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Intra-Metropolitan Crime Patterning and Prediction

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Note to reader.

Two manuscripts produced in the course of the current project do not appear in this final report. Those manuscripts are:

Groff, E. R., Taylor, R. B., Elesh, D., Johnson, L. T., & McGovern, J. (2014). Permeability across a metropolitan area: Conceptualizing and operationalizing a macro level crime pattern theory. *Environment and Planning A, 46*(1), 129-152.

Johnson, L. T., Taylor, R. B., & Groff, E. R. (2015). Metropolitan local crime clusters: Structural concentration effects and the systemic model. *Journal of Criminal Justice, 43*(3), 186-194. http://dx.doi.org/10.1016/j.crimjus.2015.03.002

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1. INTRODUCTION

> “The term ‘metropolitan area’ has come to signify the territory in which the daily economic and social activities of the local population are carried on through a common system of local institutions. (McKenzie, 1933/1967: 84).

> “L.A. scholars frequently urge policymakers across the region to respond to social problems in concert. The region, however, is unusually ill-equipped for such cooperation” (Miller, 2000).

1.1. The Focus and the Setting

This work examines the patterning and predictability of jurisdictional-level reported crime in the Philadelphia-Camden primary metropolitan statistical area. Spatial, temporal, and spatiotemporal features of the crime patterning are each investigated. The patterns are examined through three complementary lenses: the ecology of crime, the geography of crime, and the political economy of crime. Then, given what those inspections suggest, we examine the extent to which crime shifts prove predictable if we forecast a year ahead, or three years ahead.

1.1.1. The Three Lenses Briefly

Ecology of crime models focus on identifying the structural and cultural correlates and precursors of community crime levels, while acknowledging that communities play specific roles in the broader system of interlocked communities making up the region.

Here the communities examined are jurisdictions and the broader region is the Philadelphia (PA)-Camden (NJ) primary metropolitan area.

Because the current study is limited to structural indicators in the form of community demographic structure, the key ecology of crime questions are: what are the impacts of different features of demographic structure on current crime or changing crime? If some jurisdictions are getting safer faster than others or more dangerous faster than others, what are the structural precursors of those shifts? The systemic model of crime (Bursik & Grasmick, 1993b) and the Land-McCall-Cohen (LMC) model of structural covariates of homicide will offer different predictions (Land, McCall, & Cohen, 1990; McCall, 2010; McCall, Land, & Parker, 2010; McCall & Nieuwbeerta, 2007).

The geography of crime lens focuses on two broad feature sets of crime patterning: spatial and spatiotemporal. Several questions arise from the spatial perspective. Of most importance are the following. If we start at the top of the cone of resolution (P. J. Brantingham, Dyreson, & Brantinghm, 1976) with the most macro-level consideration: How are crime levels patterned across the metro region?; Are some parts of the region safer than others? Coming down the cone: can we statistically identify sub-regions of geographically adjoining jurisdictions where crime levels are higher than the surround? Or lower than the surround? Coming even further down the cone: Are crime levels of focal jurisdictions spatially influenced, due to spatial autocorrelation between their levels and crime levels among the immediately surrounding jurisdictions of each focal jurisdiction? Further, how do such dependencies shift the answers to questions about the ecology of crime?

Turning to spatiotemporal variation, if some places are getting safer or more dangerous faster than other places, are those differences in the rates of change spatially patterned? For example, area there clusters of geographically proximate jurisdictions where violent crime rates were going up faster than anywhere else in the region?

The political economy of crime lens considers the implications of crime structural covariates and determinants, and of spatial and spatiotemporal patterning, for broader questions of structural inequality and power differentials across jurisdictions. Previous work (see below) on the region has highlighted strengthening structural inequality in recent years. Is there also a pattern of inequality based on crime? If so, how does that align with and perhaps reinforce broader structural inequalities across the region? What are the implications of the spatiotemporal shifts in crime for such inequalities? Do the spatio-temporal patterns seen suggest *increasing* inequalities across the region over the decade examined?

1.1.2. Setting: Metropolitan Areas and This Metropolitan Area [1]

Metropolitan areas emerged in the United States in the first decades of the Twentieth Century and represented a new type of community "which is unique in the history of settlement" (McKenzie, 1933/1967: 6). Writing in the 1930s, Chicago

[1] The purpose of this section is not to provide a historiography of the Philadelphia metropolitan area, or of US metropolitan areas broadly. The purpose is simply to explain the scholarly origins of the term metropolitan community as a prelude to offering the current definition of a metropolitan area.

sociologist Rod McKenzie divided settlement in the United States into three periods. In the first period, up until about 1850 in the US, cities were

> entrance points to producing regions [and] functioned as collecting centers for the basic products from surrounding settlement and as distributing points for manufactured good brought in from outside territory. These gateway centers maintained contact with tributary territory through a community hierarchy of villages, towns, and cities... (McKenzie, 1933/1967: 4)

In the second period, from about 1850 to about 1900, railroads became increasingly prominent and "the city acquired an increasing range of economic and social functions which it performed not only for its own inhabitants but for rural settlements as well" (McKenzie, 1933/1967: 5). This increased each city's economic and cultural dominance over its region. Cities became centers for more than just goods passing through. People in the wider region could now more easily get to the city for a range of employment, entertainment, purchasing, or business purposes. Around larger, older cities the rise of railroads affected not only inter-region but intra-regional travel as well. Trolley lines or regional rail lines extended far from cities, giving rise to streetcar suburbs, for example (Warner, 1962).

But from a spatial perspective, it was still hard for people to move around except along rail lines; thus it was still hard to them to get to know those nearby. Or, as McKenzie put it: "the railroads … did not materially change the traditional pattern of life within the local community" even though rails now connected smaller and bigger communities like different size beads on a string. Except in "the larger cities where mechanical forms of transportation were introduced …local institutions and social relations persisted in the railway regime on much the same basis as in the previous era" (McKenzie, 1933/1967: 6).

But "the third period of settlement" which "began about 1900 or shortly thereafter" was different (McKenzie, 1933/1967: 5). Broadly, McKenzie labeled this era "an era of city regionalism which is developing under the influence of motor transportation" (McKenzie, 1933/1967: 5). Broadly, but significantly, "this new motor-highway net" which was "superimposed on existing rail networks and settlements" resulted in marked changes. Most importantly, "by reducing the scale of local distance, the motor vehicle extended the horizon of the community and introduced a territorial division of labor among local institutions and neighboring" (McKenzie, 1933/1967: 6). Numerous consequences followed. The ensuing changes were "more disturbing to the social fabric" than had been the changes introduced by the rail era (McKenzie, 1933/1967: 6). Of most interest to us here among those changes are the emergence of centers and sub-regions of the metro area that are differentiated by land use and industry type, with implications for the differentiation in the types of residential settlements emerging close to such centers.

A metropolitan area in the US is a cluster of geographically adjoining counties that has two parts: an urban nucleus and a surround. The nucleus must be an urbanized area (county) with a population of at least 50,000 residents (Office_of_Management_and_Budget, 2000). The surrounding counties, called "outlying" counties in the metro area, connect at least one of the urban core counties in the metro area. Commuting data as reported in the Census provides information on the counties where residents hold jobs (Office_of_Management_and_Budget, 2000). According to the

2000 definition, the urban core county is sufficiently connected to each of the immediately adjoining "outlying" counties in the metro area, and vice versa, if either of the following conditions hold: "at least 25 percent of the employed residents of the [outlying] county work in the ... [metro area's] central county or counties, or (b) at least 25 percent of the jobs in the potential outlying county are accounted for by workers who reside in the ... central county or counties" (Office_of_Management_and_Budget, 2000: 82233).

So counties are the basic building blocks of metro areas. The nine counties in the metro area appear in Figure 1. Burlington, Camden, Gloucester and Salem counties in New Jersey are on the east side of the Delaware River, and Bucks, Chester, Delaware, Montgomery and Philadelphia counties are in Pennsylvania on the west side of the Delaware River.

Figure 1 also outlines the sub-county political units that are the primary focus of the current project. These sub-county geographic/political units, which we call jurisdictions, are comprised of two types: "municipalities" and "minor civil divisions". Both of these types are included in the broader term "Incorporated Places." The latter include cities as well as towns, townships, and boroughs (US_Bureau_of_the_Census, 2013).

The jurisdictions investigated here are

> legally defined county subdivisions" and they "are the primary divisions of a county. They comprise both governmentally functioning entities — that is, those with elected or appointed officials who provide services and raise revenues — and

> nonfunctioning entities that exist primarily for administrative purposes, such as election districts….the legal powers and functions of jurisdictions vary from state to state (US_Bureau_of_the_Census, 2013).

In Pennsylvania and New Jersey, jurisdictions "serve as general-purpose local governments … [and] are commonly known as … townships, and districts, but also include a variety of other lesser known identifiers" including boroughs.

Turning to the second type of incorporated place, we have "municipal governments" as distinct from "town or township governments" The scope of governmental services provided by these two types of governments varies widely from one state to another, and even within the same state. The area served by municipal and town/township governments may overlap in some states. But Pennsylvania and New Jersey are both "town or township states" and "there is no geographic overlapping of these two kinds of [governmental] units" (US_Bureau_of_the_Census, 2012). Cities in the Philadelphia-Camden metropolitan region have municipal governments.

Figure 2 maps the different jurisdiction types. The cities of Philadelphia; Chester, located three or so jurisdictions south-southwest of Philadelphia; and Camden, immediately to the east of Philadelphia, are readily recognizable. But there are other cities as well including places like Coatesville in mid-Chester County and Salem City. Clearly, however, the most frequent jurisdiction type in the metro region is the township.

This region qualifies as complex for several reasons. Its physical geography includes two large rivers. Its political geography includes two different states and 355 jurisdictions, those jurisdictions ranging in population size from more than a million to a few dozen. Those jurisdictions are of several different types: cities, townships, and boroughs. Its settlement geography ranges from multiple densely settled cities either within the core counties of the MSA (Philadelphia and Camden) or further out in the region (e.g., Coatesville), to older dense suburbs to newer more spacious suburban locales to rural farming communities.

To provide just a flavor of the stark contrasts around the region, consider the following socioeconomic extremes. The metropolitan community is home to two of the 50 richest zip codes in the US. 19085, home to Villanova University and Radnor Township in Montgomery County along the Main Line in the near western suburbs of Philadelphia, clocks in as the 30th richest in 2011 (Stonington & Wong, 2011). But Gladwyne, 19035, sandwiched between the Main Line communities strung along US Route 30 and the Schuylkill Expressway, with its curving streets, winding driveways and stately manors generally invisible from the road, beats it out, earning 7th place. If we want to focus on areas smaller than zip codes, then perhaps the pinnacle of privilege is the borough of Pine Valley in New Jersey, home to one of the world's most challenging and exclusive [2] golf courses, and a few dozen houses occupied by club members (Fensom, 2012).

Turning from the pinnacles of privilege to the most deeply disadvantaged communities in the region and perhaps the country, only 13.58 miles west of the police

[2] Women are only allowed to play one day a year. No one can play on the course unless invited to do so by a member. Tiger Woods has never been invited to play there (Fensom, 2012).

station guarding the golfers and residents at Pine Valley one finds Camden's iconic RCA Victor (Nipper) building, with the stained glass images of the classic RCA label, the attentive hound, ears cocked, perched high above the Camden city waterfront. Only this building remains from the sprawling RCA industrial complex where recordings, records and Victrolas were made in the first years of the 20th Century, and radios and televisions in mid- and late-century. Based on recent (2011) Census data, Camden was labeled "the poorest city in the country with a poverty rate of 42.5 percent" (Terruso, 2012). The city hosts block after block of vacant, boarded up housing or vacant lots. In 2014 about one out of seven houses were abandoned, totaling over 3,000; there were also over 8,000 vacant lots in the city (Shelly, 2014).

The City of Camden is so poor that it recently (2012-2013) had its roughly 400 officer police department cut in half and then disbanded (J. Goldstein, 2011; Zernike, 2012). And in late March of 2013 Governor Christie of New Jersey announced that the state was taking over the city's schools, although not infusing any new funds. On the Pennsylvania side, the cities of Chester and Coatesville have extremely high poverty rates as well.

Complexities appear in the transportation network infrastructure as well. It includes some of the most heavily used sections of interstate highway in the country (I-95), five major bridges spanning the Delaware River at different points, and two extensive regional public transportation networks (PATCO (Port Authority Transit Corporation) and SEPTA (Southeastern Pennsylvania Transportation Authority)). The latter manages, in addition to the subways in Philadelphia, regional rail lines running throughout the region, as well as bus and trolley lines. At the same time, the metro region also hosts Washington

Township in Burlington County (NJ). The second largest jurisdiction in the region (102 square miles), only two state routes run through it. This is because much of the township is home to Wharton State Forest, "the largest single tract of land within the *New Jersey* State Park System." [3]

Its policing geography proves varied as well. Safety is produced by different types of police agencies. Most frequently found here are municipal producers: city, township or borough-level police departments. State police agencies also play a major role in producing safety. In New Jersey the state police provide exclusive police coverage in 15 jurisdictions; in Pennsylvania the state police provide exclusive police coverage in 40 jurisdictions. A small number of rural departments demonstrated an "alternation in time" pattern of police patrolling, with state police assuming those functions during certain hours (Ostrom, Parks, & Whitaker, 1978: 30-31). Another complication in policing, which is not surprising given the variation in populations across jurisdictions, is that local police departments of many different sizes. Local police departments dedicated to just one jurisdiction and with at least one sworn full time officer ranged in size from 1 to 6,781 sworn officers. The typical (median) local police department employed 14 sworn officers. Such variation in policing arrangements is not atypical.

In addition to being complex, the metro area is big and home to a lot of people. The metro area covers 3,830 square miles; 5,383,081 people called someplace within the

[3] Wharton State Forest – State of New Jersey. [ONLINE: www.state.nj.us/dep/parksandforests/parks/wharton.html ; accessed 9/13/2014]

nine counties "home" in 2013. [4] Its land area is almost four times the size of Rhode Island, and about half the size of Hawaii. Its population is about 3.8 times the size of Hawaii's and 5.1 times Rhode Island's. The population on the Pennsylvania side represents 31.8 percent of the entire population in the Commonwealth of Pennsylvania.

1.2. More on the Three Lenses

This section amplifies the conceptual underpinnings of each of the three lenses brought to intra-metropolitan crime patterns in the current work. Each amplification is not meant to be exhaustive. The point is simply to outline how the answers to the questions investigated here have import for these three different theoretical frames.

1.2.1. The Ecology of Crime

Its complexity and size notwithstanding, the Philadelphia metro region is still a *system*, whose different parts influence one another. For the purposes of understanding crime patterns, "an important part of the ecological perspective concerns the symbiotic relationships between different parts of the system" if we are to avoid "an incomplete understanding" of the relevant dynamics (Bursik, 1986b: 60). To understand the jurisdiction-level relationships among the "different parts of the system" requires analyzing the *entire* metropolitan. Otherwise, researchers and policy makers run the risk of making mistakes, like confusing "exogenous shocks to an ecological system" with "integral, endogenous developments within the system itself" (Bursik, 1986b: 60).

[4] quickfacts.census.gov; county totals retrieved July 12, 2014; calculations by the authors.

As Bursik has argued, although the city was the "entire ecological structure" when Chicago researchers investigated delinquency in the second quarter of the last century, given suburban development for the last five decades, current researchers who limit delinquency or crime research to "an ecological system as defined by the political boundaries of the central city may be ignoring a significant portion of the actual system" (Bursik, 1986b: 60).

We suggest that the primary metro area, the geographic container examined here, captures the vast majority of the "actual [ecological] system." According to Bursik's argument, a full understanding of crime dynamics will emerge only from examining the ecology of crime across the *entire* ecological system. Others, most notably McKenzie (1933/1967), have previously made the case that the metropolitan community shifts local social life, the organization of employment and settlement patterns of different segments of the population, and deserves consideration as a unit unto itself.

Understand the ecology of intra-metropolitan crime patterns *as a system* means being geographically complete. To the best of our knowledge, this is the first study to examine jurisdiction-level intra-metropolitan crime patterning using complete geographical coverage. That completeness proves especially critical for several reasons.

Most importantly and most simply, unless we can examine crime across the entire system, that is the entire metropolitan region, we have an incomplete idea of the correlates of crime, of the relative crime niches occupied by different jurisdictions and, most importantly, of the net contribution of jurisdiction level factors vs. surround to a jurisdiction's crime rate. This is because we need information from the entire metropolitan region if we are to model the impacts of spatial dependencies in crime rates across jurisdictions (see below on geography). If those are not taken into account, we mis-estimate the net contributions of specific jurisdiction structural factors to jurisdiction crime levels.

The size of the relative contributions of the three fundamental structural dimensions of community fabric – socioeconomic status, residential stability, and racial composition – to a jurisdiction's crime level, *net* of the influence of surrounding crime levels in nearby jurisdictions, sheds light on the relative merits of two different perspectives linking community demographic structure and violence levels. The basic systemic model of crime (Bursik & Grasmick, 1993b: 39) highlights the structural relevance of socioeconomic status, residential stability, and race to community crime and delinquency levels. By contrast the LMC research approach to structural covariates, especially in light of replication efforts mostly at the city level, highlights the relevance of a resource deprivation/affluence factor which is composed largely of socioeconomic variables (Land & McCall, 2001; McCall, 2010; McCall, et al., 2010; McCall & Nieuwbeerta, 2007). The importance of socioeconomic variables is also underscored by recent summaries of research on community crime correlates (Pratt & Cullen, 2005). That meta-analysis found economic variables like poverty to be the strongest correlates of higher crime rates, with racial composition also proving important in most works.

Therefore, should the current work find that *all three* of the fundamental demographic dimensions of community – SES, stability and race – link to community (especially violent) crime levels, such a finding would lend more support to the basic systemic model of crime than to the LMC view on community structural correlates of violence. This is because stability's influences figure centrally in the dynamics of the basic systemic model.

Further, structural correlates could prove interesting for a different reason: they may link to later crime levels. Cross-sectional and longitudinal analyses often produce disparate results (Lieberson, 1985: 180-182). Well known cross-sectional correlates of violent and property crimes may link less strongly to crime when crime changes are considered.

Of course, since policing levels and arrangements vary across the metro area, it will be important to control for those as well. Previous studies on structural correlates of jurisdiction crime have not done so.

1.2.2. The Geography of crime

Spatial

When considered through a geography of crime lens, several features of crime levels will prove noteworthy. Starting with descriptive matters: looking at the metro area as a whole, how are crime levels patterned geographically?

Both McKenzie and Hawley expected deconcentration of centrally located populations to outlying areas as metropolitan regions grew, that shift facilitated by easier transport. "But the most important of all redistribution trends is the centrifugal movement from the metropolis and, in fact, from virtually all sizeable cities in the metropolitan area" (Hawley, 1950: 421). These expansion patterns suggest concentric zonal differentiation.

At the same time, both also recognized that nucleation would occur because "like units … subsist upon the same conditions, seek the same locations. This simple principle appears to operate in all sections of the community" (Hawley, 1950: 274). So, broadly, if the geography of crime follows the geography of structural patterns, we would expect to see a concentric zonal patterning of crime *and* polynucleation of high crime levels around local subcenters.

Shifting down from the entire region to sub-regions, we can ask: are there local clusters of contiguous jurisdictions comprised of relative safety or relative danger? If so, where are they, and how do we make sense of their location in the broader metro region? Further, if we look at these sub-regions over time, how much do they from year to year? Do they stay in relatively the same place? Or move markedly?

Shifting even further down the spatial scale, we can ask about crime levels across neighboring jurisdictions. Do we see patterns of spatially autocorrelated crime levels? In past works, crime levels and to a lesser extent crime changes have proven spatially autocorrelated at a number of scales ranging from census tracts within cities to counties in the US (Baller, Anselin, Messner, Deane, & Hawkins, 2001; Chainey & Ratcliffe, 2005; Lersch, 2007; Walsh & Taylor, 2007). This means two things. First, distance-dependent, crime-relevant dynamics operating at spatial scales greater than the geographic units analyzed are operative. Second, if researchers fail to reflect these spatial autocorrelations in their models, either by including spatially lagged outcome variables as predictors, or by including spatially patterned error terms, impacts of predictors included in these models are likely to be mis-estimated, at the least.

We have no studies of intra-metropolitan, jurisdiction-level crime that properly reflects such spatial dependencies. One study of jurisdictions in a large number of metropolitan areas failed to analyze geographically complete surfaces in each metro area, and thus was unable to assess and control for spatial dependence of crime rates (Kneebone & Raphael, 2011). Consequently, that study may have mis-estimated intra-metropolitan connections between structural features and crime, and between crime and geography.

Spatiotemporal

If we add a temporal dimension, additional geographic questions surface, but they are now spatiotemporal rather than temporal in nature. We build here on substantial spatiotemporal research at various sub-city levels. That scholarship has investigated differential crime changes over time in hot spots, streetblocks, and neighborhoods (P.L. Brantingham, Glasser, Jackson, Kinney, & Vajihollahi, 2008; Bursik & Grasmick, 1993a; E. Groff, Weisburd, & Yang, 2010; Hermann, 2013; Ratcliffe, 2002; Ratcliffe, 2004, 2006; Sorg & Taylor; Weisburd, Groff, & Yang, 2012) Related work includes studies on the spatiotemporal patterning of fear of crime or insurgent attacks (Doran & Lees, 2005; Townsley, Johnson, & Ratcliffe, 2008). At the micro-scales of time and space these works consider impacts of daily, weekly, and seasonal variation on crime locations or reactions to crime, and address potentially relevant micro-level victim, offender or policing dynamics. At somewhat larger temporal and spatial scales these works consider the factors shaping localized crime trends at the streetblock or neighborhood levels across a series of years, a decade, or multiple decades. Spatiotemporal interactions are a booming area of investigation in both the geography of crime and community criminology literatures.

In this study, the most basic spatiotemporal question is whether crime levels are shifting at different rates in different parts of the metro area. Controlling for the features of the jurisdiction, is the passage of time associated with more rapid crime shifts, either up or down, in some jurisdictions compared to others? This is a question about spatiotemporal patterning of crime changes at the jurisdiction level.

The same question can be organized to ask about extralocal effects. If a jurisdiction is experiencing faster than average crime level increases over time, is it likely to be surrounded by nearby jurisdictions where crime is also increasing faster than average? Are the rates of crime change spatially autocorrelated at the jurisdiction level? If this turns out to be true, the same question can be organized at a higher, sub-regional level. If rates of crime change are spatially autocorrelated, do geographic clusters of adjoining jurisdictions emerge that share a similar rate of crime change? This would suggest local diffusion processes (Loftin, 1986) are shaping the changes. Broadly, are there some sub-regions within the metro area that are all getting worse together on crime over time? Or where they are all getting better together on crime over time?

1.2.3. Political Economy

The findings that emerge in response to the geographic and ecology of crime questions described above have implications for the broader political economy of the region. Political economy questions emerge from this simple fact about metropolitan areas: "Every great city now has around it a metropolitan area, one with it economically and socially but without political unity. The consequences in many instances have been little short of disastrous" (McKenzie, 1933/1967: 303) because this political differentiation sets the stage for socioeconomic and racial disparities, and thus political conflict. (A comprehensive review of scholarship and debate about the structure of metropolitan governance and issues of inequality is not intended here (L. A. Brown & Sharma, 2010; Jimenez, 2014; Jimenez & Hendrick, 2010; Ostrom, 1983).)

From this perspective there are two broad matters of concern. First, how do spatial differentials in structure and crime map onto the political landscape? Does the geography of crime inequalities map out in similar ways to the observed structural inequalities? Are the inequalities in crime capturing the same features of inequality patterns seen with the structural variables alone? Or are the crime inequalities capturing something different? Second, what are the implications of the crime patterns, and links between crime and structure over time, for broader inequality throughout the region? If crime disparities reinforce structural disparities, and vice versa, over time doesn't that widen public safety as well as structural inequalities across the region? Do we see such a widening in the first decade of the 21st Century?

Political economists attend not only to inequalities across space, but also to the ways metropolitan space is organized. Different sociological and geographical schools of anticipate that metropolitan space will be organized in different ways (Adams, Elesh, & Bartelt, 2008; Dear & Dishman, 2001; Erie & Mackenzie, 2009; Gottdiener, 1994; Molotch, Freudenburg, & Paulsen, 2000). To oversimplify, when thinking not about crime but about jurisdiction-level features of population, employment, land use and housing, some scholars expect patterns dominated by center-periphery gradations, others expect polynucleation, others expect road network structures to be determinative, while others expect historical influences to predominate. To our knowledge, no scholars to date have examined complete intra-metropolitan crime patterns to see how those patterns align with these different expectations. It bears pointing out, however, that some of the earliest scholars of metropolitan areas anticipated that these arenas would exhibit both center-periphery gradient features and polynucleation (Hawley, 1950; McKenzie, 1933/1967).

Current scholars also have noted this differentiated, polynucleated structure, but have offered different explanations than have McKenzie and Hawley. In contrast to the “biological organicism” of human ecologists, current more conflict-oriented scholars see forces outside metropolitan communities as the key shapers of the metropolitan geographies. The views of one new urban sociologist, Gottdiener, are a case in point (Gottdiener, 1994: 68). A state/capital/land nexus restructures metropolitan space in accordance with “monopolistic development interests” at different scales, and “other societal actors, including businesses and residents, must adjust” (Gottdiener, 1994: 67). Such scholars see and reject a “technological determinism at the very core of ecological thought” expressed in the writings of McKenzie, Hawley, and others (Gottdiener, 1994: 40). They disagree that “the quality of movement abstracted as transportation and communication” has been the “spatial generating factor of complex modern social formations” in metropolitan areas (Gottdiener, 1994: 40).

Gottdiener, and others including Harvey, Logan, and Molotch, critique the ecologists on a number of grounds. Most important has been their critique of what the ecological models have left out: “factors such as class conflict, the voluntaristic impulse in environmental decision making, the vested interests operating in space, the influence of government programs and policies, the changing nature of economic organization, and the production of uneven spatial development” (Gottdiener, 1994: 40-41).

