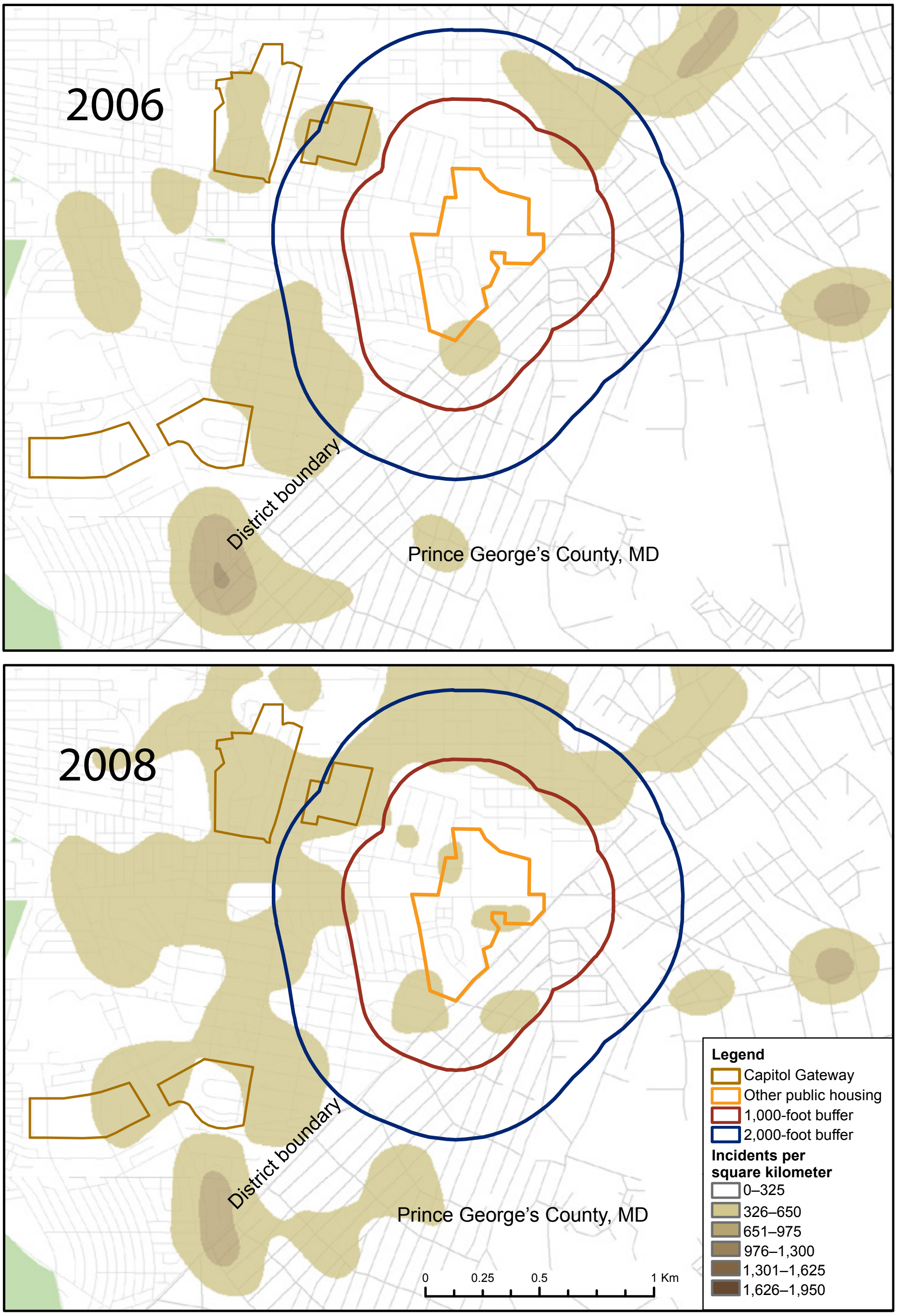


Exhibit 11

Weighted Displacement Quotient Results, Capitol Gateway, Washington, D.C.

Pre/Post Length	t_0 (Pre-Intervention Period)	t_1 (Intervention or Post-Intervention Period)	Type of Crime	Success Measure	WDQ 1,000-Foot Buffer	WDQ 2,000-Foot Buffer
12 months	October 2001–September 2002	August 2006–July 2007	All	– 1.38	2.92	3.58
			Personal	– 1.07	1.39	1.86
			Property	– 1.79	3.92	4.75
12 months*	October 2001–September 2002	October 2002–September 2003	All	– 0.63	0.91	1.62
			Personal	– 0.80	0.94	1.86
			Property	– 0.03	– 46.00	– 60.00
18 months	April 2001–September 2002	August 2006–January 2008	All	– 1.06	2.81	3.56
			Personal	– 0.88	1.11	1.43
			Property	– 1.36	4.22	5.33
18 months*	April 2001–September 2002	October 2002–March 2004	All	– 0.42	– 0.71	– 1.18
			Personal	– 0.65	0.61	1.39
			Property	0.20	—	—

WDQ = Weighted Displacement Quotient.

**Searched for displacement during intervention period.*

Note: The intervention period was October 2002 through July 2006.

period. For both types of crime, the 12-month pre- and post-intervention periods produced WDQs that were positive and greater than 1, indicating that a diffusion of benefits took place and that the decreases in crime in the buffer areas were at least as strong as the effects in the target area itself.

When we compared crime levels for the 12 months before and 12 months during the intervention, we found mixed results. For all crime and personal crime, the WDQs were positive and at or greater than 1, indicating that a diffusion of benefits took place immediately after the start of the intervention (while the redevelopment activities were continuing).

For property crimes, the success measure was negative but very near 0. The WDQs for property crimes in both buffer areas were negative and very large. In their presentation of the WDQ, Bowers and Johnson (2003) cautioned that the measure should not be used to quantify the *absolute* amount of displacement that occurred, only the amount relative to the target area; therefore, the large WDQ values should not be alarming.

The 18-month pre- and post-intervention periods yielded positive WDQs, providing additional evidence that a diffusion of benefits from the Capitol Gateway site to nearby areas took place. The results for the 18-month periods for the pre-intervention period and during the intervention, however, revealed that some displacement might have occurred: the all crime category had negative WDQ values less than -1. The personal crime category had small positive WDQ values, and the property crime category actually had a positive success measure, so no WDQs were calculated for that crime category. Taken together with the property crime results discussed above, it appears that any positive effects of the intervention on neighboring areas (that is, diffusion of benefits) lagged behind the actual intervention, possibly for several years. There may have been some crime displacement early on, but that disappeared as the redevelopment progressed. In addition, the values of the WDQ were larger for the 2,000-foot buffer, so the effects did not wash out toward the outer boundaries of the study area.

To summarize, the WDQ effort for Capitol Gateway had strong results indicating a diffusion of benefits for most time periods and areas that was delayed until after the end of the intervention. The exceptions were the 12-month pre- and during-intervention periods for property crime and the 18-month pre- and during-intervention periods for all crime, during which time some displacement of those crimes may have occurred. That effect, however, had disappeared by the end of the redevelopment period, by which point diffusion of benefits was observed.

Results: Capper/Carrollsburg, Washington, D.C.

Exhibit 7 includes line graphs of all crime in the four main study areas (the site, two displacement buffers, and the comparison area—Syphax/Greenleaf Gardens) and dotted lines delineate the different study periods selected by the research team. Crime in the site dropped significantly in mid-2003; in the two buffers, it also dropped starting at the same point, although not to the same degree.

The Capper/Carrollsburg redevelopment had the longest timeline of the three sites under examination. The intervention periods generally center around the July 2003-through-December 2006 period, which is roughly the period of construction of the first senior building. Exhibit 12 provides crime density maps for 4 selected years in the study period: 2002, 2004, 2006, and 2008. The density maps were created using data covering a 0.5-mile radius around the site and reveal that the density of crime inside the site appeared to lessen with time. By 2008, most of the crime hot spots appeared to have moved outside of the 2,000-foot buffer area. After 2002, the target area itself had a very low density of crime, but a stable hot spot existed just to the northwest of the site that remained there throughout the study period.

The WDQ was calculated for four different time periods and in two buffers. Exhibit 13 provides the WDQ for each of the time periods and buffers considered. The exhibit also provides the success measure, or the denominator, of the WDQ. WDQs were only calculated where the success measure was negative.

The WDQ results for the Capper/Carrollsburg site were similar to those observed for Capitol Gateway. All success measures were negative, confirming that crime decreased over the study period. The results consistently indicated that a diffusion of benefits took place from the site, with two exceptions. For personal crimes during the first 12 months after the intervention period, the WDQ was negative. The same was true for the 18-month period following redevelopment for personal crimes. This pattern is similar to that observed for property crimes in Capitol Gateway, where a displacement effect was noted soon after the intervention started, the effect, however, disappeared with time following the intervention. It is unclear why this result occurred, but one thing to note is that in both of these instances, the success measure was very low, which could very well have skewed the results. One other factor to note in interpreting these findings is that other redevelopment projects were taking place in the larger area, and they may have accounted for the apparent diffusion effects noted in this site.

To summarize, the WDQ effort for Capper/Carrollsburg had the strongest, most consistent results of the three sites. The WDQs showed a diffusion of benefits across several different time periods, and in both the 1,000- and 2,000-foot buffers. Contextual knowledge of the greater redevelopment area, however, invites caution in interpreting these findings.

Exhibit 12

Density of Crime Over Time, Capper/Carrollsburg, Washington, D.C. (1 of 2)

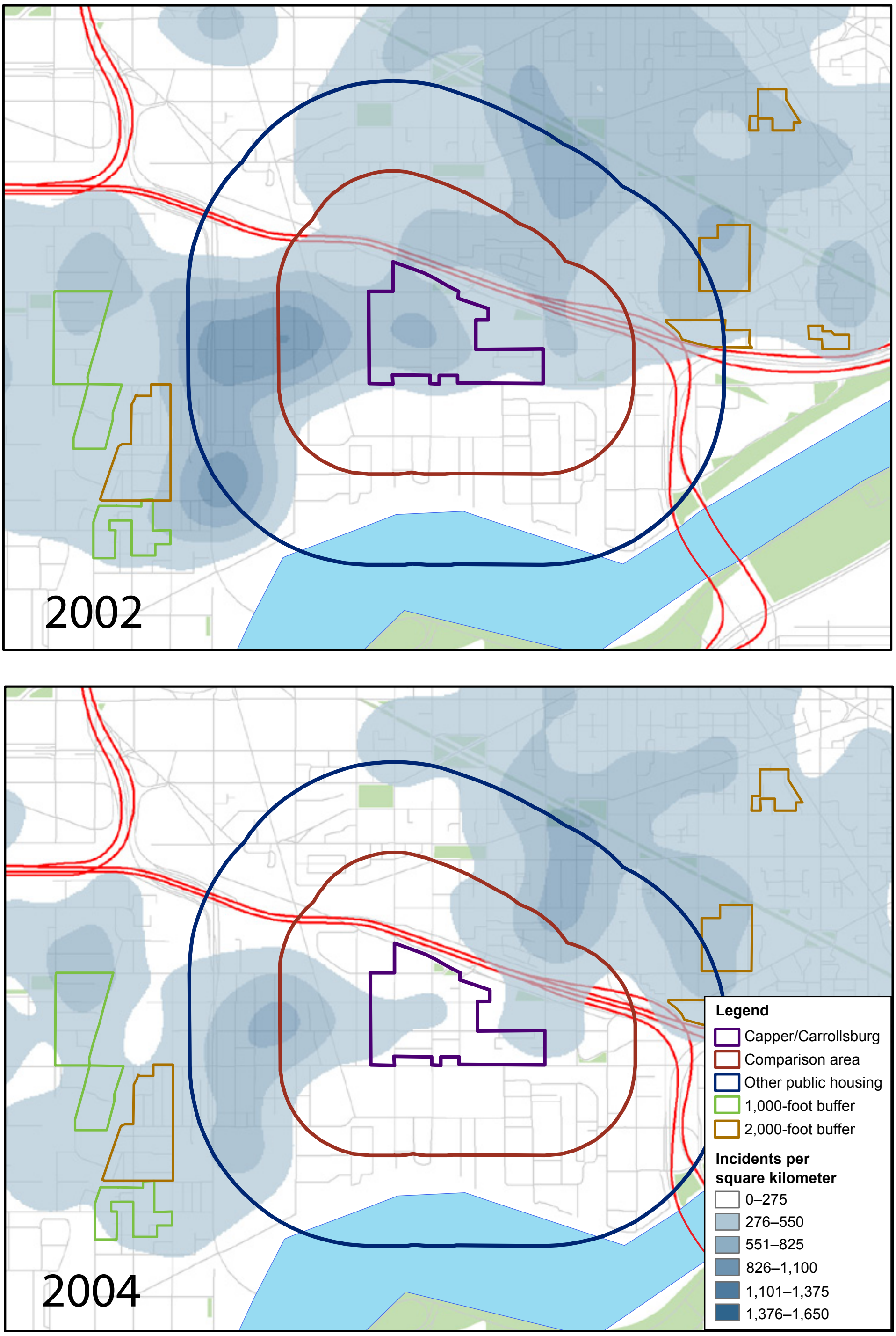


Exhibit 12

Density of Crime Over Time, Capper/Carrollsburg, Washington, D.C. (2 of 2)

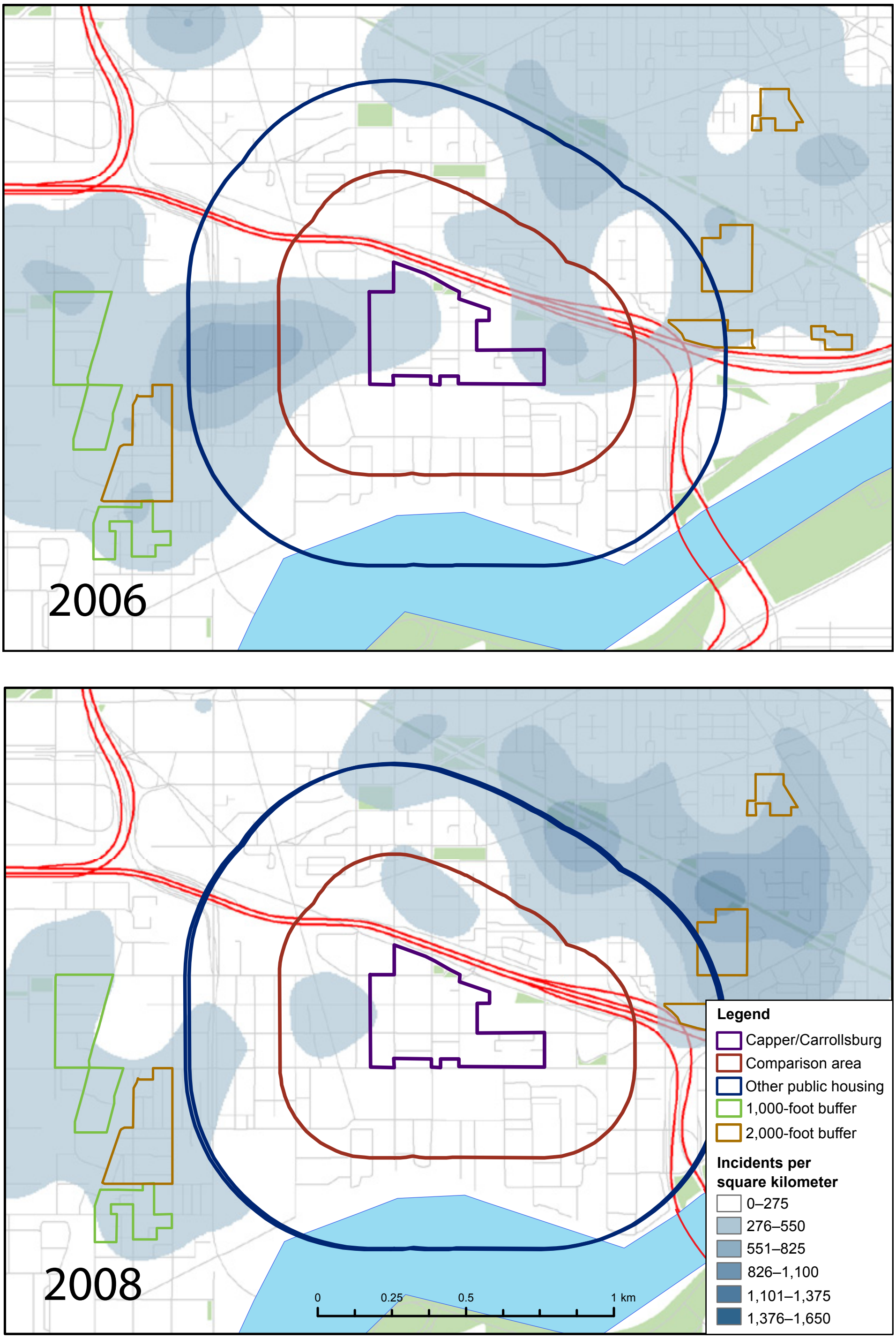


Exhibit 13

Weighted Displacement Quotient Results, Capper/Carrollsburg, Washington, D.C.

Pre/Post Length	t_0 (Pre-Intervention Period)	t_1 (Intervention or Post-Intervention Period)	Type of Crime	Success Measure	WDQ 1,000-Foot Buffer	WDQ 2,000-Foot Buffer
12 months	July 2002–June 2003	December 2004–November 2005	All	– 1.072	3.198	3.379
			Personal	– 0.381	0.125	– 3.258
			Property	– 2.488	4.118	5.250
12 months*	July 2002–June 2003	July 2003–June 2004	All	– 0.838	2.004	1.729
			Personal	– 0.451	1.496	1.994
			Property	– 1.711	2.682	2.464
18 months	January 2002–June 2003	March 2005–August 2006	All	– 1.040	3.045	3.100
			Personal	– 0.539	0.765	– 0.739
			Property	– 1.958	4.077	4.880
18 months*	January 2002–June 2003	July 2003–December 2004	All	– 0.843	1.657	0.843
			Personal	– 0.539	1.088	1.402
			Property	– 1.337	2.103	0.701

WDQ = Weighted Displacement Quotient.

**Searched for displacement during intervention period.*

Note: The intervention period was July 2003 through February 2005.

Discussion

The results from Milwaukee were the most mixed, with evidence of crime displacement provided by some of the WDQs. The results from Capitol Gateway and Capper/Carrollsburg were much more consistent than those from Milwaukee in that the WDQs for different areas and time periods produced similar results. Exhibit 14 provides a summary of the WDQ values for each site for each buffer (1,000 and 2,000 feet). This exhibit is simply the count of all WDQs that fell into each range (less than -1, -1 to 1, and greater than 1). Numbers smaller than -1 indicate displacement and numbers greater than 1 indicate diffusion of benefits. This exhibit does not differentiate between different types of crime.

Exhibit 14

Summary of Weighted Displacement Quotient Results Across All Sites

	Buffer Distance	< – 1	– 1 to 1	> 1
Milwaukee	1,000 feet	0	7	0
	2,000 feet	1	3	3
Capitol Gateway	1,000 feet	1	4	6
	2,000 feet	2	0	9
Capper/Carrollsburg	1,000 feet	0	2	10
	2,000 feet	1	3	8
Total	1,000 feet	1	13	16
	2,000 feet	4	6	20
	All	5	19	36

Only about one-half of the success measures for the different crime type/buffer/time period combinations studied in Milwaukee were negative, indicating that crime decreased in the target area (see exhibit 8). All of the success measures, however, were near 0, indicating that the effects—whether positive or negative—were minimal. The fact that the success measures were all positive for the 18-month pre- and post-intervention WDQ indicates that the redevelopment's reduction effects on crime grew with time and were stronger later in the study period. The WDQs indicated that some personal crimes were displaced—starting just after the intervention period ended—but that effect got smaller with increased time from the intervention period.

Exhibit 14 indicates that the Capitol Gateway site had more large and positive WDQs than neutral or negative WDQs, indicating that diffusion of benefits occurred. The WDQs indicated that the results varied with type of crime but the success measures were all negative, indicating a drop in crime in the target area. Property crimes in particular showed evidence of displacement early in the redevelopment period, but after the redevelopment period, showed strong evidence of diffusion of benefits. The initial displacement may have been an immediate reaction to the redevelopment activities that dissipated after all residents moved out and the site was empty. The success of the redevelopment efforts is judged more accurately by considering crime at the site when residents move back in, and during that period, the WDQs all pointed to a diffusion of benefits. Results for personal crime and all crime also showed evidence of a diffusion of benefits, and that diffusion started immediately after redevelopment.

In Washington, D.C., more than in Milwaukee, the residents of the redeveloped site were likely different than those who moved out before redevelopment. In all sites, and in HOPE VI in general, criteria to move into a redeveloped or new unit are much stricter than for other public housing. This results in residents who are more likely to be "successful"—at maintaining a housing unit, finding and maintaining employment, or participating in governance of the development (as is required in Milwaukee). Although we were unable to collect any data on residents' characteristics, we assume that with these kinds of stricter resident criteria in all three sites came less criminally inclined residents, and residents who had higher stakes in maintaining the safety and quality of their housing. The results we observed in the Capitol Gateway site, then, where diffusion of benefits increased after residents moved back in, are likely one manifestation of the stricter resident criteria.

All of the success measures calculated as part of the WDQ analysis for Capper/Carrollsburg were negative, indicating that crime did drop in the site during and after redevelopment. Nearly all of the WDQs were positive, indicating a diffusion of benefits took place from the target area to the buffers. Many of those WDQs were also greater than 1, pointing to a large positive effect in the buffer areas (see exhibit 8).

Two important details of the Capper/Carrollsburg site should be kept in mind when interpreting the results. First, the timeline for both of the Washington, D.C. sites, including Capper/Carrollsburg, was much longer than for the Milwaukee site, meaning those sites had a longer time period with fewer residents on site. Given the lack of residents on site, combined with the construction efforts at each site—making the site unattractive in terms of criminal opportunity—it is not surprising that crime dropped more quickly at the Washington, D.C. sites than in Milwaukee, where residents were on site throughout redevelopment.

A second important feature of the Capper/Carrollsburg site, mentioned above, was the large amount of redevelopment not associated with HOPE VI that was going on in the area immediately surrounding the site. These other redevelopment efforts should have served to decrease criminal opportunity at the site, and prevent much displacement from taking place to the buffer zones surrounding the Capper/Carrollsburg site.

Conclusion

Most previous displacement studies have focused on interventions with problem-oriented policing strategies, such as enhanced enforcement in a hot spot or small geographic area. We should not ignore the difficulties with applying the techniques and theories from that type of study to one like this where the intervention is long-term and takes place over a large geographic.

First, identifying the specific period of intervention is difficult—in each site, we did our best to use the redevelopment timeline to make educated decisions about when the most intense changes on the site occurred and used that period as our intervention. Second, choosing the boundaries of the sites proved difficult, especially in Milwaukee, where one redevelopment project bled into another and the redevelopment process for each building or unit was intertwined with the others. We chose a large target site to encompass all redevelopment activities in Milwaukee, but the results indicated that there may have been differential effects from the redevelopment of each portion of the larger site (for example, the effects of changes to Cherry Court may have been different from the effects of changes at Highland Gardens). In Washington, D.C., public housing site definition was more straightforward, but for Capper/Carrollsburg, nearby redevelopment efforts made the actual boundaries of redevelopment efforts difficult to identify.

For practitioners especially, we suggest that the WDQ is one of the most accessible and appropriate methods for studying displacement. It could easily be implemented by a housing authority or other practitioner looking to better understand displacement from public housing in his or her city. The WDQ requires a low level of resource commitment; different parameters can easily be tested by anyone with basic arithmetic aptitude, and extensive data holdings over several years are not necessary. We suggest that the WDQ be used as a useful but descriptive and intermediate tool in studying displacement. The results of the WDQ can be used to inform expectations of more rigorous statistical testing but cannot be relied upon solely for quantifying displacement or diffusion.

Although this research has shown that the HOPE VI effort has significantly positive effects on crime, especially in the target sites themselves, not all credit for the changes in the surrounding areas can be directly attributed to HOPE VI. Statistically, we were unable to control for all other redevelopment efforts that were taking place in the areas surrounding the target sites: in Milwaukee, for instance, the city assembled non-HOPE VI funding for the redevelopment of Cherry Court, which was in the neighborhood of the two HOPE VI sites (Highland Gardens/Homes and the scattered sites); in Washington, D.C., the area surrounding the Capper/Carrollsburg site concurrently underwent significant redevelopment with non-HOPE VI funds. We did not quantify these other efforts, and thus can only suggest that HOPE VI appeared to have a positive effect in the buffer areas. In these cases, however, the HOPE VI efforts can be seen as a catalyst for, or an early stage of, longer horizon redevelopment plans for a neighborhood. In the traditional sense of diffusion of crime reduction benefits from a site, then, HOPE VI cannot be given direct credit. In the sense that HOPE VI funds allow a city to target the greater neighborhood for additional redevelopment, however, HOPE VI can be credited with a diffusion of benefits to areas outside the site.

To the extent that the three HOPE VI sites in two cities are representative of other actual and possible HOPE VI sites, the results are applicable to other public housing sites undergoing this type of large-scale redevelopment, especially given the comparability of results we found across sites. The consistency with which we found evidence of diffusion from the sites is an indication that redevelopment under HOPE VI does indeed lead to diffusion of crime reduction, whether via changes directly attributable to HOPE VI in the target area or indirectly via encouraging additional investment in the larger neighborhood, leading to additional redevelopment efforts in areas surrounding the HOPE VI site itself. In addition, including the three sites allowed for, at the Milwaukee sites, a purer test of the physical site designs because residents were largely the same before and after redevelopment; at the Capitol Gateway site, an examination of changes in a site where little concurrent redevelopment was taking place outside the site; and, at the Capper/Carrollsburg site, an examination of effects where a massive amount of additional development was taking place. The variety presented by the sites makes the results applicable to a number of other, similar sites. Additional research in this vein that confirms the results of this study would add to the case presented in this article for the positive effects of HOPE VI on target sites and on surrounding neighborhoods.

Despite these challenges, studying displacement from public housing is an important undertaking, and the possibility of displacement should be considered by housing authorities either already undertaking large-scale public housing redevelopment projects or considering whether to start such an effort. Although this research showed that diffusion of benefits is likely from redeveloped public housing, more work of this type—exploring different options for target area boundaries, intervention periods, and displacement areas—can provide more evidence of the best approaches to this type of effort and inform housing authorities of the most efficient ways to include studies of displacement and diffusion in their redevelopment efforts.

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Do Vouchers Help Low-Income Households Live in Safer Neighborhoods? Evidence on the Housing Choice Voucher Program

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Abstract

This article examines an important potential justification for the Housing Choice Voucher Program, namely, whether participants are able to access safer neighborhoods. Using neighborhood crime and subsidized housing data for 91 large cities, we examined whether voucher holders are able to reach communities with lower levels of crime. We found that, in 2000, voucher households occupied neighborhoods that were about as safe as those housing the average poor renter household and were significantly safer than those in which households assisted through place-based programs lived. Notably, Black voucher holders lived in significantly lower crime neighborhoods than poor households of the same race, but Hispanic and White voucher holders did not. In a separate analysis of seven cities, we found that voucher holders lived in considerably safer neighborhoods in 2008 than they did in 1998, largely because crime rates fell more in the neighborhoods where voucher holders live than in other neighborhoods.

Introduction

Many scholars have argued that crime rates shape residential decisions and can thereby modify urban form. For example, several researchers have pointed to high rates of urban crime as a contributor to suburban flight (Cullen and Levitt, 1999; Mieszkowski and Mills, 1993). Although some debate exists about how dramatically changes in crime per se can alter the decision about whether to live in a city versus the suburbs (Ellen and O'Regan, 2010), researchers generally agree that crime is a significant concern for households and can influence households' neighborhood choices. Virtually all of this research has focused on the residential decisions of middle-income households.[1] Lower income households, however, care a great deal about neighborhood crime, too, although they may not have the same means to avoid it. In surveys of both Gautreaux and Moving to Opportunity (MTO) participants, respondents consistently cited crime as a primary motivation for wanting to enroll in those programs and move out of original high-crime neighborhoods (Goering, Feins, and Richardson, 2002; Hanratty, McLanahan, and Pettit, 1998; Rubinowitz and Rosenbaum, 2000).

One key justification for the Housing Choice Voucher Program (vouchers) is to provide assisted tenants with a greater range of neighborhood choices and, hopefully, enable them to reach better—and safer—neighborhoods.[2] Although previous research has examined the extent to which voucher holders reach lower poverty neighborhoods, virtually no work has examined the safety levels of the neighborhoods in which voucher holders live. This article aims to fill that gap.

The public safety risks of living in high-crime environments are substantial. People living in high-crime neighborhoods are more likely to be victims of crime, suffering physical, financial, and psychological harm. Votruba and Kling (2009) estimate that moving to safer neighborhoods saved up to 17 lives for 2,850 participants in the MTO program, with 13 of those lives saved from averted homicides. Moreover, being a witness to violent crime or living in fear of victimization can lead to stress and even diminished performance in school (Garbarino et al., 1992; Sharkey, 2010; Stafford, Chandola, and Marmot 2007). Finally, evidence suggests that youth who grow up in high-crime neighborhoods are disproportionately more likely to begin criminal careers and engage in risky behaviors, such as drug and alcohol use (Case and Katz, 1991; Ellen and Turner, 1997). Indeed, some researchers have argued that the disparate results across MTO sites may be partly explained by variation in crime among these different locations (Burdick-Will et al., 2010).

Clearly, crime is a vital component of neighborhood quality and thus a key outcome of interest in evaluating the efficacy of subsidized housing policies that seek to move program participants to better neighborhoods. This article aims to shed light on this critical dimension of the Housing Choice Voucher Program in cities. Specifically, we address the following questions: (1) How does the safety of the neighborhoods where voucher households live compare with the safety of the neighborhoods where they might have otherwise lived? (2) How does exposure to neighborhood crime vary across different types of voucher households? (3) How has crime exposure changed over time for voucher households? To what extent can these changes be attributed to shifts in the geographic distribution of these households versus improvements in neighborhoods where these households are concentrated?

Using data on annual census tract-level crime rates in 91 large cities that were averaged for the years 1999 to 2001, we address our first question by examining the exposure of voucher holders

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[1] Greenwood and Stock (1990) is an exception; they found that residential decisions of low-income households are also affected by crime.

[2] This increased choice itself may affect urban form, but we do not examine that in this article.

to crime.[3] We experiment with a variety of counterfactuals to assess whether vouchers are enabling households to reach safer neighborhoods than those in which they would have likely lived absent their vouchers. We shed light on our second question by exploring differences in exposure to crime across subgroups of voucher holders. Finally, using tract- and neighborhood-level crime data from 7 cities in 1998 and 2008, we describe changes over time in the degree to which voucher holders in those cities were exposed to crime in their neighborhoods.

Before conducting these empirical analyses, we provide a summary of the relevant literature. Next, we describe the data and our methods. We then present the empirical results of our analyses and conclude with a discussion of the key findings and the policy implications. As a preview, we find that, in the large cities we studied, voucher households live in lower crime neighborhoods than other subsidized households. The findings regarding subgroups are nuanced. Black voucher holders face higher neighborhood crime rates than White and Hispanic voucher households, but Black voucher holders live in safer neighborhoods than other renters of the same race, whereas White and Hispanic voucher holders do not. As for changes over time, voucher holders in our seven sample cities lived in substantially safer neighborhoods in 2008 than they did in 1998. The movement of voucher households, however, contributed little to those improvements. Rather, the key change was that the crime rates in the neighborhoods where voucher holders typically live fell markedly.

Previous Literature

Despite being discussed in policy circles as far back as the 1930s, vouchers did not become a feature of federal housing policy until 1974 (Orlebeke, 2000; Schwartz, 2006), but the program grew quickly. By 1980, more than 625,000 households held vouchers; in 2008, that number ballooned to more than 2.2 million. Voucher households comprised 44 percent of U.S. Department of Housing and Urban Development (HUD)-assisted households in 2008.

A key potential benefit of vouchers is that they provide households much more flexibility over location choice than project-based assistance does. Enhanced location choice, proponents argue, will likely reduce urban poverty concentration and allow voucher households access to higher opportunity neighborhoods. Whereas public housing and low-income housing tax credit (LIHTC) residents are typically quite limited in their choice of developments and units, voucher households should be able to select from a much wider array of neighborhoods and, therefore, have the opportunity to choose lower crime areas. In addition, voucher tenants are less visible to neighbors than public housing and LIHTC developments and, thus, may have an easier time reaching neighborhoods with lower crime and poverty rates.

Moreover, recent policy changes have expanded the portability of vouchers. In 1987, Congress amended the Section 8 statute to permit voucher holders to use their subsidies anywhere within a given metropolitan area and, in 1999, further amended the statute to allow for voucher use anywhere within the United States. In addition, the HOPE VI Program and the Quality Housing

[3] Note that we do not have census tract-level crime data in the suburbs of these large cities (although some of the cities themselves are considered suburban), so our analysis is limited to central cities.

and Work Responsibility Act of 1998 have provided HUD with additional tools to help local public housing authorities deconcentrate assisted households, frequently with the use of housing vouchers.

Still, voucher location choice is surely constrained. Maximum rents paid are capped by Fair Market Rents, potentially limiting neighborhood options (although Devine et al. [2003] show that almost all communities have rental housing units that would be affordable to voucher holders). In addition, landlords may resist accepting tenants with vouchers, especially in lower crime and lower poverty environments, and voucher holders may have limited information about alternative neighborhoods when making their choices.

Poverty Exposure for Subsidized Households

Most of the literature describing the neighborhoods in which assisted households lived focuses on poverty rates. For traditional public housing residents, the evidence clearly illustrates that they live in comparatively poor neighborhoods. Goering, Kamely, and Richardson (1997) found that, in 1990, slightly less than one-half of all public housing tenants lived in high-poverty census tracts (tracts with poverty rates of 40 percent or higher). Similarly, Newman and Schnare (1997) reported that more than 43 percent of tenants in family public housing lived in high-poverty census tracts in 1990.

Evidence suggests that voucher households also live in neighborhoods with higher than average poverty. Pendall (2000), examining census tract-level data from HUD on 1998 voucher households, found that neighborhoods with voucher holders had a 1990 poverty rate of 20 percent on average, compared with the nationwide average of 15 percent. In addition, tenants receiving all forms of assistance were more likely than renters as a whole to live in neighborhoods scoring high on a neighborhood distress index, constructed from poverty rates; public assistance receipt; and the proportion of female-headed households, high school dropouts, and labor force participants.

Nonetheless, studies typically find that voucher holders live in somewhat less distressed census neighborhoods than other assisted households. For example, in their comprehensive examination of the location patterns and neighborhood characteristics of the entire voucher population, Devine et al. (2003) found that almost 83 percent of census tracts in the 50 largest metropolitan statistical areas (MSAs) included at least one voucher household. By contrast, only 8 percent of all census tracts in these MSAs included public housing units. The relatively high dispersion of voucher households suggests that at least some voucher households must live in high-quality neighborhoods. Indeed, in the same study, the authors found that, in 1990, almost 30 percent of voucher households lived in census tracts with fewer than 10 percent of the residents living in poverty. Another 30 percent lived in tracts with 10- to 20-percent poverty rates. Approximately 22 percent of voucher families lived in neighborhoods with poverty rates of 30 percent or more.

