Document Title:	**Intra-Metropolitan Crime Patterning and Prediction, Final Report**
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Document No.:	**249739**
Date Received:	**February 2016**
Award Number:	**2009-IJ-CX-0026**

Intra-Metropolitan Crime Patterning and Prediction

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FINAL REPORT:

GRANT: 2009-IJ-CX-0026 from the National Institute of Justice

REVISIONS: October 30, 2014, June 26, 2015

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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 30^{th} 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 7^{th} 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.

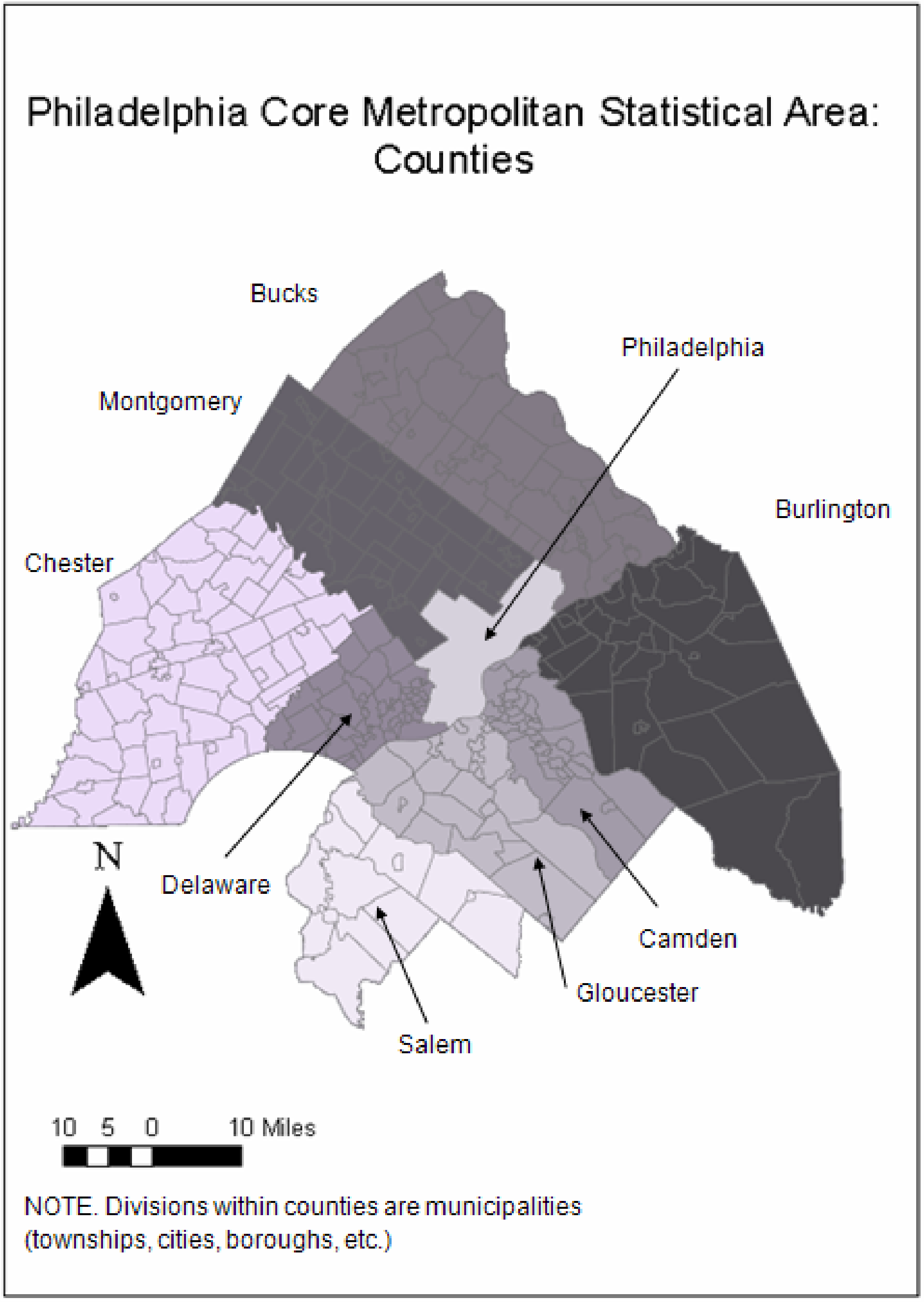

Figure 1. Counties in Philadelphia-Camden primary metropolitan statistical area

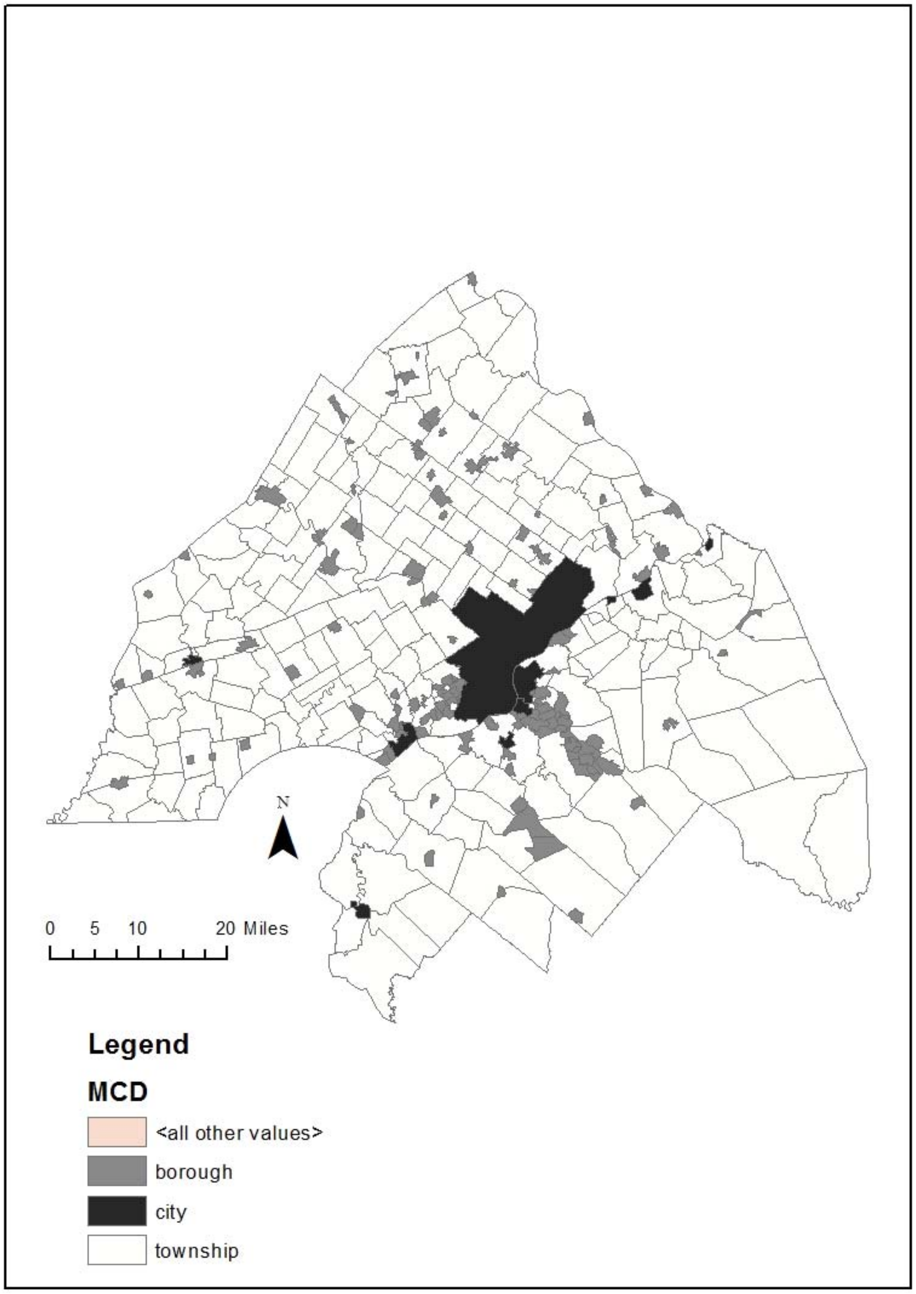

Figure 2. Jurisdiction types

2. SPATIAL PATTERNS

2.1. Overview

This chapter describes crime spatial patterns. The next chapter describes temporal ones Appendix 1 explains where we obtained crime and enforcement data, how we organized demographic data into indices, and the latter into population weighted percentiles.

This chapter provides a spatial overview of law enforcement, law enforcement coverage, property crime, violent crime, and three aspects of community demographic structure across the metro region. These demographic patterns will be mapped for three aspects of jurisdiction structure: socioeconomic status, racial composition, and residential stability.

For policing, perhaps the most important feature of arrangements is that many municipalities, about a quarter, do not have their own police department. For these places policing can be provided in different ways. Some are covered by their respective state police forces, others by a small regional police department, others by a neighboring or surrounding department, and others by multi-municipality, multi-named departments (e.g., East Goshen-Westtown in Chester County).

But some municipalities with their own departments might, if it is small, receive partial coverage from another department because their own force does not provide full time coverage. The backup coverage might be provided by the respective state police, or another jurisdiction. So these variations in arrangements also will be mapped and described.

There is nothing new here about the complexities of policing across municipal areas; earlier work has noted such varieties (Ostrom, et al., 1978). Substantial work since Ostrom and colleagues' original work has further developed the concept of governance polycentricity and the implications for differences in agency sizes and service delivery (Aligica & Tarko, 2012; Langworthy, 1985; Ostrom, 2010). It is not clear that amalgamation of agencies provides a superior result to the complex organizational patterning seen in metro areas (McDavid, 2002).

Once the dedicated force is known, it is possible to create law enforcement coverage rates. As presented here they reflect the rate of within-municipality-department-based sworn officers per 1,000 residents. There will be places that have coverage rates of zero, but this does not mean there is no law enforcement there. Rather it means that there is no *local* law enforcement where local means no full time officers employed by a department devoted exclusively to that jurisdiction. Because the coverage rates are local, it also means they will not reflect backup arrangements provided either by a state police force or a surrounding or neighboring department. As noted in Chapter 1, there are concerns about coverage indicators.

Following the coverage arrangements, we describe average property and violent crime rates over the period. These appear in two forms: rates per 100,000 residential population and population weighted percentiles. The latter provides a clearer picture of the crime "niche" occupied by the different municipalities. Percentile scores and raw rates are cross-referenced graphically.

Demographics presented date from the beginning of the period, 2000. All other figures describe an average or median figure for the entire study period, 2000-2008.

Sometimes maps can lie (Monmonier, 1991). So for coverage and crime rates, two types of maps are presented: quintile maps presenting municipalities by fifths, and natural break maps.

See Appendix 1 for all data processing details, and more descriptive information about individual indicators.

2.1.1. What is new

To the authors' knowledge, no one to date has presented a complete mapping, across the entire Philadelphia metropolitan community, of local police department sizes, police enforcement coverage rates, reported violent crime, or reported property crime, either for a single year or a multi-year period; no one has presented this information based on an average spanning almost a decade; nor has anyone presented such information for any other large, complex metropolitan community in the United States. Therefore, the first purpose of this chapter is just to present and describe these spatial patterns.

The second purpose is to provide spatial details which we later cross-reference with both temporal shifts in demographics and crime. Those shifts are presented in the next chapter. There are local features here which will "play out" in a number of ways once crime shifts in time are examined.

2.2. Demographic structure

2.2.1. Socioeconomic status (SES)

The patterning of status across the metropolitan community at the beginning of the new century appears in Figure 3. Status is expressed in population weighted percentile (PWP) form. So a municipality with a score of 83 has a status value placing it above or equal to the status scores in the municipalities covering 83 percent of the metro population. This map uses natural breaks to create five groups.

SES presents a complicated picture, with both expected and unexpected features. On the expected side, the large urban core, Philadelphia, and some immediately adjoining small jurisdictions appear in the lowest status grouping. So too do the other best known major cities in the region, Camden and Chester. But other pockets of relatively low socioeconomic standing also appear. Some of these are older cities that have experienced significant demanufacturing like the city of Coatesville and immediately adjoining borough of South Coatesville in Chester County along US-Route 30 (Business) (Adams, et al., 2008). The borough of Norristown in Montgomery County at the bend in the Schuylkill River also is in this lowest group. This locale, the seat for Montgomery County, experienced not only losses in light industry and manufacturing, but also the closing of a mental hospital and an increasing concentration of Montgomery County's public housing in the last few decades (Adams, et al., 2008).

But some of these locales in the lowest standing group are not urban centers as defined by Adams et al (Adams, et al., 2008). These include Bristol borough in Chester County along the Delaware River, and rural locations: Wrightstown borough and Washington Township in Burlington County; and Quinton and Carney's Point townships in Salem County.

Turning to the opposite end of the socioeconomic ladder, four clear cut clusters of adjoining pockets of privilege appear, all on the Pennsylvania side of the metro area. Moving from west to east, the first that appears is a string of municipalities elongated along a rough north/south axis in central Chester County. A smaller grouping shaped like an upside down horseshoe and including jurisdictions in both eastern Chester and western Montgomery counties appears just to the east of this first grouping. Just to the east and north of this second group a third cluster appears in eastern Montgomery County, starting just northwest of northwest Philadelphia and stretching in a northwesterly direction. Finally, east and somewhat north of that group a fourth cluster of relatively well-off communities appears in the middle of Bucks County, stretching one to three layers deep extending southward from the Delaware River.

Using these cut points, the New Jersey side of the metropolitan community reveals only one cluster of relatively upper-crust communities: Tabernacle and Medford Townships, and Medford Lakes borough in Burlington County fall into the top-most group. Moorestown and Chesterfield townships in Burlington County and Haddon Township in Camden County are also in the top-most group, but these three do not adjoin one another.

In sum, at the beginning of the new century, based on a broad-based residential index of relative socioeconomic standing, the Pennsylvania side of the metropolitan community was more likely to be home to clusters of the most privileged municipalities in the region.

Socioeconomic status groups are mapped by fifths or quintiles rather than by natural breaks in Figure 4. So here, each socioeconomic grouping has the same number of communities in it. There are numerous differences between this map and the preceding one. Of particular interest, and potential crime relevance, is the different spatial distribution of lowest SES municipalities. Changing the top boundary of the lowest group just slightly, from 37 to 42, markedly changes the classification of several communities close to Philadelphia. In Camden County, an elongated cluster of low-SES communities roughly straddling US Route 30 and the Atlantic City Expressway stretches southwestward almost continuously from the Camden city line past Clementon, ending at Berlin Cross Keys Road. The fabled Pine Valley Country Club mentioned earlier lies within this least well-off grouping.

On the Pennsylvania side, another elongated string of least privileged communities stretches southwest from Philadelphia's southwestern section down through the city of Chester and beyond. Many of these communities had been sites of major manufacturing facilities like the already mentioned Eddystone (Baldwin Locomotive). Marcus Hook, Trainer, and Lower Chichester, south of the city of Chester, are in this group as well. Sunoco ran a sizable refinery in Marcus Hook for several decades, and Trainer also hosted a refinery. Interstate 95 and the Blue Route (Interstate 476) pass through several of the municipalities in this corridor.

Another cluster in the lowest SES grouping almost emerges just north and west of northeast Philadelphia on both the NJ and PA side of the Delaware River: Bristol Borough, Bristol Township, Burlington and Beverly cities in Burlington County, and Delanco and Riverside townships also in Burlington County. Bensalem Township, however, bisects these communities, preventing a larger cluster from appearing.

Although the quintile map reveals a different spatial pattern for the least socioeconomically advantaged communities as demonstrated with these two strings just described, the pattern of privileged pockets is generally unchanged. Four pockets of privilege appear again on the PA side of the metropolitan community.

To better ground the scaling of the socioeconomic status index Figure 5 cross references 2000 index scores with 2000 median house values. Corresponding house values for those municipalities with scores of 40 or lower were generally under $100,000. At the top end of the socioeconomic ordering, however, the link with house value was looser, however. Municipalities with index scores of eighty or higher had median house values ranging from slightly less than $150,000 to almost $400,000.

2.2.2. Residential stability

Municipality 2000 percentile scores on stability appear in Figure 6, grouped according to natural breaks in the index scores. Starting with the lowest stability group of communities, some in this classification already have been discussed either as challenged cities like Camden or Chester, older small cities located far from Philadelphia like Coatesville, Phoenixville and Pottstown, and some small municipalities sometimes close to one of the three major cities in the region: Collingswood in New Jersey or Conshohocken or Morton in Pennsylvania.

Turning to the most stable communities, the Pennsylvania side of the metro area showed, as it did with high status, several clusters of adjoining municipalities; there were three clusters of high stability in Chester County, the most compact being a group above US-30 and intersecting the Pennsylvania Turnpike. In Bucks County, along the Delaware River and directly north of Northeast Philadelphia another half dozen very stable municipalities group together. Two clusters of spatially adjoining high stability municipalities, with at least three communities in each cluster, appear in Burlington County on the New Jersey.

The same variable but mapped using quintiles appears in Figure 7. This classification increases the number of communities in the least stable category. Some of the communities added to this group are in the stretch of municipalities trailing to the southwest from southwest Philadelphia, or the group trailing southeast from the city of Camden in Camden County. The city of Philadelphia now is included in the least stable grouping.

To better ground the index, Figure 8 cross references scores on the variable percent owner occupied with index scores in percentile form. At the upper end of both variables stability and home ownership correspond closely; at the lower levels the relationship is more open as high scores on other variables in the index sometimes diverge from homeownership levels.

2.2.3. Percent African American

Turning to racial composition, the last of the three traditional structural community dimensions, Figure 9 maps the variable using five groups and natural breaks. The most readily apparent feature of this map is the absence of municipalities with substantial proportions of African-American population from most of the metro area. Sizable African-American populations, in relative terms, concentrate in a small portion of the metro area. The bulk of the municipalities in Bucks County, and vast stretches of outer Montgomery and outer Chester counties have populations that are less than four percent African-American. Municipalities in outer Burlington County similarly have very low percentages of African-Americans.

Turning to the opposite end of the racial composition spectrum, the municipalities in the highest category with at least about half of their population being African-American include some expected places like the cities of Camden and Chester, and older small cities like Coatesville and adjoining South Coatesville borough. But sizable relative African-American populations surface in some unexpected places as well like Willistown Borough (Burlington County), Lawnside Borough (Camden County), and Yeadon Borough (Delaware County).

This map presents a markedly different picture of relative African-American composition than does the work presented by Adams and colleagues (Adams, et al., 2008). Their map (their Figure 1.3) defined substantial African-American populations as being **both** ten percent or more of the municipality population and comprising at least 2,500 persons. Their map shows two large clusters of relative African American population: in parts of Philadelphia and adjoining locales including the city of Camden and some adjoining municipalities to the southwest; and in central and eastern-most Camden County. It also shows additional pockets of African-American concentration in Burlington County and again in some of the older cities (Coatesville, Pottstown). But their portrait is of a much more spatially restricted African-American population than shown here. The map here shows Salem and Montgomery counties, and to a lesser extent Chester county, as being somewhat African-American. In short, the mapping here based on percent of the community which is African-American, and not considering the number of African-Americans in a jurisdiction, suggests a more spread out pattern of African-American settlement than observed by Adams and colleagues.

Of course the same variable in a quintile map, see Figure 10, shows a markedly different picture because of how the variable is distributed. The communities in the lowest fifth on percent African-American have anywhere from zero percent to .78th of a percent African-American. These communities with no African-Americans or just a minute fraction were most likely to appear in the outermost segment of Bucks and Burlington counties.

Communities in the top fifth on this variable had anywhere from thirteen percent to 90 percent African-American populations. In addition to the three major cities and some of their neighboring municipalities being in this highest grouping, clusters of relative concentration also appear in western Burlington and western Salem counties. Various isolated older cities, Coatesville and Pottstown again for example, and boroughs or small townships scattered throughout the region also fall into this grouping.

2.2.4. Percent Asian

After African-Americans, the most sizable other non-white racial or ethnic groups in the metropolitan region are Asians and Hispanics.

Figure 11 maps the 2000 percent Asian population using natural breaks. Only one majority Asian (52 percent) municipality appears in the highest group, and is so tiny it is hard to spot on the map. As one exits Philadelphia on the west side using SR 3 (Walnut Street), one passes under the subway station at 63rd Street and climbs up the long hill to the business and transportation hub at 69th Street and Terminal Square. Millbourne Borough is on the right. Millbourne Police patrol vigorously for motorists traveling above the 25 mph limit. This tiny sliver of a borough adjoins Upper Darby Township immediately to its south.

Upper Darby Township itself, in the second highest grouping with anywhere from 8 to 13 percent of its 2000 population classified as Asian, is one of the most racially diverse in the entire metro area with substantial Korean, Indian, Pakistani, and Greek populations. In addition to Upper Darby, additional concentrations of Asian population appear in northern Camden County, mid Montgomery County, and Upper Merion in the southern section of Montgomery County.

2.2.5. Percent Hispanic

Figure 12 maps the percent Hispanic throughout the region. The natural breaks map places three jurisdictions in the highest group with between 28 and 39 percent Hispanic: the city of Camden, and the boroughs of Kennett Square and Avondale in lower southeastern Chester County. The latter two locations are close to large numbers of mushroom farms in Chester County. "*Half* of America's mushrooms are grown in one tiny corner of southeastern Pennsylvania, near the town of Kennett Square" (D. Charles, 2012).

Locations in the next to highest group, with between thirteen and 24 percent Hispanic appear in the same section of Chester County, north and east of the city of Camden (Woodlyne borough, Pennsauken township), and in mid or outer Burlington County. Areas with low percentages Hispanic include much of Montgomery County and Delaware County, and much of northern and western Chester County.

2.2.6. Reflection on dynamics of different settlement patterns for different groups

Reflecting on the discrepant settlement patterns seen for African-American, Asians, and Hispanics calls to mind Charles's argument that different processes are at work over time linking different racial and ethnic groups to the broader society (C. Z. Charles, 2003). The patterns seen here confirm the existence of suburban jurisdictions with notable racial/ethnic concentrations for all three groups. For African-Americans, Asians and Hispanics, we find jurisdictions with at least roughly half of its population belonging to the racial/ethnic group. Although these fewest for Asians (only Millbourne), and less numerous for Hispanics than African-Americans, all three groups show some degree of suburban concentration. This finding aligns with work by Alba and others examining different metropolitan areas (Alba & Logan, 1991).

Little spatial overlap appears between the three types of suburban racial/ethnic concentrations. The different high (relative) concentration municipalities are positioned in in different locations across the metro area. What might be behind this?

Part of it may be the polynucleation mentioned earlier. The mushroom farms in lower Chester County are a case in point.

But part of it also could be different dynamics. Charles suggested different spatial assimilation models might be relevant to different racial/ethnic groups (C. Z. Charles, 2003). More specifically, she proposed that residential patterning of Asian and Hispanic populations was most likely to follow spatial assimilation models while the patterning of African-American populations was likely to follow a place stratification model. In the assimilation model, members of nonwhite racial/ethnic groups convert economic gains into higher status residential destinations. In the place stratification model such gains are blocked by persistent prejudice and discriminatory practices.

Of course, it is difficult to definitively interpret the varying suburban concentration patterns in part because the sizes of the total populations are so discrepant. In 2000 the population “black alone” was 1,017,762; “Asian alone” was 171,242; and “Hispanic alone” was 256,374. Whites alone numbered over 3.67 million. In other words the Hispanic population was about a quarter of the African-American population and the Asian population about a sixth.

That difficulty aside, these different relevant dynamics could be further researched looking at returns on socioeconomic status attained by members of different racial/ethnic groups. Such an investigation, albeit worthwhile, goes beyond the scope of the current effort.