Stated at its broadest, a political economy perspective assumes that underlying the ecological patterns seen -- whether the patterns concern crime or demographics of resident populations or housing, resources, land use, or amenities -- are complex influences arising from history, political and economic power differentials, and race-and status-linked dynamics (Logan, 1978; Logan & Molotch, 1987). Conflict and divergent histories create spatial and structural inequalities throughout the region.

For example, work on the Camden syndrome was based originally on studies examining patterns of disinvestment in jurisdictions in Camden County outside of the impoverished city of Camden (Smith, Caris, & Wyly, 2001; E. K. Wyly, 1999; E.K. Wyly & Hammel, 1999). That work showed patterns of disinvestment afflicted jurisdictions in proximity to Camden city, even before those jurisdictions began to change racially or socioeconomically. Mortgage loan denial rates in jurisdictions elsewhere in Camden County were as high as the denial rate in the extremely disadvantaged city of Camden, or sometimes even higher, even though those jurisdictions outside the city were socioeconomically and racially quite dissimilar from the City of Camden. The jurisdictions experienced pre-emptive disinvestment on the expectation that later economic and racial changes would adversely affect future house prices. Of course such pernicious practices hastened the very outcome they tried to avoid.

Scholars of the Philadelphia region such as Carolyn Adams and colleagues (Adams et al., 1991; Adams, et al., 2008), and earlier researchers (Muller, Meyer, & Cybriwsky, 1976), have observed patterns of sizable and increasing spatial inequality at least since the 1970s. They have documented racial, economic, employment, housing and service differentials. They link such increasing inequality to pre-existing, emerging, and intensifying power and resource differentials across different governmental units in the region and the spread of governance functions across these 355 jurisdictions. Adams and colleagues have argued that "governmental fragmentation in our metropolitan region establishes incentives that exaggerate social and economic inequalities (Adams et al., 2008: 32)." They describe a region "that is decentering and has balkanized into hundreds of small, separate jurisdictions that offer their residents widely differing opportunities to work, live, and educate their children (Adams et al., 2008: 193).

Theoretically, this Balkanization supports Warner's (1968) privatism thesis, elements of which were repeated by Baltzell (1979) in his discussion of civic leadership in Philadelphia. Warner's (1968) model, originally just applied to the city of Philadelphia, describes the roles of local traditions which benefit from a city and a region Balkanized along lines of race and class while simultaneously strengthening such compartmentalization. Adams and colleagues (2008) apply the core idea of the thesis to the metro region, documenting how these inequalities continue to develop throughout a region dominated by private business interests where regional planning is almost nonexistent.

That said, the analyses to date of jurisdiction-level spatial inequality in the Philadelphia metro area offered by Adams and colleagues have been limited in two important respects. First, their analysis failed to include reported crime. So it is not clear whether patterns of inequality will be reflected in crime levels in the same ways that they have been reflected in SES, housing, and education. Second, their analyses failed to take into account the extent to which the inequalities they described were explicitly spatially patterned. In their analyses, spatial dependencies were not explicitly described or modeled. Therefore, we include spatial analyses of crime patterning which describe the geography of crime inequality, and gauge its statistical strength, across the region.

The current work also makes a third contribution to understanding the political economy of the region. We can see if spatial inequalities in crime are increasing over the years of the first decade of the new century. If they are, this portends deeper structural inequalities for the region in the future; crime rates, in addition to being an outcome of community structure, also shape later community structure (R. B. Taylor, 1995). So increasingly spatially unequal crime rates are likely to contribute to increasingly spatially unequal structural differences across the region in the future.

1.3. Implications for prevention and forecasting

What we learn about the ecology of crime, the geography of crime, and the political economy of crime at the jurisdiction and sub-region levels will have two important sets of implications. First, controlling for jurisdiction composition, do policing coverage rates, or police department size, affect later crime changes? Can more police or higher levels of police coverage prevent later increases in property or violent crime? After factoring in community residential composition, and surrounding crime, do police levels matter? This is the main prevention implication of the current work. Specific results relevant to prevention are noted in later chapters as appropriate.

Second, can current crime or current jurisdiction structure or both do a decent job of forecasting future crime levels? This is the main policy implication of the current work, and is addressed in a separate chapter.

Both these issues are introduced briefly below.

1.3.1. Police coverage and prevention

The main implication for prevention explored in this project is the impact of police coverage rates on later changes in crime. The current data set provides no information on police cultures and the associated "varieties of police behavior" (Wilson, 1968). It does, however, provide information on police/population coverage ratios while controlling simultaneously for police arrangements, residential composition, and surrounding crime.

As Harries pointed out almost 4 decades ago, "the quality of law enforcement in a given area is a function of a number of factors" (K. Harries, 1974: 91). The current work is only able to gauge law enforcement quality in a very limited way.

Scholarship has investigated a number of different types of indicators of policing coverage. Those indicators fall roughly into two groupings. Economists interested in crime spillover effects have investigated impacts of police coverage, often but not always operationalized as the ratio of sworn officers to 1,000 residential population (Becker, 1968; Burnell, 1988). The ratio of sworn officers appears preferable to the ratio of total employees given that inconsistencies sometimes appear with reporting the civilian side of police departments (Uchida & King, 2002). The assumption behind a mere coverage indicator is that mere variations in police presence have significant implications for arrest probabilities.

But policing scholars have pointed out that officers spend much time doing things other than investigating and making arrests, and that police departments organize themselves along different cultural and mission lines. In Wilson's terms, there are different "varieties" of police behavior, and those different varieties can be found in different departments, and perhaps even in different precincts within one department (Klinger, 1997; Wilson, 1968).

Such recognition of the complexities and varieties of police work and police organizations has led to scholars to investigate indicators of policing that better capture police aggressiveness or proactivity. From a deterrence perspective such indicators are of interest. The extent to which police are policing proactively and aggressively is likely to have a stronger deterrent on past or would-be offenders than indicators merely capturing police presence. Of course, as always with macro-level deterrence theory, there are a lot of assumptions about the underlying dynamics. “Consistent with the deterrence perspective, it is assumed that a greater police presence will reduce crime rates because would-be offenders adjust their perceptions to the increased probability of arrest” (Kubrin, Messner, Deane, McGeever, & Stucky, 2010: 59).

In order to minimize the stretch required by such assumptions, crime scholars interested in deterrence have sought conceptually cleaner indicators of police proactivity or aggressiveness. A range of indicators have been used, many widely criticized (Wilson & Boland, 1978). These include, in addition to police coverage rates: clearance (arrest/reported crime rates) and moving violation citation rates. These indicators, and measures of mere police presence, have generated conflicting findings (Kubrin, et al., 2010). Perhaps the most innovative indicator of police aggressiveness/proactivity is Sampson and Cohen’s proposal to use the rate of (arrests for (DUI +disorderly conduct)/n sworn officers) (Sampson, 1986; Sampson & Cohen, 1988a). Sampson and Cohen’s work, and Kubrin and colleagues’ follow-up work, have suggested deterrent impacts of police aggressiveness/proactivity, although different studies find different crimes are affected.

The work done using police aggressiveness/proactivity has been limited to large cities with populations of 100,000 or more. The data in those studies were derived from the same UCR annual reports (Return A) that we have used here both for crime counts and for sworn officer counts.

In the current work we opted to use indicators of police presence expressed as coverage rates rather than police aggressiveness/proactivity. There were several reasons. First, the work with aggressiveness/proactivity has been restricted to much larger jurisdictions – cities with over 100,000 population – than are being investigated here. Second, there are many different types of policing arrangements across the metro region. These will be described below. It is not known how the summoning of police resources to address disorderly conducts, or the positioning of officers to observe DUIs, might depend on these different types of arrangements. Finally, and most simply, the needed information for the proactivity/aggressiveness indicators in use in current studies is simply not available for large numbers of jurisdictions either because of their policing arrangements or because of jurisdiction/department matching or reporting issues.

Given these issues, we opted to rely on ratios of sworn officers/1,000 residents. We also have available an alternate measure of police strength, total law enforcement employees/1000 residents, which is used in some work (Zhao, Ren, & Lovrich, 2012). It is possible in the current work to gauge temporally lagged impacts of police coverage rates, on later crime levels, while controlling for policing arrangements.

Organizing these policing data proved **challenging**. See Appendix 1. These challenges are substantial, as are the implications of the availability. The implications get addressed in the final chapter.

Police strength indicators have been accepted by econometricians in their work. In addition, recent work supports the construct validity of such measures (Zhao, et al., 2012). Crime, economic resources, and racial composition drive strength levels. That recent work further suggests that municipality cultural factors, expected to drive police aggressiveness/proactivity, do not shape police strength levels (Wilson, 1968; Zhao, et al., 2012). The implication is that these two aspects of police presence – strength and aggressiveness/proactivity – are likely to be reflecting relatively independent aspects of police operations. Therefore, impacts observed or not observed here for police coverage should not be generalized to indicators of police aggressiveness/proactivity.

1.3.2. Look-ahead Forecasts

Crime forecasting is one of several "Holy Grails" avidly pursued over many decades in criminal justice and criminology. Strong forecasting capabilities, properly integrated into organizational structures in law enforcement, public safety, budgeting, oversight, or prevention can enhance ongoing or special occasion planning reviews, and inform resource allocation decisions. In times of progressively tightening budgets and keener competition for funds from Federal and state sources, such forecasts might prove extremely useful both for those disbursing and those seeking funding. Whether forecasting enhancements could end up transforming these reviews and allocation decisions in the ways that CompStat has modified ongoing strategic and tactical reviews within police departments remains to be seen (Klinger, 2003; Silverman, 1999; Weisburd, Mastrofski, McNally, Greenspan, & Willis, 2003). Nevertheless, the potential is there, especially if integrated into an intelligence-led policing and public policy framework (Ratcliffe, 2008). All that is required is that the crime forecasts be relatively accurate, easily understood, routinely produce-able without significant reliance on external expertise, low cost, and easily institutionalized into one or more organizations' current decision-making structures. Both a review of current research (below), and a National Academy recent report suggest we have not yet attained that goal (Council, 2008). Current work on predictive policing at the micro-scale (see below) may, however, be getting us somewhat closer, albeit at substantial societal cost.

Background

Extensive studies of crime forecasting exist for a wide variety of forecast periods and an array of spatial units (Cohen, Gorr, & Olligschlaeger, 2007; Deadman, 2003; Fox, 1978; Gorr & Harries, 2003; Gorr, Olligschlaeger, & Thompson, 2003; E.R. Groff & La Vigne, 2001; Elizabeth R. Groff & La Vigne, 2002; Land & McCall, 2001; Pepper, 2008; Rohde, Corcoran, & Chhetri, 2010). We are not aware, however, of any studies which engaged in one-year crime forecasts at the jurisdiction level for an entire MSA. Such a study is completed here.

At bottom there are three practical concerns behind this question. First, how good are the forecasts? What is the typical error rate for one-year, look-ahead crime forecasts? Is the error rate low enough to make such forecasts practically useful? Second, given higher frequencies of property as compared to violent crimes, and therefore higher rates for the former, are forecasts more accurate for property as compared to violent crimes? Third, are forecasts based solely on crime as good, or almost as good, as forecasts based on crime and additional factors like community structure? Criminal intelligence analysts are used to working with crime data. Although many may be somewhat proficient with census data, forecasts based solely on crime data are probably easier for analysts to implement into routine procedures. If forecasts based only on crime are almost as good as more complex forecasts, it may make sense to encourage analysts to rely primarily on crime for crime forecasting at the jurisdiction level. The forecast models examined here can be contrasted with results from a recent forecast modeling of city crime rates (Pepper, 2008).

Variations in meaning

The meaning both of forecasting and of community have varied significantly across studies. Forecasting has been concerned especially with the accuracy of "near term" crime changes (Gorr & Harries, 2003). "Near term" has meant different things in different studies. It may be a two week window or a two year period or even longer (Cohen, et al., 2007; Pepper, 2008). "Communities" range in size from hot spots to street blocks to communities to cities (Baumer, 2008; Jeffrey Fagan, 2008; J. Fagan & Davies, 2002; Kianmehr & Alhajj, 2008; Pepper, 2008; Weisburd, Bushway, Lum, & Yang, 2004). Of course, there also has been significant work at even the national level (Blumstein & Rosenfeld, 2008; R. Harries, 2003; Pyle & Deadman, 1994). The crimes of interest may be broad categories or specific crime types like burglary (Deadman, 2003; Liu & Brown, 2003).

Variations in methods

Not only does one find dizzying variation in spatial and temporal scales, so too in the range of methods applied. They vary from relatively simple autoregressive or exponential smoothing models; to moderately complex univariate and transfer-function (multivariate) time series, cross-sectional (panel) time series, and growth curves; to highly complex machine learning, neural network, trajectory and regional econometric approaches (Anselin, 1988; Anselin, Florax, & Rey, 2004; Cohen, et al., 2007; Deadman, 2003; Gardner, 1985; Kianmehr & Alhajj, 2008; Nagin, 2005; Olligschlaeger, 1997; Pepper, 2008; Phillips & Greenberg, 2008).

Additional regional science models like spatial multilevel Bayesian approaches would also seem to hold considerable promise (Banerjee, Carlin, & Gelfand, 2004) (I. Langford, Leyland, Rasbash, & Goldstein, 1999; I. H. Langford et al., 1999). Some studies seek to demonstrate the superiority of one analytic approach over another while others argue for the stronger practical relevance of ensembles of models (Cohen, et al., 2007; Durlauf, Navarro, & Rivers, 2008).

Theoretical advances and outstanding questions

Accurate crime forecasting could yield much-needed theoretical as well as practical benefits. Over the last two decades interest in predicting the "wheredunit" of crime as well as the "whodunit" has grown (Sherman, Gartin, & Buerger, 1989; R. B. Taylor, 1998; Weisburd, 1997). Resulting work has yielded not only practical insights into crime and prevention but also theoretical advances (Bennett, 1995; Braga et al., 1997; Eck & Weisburd, 1995; Mazerolle, Soole, & Rombouts, 2007; Sherman, et al., 1989; Weisburd, et al., 2004; Weisburd & Eck, 2004; Weisburd & Lum, 2005; Weisburd et al., 2006). Save for a small number of notable exceptions, it is only very recently that micro-level, sub-city studies of crime changes have started to yield important insights into the local processes contributing to rising or dropping crime rates (Bottoms & Wiles, 1986; Covington & Taylor, 1989; Harrell & Gouvis, 1994; Liu & Brown, 2003; Schuerman & Kobrin, 1986; R. B. Taylor & Covington, 1988). These recent advances notwithstanding, we are still at sea theoretically. One senior scholar recently stated "given the current state of research and theorization, no definitive explanatory framework can be offered" for understanding how and why features of local context link to crime or crime changes (Bottoms, 2007: 565). Thus, if we can learn more about what predicts crime changes, it might move us closer to such a definitive explanatory framework

The Need

These variations notwithstanding, researchers and policy makers alike agree that accurate and efficient short- and long-term trend reports and projections are needed (Gorr & Harries, 2003). A recent National Academy of Sciences report tells us: "Descriptive information and explanatory research on crime trends across the nation that are not only accurate but also timely are pressing needs in the nation's crime control efforts" (Rosenfeld & Goldberger, 2008: 1).

What could forecast crime at what levels?

An enormous range of features could link to crime changes. At the city level these might include changes in: offender removal rates, offender return rates, illegal drug use and market activity, employment and immigration, policing available, gun availability, and percent of the population in high crime groups (Baumer, 2008: Figure 5.1, p. 129). In the same way that different structural changes accompanied delinquency changes at the community level in different decades, links to crime changes at the city level depend in part on the decade in question (Baumer, 2008: 164; Bursik, 1986b). In the 1990s, for example, for large cities the most important correlates of declining crime were increasing incarceration rates, an improving economy, and smaller groups entering high crime teen years. Another analysis of the same cities over the same period, however, suggests a substantially overlapping but slightly different set of covariates of changing crime rates (Pepper, 2008: 193). Regrettably, we cannot say firmly which are the strongest covariates of changing community or city crime rates; this is because extremely few studies include good indicators of all potential predictors of crime changes (Baumer, 2008). This is in contrast to the work with cross sectional community- or city-level crime where results are *somewhat* more consistent across studies (Pratt & Cullen, 2005). Differences between cross-sectional and time-varying linkages may reflect differences between two types of predictors representing, respectively, stocks and flows (Phillips, 2006).

It is also difficult to say whether the link between predictors and later crime is better modeled as uniform or varying across cities. In one case the latter type of model provided better "in sample" forecasts but the former provided better "out of sample" forecasts (Pepper, 2008; Swanson & White, 1997).

Despite the variation in study methods, sets of predictors, and levels of analysis, the work on forecasting and on the crime drop does suggest some factors which link to and could serve as leading indicators of crime changes. At the national level unemployment and crime do connect (Hale & Sabbagh, 1991a, 1991b; R. Harries, 2003). That said, the specifics of that connection and its variation across specific crime types are debated. Similarly with the connection between incarceration and crime at the state level; more in prison may link to lower crime but we may disagree on which crimes were affected and by how much (Levitt, 1996; Marvell & Moody, 1994).

Different factors may be relevant at different levels of aggregation. For example, Blumstein and Rosenfeld suggest good leading indicators of crime changes at the national or state levels could be demographic changes in age, ethnic/race composition, incarceration, and economic shifts (Blumstein & Rosenfeld, 2008: 18). Others disagree on some of these like incarceration (DeFina & Arvanites, 2002). At the city level Blumstein and Rosenfeld suggest a different set of relevant factors: cross-city variations in policing, firearm possession, firearm suppression rates, drug market activity and use patterns, gangs, and service availability.

In addition to framing different sets of causes at different units of aggregation, recent lessons learned from investigations of the crime drop include: disaggregate crimes as much as possible, separate longer term from shorter term trends, and allow for specific local histories to shape trends (Rosenfeld & Goldberger, 2008). This last point suggests crime trends over time may vary by location. This is one of the points raised in discussing spatiotemporal patterning of the geography of crime.

There is no question that current theories suggest a very broad array of factors that could shape future crime trends, especially at the municipality or city levels (Bursik & Grasmick, 1993b; Pratt & Cullen, 2005). For any one cluster of predictors–economics; race/ethnicity including composition, heterogeneity, and segregation; gangs; drug and drug market activity; firearms and firearm suppression efforts; police; social services;

removal and return rates of offenders and ex-offenders; demographics–we could have lengthy debates about which indicators to choose and how to model them. Much past research has been constructed to address just such choices (Shihadeh & Ousey, 1996).

Theoretically relevant vs. practically available

The theoretical richness, however, contrasts painfully with the range of indicators *routinely available with only low effort and low cost* to administrators, policy makers and planners at the municipality, city, or regional levels. That much shorter list boils down, at present, to two classes of variables: crime and demographics. Law enforcement personnel data are available on an annual basis, but not for all localities.

Using crime to predict crime

Police routinely record non-serious (Part II) as well as Part I crimes. Past studies have used Part II crimes or calls for service for Part II offenses to predict later crime changes or later changes in call rates. The prediction window has ranged from census tracts over a decade to precincts over a month to .64 $mi.^2$ cells over two weeks (Cohen, et al., 2007; Gorr, et al., 2003; Harrell & Gouvis, 1994).

It turns out that crime or calls for service can decently predict small scale, short term changes over the next fortnight or month. For example, exponential smoothing with pooled controls for seasonality generated one-month look-ahead forecasts at the precinct level in Pittsburgh with mean absolute percentage errors (MAPE) of about 24 percent (Gardner, 1985; Gorr, et al., 2003). In one of the few studies to take into account changing crime or crime call counts in adjoining areas, about one half of large crime changes appearing in small grid cells in Pittsburgh were forecast using a fortnight look-ahead window and a variety of different models (Cohen, et al., 2007). Even simple autoregressive models just using lagged crime rates might provide decent prediction for city-level, one year look-ahead forecasts. "In these short-run forecasts, one might not be able to do better than predicting that tomorrow will look like today" (Pepper, 2008: 207). Autoregressive models, however, may miss big changes or turning points.

Controversies

Crime forecasting, and related concepts such as "predictive analytics" for crime or "predictive policing," have proven controversial since their inception. Fox's forecasting work in the late 1970s sought to predict future US crime trends at the national level, and earned sharp criticism on analytic and conceptual grounds (Brenner, 1979; Felson, 1981; Fox, 1978).

Current predictive policing models like PredPol used by the Los Angeles Police Department, and others, seek to forecast where particular types of crimes will emerge in the near future and orient to small scale grid squares, perhaps as small as 500' by 500' on a side (Goode, 2011). Conceptual underpinnings connect to well-known near-repeat phenomena in crime patterns (Bowers & Johnson, 2004; Ratcliffe & Rengert, 2008; Townsley, Homel, & Chaseling, 2003). But, again, substantial controversy surfaces. There are important legal procedural concerns related to privacy.

> Many aspects of current Fourth Amendment law are implicitly or explicitly based on prediction. Search warrants are predictions that contraband will be found in a particular location. Investigative detentions are predictions that the person is

> committing, or about to commit, a crime. Fourth Amendment concepts like probable cause, reasonable suspicion, informant tips, drug courier profiles, high crime areas and others are based on evaluating levels of probability that criminal activity will occur or is occurring. Predictive policing both fits within this established tradition and also challenges it in novel ways. As will be argued, predictive policing may, in fact, necessitate a reconsideration of some of the existing reasonable suspicion doctrine, as well as point to refinements in future application (Ferguson, 2012: 262-263).

There are also important conceptual questions about such predictive analytics. One such technique is risk terrain modeling (RTM). This embodies a broad risk factor approach, another long and controversial tradition in criminology (Wikstrom, 2006, 2007; Wikstrom & Teiber, 2009). What is new here is that it is applied to places. But there is the same problem with risk factors applied to individuals: the researcher has no idea *why* these factors link to criminality or crime. The mechanisms are not specified.

> Caplan et al. (2010) have proposed that risk terrain modeling (RTM) offers a way of looking at criminality as less determined by previous events and more a function of a dynamic interaction between social, physical and behavioral factors that occurs at places. They suggest that the ways in which these variables combine can be studied to reveal consistent patterns of interaction that can facilitate and lead to crime. The computation of the conditions that underlie these patterns is a key

> component of RTM, with the ability to weigh the importance of different factors at different geographic points in enabling crime events to occur. *These attributes themselves do not create the crime*. As Caplan et al. suggest, *they simply point to locations where, if the conditions are right, the risk of crime or victimization will go up* (Kennedy, Caplan, & Piza, 2011: 342-343, emphasis added).

Such an open-ended, a-theoretical approach contains both risks and limitations. Researchers may develop models that are largely data-fitting exercises. Covariation between predictor scores and outcome scores in a sample of data arise from many sources: underlying theoretical dynamics at work, peculiarities of the place and period being modeled, and measurement error. A data fitting exercise that is a-theoretical risks focusing too much on the latter two factors, and less on the first one. Such an approach makes it difficult to generalize about such predictive relationships.

On the other hand, if a theoretical frame guides the selection of predictors from the first, then the researcher at least has some clues about two things: first, what underlying mechanisms might be responsible?; and, second, in what direction *should* the predictors link to crime risk? If forecast models contain links opposite to the theoretical direction expected, that should be concerning.

Current focus

The goal here is to see how well three different forecast model types – using current crime rates, or current demographic structure, or both – predict future crime rates while controlling for law enforcement levels and arrangements. There are sound *theoretical* reasons why earlier crime should link to later crime, and why earlier community demographic structure should link to later crime. In addition, the model hopes to learn whether the better forecasting model depends upon either the specific crime type, or the length of time used to build a model, or both. If earlier crime predicts later crime as well as earlier demographics-plus-crime predicts the same outcome, then police analysts need not compile yearly demographic information to make their one-year, look-ahead crime predictions. On the other hand, if demographic information does contribute to superior forecasts, then law enforcement analysts concerned with regional crime patterns will want to use such factors in their crime forecasting.

More specifics on how the three types of models are formulated are provided in the chapter on forecasting. Further, that chapter will introduce results from one of the most comprehensive, recent jurisdiction-level crime forecast studies (Pepper, 2008). Of interest in the current work are the ways current forecast patterns agree and disagree with this recent comprehensive study.