Hartung and Henig (1997) provided evidence that the voucher program in the Washington, D.C. metropolitan area has been more effective in providing access to lower poverty neighborhoods than other forms of housing assistance. They found that, although 76 percent of the public housing and 50 percent of the other HUD-assisted developments are in tracts with median incomes below $25,000, only 32 percent of voucher households live in such tracts. Thus, although about 90 percent of Washington, D.C.'s voucher households lived in tracts with median incomes below $75,000, they were less concentrated in poor tracts than their counterparts living in public housing and other place-based, subsidized housing.

Most recently, McClure (2006) compared locational outcomes for the voucher and LIHTC programs. Using 2002 administrative data on voucher households and LIHTC units placed in service through that year, he found that about 30 percent of LIHTC households and 26 percent of voucher households lived in low-poverty census tracts and, on average, voucher households lived in very slightly lower poverty neighborhoods than LIHTC households.[4] Significantly, the proportions of LIHTC and voucher households in high-poverty tracts were slightly lower than the percentages of poor households that lived in high-poverty tracts, although they were higher than the share of all renters who lived in such tracts. The households assisted through both of these programs, in other words, were reaching neighborhoods with somewhat lower poverty rates than poor households, but they were still living in neighborhoods that had significantly higher poverty rates than other renters (at least in 2002).

A number of authors have documented the tendency for the voucher population to cluster geographically (Wang and Varady, 2005; Wang, Varady, and Wang, 2008). This clustering does not appear to be simply the result of the clustering of units with rents below Fair Market Rents. Racial segregation, imperfect information, and the refusal of landlords to rent to voucher households all likely contribute to clustering as well (Turner, Popkin, and Cunningham, 1999). Even these clustered households, however, live in significantly lower poverty neighborhoods compared with public housing households.

Neighborhood Crime Rates

Few studies examine the neighborhood crime rates experienced by voucher holders, largely because of a lack of suitable data. However, studies of three major mobility programs—Gautreaux, MTO, and HOPE VI—provide some evidence on the neighborhood safety of both public housing residents (pre-move) and voucher households (post-move). Because participants were chosen precisely because they lived in distressed neighborhoods, the reported numbers are not generalizable to all subsidized households. Nonetheless, the figures are illuminating. In brief, these groups were located in very high-crime areas when living in their original public housing developments and chose to move to lower crime (yet still relatively unsafe) areas after receiving their vouchers.

The Gautreaux program was created in Chicago in 1976 as a result of a series of lawsuits against the Chicago Housing Authority (CHA) and HUD. Gautreaux offered Black families in CHA housing the opportunity to move to desegregated areas around the Chicago area, including the suburbs. The program moved more than 7,000 families between 1976 and 1998 (Keels et al., 2005). According to Rubinowitz and Rosenbaum (2000), nearly one-half of Gautreaux participants reported that violent incidents occurred regularly in their neighborhoods. Criminal victimization rates were twice as high among Chicago public housing tenants compared with the city as a whole. Keels et al. (2005) estimated that violent crime rates in Gautreaux participants' original neighborhoods were three times as high as those in the average Chicago neighborhood.

[4] It is worth noting that LIHTC units were relatively more concentrated in low-poverty neighborhoods than voucher units were in the suburbs, but that they were slightly less concentrated in central cities. Our analysis focused on large cities.

In the short-term, those households that moved to new neighborhoods through the program continued to face higher crime rates than others in their surrounding areas. Suburban movers landed in neighborhoods with a violent crime rate about five times as high as the crime rate in the Chicago suburbs at that time, and those that moved within the city faced violent crime rates about one and one-half times as high as the average neighborhood in the city. In the longer term, however, the Gautreaux households tracked by Keels et al. (2005) lived in neighborhoods with violent and property crime rates that were comparable to the rates for the county as a whole.

HUD launched MTO in 1993 as a five-city experimental demonstration to move subsidized households living in high-poverty public housing developments into low-poverty neighborhoods. Goering, Feins, and Richardson (2002) reported that more than one-half of MTO participants identified crime, gangs, and drugs as the principal motivation for wanting to move out of their neighborhoods. Hanratty, McLanahan, and Pettit (1998) reported that almost 60 percent of the Los Angeles participants cited getting away from drugs or gangs as the primary reason for wanting to move. A shocking proportion of these respondents reported that one or more of their household members were the victim of a crime in the past 6 months. Administrative data supported these reports of victimization. Violent crime rates for the baseline MTO census tracts in Boston, Chicago, and Los Angeles were three times higher than in the metropolitan areas as a whole (Kingsley and Pettit, 2008).

As for the post-move neighborhoods, some evidence indicates that MTO participants occupied lower crime neighborhoods after participating in the program. Kingsley and Pettit (2008) found that violent crime rates in Boston, Chicago, and Los Angeles were almost twice as high in the MTO origin neighborhoods than in the Section 8 movers' initial post-move neighborhood. Feins and Shroder (2005) reported results of pre- and post-move surveys for the MTO treatment, comparison, and control groups (the comparison group include households that received vouchers but were not restricted to use them in low-poverty neighborhoods). Survey respondents in the two groups that received vouchers reported significantly greater improvements in neighborhood safety than the control group for every question asked.[5] Thus, MTO participants were successful in using vouchers to move to safer neighborhoods.

Similarly, some evidence suggests that participants moving out of HOPE VI sites are moving to safer and more affluent neighborhoods. Buron et al. (2002) provided a snapshot of post-revitalization neighborhood conditions in eight cities and found that post-revitalization households still occupy relatively unsafe neighborhoods. Overall, about 40 percent of the respondents reported "big problems" with drug trafficking and gang activity in their current neighborhood, and fewer than 20 percent reported big problems with violent crime. Households in the sample that were no longer receiving a housing subsidy were the least likely to report big problems with drug trafficking and gang activity, while returning HOPE VI residents were the most likely to report big problems. The evidence that HOPE VI revitalization projects are moving households to safer neighborhoods is preliminary, however, because the revitalization projects and voucher mobility HOPE VI spawned are still in progress.

[5] Questions address perceived safety during the day, safety during the night, drug activity in view in the neighborhood, and whether a household member was a crime victim in the past 6 months.

Considered as a whole, previous work on the neighborhood conditions faced by subsidized households suggests that voucher households, on average, live in neighborhoods with higher poverty rates than the average renter, but they live in lower poverty areas than public housing tenants and in areas with slightly lower poverty rates than other poor households. Thus, tenants assisted through these programs have had some success in reaching low-poverty neighborhoods, but the success has been relatively modest. We know little about the exposure of voucher households to crime. What we do know comes from the experience of a very particular subset of voucher holders that moved out of distressed public housing developments through the Gautreaux, MTO, or HOPE VI programs. This body of research offers some suggestive evidence that these selected voucher recipients have been successful in moving to safer neighborhoods. It remains to be seen if the broader voucher population—those not necessarily eligible for and selected into specialized programs, and representing a wider array of cities—has been able to reach safer neighborhoods.

Data and Methods

Our analysis relies on two sets of crime data, all restricted to large cities (rather than MSAs). First, we use data from the *National Neighborhood Crime Study* (Peterson and Krivo, 2010), a nationally representative sample of crime data for 9,593 census tracts in 91 U.S. cities, collected by Ruth Peterson and Lauren Krivo of Ohio State University. Crime counts from 1999 to 2001 were provided to Peterson and Krivo by local police departments. The data set includes an average of the Part I crime categories over the entire 3 years for each census tract. Such 3-year averages allow for abnormal spikes to be smoothed out over the sample period, and are frequently used in crime research when available (Sampson, Raudenbush, and Earls, 1997). The sample of 91 cities was randomly chosen from all cities with at least 100,000 people as of the 2000 Census, and then was stratified by region. In the event that a city's police department was not able to provide crime data, the city was replaced with a city that was similar in terms of geography and demographics. A list of the 91 cities, in addition to basic descriptive statistics on crimes and subsidized housing units for each city, is shown in appendix A-1.

The second data set includes annual census tract-level crime data for seven U.S. cities—Austin, Chicago, Cleveland, Denver, Indianapolis, Philadelphia, and Seattle—from 1998 to 2008. Appendix A-2 displays the crime data availability for those years and describes the sources of the data.[6]

We merged census tract-level counts of four types of households to the crime data—voucher households, renter households below the poverty line, public housing tenants, and LIHTC households. We obtained voucher and public housing data from HUD's Picture of Subsidized Households. At the present time, voucher data are available through this data set for 1998, 2000, 2004, and 2008. In addition, we obtained access to household-level voucher data from HUD for 2000 to estimate

[6] We do not have 2008 data for three of the cities. For these cities, we use 2007 crime data to estimate 2008 voucher crime exposure rates. Although this is not ideal, there is not much reason to expect substantial changes in the neighborhood distribution in crime from 2007 to 2008 in these cities, and this is preferable to limiting the 2008 analysis to four cities. In Cleveland, which has missing crime data for 1998, we use 1997 and 1999 crime data to estimate 1998 crime rates using a linear interpolation.

crime exposure rates for voucher households with different demographic characteristics. Public housing data are available for 1996 to 1998, 2000, 2004, and 2008. LIHTC data are available from HUD's LIHTC database from 1987 to 2007. U.S. Census data on poor renter counts are available for 2000. Finally, we merge these data with 2000 Census counts of total housing units and tract-level demographic statistics from the Urban Institute's Neighborhood Change Database.

As with all administrative data sets, gaps in coverage and variation in quality exist. HUD collects voucher and public housing data from local housing authorities, and in the early years of our sample, reporting rates were sometimes well below 100 percent. (The data set provides complete information for 87 percent of voucher recipients in 1998, for example.) By 2008, reporting rates rose to 98 percent. HUD publishes the percentage of vouchers and public housing units that are reported by each city, so we can identify which cities were most affected by these data gaps. Appendix A-3 displays the percent reported by each city's housing authority for the longitudinal sample (Austin, Chicago, Cleveland, Denver, Indianapolis, Philadelphia, and Seattle) in 1998 and 2008. In 1998 (and presumably 2008), the reporting rate for vouchers was consistently very high. For all cities aside from Indianapolis (84 percent), the reporting rate was 99 percent. Public housing reporting rates were considerably lower, at least in 1998. In that year, reporting rates for public housing were just 54 percent in Chicago and 50 percent in Philadelphia. We have little reason to believe, however, that reporting rates would vary with the crime rates of the development. If they did vary, we expect that they would be lower in higher crime developments, suggesting that our results could potentially understate the crime rates experienced by public housing residents.

Exhibit 1 displays descriptive statistics as of 2000 for the 91-city cross-sectional sample and the 7-city longitudinal sample. Because our samples are restricted to large cities (that is, not MSAs) we also provide descriptive statistics for all tracts in U.S. cities with populations greater than 50,000 as a comparison.

Exhibit 1

Average City and Census Tract Characteristics in 2000

	91-City Cross-Sectional Sample (N=9,583)	7-City Longitudinal Sample (N=1,806)	All Tracts in U.S. Cities > 50,000 Population (N=25,893)[a]
Crimes per 1,000 people	62.0	71.4	75.8
Average Tract Characteristics			
Voucher holders per tract	31.8	28.7	30.4
LIHTC units per tract	22.7	23.0	19.6
Public housing per tract	26.3	43.3	27.7
Poor renters per tract	184.4	196.3	170.3
Population per tract	4,114	3,765	4,111
Poverty rate (weighted average)	16.9%	19.5%	15.5%
Percent non-Hispanic White (weighted average)	48.4%	42.1%	53.2%
Percent non-Hispanic Black (weighted average)	22.5%	33.3%	18.8%
Percent Hispanic (weighted average)	22.9%	19.2%	20.4%
Total population in tracts	39,426,839	6,799,280	106,466,565

LIHTC = low-income housing tax credit.

[a] All core cities of metropolitan areas, FBI Uniform Crime Reports, 2000.

Comparing the three samples in exhibit 1, we see that the tracts in the longitudinal sample differ slightly demographically from the full set of urban tracts, but the tracts included in the 91-city sample are quite similar to the full set. Specifically, the tracts in the seven-city sample have larger percentages of poor and Black residents than the full city sample. The tracts in the 91-city sample contain similar proportions of people in poverty and in different racial groups as those in the full city sample, although the 91-city sample is slightly more non-White. The largest difference between the two samples is the city crime rates; the average crime rate is considerably lower for the 91 cities than for the full set of U.S. cities.

As for subsidized housing, average voucher concentrations within census tracts are fairly uniform throughout the two samples and all U.S. cities, ranging from 29 to 32 voucher holders per tract, or approximately 2 percent of all housing units. LIHTC concentrations also vary little across the samples, ranging from 20 to 23 per tract (less than 2 percent of a tract's housing units on average). Public housing concentration is much more varied across the samples. In the longitudinal sample, Chicago's presence among the seven cities leads to a larger average number of public housing units per census tract than the other samples.

Appendix B-1 displays how crime and housing variables change over time in the cities in the longitudinal sample. As shown, crime rates decreased over time, as they did across the United States, while the number of voucher households and LIHTC units increased, but the number of public housing units declined. Aggregate crime rates (expressed as crimes per 1,000 people)[7] declined 23 percent from 1998 to 2008. From 1998 to 2008, the number of voucher and LIHTC households doubled. Public housing units did the opposite—declining over the decade from 73,181 to 57,207 units.

Finally, we have access to data from more than 212,000 individual voucher households that, in 2000, lived in one of the 91 cities for which we have crime data. This represents 17 percent of all voucher holders nationwide in 2000. (These cities also contain 23 percent of LIHTC tenants and 19 percent of all public housing tenants.) From these data we can determine whether the household used a voucher to move into that census tract in that year, the race of the household head, whether the household contains children under 18, and the total household income.

Estimating Group-Specific Crime Exposure

To estimate the crime rates faced by the typical household in each group, we estimate crime exposure rates, which weight a neighborhood's crime rate by the proportion of the sample's relevant household type (voucher, LIHTC, etc.) within that neighborhood. These exposure rates, in other words, essentially show the neighborhood crime rate experienced by the average member of the given group. Specifically, the crime exposure measure is expressed for voucher households as

$$\sum_{i=1}^{n}\left[[Crime]_i * \left(\frac{v_i}{V}\right)\right] \tag{1}$$

[7] Crime rates are expressed both as crimes per 1,000 people and as crimes per 1,000 housing units. In the results section, however, we present crime exposure rates as crimes per 1,000 people, with crimes per 1,000 housing units and crimes per square mile as robustness checks, included in the appendix.

where $Crime_i$ is the crime rate (either total or violent) in census tract i, v_i is the number of voucher households (or public housing, LIHTC, or poor renter households) in census tract i, and V is the number of voucher households (or public housing or LIHTC units, or poor renter households) in the sample. The resulting value is essentially a weighted average neighborhood crime rate, or the crime rate faced by the typical household in that group. We conduct statistical tests to learn if the differences in means across groups are statistically significant. In addition, we estimate the percentage of each housing subgroup population that resides in a high-crime neighborhood, which is defined as a neighborhood with a crime rate at least one standard deviation above the mean. In robustness checks, we also use the number of crimes per square mile of land area and the number of crimes per 1,000 housing units.

Comparing voucher household crime exposure with that of the general population is informative, but it does not provide a very good counterfactual for where voucher households would have lived if they had not had the benefit of a housing voucher. To provide a sense of the other options that voucher households might have in the absence of a voucher program, we consider the average crime rates in the neighborhoods where LIHTC units, public housing units, and all units occupied by poor renters are located. These housing units represent locations where voucher households might live in the absence of the program. Comparing the neighborhoods of voucher holders with those of tenants in place-based programs sheds light on whether the increased choice provided by vouchers helps subsidized households reach better neighborhoods. Because much of the growth in the voucher program is a result of the demolition of public housing, public housing locations serve as a viable counterfactual for where voucher holders could be living if such demolitions had not occurred. The LIHTC, as the largest place-based housing subsidy in the country, is another relevant place-based counterfactual.

Identifying Changes in Voucher Crime Exposure Over Time

To estimate the relative changes in crime exposure among the voucher households from 1998 through 2008, we first limit the sample to a balanced panel, which includes only neighborhoods for which we have crime and housing data in 1998 and 2008. Note that we have two mechanisms through which crime exposure could change over time for voucher holders. First, the distribution of voucher households across neighborhoods could shift to neighborhoods with higher or lower crime rates. Second, the distribution of voucher holders could remain constant, but crime rates could increase or decrease in the neighborhoods in which voucher holders are located. This is an important distinction for policy. If the gains in public safety for voucher holders were largely a result of safety gains within their existing neighborhoods, the continued mobility allowed by the voucher program may not deserve a lot of the credit for these gains. If, however, the vouchers enabled tenants to move to safer neighborhoods, then continued mobility deserves the credit.

To test whether changes in crime exposure for voucher households were due to spatial shifts in crime patterns, we decompose the crime changes and compute a hypothetical crime exposure rate, showing what the crime exposure rate would have been for voucher holders in 2008 if the distribution of voucher holders had remained unchanged between 1998 and 2008. This rate uses the 1998 voucher neighborhood distribution with 2008 crime rates, defined notationally (for vouchers) as

$$\sum_{i=1}^{n}\left[[Crime]_{i,2008} * \frac{v_{i,1998}}{V_{1998}}\right]. \qquad (2)$$

If the actual crime exposure rate in 2008 (using 2008 crime and voucher distributions) is roughly the same as this hypothetical rate, then we can infer that changing conditions in the neighborhoods where voucher holders tend to live largely drove any changes. By contrast, if we find that the actual crime exposure rate is significantly lower than the hypothetical crime exposure rate, then we infer that changes in the distribution of voucher holders likely explained a large part of any reduction in exposure.

Cross-Section Results

Exhibit 2 displays crime exposure rates for the 91 cities in the cross-sectional sample covering the year 2000. We include in the exhibit crime exposure rates for all households, voucher households, LIHTC tenants, public housing tenants, and poor renters living in these cities.

The exhibit shows that voucher holders, on average, lived in neighborhoods that had significantly higher crime rates than those lived in by all households but slightly lower crime than those lived in by poor renters.

As for comparisons to residents living in other types of subsidized housing, voucher holders lived in neighborhoods that were significantly more safe than those lived in by tenants in place-based subsidized housing programs. In 2000, public housing tenants and, perhaps surprisingly, LIHTC tenants, lived in significantly higher crime neighborhoods than voucher holders. (All of these results are robust to modifications in the crime rate denominator.)

What about exposure to violent crimes in particular? Total crime rates are largely driven by property crimes, particularly larceny and other thefts. (In this sample, only 15 percent of the crimes are violent crimes.) Exposure to violence, however, may be a particular concern. Aizer (2008) found that lower youth cognitive test scores can be explained in part by association with violent peers and exposure to neighborhood violent crime. Sharkey (2010) found that children living in census block groups where a homicide occurs 1 week before a standardized test perform worse than other comparable children.

Exhibit 2

Crime Exposure Rates in 2000 (sample: 91 cities)

Type	Crimes per 1,000 People	Statistically Different From Voucher Crime Exposure Rate?	Violent Crimes per 1,000 People	Statistically Different From Voucher Violent Crime Exposure Rate?
All households	62.0	Significantly lower (1%)	9.2	Significantly lower (1%)
Voucher households	76.9	NA	14.3	NA
LIHTC tenants	100.6	Significantly higher (1%)	16.9	Significantly higher (1%)
Public housing tenants	108.4	Significantly higher (1%)	22.3	Significantly higher (1%)
Poor renters	82.2	Significantly higher (1%)	14.4	No

LIHTC = low-income housing tax credit. NA = not applicable.

The patterns for violent crime exposure are fairly similar to those for total crime exposure. Among assisted households, public housing residents lived in the most violent neighborhoods on average, while voucher holders lived in the least violent. On average, voucher holders lived in neighborhoods with safety levels very close to those of the neighborhoods lived in by the average poor renter.

Another way to measure differences in crime exposure is to compare the proportion of each population that lived in a high-crime neighborhood, defined as neighborhoods with crime rates more than one standard deviation above the mean. Exhibit 3 displays these proportions, together with results from statistical tests of differences in proportions between tenants in each housing program.

The share of voucher holders who lived in high-crime neighborhoods was significantly lower than the proportion for either LIHTC or public housing tenants. The only difference between these results and those in exhibit 2 is that the proportion of LIHTC households living in high-crime neighborhoods was slightly higher than the share of public housing residents, although the difference is not statistically significant. The violent crime results are also very similar.

These promising findings on voucher crime exposure appear to contradict previous work that finds that voucher households have had limited success in gaining access to higher quality neighborhoods (McClure, 2008; Pendall, 2000; Wang, Varady, 2005; Wang, Varady, and Wang, 2008). These differences could be because of idiosyncrasies in our sample or they could reflect differences in patterns of exposure to crime as compared with exposure to poverty and racial minorities. To test this using the 91-city sample, exhibit 4 expands on the analysis presented in exhibit 2, displaying poverty and minority exposure rates and average crime rates for the housing subgroups in 2000.

Exhibit 3

Percent in High-Crime Neighborhoods by Type of Housing in 2000 (sample: 91 cities)

Type of Housing	Percent in High-Crime Neighborhoods	Statistically Different From Voucher Proportion?	Percent in High-Violent Crime Neighborhoods	Statistically Different From Voucher Proportion?
Total	3.1	Significantly lower (1%)	5.1	Significantly lower (1%)
Voucher households	4.4	NA	11.0	NA
LIHTC tenants	11.3	Significantly higher (1%)	16.4	Significantly higher (1%)
Public housing tenants	10.8	Significantly higher (1%)	23.9	Significantly higher (1%)
Poor renters	6.0	Significantly higher (1%)	11.4	Significantly higher (1%)

LIHTC = low-income housing tax credit. NA = not applicable.

Exhibit 4

Neighborhood Crime, Poverty, and Minority Exposure Rates in 2000 (sample: 91 cities)

	Crimes per 1,000 People	Average Poverty Rate (%)	Average Percent Minority (%)
Voucher households	76.9	24.4	59.3
LIHTC tenants	100.6	26.8	58.1
Public housing tenants	108.4	36.7	65.7
Poor renters	82.2	26.9	51.8

LIHTC = low-income housing tax credit.

The exhibit clearly illustrates that crime exposure patterns are indeed different. LIHTC and voucher households, on average, live in communities with virtually identical poverty rates and minority population shares, but they live in communities that are quite different in terms of crime. Household preferences might help to explain the differences and similarities between crime, poverty, and minority exposure among these different types of households. The households with greater residential choice—vouchers and poor renters—live in neighborhoods with dramatically lower crime rates but with fairly similar poverty rates and racial compositions. This suggests that voucher holders and other poor households, when choosing neighborhoods, may prioritize the avoidance of high-crime areas, not neighborhoods with high minority and/or poor populations. This prioritizing also suggests that if our key interest is facilitating access to safe neighborhoods that offer a rich set of opportunities, then poverty rates and minority concentration may not serve as ideal proxies.

Differences Across Subgroups of Voucher Holders

Although the previous exhibits provide useful information about the location and neighborhood choices of the average voucher holder, this section explores whether notable differences across subgroups exist. We know that housing market opportunities and outcomes differ noticeably by income, race, and family structure; the opportunities and outcomes of housing voucher holders may differ as well. Exhibit 5 displays crime exposure rates for voucher households, disaggregated by the race of the household head, household income strata, and the presence of children.

The largest differences are across income groups, where we see a monotonic decline in voucher exposure to neighborhood crime as household income increases. This seems surprising given that vouchers should technically neutralize income differences by allowing households to pay only 30 percent of their income for rent. As for racial differences, Hispanic voucher holders lived in neighborhoods with the lowest crime, and Black voucher holders lived in the highest crime

Exhibit 5

Voucher Crime Exposure in 2000 by Demographic and Mobility Characteristics (sample: 91 cities)

Subgroup of Voucher Holders	Crimes per 1,000 People[a]
All voucher holders	78.4
White voucher holders	76.7*
Black voucher holders	81.4
Hispanic voucher holders	69.3*
Household income < $10,000	81.8
Household income $10,000 to $19,999	75.1**
Household income $20,000 to $29,999	69.3**
Household income > $30,000	63.7**
Households with children (NS)	77.0
Households without children	80.7

NS = Not statistically different from relevant reference category.

[a] These rates are slightly higher than the voucher crime exposure rates reported in exhibit 3 because of differences between the household data and those reported in HUD's Picture of Subsidized Households.

**Significantly different from Black voucher holders at the 1-percent level.*

***Significantly different from voucher holders with incomes below $10,000 at the 1-percent level.*

neighborhoods. Crime exposure rates for voucher households with children were only very slightly lower than those for households without children, and the difference was not statistically significant.

Although exhibit 5 suggests that Hispanic voucher holders are the least exposed to crime, and that Black voucher holders are the most exposed, it fails to take into account the safety level of the neighborhoods that households of different races tend to live in absent housing assistance. Although it is impossible to know exactly where households would have lived absent their voucher, exhibit 6 approximates such a counterfactual by comparing exposure to neighborhood crime for voucher households of different races with exposure of poor households and renter households of the same race. The implicit assumption, in other words, is that absent a voucher, households would have lived in the neighborhoods lived in by unassisted, poor, and renter households of the same race. This comparison does not suggest that voucher holders should be constrained or guided in their residential choices by their race; it simply assumes that they are as likely to operate under such constraints, just like unassisted poor and renter households of the same race.

The results are surprising. White and Hispanic voucher holders tend to live in *higher* crime neighborhoods than their counterparts who do not receive vouchers (poor households and renter households). By contrast, Black voucher households live in census tracts with slightly *lower* crime rates than Black poor and Black renter households. The voucher program is helping to close the Black-White and Black-Hispanic racial gaps in exposure to crime. Of course, our comparison groups may differ from voucher holders in unobserved ways, and these differences may be more pronounced for particular racial groups. For instance, White and Hispanic voucher holders may have quite different location preferences or face very different constraints compared with the full set of White and Hispanic poor households, but Black voucher holders may be more similar to other Black poor households. Thus, we should be cautious in drawing conclusions from these findings.

Exhibit 6

Voucher, Poor, and Renter Household Crime Exposure Rates by Race (sample: 91 cities)

Population	Crimes per 1,000 People
White	
Voucher households	76.7
Poor households	65.1
Renter households	70.3
Black	
Voucher households	81.4
Poor households	87.5
Renter households	88.3
Hispanic	
Voucher households	69.3
Poor households	64.0
Renter households	66.5

Longitudinal Results

The cross-section analyses suggest that, at least in cities, voucher households lived in neighborhoods that were about as safe as those where poor renters lived, and they lived in lower crime neighborhoods than where other subsidized households lived. We now examine how voucher crime exposure changed over time. Exhibit 7 displays 1998 and 2008 crime exposure rates for all households and for voucher households in Austin, Chicago, Cleveland, Denver, Indianapolis, Philadelphia, and Seattle.

Exhibit 7 illustrates that total crime dropped considerably in the entire sample (from 79 to 64 crimes per 1,000 people), but the reduction was not statistically significant and not every city enjoyed these reductions.[8] Austin, Denver, and Indianapolis actually experienced slight increases in overall crime rates. Notably, the reduction in the crime rates in the neighborhoods where voucher holders lived was even larger than that for all tracts and was statistically significant, unlike the reduction for all tracts. The typical voucher household experienced a reduction in crime in every city except for Austin (where average crime rates rose slightly from 69 to 72 crimes per 1,000 people), and even in that city, the crime increase for voucher holders was smaller than that experienced by the average household in the city. The only city where the overall crime decrease was greater than the crime decrease for voucher holders was Chicago. In Cleveland, Denver, Indianapolis, and Seattle, voucher holders experienced greater decreases in neighborhood crime than the overall population.

Although it is impossible to know exactly what drove these reductions in exposure to neighborhood crime, a simple decomposition can shed some light on the causes.[9] Two possible explanations emerge. Either the spatial distribution of voucher households changed and they moved disproportionately to lower crime neighborhoods, or it remained the same but the neighborhoods voucher holders lived in experienced disproportionate declines in crime. To tease out the correct

Exhibit 7

Changes in Crime Exposure, 1998–2008 (sample: 7-city longitudinal)

	1998		2008	
	All Households	**Voucher Households**	**All Households**	**Voucher Households**
All	78.9	101.9	64.3	79.0
Austin	63.2	69.3	68.0	72.6
Chicago	81.5	103.1	55.8	77.5
Cleveland	68.5	69.8	63.0	63.6
Denver	67.4	104.1	71.7	76.1
Indianapolis	117.3	135.5	120.7	124.9
Philadelphia	74.0	80.1	64.7	63.9
Seattle	94.2	181.5	66.8	122.0

[8] Note that the value of the crime rate denominator does not change from 1998 to 2008. Thus, we are underestimating crime rate decreases in neighborhoods and cities with population growth.

[9] The analysis does not take into account the possibility that the spatial location of these households could affect neighborhood crime rates but still allows us insight into whether crime decreases were more related to household movements or within-tract improvements.

explanation, we estimate how average neighborhood crime rates for these subgroups would have changed over time if the geographic distribution of each subgroup had remained constant. Specifically, exhibit 8 presents what crime exposure rates would have been in 2008 had the distribution of voucher holders across neighborhoods remained identical between 1998 and 2008. (In other words, we calculate the exposure of 1998 voucher holders to 2008 neighborhood crime rates.) We compare these hypothetical neighborhood crime rates with the actual 2008 crime exposure rates.

Exhibit 8

Decomposition of Crime Rate Changes (sample: 7-city longitudinal)

	1998 Voucher Location, 2008 Crime	2008 Voucher Location, 2008 Crime
All	82.4	79.0
Austin	76.0	72.6
Chicago	77.7	77.5
Cleveland	64.3	63.6
Denver	109.7	76.1
Indianapolis	122.1	124.9
Philadelphia	68.9	63.9
Seattle	117.9	122.0

As shown in exhibit 8, the hypothetical crime exposure rates in the 1998 voucher location column the left are generally only slightly larger than the actual 2008 crime exposure rates on the right, suggesting that improvements in crime exposure were mostly driven by improvements in the neighborhoods where the various housing groups lived at baseline, rather than by the movement of voucher recipients to lower crime neighborhoods. Still, the hypothetical crime exposure rates are typically somewhat higher than actual crime exposure rates (and significantly higher in Denver), suggesting that some portion of the reduction in exposure of voucher holders to crime likely resulted from shifts in the distribution of voucher holders towards lower crime neighborhoods. This shift suggests that ongoing mobility (rather than initial access to particular neighborhoods) contributed a small amount to improvements in voucher neighborhood safety.

Discussion

Using a number of different data sources, this article has described the extent to which voucher households are exposed to neighborhood crime, as compared with public housing residents, LIHTC tenants, and other poor renter households, in a representative sample of U.S. cities. Our key finding is that, overall, in 2000, voucher households occupied significantly lower crime neighborhoods than LIHTC and public housing tenants and slightly lower crime neighborhoods than poor renters as a whole. Voucher households are less likely to live in neighborhoods with particularly high crime than any of these comparison groups. Interestingly, the safety benefits of vouchers appear to be especially pronounced for Black voucher holders. Black voucher holders lived in safer neighborhoods than other Black renters and Black poor households.

In sum, vouchers appear to be helping low-income households reach safer neighborhoods or at least avoid neighborhoods that are the least safe. Given the growing evidence about the importance of crime in shaping children's outcomes, this greater access provides an important argument in favor of switching from reliance on production-based housing to reliance on vouchers. In the long run, our findings also suggest that, if given the means, a greater share of low-income households would be able to avoid very high-crime neighborhoods.[10]

It is worth underscoring that, by limiting our analyses to large cities, we are likely overstating the neighborhood crime rates faced by voucher holders and LIHTC tenants, because we are omitting the large number of them who live in suburban communities. By 2000, voucher holders—and LIHTC tenants—were much more likely than public housing tenants to live in the suburbs (Devine et al., 2003). Although central city and suburban poverty rates have been converging in recent years, crime rates are still lower, on average, in suburban communities than they are in central cities (Ellen and O'Regan, 2009). Finally, because patterns of suburbanization may differ across races, the relative exposure to crime of different subgroups might differ in the suburbs.

Appendix A

We collected crime data from one of three sources: (1) directly from police department websites or data requests to the department (Austin and Seattle); (2) from researchers who obtained these data from police departments (Chicago); or (3) from the National Neighborhood Indicators Partnership, a consortium of local partners coordinated by the Urban Institute to produce, collect, and disseminate neighborhood-level data (Cleveland [Case Western Reserve University], Denver [The Piton Foundation], Indianapolis [The Polis Center], and Philadelphia [The Reinvestment Fund]). For all cities, total, property, and violent crimes are included, and for all cities except Denver and Indianapolis, crimes are further disaggregated into all Part I crimes (violent crimes—assault, sexual assault, homicide, and robbery; property crimes—larceny, burglary, motor vehicle theft, and arson).[11] In all cities except for Denver, neighborhoods are proxied by census tracts.[12] Denver crime data are aggregated to locally defined neighborhoods, which are typically two to three census tracts. In Denver, we aggregated the tract-level housing data to the neighborhood level and linked these variables to the neighborhood crime data.

[10] In addition to showing these positive impacts for households, the results suggest that vouchers do contribute to a different spatial distribution of subsidized households.

[11] Philadelphia was unable to share numbers on sexual assaults or homicides; thus, those crimes are not included in overall totals or the individual categories. Given Philadelphia crime data were available from 1998 through 2006, we used 1998 and 1999 crime data to estimate 1997 numbers and 2005 and 2006 crime data to estimate 2007 numbers.

[12] Although Denver data are at the neighborhood level, 4,447 of our 4,523 neighborhoods are equivalent to census tracts. Thus, in describing data and results, we often use the term "census tract."