2.2.7. Percent white

Finally, a more integrative view across different racial groups can be provided by classifying jurisdictions as predominantly white alone (>=70 percent), minority white alone (<= 30 percent), and mixed (30 percent < white alone > 70 percent). Those in the latter group would represent substantially integrated locales while those in the next to last group might reflect locales that already have resegregated into a largely minority status municipality. The corresponding map appears in Figure 13. The two smaller urban cores, the cities of Chester and Camden appear largely minority, as expected. Similarly classified are small jurisdictions next to the cities of Chester (Chester Township) or Philadelphia (Millbourne and Yeadon). But a couple of additional resegregated communities also surface, further away from these urban cores:

Willingborough Township (Burlington County), Lawnside borough (Camden County), and part of Coatesville (Chester County).

Moving from resegregated to integrated municipalities, in addition to Philadelphia, integrated locales appear in every county save Bucks. The number of these integrated municipalities in each of these counties, however, is quite low. This threefold classification based simply on relative dominance of the white population shows a heavily segregated metro area.

2.2.8. Closing comment, race and ethnicity

Inspection of the spatial patterning at the jurisdiction level of race and ethnicity at the beginning of the 21st Century demonstrates several points about residential patterning which may prove relevant to crime or crime shifts. Some of these features are quite expected, including resegregated urban cores of Camden and Chester and, for some racial/ethnic groups, suburban concentrations relatively close to these two cities or to Philadelphia. Some older, outlying cities victimized by demanufacturing like Coatesville appear heavily minority.

But there are less expected features as well. Polynucleation/structuration appears relevant to the concentration of Hispanics in small municipalities in lower Chester County near mushroom farms. In addition, the metro area appears more heavily segregated white on the Pennsylvania compared to the New Jersey side of the metro region. Third, the suburban African-American population, when considered in terms of its relative contribution to a municipality's population profile, is more spatially spread than the suburban Asian population. This *perhaps* goes somewhat against Charles's application of the place stratification model to African Americans and the spatial assimilation model to Asians. Finally, the suburban African-American population when viewed solely in terms of relative population contribution appears more dispersed than previous scholars of the region have depicted.

2.2.9. Household age composition

Following up on the suggestions of both Anderson and Sampson, an index contrasting the ratio of supervisory age adults to in-need-of-supervision preteens, teens, and young adults, was created. Places with higher scores have more children, teens and young adults needing supervision, and fewer mature adults in their 50s and early 60s to do the supervising. The natural breaks map appears in Figure 14.

All three core cities – Philadelphia, Camden, and Chester – appear in the highest group, with the largest ratio of (population portion needing supervision/population portion of supervisors). But few municipalities immediately adjoining these cities also place in the highest grouping on this index. Three municipalities immediately to the southwest of Philadelphia are in this highest grouping: the boroughs of Collingdale, Darby, and Sharon Hill. The Upland borough adjacent to Chester City places in this group as well. Also perhaps somewhat expected is the placement in the highest grouping of three small urban areas located well away from these three core municipalities: Coatesville, Downingtown, and Bristol borough. But far less expected is the inclusion in this highest grouping as well of numerous small to medium size municipalities, spread widely throughout the metro region.

Turning to the opposite end of the variable, places with few preteens, teens and young adults and many mature adults, a number of small clusters of adjoining municipalities emerge in this grouping: in the northernmost corner of Bucks County, in Montgomery county just west of northwest Philadelphia and stretching southwest into Delaware County; in the northwest corner of Chester County; in the mid-southern portion of Chester County snaking back from the Delaware state line; in the southern portion of Salem County; and finally two small clusters in mid- and upper Burlington County. Municipalities in this classification had lower scores than about three quarters of the municipal population.

The map using quintiles for the age index is not shown. The cut points used to create the five groups closely matched the cut points seen in the natural breaks map, resulting in a map that was substantively close to the pattern shown in Figure 14.

2.2.10. Demographic structure: Closing comment

The spatial patterns of municipality demographic structure across the metro region at the dawn of the new century defy easy summation.

The idea of concentric organization across the region receives some support. Urban cores like the cities of Chester and Camden appear resegregated minority and are some of the economically worst off municipalities in the region. On some dimensions immediately adjoining small municipalities seem comparably positioned on these attributes.

But ideas of polynucleation/structuration also receive support in a number of different ways. Examples include the relative concentration of Hispanics in southern Chester County near numerous mushroom farms in Kennett Square; relative concentrations of African-Americans in a range of locations like Coatesville and Norristown; or two strings of small communities with low economic standing stretching southwest from Philadelphia and southeast from Camden.

But beyond polynucleation, there are also some features of the broader region that appear just plain idiosyncratic. Most notable is the larger number of high socioeconomic status communities in the Pennsylvania as compared to the New Jersey side of the region, despite the latter state hosting the world's most exclusive golf course. In addition, save for Philadelphia, the Pennsylvania side of the metro region appears less likely to host sizable relative populations of African Americans (Figure 9).

2.3. Policing

This section describes three different aspects of policing across the metropolitan region: the different types of arrangements, department size, and law enforcement coverage rates.

2.3.1. Arrangements

Table 1 describes the frequency of different types of arrangements. About one seventh of the municipalities relied solely on their respective state police for coverage. New Jersey and Pennsylvania are not the only states that provide policing coverage through state police departments to rural and exurban locations; other states in the Mid-Atlantic and New England have similar arrangements (Coate & Schwester, 2009). The municipalities in this metro region relying on a state police might have a director of public safety.

Figure 15 shows where the municipalities are located which rely solely on the state police for law enforcement. [5] Although they are generally in the outer regions of the metro area, several

[5] This mapping of state police covered jurisdictions disagrees slightly with a mapping of PA-only jurisdictions done in 2008 by MPIP researchers at Temple University. (http://mpip.temple.edu/mpip/documents/PolicyBrief_StateTroopers_with_land_area_2.pdf) We also differ with this earlier mapping on the number of jurisdictions receiving partial state police coverage. It is not known if the differences arise from the different time period or a different methodology. Most importantly, the methodology used here was applied consistently to both the PA and NJ sides of the metro region.

jurisdictions in Delaware County receive state police coverage. Chester and Salem counties appear to have the largest number of municipalities covered exclusively by police coverage. But the same arrangements appear in some jurisdictions in Bucks, Montgomery and Burlington counties as well.

Five municipalities (map not shown) received partial state police coverage, with the state agency stepping in either at certain times (e.g., nights), or when local officers were not available. With a small force it is not unusual for occasional assistance to be needed. Two large jurisdictions in southern Chester County had this arrangement (East Marlborough and Kennett townships), two small boroughs in eastern Bucks County (Hulmeville and Langhorne boroughs) and one in western Burlington County (Fieldsboro Borough in Burlington County).

There were an additional 20 jurisdictions with a police department, and a sworn officer, but the officer was not full time. These places were *not* coded as relying exclusively or partially on state police.

About three quarters of the municipalities had their own full service department which was devoted only to that target jurisdiction (n=272). These are the departments whose law enforcement coverage rates will later be calculated. Figure 16 maps municipalities which "own" their own department, run by that municipality and dedicated exclusively to that municipality. The places without their own, exclusively dedicate departments are clearly spatially patterned. Parts of lower Delaware County, southeastern Chester County, eastern Burlington County, and much of rural Salem County have municipalities without dedicated departments. Policing arrangements are clearly different in these segments of the outer portions of the metro region.

Perhaps the most complicated policing arrangements applied to some 27 municipalities that either were part of a multi-municipality force, or received coverage from an adjoining force. Multi-municipality forces included self-labeled regional police departments as well as departments with multiple municipality names incorporated in the organization name. An example of an adjoining arrangement is Tavistock Borough in New Jersey. The land in the borough is largely occupied by a golf course. The borough seceded from Haddon Township of which it was a part in 1921 so that Sunday golfers would not be in violation of Haddon Township's blue laws. For the last decade the borough has been home to less than two dozen people. Policing coverage is provided by the nearby Haddonfield Police Department. An example of a shared name department is East Goshen-Westtown in mid-Chester County. An example of a named regional department would be the Pennridge Regional Police Department.

Figure 17 maps the location of the municipalities that either have a multi-municipality police force, a named regional department, or receive coverage from another nearby department. It looks like both sizable and tiny municipalities have these arrangements. Starting with the smaller jurisdictions, in addition to Tavistock on the New Jersey side in Camden County, on the Pennsylvania side a number of small boroughs in Bucks, Montgomery and Chester counties, and one in Delaware County (Rutledge borough), have some type of coverage arrangement. Turning to the sizable municipalities, those receiving coverage from a nearby department or sharing a multi-jurisdiction force seem to crop up most often in Chester County.

Only one locality was impossible to classify. Woodland Township in Burlington County, as best we could determine from the UCR data and contact with the jurisdiction, went from a police force of a few dozen early in the decade, to the police force being abolished and policing provided by a broader Human Services Department. In many analyses a special dummy variable for that township is included.

2.3.2. Arrangements and analytic implications

The wide variety of policing arrangements across the metro region makes it hard to gauge the impacts of police coverage rates on crime and crime changes. In order to include a coverage variable, if a municipality received policing either from a covering nearby local agency, or was exclusively covered by the respective state police, its rate of *local* officers per thousand population will be zero even though it is being served by some police officers. They are just not local in the sense that they are not affiliated with a department primarily dedicated to serving that locale. So the coverage variable will be scored zero in these instances.

But to reflect that there is still policing going on there, additional dummy variables reflecting other arrangements will be incorporated in the analyses. These will include:

- A dummy variable for complete state police coverage
- A dummy variable for partial state police coverage
- A dummy variable for being a municipality with a regional or multi-jurisdictional police department, or a municipality which receives coverage from a nearby local agency
- A dummy variable for Woodland Township whose policing arrangements changed markedly during the study period.
- A dummy variable for places with their own dedicated police department, but less than one full time officer.

2.3.3. Department size

Any discussion of department size in the region at the outset recognizes two outliers: Philadelphia and the city of Camden. During the period the typical number of employees in these two was, respectively, 7704 and 492, and the typical number of sworn officers was 6,781 and 416. After these two, the next biggest department, Lower Merion in Montgomery County typically had 166 employees and 139 officers.

Updating beyond the study period, and as mentioned earlier, the Camden City Police Department is no more. In early 2011 the department laid off about half of its sworn officers (J. Goldstein, 2011). In late 2012 the city announced plans to lay off its unionized force and their expensive contract, and have policing delivered by a new Camden County-based police force of non-unionized officers (Zernike, 2012).

Figure 18 shows the distribution of police department size, in terms of median number of full-time sworn officers for the period, for places covered their "own" department, run by that municipality. To better capture the lower end of the force size distribution, Philadelphia and Camden city are not shown.

Twenty jurisdictions have their own department but have zero for a typical number of officers over the period. In most cases this was because department full time size decreased to zero at some point in the period. In a minority of cases this was because the municipality had its own police force, but these were only part-time employees, backed up either by another agency or by the state police. Since there were no full time officers, the median count was zero. West Nottingham Township in Chester County is an example.

Figure 18 clearly shows the “typical” department controlled by one jurisdiction was relatively small. Descriptive statistics appear in Table 2. The typical number of officers was 13 or 14 depending on whether departments averaging zero full time officers were included. Focusing on sworn and civilian employees both, the typical department size was either 14 or 16, again depending on whether the zero full time officer departments were included.

Police strength patterns geographically in interesting ways. Using all jurisdictions, regardless of policing arrangement, and number of sworn officers as an indicator of department strength, Figure 19 maps median department size. At the two ends of the variable, Philadelphia and jurisdictions with a median zero count each receive their own size category. Small departments with between one and ten officers do not, as one might expect, *only* appear in the most outer zones of the metro region. It is true that among sizable jurisdictions, small departments are more likely to be located toward the outer metro region in Burlington, Bucks, and Montgomery Counties. But small departments appear widely dispersed throughout Chester County, and in a couple of sizable jurisdictions in Gloucester County. But when jurisdictions smallish in geographic size are considered, mostly boroughs, small departments are spread throughout the region, in inner and outer portions of the region.

By contrast, medium small departments with between eleven and 25 officers are quite geographically concentrated, being most likely to appear in one of two clusters. A group of jurisdictions extending from mid-Bucks down into mid-Montgomery County hosts departments of this size, as does another group of jurisdictions extending from mid-Delaware County, eastward across the river into Gloucester County.

Returning to the two extended trails of small jurisdictions stretching between southwest Philadelphia and the City of Chester on the PA side, and stretching southwestward from the city of Camden along US Route 30 in Camden County, departments in the PA grouping appeared more likely to fall into the small grouping (orange) while departments in the NJ grouping appeared more likely to fall into the medium small grouping (yellow).

Medium size departments with 26-50 officers were most common in inner Bucks or inner Montgomery county locations, relatively close to or immediately adjoining Philadelphia. Large departments with between 51 and 100 officers often were positioned between the jurisdictions with medium size departments and Philadelphia.

Finally, very large departments with over 100 officers, in addition to the City of Camden and Philadelphia, included the city of Chester, Upper Darby and Lower Merion on the Pennsylvania side; and on the New Jersey side Cherry Hill Township and Gloucester Township (in Camden County).

Although it is not apparent along all points of the compass moving outward from Philadelphia, putting aside small locales and the two extended vectors stretching southwest from southwest Philadelphia, and southeast from the city of Camden, a clear center/periphery gradient of decreasing department size does appear, especially on the PA side of the metro area. Generally, overlooking small jurisdictions which are mostly boroughs, departments are smaller the further out one is from Philadelphia on the Pennsylvania side.

Size and composition compared to national data

Reaves, analyzing 2007 LEMAS (Law Enforcement Management and Administrative Statistics) data, provides nationwide information on local police departments. His analysis presents an interesting comparison point for these regional figures (Reaves, 2010).

One point of comparison is the ratio of full time sworn to (full time sworn plus full time civilian) across all departments which are a municipality's "own" department, and have at least one full time sworn officer. This provides an indication of the extent to which, across all 252 of these departments, personnel are patrolling.

Nationally, based on the totals for each category across all local police departments, that ratio is 77.1 percent (463,147/601,027). In the metropolitan region that ratio is slightly higher at 87.2 percent (12,651/14,505) when typical (median) numbers within the 2000-2008 study period are used for each of the 252 departments, and then totaled.

Turning to size, median department size, in terms of sworn officers, appears slightly larger in the metropolitan region compared to 2007 national figures. Reaves reported that "half of all departments employed fewer than 10 officers" and five percent of departments included just one officer (Reaves, 2010).

Median officer size, noted above at 13 or 14, seems to be slightly higher than Reaves' figure during the entire study period. Concentrating just on figures for 2007, the same year as the latest LEMAS data, median department size for local departments "owned" by one jurisdiction and with at least one full time sworn officer, was 15 officers.

Extremely small, one *full time* sworn officer departments appear to be rarer in this region than nationwide. While they represented five percent of departments nationwide, here there was only one with a typical officer count of one during the study period, representing less than half a percent of the owned departments. (There were, in addition, 20 departments with only one sworn officer, but that officer was part time, not full time.)

So compared to national figures, typical local "owned" departments in the metropolitan region appeared larger, and were less likely to be a department where one officer was flying solo. Given that the Philadelphia metropolitan region by definition includes no rural counties, and given that departments in rural counties tend to be smaller, these departures from national norms of local police department size are comprehensible.

2.3.4. Law enforcement coverage rates

The Distribution, and national comparisons

Following Reaves, the coverage variable reported here is the ratio of sworn officers per 1,000 residents (Reaves, 2010). [6]

After West Conshohocken (6.64), the next highest coverage rate municipalities over the period were the City of Camden (5.19), Chesilhurst borough (5.66) and Langhorne Manor borough (5.64), the latter two in Camden County; Hulmeville borough (5.63) in Bucks County; then Philadelphia (4.57). The entire distribution of coverage rates appears in Figure 20. Rates are shown for jurisdictions with their own police department devoted to that jurisdiction, and with at

[6] The numbers here exclude the Pine Valley Police Department. This department covers a borough most of which is taken up by the world's most exclusive golf course; it also has a population of between 20 and 51 residents during the period. (And, yes, there were a couple of property crimes reported in a years in this borough. There were no reported violent crimes, however, during the period.) Given 4 full time officers, its coverage rate during a typical year (80 officers/thousand residents) represented a marked departure from coverage rates elsewhere in the region. The next highest coverage ratio was more than an order of magnitude lower; in West Conshohocken in a typical year there were 6.64 sworn officers per 1,000 residents.

least one full time sworn officer. For these 251 jurisdictions with Pine Valley excluded, during a typical year the typical (median) coverage rate was 1.96 sworn officers per 1,000 residents. This figure seems slightly lower than the average US 2007 coverage rate for municipal and township police departments of 2.3 (Reaves, 2010). [7] In the metro region for these jurisdictions, the middle half of the coverage rates ranged between 1.45 and 2.65 officers per thousand population in a typical year for each jurisdiction.

To better compare the metro region coverage rate with the national average, data for 2007, the same year as the data used in the latest LEMAS report, were examined. The (unweighted) average sworn officer coverage rate for jurisdictions with their own department and at least one full time employee, excluding Pine Valley, was 1.96 (95% UCL = 2.08; 95% LCL=1.84; n=251). It does appear then, at least for this year, that the typical coverage rate was significantly lower in the Philadelphia metro region than the national average, despite the region including no rural counties.

The significantly lower than national average coverage rate in the Philadelphia metro region, in 2007, could be due to the large numbers of boroughs with police departments, relative to the number of township departments, in the metro region. But this factor would suggest the region should demonstrate smaller-than-national median department sizes. The numbers, however, showed the opposite, with departments here being larger than the national median, for the period, and for the comparison year 2007. A second possible reason for the discrepancy

[7] The figure reported here is a median of a median, and that is contrasted with an average reported by Reaves. It is not recommended to take an average across medians.

arises from the sampling plan used for LEMAS and the consequent weighting applied in nation-level analyses (Reaves, 2010). Since agencies with less than 100 sworn personnel were sampled and therefore not self-representing (NSR), they were weighted substantially in the LEMAS analyses. Here, each agency is assumed to be self-representing (SR) and thus no weights are applied.

Bearing in mind the above cautions, it nevertheless may be the case that the Philadelphia metropolitan region, relative to the nation as a whole, is somewhat under-policed; in 2007 sworn officer coverage rates based on departments owned by one municipality and with at least one full time sworn officer, and excluding Pine Valley, are significantly below the national norm, based on 2007 data. If so, this would be surprising since police coverage rates are generally assumed to be the lowest in rural areas, and this metro region includes only a relatively small portion which is rural in character (Bass, 1995).

The authors are not aware of other studies on metropolitan law enforcement coverage rates that have addressed the significant missing data problems presented by the UCR so as to obtain a complete picture of coverage rates. Nor are we aware of any research specifically on the Philadelphia metro region using complete data. This may be the first reporting of the finding that the Philadelphia region, in 2007 and perhaps for the entire study period, was under-policed relative to the national norm. A closer examination of the geographic patterning of coverage rates, however, will show that the under-policing was confined to one side of the metro region.

Geographic patterning of law enforcement coverage rates

How are the law enforcement coverage rates organized spatially? Figure 21 displays the pattern using manual cut points. Jurisdictions with zero coverage rates – those places part of a regional or shared department, or covered by another nearby local department, or with only state police coverage, or with their own department but no full time sworn officers – are most likely to appear in southern and to a lesser extent mid-Chester County, and in Salem County. There are also smaller clusters of zero coverage jurisdictions in outer Burlington County and lower Delaware County.

Moving past zero, and focusing now just on jurisdictions with their "own" departments of at least one full time sworn officer, the lowest coverage rate jurisdictions appeared in three spatial clusters with rates between .1 and 1: outer Bucks County at its northwestern corner, along the northwestern edge of Montgomery county, and in a band stretching in a roughly north to south vector in mid-Chester County.

Turning to the next group where coverage was lower (1-1.5) than the typical rate for the period in the region, these jurisdictions appeared almost exclusively on the PA side of the region, showing up in sizable numbers throughout Bucks County, in outer Montgomery County, and in the string of small jurisdictions in Delaware County stretching southwestward from Philadelphia.

The next group of jurisdictions with typical or slightly below typical coverage rates for the region (1.5-2) also were more likely to appear on the PA side, with one spatial cluster along the Bucks/Montgomery county border, and another in central Delaware County just west of the "Main Line" Communities. On the New Jersey side the only sizable cluster of jurisdictions in this coverage category appeared in a small group stretching from central Camden County to central Gloucester County.

Taking the next two above average (for the region) coverage rate categories together (2-2.5, 2.5-4), these are most likely to appear just west of Philadelphia, north of Philadelphia in the space between the two branches of the “Y” that are northeast or northwest Philly. They also appear east of Philadelphia or Camden on the New Jersey side, or south of Philadelphia on both the PA and NJ sides of the region.

Finally, the highest coverage rate group, in addition to the small-sized, high coverage places already mentioned, includes Philadelphia, Camden city, and Greenwich Township in Gloucester County.

Considered broadly, the spatial patterning of law enforcement coverage rates suggests three features. First, a center/periphery gradient appears moving away from Philadelphia in a northern or western direction. When moving out from the largest urban county in the metro region in these particular directions, rates shift in ways one might expect, from higher to lower coverage.

Second, polynucleation shapes coverage. The small jurisdictions stretching southwest from Philadelphia toward the city of Chester have lower coverage than other places nearby. Jurisdictions in western Gloucester County, across the river from the city of Chester, have relatively higher rates than places immediately surrounding them. Heavily traveled US 322, especially busy in summer months as a shore route, crosses the Delaware River on the Commodore Barry Bridge and passes through this latter sub-region.

Finally, putting aside the zero coverage rate jurisdictions and multi-jurisdiction policing arrangements, the PA sub-region has lower law enforcement coverage rates than the NJ sub-region of the metro area. Multivariate analysis of variance (MANOVA) simultaneously analyzing the officer coverage rate for all years in the study period, focusing on “own” departments with at least one full time sworn officer and excluding Pine Valley, confirmed significantly (Wilks' lambda multivariate $F(9,240)=8.67$; $p < .001$) lower coverage rates in Pennsylvania as compared to New Jersey. The respective state means on coverage rates, by year, appear in Table 3. The NJ coverage rate over the period ranged roughly from 2.4 to 2.5, while the PA coverage rate ranged from 1.51 to 1.65; the typical NJ rate was about 50 percent higher than the typical PA rate.

Even though the overall region appears under-policed compared to a national 2007 benchmark rate, this under-policing is concentrated on the Pennsylvania side of the region. The coverage rate on the New Jersey side of the region appears typical compared to national figures.

2.4. Average spatial pattern of crime rates over the period

Turning to the geography of crime rates, we consider violent and property crime rates separately. What are the typical levels and geographic pattern over the entire period?

2.4.1. Violent crime

Distributional properties

Descriptive statistics for reported violent crime rates over the nine year period, in raw and population weighted percentile (PWP) form, appear in Table 4. The distribution of jurisdictions' reported violent crime rates, using either the average for the period for each jurisdiction, or the median, appears in Figure 22. Not surprisingly, typical jurisdiction-level rates for the period exhibit strong positive skewness. Rates range from zero to about 3,000/100,000 population. A typical jurisdiction in a typical year (median of medians) had a reported violent rate of about 128/100,000. In a typical year half the jurisdictions reported between 91 and 270 violent crimes/100,000. The maximum typical rate was around 3,000/100,000.

Figure 23 illustrates how the rates cross-reference with the population weighted percentile (PWP) transformation. As rates climb from zero to about 400/100,000, PWPs increase quickly as well because there are so many communities in this rate range. Beyond the 60th PWP, additional crime rate increases, even if substantial, translate into only slightly higher PWPs. This is because there are only a few jurisdictions in this rate range relative to the lower rate range. The figure "jumps" from the 70th PWP to the 98th PWP because of Philadelphia's huge population, about 1.5 million, making up slightly less than a third of the entire region's population. For the jurisdiction with a typical violence rate just less than Philadelphia's, the population in jurisdictions with that rate or lower included slightly less than 69 percent of the population of the total region. But about 98 percent of the jurisdiction population has typical violence rates equal to or lower than Philadelphia's rate, because "equal to or lower than" now includes the Philadelphia population. Finally, the figure also shows three other jurisdictions whose typical reported violence rate during the period was markedly higher than Philadelphia's typical rate.