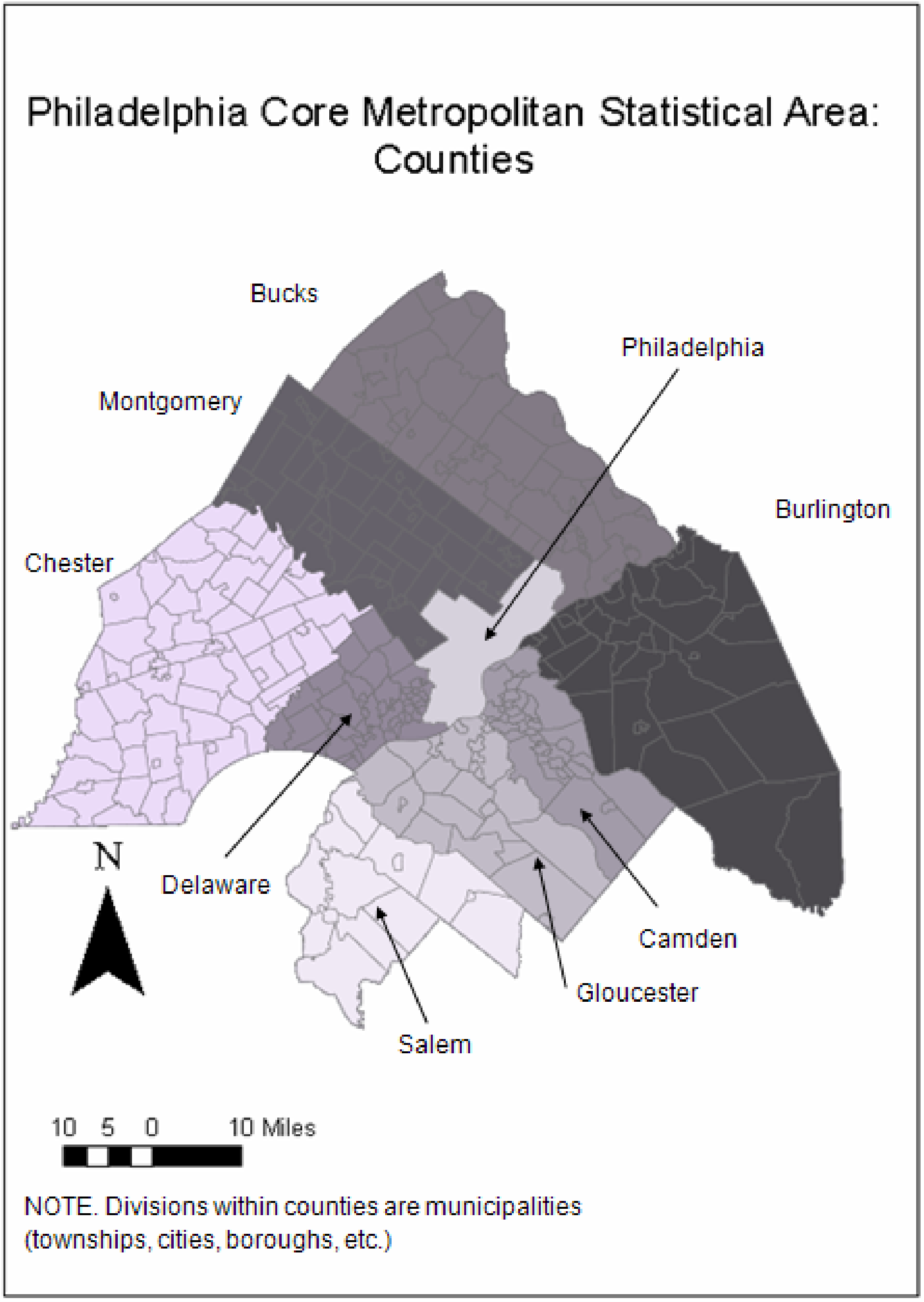

Figure 1. Counties in Philadelphia-Camden primary metropolitan statistical area

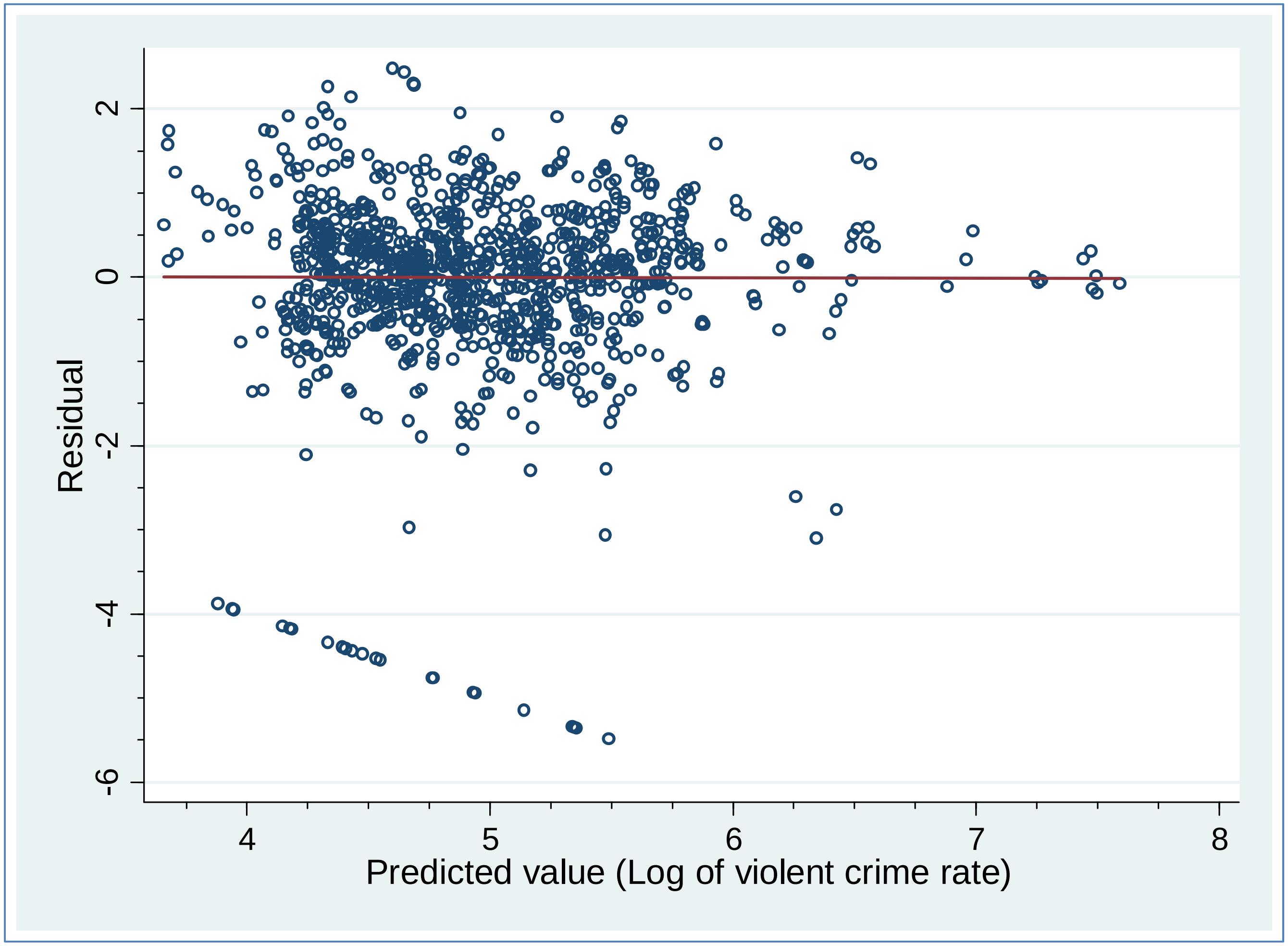

Figure 76. Log of violent crime: Predicted scores and residuals.

Note. Predicted values from Model B (demographics only), three-year forecast window, appear on X axis. Residuals appear on Y axis. Line = linear regression of y on x. (run = 126)

7. IMPLICATIONS FOR THEORY, POLICY AND PRACTICE

7.1. Overview

We can consider the implications of the results presented in the previous chapters from six different angles. There are three theoretical angles: implications for the ecology of crime, the geography of crime, and the broader political economy of the region. For policy and practice concerns there are three issues: agency crime data collection mandates; given how crime changes are patterned, why nearby departments need to share police intelligence; and variations in police coverage rates.

7.2. Implications for Theory

7.2.1. Ecology of crime

One well established stream of ecological research on community structure and homicide, the Land-McCall-Cohen (LMC) school of research, has provided evidence over the past two decades that, aside from spatial unit size/density, the only consistently important demographic covariate of community homicide levels is a broad-based low-SES/racial composition factor (Land, et al., 1990; McCall, 2010; McCall, et al., 2010; McCall & Nieuwbeerta, 2007; Parker & McCall, 1999). Researchers in this group also say that size of spatial unit is largely irrelevant, and that the same basic relationship can be uncovered using different types of spatial units (e.g., city vs. metropolitan area). This last claim is not fully supported (Ralph B. Taylor, 2015). Nevertheless, this group's emphasis on SES-linked variables and race seems supported by Pratt and Cullen's (Pratt & Cullen, 2005) meta-analysis which found that SES linked variables like poverty, and racial composition, were the two strongest correlates of community crime rates.

But Bursik and Grasmick's basic systemic model of crime presents a different view (Bursik & Grasmick, 1993b: 39). These researchers emphasize the importance of all three well known dimensions (Golledge & Stimson, 1997) of community demographic structure: race, SES, and residential stability. Considerable empirical work underscores the net relevance of residential stability to changes in crime and delinquency (e.g., (Bursik & Webb, 1982)). But Pratt and Cullen's meta-analysis results suggest it is less important than status or residential composition.

Results from different models provide more support to the basic systemic model than the LMC model. All three demographic components -- SES, residential stability, and racial composition – linked with crime or crime changes in the ways anticipated by the systemic model. In fact, of the three components of community structure, residential stability proved **the most important**. Arguably, the ability of each community factor to predict later crime changes is the most important benchmark of the worth of each. Across all four changes, stability was the only community demographic feature that had a significant net impact for each outcome (see section 5.5.1).

Such a pattern raises questions about past work in this area. Are the results here different from LMC research because a) a broader category of violent crime rather than just homicide was investigated? Or b) because other studies have under-operationalized residential stability (Messick, 1995)? Or c) because the spatial units investigated here are not cities or entire metro areas, some of the two most common spatial units used in that stream of research?

In addition to the questions raised about the LMC research stream, the results call into question one of the most comprehensive recent studies of intra-metropolitan crime patterning. Kneebone and Raphael (2011) failed to include any stability indicators in their multi-metro area investigation. If they had included it, their results could well have been quite different since stability appears theoretically central. The connections observed in that study between jurisdiction demographic structure and crime should therefore be viewed with extreme caution.

Of course, the current results, based on models where predictors included only law enforcement and community demographics, don't provide a test of the overall adequacy of the basic systemic model of community crime. Social, organizational and cultural dynamics included in that model have not yet been measured, nor have their connections with structure and crime been examined. One advantage of the basic systemic model, as compared to others such as LMC, is that it specifies particular social, organizational, and cultural dynamics that respond to changes in community demographic structure, and that in turn affect delinquency and crime. Hopefully in future researchers will be gathering the data needed for such tests of the model.

An important question as that future research unfolds is whether the meaning of local social dynamics will be different at the jurisdiction level than at the intra-city community level. For example, collective efficacy dynamics may be less relevant to jurisdictions than communities (Gerell, 2014).

We can consider what the results say about the ecology of crime at a more general level. They confirm the system aspect of the ecological perspective in numerous respects. Jurisdiction structure affects crime now and crime later. Once we know the kind of people living in a jurisdiction, we can estimate current crime levels, we can predict spatial and temporal changes in crime and, to a lesser extent, we can predict the temporal shifts of crime levels within a particular jurisdiction. Second, results show repeatedly and in different ways how jurisdictions are affected by nearby jurisdictions. There are system-like connections across jurisdictions. Not only do the results included in this report make this point. Two other papers emerging from this project but not included in this report demonstrate this as well. Groff and colleagues (2014) show how the effects of nearby crime on a focal jurisdiction depend on the physical barriers between adjoining jurisdictions. Johnson and colleagues (2012) observed the structural correlates of sub-regions of relative safety and relative danger.

7.2.2. Geography of crime

The results from the current study have revealed several features of the jurisdiction-level geography of crime in the Philadelphia metropolitan area.

Some of the geographic findings that surfaced appear to be novel. Sub-regions of the metropolitan region, i.e., geographic clusters of adjoining jurisdictions, appeared where all the jurisdictions in the cluster were becoming more dangerous on violent crime faster than places in the rest of the region, or were becoming safer faster than places in the rest of the region. Such clusters were especially likely to be found in particular parts of the metropolitan region. Jurisdictions on the west side of the Delaware River located between southwest Philadelphia and the city of Chester were most likely to be in this getting-more-dangerous-fastest sub-region. Some of the smaller jurisdictions just southwest of the city of Camden in Camden County also seemed likely to be in this group (see Figure 49, Figure 51). Both these sub-regions are characterized by being near high crime areas (city of Camden, city of Chester, southwest Philadelphia), being small, having substantial non-white populations, and being along major traffic arteries for the region.

At the same time, on the flip side, there was one large sub-region where jurisdictions were doing a better job of going up less slowly on violent crime, or moving down more quickly on violent crime, compared to those jurisdictions around them (Figure 49, Figure 52). This sizable sub-region straddled mid-Delaware County and mid-Chester county.

Putting these two sub-regional changes over time together points toward a disturbing conclusion: within the metro region, sub-regional inequalities in public safety from violent crime were increasing during the first decade of the 21st Century. As the decade progressed, some sub-regions were getting more dangerous faster than the rest of the region, and some sub-regions were getting safer faster than the rest of the region. Public safety inequality across the entire region worsened.

Somewhat less novel and in line with voluminous research on the geography of crime with smaller and larger geographic units than used here, results underscored the crucial and *multiple* roles of spatial dependence. Jurisdictions' crime levels were shaped by the crime levels around them, and specific sub-regions of relative safety or relative danger surfaced. Taking these spatial dependencies into account requires data sources which are geographically complete (see more below under policy). Models in other studies (Kneebone & Raphael, 2011) which have failed to model these spatial dependencies may have provided misleading results.

7.2.3. Political economy of crime

The Challenges given metropolitan growth

Metropolitan areas lacking metropolitan governance, especially if they have a long history, have many older and smaller jurisdictions which are afflicted with resource and governance challenges. These challenges arise from the outward migration of residents and jobs in metropolitan areas over time, migrations that have been taking place in American metropolitan areas for over a century (McKenzie, 1933/1967). This expansion and outward migration creates “frictions” that “may remain as permanent stresses in the expanded [metropolitan] community” (Hawley, 1950: 425). “An expanding [metropolitan] organization engulfs and spreads over many political subdivisions such as smaller cities, village, townships” (Hawley, 1950: 425). But, despite shifting “manufacturing and service functions” there is “no redistribution and reorganization of administrative or governmental functions” (Hawley, 1950: 425).

> The net result is a confusion of jurisdictional boundaries, or unequal governmental powers, and of conflicting administrative polities ... concerted action in dealing with communitywide [metropolitan] problems is virtually impossible. The protection of public health, the efficient exercise of police power, the control of land use ... the equitable distribution of tax burdens, and many other such matters are severely hampered, if indeed they are accomplished at all (Hawley, 1950: 426).

Sub-regions of high and increasing violent crime

Results seen here align with Hawley’s expectation that the smaller jurisdictions in the older part of the metropolitan area, left behind by out-migrating middle class households and living wage employers, would be the most “severely hampered.” Repeatedly, the smaller jurisdictions on the west side of the Delaware River, spreading from southwest Philadelphia down to the city of Chester and beyond, had the most problematic violent crime rates and the fastest increasing violent crime rates. Eddystone, right next to the city of Chester, surfaced repeatedly as an outlier. To a lesser extent jurisdictions in Camden County just outside the city and further southeast along US Route 30 proved problematic as well.

Contributing factors

What seems to make these sub-regions problematic is that there are a) *several* smaller jurisdictions located near one another, b) most of them populated by households of modest means, c) in proximity to a larger and extremely disadvantaged city or portion thereof (Chester or Camden or southwest Philadelphia), and d) traversed by some of the most heavily traveled portions of the region's road network. There is a concentration problem: several probably inadequately policed jurisdictions are co-located. This creates a broader, sub-regional vulnerability given possible spillover effects (Fabrikant, 1979). There is an adjacency problem: the sub-region adjoins some of the poorest, highest crime places in the metro region. And there is a burden problem: easy access and high volume transportation networks increase drug market activity and thus violence (Rengert, 1996).

A Cultural component to vulnerability?

An analysis by Dayanim (2014) of inner ring suburbs on the Pennsylvania side of Delaware River confirms the vulnerability of the smaller jurisdictions stretching from southwest Philadelphia to the city of Chester, and suggests cultural as well as structural dynamics are likely relevant. She anticipated that "community institution vibrancy" (Dayanim, 2014: 102) at the beginning of the decade (2000) would correlate positively with changes later in the decade on "local resilience" which reflects "an MCD's ability to attract and retain residents" (Dayanim, 2014: 102) . Resilience included measures of economic change (e.g., dropping house value) and shifts in perceived local social climate including latent neighborliness (Mann, 1954). Community institution vibrancy captured both "municipal financial commitment to community institutions" (e.g., municipal budget share of spending on parks and recreation) and "resident participation at community institutions" (e.g., per capita library circulation) (Dayanim, 2014: 102).

Although questions surface about the indicators used by Dayanim (2014), [21] what proves intriguing is that the same jurisdictions proving in this study vulnerable to high violent crime and rapidly increasing violent crime get labeled by her as low on *both* resilience and vibrancy. See Figure 77.

Dayanim's (2014) work suggests there is a cultural thread involved in the vulnerability to high and rapidly increasing violent crime demonstrated by these small jurisdictions between southwest Philadelphia and the city of Chester. Such concordance aligns well with key points in the basic systemic model of crime (Bursik & Grasmick, 1993). In fact, if a cultural component in the form of local social climate dynamics was *not* suggested, that would prove problematic for the basic systemic model and other frames in community criminology as well.

Important question

From a political economy perspective, the worsening spatially organized public safety (from violent crime) inequalities across the region prove concerning. The current study spreads the discussion of intra-metropolitan crime patterns beyond the already-known features: higher violent crime in centrally located urban cores and immediately adjoining suburban jurisdictions. Results here show that outlying urban cores, places like Coatesville, Pottstown and Salem City,

[21] Scores on local social climate were not independent across jurisdictions. Not all resilience indicators reflected changes.

have violent crime problems as well. Further, they show that immediately adjoining suburban jurisdictions may have violent crime rates that are sometimes higher than those in urban cores. And finally, they highlight specific sub-regions of high and increasing vulnerability while at the same time other sub-regions are doing better at staying safer.

Perhaps the most important question for this perspective is determining the local and extra-local structural, cultural, and crime contributions to the geographically organized picture of increasing violent crime inequality. *Over time,* how do earlier positions on and changes in structure, culture, and crime, affect later crime changes? This work has suggested there is something going on in some sub-regions of the metropolitan area. We don't know yet the extent to which that reflects broader structuration dynamics (Molotch, et al., 2000), or more specific dynamics like the Camden syndrome (Smith, et al., 2001). We also don't know specifically how crime *as a cause* contributes to such shifts. Nor do we know how cultural dynamics, especially around local social (R. B. Taylor, 2002) and local political dynamics (Crenson, 1983) link in to these dynamics.

7.3. Implications for Policy and Practice

Four main policy-related implications emerge from this research. All have relevance to state and local governments as well as police. The first relates to the difficulty of assembling complete information for *all* jurisdictions in a major metropolitan area, and the impact this has on our potential for recognizing the important role of jurisdictions in preventing crime. Obtaining accurate and timely data, the first implication, is a necessary precondition if one is to act on the other three implications. The second concerns the movement to evidence-based practice in law enforcement. This requires information about crime and police coverage in order to fuel conversations and evaluations about what is working in policing. The third relates to the critical role of information sharing among jurisdictions. The fourth, and broadest, concerns the important role of the built environment in setting the stage for crime.

7.3.1. Data assembly difficulties

The current study unearthed several difficulties with obtaining complete crime data information for all jurisdictions in the metro area. At the Federal level, the Uniform Crime Report Return A data, provided by the FBI, were both incomplete, because there were no data from jurisdictions which did not report their own crime data, and presented some tangles. As an example of the latter, a separate field for counties was not included. So we had to figure out, cross referencing UCR and Census population numbers, where the data for each of the three Springfield Townships in the metro area should be geo-located. The bigger issue, incompleteness, arose because different policing arrangements obtained in different places. If there was no local police department, no crime numbers were funneled up through the respective state police agency and thus to the FBI. The New Jersey State Police at the state level *did* remedy the incompleteness issue. Their annual reports provided separate counts for each jurisdiction where they were the sole police agency. The Pennsylvania State Police (PSP), however, did not do this. The PSP did provide county crime counts for places where they were the sole policing agency. But, *these data are not geo-located to the individual jurisdiction within a county.* Therefore, for the several dozen jurisdictions in the metro area where the PSP were the exclusive policing agency, it was necessary for us to allocate unallocated crime counts at the county level appearing in the PSP reports to individual jurisdictions. This took some work. (See full report, appendix 1).

Analysts whether in police agencies or other local or regional agencies need crime and police coverage data that are consistent across jurisdictions, easily accessible, and timely. Without these data, jurisdictions and law enforcement agencies often lack the basic information necessary to understand crime trends.

This leads to our suggestion that state police agencies should be required to report annually on the reported crimes taking place in *each* of the MCDs where they are the exclusive law enforcement agency. Most local police or other local or regional governmental agencies do not have the capability to routinely estimate crime through allocation by population.

The availability of such data is necessary to allow the implementation of the other policy recommendations that follow.

7.3.2. Evidence based practices and nearby crime trends

This initial investigation into jurisdiction-level crime trends highlights the importance of neighboring jurisdictions' crime trends. There is a strong geographic effect especially for violent crime. There are sub-regions identified where jurisdictions near one another were experiencing worsening crime problems at the same time. This suggests that police in these neighboring jurisdictions may have been confronting *a common crime problem shared to a degree across the sub-region.* Therefore, agencies in jurisdictions would do well to consider their neighbors' crime trends when planning their own crime responses.[22] As outlined above, crime analysts will likely

[22] Imagine a township bordered by six other townships, with each of those six neighboring townships sharing an equal portion of the focal township's geographic boundary. Imagine further that the land use patterns along and

encounter significant obstacles in gaining access to those data. But given the recent emphasis on encouraging evidence-based practice in policing, pressure to analyze data and take into account best practice will be increasing and perhaps force greater *shared* availability of crime data.

7.3.3. Shared data and criminal intelligence analysis

Finding ways to achieve more systematic data sharing would address the related needs for: 1) better quality and more timely data and 2) consideration of crime trends in neighboring MCDs. Since most jurisdictions have several neighbors, regional data sharing initiatives and agreements seem like a 'logical' first step. Potential economies of scale that can be leveraged to maximize local investments in police systems should be explored earlier rather than later. But the most basic policy change would be to recognize and act as if the jurisdiction is a part of a larger group rather than an island, part of a "metroquilt" (Felson, 1987) or an entire ecological system (Bursik, 1986a: 60-61) rather than an isolated patch of fabric. This will require members of government at all levels look beyond their boundaries at neighboring jurisdictions in order to 'see' crime trends. Working collaboratively with neighboring jurisdictions, agencies can work toward policies that discourage crime before it becomes a reality in their own jurisdiction. [23]

around the focal township's border are exclusively residential. In addition, consider a situation where the robbery rate in the focal township is increasing over time. Finally, having complete and relatively current information available from neighboring jurisdictions, the police department in the focal township learns that robbery rates are going up simultaneously in three immediately neighboring townships spread along the eastern boundary of the focal township. That information leads to planning a different type of police response than a situation where robbery rates were increasing simultaneously in all of the immediately adjoining townships.

[23] These strategies only make practical sense under assumptions of relatively low levels of spatial displacement in response to crime prevention initiatives (Weisburd, et al., 2006).

7.3.4. *Street and public transit networks* [24]

Fourth, urban and transportation planners could draw from these findings and consider the potential effects of changing the permeability of their MCD on crime. Features that contribute to internal accessibility such as street networks and public transportation are consistently associated with higher levels of both property and violent crime. At the same time, MCDs with less permeable boundaries were less affected by the crime rates of neighboring MCDs. Thus, planners should consider the negative externalities associated with increased accessibility and include strategies to mitigate crime impacts as a component of their proposals for changes in the number and type of roads and public transportation.

7.3.5. *Along a related line: large scale retail and property crime*

One final related implication is offered based on the effects of suburban large-scale retail complexes (malls and complexes of malls) on property crime. These large-scale land uses are clearly creating additional property crime risk. Although this is not surprising given literatures on crime attractors in crime pattern theory more broadly, it does point up a sizable and often hidden cost. These concentrated retailing complexes are creating significant negative externalities for local governments who have more property crime to manage. Of course, the largest complexes have their own private security forces making security governance in and around these land uses complicated (Wood & Shearing, 2007). The implication here is that proprietors of these large-scale retail complexes should perhaps be assessed a negative externality fee by the hosting MCD

[24] This section draws on findings presented in Groff et al (Elizabeth R Groff, et al., 2014).

for the property crime risks created by these businesses. It's clear these land uses bring more property crime, and therefore the local jurisdictions need more police.

Of course a matter such as this has troubling political wrinkles. As Adams and colleagues have pointed out, local jurisdictions are often seriously outmatched by outside development interests (Adams, et al., 2008). Threats of litigation usually result in local government acceding to what these outside groups want. It is a bit challenging to imagine a small local government placing demands on a major corporation running a mall complex. At the same time, it is abundantly clear that these large-scale retail complexes are having sizable adverse impacts on the use value of the hosting community for the residents; quality of life is adversely affected. And right now, it's the MCDs not the developers behind the retail complexes who are footing the bill for coping with this adverse impact.

7.3.6. Practice

There are three main practical implications that emerge from this research effort. Two findings are of particular interest to strategic crime analysts. A third is of interest to local government officials generally and police executives.

First, demographic variables are not critical for forecasting short term crime. Relatively decent one-year, look-ahead crime rate forecasts can be constructed for both property crime and violent crime levels using just current crime. Including social and demographic data can add accuracy to these forecasts but in practical terms the gain is not worth the effort. Using just current crime to predict future crime seems a defensible practice.

Second, crime trends in adjacent MCDs are important to consider when forecasting crime in your jurisdiction. Looking at within-MCD crime trends offers only part of the picture. By sharing crime data across MCDs, each police department could see how its crime dynamics are part of a larger pattern. Exactly how this shared intelligence would translate into tactical policing decisions depends on a range of issues. Could shift supervisors have access to daily or weekly *geolocated* calls for service by crime category and arrests by crime category, for surrounding MCDs within an X mile radius? If they could, that input might prove useful for daily deployment decisions. But providing the infrastructure for such timely information sharing, and getting the cooperation of the relevant agencies, are both daunting tasks.

Nonetheless, there have been different organizational models for such sharing. Fusion centers provide one model.