Exhibit A-1

City List and Descriptives for 91-City Cross-Section, 2000 (1 of 4)

City	Population	Housing Units	Crimes per 1,000 People	Crimes per 1,000 Housing Units	Vouchers	LIHTC Units	Public Housing Units	Rental Units Occupied by Poor Households
Akron, OH	240,756	107,544	58	129	2,852	1,818	3,647	11,753
Albuquerque, NM	481,532	211,547	80	182	4,058	1,945	846	17,601
Alexandria, VA	128,283	64,251	44	88	991	987	889	3,647
Anchorage, AK	258,847	99,932	39	102	1,657	401	588	4,372
Arlington, TX	347,483	136,874	64	162	2,203	2,509	0	9,058
Aurora, IL	232,741	80,070	24	70	703	736	656	2,692
Austin, TX	739,944	310,334	53	127	2,415	3,397	2,036	29,051
Bellevue, WA	132,235	57,274	29	67	454	675	109	2,129
Boston, MA	571,815	248,834	62	142	9,590	10,426	9,879	39,801
Buffalo, NY	287,217	144,961	64	127	5,674	1,627	4,740	26,526
Carrollton, TX	125,315	48,150	29	75	199	1,015	94	1,647
Chandler, AZ	180,269	68,123	55	145	334	240	312	2,158
Charlotte, NC	600,199	256,489	78	182	2,462	2,223	3,345	15,437
Chicago, IL	2,871,155	1,149,324	68	169	22,711	17,893	36,840	153,744
Chula Vista, CA	176,724	60,352	37	107	1,642	428	121	4,045
Cincinnati, OH	342,844	171,839	69	137	5,292	4,260	6,793	26,849
Cleveland, OH	471,265	213,876	65	144	6,788	4,762	10,267	36,490
Columbus, OH	810,375	370,569	76	166	5,354	9,386	3,588	36,409
Coral Springs, FL	123,002	43,478	32	89	265	0	0	2,077
Dallas, TX	1,218,325	498,651	81	198	10,244	14,591	4,384	50,257
Dayton, OH	188,930	90,573	84	175	1,407	2,279	3,736	11,877
Denver, CO	545,324	248,236	48	106	4,291	2,248	3,849	22,761
Des Moines, IA	204,995	87,469	59	139	1,775	1,352	907	5,885
Detroit, MI	830,044	325,923	106	270	6,113	4,192	3,296	46,056
Eugene, OR	163,496	72,470	55	125	1,113	539	322	9,016
Evansville, IN	130,246	61,034	47	100	1,483	781	871	5,263
Fort Collins, CO	145,762	59,718	31	76	839	1,089	154	5,009
Fort Wayne, IN	222,320	98,145	51	115	1,205	850	703	6,861

Exhibit A-1

City List and Descriptives for 91-City Cross-Section, 2000 (2 of 4)

City	Population	Housing Units	Crimes per 1,000 People	Crimes per 1,000 Housing Units	Vouchers	LIHTC Units	Public Housing Units	Rental Units Occupied by Poor Households
Fort Worth, TX	560,623	223,464	65	164	2,582	4,123	1,134	18,606
Fullerton, CA	150,346	53,084	28	80	945	822	0	4,030
Garden Grove, CA	207,774	58,627	24	84	1,878	612	0	4,705
Glendale, AZ	229,093	83,080	58	160	1,080	320	155	5,688
Hampton, VA	133,657	56,431	44	104	1,822	817	585	4,343
Hartford, CT	120,563	50,622	86	206	4,322	991	2,262	11,960
Hialeah, FL	243,532	77,176	50	159	2,796	106	1,116	11,610
Houston, TX	1,786,008	710,802	73	183	7,812	9,578	2,863	77,360
Inglewood, CA	124,959	42,644	37	107	1,398	21	0	6,536
Irving, TX	191,611	80,315	49	116	629	1,808	0	5,551
Jacksonville, FL	736,273	311,388	66	156	5,376	4,051	2,679	21,224
Kansas City, MO	460,059	209,785	87	192	4,488	7,140	1,032	17,733
Knoxville, TN	203,648	101,764	48	96	1,930	529	3,848	13,702
Lexington, KY	255,676	115,769	47	105	1,730	365	1,535	11,415
Lincoln, NE	224,388	96,598	61	143	890	1,068	320	8,342
Livonia, MI	100,545	38,658	30	79	17	0	177	525
Long Beach, CA	460,927	172,305	37	99	5,271	645	713	25,881
Los Angeles, CA	3,658,681	1,333,008	45	123	30,902	15,462	6,479	202,406
Louisville, KY	306,550	144,563	46	99	5,009	1,604	4,784	18,585
Madison, WI	236,303	106,456	33	72	1,138	1,832	758	11,493
McAllen, TX	113,041	40,486	74	207	726	6	199	4,347
Memphis, TN	687,414	287,986	81	192	4,057	4,028	5,928	32,143
Miami, FL	369,590	151,261	62	152	2,231	2,484	7,346	34,253
Milwaukee, WI	557,852	235,699	77	183	4,775	1,532	4,807	34,064
Minneapolis, MN	370,201	165,817	68	152	2,601	579	5,863	18,041
Naperville, IL	166,283	58,960	12	34	145	180	0	588
Nashville, TN	547,083	245,891	82	182	3,917	3,486	5,805	21,076
New Haven, CT	117,584	52,498	86	191	2,314	1,055	3,028	9,953

Exhibit A-1

City List and Descriptives for 91-City Cross-Section, 2000 (3 of 4)

City	Population	Housing Units	Crimes per 1,000 People	Crimes per 1,000 Housing Units	Vouchers	LIHTC Units	Public Housing Units	Rental Units Occupied by Poor Households
Newport News, VA	174,412	73,129	54	129	1,450	2,215	2,189	7,527
Norfolk, VA	208,040	91,472	65	147	1,826	1,915	3,020	13,018
Oakland, CA	399,383	157,452	64	162	9,272	2,385	3,306	19,824
Oklahoma City, OK	527,044	238,989	75	166	5,242	3,643	2,942	22,088
Ontario, CA	206,229	60,488	35	119	588	168	20	4,995
Overland Park, KS	169,949	70,722	35	84	425	414	0	1,400
Pasadena, CA	135,341	54,663	38	93	1,080	896	0	5,470
Pasadena, TX	157,986	55,860	39	111	919	1,573	0	4,818
Pembroke Pines, FL	151,958	60,158	32	81	56	0	0	1,054
Philadelphia, PA	1,495,623	658,462	56	126	9,442	6,546	17,709	79,252
Phoenix, AZ	1,331,761	504,038	71	189	4,142	843	2,939	40,001
Pittsburgh, PA	256,847	126,485	71	145	3,094	885	6,292	17,620
Plano, TX	244,977	95,553	34	86	223	240	50	2,001
Portland, OR	548,383	246,513	71	159	4,583	6,144	2,690	21,432
Rockford, IL	173,119	73,597	72	168	1,397	648	2,215	6,080
San Antonio, TX	1,207,251	455,046	60	158	10,831	1,827	5,405	42,418
San Bernardino, CA	246,966	88,086	45	125	2,545	694	664	13,704
San Diego, CA	1,206,318	470,285	39	99	8,507	3,169	1,401	43,938
Santa Rosa, CA	180,030	69,451	30	78	1,683	1,485	0	3,605
Seattle, WA	509,031	246,431	84	173	3,740	4,123	5,580	19,867
Simi Valley, CA	115,787	38,858	14	42	614	793	0	764
St. Louis, MO	346,326	175,820	134	264	3,426	3,466	4,710	25,443
St. Petersburg, FL	258,395	130,993	80	158	2,048	34	687	7,978
Stamford, CT	117,083	47,317	26	64	566	1,038	841	2,638
Sterling Heights, MI	124,263	47,398	24	63	149	200	153	1,129
Tampa, FL	330,721	149,124	92	203	2,502	470	3,429	15,213
Tempe, AZ	155,877	66,711	93	216	696	0	0	7,036
Toledo, OH	321,871	144,193	76	170	2,320	2,109	2,843	16,373

Exhibit A-1

City List and Descriptives for 91-City Cross-Section, 2000 (4 of 4)

City	Population	Housing Units	Crimes per 1,000 People	Crimes per 1,000 Housing Units	Vouchers	LIHTC Units	Public Housing Units	Rental Units Occupied by Poor Households
Topeka, KS	132,199	59,949	94	208	713	1,207	634	4,774
Tucson, AZ	518,337	228,413	84	189	3,474	2,413	1,440	24,822
Virginia Beach, VA	423,697	162,194	38	98	880	1,784	0	6,657
Waco, TX	125,127	51,640	76	184	1,530	488	889	8,970
Washington, DC	558,502	272,899	63	129	5,264	4,817	10,277	35,569
Waterbury, CT	107,271	46,827	57	130	754	454	716	5,531
Worcester, MA	169,028	70,604	48	116	2,015	1,011	2,181	9,881

Exhibit A-2

Seven-City Longitudinal Crime Data by City and Year, 1998–2008

	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Austin	X	X	X	X	X	X	X	X	X	X	X
Chicago	X	X	X	X	X	X	X	X	X	X	X
Cleveland		X	X	X	X	X	X	X	X	X	X
Denver*	X	X	X	X	X	X	X	X	X	X	
Indianapolis**	X	X	X	X	X	X	X	X	X	X	X
Philadelphia***	X	X	X	X	X	X	X	X	X		
Seattle	X	X	X	X	X	X	X	X	X	X	

*Neighborhood level. **Crime data missing for one-half of the tracts. The tracts included represent slightly fewer than one-half of the Indianapolis population. ***No homicide or rape data.*

Exhibit A-3

Percent of Public Housing Units and Vouchers Reported by Housing Authority, 1998 and 2008

	1998		2008	
	Public Housing (%)	Vouchers (%)	Public Housing (%)	Vouchers (%)
Austin	96	99	99	NA
Chicago	63	99	54	NA
Cleveland	85	99	100	NA
Denver	98	99	99	NA
Indianapolis	74	84	97	NA
Philadelphia	50	99	87	NA
Seattle	95	99	89	NA

NA = data not available.

Appendix B

Exhibit B-1

Seven-City Longitudinal Sample, Crime and Housing Variables, 1998–2008

Year	1998	2000	2004*	2008**
Crimes per 1,000 people	78.9	71.4	65.9	64.3
Crimes per 1,000 housing units	186.2	168.4	155.4	151.6
Number of vouchers	35,351	51,819	45,528	72,894
Number of LIHTC units	34,594	41,491	57,373	72,281
Number of public housing units	73,181	78,206	58,179	57,207
Philadelphia	50	99	87	NA
Seattle	95	99	89	NA

LIHTC = low-income housing tax credit. NA = data not available.

** Voucher counts for 2004 are low because of missing data in Philadelphia and Seattle. **LIHTC units reported use 2007 totals.*

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Modeling Criminal Distance Decay

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Abstract

Criminal distance decay is the fundamental notion that a relationship exists between the distance from an offender's home base to a potential target location and the likelihood that the offender chooses to offend in that location. This relationship is important both for its operational effect on police agencies and on models for offender behavior. A number of factors influence the distance decay function of an offender, including the local geography and the offender's decisionmaking process.

This article addresses a study of the interactions between the two-dimensional offense distribution that describes how offenders select targets and the corresponding one-dimensional distance decay function. It also presents the calculation of the coefficient of variation for 324 residential burglary series in Baltimore County, Maryland. These data do not support the notion that the distance decay behavior of an individual offender is governed by a number of common choices for distance decay, including the negative exponential, even allowing for the parameters to vary between offenders. Finally, the article examines geographic patterns for residential burglary in Baltimore County and the finding that, although offenses committed in rural portions of the county are committed by offenders with larger travel distances, it does not appear that this variation can be explained simply by the local population density.

Introduction

Distance decay is the observed fact that offenders tend to commit more crimes closer to home than farther away. Although this qualitative fact is well known, no consensus has been reached about the correct quantitative approach to distance decay. Several researchers have put forward a number of mathematical models. Levine (2010), chapter 10, for example, discusses five different mathematical forms for distance decay built into the CrimeStat tool; CrimeStat also enables the user to create his or her own empirically defined distance decay function. This notion that an offender's crime locations are related in some meaningful way to the offender's home location is central to the idea of geographic profiling and motivates this work.

Our primary interest is in the distance decay behavior of a single offender over the course of a single crime series. We assume that the offender has a single, well-defined home base or anchor point, which can be the offender's home, workplace, or other well-defined location of importance to the offender that serves as the origin of the offender's base of operations. We acknowledge that this assumption does not apply to all offenders, because not all offenders meet these criteria. We also assume that each crime site has a single well-defined location, but we also acknowledge that this need not be the case for every crime. Indeed, some crimes may take place in multiple locations. As an example, in a car theft, not only is there the location from which the vehicle was stolen but also the possible chop shop location or the location where the vehicle is abandoned; also see Lu (2003) and the discussion of the "journey-after-crime." By distance, we mean the distance from the anchor point of the offender to the location of the crime site. This distance can be measured in a number of different metrics, with Euclidean and Manhattan distance metrics being the most common but not the only reasonable choices. We also note that the distance the offender actually traveled may be at variance with the distance from the anchor point to the crime site, because it is possible that the actual journey to the crime site began at some point other than the offender's anchor point. (See also Wiles and Costello, 2000; Santtila et al., 2008.) Finally, because we are considering the distance decay behavior of individual offenders, we note that these behaviors may vary, based on particular characteristics of the offender, the crime type, and/or the underlying local geography and landscape.

In this article, we focus on the mathematics of distance decay; in particular, we examine different quantitative models for distance decay behavior of an individual offender. We discuss the important relationships between one-dimensional models of distance and the corresponding two-dimensional models of offender behavior and show that the mathematics is responsible for some perhaps nonintuitive results. We then discuss a new method to analyze the distance decay curve for an individual offender, using aggregated data by analyzing a graph of the coefficient of variation for different offenders. Finally, we look at how geography affects the distance decay behavior of offenders, paying particular attention to the role of population density.

Literature

Clearly, the distance from the offender's anchor point to the offense site is one of the important variables that characterize the geography of the offense(s); however, it is also important to remember that offenders select targets, not distances. In particular, the local geography and the underlying two-dimensional nature of space must be accounted for in any analysis of distance decay patterns.

Although offenders select targets, not distances, it does not mean that distance should be considered to be solely a dependent variable that arises as a consequence of a particular target choice. As noted by Bernasco and Block (2009), the distance to the target may be one of the criteria that the offender uses to make the decision on where to offend.

The fact that the distance to the offense site is one decision variable is the only reason that techniques such as geographic profiling can work. If the offender selected targets without reference to their distance from the offender's anchor point, then the crime site location would be mathematically independent of the anchor point location and, in this hypothesized scenario, it would not be possible to draw inference about the anchor point location from the locations of the elements of the crime series.

In reality, it has been well established that distance decay exists, at least for crime data at the aggregate level, because this behavior has been seen in numerous studies. For example, van Koppen and Jansen (1998) found strong evidence of the existence of a distance decay effect in their study of 434 robberies committed by 585 offenders in the Netherlands in 1992. Bernasco (2006) analyzed and compared the distance decay behavior for 809 individual and 365 group residential burglaries in The Hague, the Netherlands, between 1996 and 2004; he found clear evidence that the behavior of both classes exhibited a distance decay pattern. Finally, Santtila, Laukkanen, and Zappalà (2007) found strong support for distance decay in their study of a collection of rapes and homicides that took place in Finland between 1992 and 2000.

Distance decay has been seen to exist in many areas of human behavior other than criminal behavior; see, for example, Gimpel et al. (2008), who studied distance decay effects in voting patterns and found a relationship between voting preferences and the distance from the voter to the candidate's hometown.

In general, the question is not to know if distance decay exists, but rather to understand more about its quantitative form. In one approach to this question, Canter and Hammond (2006) evaluated a number of candidate models for distance decay, with the goal of selecting the form that provided the best results when incorporated into Dragnet.

Before we consider different possible mathematical forms for distance decay, it is important to note that the distances offenders are willing to travel depend on a number of different factors, such as the type of crime. Hesseling (1992) found that for crimes committed in residential areas of Utrecht, violent crimes and vandalism were generally committed by more local offenders than were property crimes.

Distance decay may depend on characteristics particular to an individual offender. In their study of 4,657 commercial robberies in the Netherlands in 2004 and 2005, Bernasco and Kooistra (2010) found that offenders were more than eight times more likely to offend in an area where they had lived in the past than in comparable areas where they had not lived; Bernasco (2010) obtained similar results in a study of residential burglary, theft from vehicle, robbery, and assault. The offender's age also appears to play a role in distance decay; in a study of 41 serial burglars in St. John's, Newfoundland, Snook (2004) noted variation in the travel distances of offenders depending on the offender's age and the value of the stolen property. Similarly, Wiles and Costello (2000) noted correlations between the offender's age and the offense distance for a range of crime types in Sheffield, England. They compared these age-related effects for offenders from 1966 with offenders from 1995.

Characteristics of the criminal event itself are linked to variations in the distance offenders are willing to travel. For example, van Koppen and Jansen (1998) examined 434 commercial robberies in the Netherlands and found not only that more professional offenders were willing to travel farther but that the more difficult the target, the farther the offender(s) tended to travel. In a study of 99 homicides and 56 rapes in Milan, Italy, Santtila et al. (2008) found that more instrumental crimes were correlated with larger travel distances for the offender. In another study of 40 homicides and 37 rapes in Finland, Santtila, Laukkanen, and Zappalà (2007) identified crime features that were correlated with distance; for example, longer distances were related to homicides that took place either in the inner city or at the victim's home. In their analysis of a selected set of 565 rapes committed by 108 serial rapists, Warren et al. (1998) found a number of characteristics of both the offender and the crime scene that were correlated with the distance traveled by the offender. Finally, in their study of commercial robbery series in Greater Helsinki from 1992 through 2001, Laukkanen and Santtila (2006) found small but statistically significant correlations between particular elements of the offense and the distance traveled.

Crime rates, and especially burglary rates, are known to depend on the characteristics of the local neighborhood; for example, Bernasco and Luykx (2003) identified three neighborhood characteristics they termed attractiveness, opportunity, and accessibility to burglars and found that they were correlated with increased burglary rates in The Hague. In a later study of 548 residential burglaries in The Hague, Bernasco and Neiuwbeerta (2005) found a number of neighborhood characteristics associated with an increased risk of burglary, including the neighborhood's ethnic composition and the relative number of single-family dwellings. More recently, in their study of 12,872 robberies in Chicago from 1996 to 1998, Bernasco and Block (2009) found that social barriers such as racial and ethnic differences and gang territorial boundaries affect the choice of a target location.

Kent and Leitner (2007) examined a mix of 97 burglary and robbery series in Baltimore County from 1994 to 1997 and compared the efficacy of circular geographic profiles with ellipses. Not only did they find that the ellipses performed better, they also found that the orientation of these ellipses were correlated with the orientation of the local road network, suggesting that the pattern of crimes might be related to the road network orientation.

When considering the geographic or geometric pattern of offense locations, it is important to consider direction as well as distance. In their analysis of 58 burglary series in rural Australian towns, Kocsis et al. (2002) found that the paths from the anchor point to the offense sites tended to proceed in the same direction. Similarly, Goodwill and Alison (2005) examined selected burglary series, rape series, and murder series; they also found that the paths from the anchor point to the offense site tended to lie in the same direction. See also Lu (2003), who examined the direction between the auto theft location and the vehicle recovery location for 1,600 incidents in Buffalo, New York.

One potential starting point for researchers constructing quantitative models for the distance decay behavior of offenders is to look at the distance decay graph for aggregated groups of offenders. These graphs have been generated for a large range of offense types and jurisdictions. We mention Warren et al. (1998), who provide a graph of the aggregated distance decay curve for 565 rapes committed by 108 serial rapists, and van Koppen and Jansen (1998), who provide a graph of the distribution of distances traveled to offend for 434 robberies committed by 585 offenders in the Netherlands in 1992. Snook (2004) provides an aggregate distance decay graph for residential burglars in St. John's, Newfoundland, while Laukkanen and Santtila (2006) provide a graph of the aggregate distance decay for a commercial robbery series in Greater Helsinki, Finland, from 1992 to 2001. Canter and Hammond (2006) provide an aggregate distance decay curve for 96 selected U.S. serial murderers. This type of analysis has been done even for offenders in India; Sarangi and

Youngs (2006) have aggregate distance decay graphs for serial burglars in both the Rourkela and Keonjhar districts. Santtila et al. (2008) present a distance decay curve for a collection of homicides, rapes, and robberies against businesses; the data in this graph are not only aggregated across offenders, but are also aggregated across offense type. Finally, in an interesting study, Lu (2003) examined the distance from the vehicle theft location to the vehicle recovery location for 1,600 incidents in Buffalo and provided an aggregate distance decay curve.

One major application of distance decay has been in the development of geographic profiling methods. Three main approaches to the geographic profiling problem use distance decay: the method of Rossmo (2000), chapter 10; the method of Canter et al. (2000); and the method of Levine (2010). (See also the approach of O'Leary, 2009.)

No consensus has been reached about the best method to evaluate the effectiveness of these systems; see the original report prepared for the National Institute of Justice (Rich and Shively, 2004), the critique of Rossmo (2005a), and the response of Levine (2005). A number of different researchers have examined the effectiveness of particular systems, however, and how to best choose the parameters that they use. For example, Sarangi and Youngs (2006) applied Dragnet to 30 Indian serial burglars committing 150 offenses and they found that Dragnet was an effective tool, while Canter and Hammond (2007) assessed the effectiveness of the Dragnet system on 96 U.S. serial murderers; they compared the search cost effectiveness of four different distance decay functions. Similarly, Laukkanen and Santtila (2006) applied CrimeStat to 76 commercial robbery series in Greater Helsinki, using empirically determined distance decay curves; they found that CrimeStat II was able to reduce the search area to roughly 5 percent of the total study area. Kent, Leitner, and Curtis (2006) constructed different distance decay functions by matching them to aggregate data and then compared their effectiveness as the distance decay function in CrimeStat, using a single serial killer in Baton Rouge, Louisiana. Not only were these comparisons made across different distance decay functions, they were also made across different distance metrics, including Euclidean, shortest path, and shortest time metrics. For a comparison of the different approaches to one another, see Paulsen (2006a, 2006b), who compared the methods with one another and with humans on crime series from Baltimore County; he found that none of these approaches were significantly better than simple centrographic measures. For a broader discussion of the comparison of geographic profiling systems with humans, see Snook, Canter, and Bennell (2002); Snook, Taylor, and Bennell (2004); Rossmo (2005b); and Snook, Taylor, and Bennell (2005b). Related discussions also occur in Snook, Taylor, and Bennell (2005a); Rossmo and Filer (2005); Bennell, Snook, and Taylor (2005); and Rossmo, Filer, and Sesley (2005) and in the papers of Bennell et al. (2007) and Bennell, Taylor, and Snook (2007).

Block and Bernasco (2009) applied the Bayesian Journey to Crime method of CrimeStat 3.1 to 62 serial burglars in The Hague and evaluated its accuracy using four different measures; they found that the new Bayesian method was an improvement over distance decay methods.

Geographic profiling methods have been applied in a variety of circumstances, including applications to obscene phone calls to children in Sweden (Ebberline, 2008) and to terrorist attacks (Bennell and Corey, 2007). Bennell and Corey (2007) examined attacks by Action Directe in the 1980s in Paris and a series by the Epanastatikos Laikos Agonas in the Athens area in the 1970s and 1980s.

Outside the broad area of law enforcement, Buscema et al. (2009) used ideas borrowed from geographic profiling to estimate the location of a point source for an outbreak of an epidemic disease. One interesting feature of their approach that has not yet been seen in criminology is that they attempt to not only model the distance from the source to a particular location, they also consider the energy expended to make the journey. Geographic profiling has also been applied to problems in ecology; Le Comber et al. (2006) and Raine, Rossmo, and Le Comber (2009) applied these techniques to problems in animal foraging, while Martin, Rossmo, and Hammerschlag (2009) examined shark predation patterns.

Brantingham and Tita (2008) discussed a model for offender motion based on ideas from foraging theory in ecology. In particular, they examined a model for offender motion based on a Lévy flight and presented the results of a number of simulations. One application of this approach to offender modeling is the geographic profiling technique of Mohler and Short (2011), which is based on a similar kinetic model for the offender's behavior.

Finally, although our emphasis throughout is on the application of distance decay to the geographic profiling problem, distance plays a role in other questions in criminology. For example, Malleson, Evans, and Jenkins (2009) presented an agent-based model for burglary rates, which they then applied to Leeds, England. Their models incorporate a strong distance decay component, in which the agent's likeliness of offending is inversely proportional to a function of the distance.

Dimensionality and Distance Decay

Criminal distance decay is the notion that a relationship exists between the distance from an offender's anchor point to a potential target location and the likelihood that the offender chooses to offend in that location. In this article, to make this idea mathematically precise, we define the distance decay function D to be the probability density that the offender chooses a target at a specified distance r from his or her anchor point. We call this function $D(r)$; then to find the probability P that the distance to the offense is between the numbers a and b, we simply sum the density and calculate $P = \int_a^b D(r)\,dr$. Note that, because $D(r)$ is a probability density and because the distance r must be nonnegative, we know that $D(r) \geq 0$ for all r and $\int_0^\infty D(r)\,dr = 1$.

Throughout this article, we use the phrase "distance decay" because it historically has been the term used to describe this phenomenon. We will not assume that the distance decay distribution, however, be monotone decreasing, but instead we explicitly allow for the possibility that increasing the distance from the anchor point can increase or decrease the probability density that an offense takes place at that distance.

One immediate consequence of this definition of distance decay is that we are necessarily focusing our attention on the behavior of a single individual. We are explicitly allowing for the possibility that the distance decay distribution varies among offenders and that it may be influenced by the crime type, characteristics of the criminal events, the local geography, and other factors.

Because offenders select targets rather than distances, it is clear that the truly fundamental quantity that describes offender target selection is the two-dimensional probability distribution that describes how offenders select targets.

Indeed, assume that points in the geographic region under study can be represented by pairs $\mathbf{x} = (x^{(1)}, x^{(2)})$, where the coordinates $x^{(1)}$ and $x^{(2)}$ represent the distances of the point $\mathbf{x}$ from a convenient pair of perpendicular reference axes. For simplicity in what follows, we will always assume that the offender's anchor point is located at the origin in this coordinate system. We define the offender's offense distribution $T(\mathbf{x}) = (x^{(1)}, x^{(2)})$ to be the probability density that the location $\mathbf{x}$ is selected by the offender as the location of an offense. Then, for any geographic region $\mathbf{\Omega}$, we can find the probability P that an offense occurs within $\mathbf{\Omega}$ by calculating $P = \iint_{\Omega} T(x^{(1)}, x^{(2)})\, dx^{(1)}\, dx^{(2)}$. Because T is a probability density, we know that $T(x^{(1)}, x^{(2)}) \geq 0$ and $P = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} T(x^{(1)}, x^{(2)})\, dx^{(1)}\, dx^{(2)} = 1$. Rossmo (2000: 197) calls a three-dimensional map of the offense distribution a jeopardy surface.

As we previously noted, the behavior of the offender, and thus the offense distribution T, can depend on factors unique to the individual committing the offenses; the crime type; the crime characteristics; and the local geographic, demographic, and other characteristics of the region.

The geometry of space imposes a fundamental relationship between the two-dimensional offense distribution $T(x^{(1)}, x^{(2)})$ and the corresponding one-dimensional distance decay distribution $D(r)$. To see this relationship, suppose we are using Euclidean distance, and we want to determine the probability P that an offense occurs at a distance between r and $r + \Delta r$. To calculate P we sum the values of T on the annulus $\mathbf{\Omega}$ with inner radius r and outer radius r and $r + \Delta r$, giving $P = \iint_{r \leq |\mathbf{x}| \leq r + \Delta r} T(x^{(1)}, x^{(2)})\, dx^{(1)}\, dx^{(2)}$. If we make the simplifying assumption that the offense distribution T depends only on the distance to the anchor point, then T is roughly constant on that annulus; say $T(\mathbf{x}) \approx T(r)$ for $r \leq |\mathbf{x}| \leq r + \Delta r$. The area A of the annulus can be calculated simply by taking the difference of the area enclosed by the outer circle from the area enclosed by the inner circle, so $A = \pi(r + \Delta r)^2 - \pi r^2 = 2\pi r\, \Delta r + \pi(\Delta r)^2$; thus, the probability that the offense takes place in the annulus is the product of the probability density and the area of the region, and so satisfies $P \approx (2\pi r \Delta r + \pi(\Delta r)^2)\, T(r)$.

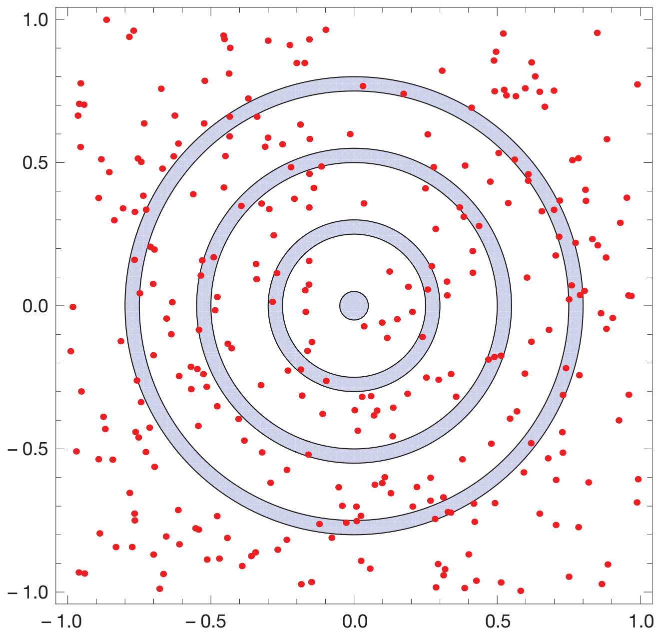
On the other hand, our definition of the distance decay distribution $D(r)$ tells us that the probability that the offense lies at a distance between r and $r + \Delta r$ is $P = \int_{r}^{r+\Delta r} D(s)\, ds$. If we make the same simplifying assumption and assume that D is roughly constant on the interval $[r, r + \Delta r]$ with the value $D(r)$, we also have the approximation $P \approx [(r + \Delta r) - r]D(r) = (\Delta r)D(r)$ formed by taking the product of the length of the interval with the value of the function on that interval. Combining these two different expressions of the same quantity P, and canceling the factor Δr from both sides, we obtain the relationship $D(r) \approx (2\pi r + \pi \Delta r)T(r)$ and for small Δr, we see that $D(r) \approx (2\pi r)T(r)$.

Although this derivation proceeded via a number of mathematical approximations, these approximations are not germane and it is simple to replace this argument with a formal mathematical proof. The fundamental relationship between the offense distribution and the distance decay function $D(r) = 2\pi r\, T(r)$ holds whenever the underlying two-dimensional offense distribution T depends only on distance where Euclidean distance is being used.

To illustrate this fundamental result, suppose we place 300 points uniformly randomly throughout the square shown in exhibit 1, effectively choosing the constant value of T=1/4 on the square $[-1,1]\times[-1,1]$.

Exhibit 1

300 Points Placed Uniformly Randomly Throughout a Square



Four subregions are shown: a disk of radius 1/20 and annuli of width 1/20 with inner radii at 1/4, 1/2, and 3/4. A simple count shows that no points exist within the inner disk while the annuli contain 6, 11, and 21 points—quite near the expected results, which would be 0.6, 6.5, 12.3, and 18.3. Although the hypothesized underlying two-dimensional offense distribution is constant, the fundamental relationship tells us that the associated distance decay function should be linear, increasing as r gets large and tending to zero as r tends to zero—which is exactly what we observe.

Rengert, Piquero, and Jones (1999), in their critique of the work of van Koppen and de Keijser (1997), have already noted that one must pay attention to the difference between the one-dimensional distance decay and the two-dimensional offense distribution.

To understand the consequences of the fundamental relationship, consider what happens when we apply it to some common distributions. Probably the most natural two-dimensional offense distribution is the bivariate normal centered at the offender's anchor point, which we have placed at the origin of the coordinate system so

$$\mathrm{T}(\mathbf{x}) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{|\mathbf{x}|^2}{2\sigma^2}\right).$$

In this case, the corresponding distance decay function $D(r)$ is

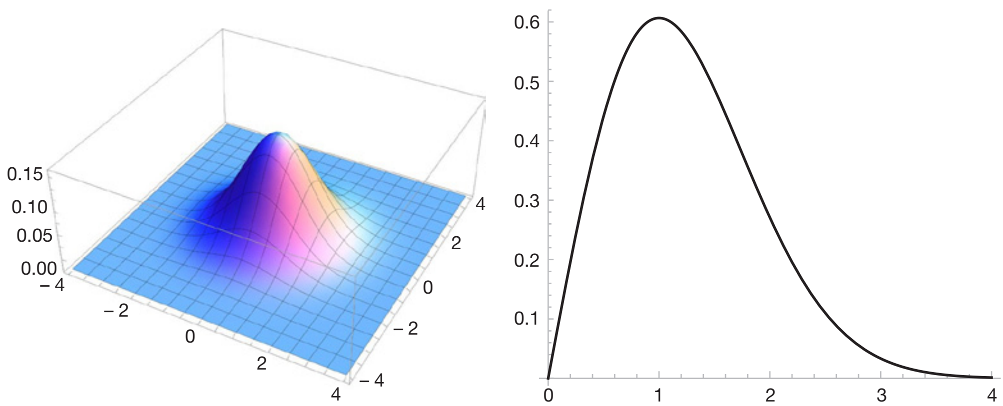
$$D(r) = \frac{r}{\sigma^2}\exp\left(-\frac{r^2}{2\sigma^2}\right)$$

which can be recognized as a Rayleigh distribution. If we graph both of these functions with $\sigma=1$, we obtain exhibit 2.

Despite the shape of the distance decay function in exhibit 2b, it is clear from the offender distribution in exhibit 2a that this offender's behavior does not exhibit a buffer zone. Indeed, the offense distribution shows that the offender is more likely, rather than less likely, to offend at locations closer to his or her anchor point. The distance decay curve $D(r)$ vanishes as $r \to 0$, not because of the existence of a buffer zone, but rather because of the underlying two-dimensional nature of space. As $r \to 0$, the area available to offend decreases, and thus the distance decay function decreases, precisely in line with our fundamental result.

Exhibit 2

Two Views of the Same Process—The Offense Distribution Is Bivariate Normal and the Distance Decay Function Is Rayleigh



(a) Offense distribution (b) Distance decay function

If the distance decay function is known, it is possible to use the fundamental result to construct a two-dimensional offense distribution that matches that distance decay. It should be noted, however, that this two-dimensional offense distribution is not unique, and that for any distance decay function an infinite number of two-dimensional offense distributions possess the same distance decay function. Only one two-dimensional distribution exists, however, that both matches a given distance decay curve and depends solely on the distance from the anchor point to the potential offense site; this distribution satisfies

$$T(\mathbf{x}) = \frac{1}{2\pi|\mathbf{x}|} D(|\mathbf{x}|)$$

if we continue to assume the use of a Euclidean distance.

The CrimeStat Manual (Levine, 2010, chapter 10) provides five built-in choices for a distance decay curve; they are

- Linear

$$D(r) = \begin{cases} A + Br & \text{if } A + Br \geq 0 \\ 0 & \text{if } A + Br < 0 \end{cases}$$

- Negative exponential

  $D(r) = Ae^{-Br}$

- Normal

  $D(r) = \dfrac{A}{S\sqrt{2\pi}} \exp\left(-\dfrac{(r-\bar{r})^2}{2S^2}\right)$

- Lognormal

  $D(r) = \dfrac{A}{r^2 S\sqrt{2\pi}} \exp\left(-\dfrac{[\ln(r^2)-\bar{r}]^2}{2S^2}\right)$

- Truncated negative exponential

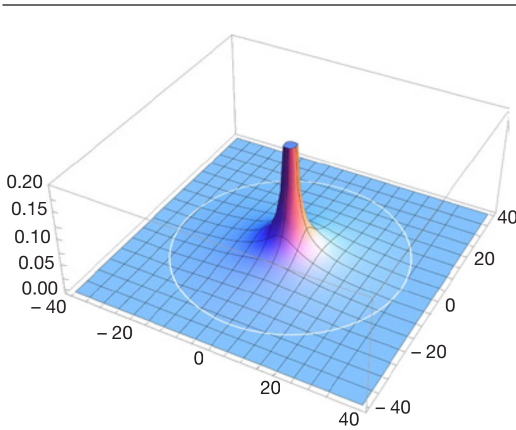
  $D(r) = \begin{cases} Br & \text{if } r \le r_p \\ Ae^{-Cr} & \text{if } r > r_p. \end{cases}$

We can then graph each of these distance decay functions together with the corresponding two-dimensional offense distribution; these graphs are shown in exhibits 3 through 7.