Geographic patterning

We examine geographical patterning using both median rates during the period, and PWPs based on those median rates. In a few cases average rates will be used. Even though as shown in the preceding figure, the PWPs represent a monotonic transformation of the median rates, mapping the two helps the reader see how the two link up geographically.

Rates

Jurisdictions are grouped by natural breaks based on their median reported violent crime rate in Figure 24. Three fall into the highest rate group (1442-3098): the city of Chester, the city of Camden and, with the highest rate of all, the borough of Darby (Delaware County), right next to southwest Philadelphia. In a typical year, Darby's reported violent crime rate was more than twice Philadelphia's.

The next-to-most violent group includes, as one might expect, places right next to the three in the highest rate group, and Philadelphia. Next to the city of Chester, Eddystone, Trainer, and Upland are in this next-to-highest group with violent crime rates typically in the range of 814-1,441 per 100,000 range. Philadelphia, and places classified by Adams et al. as older urban centers like Coatesville, Pottstown, and Salem city (NJ) also are in this group (Adams, et al., 2008). [8] Norristown, the Montgomery County seat, also appears in this group. A more surprising entry in this group is Westtown Township (Chester County).Crime for this township, however, was allocated because it was protected by a multi-jurisdiction department. Thornbury Township-Chester County, adjoining Westtown, was in this group as well. This township is also served by the same multi-jurisdiction department, Westtown-East Goshen. So, again, our crime allocation methodology needs to be kept in mind as a potential contributor to this township's classification as well.[9] Finally, two other boroughs somewhat close to Philadelphia (Collingdale) or Camden

[8] The classification of the city of Salem as an urban center may be somewhat surprising. This is the county seat for Salem County (NJ), the most rural county in all of New Jersey. The city has a rich colonial history and is isolated amidst farmlands and a nearby wildlife refuge. But digging a bit deeper with the 2000 demographics confirms its status as a place with a history of significant manufacturing but which is "now on the decline" (Adams, et al., 2008: 20). In 2000 the vacant unit rate was 17.6 percent, the family poverty rate was 24.7 percent and the unemployment rate was 10.3 percent. It appears the city's population is struggling economically. The population was 56 percent African-American and five percent Hispanic in the same year, and the percent owner occupied housing units was 40.2 percent. Based on 2000 data, on the PWP SES index Salem City was in the 12th percentile for the region; on stability it was in the 10th percentile, and on the age structure index (ratio of young persons needing supervision/lack of mature people of supervising age), Salem City was in the 83rd percentile. Its median reported violent crime rate during the period was 1,298/100,000.

[9] Thornbury Township, Delaware County, immediately to the southeast of Thornbury Township, Chester County, has its policing handled by the Pennsylvania Police.

city (Brooklawn) fall into this next-to-highest group as well. Each of these has its own small police departments dedicated just to the jurisdiction.

In the group of places with moderate violence rates (433-813/100,000) during the nine year study period, two interesting loose groupings of jurisdictions surfaced. A number of jurisdictions along the US-Route 30/Atlantic City Expressway spine in central Camden County fell into this classification, along with Pennsauken and Woodlynde, immediately adjacent to the city of Camden. On the Pennsylvania side, several municipalities next to or relatively close to southwest Philadelphia appeared in this group as well: Tinicum, Folcroft, Sharon Hill, Lansdowne, Yeadon, and Clifton Heights.

Places with moderately low violence rates (195-432/100,000) appeared clustered in three locations: central Chester County, stretching north of the aforementioned Thornbury Township, along the central spine of Camden County, and just north of northeast Philadelphia in Bucks or Burlington counties. In addition to these three clusters, many small boroughs and some sizable townships also were in this next-to-safest grouping.

Given the positive skewness in these rates, a map using natural breaks naturally shows lots of places in the lowest violence grouping (0-194). Although many of the outer-region jurisdictions were in this lowest violence grouping, also of interest was that many locations quite close to one of the three urban cores also were in this safest grouping.

Turning to a quintile map of typical violent crime rates, Figure 25 naturally shows many more communities in the highest violence group, and many fewer communities in the lowest violence group. A geographically continuous string of highest violence communities now stretches southwest from Philadelphia down to and beyond the city of Chester. A geographic string of jurisdictions in this highest quintile, albeit not completely continuous, stretches south and east from the City of Camden.

On the opposite end of the variable, there are five sizable geographically clustered groups of the safest communities: in the northern tier of Bucks County, in the northernmost corner of Burlington County, along central Burlington County, in mid-Delaware County northwest of US-Route 1, and along the Chester/Montgomery county border. Although the geographic cluster with the largest number of jurisdictions in this most-safe category is at the outermost northern edge of the metro region in Bucks County, one of these pockets of safety is centrally located on the Pennsylvania side of the region and quite close to Philadelphia (Haverford, Marple, Newtown, Upper Providence, Easttown, and Willistown townships).

Population weighted percentiles

The population weighted percentile version of typical violent crime rate quintile map appears in Figure 26. The translation between jurisdiction quintiles and percentiles of the metro region population proves disturbing. The top one fifth of jurisdictions on violence is home to about 45 percent of the population in municipalities across the entire region. At the other end of the variable, the safest one fifth of jurisdictions is home to about sixteen percent of the population. Putting the two ends together, the ratio of jurisdiction population living in the most dangerous fifth of communities to the safest fifth of communities is about 3:1. Of course part of this is driven by Philadelphia, home to a bit less than 1/3 of the region's population, appearing in the most dangerous fifth.

PWP violence differences by state

Analysts of city-level robbery rates have discovered within-state dependencies (Deane, Messner, Stucky, McGeever, & Kubrin, 2008). That raises the possibility of within-state dependencies for municipality-level violence rates. Given that the New Jersey side of the region appears to be more heavily policed than the Pennsylvania side, one might expect that relative violence rates there might be higher. The violence variable in PWP form directly addresses relative differences.

Should these state differences be analyzed parametrically or non-parametrically? Except for the four jurisdictions whose typical violence percentiles were in the upper 90s (Philadelphia, Camden, Chester, Darby), the distribution of typical violence percentiles was relatively normal. Even with these outliers, skewness was $<|1|$ regardless of whether the percentile was based on the average reported violence rate or the median reported violence rate over the period.

Starting non-parametrically, the Kruskal-Wallis rank test suggested the Pennsylvania sub-region was significantly lower on relative violence in a typical (median) year based on its jurisdictions' violence percentiles ($p < .01$). Treating the data parametrically and analyzing the average reported violence percentile showed the relative violence percentile over the period was significantly lower in Pennsylvania (mean=32.7) compared to New Jersey (38.5) ($F(1,353) = 7.55$; $p < .01$). A MANOVA analyzing all the years simultaneously confirmed a significant difference (multivariate F Wilks' Lambda(9,345) = 3.26; $p < .001$). In sum, over the period, treating each municipality equally regardless of size, jurisdictions on the Pennsylvania side were relatively lower on violent crime than jurisdictions on the New Jersey side. The average difference was about 6 percentiles.

But that difference may have been more sizable earlier in the period. Turning back to the rates themselves, Table 5 displays the unweighted average reported violent crime rate across jurisdictions, by state, and by year. It appears that in some of the years earlier in the study period (2001- 2004), the cross-state violence crime differential in the region was more sizable. Toward the end of the period, however, the average unweighted difference was much smaller.

Violent crime: Spatial summary

The spatial patterning of violent crime across the metro region confirms some commonsense suspicions but also contains some surprises. As expected, the two poorest urban cores, the cities of Camden and Chester, fare badly. But unexpectedly, they weren't consistently the most violent. This dubious honor went to Darby borough in Delaware County. This location was generally more than *twice* as violent as Philadelphia. As expected, Philadelphia overall was quite violent, coming in fourth from the top. But, unexpectedly, old urban centers quite far out in the metro region, like Salem City in mostly rural Salem County, had an average violent crime rate (1,301) closely comparable to Philadelphia's (1440/100,000). As expected, some communities close to high violence locations like Philadelphia were themselves relatively violent. This is seen, for example, in the string of contiguous municipalities stretching southwest from Philadelphia down toward Chester along Interstate 95 and US-13. But, unexpectedly, in some sectors Philadelphia's next-door neighbors were extremely safe. This is seen in easternmost Montgomery and Delaware counties.

Thinking broadly, one theme does not seem generally supported by the violence spatial pattern. Moving outward toward the periphery of the metro region from the centroid of Philadelphia, and following several different directions of the compass, generally does *not* reveal a *consistently* declining violence rate. There are a number of jurisdictions, some sizable in area, on or close to the periphery of the region, with high violence rates. In *some* directions, for example moving eastward from the center of the city of Camden, violence drops consistently as one moves further away. But in many other directions this trend does not hold. In short, although there is some evidence of concentric organization of violence rates, there is also substantial evidence of other important themes: differentiation (more low crime jurisdictions on the PA side), polynucleation (from Philadelphia down to Chester), and structuration (urban legacies in Norristown, Pottstown, Coatesville, Salem City, and Bristol).

2.4.2. Property crime

Distributional properties

Descriptive statistics for raw reported property crime rates, and for property crime rates converted to PWPs, appear in Table 6. Considerable positive skew in the raw rates is evident with the average of the average rate (1914) markedly higher than the median of the median rate (1523). The distributions of the average and median rates appear in Figure 27. About half the jurisdiction typical property rates are between roughly 900 and 2,500 reported property crimes/100,000 population.

Figure 28 illustrates how the median rates cross-reference with the PWP transformation. Compared to the violent crime transformation to percentiles, the property crime transformation "behaves" differently in the lower percentile range. The relationship is less "steep" than it was for violent crime meaning that property crime rates are increasing substantially as PWPs increase from about 5 to about 50. Stated differently, the raw rate difference between a PWP of 50 and a PWP of 10 involves a greater range of rates than did the corresponding raw rate difference for violent crime. Another difference is that more jurisdictions score above Philadelphia on property PWPs than violent PWPs. Philadelphia is the first jurisdiction after the “jump” from a PWP of about 65 to a PWP of about 95. More than a dozen jurisdictions score higher because of their higher median property crime rates. For violent crime, only three scored higher.

Geographic patterning

As with violent crime, geographic patterning is examined both using median rates for the period and PWPs based on those median rates.

Rates

Jurisdictions are grouped on their typical property crime rate using natural breaks and mapped in Figure 29. In the highest rate group are large urban centers like the city of Camden, and smaller urban centers like Pottstown and Salem City. Suburban locations with sizable shopping centers also are in the highest group: Deptford Township (Gloucester) hosts the Deptford Mall, and Upper Merion Township hosts the behemoth King of Prussia multi-mall shopping complex. Land use, albeit of a different variety, is probably relevant to Tinicum Township’s membership in this category. This township includes part of the Philadelphia Airport itself, and extensive parking and hotel facilities just to the south of the airport. The inclusion of Franklin Township (Gloucester County) in this grouping is a bit more challenging. No particular land uses come to mind. The township does include SR 55, a major commuting route in NJ both for daily commutes into Philadelphia and for weekend and seasonal shore-bound travelers, and US-Route 40, as well as an interchange where the two cross.

The next to highest property crime group includes a spatial cluster of Philadelphia and several nearby jurisdictions to the northeast in Bucks county, and to the north or east of the City of Camden. The city of Chester and a couple of its neighbors make another spatial cluster in this next-to-highest rate group.

Turning to the lowest property crime rate sub-regions, western Chester County, northwest Bucks County, the northwestern corner of Montgomery County, and mid Burlington County, each hosts a cluster of contiguous, low property crime rate municipalities. In each of these clusters, most of the included jurisdictions are quite rural/small town in character. Some of these clustered jurisdictions also host either significant state parks, state forests, or substantial farmland.

Figure 30 maps the same data but uses quintiles rather than natural breaks. Of course, given the positively skewed rates, there are far more highest crime category jurisdictions in this map, and far fewer lowest crime category jurisdictions in this map, compared to the natural breaks version.

But what is interesting is where the highest crime grouping grows. Starting with the well-known-to-the-reader-by-now sub-region, the string of small jurisdictions stretching southwest from southwest Philadelphia toward the city of Chester, many of these are now in the highest property crime rate group. Another string of jurisdictions often of interest are the small ones southeast of Camden city in Camden County along US-30. Many of these are now in the highest property crime rate grouping as well. So too is the adjacent and much larger Cherry Hill Township. This township hosted one of the first major suburban shopping malls in this region, Cherry Hill Mall, along SR-38. A good number of smaller malls pop up elsewhere in the township along SR-70. Vorhees Township, next door to Cherry Hill and now in the highest crime grouping, has a sizable number of shopping centers and at least one large office park.

Eastern Bucks County now has several townships just northeast of northeast Philadelphia in the highest crime group with this mapping. Just north of Philadelphia, Neshaminy Township hosts the moderate sized Neshaminy Mall. A casino also has been added to the renamed horse racing track located in the township. The other jurisdictions in this segment of Bucks County which also are in this highest crime group also host substantial shopping centers or malls, or are traversed by Interstate 95.

Just north of Philadelphia, Cheltenham Township (Montgomery County) now gets included in the highest crime group. There is some commercial activity along Cheltenham Avenue, the border with Philadelphia. Cheltenham Mall, a moderately large and quite busy shopping center, is located in this township. There is also some commercial activity along SR-309 alongside the mall.

In Delaware County, Springfield Township surfaces for the first time as a place of interest. US-1 runs through a sliver of the township at the northern end, a sizable shopping center sits just outside its northern boundary, and its southern region along Baltimore Pike hosts mile after mile of a wide variety of shopping: several auto dealerships, Best Buy, numerous restaurants and fast food places, supermarkets, and much more.

Further west of Springfield Township in Chester County, West Whiteland Township appears as a place of interest for the first time. It is home to the sprawling Exton Square Mall north of US-30-Business. The mall takes up a substantial fraction of the township's footprint.

Switching back to New Jersey, Lumberton Township (Burlington County) is placed in the highest crime group. The northwest corner of the township is occupied by the moderate sized

Crossroads Plaza shopping center. There also is substantial commercial activity along SR-38 nearby.

In sum, proximity to high property crime places, like Philadelphia, the city of Camden, and the city of Chester appears responsible for some of the places in the highest property crime quintile. In addition, for many places further away from these three urban cores, sizable commercial/shopping complexes also link with high property crime rates. The linkage is not perfect. There are some high crime places located in the mid to outer region of the MSA which lack such commercial centers (e.g., Franklin Township, Gloucester County). But the number of suburban municipalities in the highest property crime grouping that do have sizable shopping/commercial hubs is certainly notable – King of Prussia, Cherry Hill Mall, Deptford Mall, Exton Square Mall.

Sometimes when the commercial land use idea does not seem relevant for a high property crime rate in a location distant from one of the urban cores in the metro region, land use can be important for a different reason. Take the position of Oldmans Township (Salem County) in the top property crime grouping. The township appears exclusively rural with a substantial number of farms. But the New Jersey Turnpike passes through the township and the intensively used Clara Barton Service Area off of the Turnpike is located here. In a township with a relatively small population of less than 2,000, 20-40 larcenies a year can contribute substantially to a high property crime rate.

Harrison Township (Gloucester County) is another semi-rural place where travel patterns are probably relevant. US-322, a major route to shore points from Philadelphia passes through here. Traffic slows in the town of Mullica Hill for traffic lights. The town itself has a restaurant and a couple of blocks of cutesy antique stores seeking to draw in a few of the less frenetic shore-bound travelers. The moseying and antiquing may have hidden costs. 160-180 larcenies a year can make a substantial contribution to a high property crime rate in a township of around 8,000 persons.

Population weighted percentile form

Figure 31 maps property crime PWPs by quintiles. Of interest here, as with violent crime, is translating one fifth of the jurisdictions into fractions of the region's population.

Starting at the safe end, about seven percent of the metro region's population resides in the safest fifth of jurisdictions. Since these jurisdictions are generally located in the outer PA sections of the MSA where rural/small town atmospheres dominate, the small fraction of the region's population in this safest zone is not surprising. The fraction of the region in the least safe group on property crime is roughly comparable to the fraction in the least safe group on violent crime (Figure 26).

Turning to the highest property crime grouping, slightly less than half – 49 percent – of the region's population lives in municipalities whose property crime rates place them in the top fifth of municipalities.

PWP property differences by state

The question arises: do the state sub-regions of the metro area show the same differences on property crime rates that emerged for violent crime? They do. Parametric and non-parametric analyses both confirmed these differences.

Starting with property crime rates in PWP form, and analyzing averages for all nine years simultaneously, New Jersey crime rates in the region were significantly higher (Wilks' Lambda Multivariate $F(9,345)=8.73$; $p < .001$) Univariate tests on summary indicators across the entire period confirmed state differences on the average property crime PWP (NJ grand average = 42.4; PA = 25.8; F(1,353=45.44; $p < .001$). Non-parametric tests on the state differences on median PWPs generated similarly significant findings as did tests of medians of raw rates (Kruskal-Wallis rank test, $p < .001$ for both).

State differences in average property crime rates, by year, by state, appear in Table 7. Throughout most years in the study period, the average Pennsylvania jurisdiction property crime rate was about 3/5th of the average New Jersey rate. The average difference seemed slightly larger in the first two years of the period, 2000-2001, because the New Jersey average rate was slightly higher. But it also looked like the average Pennsylvania rate started to increase slightly during the last two years of the series.

Property crime: Spatial summary & comparison to violent spatial pattern

Property crime is distributed differently than violent crime in other studies (Trickett, Osborn, Seymour, & Pease, 1992). The current descriptive analyses demonstrate how this is true as well for intra-metropolitan property crime patterns at the municipality level. The powerful influence of large scale centers of commercial activity is much more apparent for property crime than it was for violent crime. Because of this influence, several jurisdictions located quite distant from major urban cores but hosting large shopping concentrations, usually in malls, were placed in the highest property crime grouping, regardless of whether natural breaks or quintiles were used to make those groupings. Large-scale commercial concentrations (King of Prussia, Deptford Mall, Exton Square Mall, etc.) draw in large volumes of people thereby creating many opportunities for property crimes like larceny. Because these locations and their surrounds become part of potential property offenders' activity spaces, such zones are likely incorporated into those same potential offenders' search spaces, thereby contributing as well to the higher burglary rates in the hosting townships. If the base population in the surrounding township is relatively low, this makes for high rates. These large-scale commercial concentrations, in the terms of environmental criminology, function as powerful nodes (Patricia L. Brantingham & Brantingham, 1993).

The mall effect on municipal-level property crime rates revives the crime denominator discussion (Boggs, 1965). Shouldn't the crime denominator used for crimes like larceny take into account the population exposed rather than the surrounding residential population? Of course, it should. But the resources required to gather such data on a yearly basis, even from archival sources, seem out of reach.

Turning to broader spatial themes, all four prove relevant to property crime as they were to violent crime. But, in the case of property crime, one theme seems to play a more prominent role.

For both crime types the maps show some evidence of concentric patterning. Depending on the type of map, the majority or all of the three major cores were in the highest crime grouping. Further, regardless of map type, for both crimes some of the safest jurisdictions were likely to be found in the outermost region of the MSA, especially on the PA side. Major road network patterns prove influential as well for both crime types. The polynucleation theme applies to both crime types, but clearly is more relevant to property crime. Around the King of Prussia mall complex, and in other townships hosting extremely large malls, very high levels of property crime are evident. The idea of structuration and legacies applies as well to both crime types. Old, smaller urban centers in the outer portions of the metro area (Pottstown, Coatesville, Salem City), and places with checkered pasts (Norristown) have high property and high violence crime rates. Finally, geographic differentiation by sub-region appears relevant as well; for both crime types the PA side is safer than the NJ side.

2.5. Closing comment

This chapter introduced the reader to the spatial patterning of municipal demographic structure, law enforcement coverage, and reported property and violent crime rates, across the Philadelphia metropolitan region. For community structure, 2000 Census data were used, providing an image of the region at the beginning of the study period. For coverage and crime, average or typical scores during the period were described. The chapter also described and mapped the wide variety of policing arrangements operative throughout the metro region.

In these descriptive analyses, each municipality was weighted equally. This is because the purpose was not to determine an estimate for the entire region, but rather to describe intra-metropolitan patterning.

The demographic structural differentiation seen across the metro region foreshadowed the geographic patterning of violent and property crime rates. Further, the geographies of demographics and crime confirm the simultaneous relevance of the previously discussed organizing frameworks for describing these patterns. (1) The concentric frame typically associated with the Chicago School has some merit. On both crime types, and on demographic disadvantage, major urban centers often fall into the highest grouping, and numerous jurisdictions located along the periphery appear in the lowest grouping.

But the concentric frame also misses a lot. Sometimes, as with violent crime, it will not be the major urban cores which score the highest, but rather one of their immediately adjoining, urban-like inner ring suburbs (Darby Borough). Further, the shift in either demography or crime as one progresses from center to periphery is not consistent. It depends on the point of the compass followed as one moves away from the center. (2) The polynucleation idea, emphasized by scholars of the LA School and new urban sociologists alike, applies to both demography and the two crime types. This is most clearly seen in the connection between jurisdictions with large scale mall complexes and property crime rates. It also applies to the jurisdictions on the west side of the Delaware River in the sub-region between southwest Philadelphia and the city of Chester. Historically, putting aside activity within Philadelphia itself, this sub-region was perhaps the premier manufacturing and industrial hub for the region. Those businesses have been cut back substantially in the last four decades. The demographic disadvantage seen here parallels the high crime rates also seen in this zone. (3) The influence of major road networks is apparent as well, especially when combined with the presence of small municipalities. The string of somewhat disadvantaged and somewhat high crime jurisdictions strung along US-Route 30 and the Atlantic City Expressway/Interstate 476 in Camden County is a case in point. (4) The influence of structuration, ongoing impacts due to historical legacies, is seen most clearly in the demographics and crime levels in small urban centers located well away from the center of the region (Coatesville, Pottstown, Salem City), and in the instance of Norristown.That same idea, probably combined with polynucleation, also explains the presence of features like the suburban Hispanic grouping in Kennett Square, in Chester County, associated with the extensive mushroom farming in that area. (5) Finally, thinking broadly about differentiation, differences in safety between NJ and PA jurisdictions has surfaced.

Table 1. 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 2. 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 3. Average law enforcement coverage rates, by year, by state

Year	Mean	se	95% LCL	95% UCL
State				
2000				
NJ	2.45	0.10	2.26	2.64
PA	1.56	0.07	1.43	1.70
2001				
NJ	2.43	0.09	2.25	2.61
PA	1.59	0.07	1.46	1.73
2002				
NJ	2.40	0.09	2.23	2.57
PA	1.60	0.07	1.46	1.74
2003				
NJ	2.42	0.09	2.25	2.60
PA	1.59	0.07	1.45	1.73
2004				
NJ	2.43	0.09	2.26	2.60
PA	1.57	0.06	1.45	1.70
2005				
NJ	2.47	0.09	2.30	2.63
PA	1.58	0.07	1.45	1.70
2006				
NJ	2.48	0.09	2.30	2.65
PA	1.62	0.07	1.49	1.75
2007				
NJ	2.51	0.09	2.34	2.69
PA	1.63	0.07	1.49	1.77
2008				
NJ	2.48	0.09	2.31	2.65
PA	1.65	0.07	1.52	1.79

Note. N=251; only jurisdictions with “own” departments and at least one full time sworn officer included. Pine Valley excluded. Unweighted average.

Table 4. Descriptive statistics for reported violent crime rates over period, 2000-2008

	Reported violent crime rate		Population weighted percentiles for reported violent crime rate	
	Period average	Period median	Period average	Period median
Variable name	vioraav	vioramd	pwpvioav	pwpviomd
Statistics				
N	355	355	355	355
Mean	245.2	---	34.6	---
SD	312.2	318.8	19.0	20.2
Median	---	127.7	---	31.3
Min	0.0	0.0	0.3	0.2
Max	3,048.9	3,097.8	99.3	100.0

Note. Rates per 100,000 population.