> They are a mechanism by which law enforcement shares information more effectively, and they serve as a resource for state and local law enforcement in their efforts to combat both terrorism and street crime. The results of the current study suggest that FCs are playing a critical role in the nation's domestic intelligence capacity and could play an even more important role in the future. The co-location of personnel from SLT [state, local, tribal law enforcement], federal law enforcement, and in some cases the private sector, appears to mitigate some of the historic, cultural and organizational barriers to information sharing (Chermak, Carter, Carter, McGarrell, & Drew, 2013: 236).

Agencies designed to coordinate information sharing provided yet another. Specifically, regional intelligence sharing centers such as the DVIC (Delaware Valley Regional Intelligence Center)[25] and HIDTA (High Intensity Drug Trafficking Area) which offer investigative support (Office_of_National_Drug_Control_Policy, 2011). Finally, ARJIS (Automated Regional Justice Information System) for San Diego and Imperial Counties in California offers an example of a locally sourced information sharing model. [26] So there are at least three different templates for coordinating police information across agencies within sub-regions of an MSA. Which model would be more effective, how these sub-regions should be defined, and how all this gets paid for and incorporated into the operations of individual departments are important open questions. But the data patterns seen here strongly suggest some type of common crime dynamic within sub-regions that would be best addressed by a regional agency.

A second model is state police agencies. Yes, these agencies do get crime and arrest data on a monthly basis. But these data are *not* geo-located. It seems unlikely that all local agencies will develop the ability to create geocoded data for forwarding to their respective state police, or that all state police will develop the capacities to receive, maintain, and make available to all local agencies such monthly, geocoded crime counts. The infrastructure enhancements required at the local and state levels would be enormous. Even the more modest goal of the state police

[25] http://stayalertnow.com/about-dvic
[26] http://www.arjis.org/

making monthly totals *readily available* to all local law enforcement agencies, with short turnaround times, would seem to create daunting personnel, budgeting, and infrastructure issues.

A third model is agencies explicitly designed to coordinate information sharing. HIDTA (high intensity drug trafficking area) federal grant programs are one example of such an information sharing model (Office_of_National_Drug_Control_Policy, 2011). ARJIS (Automated Regional Justice Information System) for San Diego and Imperial Counties in California is an example of a locally sourced information sharing model. The Regional Information Sharing System is yet another. So there are at least three different templates for coordinating police information across agencies within sub-regions of an MSA. Which model would be more effective, how these sub-regions should be defined, and how all this gets paid for and incorporated into the operations of individual departments are important questions. But the data patterns seen here strongly suggest violent crime levels are shifting within particular sub-regions suggesting some type of common crime dynamic these sub-regions.

Before leaving the topic of information sharing, one minor policy suggestion deserves merits. State police agencies should be required to report annually on the reported crimes taking place in *each* of the jurisdictions where they are the exclusive law enforcement agency. New Jersey State Police do this. The Pennsylvania State Police do not. This required that we estimate crime through allocation by population for the PA jurisdictions exclusively covered by the Pennsylvania State Police. This makes it more difficult to be certain about how much crime is happening where. These data should be routinely available for all jurisdictions, including those covered only by a state police agency.

A pretty clear implication emerges from the forecasting results. Leaving out extremely small jurisdictions, the one year look-ahead forecasts had errors ranging from about 3 percent to about 10 percent when based only on earlier crime. These accuracy levels may be acceptable for some police or governmental planning purposes. The good news in addition to the relatively decent accuracy is that although forecasts including earlier community structure sometimes did better than forecasts based just on earlier crime, for practical purposes these differences are minimal. Substantial ecological crime continuity at the jurisdiction level means that police or policy analysts can make acceptable forecasts based solely on current crime levels. Of course, such forecasts have important limits, including an inability to foresee major crime shifts. But the forecasts may prove worthwhile for a number of purposes nonetheless.

The third finding of interest to both local government officials generally and police executives is that police coverage rates (sworn officers per 1,000 residents) have a deterrent impact on later unexpected property crime changes at the municipality level. Years when the coverage rate is higher are more likely to be followed the next year by a lower property crime level. So, at least at the jurisdiction level, funding a higher rate of police coverage translates into reduced property crime. [27]

One final implication is offered based on the effects of suburban large-scale retail complexes (malls and complexes of malls) on property crime. These large-scale land uses are clearly creating additional property crime risk. Although this is not surprising given literatures on crime attractors in crime pattern theory more broadly, it does point up a sizable and often hidden cost. These concentrated retailing complexes are creating significant negative externalities for local governments who have more property crime to manage. Of course, the largest complexes have their own private security forces making security governance in and around these land uses complicated (Wood & Shearing, 2007). The implication here is that proprietors of these large-scale retail complexes should perhaps be assessed a negative externality fee by the hosting jurisdiction for the property crime risks created by these businesses. It's clear these land uses bring more property crime, and therefore the local jurisdictions need more police.

Of course a matter such as this has political wrinkles. As Adams and colleagues have pointed out, local jurisdictions are often seriously outmatched by outside development interests (Adams, et al., 2008). Threats of litigation usually result in local government acceding to what

[27] Although this deterrent impact of police coverage rate is extremely intriguing, it should be viewed with considerable caution. To fully understand the intra-metropolitan impacts of policing variation, a study is needed that includes more than information about policing arrangements, department size, and coverage rates. Also needed is information about department styles or "varieties of policing behavior," police proactivity, and police spending per capita (Wilson, 1968). Such information would need to be available for all the jurisdictions in the metro area, and in the ring of communities immediately beyond the MSA. The final crucial piece of information needed is the levels of state police activity in those jurisdictions partially or wholly covered by their respective state police agency. Getting all these pieces of information together for a sizable multiyear time frame for a metro area with hundreds of jurisdictions represents an enormous research funding and data collection challenge. That said, coverage levels, despite their checkered history, inherent limitations as an indicator, and questions surrounding their interpretation, do appear to matter given the current results.

these outside groups want. It is a bit challenging to imagine a small local government placing demands on a major corporation running a mall complex. At the same time, it is abundantly clear that these large-scale retail complexes are having sizable adverse impacts on the use value of the hosting community for the residents; quality of life is adversely affected. And right now, it's the jurisdictions not the developers behind the retail complexes were footing the bill for coping with this adverse impact.

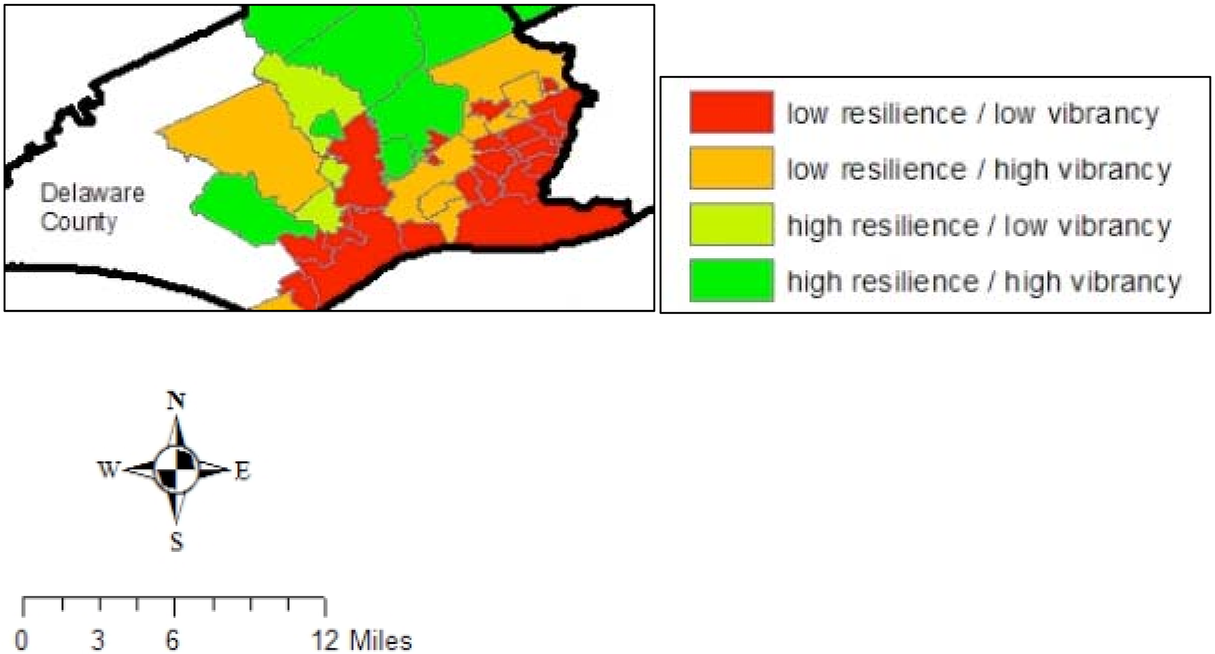

Figure 77. Jurisdictions classified by resilience and vibrancy.

Source: (Dayanim, 2014: Figure 4.12, p. 129).

Note. Only a portion of original map is shown.

8. APPENDIX 1

8.1. Overview

This appendix outlines details of data collection for demographic, crime and law enforcement indicators. It also describes organizing demographic data into indices and conversion of demographic variables into population weighted percentile (PWP) format. Data collection challenges for crime and law enforcement data are substantial and are described.

We start by reviewing the evidence behind the three main dimensions of community demographic structure used in the current work, and the data sources from which information was obtained.

8.2. Demographic data

8.2.1. Source

For the year 2000, jurisdiction-level Decennial Census data were used. For the years 2001 through 2008, jurisdiction-level annual estimates were obtained from the Geolytics product (now called) Annual Estimates Professional. [28] These data provide indicators like median income and median house value at the jurisdiction level.

8.2.2. Which Structural dimensions and why

[28] Geolytics describes the methodology used at: http://www.geolytics.com/USCensus,Annual-Estimates-2001-2005,Data,Methodology,Products.asp

Appendix 1

Past communities and crime work is of some help in directing attention to particular broad dimensions. Previous intraurban work at the community level has identified dimensions of socioeconomic status, stability, racial/ethnic composition, racial/ethnic mixing, and household structure (Brian J.L. Berry, 1972; B. J. L. Berry & Kasarda, 1977; Golledge & Stimson, 1997). The communities and crime work finds some of these more consistently relevant to crime rates than others (Pratt & Cullen, 2005; Sampson & Lauritsen, 1994). Past work at the city or county levels focusing just on homicide agrees that SES and racial composition are relevant, and also suggests an additional factor linked to city size (Land, et al., 1990; McCall, 2010; McCall, et al., 2010). The homicide work appears to have overlooked residential stability.

Specific indicators used for demographic indices appear in Table 30.

Deciding a priori which dimensions might be observable with broad indices, and which might prove relevant to crime, is especially challenging when the units under consideration vary in size, as is the case here with jurisdictions in the Philadelphia MSA, from populations of several hundred to over a million. The size range, geographically and in terms of population, is simply too drastic. It is more than four orders of magnitude.

Although the jurisdictions here range widely in their populations and areas, the populations of most of them are on the order of large urban neighborhoods. Using unweighted data, between 2000 and 2008 median population size ranged from a low of 6,165 in 2000 to a high of 6,537 in 2008. The 25th percentile ranged from 2,796 in 2000 to 3,024 in 2008, and the 75th percentile ranged from 11,660 to 12,835. Using data weighted by the log of the population the ranges for 50th, 25th, and 75th percentiles are: 7,054-7,447; 3,149-3,409; and 14,337-14,727.

A typical census tract in a large urban core city of an MSA will contain about 4,000 persons. Looking at the populations of the jurisdictions here, the prototypical middle of the distribution of jurisdiction populations ranges from about ¾ of a census tract to about six or seven census tracts.

Given the population size of these jurisdictions, a case can be made that the same structural dimensions proven relevant to crime at the intraurban community level, where communities are often defined using census tracts, could be relevant to jurisdictions in the Philadelphia MSA, given the sizes of the populations in typical jurisdictions. We therefore focused our attention on variables reflecting these previously identified dimensions. These include socioeconomic status, stability, racial/ethnic composition, and racial mixing.

A comment is in order about racial mixing or racial heterogeneity. Although these indicators are calculated, they are not feasible given the large numbers of jurisdictions with extremely small populations. Therefore, throughout, the racial factor considered, which seems most broadly applicable to the *entire* MSA, is the percent of the population that is African-American. Are other non-white ethnic groups like Asians and Hispanics distributed in interesting ways around the MSA and are those groups important? Yes, and of course. But since a) African-Americans are by far the largest non-white racial/ethnic group in the region, b) Asians have a small relative presence, with one exception, in jurisdictions outside of Philadelphia, and c) there are just a small number of Hispanic concentrations outside of Philadelphia, the analysis uses percent African-American to capture race.

There has been less agreement about which specific features of household structure might prove relevant to crime at the community level, although it is clear that these features are relevant (Sampson & Lauritsen, 1994). Prior to about 1970, household structure variables like presence or children linked to indicators of stability like percent owner occupied households, leading to identification of a broad stability/familism dimension (Hunter, 1974a, 1974b). From 1970 forward, however, household structure variables reflecting presence or absence of children in specific age groups, or single parent households, diverged from stability, at least in some cities (R. B. Taylor & Covington, 1988). Household structure, of course, is extremely complex and has many components.

Perhaps the clearest theoretical statement about the micro-level dynamics that might link household structure to street crime and property crime comes from Anderson [29] (Anderson, 2000: 102-146). He argued that a particular combination of two household structure features contributed to high crime rates and generally high levels of disorderly behaviors in many urban African-American urban, low income communities. The disorder-inducing combination was large numbers of unsupervised children whose ages made it likely they could be out on the street, and a lack of "old heads," mature and respected adults, who tell younger people how to behave.

There is no reason to believe that the dynamics described by Anderson would *not* apply to suburban as well as urban communities or to white or racially mixed communities as well as predominantly African-American ones. Consequently, we examined the relative prominence of two age groups in jurisdictions: children and young adults of an age where it is likely they could

[29] Anderson's argument is complex and goes beyond mere demographics. He addresses how mature adults may become disengaged as they cope with their own economic challenges, and that street youth may see the older adults as irrelevant. But if there are to be "old heads" who mentor street youth, there first need to be adults in these age categories. Further, the greater the number of street youth, the greater the need for such supervising adults. So although the ratio of "old heads" to street-aged youth captures only a segment of Anderson's suggested dynamics, it is theoretically aligned with his concept.

be out on the street, defined here as ages 10-24, and adults old enough to be fully mature and perhaps beyond the years of intensive supervision of their own children, but not so old as to be frail. The adult ages of interest were 50-64. If the proportion of children and young adults is positively weighted, and the proportion of adults of an age to be respected supervisors is negatively weighted, we can capture some of the dynamics described by Anderson.

8.2.3. Description, Not Parameter Estimation

Because the purpose here was to describe the changes of jurisdictions over time, rather than to estimate particular parameters for the entire MSA, unweighted results are used for describing changes over time for jurisdictions in different counties. Each jurisdiction contributes similarly to the indicator, regardless of population size. With the use of weighted data, the features of the more numerous but very low population jurisdictions would be overwhelmed by the small number of very populous jurisdictions like the city of Camden (Camden County), Lower Merion (Montgomery County), the city of Chester (Chester County), and of course Philadelphia. Statistical analyses, therefore, will use unweighted data.

Descriptive statistics for demographic indicators appear in Table 31 to Table 39.

8.2.4. Population Weighted Percentiles (PWPs)

A population weighted percentile (PWP) form of an indicator or index captures the position of the jurisdiction, relative to the entire population in the rest of the MSA, in that year. Each PWP equals the percent of the population, at the jurisdiction level, in the entire MSA, with scores equal to or less than the PWP of the target jurisdiction.[30] For example, in 2008 the city of Camden in Camden County (NJ) had a PWP on the SES index of 2.03, the lowest, and the city of Chester in Chester County had a PWP on the socioeconomic status index of 2.73. This means that, respectively, residents in these two locations had status scores lower than 97.97 and 97.27 percent of the population in the rest of the MSA. In the same year, Birmingham in Chester County had the topmost SES with a PWP of 99.27. A PWP form of a variable is a monotonic transformation of that variable, except in the case of ties. Thus, for the most part the PWP form and the original form have a rank order correlation at or close to 1.

8.2.5. Index Construction Protocol

In the construction of multi-item indices where index scores capture an average, to avoid the well-known "validity, reliability and baloney" problem, data were split into two random halves (Cureton, 1967). The first random half was used to develop internally consistent indices, adding and removing candidate indicators as needed. Once an index was developed that appeared to have an acceptable level of internal consistency as reflected in a Cronbach's α of .70 or greater, its internal consistency was re-estimated using the second random half of the data. Table 31to Table 39 report α values based on this second cross validation random half.

[30] The variable determines what type of counting is done. For people variables persons are used. Other counters were occupied housing units, total housing units, households, or population over 16, depending on the variable.

To construct the final PWP version of each multi-item index, for each year, the relevant population weighted percentile (PWP) scores were averaged rather than standardized to ease interpretability. For index construction, all jurisdictions were weighted equally.

This means the PWP-based indices are not, strictly speaking, unit weighted with each item contributing equally. But they come pretty close. This is because each variable, within each year, generates a PWP distribution that roughly approximates a uniform distribution, save for a gap between Philadelphia and the next highest score. This is because Philadelphia's population represents about a third of the population of the entire metropolitan community. The uniform distribution creates standard deviations across items that also are roughly comparable.[31]

8.2.6. Order of Presentation

Information is presented by community dimension, starting with the dimensions for which a multi-item internally consistent index was created. The relevant variables and index Cronbach's α s are presented. The Cronbach's α s appear in the first table presenting specific variables used in an index.

8.2.7. Socioeconomic Status (SES)

Variables

[31] With the SES index, the rank order correlations, by year, between the PWP scored index and the unit weighted index were always above .975. For the stability index, the correlations were always above .991. For the age structure index, the correlations were always above .953.

The socioeconomic status (SES) index was based on the average population weighted percentile (PWP) of the following variables, each in PWP form:

- Median home value
- Median household income
- Percent families above the poverty level
- Median gross rent
- Employment rate for those 16 and older
- Percent of the population 25 and older with a college education

Internal Consistency

Cronbach's α ranged from .86 to .88, depending on the year, based on the validation random half of the data for each year.

8.2.8. Stability

Variables

The stability index was based on the average of the following variables in PWP form

- Percent owner occupied housing units
- Percent non vacant housing units
- Percent married households
- Percent multi-person households

Internal consistency

Cronbach's α for the index ranged from .84 to .88 based on the validation random half of the data.

8.2.9. *Household Age Structure ("Code" Index)*

Variables

The following variables were used to construct an index intended to capture Anderson's (2000) idea about one crime-relevant feature of household structure at the community level: the presence of children or young adults and the lack of mature adults to serve as supervisors. The index was composed of the following variables:

- Percent of persons aged 10-14
- Percent of persons aged 15-19
- Percent of persons aged 20-24
- Percent of persons aged 50-54, multiplied by -1
- Percent of persons aged 55-59, multiplied by -1
- Percent of persons aged 60-64, multiplied by -1

Jurisdictions with higher scores on the index will have more pre-teens, teens, and young adults, and fewer older adults to supervise them.

Internal Consistency

Cronbach's α for the index ranged from .71 to .84, depending on the year, for the second random half of the data.

8.2.10. *Racial Heterogeneity*

8.3. Crime

This project started with the most basic form of UCR data, obtained directly from the FBI: Return A. Although data from recent years is available on the FBI UCR website with some searching, earlier years were not and had to be specifically requested. These data are fixed length records with monthly counts, by crime category, of unfounded offenses, actual offenses, total offenses cleared by arrest, and juvenile arrests.

We recognize there has been extensive scholarly discussion of missing data problems with UCR data at the county level. That background appears immediately below. But the UCR data issues faced here were of a different variety, arising from the varied nature of policing arrangements at the jurisdiction level in the Philadelphia MSA. After background on UCR missing data issues at the county level, the specific challenges and approaches adopted are described

8.3.1. The UCR missing data discussion

Google Scholar was used to perform a systematic search of criminological literature using the term: allocate crime counts. Search results provided insight into the missing data problems of the FBI's Uniform Crime Reporting (UCR) program. A cited reference search was conducted using as the search basis two articles by Michael Maltz (Maltz & Targonski, 2002, 2003).

Not all police agencies provide 12 months of crime data to the FBI: natural disasters, budget restrictions, personnel changes, inadequate training, and conversion to new computer or crime reporting systems all have affected the ability of police departments to report consistently, on time, completely, or at all. And some agencies may not fill out crime reports simply because they rarely have any crime to report (Maltz & Targonski, 2002: 299).

This, of course, has implications for the missing data. Missing data is a sizable area of scholarly inquiry in itself (Calder & Holloman, 2000; Dempster, Laird, & Rubin, 1977; Little & Rubin, 1987; Rubin, 1987; Schafer, 2000). When an agency fails to submit 12 months of data the FBI uses a binary imputation approach to fill gaps. For example, if an agency reported at least 3 months of data, its total crime count will be computed as the total number of reported crimes multiplied by 12 (total months in a year), divided by the number of reported months (Lynch & Jarvis, 2008; Maltz & Targonski, 2002) If an agency reported less than three months of data the FBI estimates the crime rate by identifying the overall crime rate of agencies within the same population group[32] and state. It then multiplies the group crime rate by the population covered by the agency, divided by 100,000 (Maltz, 1999). Although data are imputed at the agency level, they are used to estimate *county*-level crime rates. Agency-level data released to the public are not imputed.

The debate about how to properly handle the missing data problem when using county level UCR data has proven intense. For example, gun researcher Lott use county-level UCR data from the National Archive of Criminal Justice Data and excluded counties s with less than 6 months of data in calculating county crime rates, for which he was criticized (Lott, 2000; Lott & Whitley, 2003; Maltz & Targonski, 2003).

[32] The FBI population classification consists of 9 groups. Group I agencies cover cities with at least 250,000 residents. Group VI agencies cover cities with less than 10,000 residents (Maltz, 1999).

In the current project, counts were not adjusted for missing months. We verified that these unadjusted data correspond closely with adjusted figures at the national level. Further, in reviewing the monthly data for the reporting agencies in the MSA vast majority of data were reported for 12 months and there were very few instances of reporting for only 11 months.

8.3.2. Subtracted crime counts

A less discussed issue is the ability of agencies to remove earlier crimes. It is possible for an agency to submit a negative number in a month for a crime count. It may decide in a later month that what it called a murder in the previous month was actually a suicide, so in the later month a letter reflecting 1- or -2 and so on can appear in these data. Because the FBI uses letters for these negative numbers, the researcher initially needs to read crime count fields as string variables. This requires some extra processing.

8.3.3. Matching up counts with the appropriate agency and jurisdiction

Even with the assistance of the “Crosswalk” file it can be hard matching up specific local departments with particular agencies identified by the FBI in Return A. Each year the FBI attaches a unique identifier to each reporting law enforcement agency within certain group categories called a sequence number. The sequence number, however, changes from year to year as the total population of law enforcement agencies across the country also changes from year to year. There is also an originating agency identifier. The file also provides agency name, state, population counts for jurisdictions, cities, counties, and, if appropriate, the relevant MSA. *It does not, however, identify the County by name within which the reporting agency is located*. As a result, it took quite a bit of time to try and match the 355 jurisdictions in the Philadelphia MSA with the appropriate FBI UCR agency. Adding further to the matching challenge was the presence in the Philadelphia MSA of multiple instances where two or in a couple of places three jurisdictions shared the same name. For example, there are three Springfield townships. These confusions required hand-matching by cross referencing addresses and population counts to insure the right crime counts went with the right jurisdiction.

8.3.4. Different local policing arrangements

Adding to the matching challenge were arrangements whereby crimes are reported for a jurisdiction either by a nearby local agency, or a regional police department, or the state police, or by the state police in combination with another agency. (We will address the state police matter separately below.) If that agency had its crime reported by another agency we called the former a "covered agency" and the latter a "covering agency."

The UCR reports provide information for *some* of these arrangements. For several dozen jurisdictions which were not listed as either a reporting, or a covered, or a covering agency, we researched websites for the municipalities and, in many instances, made phone calls to verify reporting arrangements. Needless to say, for covered jurisdictions there were no UCR crime data of any type.

Further, the UCR reports about some of these arrangements are not always current. This is important because the UCR supplied population information so that rates could be determined. If the FBI reported that during year Y Agency A covered jurisdiction A and jurisdiction M, but that arrangement had ended in Year Y-1, the crime rates for jurisdiction a and M will be off. Sometimes the population figures reported by the FBI did not shift as quickly as actual shared policing arrangements did.

But during the study period, 2000 – 2008, UCR information about coverage arrangements was largely incomplete. To learn more we scoured web sites and, as needed, called and sometimes emailed police departments and municipal offices to determine the jurisdiction organizational arrangements for police protection, and to determine if UCR data have been submitted. Google search was used to find municipal websites describing police coverage arrangements. We asked via phone and/or email (1) if a local police department provided exclusive coverage of the municipality or if a state, regional, or other local department provided coverage, (2) the time period of each coverage arrangement, and (3) if the agency submits data for inclusion in the UCR. Multiple police coverage arrangements were present across the Philadelphia MSA. Most of these different arrangements are mapped in chapter 5. The different arrangements are described below.

The most common coverage style was that a jurisdiction maintained its own police department, responsible for the population of the jurisdiction. See Table 40. During the period 276 out of 355 jurisdictions had this arrangement (76.6 percent). But during this time anywhere from 13 to 20 of these same departments had less than one full time sworn officer, depending on the year. So the number of jurisdictions with their own, dedicated department and at least one full time sworn officer ranged from 256 to 263, depending on the year.

A second possibility was that a local, dedicated department would provide *partial* coverage, usually between 9 and 5. Often, but not always, the respective state police would provide coverage during the local department's off hours. Sometimes another nearby department would do this.