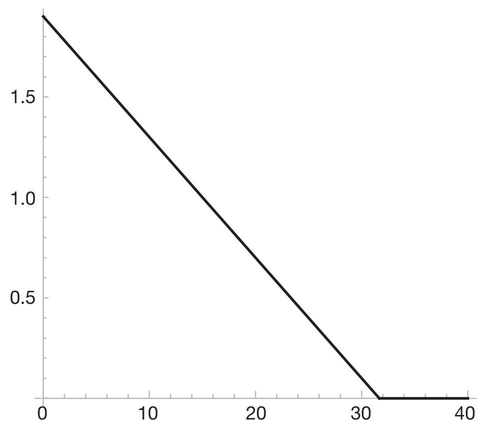
To create each of these exhibits, we used the default parameters provided in the CrimeStat Manual (Levine, 2010, chapter 10); thus, the horizontal axes in each graph should be considered to be distances measured in miles. Because we are using the parameters from that manual, the distance decay curves do not satisfy the normalization requirement $\int_0^\infty D(r)\,dr = 1$. This does not affect CrimeStat because it uses these functions to generate hit scores for which comparisons are made between regions where these scores are large and areas where these scores are small. Each of these distance decay curves can be made into a properly scaled probability distribution by simply scaling each function by an appropriate multiplicative constant.

Exhibit 3

Linear Distance Decay of Levine; A = 1.9, B = – 0.06



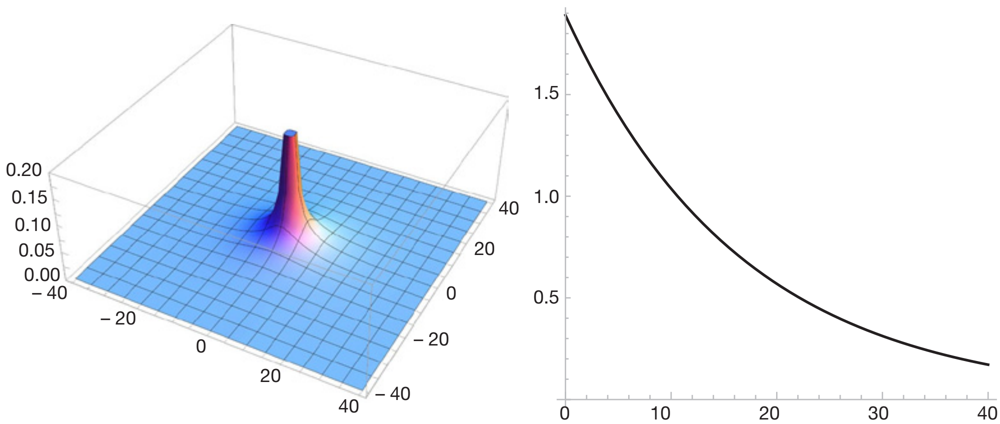
(a) Offense distribution



(b) Distance decay function

Exhibit 4

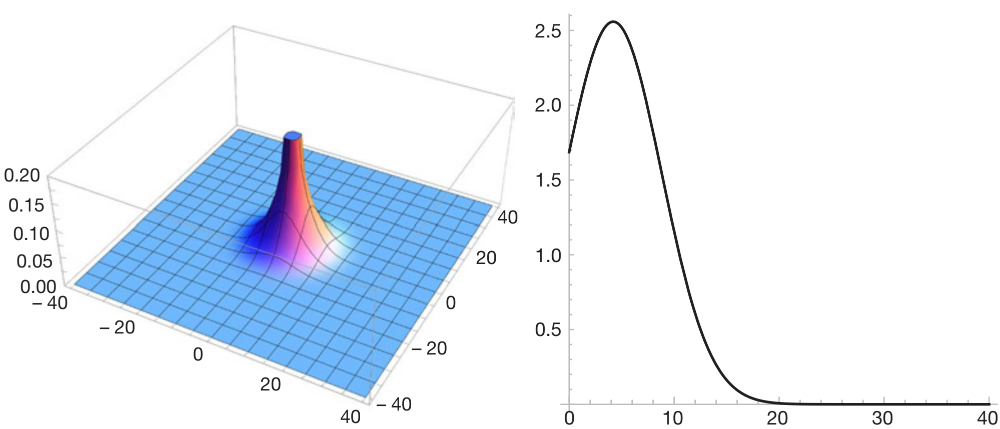
Negative Exponential Distance Decay of Levine; A = 1.89, B = – 0.06



(a) Offense distribution (b) Distance decay function

Exhibit 5

Normal Distance Decay of Levine; A = 29.5, S = 4.6, $\bar{r}$ = 4.2

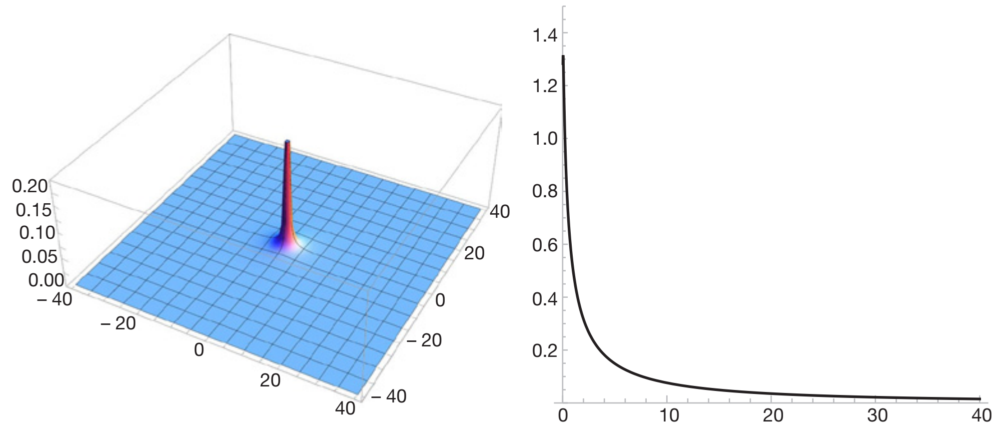


(a) Offense distribution (b) Distance decay function

Examining the graphs of these offense distributions, we see that none of these distributions exhibit a buffer zone. In fact, in all these graphs, the two-dimensional offense distribution is strongly concentrated at the origin, and, in four of the five graphs, the offense distribution becomes infinite as we approach the origin. The only exception is the truncated exponential in exhibit 7, although that may not be clear from exhibit 7a. A closer look near the origin of that distribution provided in exhibit 8 shows that the two-dimensional offense distribution actually exhibits a flat plateau in the region $r < r_p$.

Exhibit 6

Lognormal Distance Decay of Levine; $A = 8.8$, $S = 4.6$, $\bar{r} = 4.2$

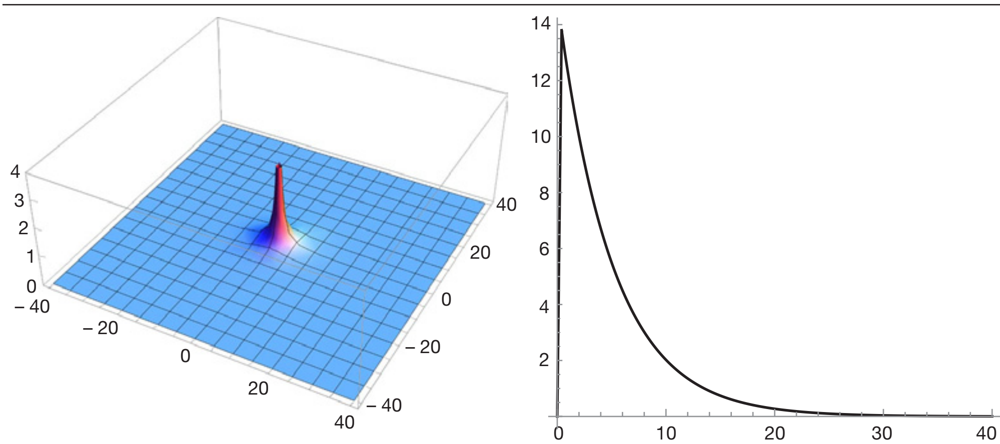


(a) Offense distribution

(b) Distance decay function

Exhibit 7

Truncated Negative Exponential Distance Decay of Levine; $A = 14.95$, $B = 34.5$, $C = 0.2$, $r_p = 0.4$



(a) Offense distribution

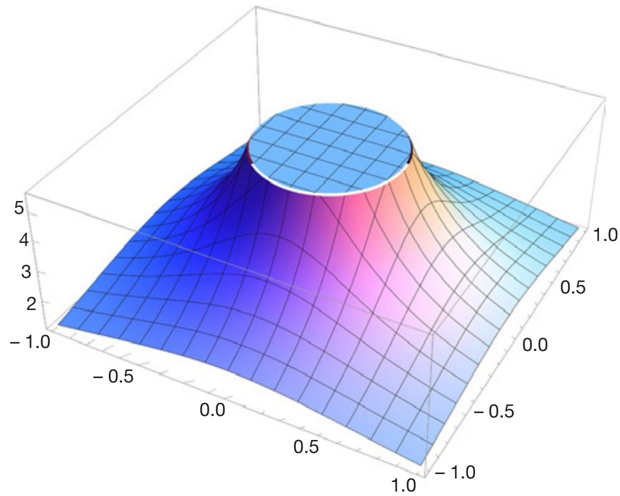
(b) Distance decay function

Rossmo (2000) takes a different approach; he uses a Manhattan distance metric together with a piecewise rational function for the distance decay function. An analogue of our fundamental result for the Manhattan distance is presented, however.

Suppose that we want to find the probability that an offense occurs where the Manhattan distance is between m and $m + \Delta m$. To calculate this, we need to sum the values of T over the annular region Ω outside the square $|x^{(1)}| + |x^{(2)}| \leq m$ and inside the square $|x^{(1)}| + |x^{(2)}| \leq m + \Delta m$, giving us $P = \iint_{m < |x^{(1)}| + |x^{(2)}| \leq m + \Delta m} T(x^{(1)}, x^{(2)})\, dx^{(1)}\, dx^{(2)}$.

Exhibit 8

The Center of the Offense Distribution Generated for the Truncated Negative Exponential Distance Decay of Levine



We again assume that T is roughly constant on this region, with a value that depends only on the Manhattan distance m so $T(\mathbf{x}) \approx T(m)$. To find the area of this region, we note that the region $|x^{(1)}| + |x^{(2)}| \leq m$ is a square of side length $m\sqrt{2}$; thus to find the area A of the region $m < |x^{(1)}| + |x^{(2)}| \leq m + \Delta m$, we take the difference of the areas of the concentric squares and find $A = \big((m + \Delta m)\sqrt{2}\big)^2 - (m\sqrt{2})^2 = 4m\Delta m + 2(\Delta m)^2$. Thus $P \approx (4m\Delta m + 2(\Delta m)^2)T(m)$.

On the other hand, our definition of the distance decay distribution tells us that the probability that the offense lies at a Manhattan distance between m and $m + \Delta m$ is $P = \int_m^{m+\Delta m} D(s)\, ds \approx [(m + \Delta m) - m]D(m) = (\Delta m)D(m)$ where again we are assuming that D is roughly constant on the interval $[m, m + \Delta m]$, with value $D(m)$. Combining these two expressions for P and considering Δm small, we see that for Manhattan distance, the fundamental relationship is $D(m) = 4mT(m)$. Again, although our argument proceeded by approximation, this result can be proven rigorously.

Rossmo uses the offense distribution rather than the distance decay; his form is

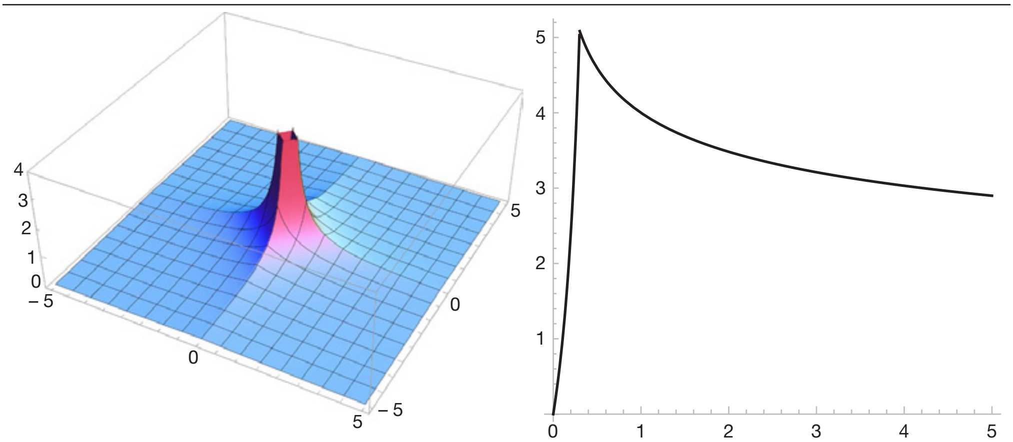
$$T(x^{(1)}, x^{(2)}) = \begin{cases} \dfrac{k}{(|x^{(1)}| + |x^{(2)}|)^f} & \text{if } |x^{(1)}| + |x^{(2)}| \geq b \\[2ex] \dfrac{kb^{g-f}}{(2b - |x^{(1)}| - |x^{(2)}|)^g} & \text{if } |x^{(1)}| + |x^{(2)}| \leq b. \end{cases}$$

For criminal profiling, Rossmo recommends the choice $f = g = 1.2$, (Rossmo, 1995) (see also Le Comber et al., [2006], §3.2 and Raine, Rossmo, and Le Comber [2009] for applications outside criminal profiling). The buffer zone parameter b is set depending on the characteristics of the crime series, while k is simply a scaling parameter (Rossmo, 1995).

The offense distribution and the distance decay function are graphed in exhibit 9. Immediately seen is the effect caused by the use of the Manhattan distance rather than the Euclidean distance in that the offense distribution is no longer radially symmetric; this behavior is more clearly seen in exhibit 10, which shows the center of the offense distribution. The distance decay function decays rapidly as $m \to 0$, although it decays very slowly for large values of m.

Exhibit 9

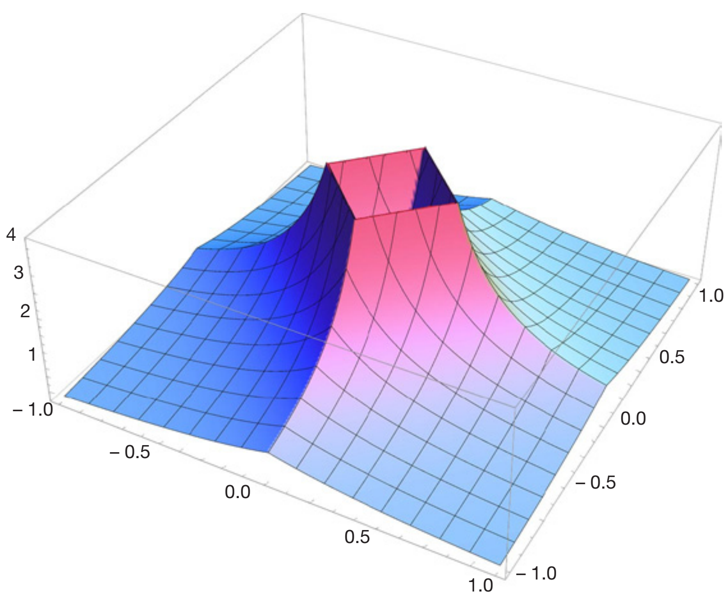
Rossmo Model; $f = g = 1.2$, $b = 0.3$, $k = 1$



(a) Offense distribution (b) Distance decay function

Exhibit 10

The Center of the Offense Distribution of Rossmo



For the values $f = g = 1.2$, the model of Rossmo cannot represent an offense distribution, because the tails are too large to allow for the required normalization $\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} T(x^{(1)}, x^{(2)})\, dx^{(1)}\, dx^{(2)} = 1$ regardless of the choice of the parameters b and k because we always have $\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} T(x^{(1)}, x^{(2)})\, dx^{(1)}\, dx^{(2)} = \infty$. One solution to this issue would be to truncate the values of the offense distribution outside some finite but large region. One concern with this approach is that it necessarily implies that the values of the other parameters, especially the parameter k, would vary significantly with the size of the region used for the truncation.

Canter and Hammond (2006) examine four different forms for distance decay using

- Logarithmic

  $$D(r) = \begin{cases} A + B \ln r & \text{if } A + B \ln r \geq 0 \\ 0 & \text{if } A + B \ln r < 0 \end{cases}$$

- Negative exponential

  $$D(r) = Ae^{-Br}$$

- Quadratic

  $$D(r) = \begin{cases} Ar^2 + Br + C & \text{if } Ar^2 + Br + c \geq 0 \\ 0 & \text{if } Ar^2 + Br + c < 0 \end{cases}$$

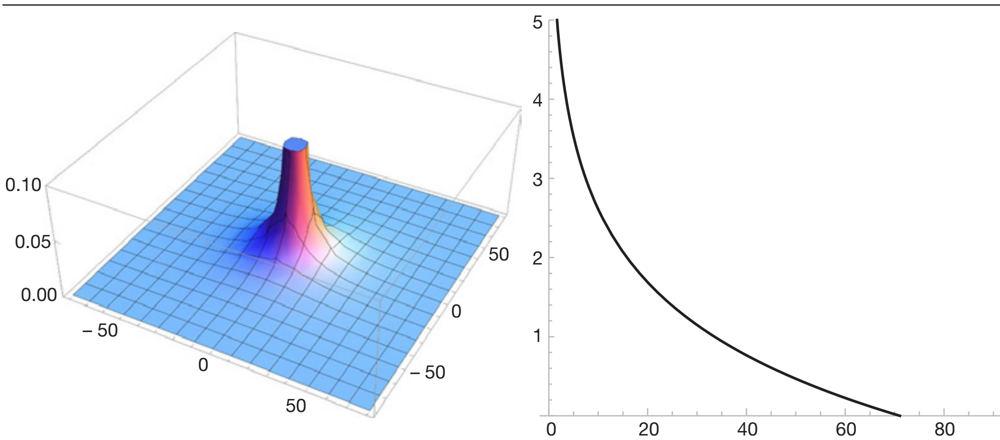
- Linear

  $$D(r) = \begin{cases} A + Br & \text{if } A + Br \geq 0 \\ 0 & \text{if } A + Br < 0. \end{cases}$$

Two of these distributions have already been analyzed, so we provide the corresponding graphs for just the logarithmic and the quadratic distributions using the parameters selected by Canter and Hammond (2006). In their work, distances were measured in kilometers, so this represents the horizontal axes in exhibits 11 and 12.

Exhibit 11

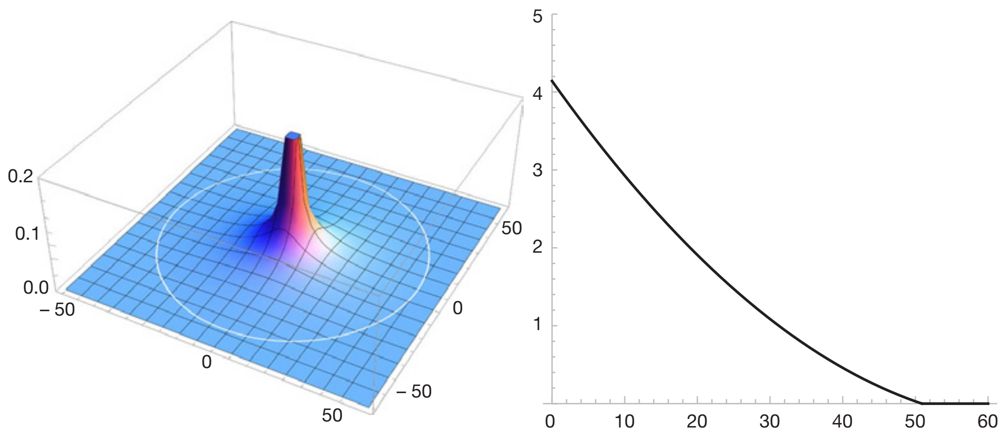
Logarithmic Distance Decay of Canter and Hammond; $A = 5.6735$, $B = -1.3307$



(a) Offense distribution (b) Distance decay function

Exhibit 12

Quadratic Distance Decay of Canter and Hammond; $A = 0.000981$, $B = -0.13129$, $C = 4.14137$



(a) Offense distribution (b) Distance decay function

Estimating the Distance Decay Function

Knowledge of the structure and form of the offense distribution of an individual offender would clearly be valuable, not only from a theoretical perspective but also for its potential value in developing improved geographic profiling algorithms. Given the difficulty and complexity of the full problem, most attention has been paid to the problem of simply determining the structure and form of the offender's distance decay function.

In the CrimeStat manual, Levine (2010, chapter 10) recommends using aggregated crime data for a jurisdiction to select the parameters that appear in the tool's provided analytically defined distance decay functions; he illustrates this process with data from Baltimore County. In particular, he recommends choosing the parameters in the decay curve so as to best fit the aggregate data. He also shows how CrimeStat can be used to generate an experimentally determined distance decay function that is an even better fit for the aggregate data.

In comparison, Rossmo (1995: 341) states that "The value of the distance exponent ($f = 1.2$) was selected from a gravity model formulation developed to describe interprovincial migration of criminal fugitives (Rossmo, 1987: 136)." The value of the buffer zone parameter b is selected heuristically and is dependent on the mean nearest neighbor distance, while the multiplicative scaling constant k is primarily used as a computational aide.

In other applications of this model, the values of these parameters are selected to optimize the effectiveness of the geoprofile. Indeed, Le Comber et al. (2006) apply this model to construct geographic profiles in animal foraging. In their analysis, they hold the constants k and B fixed, with the latter dependent on the trip distance of the species under study. Then a collection of values for the exponents *f* and *g* were selected; for each exponent pair, the effectiveness of the geoprofile was evaluated to determine the best choice for the exponents. Raine, Rossmo, and Le Comber (2009) took a similar approach.

This technique of choosing distance decay parameters so as to optimize the effectiveness of the geoprofile was used earlier by Canter et al. (2000). They examined a collection of negative exponential models for distance decay and then considered variants that contained buffer zones and/or plateaus; in all, they evaluated 285 different functions for their effectiveness as geographic profiling tools.

Canter and Hammond (2006) took a hybrid approach; they selected four general models for offender distance decay—logarithmic, negative exponential, quadratic, and linear. For each model, they obtained the parameters that describe the model by fitting the decay curve to a collection of aggregate data. Each function generated a slightly different geographic profiling algorithm; they compared these algorithms for effectiveness.

Although all these approaches to the geographic profiling problem select a distance decay function, their focus naturally is on determining the effectiveness of geographic profiling algorithms, rather than on the problem of estimating the offense distribution or the distance decay function of an individual offender.

The primary issue in any approach to determining the distance decay behavior of an individual offender is one of data. Although researchers have access to data sets from a number of jurisdictions covering a wide range of crime types, the data available about any one offender are necessarily limited. In general, the series size for an individual offender is small, and although there are series in which the number of elements is large, it is possible that offenders who successfully complete a large series are special in some way. As a consequence, the individual series contain insufficient amounts of data to reliably estimate much more than some elementary parameters of the series; for example, the mean and the standard deviation of the distance from the offender's anchor point to the crime sites.

If all offenders behaved in the same fashion, then it would be a simple matter to aggregate data collected across a suitably large set of offenders to obtain a reliable estimate of their distance decay patterns. The literature has well established the existence of significant variation in offense patterns, however, depending on characteristics of the offender, the criminal event, and the local geography.

Van Koppen and de Keijser (1997) noted that it may not be appropriate to try to draw inference about the distance decay patterns of an individual offender based on the distance decay behavior observed when aggregated across offenders. Although Rengert, Piquero, and Jones (1999) disagreed with many of the conclusions in that work, they unequivocally stated that "We do not dissent from Van Koppen and De Keijser's assertion that researchers cannot and should not make inferences about individual behavior with data collected at the aggregate level."

Recently, Smith, Bond, and Townsley (2009) analyzed residential burglary in Northhamptonshire, England, from 2002 to 2004. They examined 32 offenders who committed a series of at least 10 crimes; together, they committed 590 burglaries. They compared the aggregate distance decay curve for all offenders with the distance decay curves found by aggregating only offenders who were alike in age and found significant qualitative differences among these graphs, providing direct evidence that offenders do not in general possess the same distance decay patterns. In fact, they found that roughly two-thirds of the variation in offense distances can be ascribed to variations among offenders, rather than to variation in an individual offender.

Townsley and Sidebottom (2010) then examined a larger data set of residential and nonresidential burglaries involving more than 1,300 offenders and 16,000 offenses. They found that nearly one-half of the variation in offense distances could be explained by variation among offenders.

Given these facts, is it possible to estimate the quantitative behavior of an individual from the available aggregate data?

Coefficient of Variation

The next step is to analyze a data set provided by the Baltimore County Police Department. Baltimore County is a primarily suburban county in Maryland that borders Baltimore City; it forms a collar around the west, north, and east boundaries of the city. The U.S. Census Bureau's 2009 estimate for the population of Baltimore County is 789,814. The portion of the county near the border with Baltimore City and inside or near the Baltimore Beltway, or Interstate 695 (I–695), is primarily urban and suburban, with much of the remainder of the county being rural. The county contains no other municipal governments; however, a number of communities have well-defined names, including Towson, Halethorpe, Dundalk, Owings Mills, Cockeysville, Baldwin, and Monkton. A map of Baltimore County is provided in exhibit 13.

Our data set for analysis consists of solved residential burglaries committed in Baltimore County between 1986 and 2008. For each incident, we identified the location of the offense and the location of the home of the offender; we also have basic demographic information about the offender, including the age, sex, race, and date of birth of the offender. The data set contains 5,859 offender-offense pairs, with 2,890 individual offenders committing 4,542 separate burglaries. The data set contains 324 series of four or more burglaries committed by the same offender.

We identified individual offenders by matching the provided demographic information and home location. It is possible that two or more different individuals may have the same demographic information and the same home address; it is also possible that a single individual offender could possess different home addresses at different times. The data set contains no instances, however, in which the date of birth matched and the home address did not, suggesting that these concerns are likely to have little practical effect. The home address recorded in the data set may not be the actual anchor point for the offender at the time of the offenses. A series is identified solely as a collection of burglaries committed by the same offender; as a consequence, we do not account for confounding factors such as the presence of multiple offenders.

Of the 324 identified series, the mean length of a series is 8.1 crimes, with a median of 6 and a maximum of 54. A histogram of the number of series as a function of the series length is provided in exhibit 14.

Exhibit 13

A Map of Baltimore County

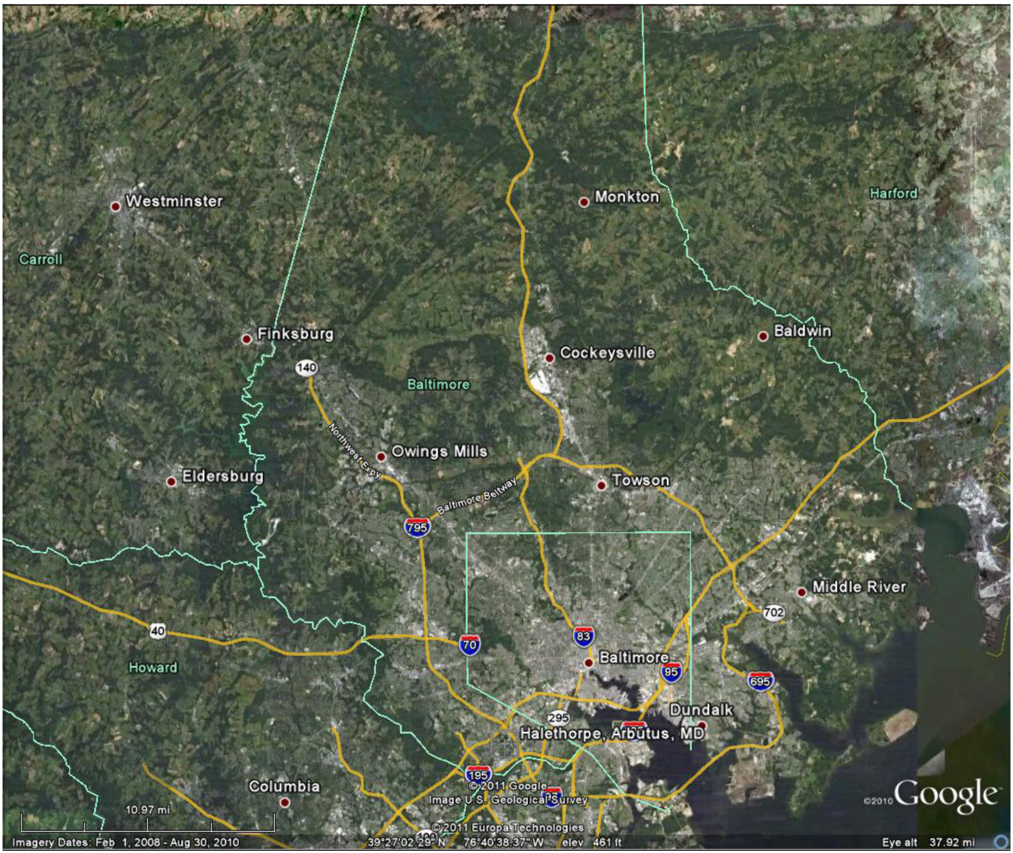
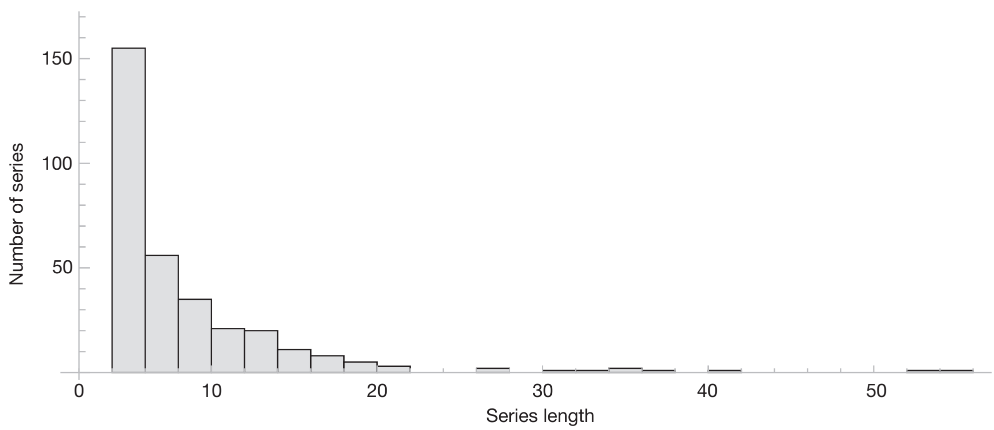


Exhibit 14

Baltimore County Residential Burglaries, 1986–2008: Number of Series As a Function of the Length of the Series



Suppose that the distance decay behavior of an individual offender is governed by a negative exponential distribution in the usual form

$$D(r|\beta) = \frac{1}{\beta} e^{-r/\beta},$$

but that the parameter β may be different for each offender. Then we do not expect that the distribution of offense distances aggregated across all offenders satisfies a negative exponential distribution. To illustrate this, suppose that offenders fall into two categories, with the fraction p_1 with parameter β_1 and the fraction p_2 with parameter β_2. Then it is clear to see that, sampling across offenders, we obtain the aggregate distribution

$$A(r) = p_1 D(r|\beta_1) + p_2 D(r|\beta_2) = \frac{p_1}{\beta_1} e^{-r/\beta_1} + \frac{p_2}{\beta_2} e^{-r/\beta_2},$$

which is not a negative exponential. In general, if the parameter β is distributed across offenders according to a probability density $\mu(\beta)$, then the distribution of offense distances $A(r)$ aggregated across offenders would then satisfy

$$A(r) = \int_0^\infty D(r|\beta)\, \mu(\beta)\, d\beta = \int_0^\infty \frac{1}{\beta} e^{-r/\beta} \mu(\beta)\, d\beta.$$

Although each individual offense series is far too small to reliably estimate the offense distribution or even the distance decay function of an individual offender, we can estimate both the mean and the standard deviation of the distance from the home location to the offense site for each series. Doing so lets us estimate the coefficient of variation of each series, which is defined to be the ratio of the standard deviation to the mean of a distribution.

We can also calculate the mean and standard deviation of the negative exponential distribution; both the mean and the standard deviation are β, and hence the coefficient of variation is identically 1. The significance of this result is that the coefficient of variation does not depend on the parameter β. Thus, if all individual offenders select targets according to a negative exponential, then we expect that the sample coefficient of variation should be roughly 1, regardless of how the parameter β is distributed across offenders in the population.

To test this hypothesis, we plotted the mean and the standard deviation of the distance from the crime site to the offender's home in exhibit 15. If individual offenders all have a negative exponential distance decay function, then we would expect these points to lie close to the line with slope 1.

Examining the graph, it is clear that the typical ratio of standard deviation to mean is much less than unity. To investigate this ratio further, we plot a histogram of the coefficients of variation for the distance decay function of our serial offenders and obtain exhibit 16, which confirms our observation that the coefficient of variation is less than unity for nearly all of our observations and suggests that the negative exponential model for distance decay is not a good fit for the behavior of individual offenders.

We can also calculate the coefficient of variation for the other commonly chosen models for offender distance decay. In many cases, the coefficient of variation is independent of all the parameters in the distribution, letting us repeat this analysis. Doing so, we find that the coefficient of variation is constant for the logarithmic model (0.882), the normal model with $\bar{r} = 0$, (0.756), the linear model (0.707), and the Rayleigh model (0.522). These results are summarized in exhibit 17.