Table 5. Average unweighted jurisdiction reported violent crime rates, by year, by state

Year	Mean	se	95% LCL	95% UCL
State				
2000				
NJ	256.5	24.3	208.7	304.3
PA	231.4	22.3	187.5	275.2
2001				
NJ	274.3	26.0	223.1	325.5
PA	220.5	16.6	187.8	253.2
2002				
NJ	284.9	28.2	229.4	340.4
PA	216.2	19.5	177.8	254.6
2003				
NJ	275.3	30.5	215.4	335.3
PA	218.8	20.4	178.5	259.0
2004				
NJ	277.3	27.5	223.1	331.4
PA	218.2	22.4	174.2	262.2
2005				
NJ	256.4	27.0	203.3	309.5
PA	235.8	23.8	189.0	282.7
2006				
NJ	265.0	29.5	207.0	322.9
PA	252.3	24.9	203.2	301.3
2007				
NJ	255.0	26.9	202.2	307.9
PA	247.0	25.4	197.0	296.9
2008				
NJ	272.0	28.4	216.2	327.8
PA	264.2	28.6	208.0	320.4

Table 6. Descriptive statistics for reported property crime rates over period, 2000-2008

	Reported property crime rate		Population weighted percentiles for reported property crime rate	
Statistic	Period average	Period median	Period average	Period median
	proraav	proramd	pwpproav	pwppromd
N	355	355	355	355
mean	1,914.5	---	31.2	---
SD	1,255.6	1,277.5	23.1	24.5
Median	---	1,523.1	---	26.7
p25	942.1	909.0	10.5	8.8
p75	2,512.6	2,465.8	47.0	47.7
Min	100.2	0.0	0.3	0.0
Max	9,029.7	9,053.9	99.9	100.0

Table 7. Average unweighted jurisdiction reported property crime rates, by year, by state

Year	Mean	Se	95% LCL	95% UCL
State				
2000				
NJ	2,643.6	135.8	2,376.6	2,910.7
PA	1,686.4	75.7	1,537.6	1,835.2
2001				
NJ	2,666.7	154.2	2,363.5	2,969.9
PA	1,671.7	76.0	1,522.2	1,821.1
2002				
NJ	2,321.1	116.4	2,092.2	2,550.0
PA	1,548.7	71.6	1,407.8	1,689.6
2003				
NJ	2,385.0	134.3	2,120.9	2,649.1
PA	1,529.8	75.8	1,380.7	1,679.0
2004				
NJ	2,465.7	144.4	2,181.8	2,749.7
PA	1,563.6	78.6	1,409.0	1,718.1
2005				
NJ	2,375.3	141.4	2,097.3	2,653.4
PA	1,527.2	79.6	1,370.6	1,683.7
2006				
NJ	2,382.9	127.4	2,132.4	2,633.3
PA	1,694.8	84.6	1,528.4	1,861.2
2007				
NJ	2,330.7	123.9	2,087.1	2,574.3
PA	1,785.4	78.6	1,630.9	1,939.9
2008				
NJ	2,609.0	172.6	2,269.5	2,948.5
PA	1,820.7	85.2	1,653.2	1,988.3

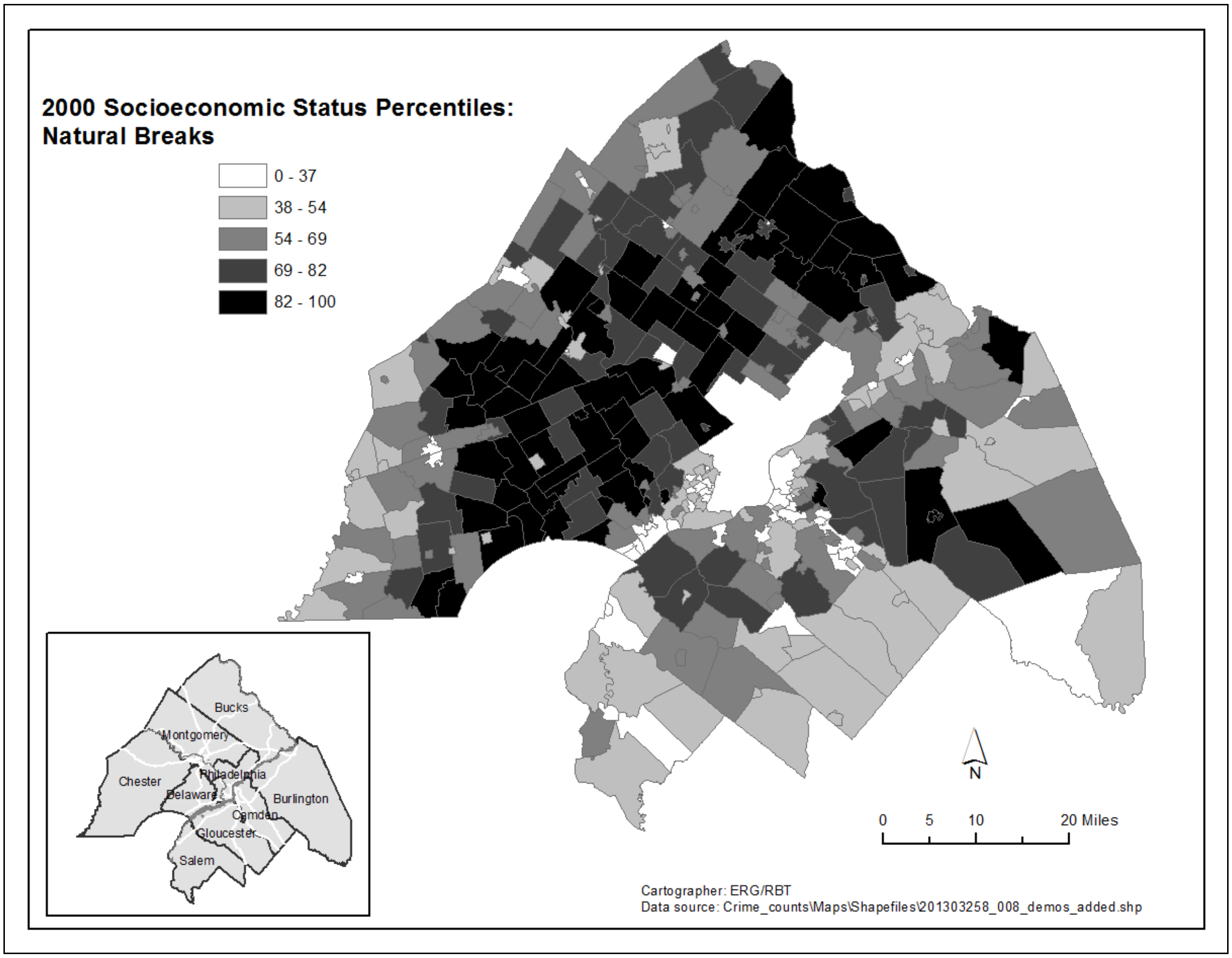

Figure 3. 2000 Socioeconomic status: Natural breaks.