A third possibility was that a jurisdiction formed an agreement with a neighboring police department for coverage. This possibility comes in different variations. For example Audubon Borough, Camden County, is covered by The Haddon Township Police Department. A different variation of sharing is when multiple jurisdictions form a regional police department. For example, East Rockhill Township and West Rockhill Township, both in Bucks County, are policed by the Pennridge Regional Police Department. A third variation of sharing a department is when the names of both jurisdictions appear in the department name. For example the Westtown-East Goshen (now Regional) Police Department serves these two jurisdictions in Chester County, along with Thornbury Township in the same county.

The final possibility is that the respective state police provided full law enforcement coverage. There were 55 jurisdictions in the metro region receiving full coverage from their respective state police.

Some jurisdictions changed covering arrangements. For example, from 2000 to 2002 Sellersville (PA) received police coverage from the Pennridge Regional Police Department. From 2003 onward, however, the jurisdiction was covered by the Perkasie Police Department.

Given these many different arrangements, it was not surprising that crime counts were missing for 890 jurisdiction-years out of a total of 3,195 jurisdiction-years. For some jurisdictions data were missing across the entire nine year study period (n=89 jurisdictions). For others, data were unavailable for select years, within jurisdictions. Differences in coverage arrangements seem likely to be responsible for the majority of the missing data

8.3.5. State police coverage

Both Pennsylvania and New Jersey have state police agencies which provide policing coverage and prepare state-level reports. Because each is a distinct governmental entity, each has the ability to organize its data as it sees fit. This has significant implications. Pennsylvania State Police data were derived from the Pennsylvania Uniform Crime Reporting webpage. [33] New Jersey data are available from the Crime Reports and Statistics webpage of the New Jersey State Police. [34] Table 40 enumerates different types of policing arrangements, including those involving a state police force. Table 41 provides information on department sizes for jurisdictions with their own department.

Pennsylvania State Police

The Pennsylvania State Police (PSP), regrettably, fails to provide annual crime counts for the jurisdictions where it provides exclusive coverage. These jurisdictions are listed in Table 42 . MCDs covered exclusively by Pennsylvania State Police. By year, only county-level totals were provided for all the locations covered by the PSP. These county level totals were available in the annual report tables showing crime counts by counties, and within counties by jurisdiction. Thus, it was necessary to allocate these county level figures to individual jurisdictions. For jurisdictions were covered exclusively by the PSP, for each incident type within each year, the crime count was calculated as:

[33] http://www.paucrs.pa.gov/UCR/Reporting/Annual/AnnualSumArrestUI.asp
[34] http://www.njsp.org/info/stats.html

[(jurisdiction population / County population) * Total number of incidents addressed by PSP for a county in a given year]

With this approach, each allocated local crime count reflects the population-based county proportion of total non-jurisdiction linked incidents in a county, in a given year, recorded by the PSP. It allowed us to estimate values for missing data for forty-seven jurisdictions and 405 jurisdiction-years.

New Jersey State Police

New Jersey State Police (NJSP) provided exclusive law enforcement coverage for fifteen jurisdictions (see Table 43). Fortunately, the NJSP provides crime counts by jurisdiction by year. Using NJSP annual reports, crime counts were added to the crime file.

8.3.6. Responding to missing due to non-reporting

As already noted, some jurisdictions which initially appeared to receive coverage from their own police departments did have crime counts in the working file. We tried to contact each of these departments by phone or email, depending on what type of contact details we could find. Results revealed several different types of policing arrangements (described earlier).

A number of approaches were used to fill missing data. They are described in turn below. The number beside each subheading corresponds to the "Missing data approach" column in Table 44.

Row numbers indicate the number of jurisdictions by year addressed using the missing data approach labeled in the left-most column.

Investigation revealed coverage by a regional police department (5)

Regional police departments are law enforcement agencies providing coverage for multiple, usually adjoining municipalities. In the event that a jurisdiction with missing data was covered by a regional police department with available data, researchers allocated crime from the regional police department to the jurisdiction, using the following formula:

[(jurisdiction population / Population covered by regional police) * Total number of incidents addressed by regional police for a given year]

Investigation revealed coverage by another jurisdiction (6)

In instances where a jurisdiction had an agreement for coverage by another jurisdiction, the following formula was used for crime count allocation:

[(jurisdiction population / (jurisdiction population + *Covering* jurisdiction population)) * Total number of incidents addressed by the *covering* jurisdiction for a given year]

The number of incidents allocated to the jurisdiction that was *covered* was then subtracted from the number of incidents reported by the *covering* jurisdiction.

Investigation revealed jurisdiction covered another jurisdiction (7)

Crime counts for jurisdictions that provide coverage to other jurisdictions were proportionally reduced in instances where *covered* jurisdictions were missing crime count data. The following formula was used:

[((*Covered* jurisdiction population / *Covered* jurisdiction population + *Covering* jurisdiction population) * Total number of incidents addressed by the *covering* jurisdiction for a given year)]

The number resulting from the above formula was then subtracted from the *Covering* jurisdiction's crime count for a given year.

Investigation revealed jurisdiction is a borough within a township (8)

In instances where a Borough was nested within- and covered by its adjoining or surrounding township, the following formula was used for crime count allocation:

[(*Borough* jurisdiction population / *Township* jurisdiction population)) * Total number of incidents addressed by the *Township* jurisdiction for a given year]

The number of incidents allocated to the *Borough* that was *covered* was then subtracted from the number of incidents reported by the *Township* jurisdiction.

Missing data by year

The approaches described so far have to do with making adjustments for different coverage arrangements and, in the PA case, the lack of jurisdiction-level data for jurisdictions covered exclusively by the PSP. A different type of problem also surfaced with these data: data that were missing by year. Depending on the structure of the missing data in the series, we used different approaches. But each approach was designed to be consistent and replicable. Again, the numbers after the heading correspond to the numbers in Table 44.

Interpolation (3)

Years of missing data were interpolated if the years of missing data were between years of non-missing data *and* if the gap was between two and four years. To do this, a yearly rate of change was calculated using the following formula.

$$[(\text{Crime count at } t_2 - \text{Crime count at } t_1) / (\text{Year at } t_2 - \text{Year at } t_1)]$$

The rate of change was then added to the crime count at t_1 to interpolate the crime count for the first missing year, and subsequent missing years.

Trend (4)

Trending was used for jurisdictions when there was only a one year gap in the data series. Trended values reflect the crime count for a missing time period assuming that the rate of change holds constant. It is computed using data from the two nearest non-missing years:

$$[(\text{Crime count at } t_2 - \text{Crime count at } t_1)]$$

The result was then added to the value of the last non-missing year.

Average (2)

The average of non-missing years was used if there were two sequential missing years but the missing data period was not bounded by available data at both the beginning and the end. It also was used if the two non-missing data time points bounding the missing data period were too divergent to reliably interpolate. The average of the non-missing data was then applied to each missing time period.

Allocation from PSP (1)

Data missing from jurisdictions were allocated from the county-level PSP data if the jurisdiction reported no data across the entire study period, or if averaging, trending, and interpolation proved unfeasible. Such jurisdictions had at least 2 years of contiguous missing data, but on average had 7 years of missing data. Allocation was done based on the proportion of jurisdiction population compared to the total population covered by PSP reported for that county.

Checking allocation from PSP data

Data were checked to ensure that the crime counts allocated based on PSP reports to missing jurisdiction-years did not exceed the yearly count of crimes, reported by the PSP at the *county* level, as PSP covered. Table 45 describes the proportion of PSP county-level data, summed up in PSP reports for places covered exclusively by the PSP, which were allocated to jurisdictions by crime type. Numbers refer to the total count of crime addressed in that county exclusively by the PSP. Percentages reflect the amount that of total count allocated to specific jurisdictions within that county.

Table 45 controls for whether numbers were allocated for jurisdictions that were exclusively covered by the PSP. Here's how. The percentages in the rows labeled "1st allocation" refer to crimes allocated to specific jurisdictions *only* if we were able to verify, on a case-by-case basis, by speaking to local law enforcement personnel and examining jurisdiction websites, that those specific jurisdictions were covered *exclusively* by the PSP.

A second stage of allocation of total county-level crime counts by crime type from PSP reports to jurisdictions was carried out for jurisdictions with missing data but we were not sure if they were covered *exclusively* by the PSP. The relevant percentages appear in the rows labeled "2nd allocation" in the table. (No jurisdictions in Montgomery County required this 2nd allocation strategy.)

The smallest proportion of county-level PSP data allocated to jurisdictions in Chester County during the first allocation was for motor vehicle theft (0.5%). The largest proportion of PSP crime allocated was for burglary offenses in Montgomery County (39.0%), also during the first allocation stage.

The 1st and 2nd allocations were added up to estimate crime counts for jurisdictions covered by the PSP.

8.4. Discussion

Crime presented two types of missing data problems: arising from different coverage arrangements, and arising from missing data for years within the series. If a jurisdiction was not covered by its own, exclusively-dedicated department with corresponding data in UCR Return A, adjustments had to be made. It took a lot of work – phone calls and web searching – to verify current and recent arrangements. Once we had verified arrangements as best we could, data were adjusted to reflect different arrangements, using the strategies described above.

We have the least confidence in the allocation used for jurisdictions covered exclusively by the PSP, although we did verify that the protocols followed did *not* result in over-allocation. Although the NJSP report specific figures on a jurisdiction-by-jurisdiction basis for those places they serve, the PSP does not. **It is strongly recommended that the PSP change its annual reporting practices**.

The methodology used here recognizes not only differences in state data collection and reporting procedures, but also variations in coverage styles at the jurisdiction level. We are able to do this with some degree of confidence by verifying reporting and policing arrangements with police and municipal administrators. Unique to Pennsylvania was the allocation of county-level data to jurisdictions based on population. Findings illustrate that the over-allocation of county-level PSP data is not a concern.

8.5. Law enforcement personnel

Appendix 1

Although some of the most recent years of law enforcement personnel yearly counts can be found online, it was necessary to request from the FBI a separate data file for each of the years 2000-2008. National data were obtained. Then departments were selected by state for each year (NJ, PA). Then departments within the Philadelphia MSA were selected. The number of the MSA changed partway through the series. Departments were dropped if either there was no corresponding population (zero appeared), or the GROUP variable did not match a municipality. Most of these were regional police, state police, and specialized agencies (park police, campus police, and special bureaus).

At this point, there are about 270-290 local departments per year with officer counts. Agencies reporting personnel varied from year to year. About 10-20 agencies either appeared or disappeared during the period.

Records for each year were sorted by the variable SEQUENCE NUMBER **(**called here ALPHASEQ for 2000 and ALPHAS01, ALPHA02, and so on).

Starting with 2000, pairs of years were merged after sorting each year by ALPHASEQ, creating a blank record in the prior year for agencies coming on line in the later year, and creating a blank record in the later year for agencies that appeared only in the prior year.

Part of the challenge here was that the ALPHASEQ variable sometimes changed value from year to year for the **same** agency. Presumably, this reflects changes in the population of law enforcement agencies nationwide.

We examined the relationship between total employees and total population by year, with both variables on a log scale. The relationship looked quite linear except for very small departments (1-4 officers) where the relationship was much looser.

Woodland Township Police Department with a population around 1,110 (NJ, Burlington County) has a department size of about 70 officers until 2003, when it goes to 2 officers, then in 2006 there are no more figures, suggesting it got merged in somewhere.

This FBI law enforcement personnel file provides one yearly population figure associated with each agency. Matching up agencies and jurisdictions was facilitated in some instances, e.g., figuring out which of two Springfield police departments in Pennsylvania belonged where, by using these population figures. Because this file provides this one population figure for each agency rather than the several population figures provided by the UCR file, **the agency population figure was used to construct crime rates**. There were some discrepancies between the law enforcement personnel population figures and the UCR population figures, but checking with Census data suggested the law enforcement personnel figures in general were better.

The two key variables of interest here were the total number of law enforcement employees associated with each agency, and the total number of sworn law enforcement officers associated with this agency. We used the number of law enforcement officers to construct a policing rate of officers per thousand population so that variation in this coverage could be considered.

To discover what was happening with jurisdictions in the MSA whose departments were not listed in the police employees file, we checked websites and called departments to verify the current number of full time sworn officers. Sometimes this information was obtained from publicly available, online documents like town council meetings. Tracking down these counts took considerable effort.

A limitation of this approach is that only full time sworn officers in local departments are counted. Some local police departments seem to have quite a number of part time personnel. The number of part-time sworn personnel is not known.

Thus, with these data it was possible to construct three variables: department size, in terms of full time sworn personnel, department size, in terms of full time employees of any type and the coverage rate, sworn officers per 1,000 residents.

Table 30. Specific indicators for demographic indices

Index	Variables
Socioeconomic status (SES)	Median home value
(Cronbach's α = .86 to .88, varies by year)	Median household income
	Percent families above the poverty level
	Median gross rent
	Employment rate for those 16 and older
	Percent of the population 25 and older with a college education
Stability	Percent owner occupied housing units
(Cronbach's α = .84 to .88, varies by year)	Percent non vacant housing units
	Percent married households
	Percent multi-person households
Household age structure	Percent of persons aged 10-14
(Cronbach's α = .71 to .84, varies by year)	Percent of persons aged 15-19
	Percent of persons aged 20-24
	Percent of persons aged 50-54, multiplied by -1
	Percent of persons aged 55-59, multiplied by -1
	Percent of persons aged 60-64, multiplied by -1

Appendix 1

Table 31. Indicators used in socio-economic status index: descriptive statistics weighted by population

Year	Statistics	Household median income (hhmedinc)	Percent of families above poverty level (pfmabpv)	Median home value (medhomval)	Median gross rent (med_grrnt)	Employment Rate (emprate)	Percent 25+ with a college degree (p25pcol)
2000	Mean		91.36			93.47	27.38
	Median	48,289	95.76	113,800	651	95.24	19.90
	SD	18,972	7.88	63,952	166	4.13	14.96
	Min	23,421	67.22	40,800	0	61.10	0.00
	Max	130,096	100.00	361,700	2,001	100.00	77.11
	Cronbach's α	0.87					
2001	Mean		91.06			94.38	27.61
	Median	49,619	95.67	111,028	637	95.40	20.32
	SD	19,675	8.22	64,271	156	3.54	14.95
	Min	24,938	66.71	1,416	2	58.30	3.23
	Max	131,392	100.00	409,169	1,401	100.00	74.69
	Cronbach's α	0.87					
2002	Mean		90.78			94.13	27.72
	Median	49,941	95.57	131,172	692	95.00	20.45
	SD	19,755	8.52	69,538	169	3.20	14.95
	Min	24,965	66.33	1,745	2	61.80	2.92
	Max	131,668	100.00	433,887	1,520	100.00	72.99
	Cronbach's α	0.88					
2003	Mean		90.51			93.98	27.81
	Median	50,122	95.40	149,139	722	95.00	21.30
	SD	19,850	8.82	76,107	178	3.32	14.95
	Min	24,755	65.97	2,036	3	60.80	2.95
	Max	131,652	100.00	464,106	1,583	100.00	72.80
	Cronbach's α	0.88					

Appendix 1

Year	Statistics	Household median income (hhmedinc)	Percent of families above poverty level (pfmabpv)	Median home value (medhomval)	Median gross rent (med_grrnt)	Employment Rate (emprate)	Percent 25+ with a college degree (p25pcol)
2004	Mean		90.21			94.31	27.88
	Median	50,139	95.35	164,964	739	95.20	21.38
	SD	19,901	9.13	84,198	182	3.35	14.97
	Min	24,784	65.62	2,415	3	60.80	3.03
	Max	131,550	100.00	491,553	1,604	100.00	72.83
	Cronbach's α	0.86					
2005	Mean		90.41			94.66	27.96
	Median	50,355	95.40	186,767	786	95.60	21.66
	SD	19,942	8.95	95,896	193	3.30	14.98
	Min	24,928	64.17	2,768	3	61.30	2.95
	Max	131,430	100.00	556,554	1,696	100.00	72.98
	Cronbach's α	0.87					
2006	Mean		90.77			94.80	28.02
	Median	50,408	95.58	205,630	815	95.80	21.70
	SD	19,971	8.65	105,455	200	3.28	15.01
	Min	24,827	65.95	3,039	3	61.30	2.98
	Max	131,317	100.00	612,660	1,741	100.00	73.13
	Cronbach's α	0.87					
2007	Mean		90.92			94.90	28.09
	Median	50,421	95.71	214,623	852	95.90	21.98
	SD	20,025	8.52	110,223	208	3.36	15.04
	Min	24,702	66.55	3,087	3	60.50	2.85
	Max	131,193	100.00	654,053	1,798	100.00	73.28
	Cronbach's α	0.86					

Appendix 1

Year	Statistics	Household median income (hhmedinc)	Percent of families above poverty level (pfmabpv)	Median home value (medhomval)	Median gross rent (med_grrnt)	Employment Rate (emprate)	Percent 25+ with a college degree (p25pcol)
2008	Mean		89.21			92.65	28.16
	Median	50,795	94.51	206,034	980	94.00	22.22
	SD	20,052	10.22	105,893	240	4.99	15.08
	Min	24,718	52.29	2,963	4	41.50	2.85
	Max	131,102	100.00	627,960	2,071	100.00	73.38
	Cronbach's α	0.88					
Total	Mean		90.58			94.14	27.85
	Median	49,880	95.50	153,613	771	95.20	21.30
	SD	19,779	8.80	95,092	217	3.71	14.97
	Min	23,421	52.29	1,416	0	41.50	0.00
	Max	131,668	100.00	654,053	2,071	100.00	77.11

Note. N=354 for 2000. N=355 for Years 2001-2008. Weighted by population. Cronbach's αs reported for unweighted data, and only for second random half of data. Means not reported for indicators based on medians.

Appendix 1

Table 32. Indicators used in socio-economic status index: Descriptive statistics, unweighted

Year	Statistics	Household median income (hhmedinc)	Percent of families above poverty level (pfmabpv)	Median home value (medhomval)	Median gross rent (med_grrnt)	Employment Rate (emprate)	Percent 25+ with a college degree (p25pcol)
2000	Mean		95.74			95.62	28.61
	Median	56,196	97.12	140,850	685	96.41	24.76
	SD	16,651	4.34	58,039	187	3.63	15.65
	Min	23,421	67.22	40,800	0	61.10	0.00
	Max	130,096	100.00	361,700	2,001	100.00	77.11
2001	Mean		95.66			95.71	28.67
	Median	56,533	97.02	134,973	672	96.50	24.62
	SD	17,560	4.38	58,614	170	3.86	15.63
	Min	24,938	66.71	1,416	2	58.30	3.23
	Max	131,392	100.00	409,169	1,401	100.00	74.69
2002	Mean		95.54			95.31	28.68
	Median	56,630	96.94	149,233	727	96.00	24.64
	SD	17,597	4.50	60,999	185	3.53	15.63
	Min	24,965	66.33	1,745	2	61.80	2.92
	Max	131,668	100.00	433,887	1,520	100.00	72.99
2003	Mean		95.43			95.24	28.72
	Median	56,647	96.84	166,866	763	96.00	24.57
	SD	17,660	4.60	65,372	192	3.57	15.63
	Min	24,755	65.97	2,036	3	60.80	2.95
	Max	131,652	100.00	464,106	1,583	100.00	72.80

Appendix 1

Year	Statistics	Household median income (hhmedinc)	Percent of families above poverty level (pfmabpv)	Median home value (medhomval)	Median gross rent (med_grrnt)	Employment Rate (emprate)	Percent 25+ with a college degree (p25pcol)
2004	Mean		95.31			95.61	28.74
	Median	56,581	96.78	185,520	780	96.30	24.66
	SD	17,686	4.72	70,831	195	3.57	15.64
	Min	24,784	65.62	2,415	3	60.80	3.03
	Max	131,550	100.00	491,553	1,604	100.00	72.83
2005	Mean		95.33			95.91	28.77
	Median	56,641	96.78	210,936	830	96.60	24.64
	SD	17,719	4.73	80,535	207	3.51	15.64
	Min	24,928	64.17	2,768	3	61.30	2.95
	Max	131,430	100.00	556,554	1,696	100.00	72.98
2006	Mean		95.52			96.01	28.79
	Median	56,600	96.90	231,904	857	96.80	24.64
	SD	17,728	4.54	88,609	212	3.50	15.65
	Min	24,827	65.95	3,039	3	61.30	2.98
	Max	131,317	100.00	612,660	1,741	100.00	73.13
2007	Mean		95.59			96.15	28.83
	Median	56,588	96.96	241,121	888	97.00	24.60
	SD	17,769	4.47	93,318	219	3.56	15.65
	Min	24,702	66.55	3,087	3	60.50	2.85
	Max	131,193	100.00	654,053	1,798	100.00	73.28

Appendix 1

Year	Statistics	Household median income (hhmedinc)	Percent of families above poverty level (pfmabpv)	Median home value (medhomval)	Median gross rent (med_grrnt)	Employment Rate (emprate)	Percent 25+ with a college degree (p25pcol)
2008	Mean		94.50	244,901			28.87
	Median	56,650	96.39	231,480	1,020	95.60	24.74
	SD	17,802	5.76	89,628	252	5.32	15.65
	Min	24,718	52.29	2,963	4	41.50	2.85
	Max	131,102	100.00	627,960	2,071	100.00	73.38
Total	Mean		95.40	199,055			28.74
	Median	56,578	96.88	186,941	798	96.40	24.65
	SD	17,563	4.69	85,407	229	3.85	15.62
	Min	23,421	52.29	1,416	0	41.50	0.00
	Max	131,668	100.00	654,053	2,071	100.00	77.11
Note. N=354 for 2000. N=355 for Years 2001-2008. Means not reported for indicators based on medians.							

Table 33. Indicators for socio-economic status index: Descriptive statistics weighted by log of population

Year	Statistics	Household median income (hhmedinc)	Percent of families above poverty level (pfmabpv)	Median home value (medhomval)	Median gross rent (med_grrnt)	Employment Rate (emprate)	Percent 25+ with a college degree (p25pcol)
2000	Mean		95.77			95.59	29.04
	Median	56,528	97.16	141,400	690	96.41	25.13
	SD	16,668	4.35	58,196	184	3.60	15.69
	Min	23,421	67.22	40,800	0	61.10	0.00
	Max	130,096	100.00	361,700	2,001	100.00	77.11
2001	Mean		95.66			95.70	29.06
	Median	57,123	97.03	136,996	677	96.50	25.03
	SD	17,591	4.45	58,841	165	3.82	15.67
	Min	24,938	66.71	1,416	2	58.30	3.23
	Max	131,392	100.00	409,169	1,401	100.00	74.69
2002	Mean		95.54			95.31	29.07
	Median	56,709	96.96	150,478	730	96.00	24.98
	SD	17,627	4.56	61,264	180	3.46	15.66
	Min	24,965	66.33	1,745	2	61.80	2.92
	Max	131,668	100.00	433,887	1,520	100.00	72.99
2003	Mean		95.42			95.23	29.10
	Median	56,770	96.85	169,019	770	96.00	24.95
	SD	17,694	4.67	65,695	187	3.53	15.65
	Min	24,755	65.97	2,036	3	60.80	2.95
	Max	131,652	100.00	464,106	1,583	100.00	72.80

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Year	Statistics	Household median income (hhmedinc)	Percent of families above poverty level (pfmabpv)	Median home value (medhomval)	Median gross rent (med_grrnt)	Employment Rate (emprate)	Percent 25+ with a college degree (p25pcol)
2004	Mean		95.30			95.60	29.12
	Median	56,809	96.79	186,700	787	96.30	25.11
	SD	17,722	4.80	71,245	190	3.52	15.67
	Min	24,784	65.62	2,415	3	60.80	3.03
	Max	131,550	100.00	491,553	1,604	100.00	72.83
2005	Mean		95.32			95.90	29.16
	Median	57,320	96.79	211,490	835	96.60	25.17
	SD	17,756	4.81	81,021	201	3.47	15.67
	Min	24,928	64.17	2,768	3	61.30	2.95
	Max	131,430	100.00	556,554	1,696	100.00	72.98
2006	Mean		95.51			96.00	29.17
	Median	57,351	96.95	232,570	862	96.80	25.11
	SD	17,766	4.62	89,149	206	3.47	15.68
	Min	24,827	65.95	3,039	3	61.30	2.98
	Max	131,317	100.00	612,660	1,741	100.00	73.13
2007	Mean		95.58			96.14	29.22
	Median	57,327	96.99	242,353	891	96.90	25.11
	SD	17,813	4.55	93,850	213	3.53	15.68
	Min	24,702	66.55	3,087	3	60.50	2.85
	Max	131,193	100.00	654,053	1,798	100.00	73.28

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Year	Statistics	Household median income (hhmedinc)	Percent of families above poverty level (pfmabpv)	Median home value (medhomval)	Median gross rent (med_grrnt)	Employment Rate (emprate)	Percent 25+ with a college degree (p25pcol)
2008	Mean		94.47			94.46	29.26
	Median	57,332	96.39	232,620	1,025	95.60	25.10
	SD	17,844	5.86	90,148	245	5.27	15.69
	Min	24,718	52.29	2,963	4	41.50	2.85
	Max	131,102	100.00	627,960	2,071	100.00	73.38
Total	Mean		95.40			95.55	29.13
	Median	56,972	96.90	188,208	806	96.40	25.11
	SD	17,597	4.77	85,985	225	3.81	15.65
	Min	23,421	52.29	1,416	0	41.50	0.00
	Max	131,668	100.00	654,053	2,071	100.00	77.11

Note. N=354 for 2000. N=355 for Years 2001-2008. Weighted by log of population. Means not reported for indicators based on medians.