Exhibit 15

Mean and Standard Deviation in Miles for 324 Residential Burglary Series in Baltimore County, 1986–2008

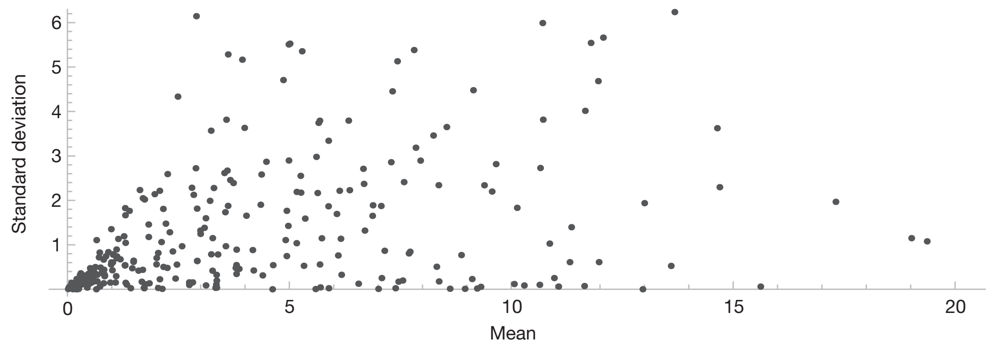
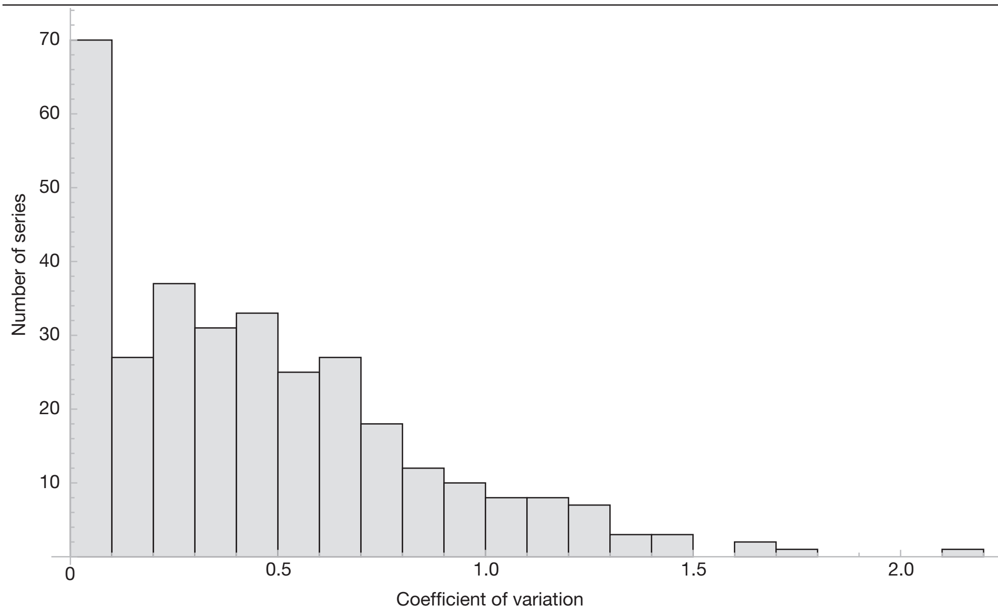


Exhibit 16

Histogram of the Coefficient of Variation for Distance From Offense Site to Offender's Home for 324 Residential Burglary Series in Baltimore County, 1986–2008



When comparing these analytically computed values to our data, we find that none of these models appears to provide a compelling explanation of the observed offender behavior. Indeed, the theoretical coefficients of variation all are at least 0.522, while the mean of the coefficients of variation for the 324 series is 0.455 and the median is 0.390.

Exhibit 17

Coefficient of Variation of Selected Distance Decay Curves

Name	Distribution	Mean	Standard Deviation	Coefficient of Variation
Negative exponential	$\frac{1}{\beta} e^{-r/\beta}$	β	β	1
Logarithmic	$A + B \ln r$	$\frac{1}{4} e^{-A/B}$	$\frac{\sqrt{7}}{12} e^{-A/B}$	$\frac{\sqrt{7}}{3} \approx 0.882$
Normal ($\bar{r}$=0)	$\frac{2}{\sigma\sqrt{2\pi}} \exp\left(-\frac{r^2}{2\sigma^2}\right)$	$\sqrt{\frac{2}{\pi}}\sigma$	$\sqrt{\frac{\pi-2}{\pi}}\sigma$	$\sqrt{\frac{\pi-2}{2}} \approx 0.756$
Linear	$A + Br$	$\frac{2}{3A}$	$\frac{\sqrt{2}}{3A}$	$\frac{1}{\sqrt{2}} \approx 0.707$
Rayleigh	$\frac{r}{\sigma^2} \exp\left(-\frac{r^2}{2\sigma^2}\right)$	$\sqrt{\frac{\pi}{2}}\sigma$	$\sqrt{\frac{(4-\pi)}{2}}\sigma$	$\sqrt{\frac{4}{\pi} - 1} \approx 0.522$

When we calculate the coefficient of variation for other distributions, we find that the result depends on one or more of the parameters in the distribution. For example, for the lognormal distribution

$$D(r|\sigma,\mu) = \frac{1}{r\sigma\sqrt{2\pi}} \exp\left[\frac{(\ln r - \mu)^2}{2\sigma^2}\right],$$

we find that the coefficient of variation is $\sqrt{e^{\sigma^2} - 1}$. Because we do not know the distribution of σ in the offender population, we can draw no conclusions about the appropriateness of the lognormal model. On one hand, we can construct a distribution of σ that will enable us to match the observed data. On the other hand, we can repeat this process with the other models, such as the normal (with $\bar{r} \neq 0$), the truncated exponential, or the quadratic model. Although the expression of the coefficient of variation for those models is algebraically unpleasant, we can still find distributions of the parameters for their models, which also enable us to match their coefficient of variation to the observed data. Thus, we do not possess evidence either for or against any of these models.

Researchers have worked to determine the distribution of the coefficient of variation from a known underlying distribution. For the case in which the underlying distribution is normal, McKay (1932) approximated the distribution of the coefficient of variation by showing that an appropriate transform can be well approximated by a chi-squared distribution. Much later Vangel (1996) gave an improved approximation. Iglewicz and Myers (1970) compared different numerical approximations and the exact values of the percentage points for the sample coefficient of variation when the underlying distribution is normal using a variety of approximations, including that of McKay (1932) and Hald (1952); see also Hendricks and Robey (1936), who approached the problem differently. Koopmans, Owen, and Rosenblatt (1964) developed confidence intervals for the coefficient of variation when the underlying distribution is normal or lognormal, while Linhart (1965) developed approximate limits for the coefficient of variation when the underlying distribution is gamma.

In particular, although we have qualitative evidence to suggest that none of the models in exhibit 17 is sufficient to describe the distance decay behavior of offenders, we are unable to present a quantitative estimate of the potential significance of this statement. We are not the first researchers to apply the coefficient of variation to problems of distance decay; see Smith, Bond, and Townsley (2009), who calculated the coefficients of variation for the different aggregated samples provided in Snook (2004).

The Impact of Geography

So far, we have considered the offense distribution and the corresponding distance decay function from the point of view of an individual offender. It is possible, however, even likely, that the distance decay function varies with location. This idea is not new; for example, Eldridge and Jones (1991) discuss how the parameters in a distance decay model may vary across geography. In particular, they consider how the parameters in a gravity-based model might also vary across space, and so allow for and estimate quadratic variation in the parameters.

To see how geography might impact distance decay behavior, let us start by examining the aggregate distance decay curve for the 5,859 offender-offense pairs for residential burglaries committed in Baltimore County. In particular, we plot a histogram of the number of residential burglary pairs against the distance the offender traveled to commit the crime, which renders exhibit 18.

To understand the role of geography, we repeat this exercise but, instead of examining all of the incidents in Baltimore County, we first select a geographic region and then select only the offenses that occurred in that region. For example, let us first examine the aggregate distance decay curve for all of the studied residential burglaries that occurred within a 2.5-mile radius of Towson, where, for definiteness, we set the center of Towson to have latitude/longitude 39.401165/-76.601827; see also the map in exhibit 13. Doing so, we obtained exhibit 19.

Comparing exhibits 16 and 18, we find no significant qualitative difference between the structures of histograms. We can repeat the process and examine the histogram of the aggregate distance decay curves for crimes committed within 2.5 miles of Dundalk (exhibit 20) and within 2.5 miles of Halethorpe (exhibit 21). As with Towson, these towns are urban/suburban areas within the Baltimore Beltway (I–695). Not only are these areas similar in their urban structure, the aggregate distance decay functions for residential burglaries in these areas show many qualitative similarities. Indeed, they all show that most crimes occur very close to the offender's residence and that the number of crimes decreases as the distance between the offender's home and the crime site increases.

Next, we examine the aggregate distance decay curves for two areas farther removed from the urban core. Owings Mills and Cockeysville are each suburban communities of roughly 20,000 people that lie on the major roads leading radially outward from Baltimore City (see the map in exhibit 13). Because of the smaller population density for these communities, we expand the size of the local region and, in exhibits 22 and 23, we plot the histogram of the number of residential burglaries versus the distance from the crime site to the offender's home for crimes committed within 4 miles of Owings Mills (exhibit 22) and Cockeysville (exhibit 23).

Exhibit 18

Histogram of Residential Burglaries in Baltimore County: Distance Is the Distance From the Crime Site to the Offender's Home Address

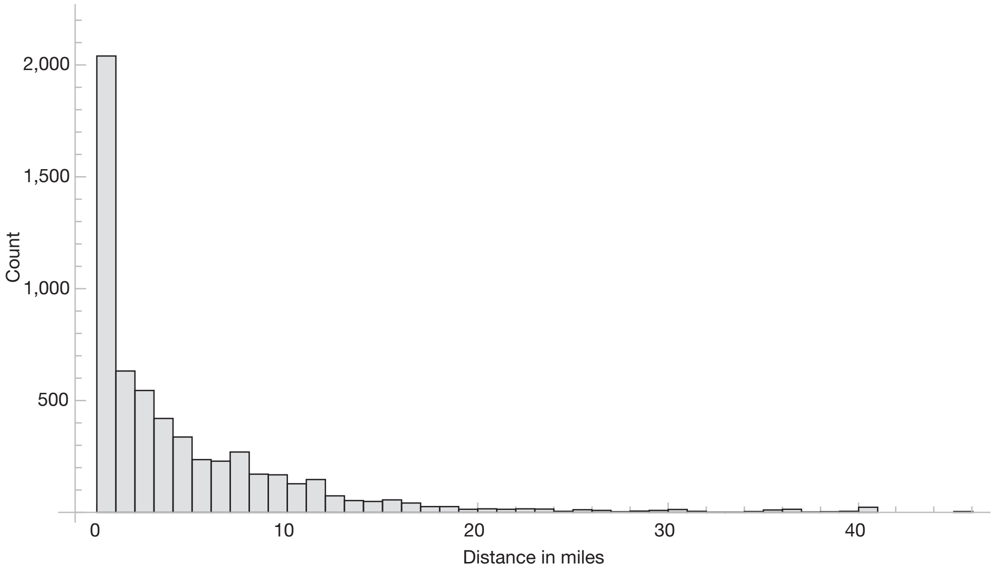


Exhibit 19

Histogram of Residential Burglaries Occurring Within 2.5 Miles of Towson (39.401165–76.601827): Distance Is the Distance From the Crime Site to the Offender's Home Address

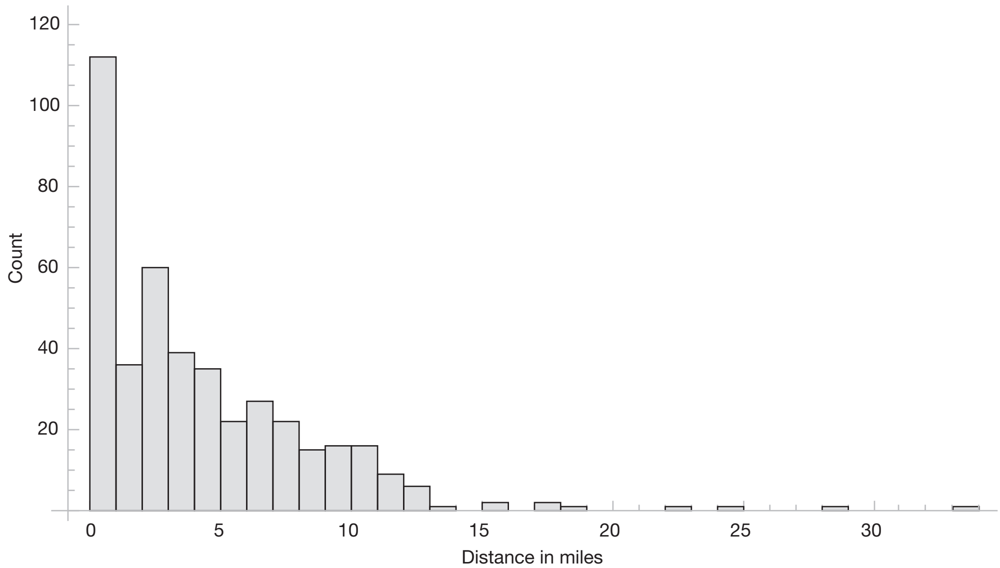


Exhibit 20

Histogram of Residential Burglaries Occurring Within 2.5 Miles of Dundalk (39.250729–76.520774): Distance Is the Distance From the Crime Site to the Offender's Home Address

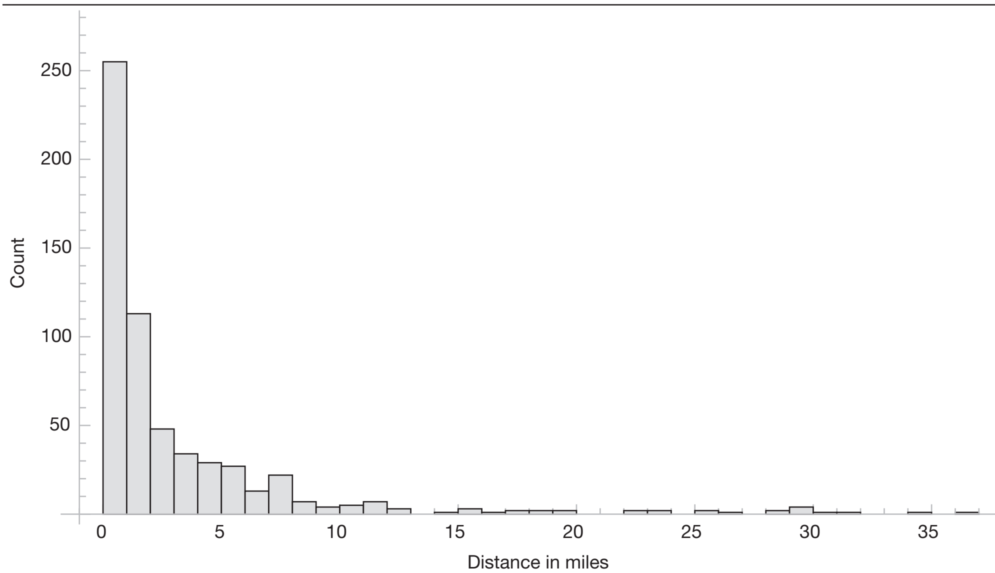


Exhibit 21

Histogram of Residential Burglaries Occurring Within 2.5 Miles of Halethorpe (39.239779–76.680183): Distance Is the Distance From the Crime Site to the Offender's Home Address

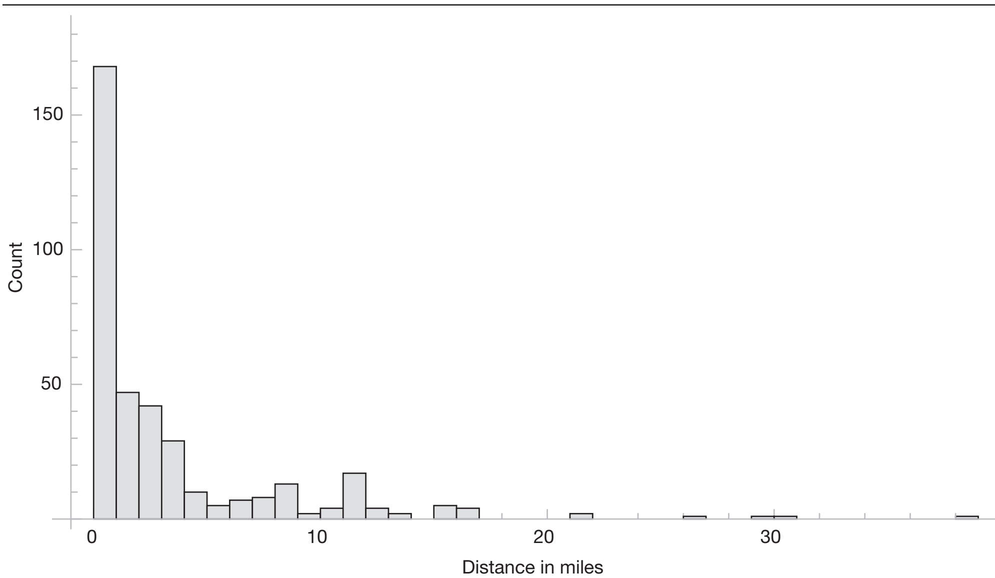


Exhibit 22

Histogram of Residential Burglaries Occurring Within 4 Miles of Owings Mills (39.419550–76.780253): Distance Is the Distance From the Crime Site to the Offender's Home Address

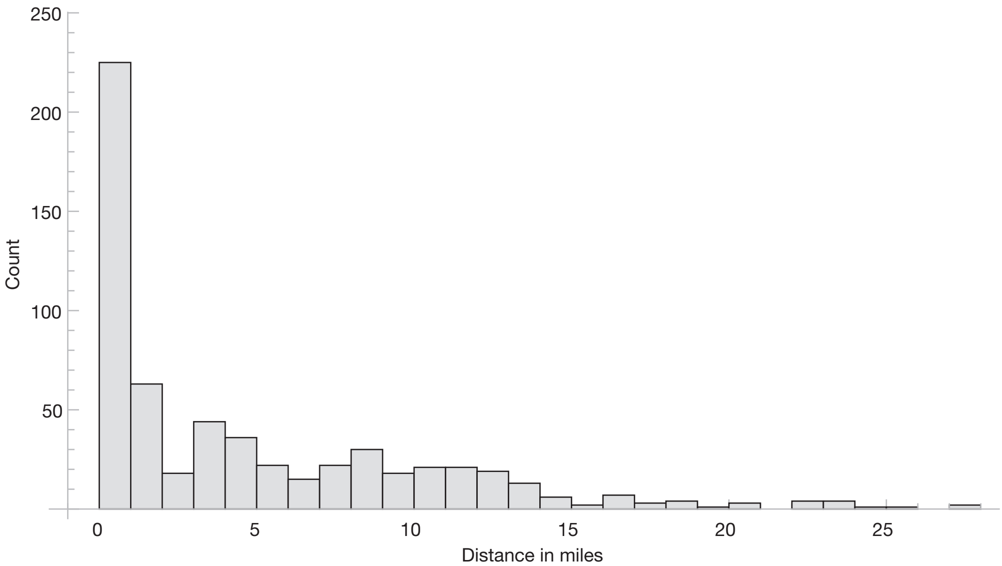
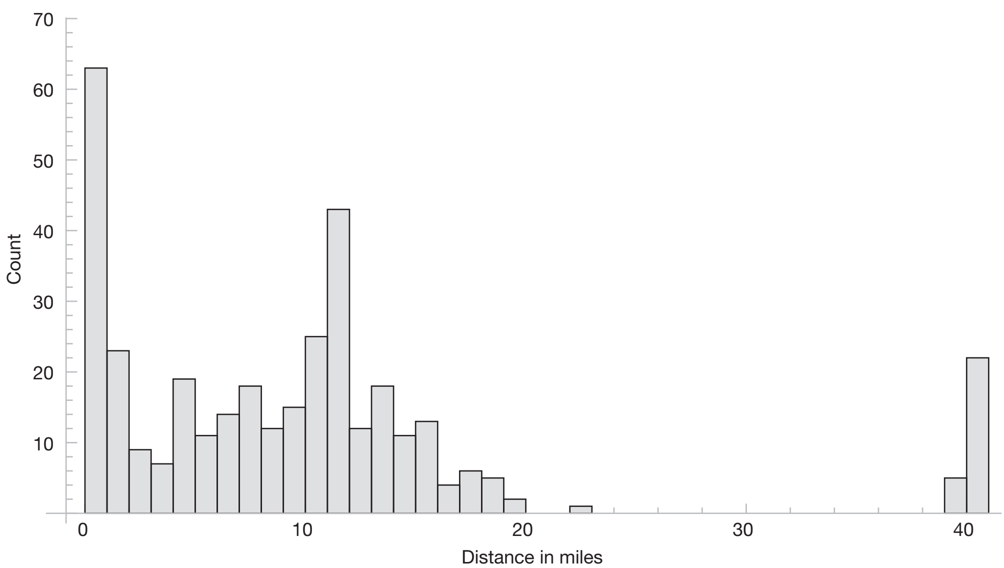


Exhibit 23

Histogram of Residential Burglaries Occurring Within 4 Miles of Cockeysville (39.481217–76.643860): Distance Is the Distance From the Crime Site to the Offender's Home Address



At this point we begin to notice significant qualitative differences in the shape and structure of the aggregate distance decay histograms. The histogram for Owings Mills remains similar to the histograms for Towson, Dundalk, and Halethorpe in that all these histograms have a strong peak at the origin, with most crimes committed close to the offender's home address. One difference is that the Owings Mills histogram does not quickly decay as the distance increases; indeed, the offense count decays only very slowly, if at all, for crimes at distances between 1 and 10 miles from the offender's home address.

These differences, however, pale in comparison with the differences observed in the histogram for burglaries committed near Cockeysville. The largest number of crimes was committed by offenders whose home address is close to the crime site; however, a significant second peak occurs for crimes in which the distance to the offender's home address is 11 to 12 miles. That graph also shows that a significant number of offenses were committed by offenders whose home address was more than 40 miles from the crime site. Even if we disregard this latter peak as being somehow unrepresentative, we still see clear differences between the aggregate distance decay behavior in Cockeysville versus the observed communities near the urban core.

We continue by examining the rural communities of Baldwin and Monkton and, in exhibits 24 and 25, we plot the histogram of the number of residential burglaries versus the distance between the crime site and the offender's home address for offenses within 5 miles of Baldwin (exhibit 24) and Monkton (exhibit 25). We once again expanded the radius around the community, now to 5 miles, to ensure that the region contained enough crime to create a reasonable histogram.

Exhibit 24

Histogram of Residential Burglaries Occurring Within 5 Miles of Baldwin (39.494772–76.470556): Distance Is the Distance From the Crime Site to the Offender's Home Address

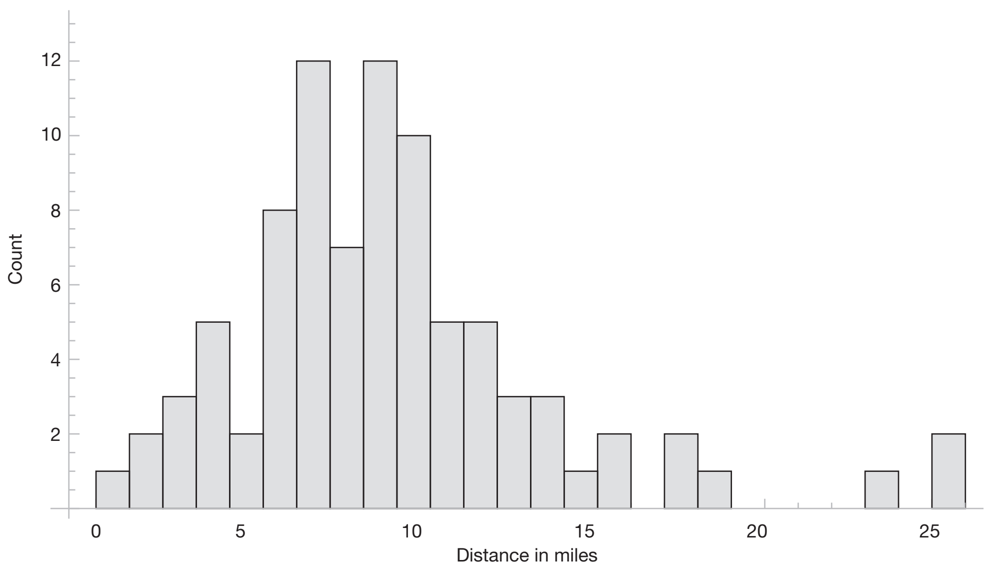
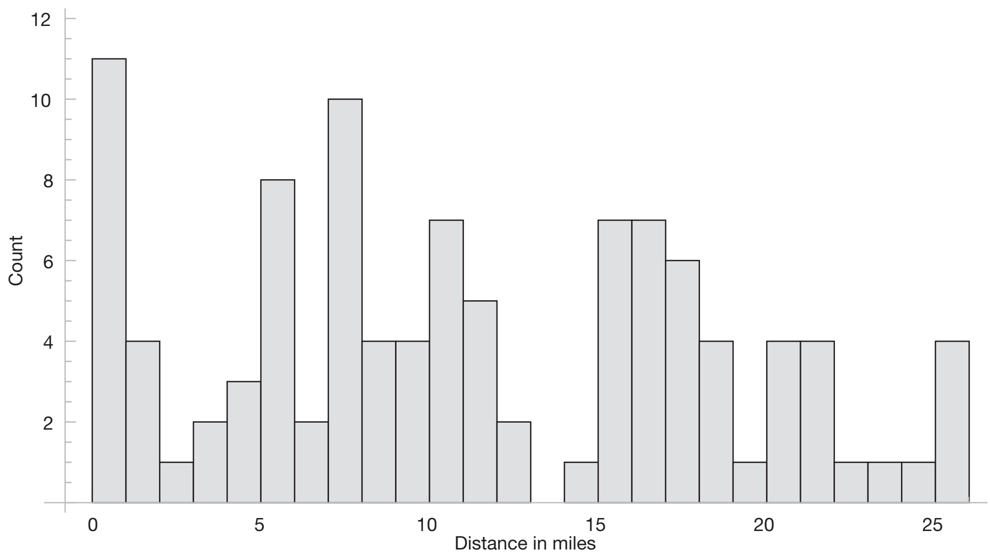


Exhibit 25

Histogram of Residential Burglaries Occurring Within 5 Miles of Monkton (39.578611–76.615833): Distance Is the Distance From the Crime Site to the Offender's Home Address



In both cases, we see significant differences in the qualitative shapes of the histogram; each is quite different from the other and from the histograms that we previously observed. The histogram for Baldwin does not show the peak at the origin that we have repeatedly observed; in fact, that histogram shows that the number of offenses appears to decay as the distance from the offender's home to the offense site decreases. On the other hand, it does appear to have a peak in crime counts for distances of 6 to 10 miles, possibly similar to the secondary peak we observed in Cockeysville. In contrast, the histogram for Monkton does not appear to show any significant distance decay behavior, with a comparable number of crimes in each bin out to 25 miles.

Clearly, these histograms show that the phenomenon of offender distance decay is closely tied to the underlying geography and that, when discussing offender distance decay, at least in the aggregate, it is necessary to account for the underlying urban form.

Although this evidence clearly indicates that aggregate distance decay curves are affected by geography, we have yet to see how. As one approach to this question, we can ask how features of the distance decay curve, such as the mean or median offense distance, vary across space. We recognize that we cannot faithfully represent the full distance decay curve with just one parameter such as the mean or median; however, doing so enables us to begin the analysis.

Exhibit 26 plots the median offense distance across Baltimore County. For each location, we constructed the distance decay distribution of all offender-offense pairs for crimes committed within 2.5 miles of that location; we then calculated the median distance for those crimes, which we then plotted along the vertical axis. Exhibit 27 does the same thing as exhibit 26 but plots the mean

Exhibit 26

Median Distance in Miles Between the Offense Site and the Offender's Home Address for Offenses Committed Within 2.5 Miles of That Location

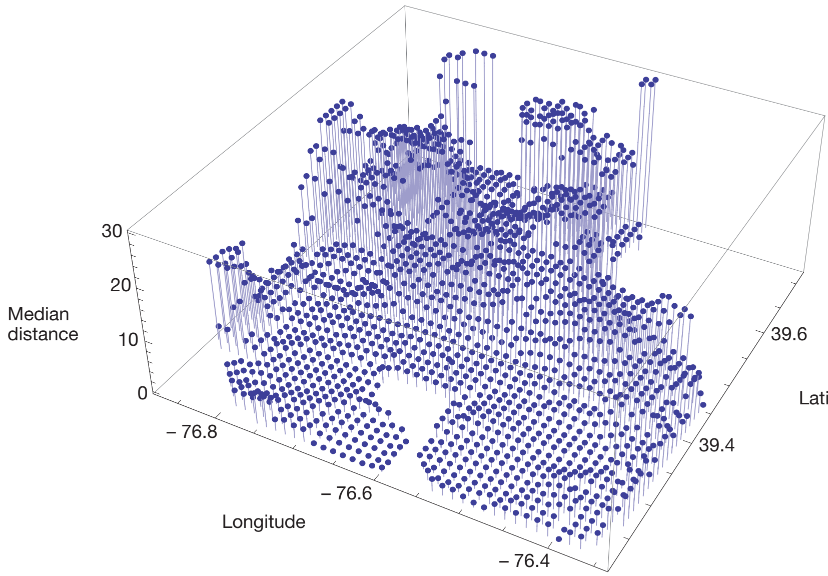
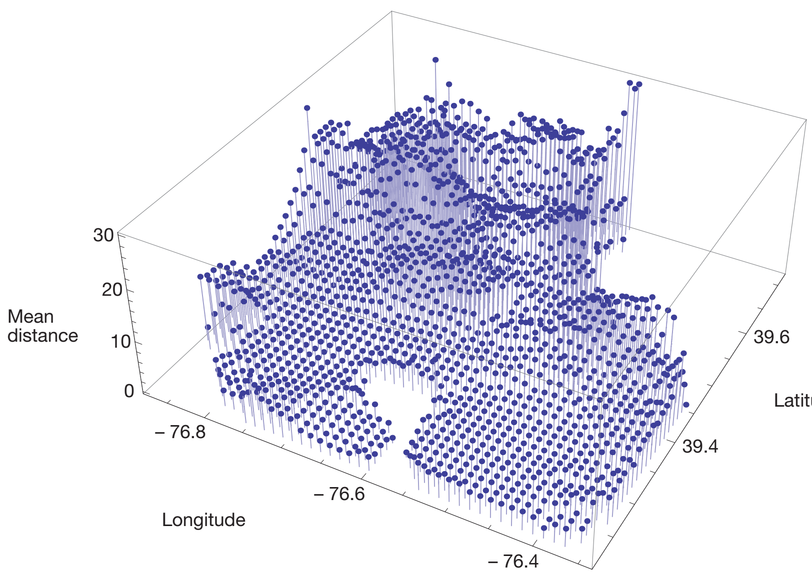


Exhibit 27

Mean Distance in Miles Between the Offense Site and the Offender's Home Address for Offenses Committed Within 2.5 Miles of That Location



rather than the median. These graphs need to be carefully interpreted near their boundaries. Although these graphs show the median or mean distance for crimes within 2.5 miles of that location, they count only those crimes that occurred within Baltimore County. Regions within 2.5 miles of a border with another county do not account for crimes that occurred outside Baltimore County—even when the point itself is outside Baltimore County.

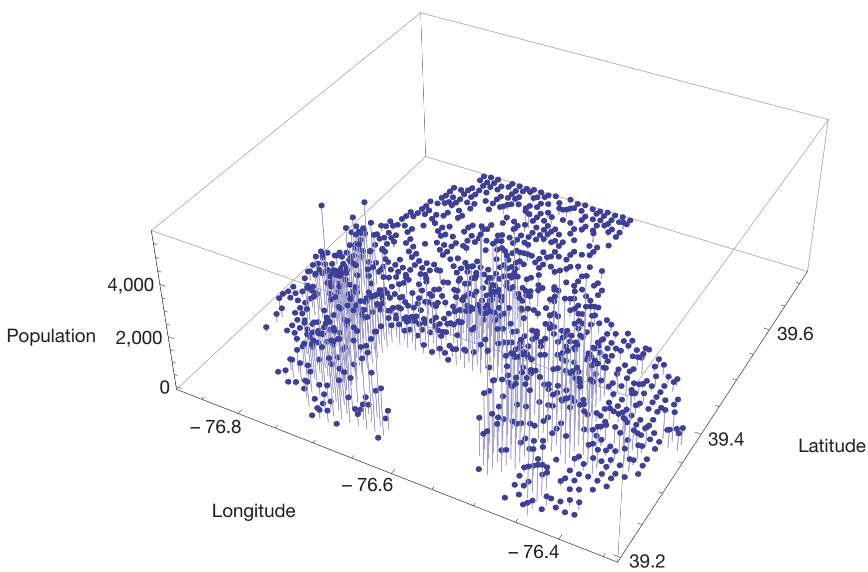
One thing that is immediately apparent from these graphs is that local geography appears to play a significant role, which is in line with what we observed in the histogram analysis. Indeed, both the mean and the outlier resistant median distance between the offense site and the offender's home vary dramatically across the area, with the urban/suburban core showing travel distances of a few miles or less and the northern, rural portion of the county showing mean and median distances of 20 miles or more.

One natural potential explanatory variable for these geographic effects is the local population density. Exhibit 28 graphs the population density of Baltimore County, using data from the 2000 Census. From this exhibit, it is clear to see that the population of the county is concentrated in a ring around Baltimore City, especially on the western, eastern, and northeastern sides of the city.

We can also map the number of residential burglaries in our data set as a function of the offense site, which we have done in exhibit 29. Examining these exhibits, we see not unexpectedly that the number of residential burglaries tracks closely with the local population. Indeed, the data are consistent with the hypothesis that the residential burglary rate is proportional to the number of residences. If this hypothesis were the case, then we would expect that the ratio of the number of residential burglaries divided by the number of residences would be roughly constant and would show no geographic pattern. We plot this ratio in exhibit 30 and verify that this occurs.

Exhibit 28

Population Map of Baltimore County



Source: 2000 Census data

Exhibit 29

Count of the Number of Residential Burglaries That Occur in a Location

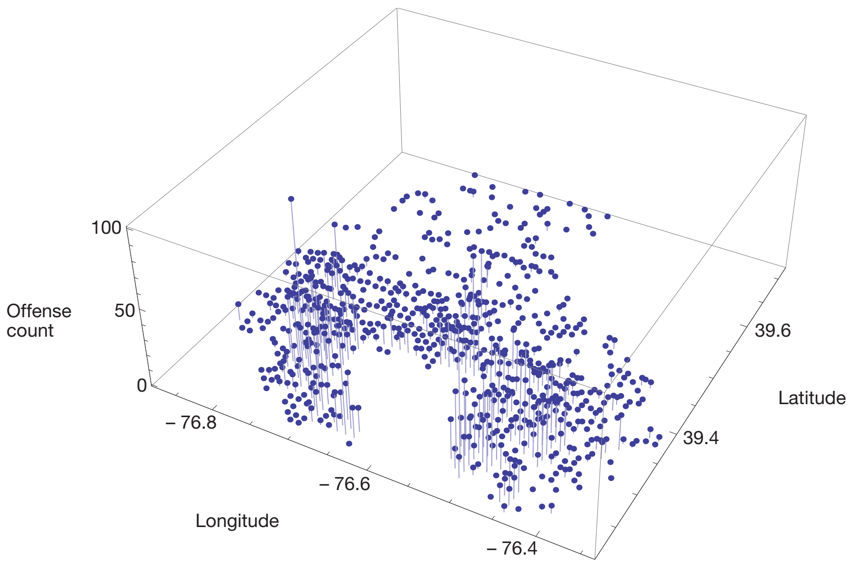
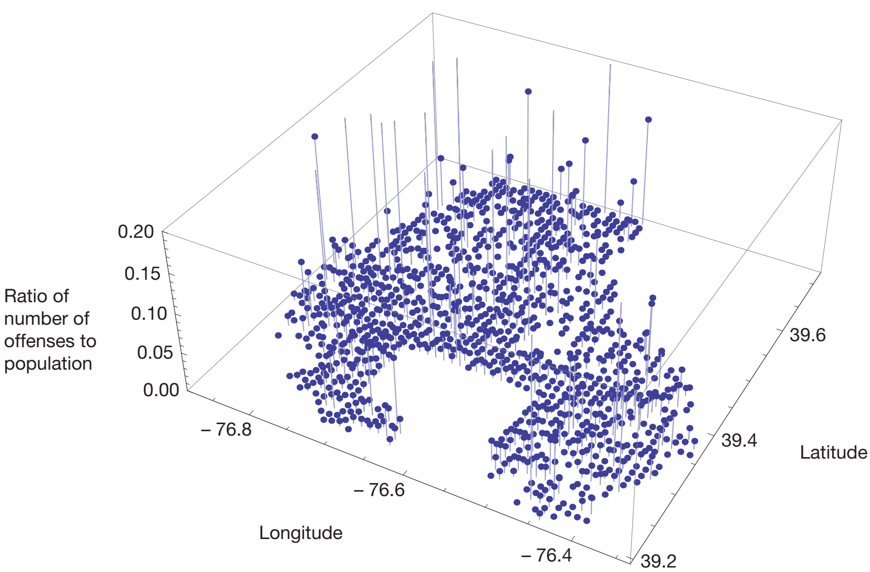


Exhibit 30

Ratio of the Number of Residential Burglaries to the Local Population



To better understand the effect of population on the aggregate distance decay histogram, let us add a third dimension to the graph and aggregate the crimes, not only by the distance from the crime site to the offender's home but also by the population density of the region where the offense was committed. Doing so, we obtain exhibit 31.