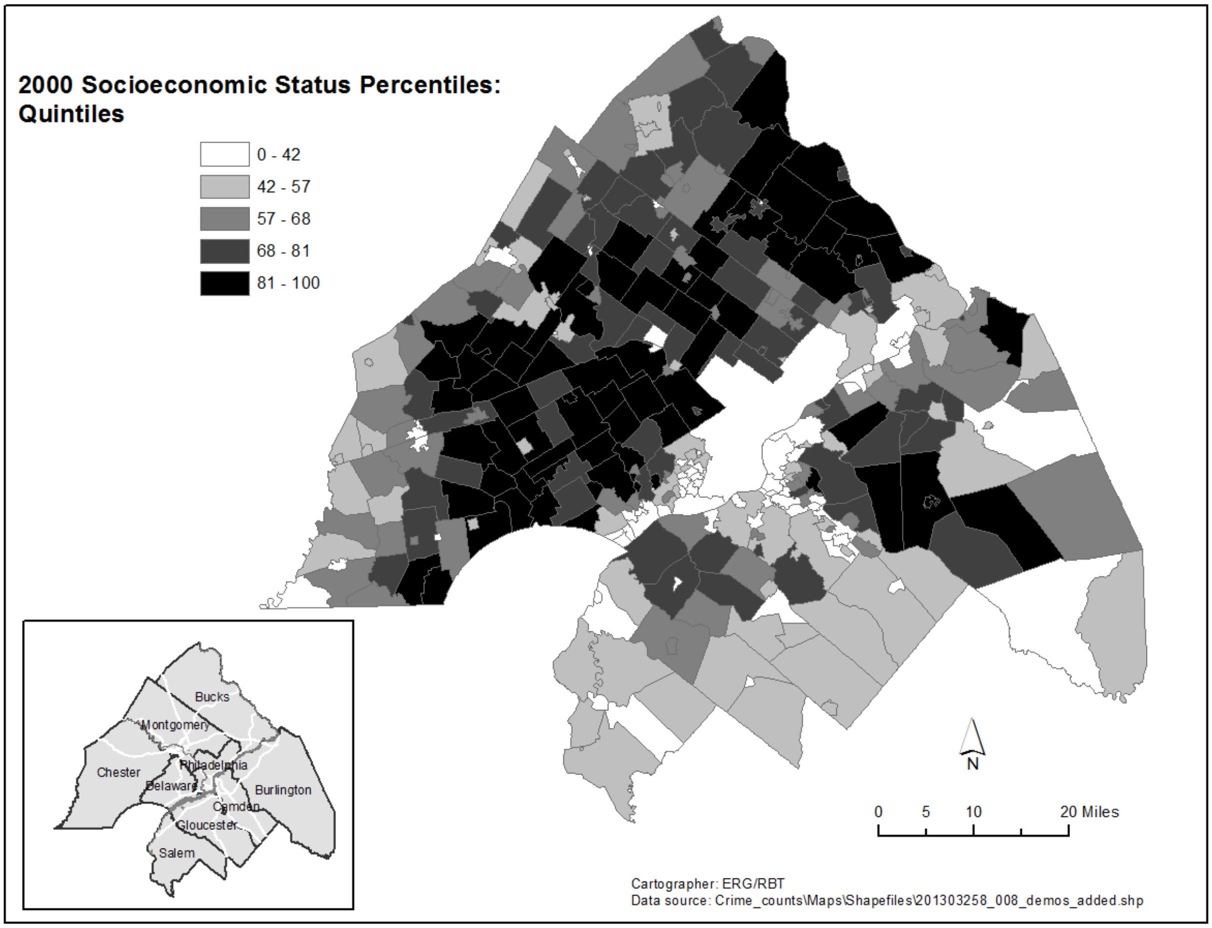

Figure 4. 2000 Socioeconomic status: Quintiles

Figure 5. Cross referencing SES index scores with 2000 Median House Value

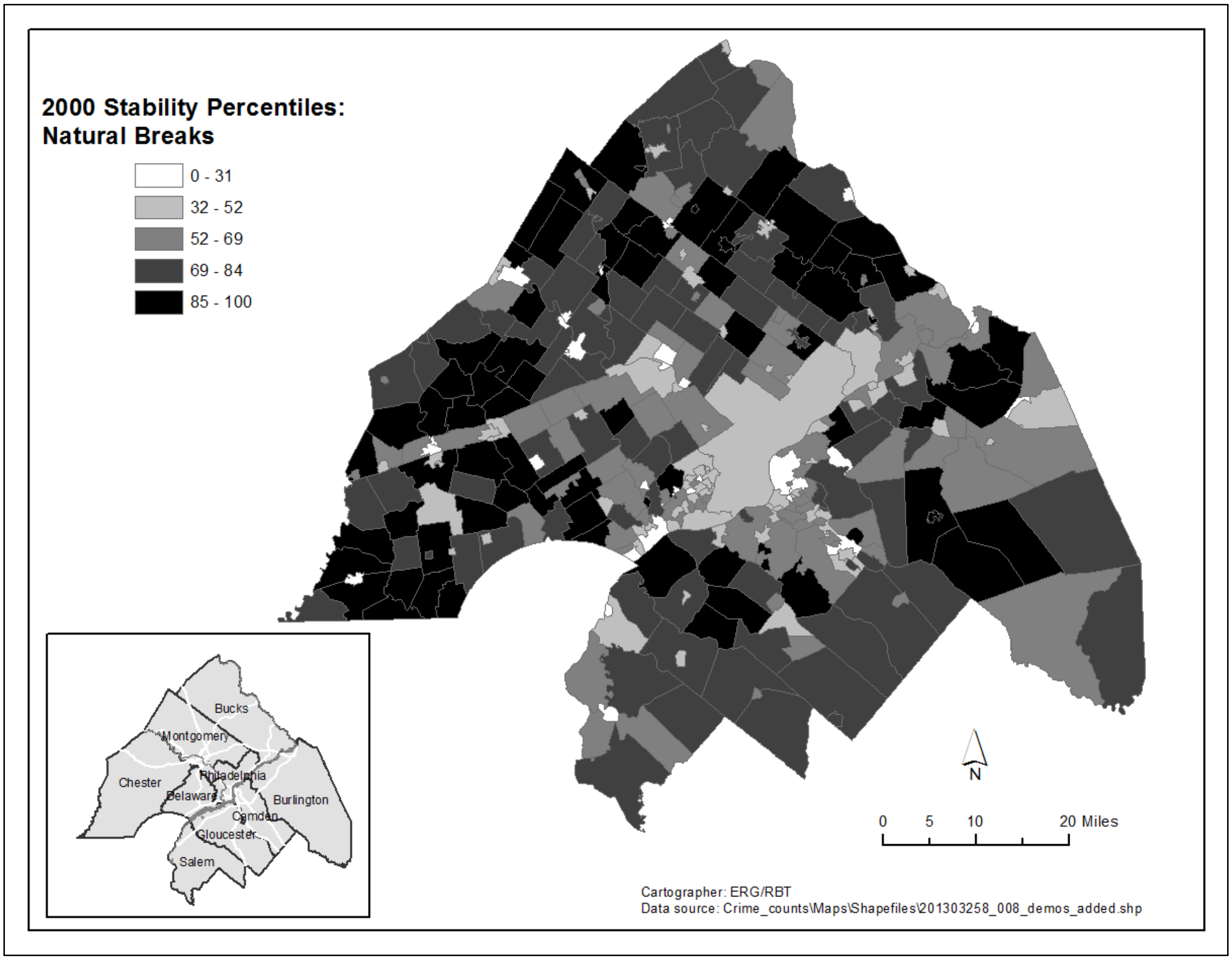

Figure 6. 2000 Stability percentiles: Natural breaks

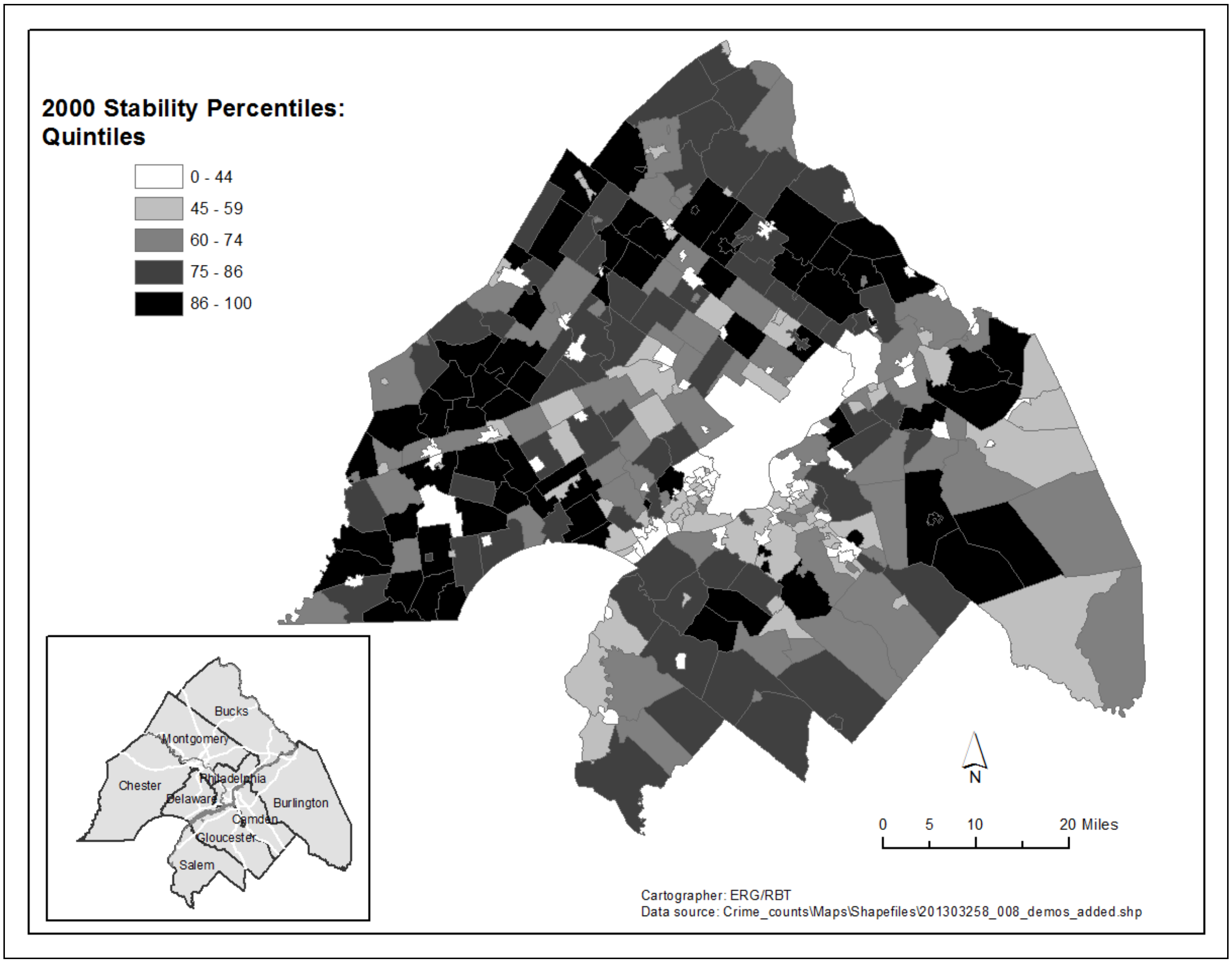

Figure 7. 2000 Stability percentiles: Quintiles

Figure 8. 2000 Stability index and 2000 percent owner occupied

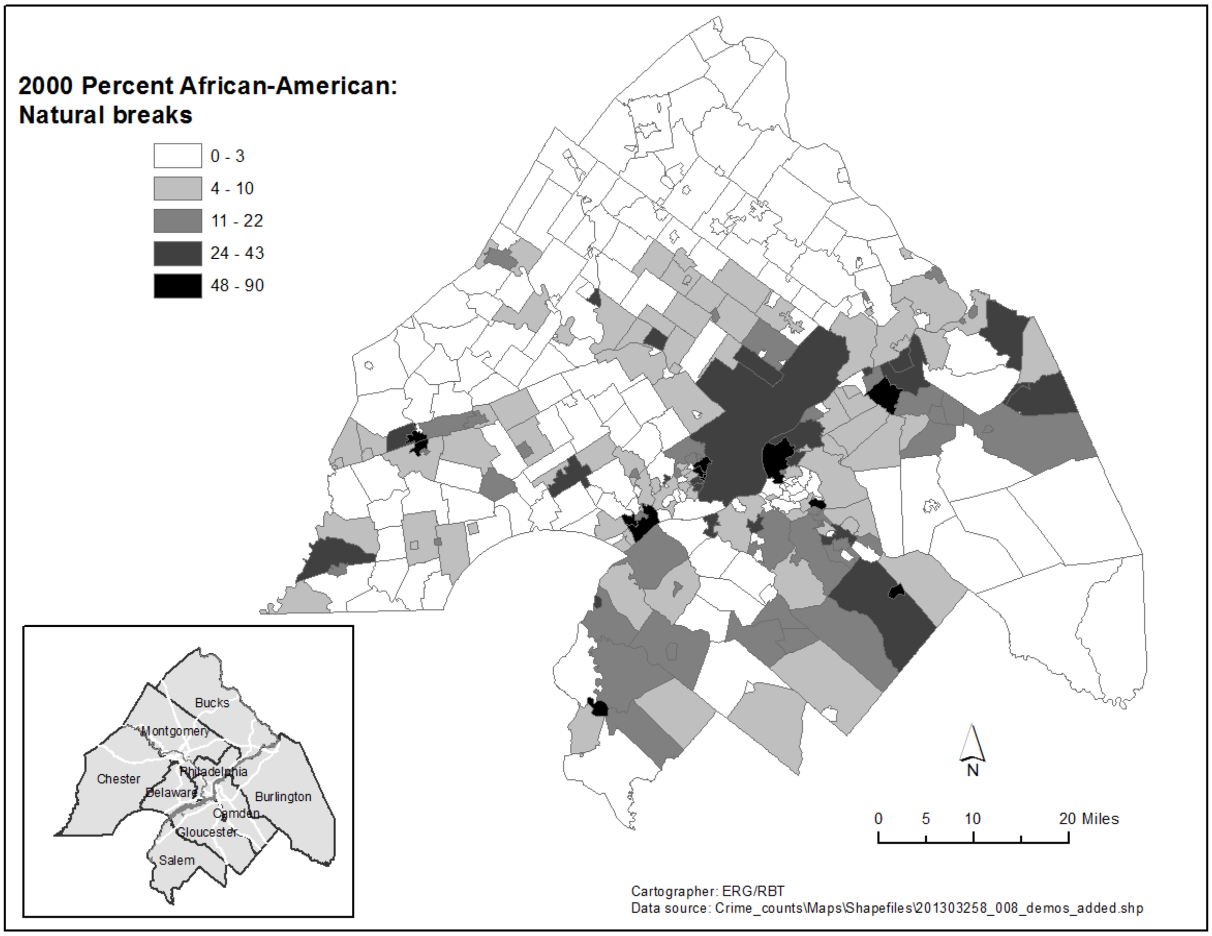

Figure 9. 2000 Percent African-American: Natural breaks

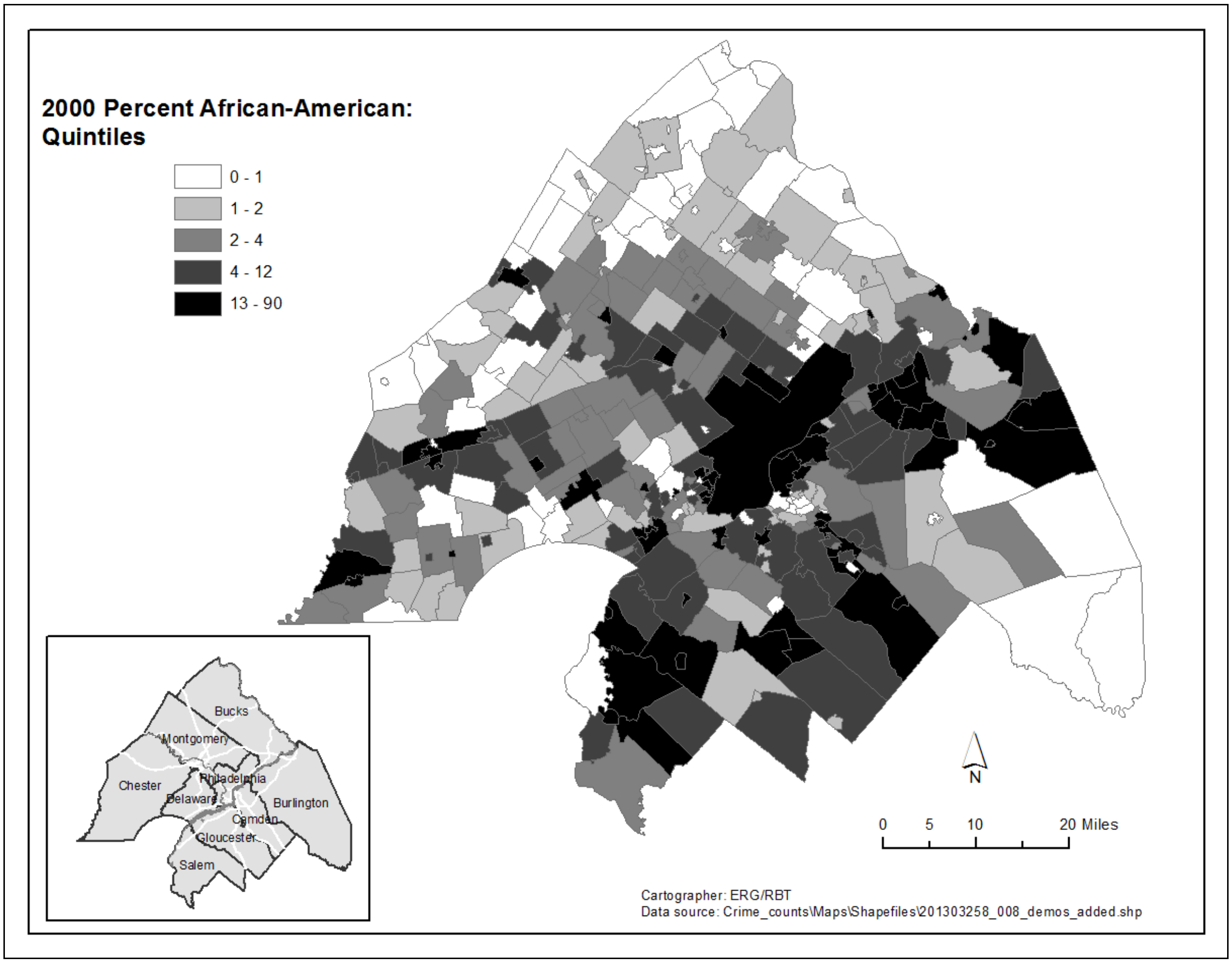

Figure 10. 2000 Percent African-American: Quintiles

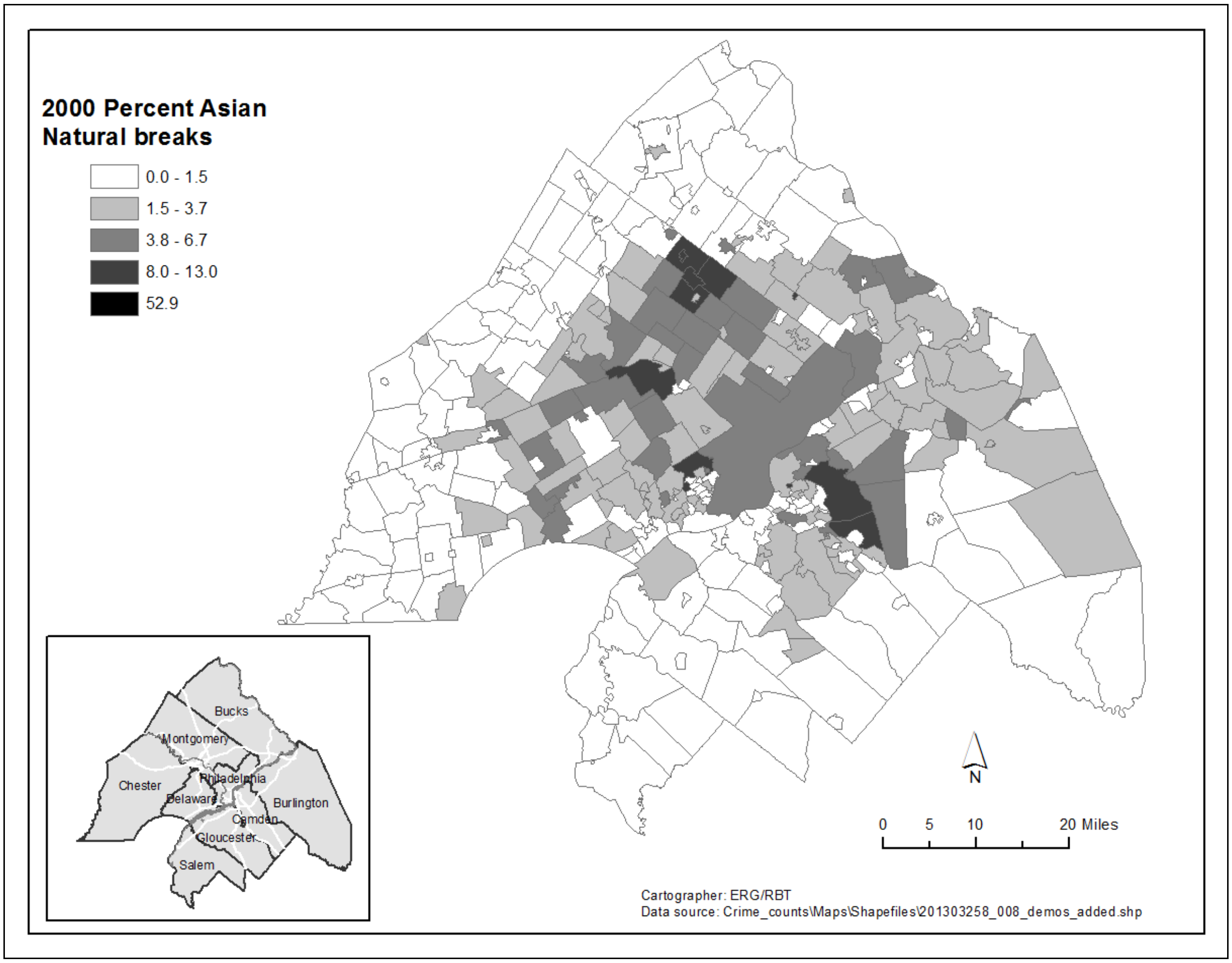

Figure 11. 2000 Percent Asian: Natural breaks

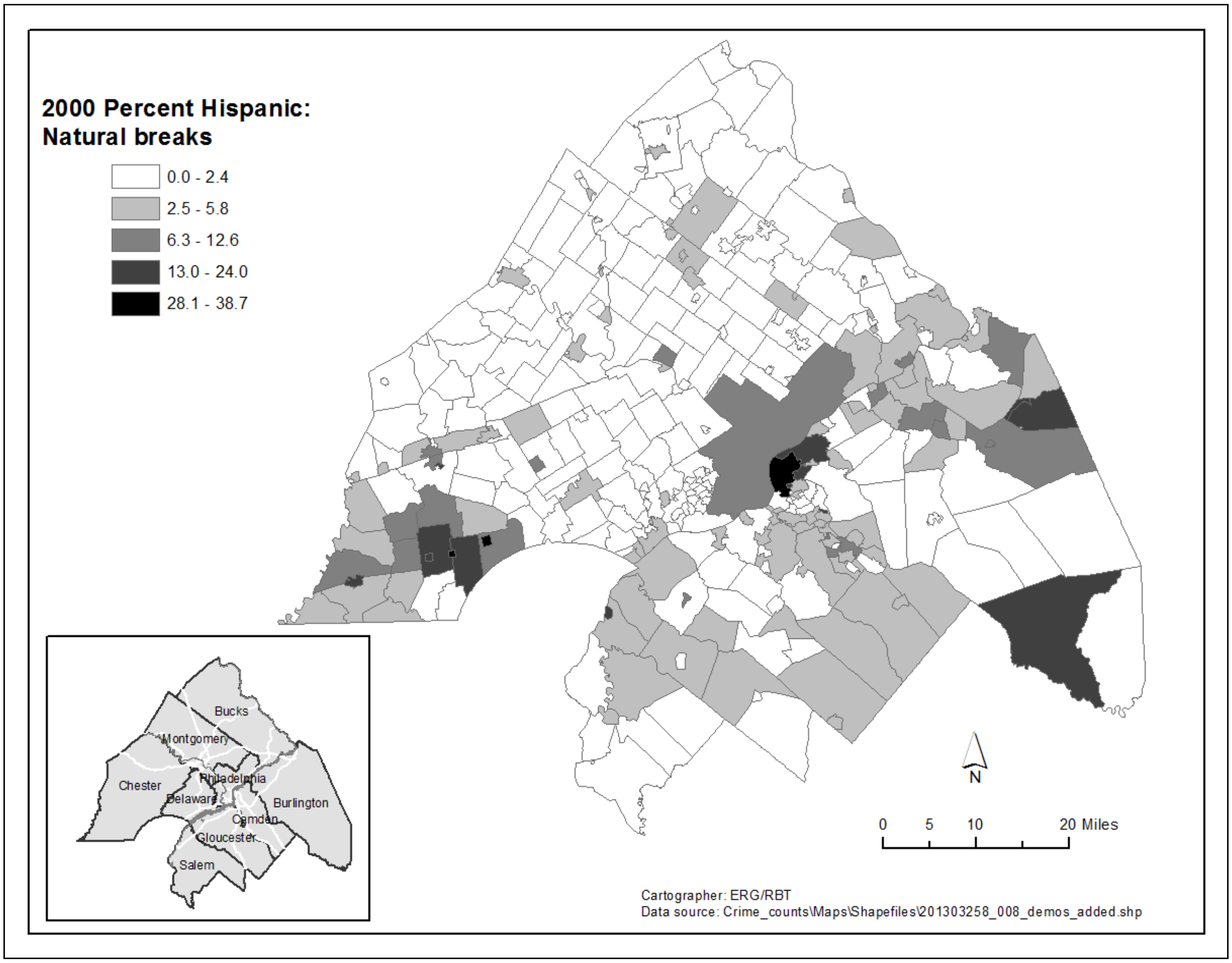

Figure 12. 2000 Percent Hispanic: Natural breaks

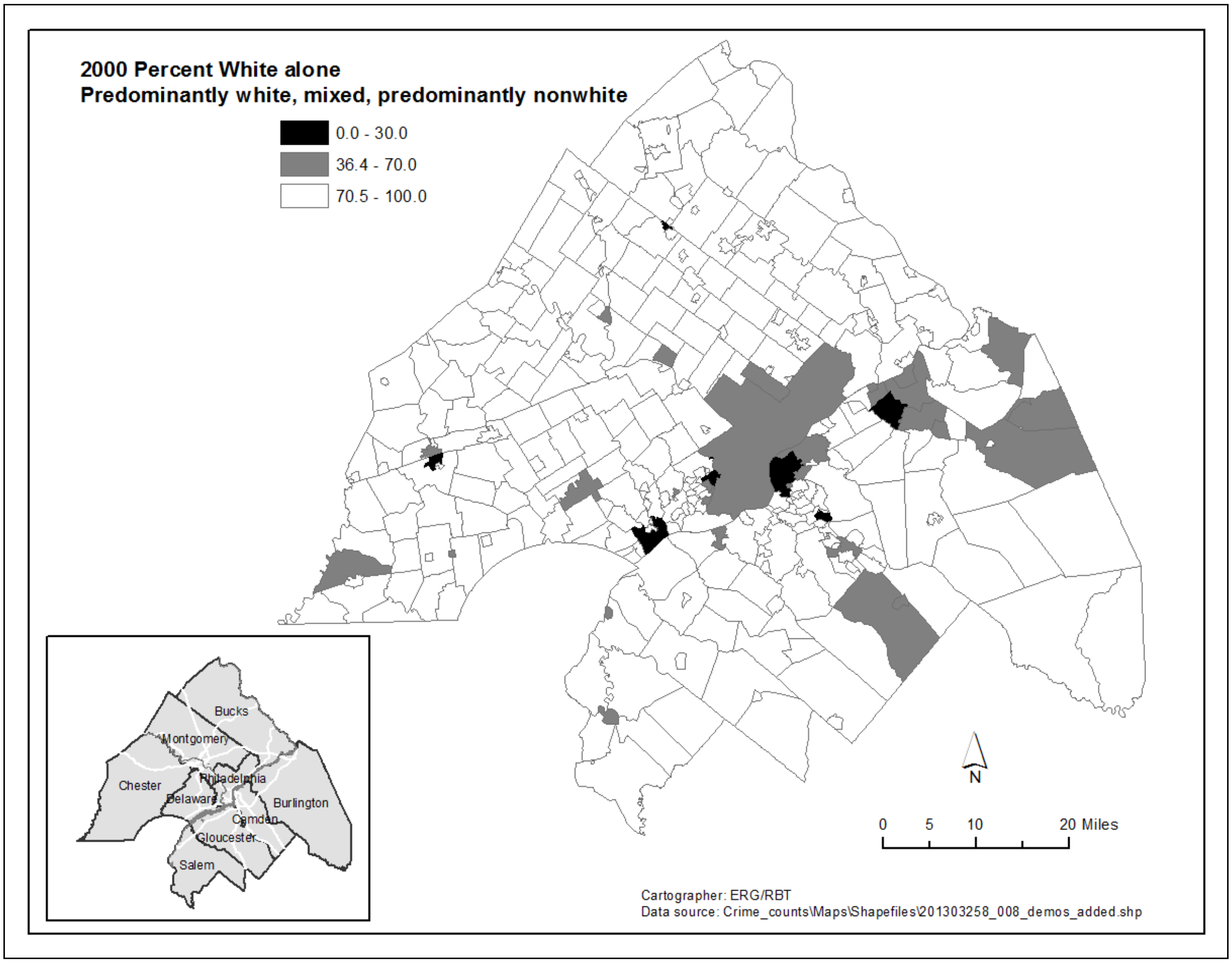

Figure 13. jurisdictions classified by percent white

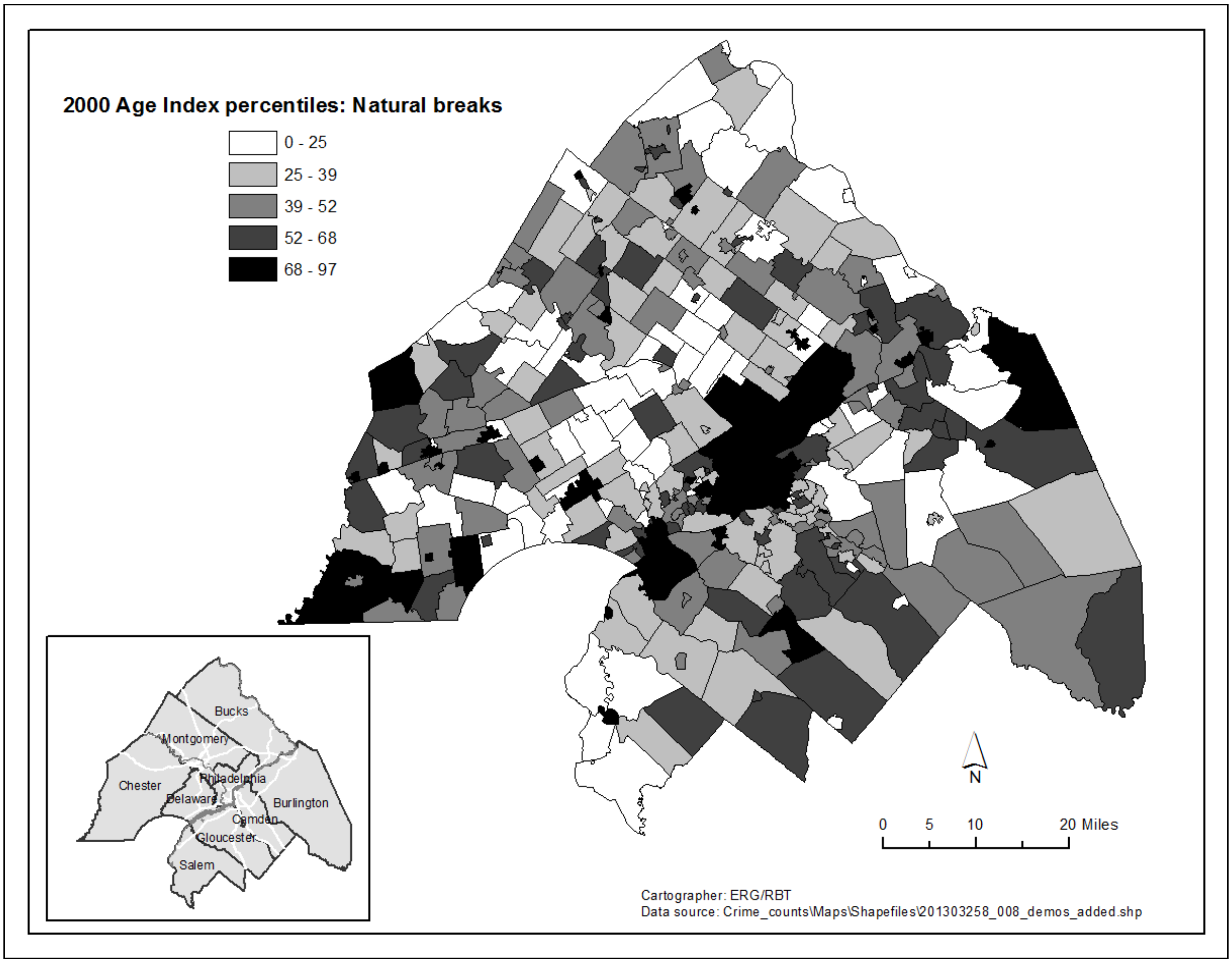

Figure 14. Age index percentile: Natural Breaks

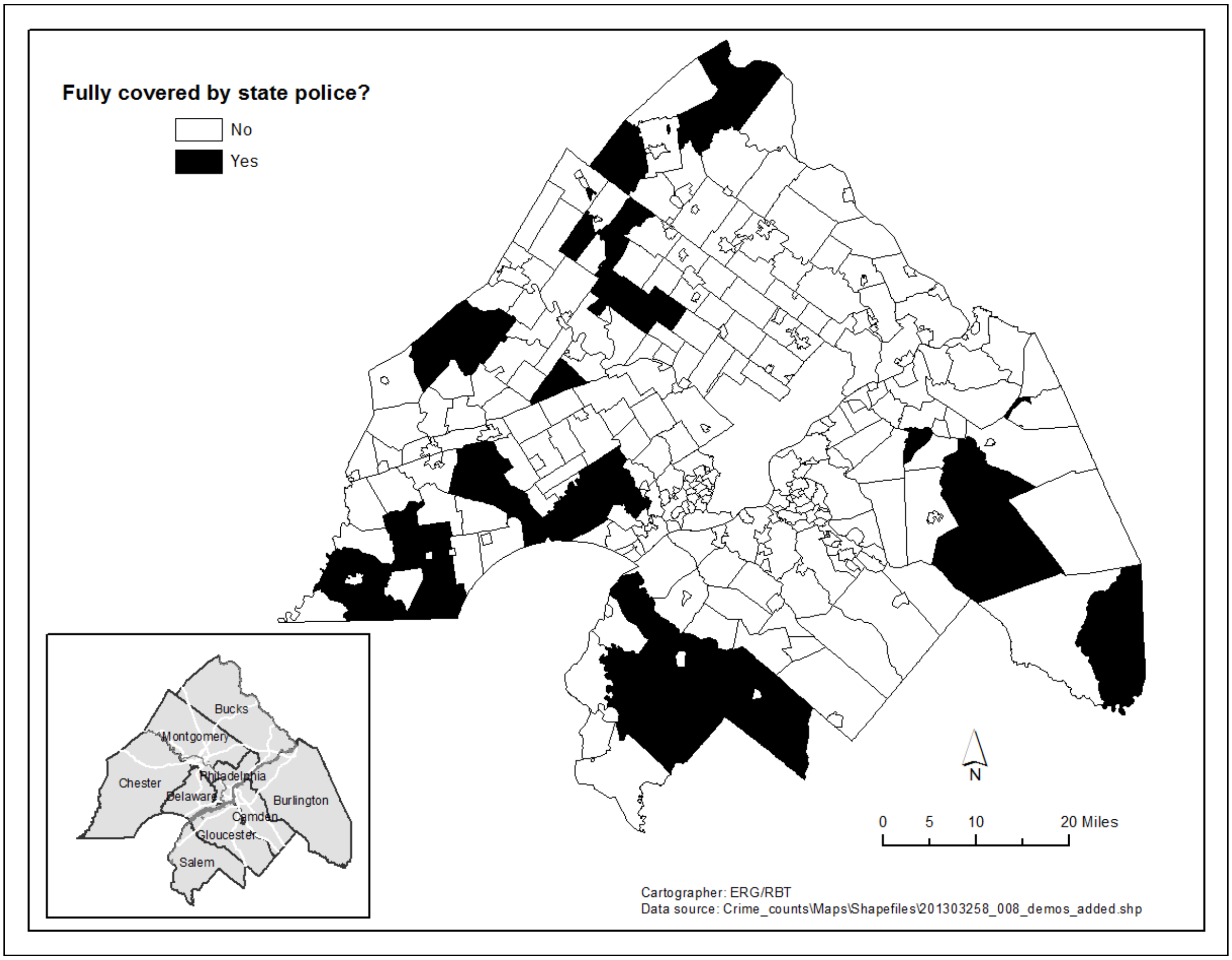

Figure 15. Municipalities receiving complete coverage from a state police agency