Appendix 1

Table 34. Indicators used in stability index: Descriptive statistics weighted by population

Year	Statistics	Percent owner occupied housing units (poohu)	Percent non-vacant housing units (pnonvu)	Percent married couple households (pmarhhu)	Percent multi-person households (pmphh)
2000	Mean	70.27	93.68	50.28	73.32
	Median	69.91	95.37	53.57	72.44
	SD	13.31	4.01	15.17	7.02
	Min	19.57	81.22	26.13	51.13
	Max	97.99	100.00	86.85	100.00
	Cronbach's α	0.84			
2001	Mean	70.33	93.68	50.25	73.51
	Median	69.62	95.39	53.13	72.32
	SD	13.27	4.04	15.45	6.93
	Min	18.24	81.01	23.40	51.21
	Max	97.85	100.00	86.85	92.60
	Cronbach's α	0.88			
2002	Mean	70.38	93.70	50.33	73.56
	Median	69.77	95.39	53.01	72.85
	SD	13.30	4.04	15.51	6.93
	Min	18.22	81.01	23.34	51.14
	Max	97.93	100.00	86.88	92.62
	Cronbach's α	0.88			
2003	Mean	70.42	93.71	50.42	73.60
	Median	69.73	95.39	52.90	72.91
	SD	13.33	4.04	15.56	6.93
	Min	18.22	81.01	23.32	51.04
	Max	97.93	100.00	86.69	92.60
	Cronbach's α	0.86			

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Year	Statistics	Percent owner occupied housing units (poohu)	Percent non-vacant housing units (pnonvu)	Percent married couple households (pmarhhu)	Percent multi-person households (pmphh)
2004	Mean	70.44	93.72	50.45	73.63
	Median	69.86	95.38	52.83	72.92
	SD	13.36	4.04	15.61	6.94
	Min	18.22	81.00	23.25	51.01
	Max	97.85	100.00	86.68	92.63
	Cronbach's α	0.86			
2005	Mean	70.46	93.72	50.51	73.65
	Median	69.84	95.44	53.14	73.09
	SD	13.39	4.05	15.65	6.95
	Min	18.22	81.00	23.23	50.92
	Max	97.93	100.00	86.58	92.62
	Cronbach's α	0.88			
2006	Mean	70.47	93.73	50.59	73.67
	Median	70.86	95.45	53.17	73.05
	SD	13.41	4.05	15.70	6.96
	Min	18.22	80.99	23.21	50.85
	Max	97.85	100.00	86.73	92.62
	Cronbach's α	0.88			
2007	Mean	70.50	93.74	50.65	73.68
	Median	70.91	95.44	53.24	72.97
	SD	13.44	4.05	15.74	6.98
	Min	18.22	80.98	23.19	50.78
	Max	97.93	100.00	86.64	92.66
	Cronbach's α	0.88			

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Year	Statistics	Percent owner occupied housing units (poohu)	Percent non-vacant housing units (pnonvu)	Percent married couple households (pmarhhu)	Percent multi-person households (pmphh)
2008	Mean	70.52	93.75	50.73	73.71
	Median	70.93	95.44	53.69	73.03
	SD	13.47	4.06	15.78	6.99
	Min	18.21	80.98	23.18	50.68
	Max	97.93	100.00	86.88	92.65
	Cronbach's α	0.89			
Total	Mean	70.42	93.72	50.47	73.59
	Median	69.84	95.39	53.18	72.92
	SD	13.35	4.04	15.56	6.95
	Min	18.21	80.98	23.18	50.68
	Max	97.99	100.00	86.88	100.00

Note. N=354 for 2000. N=355 for Years 2001-2008. Weighted by population. Cronbach's αs reported for unweighted data, and only for second random half of data.

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Table 35. Indicators used in stability index: descriptive statistics, unweighted

Year	Statistics	Percent owner occupied housing units (poohu)	Percent non-vacant housing units (pnonvu)	Percent married couple households (pmarhhu)	Percent multi-person households (pmphh)
2000	Mean	75.22	95.53	58.69	76.67
	Median	77.52	96.16	59.59	77.20
	SD	14.32	2.73	12.17	7.38
	Min	19.57	81.22	26.13	51.13
	Max	97.99	100.00	86.85	100.00
2001	Mean	75.31	95.53	58.67	76.66
	Median	77.98	96.16	59.76	77.26
	SD	14.17	2.73	12.24	7.22
	Min	18.24	81.01	23.40	51.21
	Max	97.85	100.00	86.85	92.60
2002	Mean	75.31	95.53	58.70	76.64
	Median	77.93	96.16	59.85	77.16
	SD	14.17	2.72	12.26	7.24
	Min	18.22	81.01	23.34	51.14
	Max	97.93	100.00	86.88	92.62
2003	Mean	75.29	95.53	58.79	76.62
	Median	77.98	96.16	60.10	77.22
	SD	14.17	2.72	12.28	7.24
	Min	18.22	81.01	23.32	51.04
	Max	97.93	100.00	86.69	92.60

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Year	Statistics	Percent owner occupied housing units (poohu)	Percent non-vacant housing units (pnonvu)	Percent married couple households (pmarhhu)	Percent multi-person households (pmphh)
2004	Mean	75.30	95.53	58.79	76.62
	Median	77.99	96.16	60.11	77.18
	SD	14.18	2.72	12.30	7.25
	Min	18.22	81.00	23.25	51.01
	Max	97.85	100.00	86.68	92.63
2005	Mean	75.30	95.53	58.83	76.61
	Median	77.91	96.16	60.13	77.21
	SD	14.18	2.72	12.32	7.27
	Min	18.22	81.00	23.23	50.92
	Max	97.93	100.00	86.58	92.62
2006	Mean	75.29	95.53	58.90	76.59
	Median	77.87	96.17	60.21	77.16
	SD	14.18	2.72	12.35	7.29
	Min	18.22	80.99	23.21	50.85
	Max	97.85	100.00	86.73	92.62
2007	Mean	75.30	95.53	58.93	76.58
	Median	77.84	96.16	60.47	77.18
	SD	14.19	2.73	12.37	7.31
	Min	18.22	80.98	23.19	50.78
	Max	97.93	100.00	86.64	92.66

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Year	Statistics	Percent owner occupied housing units (poohu)	Percent non-vacant housing units (pnonvu)	Percent married couple households (pmarhhu)	Percent multi-person households (pmphh)
2008	Mean	75.30	95.53	58.96	76.56
	Median	77.88	96.15	60.57	77.11
	SD	14.19	2.73	12.39	7.33
	Min	18.21	80.98	23.18	50.68
	Max	97.93	100.00	86.88	92.65
Total	Mean	75.29	95.53	58.81	76.62
	Median	77.85	96.16	60.08	77.18
	SD	14.18	2.72	12.28	7.27
	Min	18.21	80.98	23.18	50.68
	Max	97.99	100.00	86.88	100.00
Note. N=354 for 2000. N=355 for Years 2001-2008.					

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Table 36. Indicators for stability index: Descriptive statistics weighted by log of population

Year	Statistics	Percent owner occupied housing units (poohu)	Percent non-vacant housing units (pnonvu)	Percent married couple households (pmarhhu)	Percent multi-person households (pmphh)
2000	Mean	75.32	95.54	58.61	76.58
	Median	77.47	96.19	59.59	77.05
	SD	14.14	2.74	12.19	7.26
	Min	19.57	81.22	26.13	51.13
	Max	97.99	100.00	86.85	100.00
2001	Mean	75.34	95.54	58.61	76.59
	Median	77.82	96.22	59.76	77.21
	SD	14.00	2.74	12.28	7.16
	Min	18.24	81.01	23.40	51.21
	Max	97.85	100.00	86.85	92.60
2002	Mean	75.34	95.55	58.65	76.58
	Median	77.80	96.21	59.85	77.10
	SD	14.00	2.74	12.29	7.18
	Min	18.22	81.01	23.34	51.14
	Max	97.93	100.00	86.88	92.62
2003	Mean	75.33	95.54	58.71	76.56
	Median	77.80	96.20	60.10	77.16
	SD	14.01	2.73	12.32	7.19
	Min	18.22	81.01	23.32	51.04
	Max	97.93	100.00	86.69	92.60

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Year	Statistics	Percent owner occupied housing units (poohu)	Percent non-vacant housing units (pnonvu)	Percent married couple households (pmarhhu)	Percent multi-person households (pmphh)
2004	Mean	75.33	95.54	58.72	76.56
	Median	77.82	96.20	60.11	77.18
	SD	14.02	2.74	12.34	7.20
	Min	18.22	81.00	23.25	51.01
	Max	97.85	100.00	86.68	92.63
2005	Mean	75.33	95.54	58.76	76.55
	Median	77.81	96.18	60.13	77.12
	SD	14.03	2.74	12.36	7.22
	Min	18.22	81.00	23.23	50.92
	Max	97.93	100.00	86.58	92.62
2006	Mean	75.32	95.54	58.81	76.53
	Median	77.81	96.19	60.21	77.06
	SD	14.03	2.74	12.40	7.24
	Min	18.22	80.99	23.21	50.85
	Max	97.85	100.00	86.73	92.62
2007	Mean	75.33	95.54	58.85	76.52
	Median	77.83	96.18	60.47	77.13
	SD	14.04	2.74	12.42	7.26
	Min	18.22	80.98	23.19	50.78
	Max	97.93	100.00	86.64	92.66
2008	Mean	75.33	95.54	58.89	76.50
	Median	77.80	96.16	60.57	77.06
	SD	14.05	2.74	12.44	7.27
	Min	18.21	80.98	23.18	50.68
	Max	97.93	100.00	86.88	92.65

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Year	Statistics	Percent owner occupied housing units (poohu)	Percent non-vacant housing units (pnonvu)	Percent married couple households (pmarhhu)	Percent multi-person households (pmphh)
Tota	Mean	75.33	95.54	58.73	76.55
	Median	77.80	96.19	60.05	77.12
	SD	14.02	2.73	12.32	7.21
	Min	18.21	80.98	23.18	50.68
	Max	97.99	100.00	86.88	100.00
Note. N=354 for 2000. N=355 for Years 2001-2008. Weighted by log of population.					

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Table 37. Indicators for household age structure: Descriptive statistics weighted by population

Year	Statistics	Percent population 10-14 (ppo10_14)	Percent population 15-19 (ppo15_19)	Percent population 20-24 (ppo20_24)	-1* % 50-54 (no5054)	-1* % 55-59 (no5559)	-1 * % 60-64 (no6064)
2000	Mean	7.49	6.82	6.12	-6.26	-4.82	-3.84
	Median	7.51	6.94	5.96	-5.96	-4.41	-3.76
	SD	1.04	1.46	2.65	1.11	0.92	0.73
	Min	3.21	0.00	0.00	-12.50	-10.16	-18.75
	Max	21.74	21.08	36.20	0.00	0.00	-1.16
	Cronbach's α	0.71					
2001	Mean	7.54	6.98	6.19	-6.51	-5.09	-3.95
	Median	7.60	7.16	5.90	-6.22	-4.78	-3.85
	SD	0.95	1.18	2.25	1.04	0.86	0.65
	Min	3.47	3.67	0.00	-16.67	-11.11	-8.57
	Max	12.14	18.72	27.92	-3.64	-2.25	0.00
	Cronbach's α	0.76					
2002	Mean	7.43	7.07	6.31	-6.63	-5.29	-4.09
	Median	7.53	7.28	6.08	-6.33	-5.00	-3.92
	SD	0.92	1.01	1.93	1.02	0.88	0.66
	Min	3.45	3.78	0.00	-22.22	-11.11	-8.69
	Max	12.00	16.32	23.28	-3.89	-2.48	0.00
	Cronbach's α	0.79					
2003	Mean	7.36	7.16	6.42	-6.75	-5.49	-4.22
	Median	7.48	7.34	6.31	-6.61	-5.19	-3.96
	SD	0.88	0.89	1.65	1.02	0.91	0.69
	Min	3.46	3.96	0.00	-22.22	-11.11	-8.33
	Max	11.76	14.24	19.56	-3.90	-2.87	0.00
	Cronbach's α	0.81					

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Year	Statistics	Percent population 10-14 (ppo10_14)	Percent population 15-19 (ppo15_19)	Percent population 20-24 (ppo20_24)	-1* % 50-54 (no5054)	-1* % 55-59 (no5559)	-1 * % 60-64 (no6064)
2004	Mean	7.27	7.26	6.51	-6.87	-5.68	-4.35
	Median	7.42	7.45	6.49	-6.78	-5.39	-4.03
	SD	0.85	0.82	1.41	1.01	0.95	0.72
	Min	3.44	4.01	0.00	-23.53	-11.76	-8.13
	Max	10.69	12.58	16.67	-3.95	-3.18	0.00
	Cronbach's α	0.77					
2005	Mean	7.19	7.34	6.61	-6.99	-5.89	-4.50
	Median	7.40	7.52	6.55	-6.95	-5.68	-4.19
	SD	0.82	0.78	1.20	1.00	0.97	0.75
	Min	0.00	4.04	0.00	-23.53	-11.76	-7.85
	Max	10.46	11.76	14.29	-3.98	-3.30	0.00
	Cronbach's α	0.79					
2006	Mean	7.10	7.39	6.70	-7.12	-6.10	-4.64
	Median	7.34	7.57	6.67	-7.15	-5.95	-4.38
	SD	0.79	0.75	1.03	0.99	0.99	0.78
	Min	0.00	4.23	0.00	-23.53	-11.76	-8.08
	Max	9.87	11.76	13.64	-4.06	-3.37	0.00
	Cronbach's α	0.73					
2007	Mean	6.99	7.42	6.77	-7.22	-6.29	-4.78
	Median	7.22	7.64	6.81	-7.28	-6.23	-4.52
	SD	0.76	0.74	0.89	0.98	1.00	0.81
	Min	0.00	4.29	0.00	-25.00	-12.50	-8.20
	Max	9.38	12.50	12.85	-4.10	-3.50	0.00
	Cronbach's α	0.82					

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Year	Statistics	Percent population 10-14 (ppo10_14)	Percent population 15-19 (ppo15_19)	Percent population 20-24 (ppo20_24)	-1* % 50-54 (no5054)	-1* % 55-59 (no5559)	-1 * % 60-64 (no6064)
2008	Mean	6.89	7.44	6.86	-7.29	-6.44	-4.93
	Median	7.10	7.63	6.92	-7.31	-6.43	-4.73
	SD	0.73	0.72	0.78	0.96	1.00	0.83
	Min	0.00	4.18	0.00	-25.00	-12.50	-8.40
	Max	9.11	12.50	12.12	-4.19	-3.51	0.00
	Cronbach's α	0.84					
Total	Mean	7.25	7.21	6.50	-6.85	-5.68	-4.37
	Median	7.34	7.33	6.49	-6.73	-5.51	-4.19
	SD	0.89	0.98	1.66	1.06	1.08	0.82
	Min	0.00	0.00	0.00	-25.00	-12.50	-18.75
	Max	21.74	21.08	36.20	0.00	0.00	0.00

Note. N=354 for 2000. N=355 for Years 2001-2008. Weighted by population. Cronbach's αs reported for unweighted data, and only for second random half of data.

Table 38. Indicators for household age structure index: Descriptive statistics, unweighted

Year	Statistics	Percent population 10-14 (ppo10_14)	Percent population 15-19 (ppo15_19)	Percent population 20-24 (ppo20_24)	-1* % 50-54 (no5054)	-1* % 55-59 (no5559)	-1 * % 60-64 (no6064)
2000	Mean	7.57	6.68	5.21	-6.61	-4.98	-3.92
	Median	7.45	6.47	4.79	-6.52	-4.93	-3.81
	SD	1.63	1.93	3.04	1.48	1.35	1.32
	Min	3.21	0.00	0.00	-12.50	-10.16	-18.75
	Max	21.74	21.08	36.20	0.00	0.00	-1.16
2001	Mean	7.56	6.86	5.46	-6.88	-5.34	-4.01
	Median	7.56	6.69	5.09	-6.70	-5.20	-3.95
	SD	1.26	1.49	2.48	1.37	1.16	0.90
	Min	3.47	3.67	0.00	-16.67	-11.11	-8.57
	Max	12.14	18.72	27.92	-3.64	-2.25	0.00
2002	Mean	7.43	6.98	5.69	-7.03	-5.57	-4.20
	Median	7.35	6.88	5.41	-6.90	-5.45	-4.09
	SD	1.22	1.30	2.11	1.46	1.15	0.95
	Min	3.45	3.78	0.00	-22.22	-11.11	-8.69
	Max	12.00	16.32	23.28	-3.89	-2.48	0.00
2003	Mean	7.34	7.09	5.90	-7.19	-5.80	-4.36
	Median	7.32	7.02	5.68	-7.09	-5.73	-4.26
	SD	1.14	1.16	1.81	1.41	1.16	0.94
	Min	3.46	3.96	0.00	-22.22	-11.11	-8.33
	Max	11.76	14.24	19.56	-3.90	-2.87	0.00

Appendix 1

Year	Statistics	Percent population 10-14 (ppo10_14)	Percent population 15-19 (ppo15_19)	Percent population 20-24 (ppo20_24)	-1* % 50-54 (no5054)	-1* % 55-59 (no5559)	-1 * % 60-64 (no6064)
2004	Mean	7.21	7.18	6.09	-7.33	-6.02	-4.53
	Median	7.17	7.16	5.91	-7.23	-5.97	-4.43
	SD	1.06	1.07	1.56	1.40	1.17	0.97
	Min	3.44	4.01	0.00	-23.53	-11.76	-8.13
	Max	10.69	12.58	16.67	-3.95	-3.18	0.00
2005	Mean	7.07	7.26	6.27	-7.48	-6.26	-4.69
	Median	7.05	7.23	6.12	-7.38	-6.22	-4.62
	SD	1.08	1.04	1.35	1.36	1.16	0.98
	Min	0.00	4.04	0.00	-23.53	-11.76	-7.85
	Max	10.46	11.76	14.29	-3.98	-3.30	0.00
2006	Mean	6.94	7.30	6.42	-7.62	-6.50	-4.87
	Median	6.93	7.26	6.32	-7.57	-6.41	-4.82
	SD	1.01	1.00	1.20	1.32	1.15	0.99
	Min	0.00	4.23	0.00	-23.53	-11.76	-8.08
	Max	9.87	11.76	13.64	-4.06	-3.37	0.00
2007	Mean	6.80	7.34	6.55	-7.73	-6.71	-5.03
	Median	6.78	7.31	6.48	-7.68	-6.63	-4.97
	SD	0.96	0.97	1.07	1.34	1.15	0.99
	Min	0.00	4.29	0.00	-25.00	-12.50	-8.20
	Max	9.38	12.50	12.85	-4.10	-3.50	0.00

Appendix 1

Year	Statistics	Percent population 10-14 (ppo10_14)	Percent population 15-19 (ppo15_19)	Percent population 20-24 (ppo20_24)	-1* % 50-54 (no5054)	-1* % 55-59 (no5559)	-1 * % 60-64 (no6064)
2008	Mean	6.69	7.35	6.67	-7.80	-6.88	-5.21
	Median	6.66	7.31	6.62	-7.80	-6.82	-5.20
	SD	0.92	0.94	0.97	1.31	1.11	1.00
	Min	0.00	4.18	0.00	-25.00	-12.50	-8.40
	Max	9.11	12.50	12.12	-4.19	-3.51	0.00
Total	Mean	7.18	7.12	6.03	-7.30	-6.01	-4.54
	Median	7.10	7.07	5.98	-7.26	-5.95	-4.46
	SD	1.20	1.27	1.91	1.43	1.32	1.10
	Min	0.00	0.00	0.00	-25.00	-12.50	-18.75
	Max	21.74	21.08	36.20	0.00	0.00	0.00

Note. N=354 for 2000. N=355 for Years 2001-2008.

Table 39. Indicators for household age structure index: descriptive statistics weighted by log of population

Year	Statistics	Percent population 10-14 (ppo10_14)	Percent population 15-19 (ppo15_19)	Percent population 20-24 (ppo20_24)	Percent population 50-54 (no5054)	Percent population 55-59 (no5559)	Percent population 60-64 (no6064)
2000	Mean	7.54	6.67	5.24	-6.61	-5.00	-3.89
	Median	7.43	6.47	4.80	-6.53	-4.93	-3.81
	SD	1.50	1.87	3.05	1.41	1.28	1.13
	Min	3.21	0.00	0.00	-12.50	-10.16	-18.75
	Max	21.74	21.08	36.20	0.00	0.00	-1.16
2001	Mean	7.54	6.85	5.48	-6.85	-5.33	-4.01
	Median	7.54	6.69	5.10	-6.70	-5.20	-3.94
	SD	1.24	1.48	2.49	1.28	1.11	0.87
	Min	3.47	3.67	0.00	-16.67	-11.11	-8.57
	Max	12.14	18.72	27.92	-3.64	-2.25	0.00
2002	Mean	7.41	6.98	5.71	-7.00	-5.55	-4.19
	Median	7.35	6.88	5.41	-6.90	-5.45	-4.08
	SD	1.19	1.28	2.12	1.28	1.11	0.90
	Min	3.45	3.78	0.00	-22.22	-11.11	-8.69
	Max	12.00	16.32	23.28	-3.89	-2.48	0.00
2003	Mean	7.33	7.09	5.91	-7.16	-5.78	-4.36
	Median	7.32	7.01	5.68	-7.09	-5.73	-4.26
	SD	1.11	1.14	1.81	1.23	1.11	0.90
	Min	3.46	3.96	0.00	-22.22	-11.11	-8.33
	Max	11.76	14.24	19.56	-3.90	-2.87	0.00

Appendix 1

Year	Statistics	Percent population 10-14 (ppo10_14)	Percent population 15-19 (ppo15_19)	Percent population 20-24 (ppo20_24)	Percent population 50-54 (no5054)	Percent population 55-59 (no5559)	Percent population 60-64 (no6064)
2004	Mean	7.21	7.18	6.11	-7.30	-6.01	-4.53
	Median	7.18	7.16	5.90	-7.23	-5.97	-4.43
	SD	1.05	1.05	1.55	1.20	1.12	0.92
	Min	3.44	4.01	0.00	-23.53	-11.76	-8.13
	Max	10.69	12.58	16.67	-3.95	-3.18	0.00
2005	Mean	7.08	7.25	6.29	-7.45	-6.25	-4.70
	Median	7.05	7.22	6.12	-7.38	-6.22	-4.62
	SD	1.02	1.01	1.33	1.16	1.12	0.94
	Min	0.00	4.04	0.00	-23.53	-11.76	-7.85
	Max	10.46	11.76	14.29	-3.98	-3.30	0.00
2006	Mean	6.96	7.29	6.44	-7.58	-6.48	-4.87
	Median	6.93	7.26	6.31	-7.57	-6.41	-4.82
	SD	0.97	0.97	1.17	1.12	1.11	0.95
	Min	0.00	4.23	0.00	-23.53	-11.76	-8.08
	Max	9.87	11.76	13.64	-4.06	-3.37	0.00
2007	Mean	6.82	7.33	6.56	-7.69	-6.70	-5.04
	Median	6.79	7.31	6.48	-7.65	-6.63	-4.97
	SD	0.92	0.94	1.03	1.10	1.10	0.96
	Min	0.00	4.29	0.00	-25.00	-12.50	-8.20
	Max	9.38	12.50	12.85	-4.10	-3.50	0.00
2008	Mean	6.71	7.34	6.69	-7.76	-6.87	-5.22
	Median	6.67	7.31	6.62	-7.79	-6.81	-5.20
	SD	0.87	0.90	0.92	1.06	1.07	0.96
	Min	0.00	4.18	0.00	-25.00	-12.50	-8.40
	Max	9.11	12.50	12.12	-4.19	-3.51	0.00

Appendix 1

Year	Statistics	Percent population 10-14 (ppo10_14)	Percent population 15-19 (ppo15_19)	Percent population 20-24 (ppo20_24)	Percent population 50-54 (no5054)	Percent population 55-59 (no5559)	Percent population 60-64 (no6064)
Total	Mean	7.18	7.11	6.05	-7.27	-6.00	-4.53
	Median	7.11	7.06	5.98	-7.25	-5.95	-4.46
	SD	1.15	1.24	1.90	1.26	1.28	1.04
	Min	0.00	0.00	0.00	-25.00	-12.50	-18.75
	Max	21.74	21.08	36.20	0.00	0.00	0.00

Note. N=354 for 2000. N=355 for Years 2001-2008. Weighted by log of population.

Table 40. Aspects of policing arrangements

Completely covered by respective state police

	N	Percent
No	300	84.51
Yes	55	15.49
Total	355	100

Receives partial coverage by respective state police

	N	Percent
No	350	98.59
Yes	5	1.41
Total	355	100

Municipality hosts or has contract to receive services from a police department that is either regional, multi-jurisdictional, or neighboring

	N	Percent
No	328	92.39
Yes	27	7.61
Total	355	100

Municipality hosts its own full service department and receives no regular support from a state police agency or another agency based wholly or in part outside of the municipality

	N	Percent
No	83	23.38
Yes	272	76.62
Total	355	100

Table 41. Statistics on department size for jurisdictions with their "own" department

	2000-2008 median N	
	Officers	Employees
Statistics		
jurisdictions with their “own” department, including those (20) with a median of zero full time officers over the period		
Statistics		
N jurisdictions	272	272
Median	13	14
IQR	20	23
Minimum	0	0
Maximum	6,781	7,704
jurisdictions with their “own” department, but with at least one full time officer over the period		
N jurisdictions	252	252
Median	14	16
IQR	20.5	23
Minimum	1	1
Maximum	6,781	7,704

Table 42 . MCDs covered exclusively by Pennsylvania State Police

	Middle year population
Bridgeton	1,223
Chadds Ford	3,150
Charlestown	4,753
Chester Heights	2,269
Concord	10,557
Durham	1,035
East Marlborough	6,898
East Nantmeal	2,059
East Nottingham	6,428
Edgemont	3,676
Elk	1,684
Elverson	1,111
Haycock	2,323
Kennett	7,491
Langhorne Manor	1,994
London Britain	3,161
London Grove	5,289
Londonderry	1,870
Lower Oxford	5,191
Newlin	1,299
Penndel	2,385
Pennsbury	3,631
Perkiomen	8,219
Pocopson	2,927
Richlandtown	1,461
Riegelsville	855
Rose Valley	850
Salford	2,308
Schwenksville	1,904
Silverdale	988
South Coventry	2,142
Trappe	3,731
Trumbauersville	932
Upper Frederick	2,748
Upper Hanover	5,166
Upper Salford	2,670
West Bradford	10,804
West Nantmeal	2,310
Worcester	7,583
Wrightstown	2,863

Table 43. Jurisdictions covered exclusively by the New Jersey State Police

	Middle year population (2004)
Alloway	2,839
Bass River	1,562
Hainesport	5,728
Mannington	1,568
Oldmans	1,801
Pilesgrove	4,054
Pittsgrove	9,182
Quinton	2,814
Shamong	6,749
Southampton	10,918
Tabernacle	7,312
Tavistock	17
Upper Pittsgrove	3,584
Washington	574
Wrightstown	749

Note. Pine Valley removed.