When examining the sections of this histogram for fixed population, we see that the distance decay behavior seems to vary with the local population; regions with smaller populations appear to possess a smaller number of offenders willing to travel a long distance to offend than regions with larger populations. The histogram also clearly shows many more regions with a small local population than regions with a large local population. Thus, the longer tails in the distance decay sections noted in the histogram may be caused by the fact that they are drawing from a larger sample. To confirm this hypothesis, we can graph the distance decay curves for regions aggregated across comparable populations, but, to account for the different number of offenses in regions of different population, we graph only the relative fraction, which we have done in exhibit 32.

The rough agreement of these curves with one another suggests that, whatever relationship exists between local geography and distance decay patterns, the interaction does not appear to be mediated by the population density of the target location.

Exhibit 31

Count of the Number of Residential Burglaries, Sorted by Both Mean Offender Travel Distance and Population of the Burglary Location

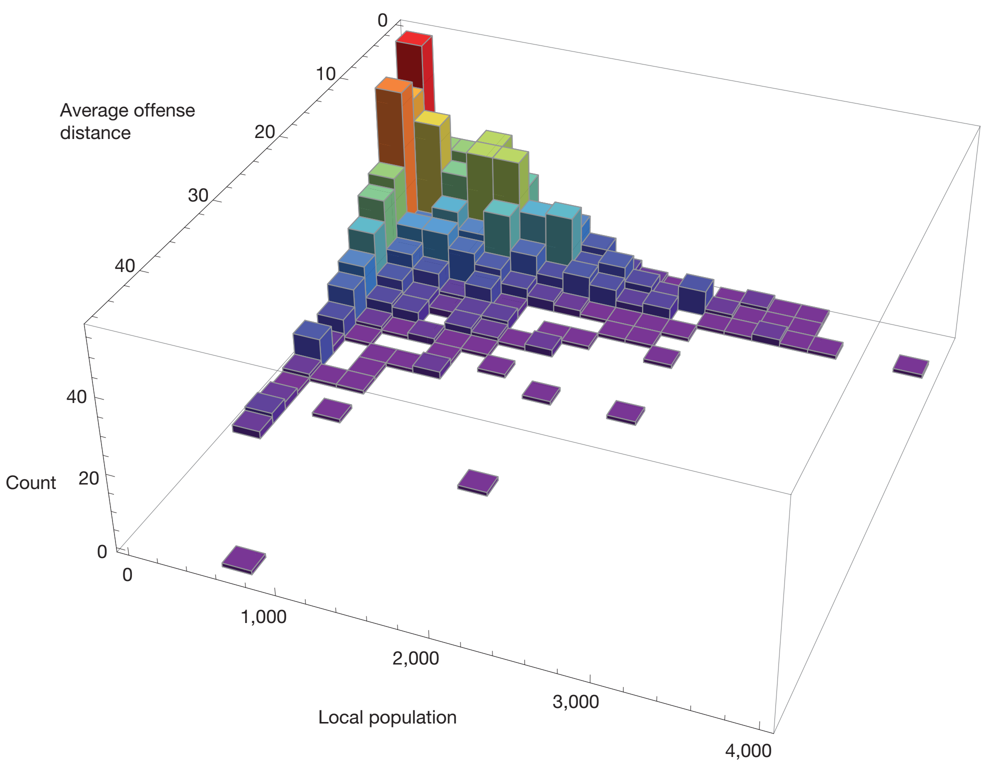
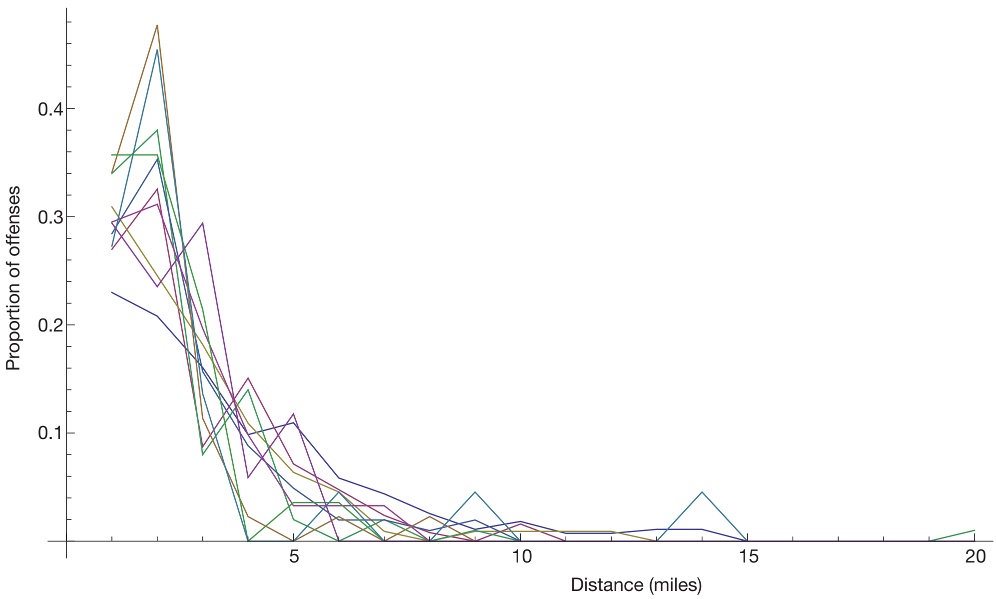


Exhibit 32

Ten Relative Distance Decay Curves for Residential Burglary



Note: Each distance decay curve is formed by aggregating across all the regions with a comparable population.

Conclusions

We have seen the relationship between the two-dimensional offense distribution T and the one-dimensional distance decay function D; in the case of Euclidean distance, this relationship takes the form

$$D(r) = 2\pi r\, T(r)$$

while, in the case of Manhattan distance, we have

$$D(m) = 4mT(m).$$

These relationships exist because of the fundamental two-dimensional nature of space. One consequence of these relationships is that we must take care when examining distance decay curves for the existence of a buffer zone, because, in general, we should expect that the distance decay function tends to zero as the distance tends to zero, independently of the presence or nonpresence of a buffer zone.

One approach we can use to study the behavior of individual distance decay functions is the coefficient of variation. In general, we cannot draw conclusions about the behavior of individual offenders from aggregate data. For some models of individual offender distance decay, however, the coefficient of variation is independent of all the model parameters; this occurs for a number of common models, including the negative exponential distribution. As a consequence, if one of these models held for all offenders, then we should see roughly constant coefficients of variation across offenders. An exploratory data analysis of Baltimore County residential burglaries shows significant variation in the coefficient of variation, however, suggesting that none of these models, including the negative exponential model, are appropriate for the modeling of individual-level distance decay.

Finally, we examined the effect of geography on aggregate-level distance decay curves. In our study of Baltimore County residential burglaries, we found that the aggregate distance decay curves varied significantly depending on the locations of the crime sites that were aggregated. In particular, we found that the average distance between the crime site and the offender's home address was dramatically larger in the rural portions as opposed to the more urban and suburban portions of the county. We performed an exploratory analysis to see if this variation could be explained by differences in local population density, but the results of our analysis did not support this hypothesis.

Acknowledgments

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Crime and Place: Rapidly Evolving Research Methods in the 21st Century

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The symposium in this issue of *Cityscape* focuses on understanding crime and the urban environment, particularly how people live in and interact with the landscape (buildings, people, roads, and activities) that surrounds them. It advances understanding of crime within the urban landscape. Ronald E. Wilson describes crime and the urban environment in the guest editor's introduction:

> Crime changes with urban development patterns. Opportunities for criminal activity emerge, disappear, or move as geography changes across the urban landscape. Patterns emerge, dissipate, or persist… . crimes are far more predictable by place of occurrence than by a particular offender… .

Exploration of crime and place is a rapidly evolving area of research in the 21st century. Some of my early work in the 1970s examined a topological structure of neighborhoods, identifying a way to measure the permeability of edges of the neighborhood, allowing crime committed by nonresidents to drift away from the usual location along major streets into roads toward the centers of neighborhoods. The computationally intensive simulation loop underpinning this research was possible only in the 1970s because I was working on a very large Cray-like standalone computer. Most people in the social sciences did not have access to such machines at that time. The movement toward personal computers that followed further limited the technical ability of researchers to take geographic ideas of a city and try finely woven analysis. Researchers were forced into data aggregation to census tracts or larger areas or were limited to the use of very small samples of cases primarily based on interviews.

The times have changed. We are now in a period of rapid advancement in computing power and the development of new algorithms. Tools and techniques are developing very rapidly. We are moving, with appropriate security and privacy in place, into a new research world. Our research laboratory, the Institute for Canadian Urban Research Studies (ICURS) at Simon Fraser University, has, for example, one data set of 9 million records of people involved in some way with 5 million criminal events that occurred during a multiple year period. Individuals, with their identity fully encrypted, included in the data set range from people who called the police to people who were victims and the people who were arrested in the criminal events. Although names are encrypted, records are linked to indicate co-offending, repeat offending, victimization, and time and place.

The data and computing power available to researchers in the ICURS laboratory is still a fairly new phenomenon in the social sciences; it will not be in a few years (see articles in this issue for examples of the future). New algorithms are now developed routinely, making it possible to explore crime and place at increasing levels of detail and complexity. Electronic data storage is now routinely available in terabytes and will soon be available in petabytes. Increases in computing power now make analysis of these large data sets increasingly tractable and agreeably fast.

The enhanced analytical capabilities that are enabled in the new computer world have brought about the increase in availability of data, the use of innovative techniques, and the linking of research in criminology to policy questions. Linking research with policy and practice leads to advances in decision support. This computational power is not yet available to researchers in general, but the direction of the field is moving toward improved access and analysis.

Theory and method are now entwined. Theory drives analysis; analysis guides theory. In particular, theory, research, and data work together to advance the knowledge of the relationship between crime and place in ways that can be used in policymaking and planning. The geographic way of thinking becomes increasingly important. The *why* and the *where* of crime require linking people to time and space. Linking people with place leads to a better understanding of how and why people move around and identifies the places that pull people in, push people away, or entrap them.

This way of thinking shapes research but is also fundamental to strategic policy formation and to designing tactical operations. Linking research, strategic policy, and tactical operations is particularly important for understanding persistent problems— especially when researchers address what some call "wicked problems." Wicked problems do not have an easy solution. These problems require innovative ideas and research methodologies to provide clarity and assess the effects of programmatic efforts. Past research indicates that advancement can be made with careful thinking and with innovation.

Understanding the pervasiveness of crime and disorder in specific places draws us into looking at human activity. Crime is the product of human activity. We need to look at daily living and the repetition of routine patterns. We know that crime and disorder can cluster heavily in certain small areas of a city and persist. We see other areas where crime can increase for short bursts but recede. We see still other areas where crime and disorder remain low. Crime patterns reflect movement and activity patterns of people. For a serial offender, the pattern would be unique to that individual and shaped by his or her knowledge of and attraction to particular places within a city. For more common crimes, aggregate crime patterns reflect aggregate pulls, pushes, and areas of entrapment within a city. But our growing computer power means that, with spatial and temporal geographic information systems (GIS) and data mining, we can begin to understand classes of pushes and pulls and build better place-based predictive models.

Think of water flow as a visual analogy of how people move around in a city and how crime hot spots form. Imagine small streams of water flowing across a flat delta toward the ocean. During periods of heavier rain, new streams and pockets or deep pools of water form. The new streams or pools make different patterns in different deltas, depending on the local topography, soil, shore structure, and actual water flow. Criminal activity—always more complex than streams of water—is influenced by many factors, including a complex template of attractors as well as socioeconomic and structural constraints. People, however, move about in a city. Some concentrate around local areas; others move longer distances. They all develop routines, concentrating their activity along paths or routes and spend more time at some locations than others. In the aggregate, there are pushes and pulls in cities that, depending on the urban backcloth or urban landscape, focus agglomerations. These pushes and pulls exist for offenders. Offenders are people who spend most of their time not committing crime and often have their use of an urban area shaped by noncriminal activity.

Exploring crime and place is a major research area that requires an understanding of people, their activities, their networks of friends, and their reasons for being attracted to certain locations or being scared away from others. According to Lynch (1960), we form images of a city and those images persist. Those images help shape our activity and our activity helps shape those images: local activities (such as work, schooling, and entertainment), the character or milieu of locales, their vernacular architecture, residents, shops, parks, and concentrations of people. The term usually used for areas that are well known to a person is his or her "awareness space"; that is, places that are recognized by an individual and where an individual knows how to get to and from. In the aggregate, cities have areas that are part of the awareness space of many individuals. These areas are usually the most active within cities.

All activity is not necessarily positive, nor do all people have the same ability to move and choose their landscape. Neighborhoods have the potential of trapping people. The risk of victimization can be the consequence of a lifestyle, but it can also be drawn from the lifestyle of others in a local area. From a policy perspective, a city helps shape crime patterns and crime patterns help shape a city. It is a challenge to policymakers and researchers to better understand this continuing, dynamic relationship between people and place and how it influences crime.

The complexity of the relationship between crime and the urban environment is very distinct for different types of crimes, different times of the day, different days of the week, and different times in a year. Crime patterns are morphed by a city's infrastructure, daily rhythm, and socioeconomic mosaic. Some patterns are so strong that they should be evident to most people. Small property crime (shoplifting, theft of personal property, and theft from autos) concentrates in major shopping areas or major transit hubs, while assaults concentrate in and near drinking establishment clusters. Yet, not all shopping areas have major concentrations of crime, nor do all bars. Crime may concentrate in very small areas, such as one apartment building or a single bar, despite lower crime rates in all adjacent properties.

Understanding the dynamics of crime requires careful thought and the ability to move between different scales of resolution. From a research perspective, it is good to start with the most detailed data possible and aggregate based on the policy or research questions. Different results are apparent at different levels of aggregation. From a geographical perspective, when the research question draws one into zooming further into a narrower time and space scale, the research will eventually reach a level where clustering fades and the pattern appears to be more random. When research zooms out to broader scales, clustering will appear. The challenge in research is to find the appropriate scale for the research question but to remain aware of the importance of understanding the finer scales. The appropriate focus keeps moving back to smaller units of aggregation. The study of crime and place focuses on understanding detailed patterns and, using these patterns, understanding what specific patterns help shape more general patterns.

In the symposium of this issue of *Cityscape,* Ronald E. Wilson's introduction sets the stage for a better understanding of what crime and place mean and how the scale of place relates to crime location theories and policy and practice. Wilson's introduction provides the reader guidance on how to navigate through the articles to build a conceptually broader framework for research on place.

In their research on sex offender legislation, Tony Grubesic, Allan Murray, and Elizabeth Mack help the reader understand that laws are different in different states and enforced in different ways. Not only does crime vary from place to place and temporally, but also what constitutes a crime and how offenders are monitored varies. Although the article is about sex offender legislation, the issue is similar for many other types of high-attention public disorder and crime. Law is a major dimension of the analysis of crime patterns.

Complexity requires consideration of additional dimensions, depending on the issue under investigation, and requires thinking at multiple scales of resolution. The article by Philip Harris, Jeremy Mennis, Zoran Obradovic, Alan Izenman, and Heidi Grunwald addresses a different question—one that requires thinking about variation again—as they explore how neighborhoods and individual traits both matter in recidivism. GIS-spatial data mining is linked to better ways of understanding recidivism. It fits naturally within the idea of people acting within a landscape, and considers how places influence people and people influence landscapes, particularly in seeing how different types of recidivistic crimes cluster in different places. Crime patterns become clearer through their analysis.

Advances in this burgeoning area of criminology require new and different ways to analyze problems. As mentioned earlier in this article, innovation is occurring in theory, research, and methodology. Joel Caplan, whose article explores both theory and method, uses risk terrain modeling and criminogenic data layers in a data fusion GIS to show how "…theoretically grounded operationalizations of spatial influence from many risk factors can be used as a control measure of environmental context when evaluating the spatial effect of place-based interventions on future crime events." Caplan asks the theoretician, researcher, and policy or operations expert to look at the landscape and to understand crime as it occurs within its environment. With this approach, it becomes very clear why crime is low in some areas and why it may appear episodically in others but not persist. This work is a major step forward for predictive policing.

Roderick Jones and Derek Paulsen focus on environmental context in their examination of HOPE VI, a national program with the goal of greatly reducing the entrapment of people in highly distressed public housing. The authors report mixed results but note that other levels of information might help explain the variation they observe. It would be valuable to see research such as this repeated.

Space and place matter in all environmental backcloth research. Michael Lens, Ingrid Gould Ellen, and Katherine O'Regan look at the effect of vouchers in enabling low-income people to become more mobile in seeking out housing in safer places. The results are supportive of vouchers but raise some alternative explanations, as good research should. The research addresses the patterns at a census tract level. It will be interesting to see what happens when the level of aggregation moves to block groups or blocks (considering adjacent blocks). It would also be interesting to see whether people with vouchers tend to move to areas close to family and friends, a common intracity migration trend.

Mike O'Leary's article challenges crime researchers to think about criminological and environmental theory but also to think about the mathematics behind some of the algorithms used. The article also reflects usage of larger data sets linking offenders to offenses and indicates some geographic research that will become possible when data sources improve. With each data source improvement, however, comes improved questions. What would have been changed if the analysis had included Baltimore city as well as the county? Would the results have changed in an ecological sense if the base population or housing unit area were different? What about sparser road networks in rural areas? A point-to-point distance could look short but actually be much longer on the road network that must be traveled. The article shows how theory, research, and methods blend when better data are available.

It would be fruitful to return to these topics annually for several years to see how geographic thinking about place, and about place and crime, affect theory, research, and strategic policy development for improving quality of life. This issue of *Cityscape* shows how we as researchers can continue to develop new and better ways to address issues. It would be of value to watch the evolution of these research themes.

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Advances in the Identification of Space As a Structuring Factor of Social Reality

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The way in which space determines the appearance, reproduction, or dissemination of violence and participates in the formation of offenders is becoming increasingly clear. Likewise, it has become much easier to determine the way in which property offenders, in particular, tend to use the specific characteristics of space to commit their acts. In addition, studies on public policies and interventions aimed at reducing crime that contemplate the possibility of redeeming spaces usually include additional evidence regarding the relevance of space in understanding the nature of the infringement of the law.

Perhaps we are on the verge of achieving a theoretical synthesis capable of definitively establishing space as a fundamental structure of social reality, together with society, the economy, culture, politics, and demography. We can no longer ignore the spatialization of social reality. It could even be said that we are getting close to acknowledging the theoretical existence of both a general and a particular dimension of space. According to the former, space would structure reality at two levels: first, by integrating the other structural properties of the population (for example, poverty, low levels of labor ratings, and racial segregation in the same locations) and, second, by developing predominant geographical form; that is, urban residential, urban commercial, or rural—if we take into account the predominant ones.

Such a structural integration based on predominant, nonspecific geographical forms can be achieved only by space, because it is able to create those moods often described by philosophers and writers. Simmel (2007: 26), for example, states that "…the mood of a landscape permeates all its separate components, frequently without it being attributable to any one of them. In a way that is difficult to specify, each component partakes in it, but a mood prevails which is neither external to these constituents, nor is it composed of them."

It is no coincidence that the different forms of interpersonal, group, and collective violence appear most frequently in the low-income, urban, residential areas of both developed and developing countries, and that most property offenders reside in these areas. Nor is it a coincidence that residents in these areas feature significantly homogeneous ratings with respect to the indicators for each social structure. Furthermore, the activities of these individuals tend to limit themselves to these same places, where the occupation density and the physical structure of the homes and public spaces force people into permanent and prolonged interactions that lead to the consolidation of behavior patterns, including those associated with crime.

On the other hand, the particular dimension of space guides our analysis toward the physical, observable form in which space is organized as a place: use of the land, architecture, public space, furniture, lighting and its operating conditions, and so on, as well as toward the routine occupations according to types of population, not just criminals, in these places.

In fact, the construction of space as that place produced by environmental criminology through its different theories has allowed criminologists to escape the spiral of macrosocial or micropsychological structural causality in which they were frequently entangled. The current increased capacity to make multiple new, extremely accurate, and simultaneous empirical characterizations of criminal acts and criminals, guided or obtained to a great extent thanks to spatial data analysis, is the basis for this breakthrough that has contributed gradually to the rediscovery of space as a fundamental structure of social reality and a facilitator of modalities of crime.

Undoubtedly, the formulation of public policies and the actions of law enforcement agencies aimed at crime reduction have benefited from this new representation of space. In finding greater theoretical and empirical support for the fact that law enforcement agencies' increasingly place-based strategies do not produce merely precarious, superficial, or cosmetic changes but also affect the opportunities for the appearance of crime, public actions can also claim that the implementation of their strategies is structuring a new space that contributes to blocking the appearance, reproduction, and dissemination of offenders and offenses.

The current issue of *Cityscape* constitutes a pertinent and updated contribution to this process of theoretical and empirical development of a renewed understanding of the dimensions of space. The conceptual and methodological turn (that is, the Risk Terrain Model) proposed by Caplan, in his effort to address how specific places are more closely associated with criminal activities, is very interesting. His thesis that the spatial influence of criminogenic features enables occurrences and determines the seriousness and longevity of crime problems makes it possible to go beyond the mere identification of hot spots, while opening a work agenda that will make it possible to determine accurately how the combination of physical form and occupation patterns facilitates opportunities for the perpetration of certain crimes.

The articles by Cahill, Lens et al., and Jones and Paulsen, which analyze or evaluate the physical reconstruction of public, low-income, homogeneous residential complexes (through the HOPE VI Program) or the relocation of residents to other neighborhoods (through the Housing Choice Voucher Program), as well as their effects on the reduction of crime or of the exposure of these households to crime, could be more optimistic in the light of the evidence they obtained. After all, no counter-evidence exists in the articles that shows the transformations of these places or the relocation of households have increased crime in the zones to which people were relocated or that crime has shifted significantly to neighboring areas.

Overall, the articles seem to lose sight of the fact that the characteristics of these residential complexes have structured the formation of criminals and created spaces favorable for the perpetration of crime in the context of a decades-long process. The shape that the general and particular dimensions of space have acquired in these residential complexes has fostered crime. Therefore, the breakup of the homogeneity of social reality through the reconstruction of the physical form or the structure of social interactions requires the establishment of longer time periods to obtain valid results that are capable of determining whether the criminality that was slowly fostered is gradually deactivated.

The study carried out by Harris et al. provides support for this perspective. The author states that residential segregation acts in such a way as to reinforce concentrated disadvantage, which is related to criminal specialization, which, in turn, is influenced by peer contagion. Perhaps it would be useful to underline the fact that this type of peer contagion can occur only in the context of a space that intensifies interactions and consolidates patterns of behavior.

Finally, although O'Leary refers only briefly to the fact that offenders are more likely to offend in an area where they previously resided than in other comparable areas, I believe that, in fact, this point constitutes one of the most important aspects of the type of studies he carries out. Perhaps it will be possible to answer the question posed by variations between distance and direction in criminal distance decay models when the familiarity of the criminal with the target-place is made operational, which, in turn, might transform the target-anchor point relation into a logical expression of that familiarity.

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A South African Commentary on the Articles in the *Cityscape* Symposium on Crime and Urban Form

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The relationship between crime and the physical environment, including urban form, is of particular relevance within the South African context. Two features of crime in this country—crime levels are exceptionally high and crime affects different people in different parts of the city differently—have important implications for interventions in the built environment.

Until 1994, when the first democratic elections were held, the country's apartheid policies directly influenced planning policies and practices that, to a large degree, shaped cities and towns in South Africa. Cities were partitioned into various zones, based on race, with vacant land and other types of buffer zones dividing communities. Informal settlements have since developed on much of the vacant land surrounding townships (Kruger and Landman, 2008). Most poor people stay relatively far from their places of employment, requiring them to spend a considerable amount of time and money on traveling and making them vulnerable during these journeys. The spatial dislocation of the poor also has resulted in the exclusion of many city residents from the amenities and economic opportunities that the city offers.

Despite the progress made since 1994, the form and structure of the apartheid city has not changed significantly. Living conditions for the poor, in many ways, have not improved significantly either (Department of Housing, 2004).

A study conducted in 1998, which addressed the link between crime patterns and urban form, clearly showed the effects of the apartheid city and its contribution to disproportionate levels of safety in different communities. Studies indicate that crime patterns and trends differ substantially, for example, between city suburbs and traditionally poorer areas. The poor in South Africa are more exposed to violent crime than are other groups in the country (Shaw and Louw, 1998).

The symposium article by Lens, Ellen, and O'Regan (2011) addresses the ability of poorer households to improve their quality of life by moving to other neighborhoods with the support of government, in the form of vouchers. More background on the purpose of vouchers would have been useful, because it is not clear exactly how the voucher program functions. The issue of mobility and quality of neighborhoods is also a matter of concern in South Africa, however, with questions being asked of the effectiveness of the government's housing subsidy scheme in creating better functioning settlements. Through the scheme, eligible poor households may receive a 40-square-meter house at no or little cost. These houses are normally provided on the outskirts of cities, however, perpetuating the inefficient structure of the apartheid city and re-enforcing existing crime patterns.

Although Lens, Ellen, and O'Regan (2011) aim to determine if the voucher program is effective in helping participants move to relatively safe neighborhoods, it may have been useful to touch on the role that potential employment opportunities could play. Despite crime being a very serious concern in South Africa, in many cases moving closer to potential job opportunities is more important than moving to a safer neighborhood.

The two articles dealing with the HOPE VI Program (Cahill, 2011; Jones and Paulsen, 2011) address issues similar to those raised about housing and upgrading projects in South Africa, including the so-called Urban Renewal Programmes and medium density mixed housing developments. One key difference between the South African initiatives and HOPE VI lies in the nature of the environments targeted for upgrading. In South Africa, these areas are often informal settlements where people live in temporary shacks and have limited access to municipal services and other resources. A significant potential exists, therefore, for improving the quality of life of the households benefiting from the initiatives. Substantial research still needs to be conducted on the displacement of crime and the diffusion of benefits from these projects, but results will likely vary, depending on the local conditions.

It would be very interesting to apply in South Africa the risk terrain modeling techniques that Caplan (2011) uses, because the criminogenic factors might well be very different in South Africa, due to the urban form in this country, as discussed earlier. For example, the private minibus taxi industry carries a major part of the commuter traffic; because they stop anywhere for passengers, bus stops might not be a criminogenic factor in many areas.

Regarding the study by Harris et al. (2011) on juvenile recidivism in Philadelphia, several studies (Altbeker, 2007; Pelser, 2008; Simpson, 1998) were conducted in South Africa on criminal activity. The urban fabric in South Africa is different from that in the United States because of the apartheid legacy and other factors, but it also contributes to juvenile recidivism as indicated by Harris et al. (2011). Further, according to Pelser (2008), a key driver in South Africa is that the political struggles during the 1970s and 1980s made crime and violence acceptable. These struggles resulted in liberation, but they also led to uneducated youth and the general breakdown of the family and schools (Pelser, 2008). This breakdown led to a culture of crime being "cool" and resulted in a high level of recidivism. Pelser (2008) further indicated that 76 percent of juvenile delinquents were themselves victims of crime, which was not part of the study by Harris et al. (2011).

In South Africa, the criminal can commute far to commit a crime, because some residential areas are far from places of opportunity and because it is common to commute far for work. The study by Schmitz (2004) on the geographic profiling of serial rapists and murderers looked informally at distance decay, which was a factor of the transportation modes available to the offender and the target backcloth. O'Leary's (2011) modeling on distance decay may provide a basis for a similar distance decay and crime modeling in South Africa.

Following the lead of countries such as the United States, South Africa established a Child Protection Register in 2010. During August 2011, however, Parliament revealed that, after being operational for 16 months, the register contained the name of only one person deemed unsuitable to work with children (SAPA, 2011). This failure emphasizes that, although a study such as that of Grubesic, Murray, and Mack (2011) would be very useful in South Africa, it is not possible without an efficient justice system.

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Graphic Detail

Geographic Information Systems organize and clarify the patterns of human activities on the earth's surface and their interaction with each other. GIS data, in the form of maps, can quickly and powerfully convey relationships to policymakers and the public. This department of Cityscape *includes maps that convey important housing or community development policy issues or solutions. If you have made such a map and are willing to share it in a future issue of* Cityscape*, please contact david.e.chase@hud.gov.*

Visualizing Racial Segregation Differently: Exploring Geographic Patterns in Context

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Visualizing geographical patterns of racial segregation is often done by mapping a proportion of a single racial group. The single proportion method, however, does not provide a context for understanding the social or economic conditions that interact with the pattern. This article is the second of two that examines segregation at the regional level. The previous article (Wilson, 2011) shows how to map two racial groups simultaneously to provide a comparative context for integration and regional segregation. The purpose of the analysis in this article is to move the reader beyond examining segregation with a single percentage map of one racial group without some comparative context. Not providing a comparison allows a reader to be misguided as to whether real problems exist. This article recasts the analysis of segregation to the interaction of the economic context with geographic patterns of segregation.

The data used in this analysis are from the 2009 Bureau of Economic Analysis (BEA) Local Personal Income Estimates.[1] An Income Inequality Index (III) is derived using three sources of income, which are earned wages, income maintenance, and unemployment insurance. Combined with measures of segregation, these categories can reveal changes in regional segregation patterns

[1] For the entire United States, 54 jurisdictions were missing from the original BEA data, all of which were in the Commonwealth of Virginia. Missing data were the result of several small independent cities—fewer than 100,000 residents—being combined with surrounding counties.

within the context of income disparities. III is multiplied with the Localized Diversity Index (LDI)[2] that was used in the analysis in the previous article to measure levels of segregation and integration within a county.

Personal income estimates are used for measuring disparities in sources of aggregate income through proportional balances. Categorized income sources represent various aspects of workforce abilities, education, job opportunities, and wage levels within a county. Net earnings represent income from wages that come from being directly employed, less contributions from other sources. Income maintenance represents supplemental government assistance toward living expenses. Unemployment insurance represents supplemental government assistance as compensation for a recent job loss. The latter two categories represent a general form of government assistance for individuals experiencing economic difficulties. Proportional measuring of all three categories situates populations with respect to the prevailing economic conditions in a county.

Proportions of income sources create a normalized context of income sources to determine whether the proportions are balanced. Net earnings will always be the dominant source of income in any county, because more adults are working than not in any local economy. Increasing proportions of income from government assistance through income maintenance or unemployment insurance, however, is indicative of negative economic conditions. As such, income disparities represent the local and regional economy through what proportion of the population is receiving how much income from what source.

In this analysis, Theil's Entropy Index[3] is used again to create the III because the mathematical properties are sensitive to disproportionality changes between two or more categories, as well as substantive meanings regarding proportionate sources of income. With net earnings always being the dominant source of population income, the proportion from government assistance will be small, and this index will be able to detect the changes between proportions. Resulting values have the same boundaries of 0 and ln $(\frac{1}{\pi})$ as the LDI from the previous article, allowing the two indexes to be combined. Although the application of this formula is similar to the LDI in its range of values, the upper and lower limits have different qualitative meanings. III values close to 0 represent populations whose dominant source of incomes is from employment (net earnings) and who are receiving little in government assistance. III values substantially above 0 represent populations who receive a larger share of income from government assistance in income maintenance and unemployment insurance. Each county will have an III value that can be thematically mapped to reveal patterns of where the poorest and richest areas of people are regarding the balance of income sources that populations in a county receive. Exhibit 1 shows the geographic patterns of III.

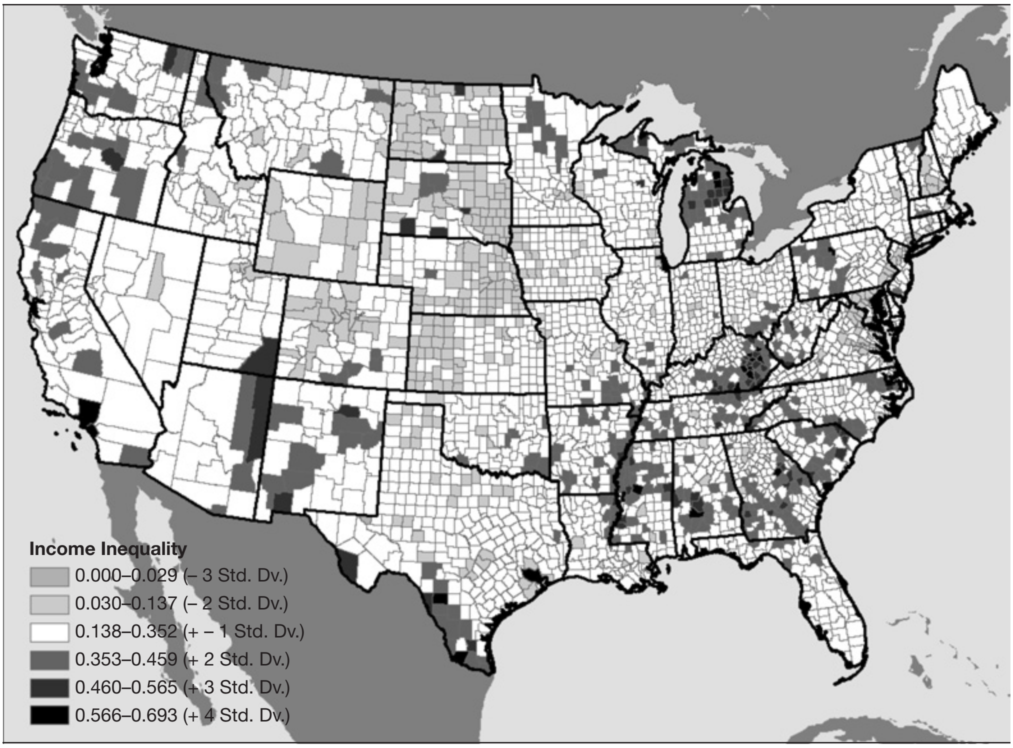
Counties in white have III values within one standard deviation greater or lesser than the mean. These counties exhibit the expected balance between income from net earnings and government assistance. Counties shaded in light gray have significant proportions of their populations receiving income from employment and receiving little income from government assistance. Counties

[2] The LDI was created using the population estimates from the U.S. Census Bureau American Community Survey 2009 5-year estimates.