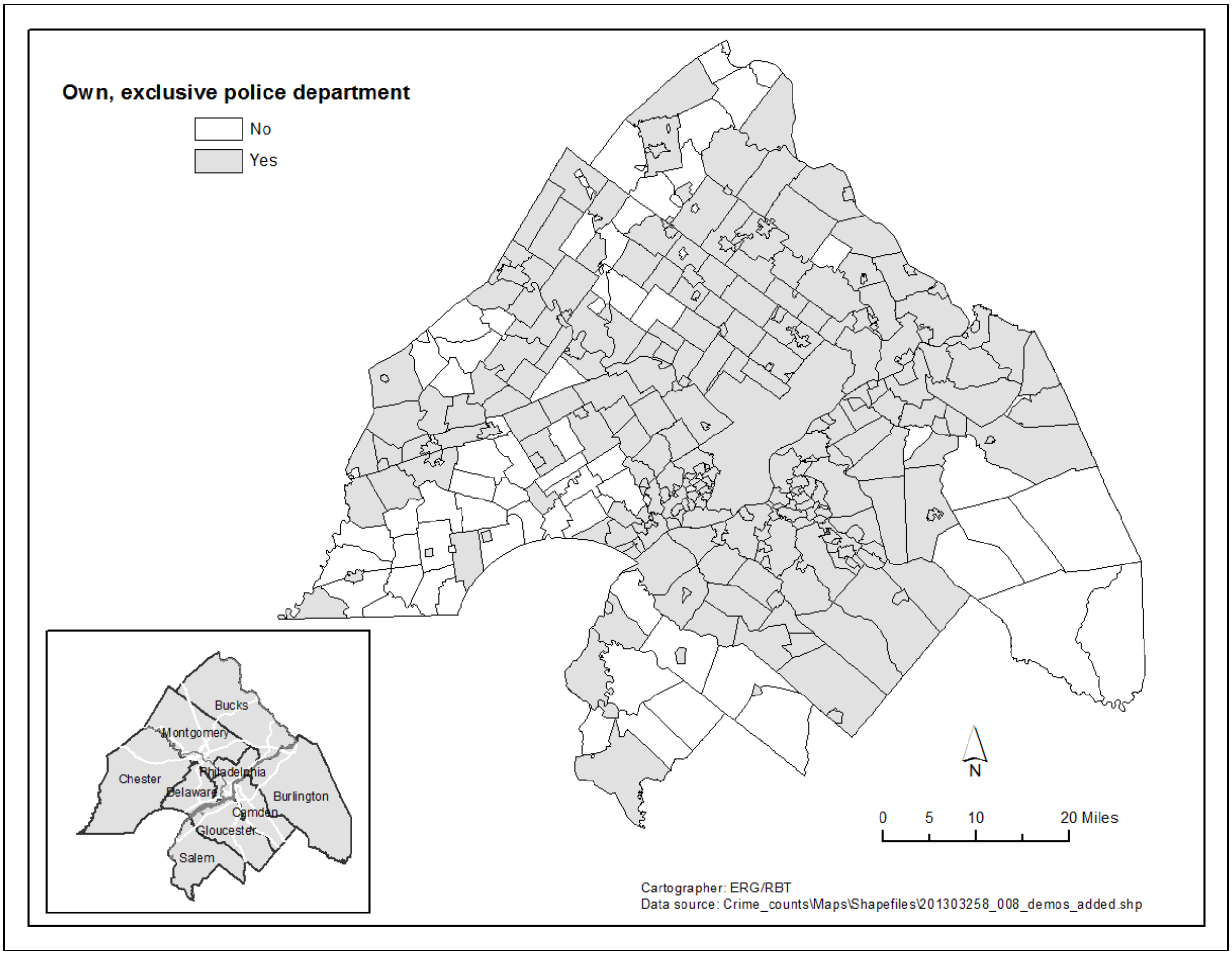

Figure 16. Municipalities with their own, single-municipality police department

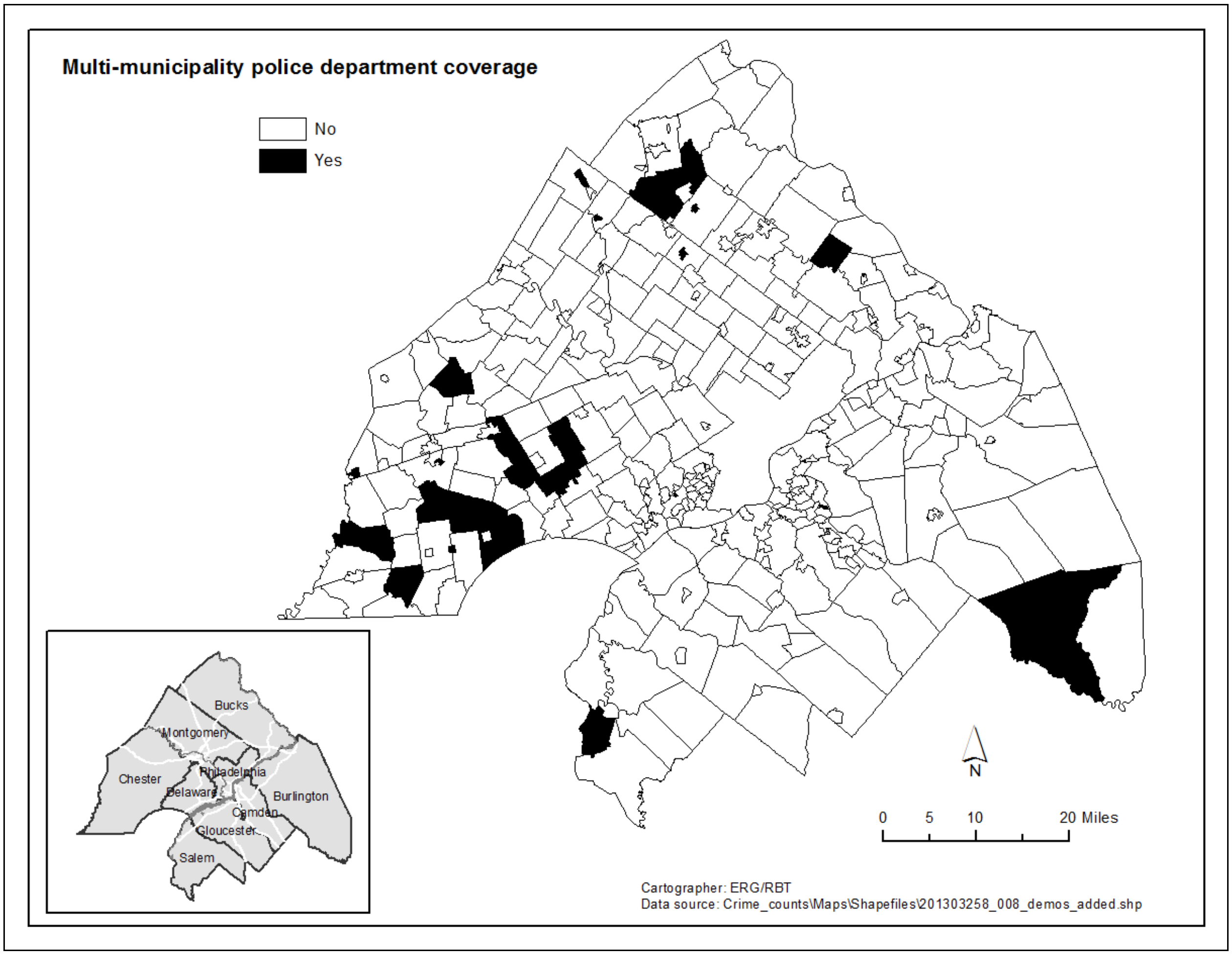

Figure 17. Municipalities with multi-municipality local police department

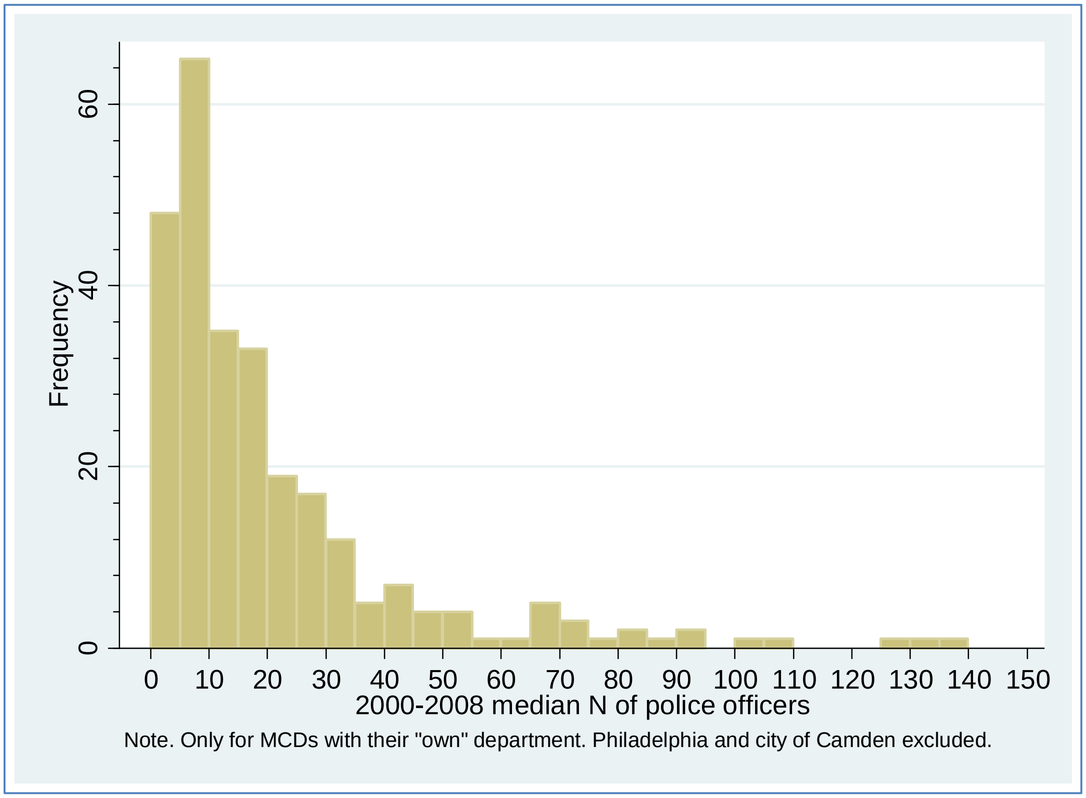

Figure 18. Distribution of police department size: Jurisdictions with their "own" department.

Note. Philadelphia and city of Camden not shown.

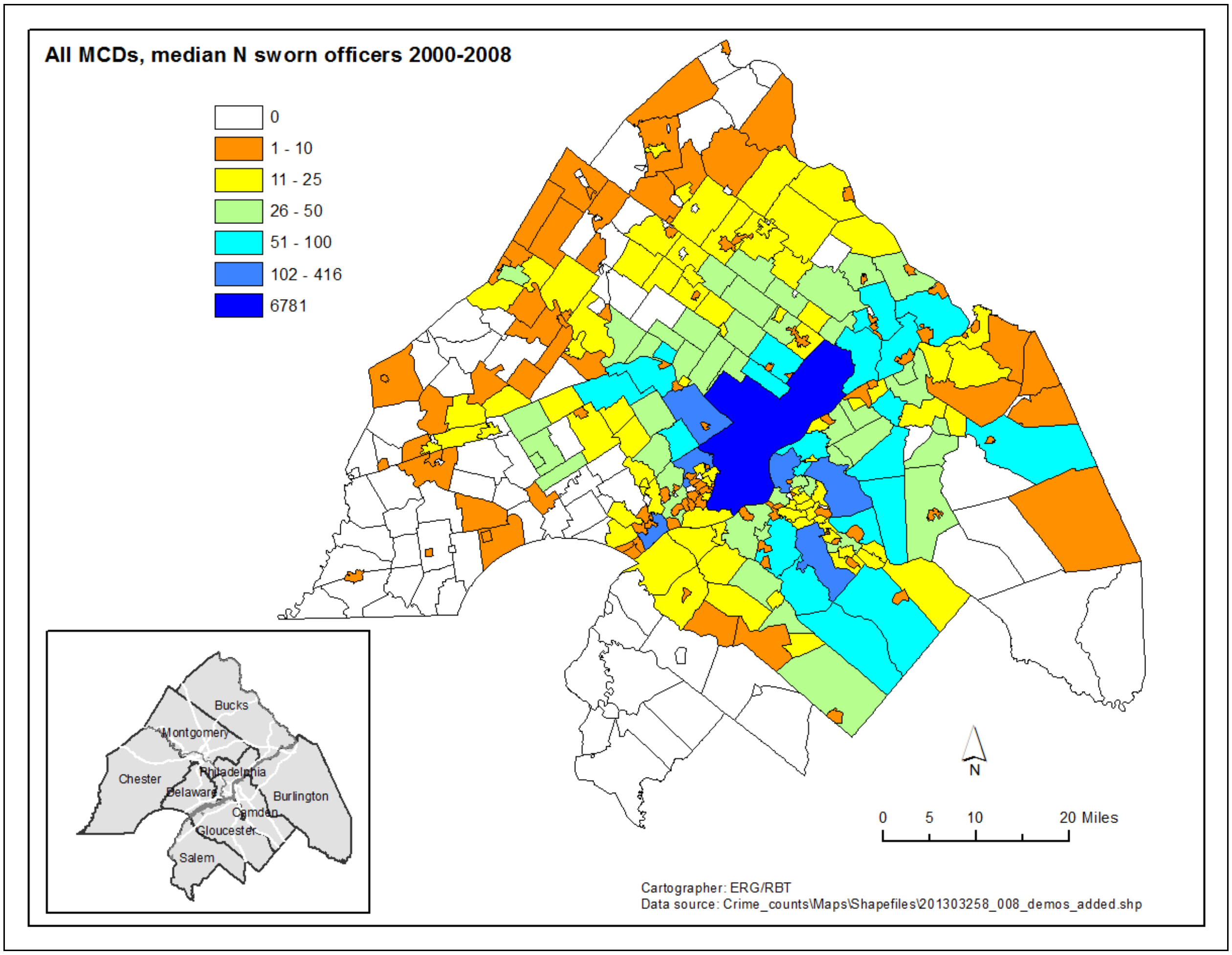

Figure 19. Median N sworn officers, 2000-2008.

Note. All jurisdictions, regardless of policing arrangement:

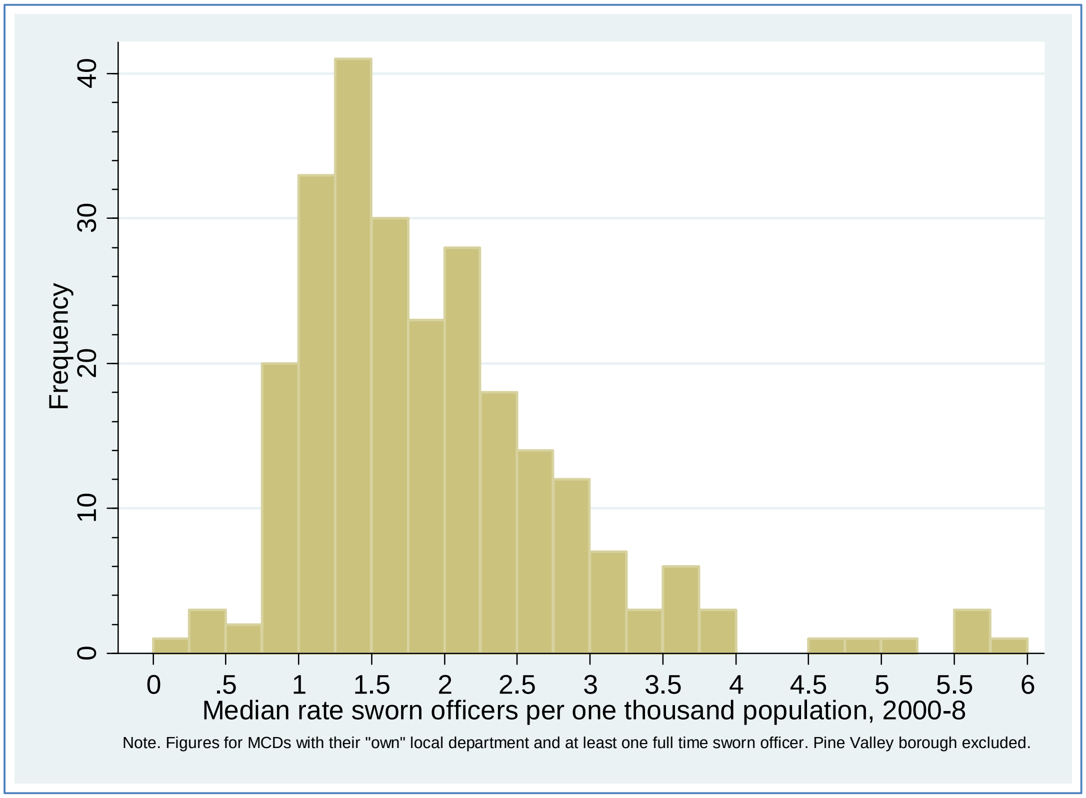

Figure 20. Distribution of typical officer coverage rates

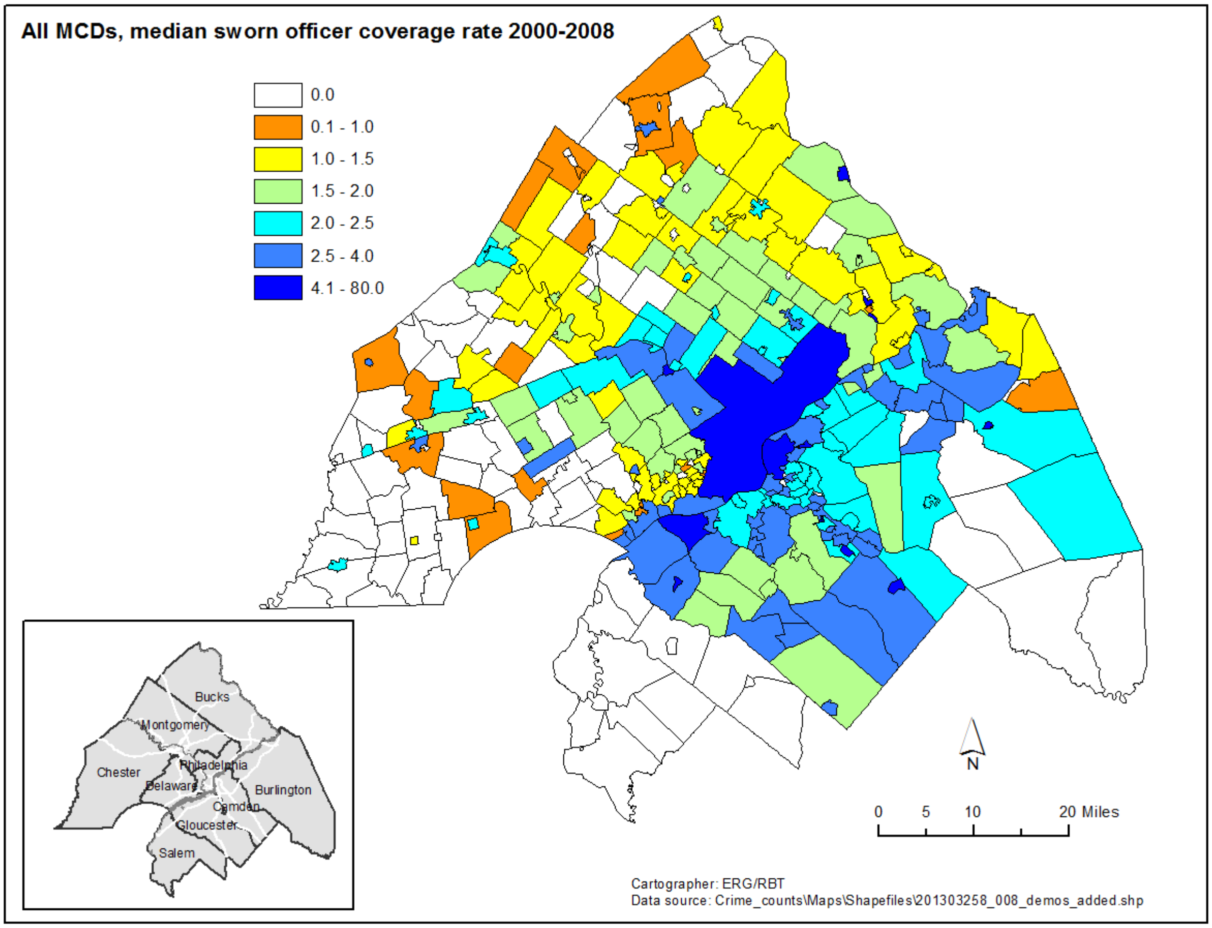

Figure 21. Coverage rate, sworn officers per 1,000 residents, typical year

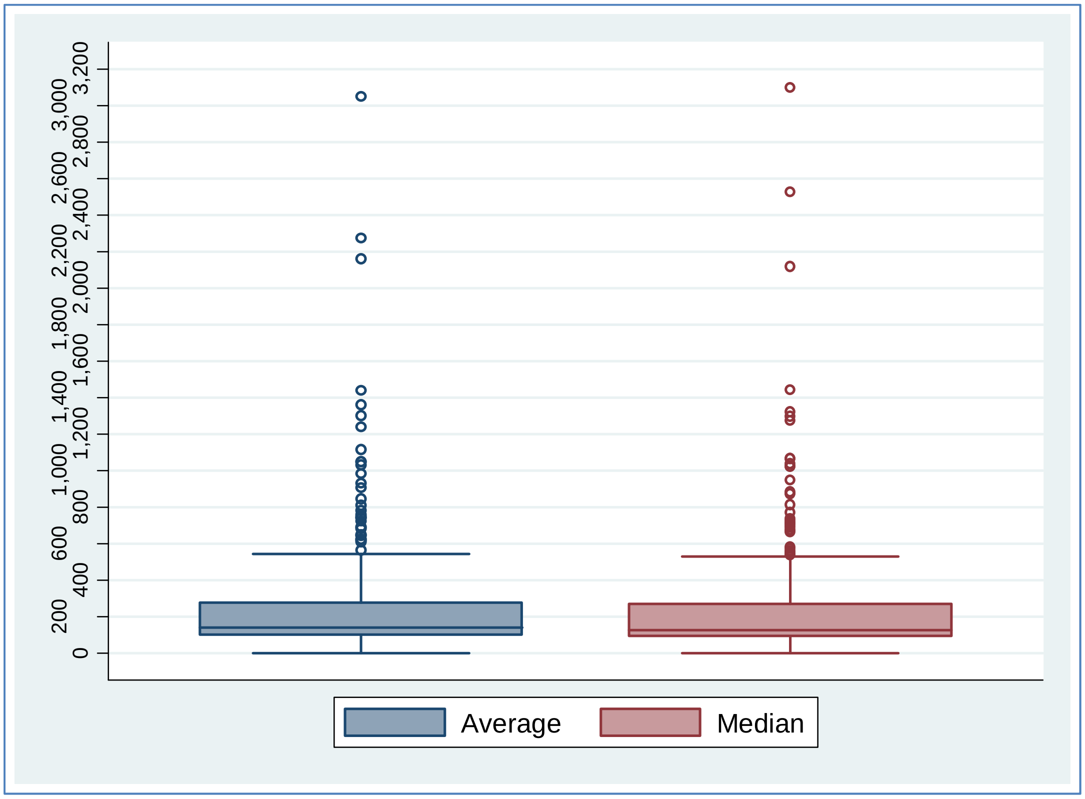

Figure 22. Box and whisker plots: Average and median reported violent crime rates 2000-2008

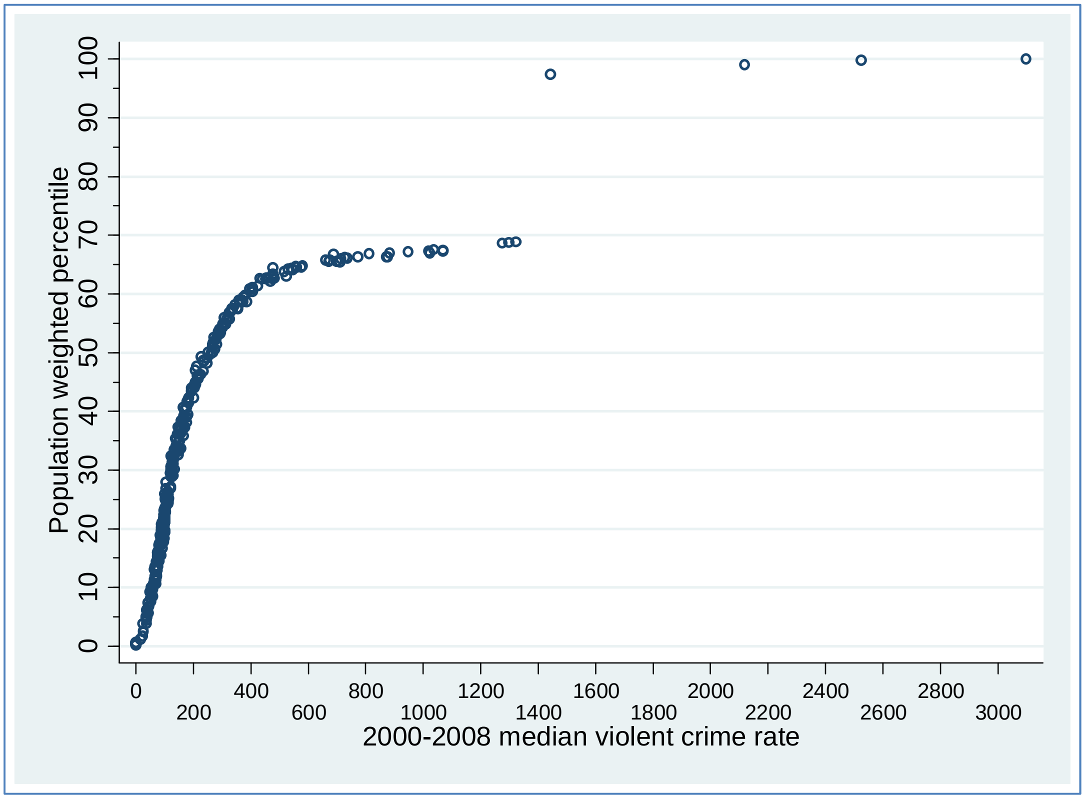

Figure 23. Typical violent crime rate and corresponding population weighted percentile (PWP)