Table 44. Missing data allocation technique by year

Missing data approach	2000	2001	2002	2003	2004	2005	2006	2007	2008
0	304	291	298	294	298	299	303	312	311
1	23	25	25	25	23	23	22	18	16
2	4	7	4	6	5	5	3	0	1
3	0	8	4	5	4	3	2	0	0
4	0	0	0	0	0	0	0	0	2
5	10	10	10	9	9	9	9	9	9
6	5	5	5	6	6	6	6	6	6
7	7	7	7	8	8	8	8	8	8
8	2	2	2	2	2	2	2	2	2

Note. Approach code
0 Not missing; jurisdictions that provided their own data
1 Allocation from Pennsylvania State Police
2 Average
3 Interpolation
4 Trend
5 Coverage by a regional police department
6 Coverage by another jurisdiction
7 Jurisdiction covered another jurisdiction
8 Jurisdiction is a borough within a township

Table 45. Proportion of county-level UCR data used during 1st and 2nd allocation procedures

	Murder	Rape	Robbery	Assault	Burglary	Larceny	Motor Vehicle Theft
Bucks	55	451	649	3,509	9,097	26,763	3,586
1st allocation	3.7%	21.7%	3.8%	3.9%	3.8%	3.8%	2.7%
2nd allocation	6.6%	6.2%	6.5%	6.5%	6.3%	6.7%	6.2%
Chester	286	3,696	5,170	18,480	78,012	138,556	20,944
1st allocation	2.6%	5.0%	2.7%	2.7%	2.7%	2.8%	0.5%
2nd allocation	1.0%	1.1%	1.1%	1.1%	1.1%	1.1%	1.1%
Delaware	45	305	895	2,115	6,555	34,140	3,445
1st allocation	6.3%	14.8%	6.2%	6.2%	6.2%	6.4%	1.3%
2nd allocation	9.1%	10.2%	9.4%	9.8%	10.0%	9.5%	9.8%
Montgomery	45	612	603	6,399	9,081	24,714	2,430
1st allocation	7.8%	12.9%	45.5%	19.7%	39.0%	36.7%	16.7%

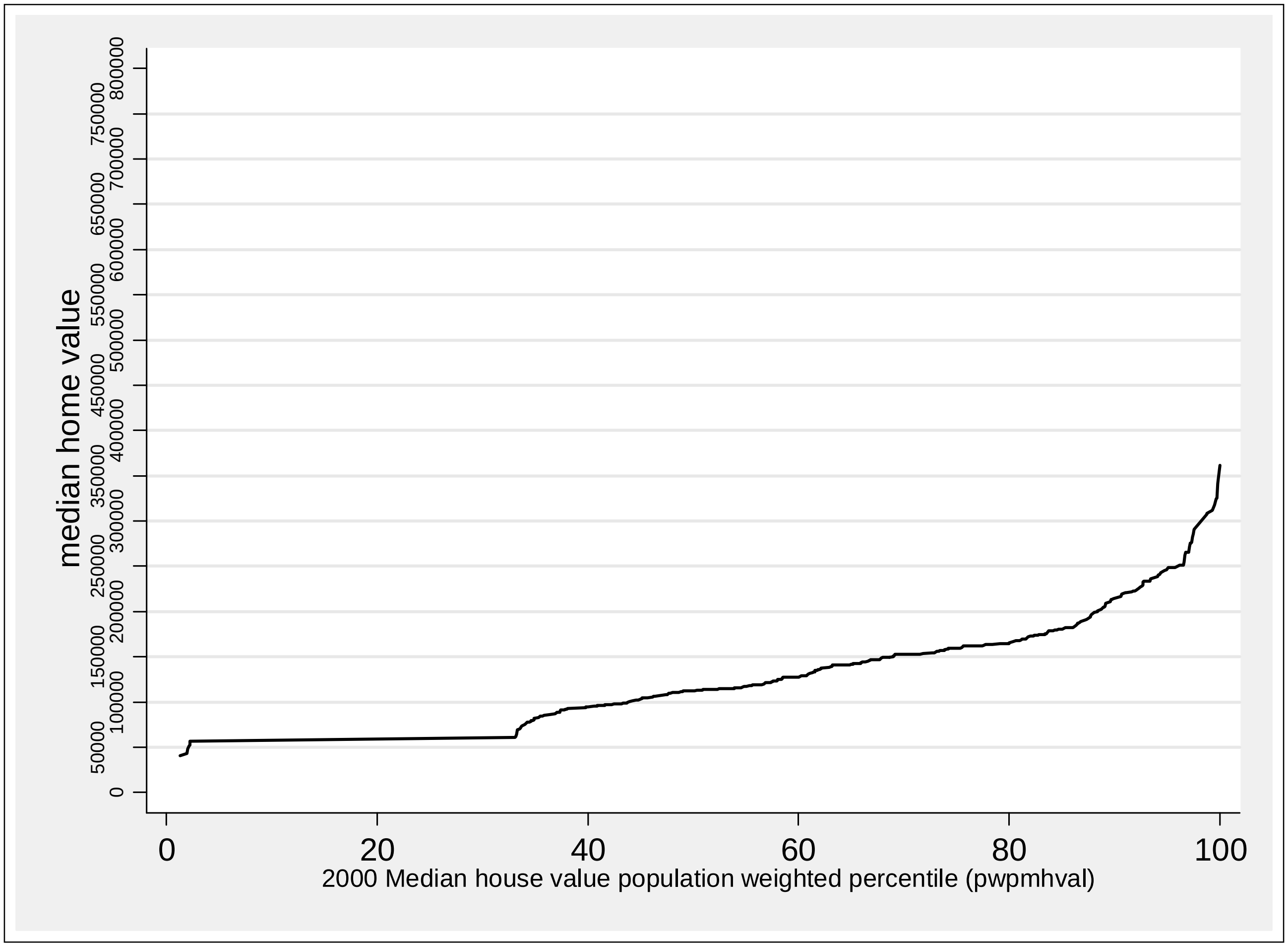

Figure 78. Relationship between population weighted percentile scores for median home value, and median home value.

Note. Year = 2000. Jurisdictions in Philadelphia metropolitan area = unit of analysis.

9. REFERENCES

Adams, C. T., Bartelt, D., Elesh, D., Goldstein, I., Kleniewski, N., & Yancey, W. (1991). *Philadelphia: Neighborhoods, Division, and Conflict in a Postindustrial City*. Philadelphia: Temple University Press.

Adams, C. T., Elesh, D., & Bartelt, D. (2008). *Restructuring the Philadelphia region: Metropolitan divisions and inequality*. Philadelphia: Temple University Press.

Alba, R., & Logan, J. (1991). Variations on two themes: Racial and ethnic patterns in the attainment of suburban residence. *Demography, 28*, 431-453.

Aligica, P. D., & Tarko, V. (2012). Polycentricity: From Polanyi to Ostrom, and Beyond. *Governance, 25*(2), 237-262. doi: 10.1111/j.1468-0491.2011.01550.x

Anderson, E. (1994). The Code of the streets.

Anderson, E. (2000). *Code of the Street: Decency, Violence, and the Moral Life of the Inner City*. New York: W.W. Norton.

Anselin, L. (1988). *Spatial Econometrics: Methods and Models*. Boston: Kluwer Academic.

Anselin, L. (1995). Local Indicators of Spatial Association—LISA. *Geographical Analysis, 27*(2), 93-115. doi: 10.1111/j.1538-4632.1995.tb00338.x

Anselin, L., Florax, R. J. G. M., & Rey, S. J. (Eds.). (2004). *Advances in Spatial Econometrics*. Berlin: Springer.

Bailey, T., & Gatrell, A. (1995). *Interactive spatial data analysis*. New York: Longmann.

Baller, R. D., Anselin, L., Messner, S. F., Deane, G., & Hawkins, D. F. (2001). Structural covariates of US county homicide rates: Incorporating spatial effects. *Criminology, 39*(3), 561-590.

Baltzell, E. D. (1979). *Puritan Boston and Quaker Philadelphia*. New York: Free Press.

Banerjee, S., Carlin, B. P., & Gelfand, A. E. (2004). *Hierarchical Modeling and Analysis for Spatial Data*. Boca Raton, FL: Chapman & Hall / CRC.

Bass, J. (1995). Rural policing: Patterns and problems of "micro" departments. *The Justice Professional, 9*(1), 59-74. doi: 10.1080/1478601x.1995.10383049

Baumer, E. P. (2008). An Empirical assessment of the contemporary crime trends puzzle. In N. R. Council (Ed.), *Understanding Crime Trends: Workshop Report* (pp. 211-241). Washington, D.C.: The National Academies Press.

Becker, G. S. (1968). Crime and punishment: An economic approach. *J. Pol. Econ., 76*, 169.

Bennett, T. H. (1995). Identifying, explaining, and targeting burglary 'hot spots'. *European Journal of Criminal Policy and Research, 3*, 113-123.

Bernardinelli, L., Clayton, D., & Montomoli, C. (1995). BAYESIAN ESTIMATES OF DISEASE MAPS - HOW IMPORTANT ARE PRIORS. *Statistics in Medicine, 14*(21-22), 2411-2431.

Bernardinelli, L., Clayton, D., Pascutto, C., Montomoli, C., Ghislandi, M., & Songini, M. (1995). BAYESIAN-ANALYSIS OF SPACE-TIME VARIATION IN DISEASE RISK. *Statistics in Medicine, 14*(21-22), 2433-2443.

Bernardinelli, L., Pascutto, C., Best, N. G., & Gilks, W. R. (1997). Disease mapping with errors in covariates. *Statistics in Medicine, 16*(7), 741-752.

Berry, B. J. L. (1965). Internal structure of the city. *Law and Contemporary Problems, 30*(111-119).

Berry, B. J. L. (1972). Latent structure and the American urban system, with international comparisons. In B. J. L. Berry (Ed.), *City Classification Handbook: Methods and Applications* (pp. 11-61). New York: Wiley.

Berry, B. J. L., & Kasarda, J. D. (1977). *Contemporary urban ecology*. New York: Macmillan.

Blumstein, A., & Rosenfeld, R. (2008). Factors contributing to U.S. crime trends. In N. R. Council (Ed.), *Understanding Crime Trends: Workshop Report* (pp. 13-44). Washington, D.C.: The National Academies Press.

Boggs, S. (1965). Urban crime patterns. *American Sociological Review, 30*, 899-908.

Bohrnstedt, G. W. (1969). Observation on the measurement of change. In E. F. Borgatta & G. W. Bohrnstedt (Eds.), *Sociological methodology* (pp. 113-133). San Francisco: Jossey-Bass.

Boiroju, N. K., Yerukala, R., Rao, M. V., & Reddy, M. K. (2011). A Bootstrap tes for equality of mean absolute errors. *ARPN Journal of Engineering and Applied Sciences, 6*(5), 9-11.

Bottoms, A. E. (2007). Place, space, crime and disorder. In M. Maguire, R. Morgan & R. Reiner (Eds.), *The Oxford Handbook of Criminology* (Fourth ed., pp. 528-574). New York: Oxford University Press.

Bottoms, A. E., & Wiles, P. (1986). Housing tenure and residental community crime careers in Britain. In A. J. Reiss, Jr. & M. Tonry (Eds.), *Communities and crime* (pp. 101-162). Chicago: University of Chicago Press.

References

Bowers, K. J., & Johnson, S. D. (2004). Who commits near repeats? A test of the boost explanation. *Western Criminology Review, 5*(3), 12-24.

Braga, A. A., Weisburd, D., Waring, E. L., Mazerolle, L. G., Spelman, W., & Gajewski, F. (1997). Problem solving in violent crime places: A Randomized controlled experiment. *Criminology, 37*(3), 541-580.

Brantingham, P. J., Dyreson, D. A., & Brantinghm, P. L. (1976). Crime seen through a cone of resolution. *American Behavioral Scientist, 20*, 261-274.

Brantingham, P. L., & Brantingham, P. J. (1993). Nodes, paths, and edges: Considerations on the complexity of crime and the physical environment. *Journal of Environmental Psychology, 13*, 3-28.

Brantingham, P. L., Glasser, U., Jackson, P., Kinney, B., & Vajihollahi, M. (2008). Mastermind: Computational modeling and simulation of spatio-temporal aspects of crime in urban environments. In J. E. Eck & L. Liu (Eds.), *Artificial Crime Analysis Systems: Using Computer Simulations and Geographic Information Systems* (pp. 252-280). Hershey, PA: Idea Group.

Brenner, M. H. (1979). Review of "Forecasting crime data". *The Journal of Criminal Law and Criminology (1973-), 70*(2), 273-274. doi: 10.2307/1142929

Brower, S. (2011). *Neighbors and Neighborhoods: Elements of Successful Community Design*. Washington, DC: American Planning Association Planners Press.

Brown, L. A., & Sharma, M. (2010). Metropolitan Context and Racial/Ethnic Intermixing in Residential Space: U.S. Metropolitan Statistical Areas, 1990-20001. *Urban Geography, 31*(1), 1-28. doi: 10.2747/0272-3638.31.1.1

Brown, M. A. (1982). Modelling the Spatial Distribution of Suburban Crime. *Economic Geography, 58*(3), 247-261. doi: 10.2307/143513

Browne, W. J., & Draper, D. (2006). Rejoinder. *Bayesian Analysis, 1*(3), 547-550.

Browne, W. J., Goldstein, H., & Rabash, J. (2001). Multiple membership multiple classification (MMMC) models. *Statistical Modelling, 1*, 103-124.

Burnell, J. D. (1988). Crime and Racial Composition in Contiguous Communities as Negative Externalities: Prejudiced Households' Evaluation of Crime Rate and Segregation Nearby Reduces Housing Values and Tax Revenues. *American Journal of Economics and Sociology, 47*(2), 177-193. doi: 10.2307/3486415

Bursik, R. J. J. (1986a). Delinquency rates as sources of ecological change. In J. M. Byrne & R. J. Sampson (Eds.), *The social ecology of crime* (pp. 63-76). New York: Springer-Verlag.

Bursik, R. J. J. (1986b). Ecological stability and the dynamics of delinquency. In A. J. Reiss & M. Tonry (Eds.), *Communities and crime* (pp. 35-66). Chicago: University of Chicago Press.

Bursik, R. J. J., & Grasmick, H. G. (1993a). Economic Deprivation and Neighborhood Crime Rates, 1960-1980. *Law & Society Review, 27*(2), 263-283.

Bursik, R. J. J., & Grasmick, H. G. (1993b). *Neighborhoods and crime*. Lexington: Lexington.

Bursik, R. J. J., & Webb, J. (1982). Community change and patterns of delinquency. *AJS, 88*(1), 24-42.

Calder, K., & Holloman, C. (2000). The EM Algorithm and Missing Data Problems.

Chainey, S., & Ratcliffe, J. H. (2005). *GIS and Crime Mapping*. London: John Wiley and Sons

Charles, C. Z. (2003). The Dynamics of racial residential segregation. *Annual Review of Sociology, 29*, 167-207.

Charles, D. (2012). How a sleepy Pennsylvania town grew into America's mushroom capital. NPR News, October 11, 2012. [ONLINE: http://m.npr.org/news/U.S./162719130 ; accessed 7/27/2013]. Retrieved from

Chermak, S., Carter, J., Carter, D., McGarrell, E. F., & Drew, J. (2013). Law enforcement's information sharing infrastructure: A National assessment. *Policy Quarterly, 16*(2), 211-244.

Coate, D., & Schwester, R. W. (2009). Use of State Police Services for Local Policing: The Case of New Jersey. *Public Budgeting & Finance, 29*(3), 97-109. doi: 10.1111/j.1540-5850.2009.00938.x

Cohen, J., Gorr, W. L., & Olligschlaeger, A. M. (2007). Leading indicators and spatial interactions: A Crime-forecasting model for proactive police deployment. *Geographical Analysis, 39*, 105-127.

Congdon, P. (2003). *Applied Bayesian Modelling*. London: John Wiley and Sons.

Congdon, P. (2006). *Bayesian Statistical Modeling (2nd Ed.)*. West Sussex: Wiley.

Corsaro, N., Hunt, E. D., Hipple, N. K., & McGarrell, E. F. (2012). The Impact of Drug Market Pulling Levers Policing on Neighborhood Violence An Evaluation of the High Point Drug Market Intervention. *Criminology & Public Policy, 11*(2), 167-+. doi: 10.1111/j.1745-9133.2012.00798.x

Council, N. R. (2008). *Understanding Crime Trends: Workshop Report. Committee on Understanding Crime Trends, Committtee on Law and Justice, Division of Behavioral and Social Sciences and Education*. Washington, DC: National Academies Press.

Covington, J. C., & Taylor, R. B. (1989). Gentrification and crime: Robbbery and larceny changes in appreciating Baltimore neighborhoods in the 1970's. *Urban Affairs Quarterly, 25*, 142-172.

References

Crenson, M. (1983). *Neighborhood politics*. Cambridge: Harvard University Press.

Cureton, E. E. (1967). Validity, reliability and baloney. In D. M. Jackson & D. Messick (Eds.), *Problems in human assessment* (pp. 271-273). New York: McGraw Hill.

Dayanim, S. L. (2014). *Examining the influence of community institutions on innter ring suburban resilience: A Study in Southeastern Pennsylvania. Unpublished doctoral dissertation. Department of of Geography and Urban Studies, Temple University, Philadelphia.*

Deadman, D. (2003). Forecasting residential burglary. *International Journal of Forecasting, 19*(2003), 567-578.

Deane, G., Messner, S. F., Stucky, T. D., McGeever, K., & Kubrin, C. E. (2008). Not 'Islands, entire of themselves': Exploring the spatial context of city-level robbery rates. *Journal of Quantitative Criminology, 24*, 363-380.

Dear, M. J., & Dishman, J. D. (Eds.). (2001). *From Chicago to L.A.: Making Sense of Urban Theory*. thousand Oaks, Calif.: Sage.

DeFina, R. H., & Arvanites, T. M. (2002). The Weak effect of imprisonment on crime: 1971-1998. *Social Science Quarterly, 83*(3), 635-653.

Dempster, A. P., Laird, N. M., & Rubin, D. B. (1977). Maximum Likelihood from Incomplete Data via the EM Algorithm. *Journal of the Royal Statistical Society. Series B (Methodological), 39*(1), 1-38.

Doran, B. J., & Lees, B. G. (2005). Investigating the spatiotemporal links between disorder, crime, and the fear of crime. *Professional Geographer, 57*(1), 1-12.

Durlauf, S. N., Navarro, S., & Rivers, D. A. (2008). On the Use of aggregate crime regressions in policy evaluations. In N. R. Council (Ed.), *Understanding Crime Trends: Workshop Report* (pp. 211-241). Washington, D.C.: The National Academies Press.

Eck, J. E., & Weisburd, D. (1995). Crime places in crime theory. In J. E. Eck & D. Weisburd (Eds.), *Crime and place (Crime Prevention Studies, Volume 4)* (pp. 1-34). Monsey: Criminal Justice Press.

Erie, S. P., & Mackenzie, S. A. (2009). THE L.A. SCHOOL AND POLITICS NOIR: BRINGING THE LOCAL STATE BACK IN. *Journal of Urban Affairs, 31*(5), 537-557. doi: 10.1111/j.1467-9906.2009.00453.x

Faber, N. M. (1999). Estimating the uncertainty in estimates of root mean square error of prediction: application to determining the size of an adequate test set in multivariate calibration. *Chemometrics and Intelligent Laboratory Systems, 49*(1), 79-89. doi: http://dx.doi.org/10.1016/S0169-7439(99)00027-1

Fabrikant, R. (1979). The distribution of criminal offenses in an urban environment: A spatial analysis of crime spillovers and of juvenile offenders. *American Journal of Economics and Sociology, 38*, 31-47.

Fagan, J. (2008). Crime and neighborhood change. In N. R. Council (Ed.), *Understanding Crime Trends: Workshop Report* (pp. 81-126). Washington, DC: The National Academies Press.

Fagan, J., & Davies, G. (2002). The Natural history of neighborhood violence. *Journal of Contemporary Criminal Justice, 20*(2), 127-147.

Felson, M. (1981). Review of "Forecasting crime data". *Contemporary Sociology, 10*(2), 230-231. doi: 10.2307/2066878

Felson, M. (1987). Routine activities and crime prevention in the developing metropolis. *Criminology, 25*(4), 911-932.

Fensom, M. J. (2012). You'll never play golf here. *The Star-Ledger. Special Reports. May 2012. [ONLINE: http://www.nj.com/inside-jersey/index.ssf/special_reports/youll_never_play_golf_here.html ; accessed 3/23/13]*. Retrieved from

Ferguson, A. G. (2012). Predictive policing and reasonable suspicion. *Emory Law Journal, 62*, 258-325.

Fischer, C. S. (1975). Toward a subcultural theory of urbanism. *American Journal of Sociology, 80*, 1319-1341.

Fischer, C. S. (1982). *To Dwell among friends: Personal networks in town and city*. Chicago: University of Chicago Press.

Fox, J. A. (1978). *Forecasting crime data: An Econometric Analysis*. Lexington, MA: Lexington.

Gardner, E. S. (1985). Exponential smoothing: The State of the art. *Journal of Forecasting, 4*, 1-28.

Gelman, A., Carlin, J. B., & Stern, H. S. (2003). *Bayesian Data Analysis* (Second ed.). Boca Raton, FL: Chapman & Hall/CRC.

Gelman, A., Fagan, J., & Kiss, A. (2007). An analysis of the New York City Police Department's "Stop-and-Frisk" policy in the context of claims of racial bias. *Journal of the American Statistical Association, 102*(479), 813-823.

Gelman, A., & Hill, J. (2007). *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge (UK): Cambridge University Press.

Gerell, M. (2014). Collective efficacy, neighborhood and geographical units of analysis: Findings from a case study of Swedish residential neighborhoods. *European Journal on Criminal Policy and Research*. doi: DOI 10.1007/s10610-014-9257-3

References

Goldstein, H. (2003). *Multilevel Statistical Models (3rd ed.)*. London: Arnold.
Goldstein, J. (2011). Police force nearly halved, Camden feels impact. *New York Times March 6, 2011 [ONLINE: http://www.nytimes.com/2011/03/07/nyregion/07camden.html?pagewanted=all&_r=0 Accessed 3/29/2013]*.
Golledge, R. G., & Stimson, R. J. (1997). *Spatial Behavior: A Geographic Perspective*. New York: Guilford Press.
Goode, E. (2011). Sending the police before there's a crime. *New York Times. August 15, 2011, p. A11*.
Gorr, W., & Harries, R. (2003). Introduction to crime forecasting. *International Journal of Forecasting, 19*(4), 551-555. doi: 10.1016/s0169-2070(03)00089-x
Gorr, W., Olligschlaeger, A., & Thompson, Y. (2003). Short-term forecasting of crime. *International Journal of Forecasting, 19*(4), 579-594. doi: 10.1016/s0169-2070(03)00092-x
Gottdiener, M. (1994). *The Social Production of Urban Space* (Second ed.). Austin: University of Texas Press.
Groff, E., Weisburd, D., & Yang, S.-M. (2010). Is it Important to Examine Crime Trends at a Local "Micro" Level?: A Longitudinal Analysis of Street to Street Variability in Crime Trajectories. *Journal of Quantitative Criminology, 26*(1), 7-32. doi: 10.1007/s10940-009-9081-y
Groff, E. R., & La Vigne, N. G. (2001). Mapping an opportunity structure of residential burglary. *Journal of Research in Crime and Delinquency, 31*(3), 257-278.
Groff, E. R., & La Vigne, N. G. (2002). Forecasting the future of predictive crime mapping. In N. Tilley (Ed.), *Crime Prevention Studies: Analysis for Crime Prevention* (Vol. 13, pp. 29-57). Monsey, NY: Criminal Justice Press.
Groff, E. R., Taylor, R. B., Elesh, D., Johnson, L. T., & McGovern, J. (2014). Permeability across a metropolitan area: Conceptualizing and operationalizing a macro level crime pattern theory. *Environment and Planning A, 46*(1), 129-152.
Hakim, S., Ovadia, A., Sagi, E., & Weinblatt, J. (1979). Interjurisdictional Spillover of Crime and Police Expenditure. *Land Economics, 55*(2), 200-212.
Hakim, S., & Rengert, G. F. (Eds.). (1981). *Crime Spillover*. Beverly Hills, CA: Sage.
Hale, C., & Sabbagh, D. (1991a). Testing the relationship between umemloyment and crime: A Methodological comment and empirical analysis using time series data for England and Wales. *Journal of Research in Crime and Delinquency, 28*, 400-417.
Hale, C., & Sabbagh, D. (1991b). Unemployment and crime: Differencing is no substitute for modeling. *Journal of Research in Crime and Delinquency, 28*, 426-429.
Harrell, A., & Gouvis, C. (1994). Community decay and crime. Final report. Grant NIJ-IJ-CX-K016. The Urban Institute. Washington, DC.
Harries, K. (1974). *The Geography of Crime and Justice*. New York: McGraw-Hill.
Harries, R. (2003). Modelling and predicting recorded property crime trends in England and Wales - A Retrospective. *International Journal of Forecasting, 19*(2003), 557-566.
Harvey, D., Leybourne, S., & Newbold, P. (1997). Testing the equality of prediction mean squared errors. *International Journal of Forecasting, 13*(2), 281-291. doi: http://dx.doi.org/10.1016/S0169-2070(96)00719-4
Hawley, A. H. (1950). *Human Ecology: A Theory of Community Structure*. New York City: Ronald Press.
Hermann, C. R. (2013). Street-level spatiotemporal crime analysis: Examples from Bronx County, NY (2006-2010). In M. Leitner (Ed.), *Crime Modeling and Mapping Using Geospatial Technologies* (pp. 73-104). New York: Springer.
Hunter, A. (1974a). Community change: A stochastic analysis of Chicago's local communities, 1930 - 1960. *American Journal of Sociology, 79*, 923-947.
Hunter, A. (1974b). *Symbolic communities*. Chicago: University of Chicago Press.
Hyndman, R. J., & Koehler, A. B. (2006). Another look at measures of forecast accuracy. *International Journal of Forecasting, 22*(4), 679-688. doi: http://dx.doi.org/10.1016/j.ijforecast.2006.03.001
Jang, H., Lee, C. B., & Hoover, L. T. (2012). Dallas' disruption unit: efficacy of hot spots deployment. *Policing-an International Journal of Police Strategies & Management, 35*(3), 593-614. doi: 10.1108/13639511211250811
Jimenez, B. S. (2014). Separate, Unequal, and Ignored? Interjurisdictional Competition and the Budgetary Choices of Poor and Affluent Municipalities. *Public Administration Review, 74*(2), 246-257. doi: 10.1111/puar.12186
Jimenez, B. S., & Hendrick, R. (2010). Is Government Consolidation the Answer? *State & Local Government Review, 42*(3), 258-270. doi: 10.2307/41057634

Johnson, L. T., Taylor, R. B., & Groff, E. R. (2012). *Municipal structural correlates of local violent crime clusters in a metropolitan area. Paper presented at the annual meetings of the American Society of Criminology, 2012, Chicago.*

Kennedy, L., Caplan, J., & Piza, E. (2011). Risk Clusters, Hotspots, and Spatial Intelligence: Risk Terrain Modeling as an Algorithm for Police Resource Allocation Strategies. *Journal of Quantitative Criminology, 27*(3), 339-362. doi: 10.1007/s10940-010-9126-2

Kianmehr, K., & Alhajj, R. (2008). Effectiveness of support vector machine for crime hot-spots prediction. *Applied Artificial Intelligence, 22*(5), 433-458.