[3] For the mathematical details of Theil's Entropy Index, see the appendix.

Exhibit 1

Distribution of the Income Inequality Index for the Contiguous 48 States (equal interval classification)

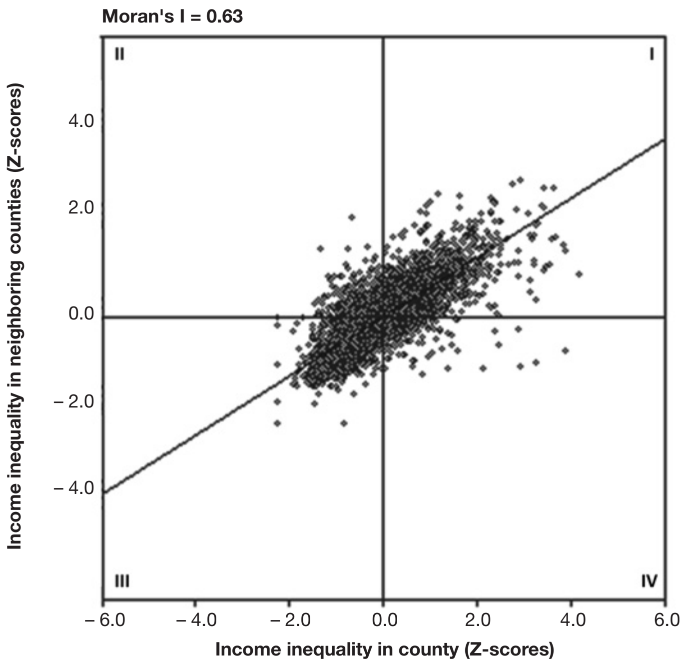


shaded in dark gray have significant proportions of their populations receiving income from government assistance. As the map shows, rural areas in Appalachia, the Deep South, the Northwest, and Northern Michigan often display the highest shares of income maintenance and unemployment benefits. Exhibit 2 shows that the economic conditions reflected in one county's I score are usually shared with its neighboring counties.

The thematic map in exhibit 1 indicates the clustering of income inequality, but it does not depict the extent of the geographic connection between and across those counties. Places that share similar geographies usually share similar histories in social, political, and economic conditions (Novotný, 2007), one of which can be income disparity. Places are not isolated from the conditions and changes occurring in surrounding geographies. Counties in proximity to each other form interactions between themselves and establish strong economic ties that form regions. Interactions between counties in proximity to each other may exacerbate any number of local problems that affect an entire region. As such, income inequality levels are not just a reflection of a single county. These interactions require an analysis that considers the spatial relationship of income inequality

Exhibit 2

Spatial Autocorrelation of the Income Inequality Index for the Contiguous 48 States (Moran's I scatter plot)



with adjacent counties.[4] To measure the strength of these spatial relationships, the Moran's I Index is used to detect significant regional spatial relationships of income inequality and racial segregation between counties.[5]

The Moran's I value of 0.63 (with a p-value of 0.001)[6] indicates the covariation patterns of III values between a county and its adjacent counties show strong regional clustering of high and low III values.[7] The data cloud in exhibit 2 depicts a strong linear pattern across quadrants I and III. Those two quadrants represent counties that are clustered together with similar values on opposite ends of the III. Counties in quadrant I are those that are surrounded by counties with similarly high

[4] The interactions between counties represent the First Law of Geography. For a discussion of this law and its importance, see Miller (2009).

[5] Neighboring counties were identified using the eight nearest neighbors. Nearest neighbors were used instead of adjacency to eliminate the effects of large and irregular shaped counties not capturing full regional relationships.

[6] Moran's I values closer to 1.0 indicate clustering. Values closer to -1.0 indicate dispersion.

[7] The strength of the Moran's I value is contingent on two elements. First, the steepness in the slope of the line between values in a county with the lagged values in neighboring counties. The steeper the slope, the stronger that spatial relationship is between a particular value in a county with its neighboring counties. Second is the p-value that measures how different the observed I value and a set of randomization I values are from the original data. P-values less than 0.05 indicate the observed pattern is statistically different from the random distribution of I values, which usually forms a normal distribution. The steeper the slope and the higher the p-value, the stronger the spatial relationship is between counties and neighboring counties.

values. Of the counties in quadrant I, 23 percent show statistically significant clustering of high III values with adjacent counties. Of quadrant I counties, 25 percent show statistically significant clustering of low III values with adjacent counties. This clustering supports exhibit 1 in which counties with plus or minus 2 standard deviations from the mean are clustered together in different regions of the United States. These counties share similarly high levels of income inequality through a regional connection. Regions in exhibit 1 that are two standard deviations or greater than the mean are grouped together in the most rural parts of the United States. Rural counties often have fewer economic opportunities to develop robust job markets. Regions with counties two standard deviations or below are those in which the populations are receiving little in government assistance and most income is from net earnings. These counties are located either in the heartland, where a lot of farming activity occurs, or in major urban areas that have diversified and robust economies.

Examining income inequality alone, however, does not answer questions regarding any regional relationship with segregation. Exhibit 2 shows an association with lack of economic opportunity in areas not known for robust economies, regardless of race. The question remains, does a relationship exist between the counties with high levels of income disparities and racial segregation? A new variable is created to measure the interaction between income inequality and racial diversity (*Interaction (I) = III · LDI*) where LDI and III are as defined previously. This interaction depicts a bivariate relationship that identifies counties with high and low proportions of the Black population compared with the White population. The index extremes are substantively opposite of each other regarding the positive and negative connotations. In interpreting the interaction, recall that an LDI value close to 0 signifies segregation, and a value closer to 1 signifies integration. In contrast, III values closer to 0 signify net earnings as the dominant source of income in a county; substantially higher values indicate that government supplementation of income makes up a larger proportion of income sources in the county. High values of the interaction indicate a county with a high proportion of the Black to White population (racially integrated) with a significant portion of income from government assistance greater than earned income. Low values indicate either a highly segregated county, a county with most income coming from net earnings rather than government assistance, or both.

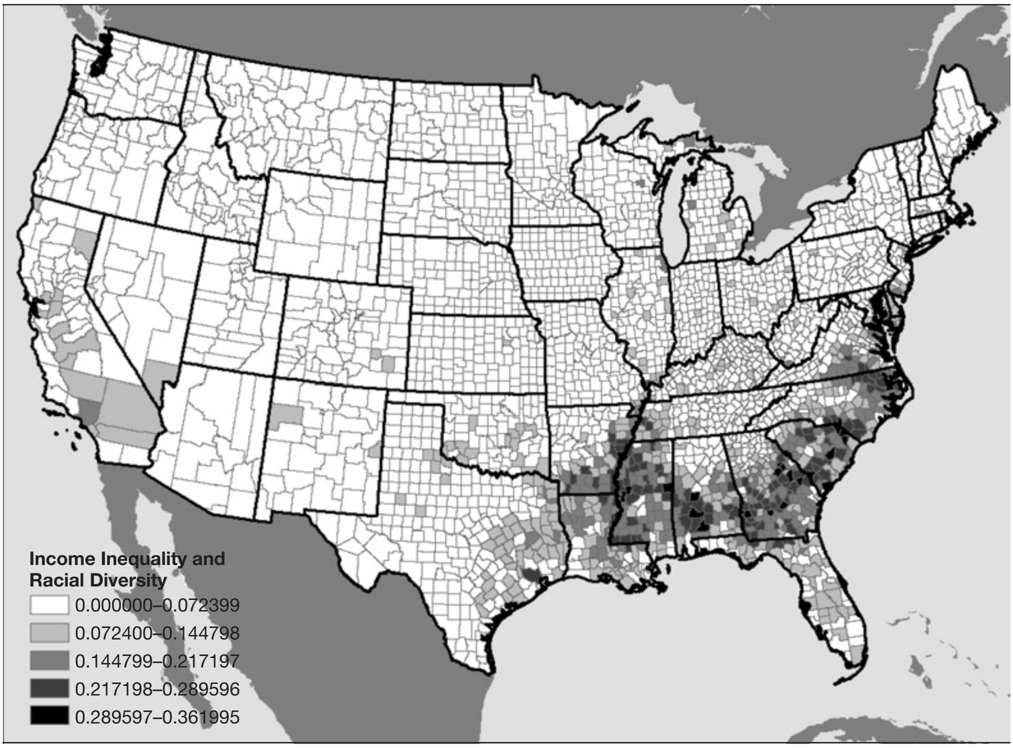
Exhibit 3 displays the map of the interaction between the two indexes. In contrast with exhibit 1, only one dominant regional pattern now exists. A belt of counties from east Texas to northeast North Carolina forms the dominant regional pattern. A lesser cluster of counties in California (mostly rural and in the interior, apart from Los Angeles County) also stands out. The latter areas have a high proportion of the Black population but far less than areas east of the Mississippi River.

As with the III, the strength of this spatial relationship needs to be measured with the Moran's I Index to detect significant regional spatial relationships of this bivariate relationship for regional income inequality and racial segregation.

Exhibit 4 displays the degree to which the interaction between the two indexes is spatially correlated. The data cloud in exhibit 4 has changed considerably and the Moran's I value (0.78 with a p-value of 0.001) is substantially closer to 1 than the III value. The covariation of interaction values between a county and its adjacent counties shows an even stronger pattern of regional clustering with the high and low LDI and III values than in exhibit 2. The tight clustering of most Z-scores near 0 is an artifact of index construction.

Exhibit 3

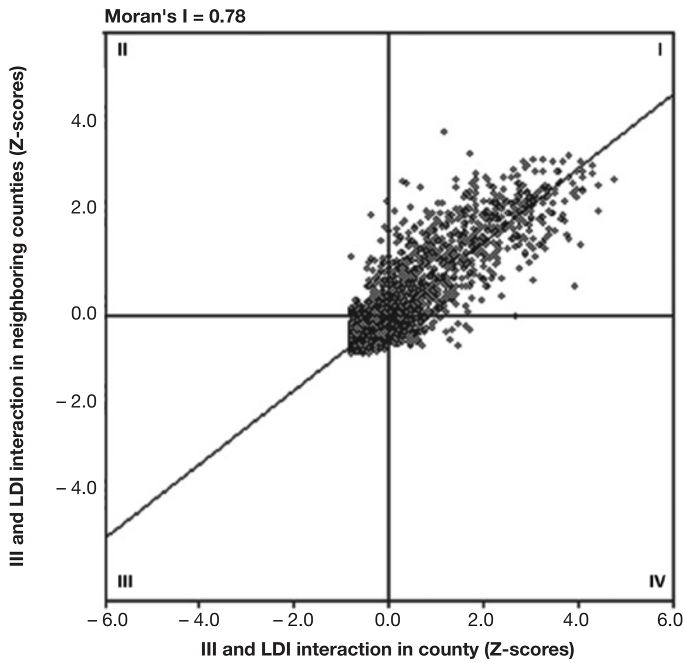
Distribution of the Interaction of Income Inequality and Localized Diversity Indexes for the Contiguous 48 States (equal interval classification)



The data cloud still shows a strong linear association across quadrants I and III, but the patterns have changed from those in exhibit 2. First, the slope is steeper. The spatial relationship between counties and neighboring counties has gotten stronger. Second, the patterns in quadrants I and III have distinctly changed. In quadrant I, the pattern is more dispersed, which signifies counties with high values are clustering in small pockets of high values. Of these counties, 19 percent show a statistically significant clustering of high values with adjacent counties, which is a decrease of 4 percentage points from exhibit 2. These changes reveal a strong local connection between income inequality and racial segregation amidst a larger regional pattern. The geographic patterns from exhibit 3 support these results because the highest proportions of income inequality and Black to White populations are concentrated and are separated from each other—forming a loosely coupled belt across the South. The pattern in quadrant III shows the opposite, with a more concentrated pattern, which signifies these counties have low values and are the dominant spatial pattern. Of these counties, 37 percent show a statistically significant clustering of low values with adjacent counties, which is an increase of 11 percentage points from exhibit 2. These changes indicate that a substantial number of highly segregated counties are clustered together with populations whose income is primarily from net earnings. Exhibit 4 reveals this clustering in a pattern across the southern states from Arkansas to North Carolina. Not only does a strong level of succinct regional clustering exist, but the pattern forms one long belt of clusters in one part of the United States. Of

Exhibit 4

Spatial Autocorrelation of the Interaction for Counties in the Contiguous 48 States (Moran's I scatter plot)



III = Income Inequality Index. LDI = Localized Diversity Index.

the southern states from Arkansas and Louisiana to Virginia, 65 percent of the area has moderate to high levels of the population receiving higher levels of income from government assistance and also higher proportions of the Black population receiving such assistance. Compared with the United States, these same counties make up 9 percent of the area. With this pattern concentrated into one part of the United States, 9 percent is a significant amount, because progress in the region is likely weighed down by a collective lack of opportunity.

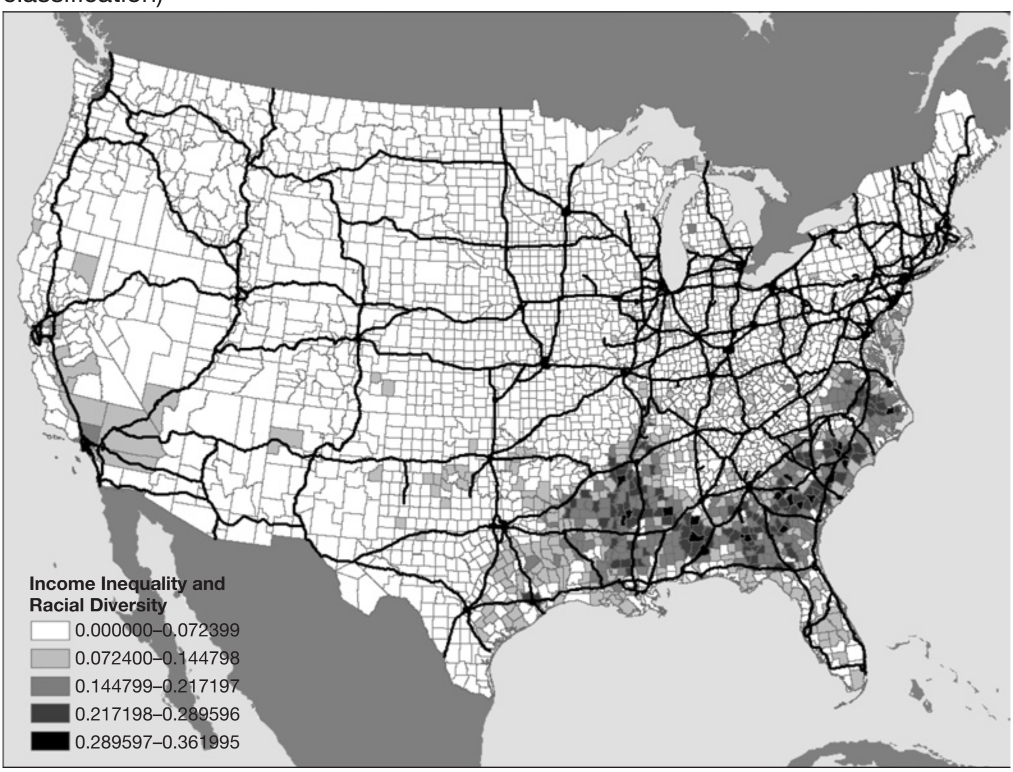
To confirm the spatial relationship that regional segregation has with income inequality, statistically significant values were removed from the scatter plot in exhibit 4 to examine the change in overall spatial relationships across the United States. When statistically significant high values are removed from the scatter plot, the Moran's I Index drops from 0.78 to 0.48. This substantial decrease demonstrates the level at which greater proportions of income inequality and Black populations affect the analysis results. These counties face specific challenges in overcoming income inequality regarding segregation that is much different from the rest of the United States. When counties with statistically significant low values were removed from the scatter plot, the Moran's I dropped to only 0.71. The slight decrease confirms that the dominant spatial pattern in the United States is of counties with low income inequality and low regional segregation and is more common than the opposite. Any challenges these counties have regarding income inequality are not associated with regional segregation.

Exhibit 5 puts regional patterns of income inequality and segregation into a final context. Overlaid with the thematic map in exhibit 3 are major U.S. highways. Highways can be lifelines for regional economic development because they provide efficient transportation of goods and services. Highways facilitate industries to locate in otherwise inaccessible areas and bring jobs and growth that work toward building robust economies. Without highways, transportation times and costs can become excessive, which leaves little incentive for economic opportunities to be created. As can be seen in exhibit 5, counties with the highest levels of income inequality and regional segregation are located in areas that are deep between these highways. This lack of access to major roadways is indicative of rural areas with little economic opportunity.

The analysis in this article reveals regional patterns of greater income inequality associated with racial segregation. The patterns are more succinct than single-race thematic map patterns and can guide place-based thinking with respect to applying policy in a geographical manner. Thematic maps using a single race or ethnicity do show patterns of segregation but do little to identify where help is needed most because the breadth of the problem is exaggerated on the map at the expense of depth. In the analysis presented here, patterns are much more succinct in identifying specific pockets of income inequality (depth) that have been identified within a larger pattern of

Exhibit 5

Distribution of the Combined Income Inequality and Localized Diversity Indexes for the Contiguous 48 States With an Overlay of Major Highways (equal interval classification)



regional segregation. The most disadvantaged counties in rural areas of the South, with respect to segregation and sources of income, are highlighted in this analysis. A number of additional reasons for these patterns exist, beyond the association of rural areas with income inequality and racial segregation. But, the point of this article and the previous article is to spur analyses of race or ethnic data within a context. Other data sources should be used to conduct more combinatorial-based inquiries. Single-race thematic maps show nothing regarding why any pattern exists and leave readers unsure of which factors might be associated with segregation. Some counties in the regional belt across the South do not have high income inequality but have high proportions of the Black population. Many of those counties are urban and have different needs regarding economic policies and opportunities than rural areas. The focus on the southern belt of counties identified in this analysis does not mean other rural regions of the United States need less attention regarding economic development. Unlike other rural parts of the United States, counties in the South may need specific policies to specifically address regional segregation and expand economic development opportunities simultaneously. A third article will look at business pattern data, with the results from this analysis providing a better understanding of the current economic opportunities in this region.

Appendix

Inequality Index (Theil's Entropy Index)

Theil's Entropy Index is formally defined as

$$Inequality_j = \sum_{j=1}^{J} \pi_j \ln\left(\tfrac{1}{\pi_j}\right) \qquad (1)$$

where j is a jurisdiction and π_j is the proportion of each income source (net earnings, income maintenance, and unemployment insurance) in jurisdiction j.[8] The result is I, which is a continuous value that ranges between 0 (if one income source is the only income source) and ln $(\frac{1}{\pi})$ (if all three income sources are equal in shares; this value is 3). The result is a nonlinear (logarithmic) curve that represents change effects in which each unit increment or decrement along the scale has a different rate and magnitude of change.[9] Values substantially larger than 0 indicate net earnings are the dominant source of income and are from employment. Values closer to 0 indicate net earnings are less dominant as the primary source of income and income maintenance and unemployment insurance (government assistance) make up a larger proportion of sources of income.

[8] For a review of the mechanics of this index, see Wong (2003).

[9] For additional details about how this index functions, see Wilson (2011).

Frequency Distributions

Each figure number corresponds with the respective map number in the main body of the article.

Exhibit A-1

Distribution of the Income Inequality Index for the Contiguous 48 States (equal interval classification)

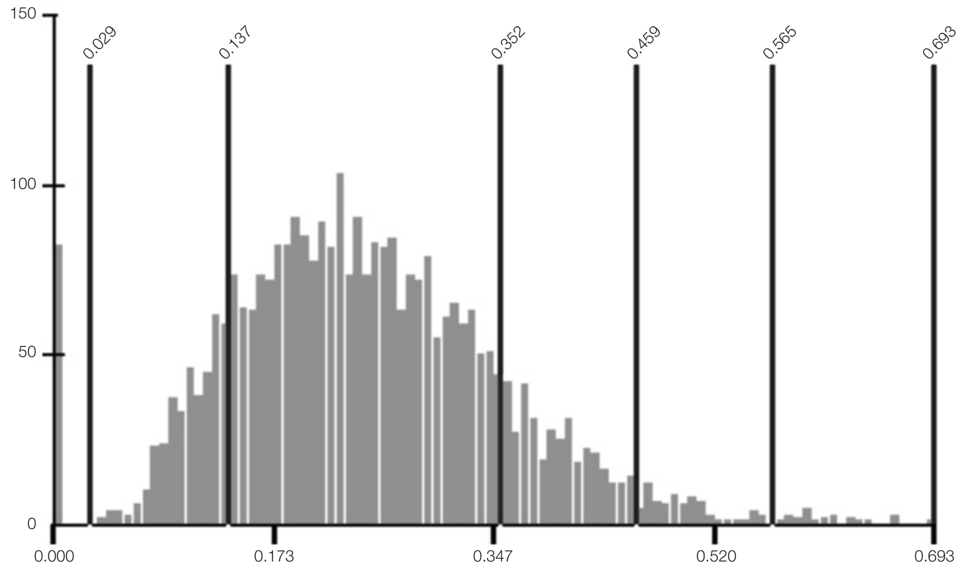
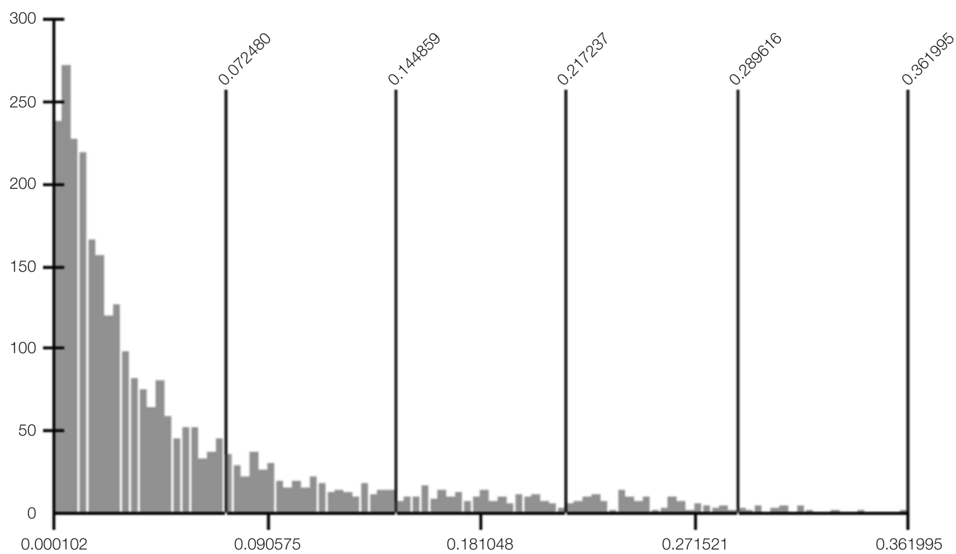


Exhibit A-3

Distribution of the Interaction Between the Income Inequality and Localized Diversity Indexes for the Contiguous 48 States (equal interval classification)



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The views expressed in this paper are those of the author and do not necessarily represent the official positions or policies of the U.S. Department of Housing and Urban Development.

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Data Shop

Data Shop, a department of Cityscape, *presents short articles or notes on the uses of data in housing and urban research. Through this department, PD&R introduces readers to new and overlooked data sources and to improved techniques in using well-known data. The emphasis is on sources and methods that analysts can use in their own work. Researchers often run into knotty data problems involving data interpretation or manipulation that must be solved before a project can proceed, but they seldom get to focus in detail on the solutions to such problems. If you have an idea for an applied, data-centric note of no more than 3,000 words, please send a one-paragraph abstract to david.a.vandenbroucke@hud.gov for consideration.*

A Beginner's Guide To Creating Small-Area Cross-Tabulations

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Gulriz Aytekin Kurban
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Abstract

This short article introduces two techniques of generating cross-tabulations in small areas (for example, block groups or tracts) for which only univariate distributions are available. These techniques require either a microsample or a cross-tabulation from a larger geographic area (for example, a Public Use Microdata Area). One technique uses hill-climbing algorithms, and the other is based on iterated proportional fitting. In this article, we identify the general characteristics of both techniques. We present and evaluate an example (generating cross-tabulations of households by housing value and number of children enrolled in public school), briefly discuss extensions of both techniques to synthetic population construction, and test the synthetic populations by comparing the estimated microsamples with the actual population.

Introduction

A common problem in small-area data analysis is the lack of cross-tabulations for minor geographic areas. For large areas, microdata are often available, from which one can construct cross-tabulations in a straightforward manner. For example, using the Census Public Use Microdata Sample (PUMS), one can construct cross-tabulations for all geographies at or above the level of Public Use Microdata Areas (PUMAs). A PUMA has at least 100,000 residents. For any smaller area, only select cross-tabulations are readily available from the census. Thus, for a census tract in the 2000 Census, American Fact Finder provided information on house value by household income, but these data were not reported for block groups. Even at the tract level, American Fact Finder provided no cross-tabulation for household value by number of household children enrolled in public schools. Recently, for a research project (Kurban, Gallagher, and Persky, 2011) on in-kind transfers, including those through public school systems, this value was one of several key cross-tabulations needed at the block-group level. An interest in imputing such small-area tables is widespread and can arise in any number of projects involving microgeography. The challenge is to build small-area tables in a reliable fashion. This article describes two relatively straightforward, and now quite accessible, techniques for generating synthetic cross-tabulations in small-area data analysis. The first technique, largely developed in Great Britain and favored by geographers (Huang and Williamson, 2002; Ryan, Maoh, and Kanaroglou, 2009; Voas and Williamson, 2000; Williamson, Birkin, and Rees, 1998), is based on hill-climbing algorithms from computer science.[1] The second technique, which is better known in the United States, is iterated proportional fitting (IPF).[2] IPF has been widely used by transportation analysts (Baggerly et al., 1998; Beckman, Baggerly, and McKay, 1996).

The common starting point for both techniques is information on small-area univariate distributions or marginals. For example, the census provides us with the distribution of households across categories of housing values within block groups. For each block group, we also have the distribution of households by number of children in the public schools. What we do not have (and what we want) is the cross-tabulation of households by housing values *and* number of children in the public schools. Both IPF and hill climbing are heuristic methods that start with a real cross-tabulation at a higher level geography and alter it in an effort to reproduce the known marginals for the lower level geography IPF works directly on the higher level table with a number of sequential adjustments aimed at bringing that table into conformity with the small-area marginals. By contrast, hill climbing begins with the raw microdata for the higher level geography and assigns the individual observations to each of the small areas, which compose a larger area. We make these assignments to match the marginals available for each small area.

In the next section, we briefly introduce the conceptual foundations of each of these techniques. We then make some suggestions for introductory software tools that are easily available on the

[1] The term “hill climbing” is used broadly in computer science to cover a range of heuristics based on random search. Given an objective function, hill-climbing methods search randomly around an initial point in an attempt to maximize that function locally (that is, to find a hilltop). To avoid being trapped at a local maximum, hill-climbing algorithms randomly restart their search at more distant points, keeping track of their global performance. See Michalewicz and Fogel (2004) and Russell and Norvig (2003).

[2] Iterated proportional fitting was first introduced by Deming and Stephan (1940).

Internet. Although we do not provide step-by-step instructions, we do present an extended example, which applies both techniques to the same problem. The last section introduces extensions of these two methods that can be used to create full-scale synthetic populations for small areas.

Two Techniques

Perhaps the easiest way to fill in a small-area cross-tabulation is simply to take a larger area cross-tabulation and scale it down to the size of the small area in question. Alternatively, if microdata are available for the larger area, a simple random assignment of household observations to the various component small areas, achieving those areas' total populations, would be expected to generate a similar result. The two techniques presented in this article offer substantial improvements on these naive approaches by incorporating iterative procedures that account for univariate marginals of the small areas. Hill climbing starts with a random assignment of microdata, while IPF starts with scaled-down cross-tabulations.

Hill Climbing

Hill climbing begins by randomly populating small areas with household observations taken from the larger area. One draws household observations from the larger area with replacement and assigns each small area only the number of households it actually holds. At this point, the simulated univariate distributions will not generally match the real distributions. Next, one randomly swaps households from one small area to another so as to improve the match between the real and simulated marginals while holding the small-area populations unchanged. Hill climbing implements pair-wise swaps only if the swaps improve the fit of the allocation. These swaps are repeated several times to improve the fit between the marginals gradually. To avoid becoming trapped in local optimums at the expense of reaching a global optimum, Huang and Williamson (2002), Voas and Williamson (2000), and Williamson, Birkin, and Rees (1998) implemented a flexible annealing procedure that allows the swapping algorithm to accept some swaps that produce poorer performance. This procedure helps improve the overall fit by allowing the algorithm to search across local optimums to get closer to a global optimum. The goodness-of-fit for each allocation is continuously recorded, and a prespecified stopping procedure determines when the swapping will come to a halt.

Iterated Proportional Fitting

A second technique for small-area table construction is iterated proportional fitting (IPF). The basic idea of IPF is straightforward. For a set of small areas that comprise a larger unit such as a PUMA, seed each small-area table with a copy of the PUMA-level table scaled to the small-area population. At this point, any cell in the large-area table just barely equals the sum of corresponding entries in the small-area seed tables; however, neither row marginals nor column marginals from the seed tables will add up to the actual marginals for the small areas. Next, multiply each row in each small-area seed table by a unique constant so that the cells in that row sum to the known corresponding row marginal for the actual small area. After these operations, column sums in the adjusted seed tables will generally not equal the corresponding true column marginals, nor will the cells in the adjusted seed tables sum to the corresponding cells in the large-area table. The second adjustment takes the new small-area seed tables and multiplies each column by a constant so that its elements add up to corresponding column marginal for the actual small-area data. Finally, a third set of multiplicative adjustments guarantees that entries in the small-area seed tables sum to the corresponding entry of the actual large-area table.

The IPF technique consists of repeated iterations of these row, column, and stack adjustments. The overall process is brought to a halt by specifying an appropriate stopping rule based on the absolute magnitude of cell adjustments. IPF has a strong intuitive appeal. It is well known to converge (Fienberg, 1970; Ireland and Kullback, 1968). In the general case, in which small-area cell entries may be generated from very different processes, the quality of IPF estimates is not guaranteed.

An Example

To illustrate the two techniques for generating small-area cross-tabulations, we now turn to an example suggested by our own work. But, as opposed to a scenario where small area cross-tabulations are not known, we use geographies in this example for which complete data are available. Therefore, for this case, the accuracy of each technique can be fully assessed and compared.

Basic Data for Both Techniques

As suggested previously, our project involved estimating cross-tabulations of households with given housing values and specific numbers of children enrolled in public schools. Although we were interested in generating data for block groups and school districts using known cross-tabulations for PUMAs, for this example, we frame the problem in terms of generating tables for PUMAs using known cross-tabulations for their super-PUMA. By doing so, we can compare the results with known values for those PUMAs.[3]

The data are from the 2000 Integrated Public Use Microdata Series (IPUMS) data file (http://www.ipums.org/)[4] for a suburban Chicago super-PUMA (17100) consisting of four PUMAs (numbers 3101, 3102, 3103, and 3104). The 2 variables of interest are housing values aggregated into 13 categories and number of children in public schools aggregated into 5 categories. The IPUMs provides these data at the household level. Exhibits 1a and 1b present the housing value and school children distributions (that is, marginals) for each PUMA. Exhibit 2 presents the relevant cross-tabulation for the super-PUMA.[5]

[3] PUMAs are defined by the Census Bureau: each PUMA must be contiguous and have at least 100,000 people. PUMAs do not cross state boundaries. Super-PUMAs have at least 400,000 people and are made up of contiguous PUMAs. Like PUMAs, super-PUMAs do not cross state lines. PUMS data allow tabulations at both the PUMA and super-PUMA levels.

[4] University of Minnesota, Minnesota Population Center. 2008. “Integrated Public Use Microdata Series: Version 4.0.”

[5] The exhibits presented here are constructed from unweighted micro-observations. They could easily be weighted for use in actual practice.

Exhibit 1a

Univariate House Value Tabulations by PUMA

House Value ($)	PUMA			
	3101	3102	3103	3104
0–49,999	147	80	15	10
50,000–79,999	176	228	41	51
80,000–89,999	137	183	55	41
90,000–99,999	161	179	84	71
100,000–124,999	351	220	196	267
125,000–149,999	356	212	264	283
150,000–174,999	248	111	282	322
175,000–199,999	182	54	247	205
200,000–249,999	164	35	295	207
250,000–299,999	99	10	201	120
300,000–399,999	58	10	96	163
400,000–499,999	13	4	24	56
500,000+	22	7	19	51

PUMA = Public Use Microdata Area.

Exhibit 1b

Univariate Public School Children Tabulations by PUMA

PUMA	Number of Children				
	0	1	2	3	4+
3101	1,381	344	259	88	42
3102	901	197	152	59	24
3103	1,053	322	286	132	26
3104	972	391	306	125	53

PUMA = Public Use Microdata Area.

Exhibit 2

Super-PUMA 17100 Cross-Tabulations

House Value ($)	Number of Children				
	0	1	2	3	4+
0–49,999	181	41	18	7	5
50,000–79,999	342	80	36	28	10
80,000–89,999	280	65	53	13	5
90,000–99,999	344	70	57	17	7
100,000–124,999	658	185	135	42	14
125,000–149,999	707	184	142	56	26
150,000–174,999	572	171	144	55	21
175,000–199,999	394	130	110	44	10
200,000–249,999	362	136	135	50	18
250,000–299,999	229	85	69	35	12
300,000–399,999	146	67	65	38	11
400,000–499,999	44	23	17	9	4
500,000+	48	17	22	10	2

PUMA = Public Use Microdata Area.

The Hill-Climbing Technique

Paul Williamson (2007) designed a readily available application of hill climbing that is suitable for beginners. Williamson calls his technique combinatorial optimization (CO) and a description of his program can be downloaded from his website.[6] Users can quickly adapt the CO application to their particular needs.

The CO program uses the household microdata for super-PUMA 17100 and all PUMA marginals. Starting with PUMA 3101, the program assigns household observations by randomly drawing (with replacement) a subset of the 2,114 households from the super-PUMA microsample (exhibit 2) to match the total population in this PUMA. After each PUMA has been randomly populated, the CO program begins the swapping and simulated annealing procedures. The fit of the swapping procedures is continuously assessed using a goodness-of-fit function proposed by Huang and Williamson (2002) and Voas and Williamson (2001).

The final output is simply a list of households allocated to each PUMA. From this list of households, it is relatively easy to construct any desired cross-tabulation, including the cross-tabulation of house value and number of children of interest here. The final estimate for PUMA 3101 is presented in exhibit 3b. Exhibit 3a contains the actual cross-tabulations for this PUMA. Across all four PUMAs, the program does quite well. The mean absolute error per household suggests that reallocating 6 percent of the households in the super-PUMA would allow an exact match to all four actual PUMA cross-tabulations.