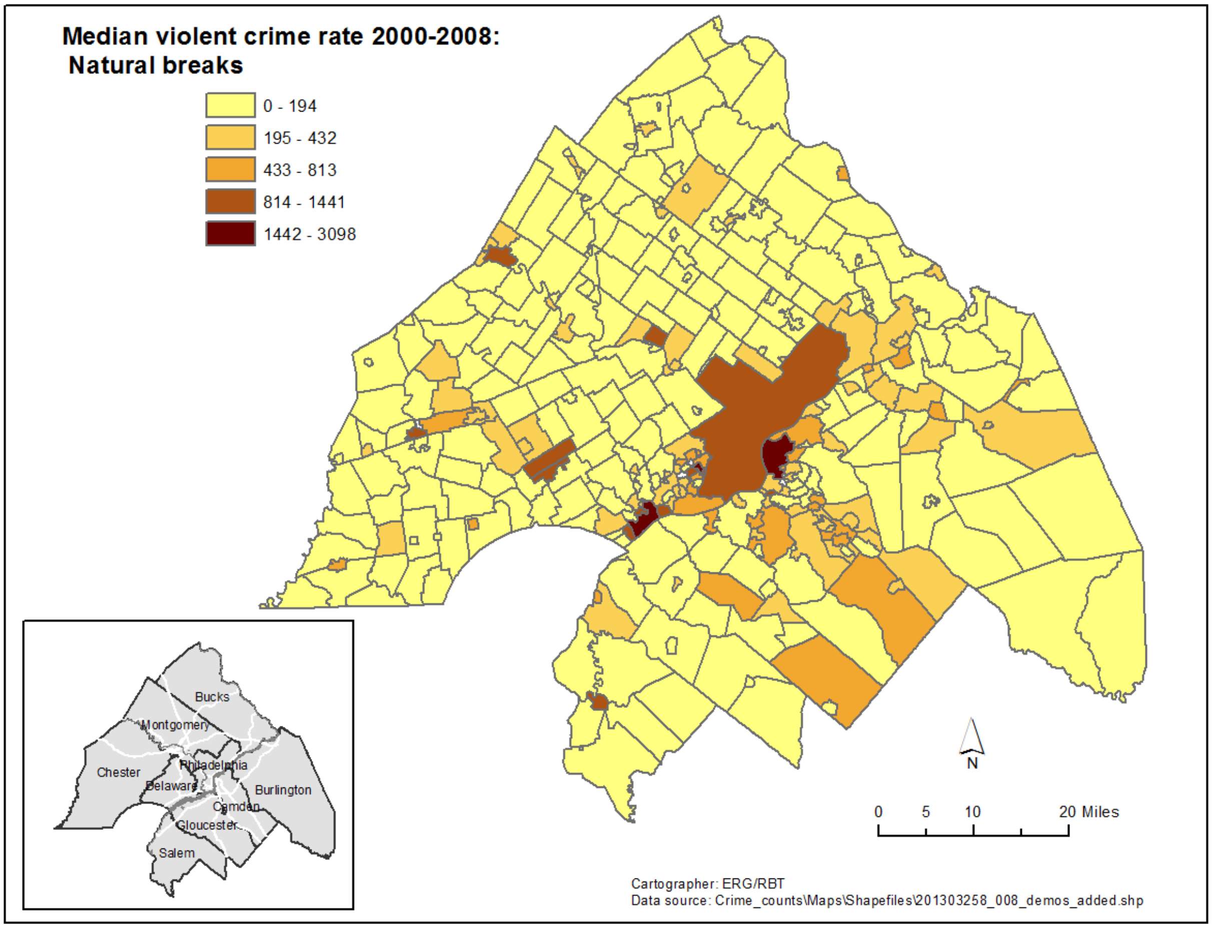

Figure 24. Median reported violent crime rate over the period 2000-2008: Natural breaks

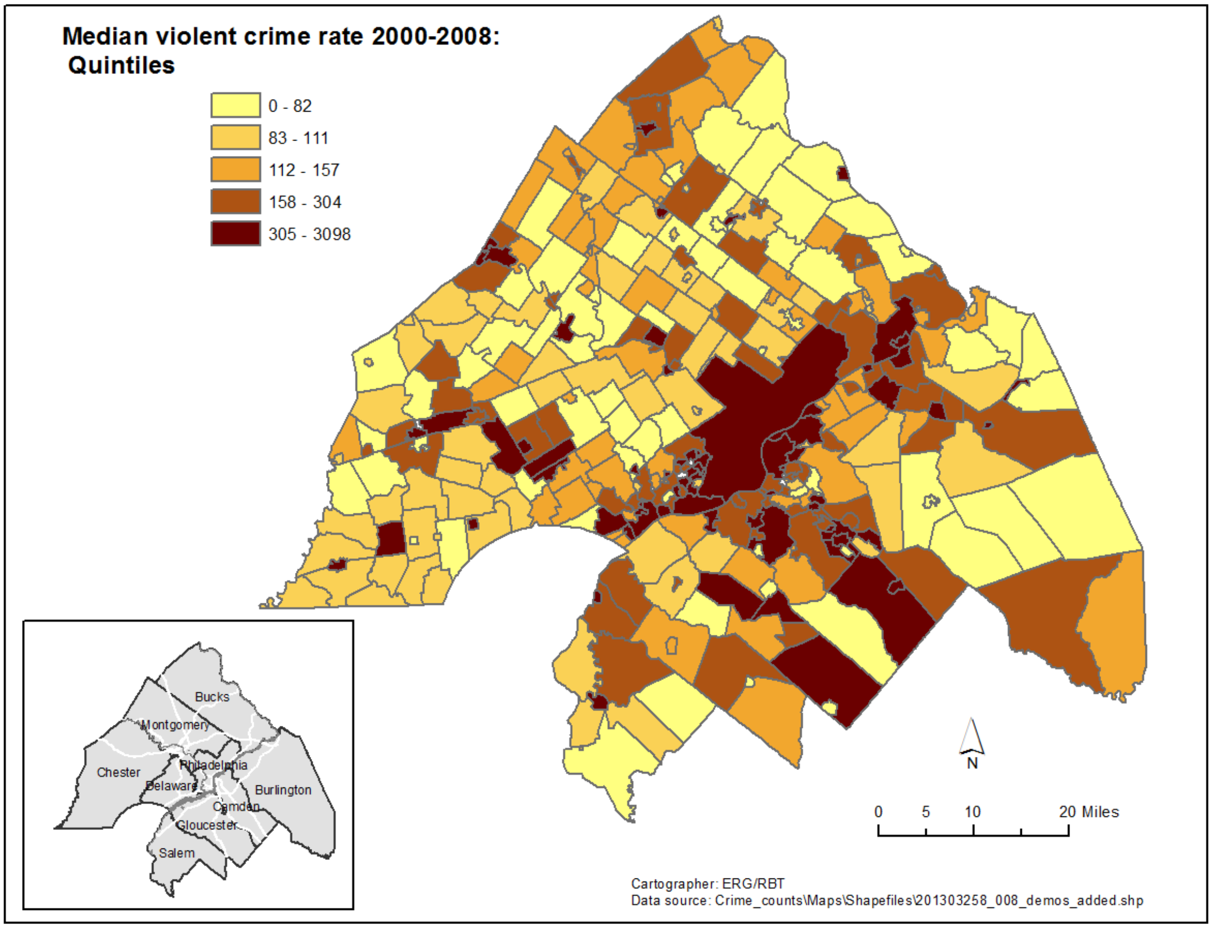

Figure 25. Median reported violent crime rate over the period 2000-2008: Quintiles

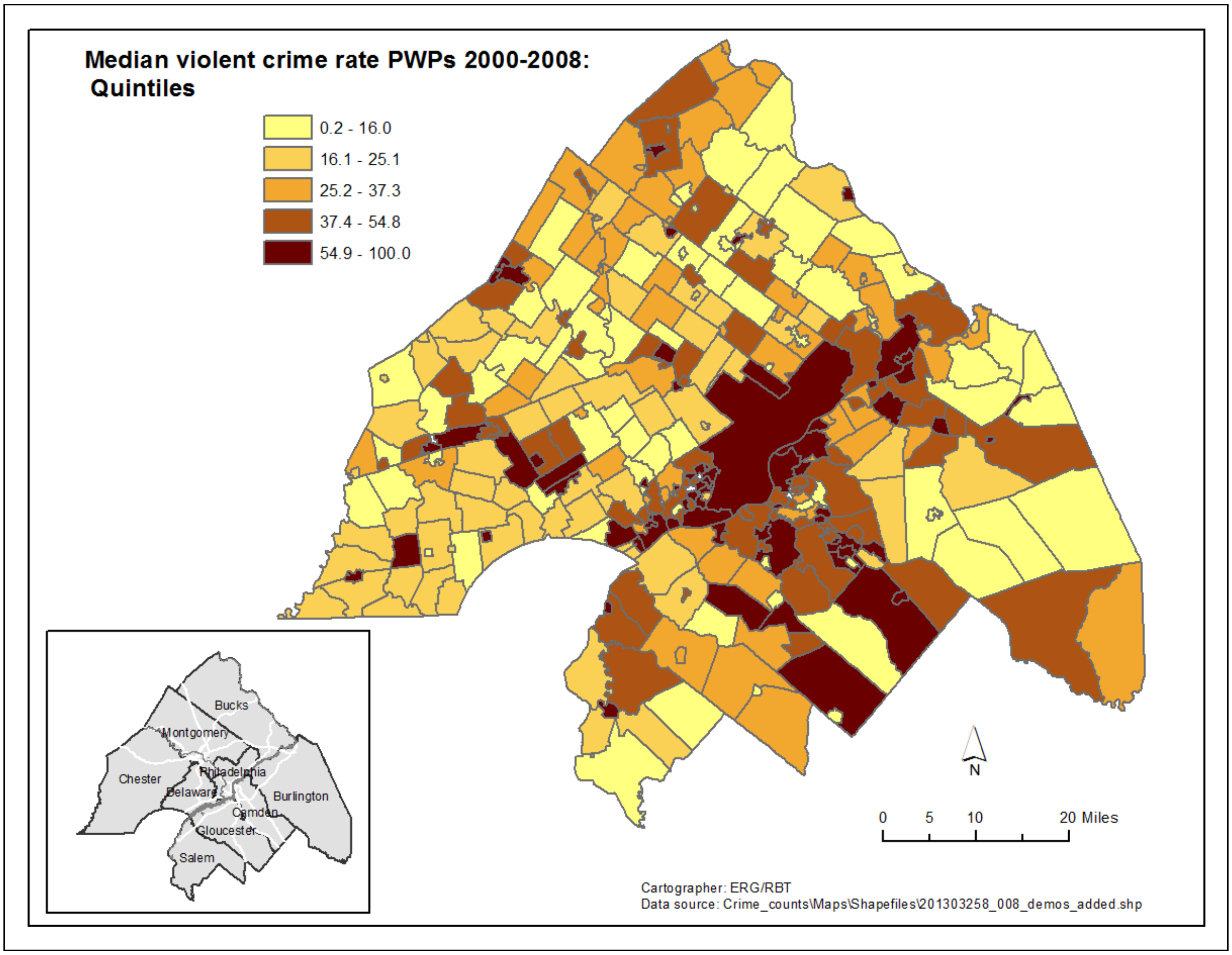

Figure 26. Median violent crime population weighted percentiles: Quintile map

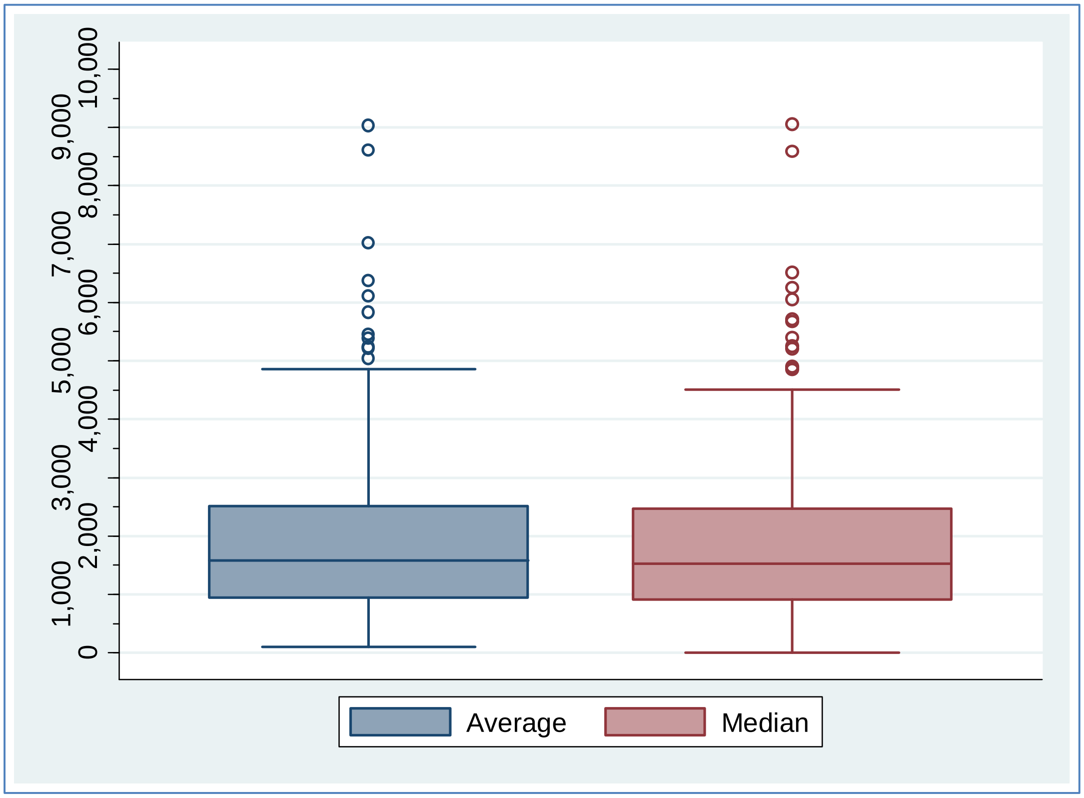

Figure 27. Box and whisker plots: Average and median reported property crime rates 2000-2008.

Note. Property crime does not include arson.

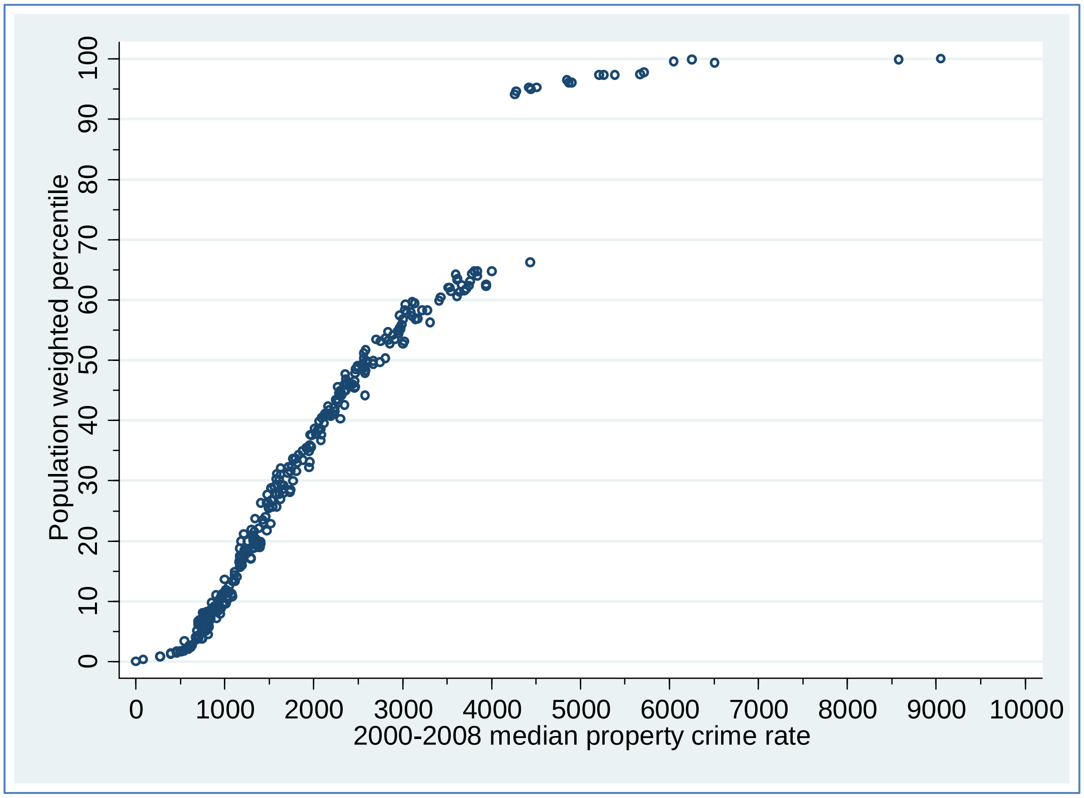

Figure 28. Typical property crime rate and corresponding population weighted percentile (PWP)

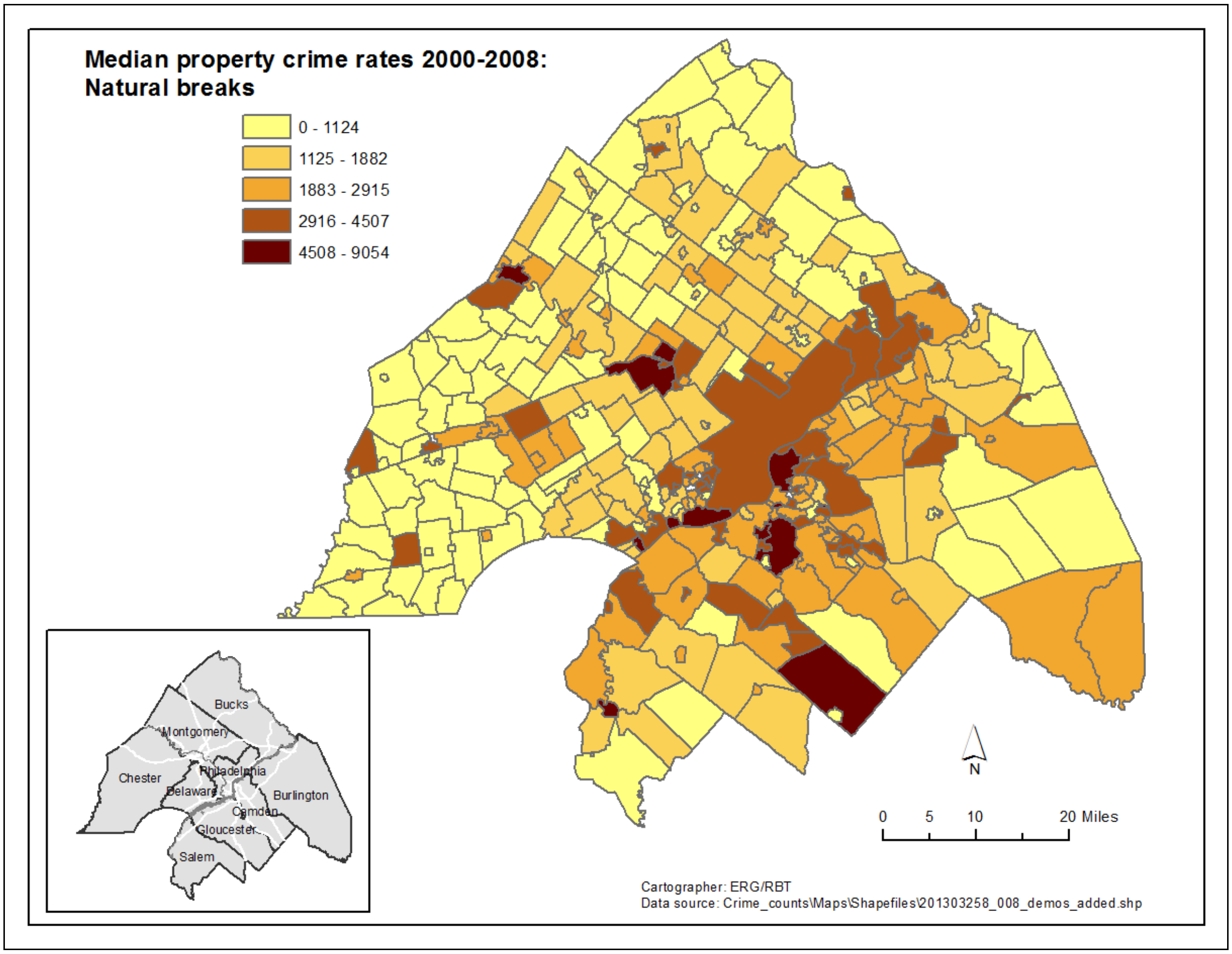

Figure 29. Median reported property crime rate over the period 2000-2008: Natural breaks

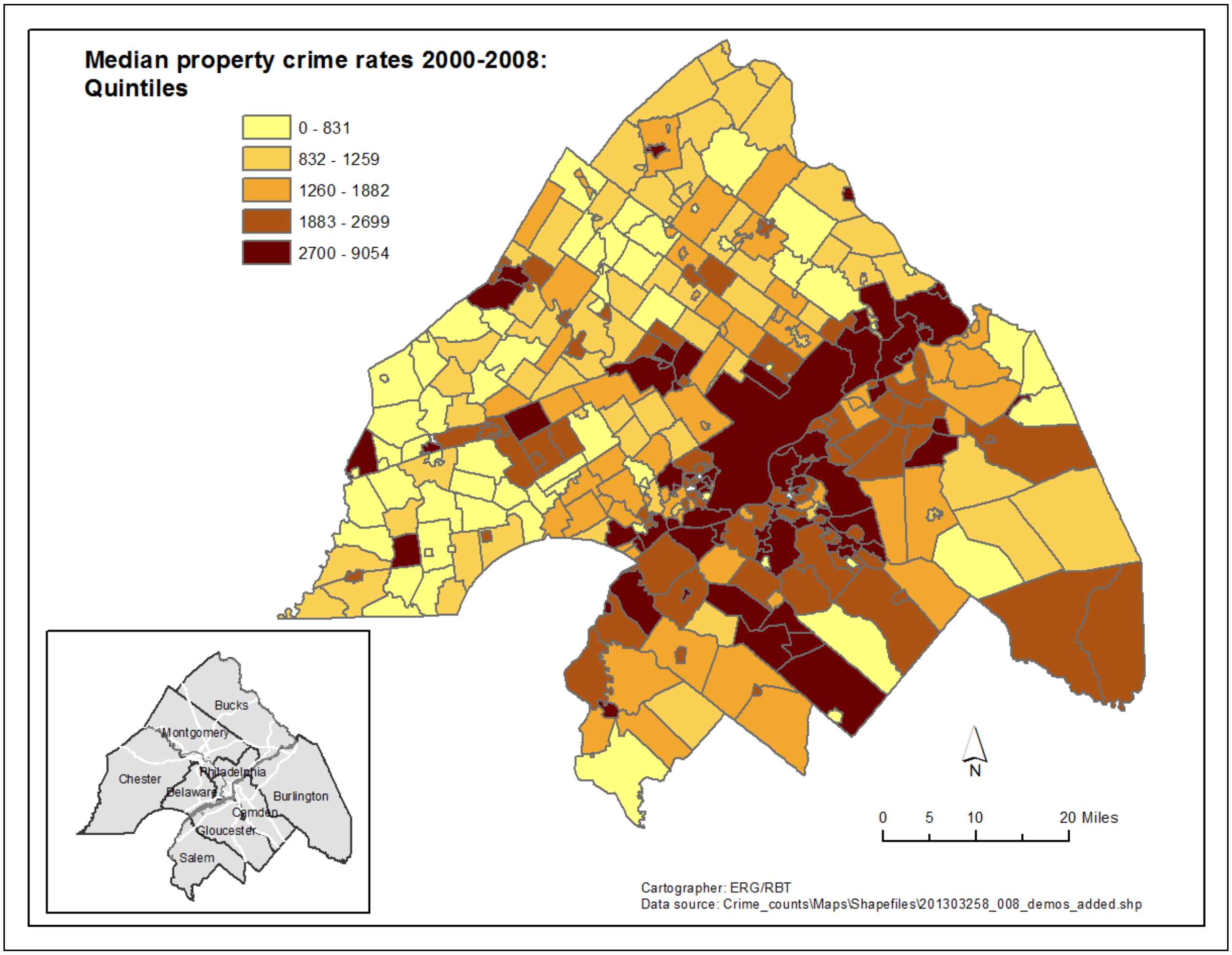

Figure 30. Median reported property crime rate over the period 2000-2008: Quintiles