Klinger, D. A. (1997). Negotiating order in patrol work: An ecological theory of police response to deviance. *Criminology, 35*(2), 277-306.

Klinger, D. A. (2003). Spreading diffusion in criminology. *Criminology & Public Policy, 2*(3), 461-468.

Kneebone, E., & Raphael, S. (2011). City and suburban crime trends in metropolitan America. Metropolitan opportunity Series. Metropolitan Policy Program at The Brookings Institutution. Retrieved from

Kubrin, C. E., Messner, S. F., Deane, G., McGeever, K., & Stucky, T. D. (2010). PROACTIVE POLICING AND ROBBERY RATES ACROSS US CITIES*. *Criminology, 48*(1), 57-97.

Land, K. C., & McCall, P. L. (2001). The Indeterminacy of forecasts of crime rates and juvenile offenses. In J. McCord & C. S. Widom (Eds.), *Juvenile Crime, Juvenile Justice (National Research Council and Institute of Medicine Panel on Juvenile Crime: Prevention, Treatment, and Control).* (pp. 319-348). Washington, DC: National Academy Press.

Land, K. C., McCall, P. L., & Cohen, L. E. (1990). Structural covariates of homicide rates: Are there any invariances across time and social space? *American Journal of Sociology, 95*, 922-963.

Langford, I., Leyland, A., Rasbash, J., & Goldstein, H. (1999). Multilevel modeling of geographical distributions of diseases. *Applied Statistics, 48*(2), 253-268.

Langford, I. H., Leyland, A. H., Rasbash, J., Goldstein, H., Day, R. J., & Macdonald, A. L. (1999). Multilevel modeling of area-based health data. In A. B. Lawson, A. Biggieri, D. Boehning, E. Lessafre, J. Viel & R. Bertollii (Eds.), *Disease Mapping and Risk Assessment for Public Health*. Chichester, UK: Wiley.

Langworthy, R. H. (1985). Police department size and agency structure. *Journal of Criminal Justice, 13*(1), 15-27. doi: http://dx.doi.org/10.1016/0047-2352(85)90023-6

Leckie, G., & Charlton, C. (2011). ***runmlwin**: Stata module for fitting multilevel models in the MLwiN software package.* Bristol (UK): Centre for Multilevel Modeling, University of Bristol

Lersch, K. M. (2007). *Space, time, and crime*. Durham, NC: Carolina Academic Press.

Levine, N., & Block, R. (2011). Bayesian journey-to-crime estimation: An Improvement in geographic profiling methodology. *The Professional Geographer, 63*(2), 213-229.

Levitt, S. D. (1996). The Effect of prison population size on crime rates: Evidence from prison overcrowding litigation. *Quarterly Journal of Economics, 111*(May), 319-351.

Lieberson, S. L. (1985). *Making It Count: The Improvement of Social Research and Theory*. Berkeley: University of California Press.

Liska, A. E., Logan, J. R., & Bellair, P. E. (1998). Race and violent crime in the suburbs. *American Sociological Review, 63*(1), 27-38.

Little, R. J. A., & Rubin, D. B. (1987). *Statistical Analysis with Missing Data*. New York: Wiley.

Liu, H., & Brown, D. E. (2003). Criminal incident prediction using a point-pattern-based density model. *International Journal of Forecasting, 19*, 603-622.

Loftin, C. (1986). Assaultive violence as a contagious social process. *Bulletin of the New York Academy of Medicine, 62*(5), 550-555.

Logan, J. R. (1978). Growth, Politics, and the Stratification of Places. *American Journal of Sociology, 84*(2), 404-416. doi: 10.2307/2777855

Logan, J. R., & Molotch, H. (1987). *Urban fortunes*. Berkeley: University of California Press.

Long, J. S. (1997). *Regression Models for Categorical and Limited Dependent Variables*. Thousand Oaks: Sage.

Lott, J. R. (2000). *More Guns, Less Crime*. Chicago: University of Chicago Press.

Lott, J. R., & Whitley, J. (2003). Measurement error in county-level UCR data. *Journal of Quantitative Criminology, 19*(2), 185-198.

Lynch, J. P., & Jarvis, J. P. (2008). Missing data and imputation in the Uniform Crime Reports and the effects on national estimates. *Journal of Contemporary Criminal Justice, 24*(1), 69-85.

Maltz, M. D. (1999). Bridging gaps in police data: A discussion paper from the BJS Fellow Program. Washington, DC: Bureau of Justice Statistics [: ONLINE: http://www.bjs.gov/content/pub/ascii/bgpcdes.txt ; accessed 5/16/2012]. Retrieved from

Maltz, M. D., & Targonski, J. (2002). A note on the use of county-level UCR data. *Journal of Quantitative Criminology, 18*(3), 297-318.
Maltz, M. D., & Targonski, J. (2003). Measurement and other errors in county-level UCR data: A reply to Lott and Whitley. *Journal of Quantitative Criminology, 19*(2), 199-206.
Mann, P. H. (1954). The concept of neighborliness. *American Journal of Sociology, 60*, 163-168.
Marvell, T. B., & Moody, C. (1994). Prison population growth and crime reduction. *Journal of Quantitative Criminology, 10*, 109-140.
Mazerolle, L., Soole, D., & Rombouts, S. (2007). Drug law enforcement: A Review of the evaluation literature. *Police Quarterly, 10*(2), 115-153.
McCall, P. L. (2010). The Invariance of Structural Covariates: Reflections on 20 Years of Homicide Research. *Homicide Studies, 14*(3), 215-218. doi: 10.1177/1088767910375351
McCall, P. L., Land, K. C., & Parker, K. F. (2010). An Empirical Assessment of What We Know About Structural Covariates of Homicide Rates: A Return to a Classic 20 Years Later. *Homicide Studies, 14*(3), 219-243. doi: 10.1177/1088767910371166
McCall, P. L., & Nieuwbeerta, P. (2007). Structural Covariates of Homicide Rates: A European City Cross-National Comparative Analysis. *Homicide Studies, 11*(3), 167-188. doi: 10.1177/1088767907304072
McCarty, W. P., Ren, L., & Zhao, J. H. (2012). Determinants of Police Strength in Large U.S. Cities During the 1990s: A Fixed-Effects Panel Analysis. *Crime & Delinquency, 58*(3), 397-424. doi: 10.1177/0011128709336942
McDavid, J. C. (2002). The impacts of amalgamation on police services in the Halifax Regional Municipality. *Canadian Public Administration, 45*(4), 538-565. doi: 10.1111/j.1754-7121.2002.tb01858.x
McKenzie, R. D. (1933/1967). *The Metropolitan Community*. New York: Russel & Russel.
Mehay, S. L. (1977). Interjurisdictional Spillovers of Urban Police Services. *Southern Economic Journal, 43*(3), 1352-1359. doi: 10.2307/1057793
Messick, S. (1995). Validity of psychological assessment: Validation of inferences from persons' responses and performances as scientific inquiry into score meaning. *American Psychologist, 50*(9), 741-749.
Miller, D. W. (2000). The New urban studies. *The Chronicle of Higher Education (August 18, 2000) [online: http://chronicle.com ; accessed 4/8/13]*.
Molotch, H., Freudenburg, W. R., & Paulsen, K. E. (2000). History repeats itself, but how?: City character, urban tradition, and the accomplishment of place. *American Sociological Review, 65*(6), 791-823.
Monmonier, M. (1991). *How to Lie With Maps*. Chicago: University of Chicago Press.
Muller, P. O., Meyer, K. C., & Cybriwsky, R. A. (1976). *Metropolitan Philadelphia: A Study of Conflicts and Social Cleavages*. Cambridge, Mass.: Ballinger.
Nagin, D. (2005). *Group-based modeling of development*. Cambridge, Mass.: Harvard University Press.
Office_of_Management_and_Budget. (2000). Standards for Defining Metropolitan and Micropolitan Statistical Areas. *Federal Register: December 27, 2000 (Volume 65, Number 249): 82227-82238 [ONLINE: https://www.census.gov/population/metro/files/00-32997.txt ; accessed 9/11/2014]*, 82227-82238. Retrieved from
Office_of_National_Drug_Control_Policy. (2011). *High Intensity Drug Trafficking Areas Program Report to Congress*. Washington, DC: Executive Office of the President.
Olligschlaeger, A. M. (1997). Artificial neural networks and crime mapping. In D. Weisburd & T. McEwen (Eds.), *Crime Mapping and Crime Prevention* (pp. 313-347). Monsey, NY: Criminal Justice Press.
Ostrom, E. (1983). The Social Stratification-Government Inequality Thesis Explored. *Urban Affairs Review, 19*(1), 91-112. doi: 10.1177/004208168301900107
Ostrom, E. (2010). A Long Polycentric Journey. *Annual Review of Political Science, 13*(1), 1-23. doi: doi:10.1146/annurev.polisci.090808.123259
Ostrom, E., Parks, R. B., & Whitaker, G. P. (1978). *Patterns of Metropolitan Policing*. Cambridge, MA: Ballinger.
Parker, K. F., & McCall, P. L. (1999). Structural conditions and racial homicide patterns: A look at the multiple disadvantages in urban areas. *Criminology, 37*(3), 447-477.
Paternoster, R. (2010). HOW MUCH DO WE REALLY KNOW ABOUT CRIMINAL DETERRENCE? *Journal of Criminal Law & Criminology, 100*(3), 765-823.
Pepper, J. V. (2008). Forecasting crime: A City-level analysis. In N. R. Council (Ed.), *Understanding Crime Trends: Workshop Report* (pp. 177-210). Washington, D.C.: The National Academies Press.
Peterson, R. D., & Krivo, L. J. (2010). *Divergent Social Worlds: Neighborhood Crime and the Racial-Spatial Divide*. New York: Russell Sage

Phillips, J. A. (2006). Explaining discrepant findings in cros-sectional and longitudinal analyses: An Application to U.S. homicide rates. *Social Science Research, 35*(4), 948-974.

Phillips, J. A., & Greenberg, D. F. (2008). A Comparison of methods for analyzing criminological panel data. *Journal of Quantitative Criminology, 24*, 51-72.

Pratt, T. C., & Cullen, F. T. (2005). Assessing macro-level predictors and theories of crime: A meta-analysis *Crime and Justice: a Review of Research* (Vol. 32, pp. 373-450).

Pyle, D. J., & Deadman, D. F. (1994). Crime and the business cycle in postwar Britain. *British Journal of Criminology, 34*, 339-357.

Raftery, A. E. (1995a). Bayesian Model Selection in Social Research. *Sociological Methodology, 25*, 111-163.

Raftery, A. E. (1995b). Rejoinder: Model Selection is Unavoidable in Social Research. *Sociological Methodology, 25*, 185-195.

Rasbash, J., Steele, F., Browne, W. J., & Goldstein, H. (2009). *A User's Guide to MLwiN*. Bristol, UK: Centre for Multilevel Modeling, University of Bristol.

Ratcliffe, J. H. (2002). Aoristic signatures and the spatio-temporal analysis of high volume crime patterns. [Article]. *Journal of Quantitative Criminology, 18*(1), 23-43.

Ratcliffe, J. H. (2004). The Hotspot Matrix: A framework for the spatio-temporal targeting of crime reduction. *Police Practice and Research: An International Journal, 5*(1), 5-23.

Ratcliffe, J. H. (2006). A Temporal constraint theory to explain opportunity-based spatial offending patterns. *Journal of Research in Crime and Delinquency, 43*(3), 261-291.

Ratcliffe, J. H. (2008). *Intelligence-Led Policing*. Cullompton, Devon: Willan Publishing.

Ratcliffe, J. H., & Rengert, G. F. (2008). Near repeat patterns in Philadelphia shootings. *Security Journal, 21*(1-2), 58-76.

Ratcliffe, J. H., Taniguchi, T., Groff, E. R., & Wood, J. D. (2011). THE PHILADELPHIA FOOT PATROL EXPERIMENT: A RANDOMIZED CONTROLLED TRIAL OF POLICE PATROL EFFECTIVENESS IN VIOLENT CRIME HOTSPOTS. *Criminology, 49*(3), 795-831. doi: 10.1111/j.1745-9125.2011.00240.x

Raudenbush, S. W., & Bryk, A. S. (2002). Hierarchical linear models: Applications and data analysis methods (2nd ed.). Thousand Oaks, CA: Sage Publications.

Reaves, B. A. (2010). Local police departments, 2007. *Law Enforcement Management and Administrative Statistics. Bureau of Justice Statistics. NCJ 231174. [ONLINE: http://www.bjs.gov/content/pub/pdf/lpd07.pdf ; accessed 3/29/2013]*. Retrieved from

Rengert, G. F. (1996). *The Geography of Illegal Drugs*. Boulder: Westview.

Rengert, G. F., Ratcliffe, J. H., & Chakravorty, S. (2005). *Policing illegal drug markets: Mapping the socio-economic environments of drug dealing*. Monsey, NY: Criminal Justice Press

Rohde, D., Corcoran, J., & Chhetri, P. (2010). Spatial forecasting of residential urban fires: A Bayesian approach. *Computers, Environment and Urban Systems, 34*(1), 58-69. doi: http://dx.doi.org/10.1016/j.compenvurbsys.2009.09.001

Rosenfeld, R., & Goldberger, A. S. (2008). Introduction. In N. R. Council (Ed.), *Understanding Crime Trends: Workshop Report* (pp. 1-12). Washington, D.C.: The National Academies Press.

Rubin, D. B. (1987). *Multiple imputation for nonresponse in surveys*. New York: Wiley.

Sampson, R. J. (1986). Crime in Cities - the Effects of Formal and Informal Social-Control. *Crime and Justice-a Review of Research, 8*, 271-311.

Sampson, R. J., & Cohen, J. (1988a). Deterrent Effects of the Police on Crime: A Replication and Theoretical Extension. *Law & Society Review, 22*(1), 163-189. doi: 10.2307/3053565

Sampson, R. J., & Cohen, J. (1988b). Deterrent effects of the police on crime: A Replication and theoretical extension. *Law and Society Review, 22*, 163-189.

Sampson, R. J., & Lauritsen, J. L. (1994). Violent victimization and offending: individual, situational- and community-level risk factors. In A. J. J. Reiss & J. A. Roth (Eds.), *Understanding and preventing violence (Volume 3: Social Influences)* (Vol. 3: Social influences, pp. 1-114). Washington, DC: National Academy Press.

Schafer, J. L. (2000). *Analysis of incomplete multivariate data*. Boca Raton: Chapman and Hall / CRC.

Schuerman, L., & Kobrin, S. (1986). Community careers in crime. In A. J. Reiss & M. Tonry (Eds.), *Communities and crime* (pp. 67-100). Chicago: University of Chicago Press.

Shelly, K. C. (2014). Survey: Nearly 15 percent of Camden properties abandoned, *South Jersey Courier-Post. August 25, 2014. [ONLINE: http://www.courierpostonline.com/story/news/local/south-*

jersey/2014/08/14/survey-nearly-percent-camden-properties-abandoned/14059361/; *accessed October 16, 2014]*.
Sherman, L. W., Gartin, P., & Buerger, M. E. (1989). Hot Spots of predatory crime: Routine activities and the criminology of place. *Criminology, 27*(1), 27-55.
Shihadeh, E. S., & Ousey, G. C. (1996). Metropolitan expansion and Black social dislocation: The Link between suburbanization and center-city crime. *Social Forces, 75*, 649-666.
Silverman, E. (1999). *NYPD Battles Crime: Innovative Strategies in Policing*. Boston: Northeastern University Press.
Smith, N., Caris, P., & Wyly, E. (2001). The "Camden Syndrome" and the menace of suburban decline: Residential disinvestment and its discontents in Camden County, New Jersey. *Urban Affairs Review, 36*(4), 497-531.
Snijders, T. A. B., & Bosker, R. J. (2012). *Multilevel analysis: An Introduction to basic and advanced multilevel modeling (2nd ed.)*. Los Angeles: Sage.
Sorg, E. T., & Taylor, R. B. (2011). Community-level impacts of temperature on urban street robbery. *Journal of Criminal Justice, 39*(6), 463-470. doi: 10.1016/j.jcrimjus.2011.08.004
Spiegelhalter, D. J., Best, N. G., Carlin, B. P., & van Der Linde, A. (2002). Bayesian measures of model complexity and fit. *Journal of the Royal Statistical Society. Series B (Statistical Methodology), 64*(4), 583-639.
Spiegelhalter, D. J., Best, N. G., Gilks, W. R., & Inskip, H. (1996). Hepatitis B: A Case study in MCMC methods. In W. R. Gilks, S. Richardson & D. J. Spiegelhalter (Eds.), *Markov Chain Monte Carlo in Practice* (pp. 21-43). Boca Raton: Chapman & Hall / CRC.
Stonington, J., & Wong, V. (2011). America's richest zip codes 2011. *Bloomberg Business Week Lifestyle. December 7, 2011. [ONLINE: http://images.businessweek.com/slideshows/20111206/america-s-richest-zip-codes-2011#slide23 ; accessed 3/23/2013]*.
Swanson, N. R., & White, H. (1997). Forecasting economic time series using flexible versus fixed specification and linear versus nonlinear econometric models. *International Journal of Forecasting, 13*, 439-461.
Taylor, R. B. (1995). Impact of crime on communities. *Annals of the American Academy of Political and Social Science, 539*, 28-45.
Taylor, R. B. (1998). Crime in small scale places: What we know, what we can do about it *Research and Evaluation Conference 1997* (pp. 1-20). Washington, DC: National Institute of Justice.
Taylor, R. B. (2002). Fear of crime, social ties and collective efficacy: Maybe masquerading measurement, maybe deja vu all over again. *Justice Quarterly, 19*(4), 773-791.
Taylor, R. B. (2010). Communities, Crime, and Reactions to Crime Multilevel Models: Accomplishments and Meta-Challenges. *Journal of Quantitative Criminology, 26*(4), 455-466. doi: 10.1007/s10940-010-9114-6
Taylor, R. B. (2015). *Community Criminology*. New York: New York University Press.
Taylor, R. B., & Covington, J. (1988). Neighborhood changes in ecology and violence. *Criminology, 26*, 553-589.
Terruso, J. (2012). Camden Flow: New Census statistics pain grim picture of Camden. September 22, 2012., *Philadelphia Inquirer*.
Townsley, M., Homel, R., & Chaseling, J. (2003). Infectious Burglaries. A Test of the Near Repeat Hypothesis. *Br J Criminol, 43*(3), 615-633. doi: 10.1093/bjc/43.3.615
Townsley, M., Johnson, S. D., & Ratcliffe, J. H. (2008). Space time dynamics of insurgent activity in Iraq. *Security Journal, 21*(3), 139-146.
Trickett, A., Osborn, D., Seymour, J., & Pease, K. (1992). What is different about high crime areas? *British Journal of Criminology, 32*, 81-90.
Uchida, C. D., & King, W. R. (2002). Police employee data: Elements and validity. *Justice Research and Policy, 4*, 11-19.
US_Bureau_of_the_Census. (2012). Lists & Stuctures of Governments: Population of Interest - Municipalities and Townships. [ONLINE: https://www.census.gov/govs/go/municipal_township_govs.html ; accessed 9/11/2014]. Retrieved from
US_Bureau_of_the_Census. (2013). Geographic terms and definitions. [ONLINE: https://www.census.gov/popest/about/geo/terms.html ; accessed September 11, 2014]. Retrieved from
Walsh, J. A., & Taylor, R. B. (2007). Predicting Decade-Long Changes in Community Motor Vehicle Theft Rates: Impacts of Structure and Surround. *Journal of Research in Crime and Delinquency, 44*(1), 64-90. doi: 10.1177/0022427806295552
Warner, S. B. (1962). *Streetcar suburbs: The Process of growth in Boston, 1870-1900*. Cambridge, MA: Harvard University Press.
Warner, S. B. (1968). *Private City*. Philadelphia: University of Pennsylvania Press.

Weidener, S. (2000). Exton Square Mall settles into its space after more than a year, work is complete. *Philadelphia Inquirer, May 3, p. B1*.

Weisburd, D. (1997). Reorienting crime prevention research and policy: From the causes of criminality to the context of crime. *Research Report. National Institute of Justice, U.S. Department of Justice. Washington, D.C.*

Weisburd, D., Bushway, S., Lum, C., & Yang, S. M. (2004). Trajectories of crime at places: A longitudinal study of street segments in the City of Seattle. *Criminology, 42*(2), 283-321.

Weisburd, D., & Eck, J. E. (2004). What can police do to reduce crime, disorder, and fear? *Annals of the American Academy of Political and Social Science, 593*, 42-65.

Weisburd, D., Groff, E. R., & Yang, S.-M. (2012). *The Criminology of Place: Street Segments and Our Understanding of the Crime Problem*. Oxford, UK: Oxford University Press.

Weisburd, D., & Lum, C. (2005). The Diffusion of computerized crime mapping in policing: Linking research and practice. *Police Practice and Research, 6*(5), 419-434.

Weisburd, D., Mastrofski, S. D., McNally, A. M., Greenspan, R., & Willis, J. J. (2003). Reforming to preserve: COMPSTAT and strategic problem solving in American policing. *Criminology & Public Policy, 2*(3), 421-456.

Weisburd, D., Wyckoff, L. A., Ready, J., Eck, J. E., Hinkle, J. C., & Gajewski, F. (2006). Does crime just move around the corner? A controlled study of spatial displacement and diffusion of crime control benefits. *Criminology, 44*(3), 549-591.

Wikstrom, P.-O. H. (2006). Individuals, settings, and acts of crime: Situational mechanisms and the explanation of crime. In P.-O. H. Wikstrom & R. J. Sampson (Eds.), *The Explanation of Crime: Context, Mechanisms, and Development* (pp. 61-107). Cambridge: Cambridge University Press.

Wikstrom, P.-O. H. (2007). In Search of casues and explanations of crime. In R. D. King & E. Wincup (Eds.), *Doing Research on Crime and Justice* (Second ed., pp. 117-139). Oxford: Oxford University Press.

Wikstrom, P.-O. H., & Teiber, K. H. (2009). Violence as situational action. *International Journal of Conflict and Violence, 3*(1), 41-62.

Wilson, J. Q. (1968). *Varieties of Police Behavior: The Management of Law and Order in Eight Communities*: Harvard University Press.

Wilson, J. Q., & Boland, B. (1978). The Effect of the Police on Crime. *Law & Society Review, 12*(3), 367-390. doi: 10.2307/3053285

Wirth, L. (1938). Urbanism as a way of life. *American Journal of Sociology, 44*(1), 1-23.

Wood, J., & Shearing, C. (2007). *Imagining security*. Cullompton: Willan.

Wyly, E. K. (1999). Continuity and change in the restless urban landscape. *Economic Geography, 75*(4), 309-338.

Wyly, E. K., & Hammel, D. J. (1999). Islands of decay in seas of renewal: Housing policy and the resurgence of gentrification. *Housing Policy Debate, 10*(4), 711-771.

Zernike, K. (2012). To Fight crime a poor city will trade in its police. *New York Times September 28, 2012. [ONLINE: http://www.nytimes.com/2012/09/29/nyregion/overrun-by-crime-camden-trades-in-its-police-force.html?pagewanted=all ; accessed 3/29/2013].*

Zhao, J. H., Ren, L., & Lovrich, N. P. (2012). Political Culture Versus Socioeconomic Approaches to Predicting Police Strength in U.S. Police Agencies: Results of a Longitudinal Study, 1993 to 2003. [Article]. *Crime & Delinquency, 58*(2), 167-195. doi: 10.1177/0011128708318947