Exhibit 3a

PUMA 3101 Real Cross-Tabulations

House Value ($)	Number of Children				
	0	1	2	3	4+
0–49,999	111	23	8	2	3
50,000–79,999	132	28	6	7	3
80,000–89,999	82	29	19	4	3
90,000–99,999	115	18	21	5	2
100,000–124,999	223	60	47	15	6
125,000–149,999	247	55	35	15	4
150,000–174,999	146	44	39	11	8
175,000–199,999	113	34	24	10	1
200,000–249,999	90	26	30	12	6
250,000–299,999	60	16	13	5	5
300,000–399,999	37	9	11	0	1
400,000–499,999	9	0	3	1	0
500,000+	16	2	3	1	0

PUMA = Public Use Microdata Area.

[6] Go to http://pcwww.liv.ac.uk/~william/microdata/CO%20070615/CO_software.html.

Exhibit 3b

Hill-Climbing Cross-Tabulations for PUMA 3101*

House Value ($)	Number of Children				
	0	1	2	3	4+
0–49,999	110	24	7	2	4
50,000–79,999	128	29	8	8	3
80,000–89,999	94	20	21	2	0
90,000–99,999	116	21	15	8	1
100,000–124,999	236	63	35	12	5
125,000–149,999	243	48	43	14	8
150,000–174,999	153	39	40	11	5
175,000–199,999	109	35	30	5	3
200,000–249,999	98	24	25	11	6
250,000–299,999	55	21	13	6	4
300,000–399,999	24	13	12	6	3
400,000–499,999	3	4	4	2	0
500,000+	12	3	6	1	0

PUMA = Public Use Microdata Area.

** Values are rounded to the nearest whole number.*

The IPF Technique

A number of programs for doing IPF are downloadable from the Internet.[7] Several of these programs are part of elaborate data processing systems and require considerable investment of energy to learn. For beginners interested in generating only simple cross-tabulations, we found the work of Nels Tomlinson and Eddie Hunsinger (Alaska Department of Labor and Workforce Development, 2011)[8] programmed in R the simplest to customize and apply.

The basic inputs to an IPF program are four simple tables. These include (1) the marginals (in our case, the material of exhibits 1a and 1b), (2) the cross-tabulations for the larger area (our exhibit 2), and (3) and (4) an initial "seed table" for each of the small areas. The seed tables are copies of the larger area table (exhibit 2) scaled to the populations of each small area. These tables are the starting points for the successive row and column adjustments that characterize this procedure.

The IPF program generates cross-tabulations for each small area. In exhibit 3c, we present the resulting table for PUMA 3101. As with the hill-climbing technique described previously, the IPF-estimated marginals for the small-area tables match the actual values almost perfectly. A comparison of the cells of the IPF-estimated tables with the actual table cells demonstrates that IPF successfully approximated the cross-tabulations. The overall mean absolute error suggests that a reallocation of 4 percent of the households in the super-PUMA would allow an exact match to all four actual PUMA cross-tabulations. Thus, for this example, the IPF technique performed somewhat better than the hill-climbing technique described previously.

[7] Two well-known software applications are the U.S. Department of Transportation's TRANSIMS program available at http://tmip.fhwa.dot.gov/community/user_groups/transims and Arizona State University's PopGen program available at http://urbanmodel.asu.edu/popgen.html.

[8] For programs, documentation, and an introduction to the iterated proportional fitting literature, go to http://www.demog.berkeley.edu/~eddieh/datafitting.html.

Exhibit 3c

IPF Cross-Tabulations for PUMA 3101*

House Value ($)	Number of Children				
	0	1	2	3	4+
0–49,999	106	24	10	4	3
50,000–79,999	124	28	12	8	4
80,000–89,999	94	21	17	4	2
90,000–99,999	115	22	17	5	2
100,000–124,999	234	58	42	11	5
125,000–149,999	238	55	41	14	8
150,000–174,999	158	40	33	11	5
175,000–199,999	113	32	26	9	3
200,000–249,999	93	29	29	9	5
250,000–299,999	58	18	14	6	3
300,000–399,999	30	11	10	5	2
400,000–499,999	7	3	2	1	1
500,000+	12	3	4	2	0

IPF = iterated proportional fitting. PUMA = Public Use Microdata Area.

** Values are rounded to the nearest whole number.*

Discussion

Both hill climbing and IPF handle the example problem quite well.[9] It should be clear that both table-generating techniques are now executable without a major investment in training and programming. Although IPF worked somewhat more effectively for our example problem, the two techniques seem quite comparable in terms of results. At this level, IPF is probably somewhat easier to implement.

The hill-climbing technique has one major advantage: The immediate product of hill climbing is a full assignment of households to small areas. After that assignment is made, it can be used directly as a set of synthetic populations.[10] From those synthetic populations, it is relatively easy to estimate not just the initial cross-tabulations of interest but also virtually any cross-tabulations of household characteristics in the original data set. Moreover, the hill-climbing technique can be easily extended to include any number of relevant marginal conditions in the initial assignment.

In contrast, constructing a synthetic population using the IPF technique requires a major second step in which household assignments are carried out using repeated random samples constrained

[9] The results achieved here by these techniques are probably better than what can be expected generally. For one thing, the PUMA marginals we used are drawn from the same basic data set as the microsample for the super-PUMA. When the marginals and sampled microdata are drawn from separate sources, a certain amount of sampling variation would be likely. More importantly, the quality of the fit at the small-area level depends on the extent to which higher level and lower level areas have similar table structures or correlations. If the small areas are quite different from each other and from their sum, both techniques are likely to suffer.

[10] Researchers are showing an increasing interest in studying small-area phenomena. For small areas such as block groups or census tracts, microdata samples are generally unavailable. Generating a synthetic population at this small-area level means formulating a collection of households appropriately selected from a larger geography, such as a PUMA. The problem, of course, is to define what selection mechanisms are "appropriate."

by the estimated table cells (Beckman, Baggerly, and McKay, 1996). A system of this type requires more sophisticated programming. It at least necessitates becoming familiar with one of the packages (for example, TRANSIMS[11] and PopGen[12] described in footnote 7) available to the public. These packages also involve considerably more sophisticated versions of the basic IPF algorithm, because extending the dimensionality of the table to be estimated requires building estimates of lower level tables as well.

IPF and hill climbing are promising techniques for creating synthetic populations, but a number of issues remain unresolved. Generating synthetic populations from IPF results involves the synthetic reconstruction of microsamples based on stochastic approaches that are often subject to sampling error. This error is likely to be more significant for small sample areas. Even if the model estimates are unbiased, there is no guarantee that the variance will not be too large. The second problem with IPF is that it uses a sequential procedure. Some error is introduced in each stage as a result of random sampling, modeling assumptions, and data consistency (Huang and Williamson, 2002). Similar to the IPF procedure, the hill-climbing procedure is a stochastic process. Variations in the sample seed values will alter the baseline household selections and estimated distributions. Two previous studies (Huang and Williamson, 2002; Ryan, Maoh, and Kanaroglou, 2009) have compared the performance of IPF and hill-climbing methods for construction of synthetic populations. Both studies concluded that hill-climbing methods outperformed IPF.

Our somewhat tentative recommendation, therefore, is to continue using IPF for simple table construction. If you are generating more complete synthetic populations, however, hill climbing is more intuitive and perhaps more accurate.

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[12] PopGen 1.1: Population Generator, Arizona State University. http://urbanmodel.asu.edu/popgen.html (accessed May 2011).

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Impact

A regulatory impact analysis must accompany every economically significant federal rule or regulation. The Office of Policy Development and Research performs this analysis for all U.S. Department of Housing and Urban Development rules. An impact analysis is a forecast of the annual benefits and costs accruing to all parties, including the taxpayers, from a given regulation. Modeling these benefits and costs involves use of past research findings, application of economic principles, empirical investigation, and professional judgment.

The Impact of Home Energy Retrofit Loan Insurance: A Pilot Program

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Summary of Impact Analysis

The *PowerSaver* pilot program will increase the availability of affordable financing for consumers who want to make energy-saving improvements to their homes. The program results from a congressional directive to conduct a pilot of energy-efficient mortgage innovation. The U.S. Department of Housing and Urban Development (HUD) responded to the directive with *PowerSaver*, a program in which the Federal Housing Administration (FHA) offers insurance for home improvement loans to finance improvements that foster lower energy consumption. The FHA guarantee will motivate both lenders and loan investors to participate in financing energy-efficient improvements and to create a secondary market.

The pilot program is expected to result in the extension of as much as $300 million in FHA-insured, energy-efficient property improvement loans over 2 years and a resulting energy savings as high as $213 million (in present discounted value) with a cost of $174 million, a total net benefit of $39 million. Over 20 years, the annualized net benefit is $2 million per year. In scenarios using alternative assumptions, the private benefits of the program could be greater or even negative. The social benefits, however, are significant and include reduced greenhouse gas emissions, reduced morbidity, and increased knowledge generated concerning the loan program.

Need for Policy Change

Affordable financing for home energy improvements can unlock substantial energy, economic, and environmental benefits for individual consumers and for society. Despite the benefits of residential energy efficiency, relatively few homes are as efficient as they could be. Estimates suggest that less than 5 percent of single-family homes have been fully retrofitted for energy efficiency (Choi Granade et al., 2009). Multiple obstacles impede retrofit activity, including inadequate information on the costs and benefits of home energy improvements, limited availability of qualified contractors to perform retrofits, various behavioral barriers, and a lack of access to capital to finance the upfront costs of energy improvements. The undersupply of financing may lead to an overconsumption of energy and a resulting environmental degradation.

Lack of Alternatives to FHA Loans

The types of loans currently available are all problematic. Unsecured consumer loans or credit card products for home improvements typically charge high interest rates. Home equity lines of credit require owners to be willing and able to borrow against the value of their homes during a period when home values are flat or declining in many markets. Funds for subsidized revolving loans are generally limited in availability and do not always cover home improvements. Utility "on bill" financing (in which a home energy retrofit loan is amortized through an incremental change on a utility bill) has been resisted by most utilities and only serves a handful of markets on a small scale. Property Assessed Clean Energy (PACE) financing programs (in which financing for retrofits is amortized through an incremental increase in property tax or similar bills) have generated resistance from federal financial system regulators because of their general requirement to have priority over all existing liens on a property, including the first mortgage. With the exception of a few small programs serving specific markets, affordable financing for home energy improvements that reflects sound lending principles does not exist (HUD, 2010).

The programs that generally reflect sound lending principles, such as the Fannie Mae Energy Loan, are typically provided as unsecured consumer loans. The lack of securitization results in higher costs for consumers and a less liquid market for financing than a more conventional mortgage product.

For mainstream mortgage financing for home energy improvements to be more available and affordable, a viable secondary market for such products is necessary to generate liquidity through capital markets investment. Piloting the viability of a secondary market for a federally insured home energy retrofit loan program is thus an appropriate goal for the *PowerSaver* program.

Market Barriers and Market Failures in Energy-Saving Investment

Market barriers and market failures in energy conservation investment in the residential sector are evident. A market barrier is a cost of doing business that is specific to a market and is uncommonly large. In the case of energy-efficient investment, a market barrier could be any private cost of adopting energy-efficient technology[1] that inhibits the diffusion of the technology compared with

[1] See Sutherland (1991) for a description of the barriers to energy efficiency in the residential sector.

other types of investment. The existence of a market does not require government intervention. By definition, however, a market failure may require government policy to intervene so the market will reach a socially optimal level of investment. Market failures in energy conservation stem from incentive structures that lead the market to underprovide energy-efficient investment.

Analyzing market barriers may give us insight into why some retrofit projects are not undertaken. Some researchers hypothesize that the simple net present value model that engineers and manufacturers use overestimates the return on an energy retrofit. In their own studies, these researchers have found that taking account of a wider set of variables have led them to conclude that no "energy paradox" exists; not investing in energy-efficient technology is an economically rational decision. Despite such studies, significant debate continues regarding whether investment in energy-saving technology occurs at efficient levels.

Two commonly cited market barriers are (1) uncertainty and (2) high required rates of return. An energy-efficient investment is an irreversible investment for which the returns are uncertain. Given the fluctuations in energy prices, consumers may be hesitant to bet on the future direction of energy prices until an obvious long-term trend has emerged. The greater the volatility, the longer investors will postpone their investment in energy-saving equipment. Hassett and Metcalf (1995) found that, accounting for uncertainty, levels of investment in energy-saving technology appear to be optimal.

High rates of return are required for energy investments by households because discount rates are high. Discount rates have been estimated for energy-efficient investments and have been found to range from 20 percent to 800 percent (Jaffe and Stavins, 1994). In contrast, Metcalf and Hasset (1999) found that the median return to an energy-efficient investment (attic insulation) is 9.7 percent. Their result is consistent with a Capital Asset Pricing Model (CAPM) estimate of a discount rate and provides little evidence of an energy paradox. It is reasonable, however, to doubt the application of CAPM to household decisions (Sutherland, 1991). A household faces market barriers such as illiquidity and high risk that they cannot diversify, so they are likely to demand a higher compensation than the prevailing average return on business investments.

The undersupply of energy-efficient investment can also be explained by three market failures (Jaffee and Stavins, 1994). First, information concerning the energy-saving technology may be in short supply.[2] Yet, having information on the range of opportunities provided by energy conservation retrofits is critical to optimal decisionmaking concerning the adoption of a technology.[3] Second, consumers may face artificially low energy prices, which discourage energy-efficient investment. Examples of artificially low energy prices are subsidized electricity prices, environmental externalities resulting from residential use, and average cost pricing of energy that does not reflect the marginal cost of supply. Third, a major incentive problem leading to an undersupply of energy-efficient investment in the residential sector is the inability of current homeowners to recapture the full value of their investment on resale. Most households make home purchase decisions infrequently, so it is not likely that they will have a sufficient background in property investment to accurately

[2] Information has characteristics of a public good. Because the supplier of information will be unable to recoup the costs of providing the information, then the market may undersupply information on retrofit technology.

[3] The empirical analysis of DeCanio and Watkins (1998) suggests the importance of informational diffusion.

assess the value of an energy retrofit. If the homebuyer is not willing to pay for energy efficiency because its value is not transparent, then the homeowner will underinvest in energy efficiency.

Finally, one of the most pressing market failures, the overproduction of emissions, merits a separate discussion.

Negative Environmental Externalities of Energy Consumption

The primary market failure in the residential energy sector is the overproduction of emissions. The household, however, does not internalize the public damage that energy consumption brings to the environment, which leads to a "common resources" market failure in which households overconsume energy (CBO, 2003). The proposed mortgage associated with the *PowerSaver* program is not the optimal solution because it does not impose the marginal damage of energy consumption on polluters. Extending the loan for retrofits, however, could reduce the negative externalities of energy consumption. The opportunities to reduce residential energy consumption, with resulting reductions in both greenhouse gas emissions and particulate matter, are significant (EPA, 2011). According to the U.S. Energy Information Agency (EIA, 2011), the residential sector accounts for 21 percent of the energy consumed in the United States and 20 percent of U.S. carbon dioxide emissions behind electricity generation, transportation, and industrial use. The FHA loan addresses this market failure by lowering the private costs to energy-saving investment.

Summary of Notice

The Consolidated Appropriations Act of 2010 directs HUD to conduct an "Energy Efficient Mortgage Innovation" pilot program. The Act provides $25 million in appropriated funds to support such an initiative. Named the Retrofit Pilot Program, this initiative will be conducted for loans originated during a 2-year period. FHA has limited participation in the program to no more than nine lenders and has defined the eligible markets that lenders may serve. FHA envisions that the pilot program will provide insurance for up to 24,000 loans during the 2 years, with an expected average loan size of $12,500.

The FHA Title I Home Improvement Loan program provided an appropriate basis for the Retrofit Pilot Program.[4] Therefore, FHA provides a set of modifications to the current Title I Property Improvement program that yield a new product for use in the pilot. Although most of the proposed changes are relatively minor, as a group, and in combination with the appropriated funds, they create an innovative pilot program. FHA proposes augmenting these changes with incentives for lenders to participate, using funding appropriated under the Act.

Risk Mitigation

Many of the changes that FHA made to the Title I Property Improvement program were for mitigating the risk of loans originated in the Retrofit Pilot Program. Creating liquidity through

[4] The Title I program insures loans to finance the light or moderate rehabilitation of properties and the construction of nonresidential buildings on the property.

securitization requires confidence on the part of the loan investors. First, FHA adopted stricter underwriting standards (a minimum credit score and a maximum combined loan-to-value ratio) to limit the probability of default. Although these proposed changes will prevent some consumers from being able to access the program, the changes are appropriate for securitized loans. Second, FHA proposes that the holder of the note will be accountable to FHA for origination and underwriting errors and that the servicer of the loan will be accountable to FHA for servicing errors. Clarity regarding FHA claim payments made because of servicer errors will mitigate risk for potential loan investors. Third, FHA proposes to disallow dealer loans[5] under the pilot program. Dealer loans have been disproportionately correlated with poor loan performance under Title I and other home improvement loan programs in the past. In summary, all these changes adjust the Title I Property Improvement program to enable the program to encourage home improvements that increase energy performance.

Interest Cost to Borrowers

Under the Retrofit Pilot Program, as under the Title I Home Improvement Loan program, the market will determine the loan interest rate. Recent reported interest rates for Title I Property Improvement loans have been 6 and 8 percent. FHA anticipates that most borrowers under the pilot program will be able to access financing at rates at or below the current interest rate for Title I loans. HUD will use the funds appropriated under the 2010 Consolidated Appropriations Act to support activities that lower costs to borrowers. FHA proposes to allow other parties to pay discount points or other financing charges in connection with loans under the pilot program.[6] FHA projects that nominal interest rates could be reduced significantly as a result of this practice.

Changes To Improve Home Energy Performance

Under the Retrofit Pilot Program, the loan proceeds may be used primarily for measures that improve home energy performance for single-family, attached, and semidetached owner-occupied homes. Condominiums and fee-simple ownership properties are also eligible. Up to 25 percent of the loan may be used for nonenergy home improvements.

FHA proposes limiting loan maturities to 15 years, except in the case of renewable energy improvements, which may be financed with 20-year loans. This change better aligns the term of financing with the useful life and benefits of typical home energy improvements.

The funds will be disbursed to the borrower(s) in two increments: (1) 50 percent of the proceeds shall be disbursed at loan funding/closing, and (2) the remaining 50 percent of the proceeds shall be disbursed after the energy retrofit improvements have been completed and verified. This schedule ensures that work may begin but also that the work completed has been approved under the pilot program.

[5] In general, dealer loans made under the Title I Property Improvement program are marketed by home improvement contractors and executed in the form of retail sales installment contracts.

[6] Under the Title I Property Improvement program, the lender may not require or allow any party, other than the borrower, to pay discount points or other financing charges in connection with the loan transaction.

Targeting Communities

FHA determined that the most effective means for testing the program is to target communities that are best suited to deploy the program. FHA therefore intends to target the pilot program to communities that received competitive grant funding under the Department of Energy's Better Buildings Neighborhood Program. This program supports place-based retrofit initiatives; that is, those initiatives that integrate consumer education and marketing, audits and other information tools, workforce capacity, quality assurance, and financing. FHA is also willing to consider additional markets proposed by the lenders seeking to participate in the program. Targeting the pilot program by choosing communities with an established retrofit program will bias the results of the experiment. FHA decided, however, that evaluating a large number of loans was more important than evaluating a wide variety of communities.

Benefits and Costs

A reduction of energy expenditures is one primary benefit to borrowers in the Retrofit Pilot Program. The American Council for an Energy-Efficient Economy found that residential retrofits deliver an "array of benefits beyond energy savings," including greater comfort, convenience, health, safety, and noise reduction (Amman, 2006). These nonenergy benefits have been estimated to be worth from 50 to 300 percent of annual household energy bill savings.

Cost of Energy-Efficient Investment

The cost of a retrofit includes not only the cost of the energy-efficient investment, but also the cost of financing the investment. The upfront development cost is assumed to be $10,000. We assume that the average loan is characterized by a term of 15 years, a down payment of 3 percent, an interest rate of 5 percent, and a 1-percent annual insurance premium. The sum of the undiscounted mortgage and insurance premium payments is $14,785. For a consumer with a discount rate of 7 percent, the present value of the cost of the investment would be $9,980. For a consumer with a discount rate of 3 percent, the present value of the cost of the loan would be $8,640.

Private Benefits of More Energy-Efficient Homes

The net benefit of an energy-saving retrofit depends on the cost of the retrofit, the resulting reduction in energy consumption, the future direction of energy prices, and the consumer's discount rate. The potential reduction in energy consumption from the retrofit (technical efficiency) provides us with the value of annual saving at current energy prices. Pike Research (2010) analysis found a 36-percent reduction in annual energy bills from an average retrofit of $3,960. The annual bill savings is $597, which is 15 percent of the original energy-efficient investment. Pike's estimate of savings is in line with other studies; the median technical potential for reduced energy consumption in the residential sector is 33 percent for electricity and 40 percent for gas (Nadel et al., 2004).

We assume a retrofit cost of $10,000 that provides energy savings over a period of 20 years. We expect a higher level of benefits than described in most studies because the level of investment is correspondingly higher. For example, if the annual savings were 10 percent of the investment, then the annual savings would be $1,000 (0.1 x $10,000), or 42 percent of a household's annual energy expenditures ($2,400 from the 2008 Consumer Expenditure Survey). Although the savings is outside the average by a few percentage points, a high return would be expected for high levels of investment.

Assuming an energy price growth of 1 percent annually and a discount rate of 7 percent, a present value of energy saving would be $12,210 over 20 years. The benefit-cost ratio would be 1.22 ($12,210/$10,000),[7] which is not far from that of other studies. For example, Clinch and Healy (2001) estimated a benefit-cost ratio of 1.24 for a discount rate of 8 percent and their estimate is about the midpoint of other studies on energy efficiency. When the discount rate is 3 percent, our benefit-cost ratio is 1.67, which is below Clinch and Healy's of 2.14 for a discount rate of 3 percent. Data from the federal Weatherization Assistance Program indicate that every $1 invested in weatherization reduces household energy bills by $1.80 (Eisenberg, 2010).

The annual benefit, as measured by the potential reduction in energy expenditure, depends on energy prices: as energy prices rise, the energy efficiency is worth more. The longer the life of the investment, the greater the sum of the benefits. Finally, because benefits are discounted at a higher rate (that is, when the future is worth less to a consumer), then the sum of the present value of benefits will be less. For a discount rate of 7 percent, no energy price growth, and a lower energy bill savings of 37 percent, then the investor would only break even after 20 years. The net benefits of an energy-efficient retrofit are not always positive under the scenarios considered above. A project lifetime of 15 years would lower the benefit-cost ratio to 0.87. On the other hand, high benefit-cost ratios are attainable under realistic scenarios: an expected energy price growth of 3 percent, a discount rate of 3 percent, and a reduction of energy bills of 42 percent would yield a benefit-cost ratio of 2.02.

Offering a loan to pursue the retrofit has two effects on costs: it adds to the cost through the interest cost and, at the same time, postpones the costs of the investment. The net effect on cost to the consumer depends on the difference between the cost of the loan and the consumer's discount rate. The benefit-cost ratio is higher with the loan if the consumer's discount rate is higher than the mortgage interest rate, and it is lower when the discount rate is lower than the mortgage interest rate. We expect the loan to have positive effects on investment. First, the consumer discount rates have consistently been at least as high as discount rates in the context of energy-saving investment. Second, even if the interest cost adds to the costs of the investment, many consumers do not have the necessary funds to undertake significant investments without a loan. The benefit-cost ratio of the loan-financed investment is 1.34 at a discount rate of 3 percent, 1.22 at 7 percent, and 1.16 at 10 percent.

Emissions

Decreasing energy consumption will reduce emissions of pollutants (such as particulate matter) that cause health and property damage and greenhouse gases (such as carbon dioxide) that cause global warming. Data from the Department of Energy (2010) suggest that residential retrofits through the Weatherization Assistance Program reduced carbon dioxide emissions by an average

[7] For a variety of estimates, see table 1, HUD (2011).

of 2.65 tons per home per year. Over the life of the measures, weatherization is expected to save 53 metric tons of carbon dioxide emissions per home. Encouraging investment in energy-efficient housing is one of the only policy instruments available to HUD for influencing energy consumption in the built environment.

Health Benefits

Health benefits resulting from reduced mortality and morbidity are one of the benefits of energy efficiency. Greater energy efficiency allows households to afford energy for heating during severe cold or for cooling during intense heat. Being able to afford energy reduces the risk of both death and illness for vulnerable populations.

Aggregate Benefits and Costs

We calculate the aggregate benefits by multiplying the per-loan benefits by the number of loans. In the 2-year Retrofit Pilot Program, FHA would provide insurance on an estimated 24,000 home energy retrofit loans. We assume that loans are distributed evenly over that period (1,000 per month). If we take the annual saving of $1,000, 1-percent price growth, and 7-percent discount rate as a base case, then the present value of the technical efficiency of the retrofit is $12,210, and the total benefits would be $147 million annually (12,000 x $12,210). Three primary leakages to the energy-conserving purpose of the pilot program are (1) a rebound in energy use, (2) the extent to which the loan product is a windfall versus an incentive, and (3) the use of a portion of the loan for purposes other than retrofits.

Rebound Effect

Whatever the predicted technical efficiencies of an energy retrofit, a household's actual savings is likely to be smaller because of a behavioral response known as the "rebound effect." By increasing energy efficiency, the retrofit reduces the expense of physical comfort and increases the demand for comfort. In fact, the retrofit could be driven by a demand for more heating in the winter and more cooling in the summer. Although it is difficult to pinpoint an agreed-upon proportion, Clinch and Healy (2001) found that the rebound effect is usually less than 50 percent. Sorrel (2007) found an upper-end estimate of the rebound effect for space heating and cooling to be 30 percent. Likewise, Boardman (1994) found that 70 percent of the benefits of energy-efficient improvements reduce energy consumption, while 30 percent go toward increased health and comfort. Assuming a rebound effect of 30 percent yields a comfort benefit of $3,660 and an energy savings of $8,550 per participant and, given 12,000 loans annually, there would be $44 million in comfort benefits and $103 million in private energy savings for each year of the program.

The size of the rebound effect does not reduce the benefit to a consumer of energy efficiency, but it informs us of how those benefits are allocated between reduced energy costs and increased comfort. The rebound effect, however, has implications for measuring the public benefit of reducing energy consumption. If the primary goal of an energy efficiency investment program is to reduce emissions, then the amount of benefits going toward reduced energy consumption is critical.

Windfall Effect

If participants had invested without the loan guarantee, then the program would result in a transfer to consumers (or windfall) equal to the decrease in the cost of capital. We have discussed, however, the existence of significant market imperfections and the lack of affordable financing; it is, therefore, reasonable to assume that a large proportion, if not all, of the loans would incentivize new investments. Indeed, the most complete study of the energy conservation tax credit illustrates the effectiveness of federal incentives that reduce the cost of capital by encouraging investment in energy efficiency (Hasset and Metcalf, 1995).

Nonretrofit Investment

The *PowerSaver* loan is not required to finance investments in only energy efficiency. Up to 25 percent may be diverted to other home improvements. If, however, all households elect to use only 75 percent of the proceeds of the loan to finance energy retrofits, then the energy-related benefits will be proportionally lower. The most common proportion of the loan devoted to energy retrofits is expected to be 75 percent. In this case, the total private energy benefits of the program would be $110 million annually and the energy savings would be $77 million annually. The nonretrofit allowance, however, does offer some benefits. First, the allowance is useful in marketing the loan and may result in a greater diffusion of the loan product. Second, efficiencies may exist for consumers in the nonretrofit portion of the loan: consumers who need to finance renovations made necessary by the retrofit will not be required to pay the transactions costs for an additional loan.

Net Aggregate Effect

The net benefit to the consumer of the loan-financed investment is equal to the total energy benefits (energy savings plus comfort benefits) less the cost of the investment and the financing costs (see exhibit 1). For example, for an annual saving of $1,000 (42 percent reduction of energy bills), the net benefit to the consumer of the loan-financed $10,000 investment is $2,230; for an annual of reduction of $888 (37 percent), the net benefit to the consumer is $860.

The aggregate net benefit to consumers is obtained by multiplying the individual net benefit by the expected number of loans. We expect 12,000 loans annually. Exhibit 1 presents three scenarios: one in which all of the energy benefits are realized by the program, one in which 75 percent of the benefits are realized, and one in which 60 percent are realized. The 100-percent scenario assumes there are no leakages: all investment is in energy retrofits. The 75-percent

Exhibit 1

Present Value of Energy Benefits and Costs for 1 Year of Pilot Program ($ millions)

Retrofits Induced by Pilot (%)	42% Reduction in Annual Energy Bill			37% Reduction in Annual Energy Bill		
	Total Energy Benefits ($M)	Total Costs ($M)	Net Benefits ($M)	Total Energy Benefits ($M)	Total Costs ($M)	Net Benefits ($M)
100	147	120	27	130	120	10
75	110	90	20	98	90	8
60	88	72	16	78	72	6

Assumptions: $2,400 annual energy bill, 7-percent discount rate, 12,000 participants annually, $10,000 cost of retrofit, 5-percent mortgage interest rate, 1-percent periodic insurance premium.

scenario assumes the maximum allocation toward nonconservation uses, with borrowers investing 25 percent of the loan proceeds in other improvements. The 60-percent scenario also assumes nonenergy leakage but also assumes that 40 percent would have been invested without the loan (windfall effect). It is reasonable, however, to assume that a large proportion, if not all, of the loans will generate benefits. Because a small share of homeowners historically has invested in home energy improvements, HUD believes that the likelihood that households that receive a loan would have renovated otherwise is small.

The estimated energy saving over the lifetime of the program, given a 100- and 75-percent incentive effect, is provided in exhibit 2.

To measure the social value of an investment in energy efficiency, one must add the expected social benefits of reduced energy consumption. An indepth analysis by Clinch and Healy (2001) of domestic energy efficiency found the benefit-cost ratio to be 2.38 (when the discount rate is 8 percent). Energy reduction benefits represent most of the benefits (52.1 percent), followed by health benefits (29 percent), comfort benefits (10.9 percent), and emissions reduction[8] (7.6 percent). Their results can be used to estimate the value of nonenergy benefits. Adding reduced emissions raises the benefit-cost ratio of energy benefits (savings plus comfort) by 12 percent (7.6/(52.1+10.9)) from 1.22 to 1.37. The benefit of reduced emissions per consumer is $1,465 ((1.37-1.22)) x $10,000). With 12,000 loans, this benefit amounts to $18 million and increases annual net benefits from $27 million to $44 million (in the 100-percent scenario) or increases the benefit amount from $20 million to $38 million (in the 75-percent scenario).

Exhibit 2

Total Energy Benefits and Costs of Program ($ millions)

	100% Participation			75% Participation		
	Total Energy Benefits ($M)	Total Costs ($M)	Net Benefits ($M)	Total Energy Benefits ($M)	Total Costs ($M)	Net Benefits ($M)
Year 1	147	120	27	110	90	20
Year 2	137	112	25	103	84	19
Total	284	232	52	213	174	39
Annualized	26	11	2	20	8	2

Assumptions: 42-percent reduction in annual energy bill, 7-percent discount rate, over 21 years.

Transfers

Transfers are neither costs nor benefits, because they do not add to or detract from social welfare but instead redistribute income.

FHA

It is difficult to calculate a precise estimate of the credit subsidy rate for this program absent any data or experience. However, we do have estimates for the Title I Property Improvement program

[8] The authors assume a rebound effect of 40 percent. The benefits from reducing emissions may be greater in the current analysis in which the rebound effect is assumed to be 30 percent.

on which the pilot is based. FHA estimated the credit subsidy rate for the Title I Property Improvement program to be -0.76 percent and the expected claim rate to be 4.51 percent. The underwriting and operating features of the pilot program will not contribute to a higher risk profile than the Property Improvement program on which it is based. Thus, the Property Improvement estimates can be used to illustrate the effect of the pilot program. If the credit subsidy rate were -0.76 percent and the loan volume $150 million annually, then the FHA could expect $1.14 million (0.76 x $150 million) from the pilot. We expect this program will generate positive transfers for FHA.

Consumers

The transfer to consumers is equal to the difference between the FHA interest rate and the interest rates on alternative types of loans available for retrofits. If the next best interest rate for the consumer were fairly low, at 9 percent, but above what is expected for a Title I Property Improvement loan, then this loan would represent a transfer of approximately $2,000 per household ($12,027 - $9,984). Such a transfer, or windfall, would apply for households that would have financed an energy retrofit without the incentive of an FHA loan. In a previous discussion, however, we concluded that most households would not invest without the FHA loan.

Conclusions

The purpose of the *PowerSaver* pilot program is to test and demonstrate the feasibility of low-cost financing for secured home energy retrofit loans. Although other financing options are available for consumers, these alternative programs typically experience minimal usage. Among the many broader objectives of this program are creating a market for a new type of loan, reducing market barriers to investment in energy efficiency, and limiting the carbon footprint of the housing stock. If FHA is able to learn from the pilot and launch a broader program, then it may achieve these broader objectives.

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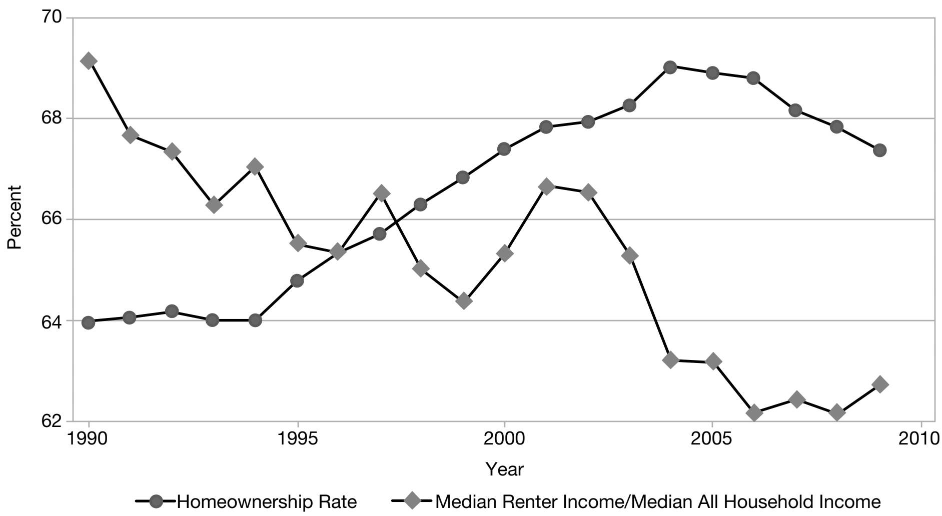
Correction

In the volume 13, number 2 issue of *Cityscape*, in the article titled, "Rental Housing Affordability Dynamics, 1990–2009," by Rob Collinson, there was an error in the legend in exhibit 2. The legend indicated that the diamond-point line corresponded to the homeownership rate and the circle-point line reflected the ratio of renter income to household income. These markers should be reversed; the homeownership rate is depicted with a circle-point line, while the ratio of incomes is represented by the diamond-point line. The correct version of this exhibit appears below.

Exhibit 2

Renter Income/All Household Income Versus Homeownership Rate, 1990–2009



Source: Census Bureau, Current Population Survey, Public Use Microdata Sample, 1990–2009

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