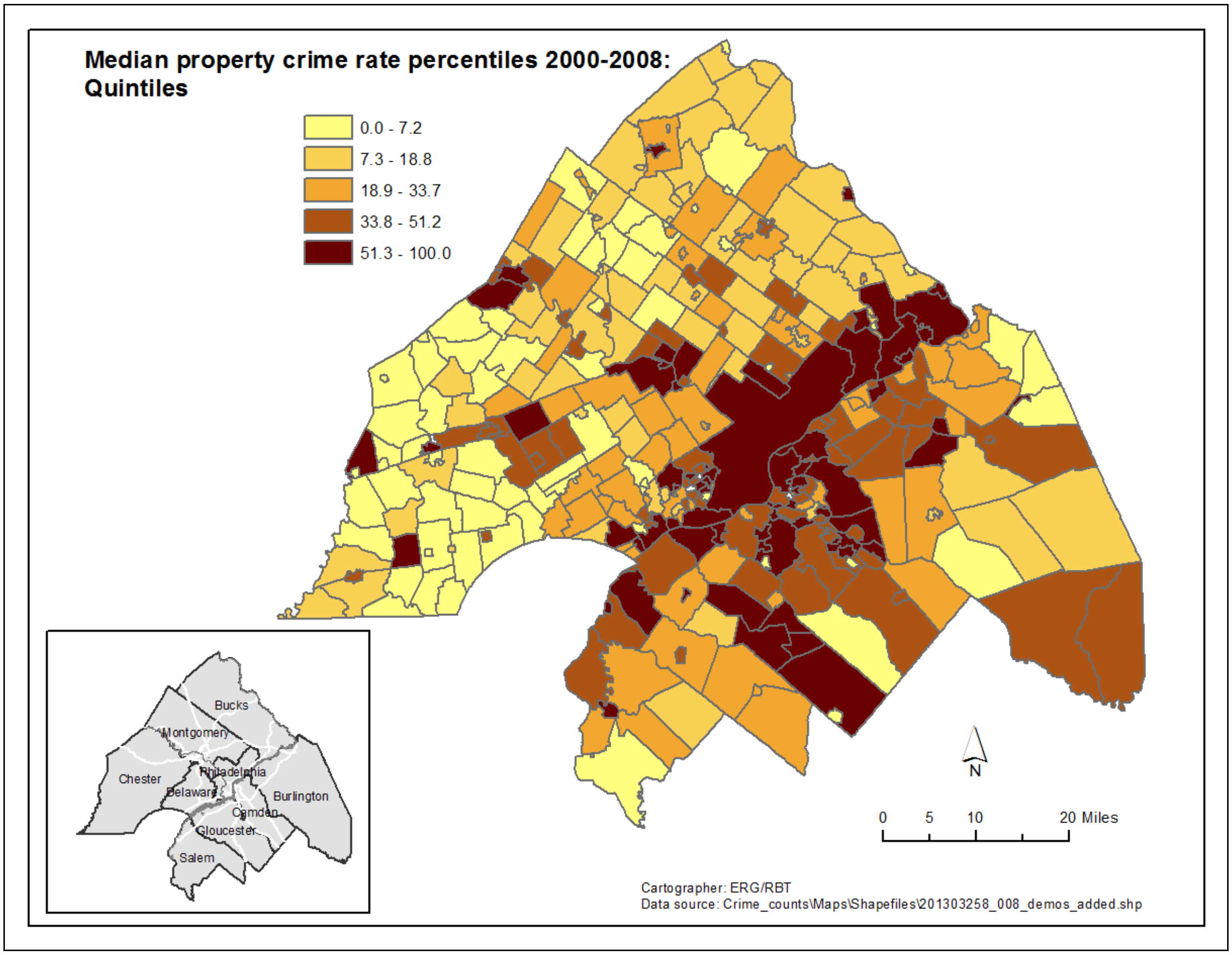

Figure 31. Median property crime population weighted percentiles: Quintile map

3. TEMPORAL PATTERNS

3.1. Overview

The current chapter complements the previous one. Whereas that chapter sought to summarize spatial variation on demographics, law enforcement coverage, and violent and property crime, this one describes temporal variation. But there is a difference. Here, demographics and coverage shifts will be described only at the county level, not the jurisdiction level. The general purpose is just to chart county-level trends over time based on unweighted averages across jurisdictions in a county. For crime shifts, jurisdiction-level analyses will be presented using LeBeau charts. [10] These categorize each jurisdiction based on the year when that jurisdiction had the highest crime rate of each type in the study period. The same can be done for the lowest crime rate of each type.

3.1.1. Theoretical agenda

Both these types of charts presented, albeit largely descriptive, advance specific theoretical purposes. Recall from Chapter 1 that investigating spatiotemporal patterning of crime changes is one area of interest in the current work. Such patterning would **not** be suggested if the average jurisdiction in each county in the metro region seemed to be changing in the same direction at the same rate throughout the study period. On the other hand, if it appeared that the average jurisdiction was shifting in different directions in different counties, perhaps at different

[10] To the best of the authors' knowledge, Jim LeBeau (Southern Illinois University) is the only scholar of crime who has presented these types of charts.

times during the study period, that would increase the chances that later we will find spatiotemporal patterning in crime changes. For the second type of charts, sub-regional dynamics are suggested if geographically proximate jurisdictions are experiencing their safest years or their most dangerous years at the same time. If the geographical pattern across jurisdictions of the safest year in the series, or the most dangerous year in the series appears spatially random, it would suggest that sub-regional spatiotemporal dynamics were probably not operative.

3.1.2. Sequence

The same sequence used in the last chapter will be followed here. Shifts in demographic structure will be described, followed by shifts in coverage and then shifts in violent and property crime rates.

3.1.3. Note to reader

The reader who is willing to accept, a priori, that different counties were changing in different directions over time on crime and demographics over the nine year study period, should feel free to skip this chapter.

3.2. Describing level demographic structural shifts across the region

3.2.1. Socioeconomic status

Figure 32 describes the average of jurisdiction-level scores on the SES index, in PWP form, by county, by year. All of the New Jersey county averages moved in a roughly similar way over the period, increasing slightly early in the period then decreasing slightly later in the period. All of the suburban Pennsylvania county averages also moved in a similar albeit different way; jurisdiction average SES PWP scores declined noticeably early in the period, then flattened out or increased slightly later in the period. Philadelphia, which represents not an average but just one score, increased slightly from 2000 to 2001, then declined slightly thereafter for each year thereafter. The arrival of the December, 2007 recession had a more marked impact on average SES scores for some counties than others. The drop-off seemed noticeable in the averages for Burlington, Camden, Gloucester and Salem counties, all in New Jersey, as well as in Philadelphia.

3.2.2. Stability

Figure 33 shows average jurisdiction stability index scores, by county, by year. The data show very s light shifts over the period. Chester remained the most stable on average, and Philadelphia the least stable. Camden and Delaware counties, each sharing substantial border with Philadelphia, remained as the second most unstable counties based on their jurisdictions' average, despite declining average jurisdiction stability in other counties.

Over the period, the county with the highest median jurisdiction stability was in Chester County, which, as mentioned above, has been growing quickly for the last decades in housing units and population. Stability index median scores ranged from 79 to 78 (results not shown). By contrast, Camden and Delaware counties, two counties with large numbers of older suburban jurisdictions, both of which adjoin Philadelphia, had the lowest median jurisdiction score on stability after Philadelphia's score (results not shown).

3.2.3. Racial composition

Figure 34 shows the average jurisdiction-level percent African-American by county and by year. Average percent African-American appeared to be slightly but steadily increasing in several counties including Burlington, Camden, Delaware, Gloucester and Philadelphia. Two other counties, Bucks, the least African-American of all the counties in the metro region, and Chester, the second least African-American in the region, changed little over the study period on this variable. Two other counties appeared to change steadily but slightly on this variable: Montgomery ticked slightly upward and Salem dropped slightly.

3.2.4. Percent Hispanic

Shifts of jurisdiction-level county averages in percent Hispanic over the study period appear in Figure 35. Although each county's starting point at the beginning of the period differed, and the amount of overall change differed, all county averages were trending, often consistently, in the same direction. All the counties, using this unweighted jurisdiction-level average, were becoming more Hispanic. After Philadelphia, the most Hispanic counties were Burlington and Camden, each ending the period with about six percent Hispanic. On this ethnic composition variable Delaware County was the lowest, barely reaching two percent by the end of the period.

3.2.5. Percent Asian

Figure 36 shows the jurisdiction averages by county, by year, for the percent Asian population. Each county's share of Asian population, based on its unweighted jurisdiction-level average, was trending up over the period. The upward trend, in several counties, seemed to temporarily reverse in 2003 and 2004. Although these percentages are low, Philadelphia has the highest relative composition of Asians, and Salem County's jurisdictions the lowest.

3.2.6. Comment in county disparities in relative racial/ethnic composition

These data present on Asian population an interesting contrast to the Hispanic and African-American data in the following way. For percent African-American, Philadelphia's percentages are substantially higher than all other county-level jurisdiction averages over the period. For percent Hispanic, although the overall percentages are much lower, again Philadelphia's share is much higher than seen in the other county averages. But when we get to percent Asian, bearing in mind of course that these percentages are quite low, and that these are *unweighted* averages across jurisdictions, at the end of the period two county averages, Montgomery and Delaware, are quite close to the beginning of the period percentage seen in Philadelphia.

3.2.7. Household age composition

Figure 37 graphs the changes in the age index, in population weighted percentile form. A higher score reflects a higher volume of preteens, teens and young adults needing supervision and a lower volume of mature-aged adults who could provide such supervision.

Of course Philadelphia stands out from the (unweighted) jurisdiction-averages by county with its much higher score than the other county averages. It stands out in a second way as well: its score was increasing over the period. By contrast, most other county jurisdiction-level averages were either staying roughly the same (Delaware, Chester, Salem), or declining relatively consistently over the period (Bucks, Burlington, Montgomery). Stated differently, this age-linked attribute of the population was holding steady or dropping in many places in the metro region but climbing in Philadelphia.

3.3. Law enforcement coverage rates

Figure 38 displays the county average coverage rates by year. For each year, the unweighted jurisdiction average is used. In all the counties, coverage rates over the period seemed relatively steady. (Personnel data from the FBI are incomplete for Salem County.)

As expected given the discussion of coverage spatial patterns in the previous chapter, and given that Philadelphia is only one jurisdiction, coverage rates appear lower in multi-jurisdiction counties in Pennsylvania compared to counties in New Jersey. Chester, Delaware, Montgomery and Bucks counties in Pennsylvania had coverage rates around 1.5, far lower than seen for Camden (over 2.5), Burlington (above 2) and Gloucester (slightly under 2.5) counties in New Jersey. Philadelphia stands out starkly with its coverage rate averaging around 4.5 for the period.

3.4. Crime at the county level by year

3.4.1. Violent crime

Figure 39 displays county average violent property crime rates per 100,000 residents for the study period, by year, using each county's unweighted average across its jurisdiction rates. Two extremely small boroughs, Pine Valley and Tavistock, each of which is largely a golf course, are excluded from these figures. The only county whose average seemed to be changing in a clear cut way was Delaware county. For the last seven years in the series, the average violent crime rate increased noticeably in the county, year after year, increasing from an average rate of 400 to an average rate of almost 600, in effect increasing by about 50 percent during the study period.

Figure 40 presents the same information, but in population weighted percentile terms. The aforementioned changes in Delaware County translated in this metric to an unweighted average slightly above the 40th percentile at the beginning of the period to an unweighted average at the 50th percentile by the end of the period.

The figure also shows that the two counties closest to Philadelphia on this relative metric were Camden and Delaware counties, two of Philadelphia's immediate neighbors.

In relative terms, the figure is not clear about which county was the safest. By the end of the period, Bucks, Burlington, Chester and Montgomery counties were each at around a 30th percentile score for their unweighted averages across jurisdictions.

3.4.2. Property crime

Figure 41 shows the average property crime rate by county by year, based on each county's unweighted jurisdiction average for each year. Of course, Philadelphia stands out as the highest crime county. But less expected were sizable and significant drops in property crime. Philadelphia started out with a rate slightly below 5,000/100,000 residents, dropped down to about 4,200, and then finished the period at around 4,400. From beginning to end of the period this amounts to about a ten percent drop. Given the size of the jurisdiction, this is a remarkable decline.

Two other counties (Burlington and Gloucester) also showed noticeable declines in the average jurisdiction-level property crime rate. Unweighted average rates Burlington dropped from around 2,200 to 1,700 and in Gloucester from about 3,000 to about 2,400.

No counties showed consistently increasing rates during the period although Bucks, Delaware and Salem counties seemed to be increasing for the last three years in the series.

Figure 42 expresses the same data but uses the population weighted percentile metric. On this metric, Delaware County was increasing somewhat during the period. Its unweighted average across jurisdictions started out around the 30th percentile and ended slightly above the 40th percentile. Burlington County, by contrast, seemed to be declining somewhat during the period. Its unweighted average started out around 35th percentile and ended around the 30th percentile.

3.5. Crime at the jurisdiction level

Having seen from the county level data that different counties had violent and property crime rates which were changing in sometimes different directions during the period sets the context for a related question: Were different jurisdictions at their highest crime point, relative to the other jurisdictions, at different years within the period? Were different jurisdictions at their lowest crime point, relative to the other jurisdictions, at different years within the period? Phrasing the question more geographically and more theoretically: did several spatially adjoining jurisdictions have their highest relative crime period in the same year?; Or perhaps in adjacent years?; and How about their lowest relative crime period?

Generally what is at issue here is gaining an initial look at how spatiotemporal interactions might shape crime rates. Stating this general point differently: if such a pattern were observed, it would raise the possibility of crime-elevating dynamics, operative at roughly the same time within the broader study period, and operative in specific sub-regions of the broader metro area. Although this question will be examined more carefully in the later analyses, it is important to gain an initial descriptive read on the broader patterning from a geography of time perspective. From a theoretical perspective population weighted percentiles are used because those address the ecological idea of shifting niches in the broader ecology.

In specific terms, these results present an attempt to replicate Kneebone and Raphael's finding that on violent crime core cities were getting safer relative to municipalities at the outer edges of metro areas (Kneebone & Raphael, 2011). If this is true, then core cities should have their safest years later in the series and their most dangerous years early in the series. Outer ring jurisdictions should have their safest years early in the series and their most dangerous years later in the series.

3.5.1. Violent crime

Figure 43 shows the LeBeau chart for the year in the period with the highest relative (PWP) crime rate. There does seem to be some geographic patterning in how relative violent crime rates were playing out over time.

Philadelphia, several of its neighboring jurisdictions in Montgomery county to the northwest of the northwest "arm" of Philadelphia, and the city of Camden and a couple of its immediate neighbors to northeast and east, were at their highest points in the violence ordering quite early in the study period, in 2000 or 2001. This also held for the third urban core, the City of Chester. Something was happening in the region such that during this period these centrally located communities were at their most violent relative to the other municipalities.

Turning to the last two years at end of the period, three spatial clusters of jurisdictions in different parts of the metro region were at their most violent position during 2007 or 2008. On the western boundary of Chester County, a north/south string of jurisdictions stretching from Warwick down to Coatesville were at their most violent during the last two years of the study period. So too was another clump of places in Chester County ranging from West Bradford southward down to the Maryland state line and aligning somewhat with US-1. Finally, a cluster of less than a half dozen late (relative) violence peaking communities appeared in New Jersey on the border of Gloucester and Salem counties.

In sum, it appears that municipalities that were one of the three urban cores, and some proximal municipalities in two different vectors were most violent, relative to other jurisdictions, in the first two years of the study period. By contrast, three connected clusters in mid- or outer-southern sections of the region were at their most violent in the last two years of the period. This spatiotemporal patterning agrees with the differences that Kneebone and Raphael saw, between 2000 and 2008, between primary cities and exurbs in the 100 largest US MSAs.

The jurisdiction-level picture, of course, contrasts with the views about county-level crime trends. The county level, PWP-based violent crime picture (Figure 40) shows Delaware County's average jurisdiction-level rate increasing over the period. And, indeed, the corresponding jurisdiction-level LeBeau chart shows several jurisdictions with their highest rates in the last two years of the period; Haverford, Radnor, and Upper Darby townships are all examples. But several other jurisdictions had their relative peak in the first year in the series, e.g., Springfield and Nether Providence townships. Considerable complexity appears in temporal patterning appears within counties, across jurisdictions.

Figure 44 shows the years when individual jurisdictions were at their safest in terms of violent crime rates relative to the jurisdiction rates around the region. The picture is quite complex, but does suggest one large spatial cluster and several smaller spatial clusters. The only sizable spatial cluster includes well over a dozen jurisdictions in central and southern Chester

County. These jurisdictions were at their safest on violent crime, relative to other jurisdictions in the region, in 2004.

Numerous smaller clusters of adjacent jurisdictions that were at their safest in the same one or two year window dot the region. Starting early in the period, two clusters of jurisdictions were at their safest in 2000 or 2001. One cluster of jurisdictions appears in Montgomery County starting between the two arms of the “Y” that is northernmost Philadelphia, and stretching northwest. A second cluster of places in New Jersey, in Gloucester and Camden counties, starts at the Delaware River with places like West Deptford and Paulsboro, and extends southeast to Winslow Township. In Chester County a string of jurisdictions stretching north from Coatesville and including that city were also at their safest during this time frame.

Moving forward to 2001-2002, several jurisdictions in southern Salem County, including Salem City, were at their safest then. So too were a large cluster of sizable municipalities in western Delaware County that included Middletown, Edgmont and Willistown townships.

Finally, jumping ahead to the last two years in the study frame, one string of jurisdictions along the southern tier of Gloucester County, another in northwestern Montgomery County, and a third in northern Burlington County were at their safest in 2007 or 2008.

Although many alternate interpretations are possible, here sizable spatial clusters of adjacent municipalities sharing the same one or two year window for greatest relative safety or danger on violent crime suggest evidence of crime trends working out differently in sub-regions across the metropolitan area. Further, those sub-regions generally form at the sub-county level. Finally, examining this spatiotemporal interaction by considering whether a jurisdiction was at its safest or its most dangerous reveals that these two different features of timing are not just mirror images of one another. The relationship between clusters of places and their safest period, and clusters of places and their most dangerous period, again with both in relative terms, is not immediately apparent.

3.5.2. Property crime

Figure 45 displays the years in the period when jurisdictions were at their highest property crime rates, relative to all jurisdictions in the region. The pattern bears some similarities to the map of highest violent crime rate years, but there are also important differences.

Starting at the core of the region spatially and the beginning of the research period, 2000 was the year of the highest relative position for Philadelphia and several of its immediate neighbors to the northwest in Montgomery County. In contrast to what was seen with violent crime, the other two urban cores, the cities of Camden and Chester, experienced their peak crime years substantially later in the research period.

Moving out from the core of the region, three other spatial clusters of jurisdictions peaked on relative property crime early in the period. Four municipalities in mid-Chester County just north and west of Coatesville were at their highest during 2000, while a slightly larger cluster of jurisdictions in mid-Bucks county were at their highest either in 2000 or 2001.

If the notion of the beginning of the period is expanded to a three year time frame, a large cluster of mostly eastern-most jurisdictions in Burlington, Camden, and Gloucester counties were at their highest relative property crime levels between 2000 and 2002.

Late in the series, a large cluster of jurisdictions in southeastern Chester County, stretching north and west from either the Delaware or Maryland state lines, were at their highest either in 2007 or 2008, A smaller cluster of jurisdictions in western Chester County also peaked in relative property crime at the same time.

In sum, it appears that the timing of highest relative susceptibility to property crime did indeed vary across sub-regions within the metro area. There were points of both similarity and difference with peak relative violent crime years. Here were some of the differences. Whereas with relative violent crime, all three core cities peaked at roughly the same time quite early in the study period (2000-2001), with relative property crime of these three only Philadelphia peaked early in the series. A larger bundle of southwestern Chester County jurisdictions were peaking quite late in the series when violent crime was examined. When property crime was examined, however, that cluster was split by a handful of places peaking early in the series.

The mapping of years of lowest relative property crime rates appears in Figure 46. The eye is drawn immediately to several small clusters of adjoining municipalities, spread widely in the region, where the last two years were the periods of greatest relative safety from property crime. Starting at the top of the figure: a thin string of jurisdictions in northern Bucks County extending southeastward; a cluster of jurisdictions in starting at or near the Delaware River in Burlington or Camden counties, stretching southeastward; several jurisdictions in western Gloucester County; and an elbow cluster of communities starting in Delaware County (Radnor Township), then curving southeastward along US 202. Finally, Philadelphia and adjacent Tinicum Township (Delaware County) were both at their safest in the last two years in the series.

Comparing the geographic patterning of years of relative safety on violent (Figure 44) versus property crime (Figure 46) suggests markedly different geographic placement for the timing of these two different safety attributes.

3.5.3. Closing comment on geography and timing of relative safety and danger

The charts examined here provide only the most preliminary descriptive inquiry into temporal crime trends across different sub-regions in the metro area. First, just highest and lowest relative years were considered, not year-by-year trends. Second, sub-regions were suggested by visually apparent clusters of adjacent jurisdictions, not rigorously defined spatial clusters. Both these issues are addressed in later chapters.

Bearing these limitations in mind, the geography of relatively safest and relatively most dangerous years, and the sub-regions suggested by clusters in the crime maps, point toward the following. First, for both property and violent crimes, there are some points in the study period when, in relative terms, several nearby jurisdictions are doing poorly *together at roughly the same point in time.* There are also points when several nearby jurisdictions are doing well at roughly the same point in the period. The theoretical reasons behind this get explored more fully in later chapters, but the point right now is simply to recognize that these patterns exist. These sub-regional features support the expectation that we will uncover spatio-temporal dynamics.

There are times and sub-regions within the overall metro region when places are at their most dangerous relative to the rest of the region, or at their safest. When and where these sub-regional windows of safety or danger surface depends on crime type. Further, it is not immediately apparent how these emergent sub-regional windows in time and space link to the broader patterning themes discussed in the last chapter. Across these four different LeBeau charts, there are no clear consistencies: the positioning of jurisdictions in the center of the region; the three urban cores (Philadelphia, Camden, Chester) being affected in the same way at the same time; center to edge gradients, even if those gradients are limited to certain directions moving out from the center of the region; or differences between the two state sub-regions. ***To put the point differently, when we move from spatial patterning of crime across jurisdictions, to spatiotemporal patterning of crime across jurisdictions in the region, some of the general themes considered earlier do not clearly apply.*** This is not an unusual occurrence as one moves from cross sectional to longitudinal models (Lieberson, 1985).

But despite these theoretical complexities, a clear policy point emerges. In the context of a metro region where policing arrangements are complex, highly localized, and not coordinated, the two maps of periods of highest relative property and violent crimes speak to the need for some variety of regional policing coordination. There are some times when nearby municipalities are similarly afflicted with high relative property or violent crime rates. This speaks to times when nearby municipalities are sharing a changing vulnerability to a particular class of crimes. Identification of these places and periods of shared vulnerability could serve as an impetus for different agencies to, at the least, share information. It also might lead to coordinated crime analyses and shared prevention responses. The mappings suggest that such coordination might be beneficial at many sub-regions throughout the region. We examine the policy implications of this patterning later.

3.6. Takeaway thoughts and next steps

The present chapter examined temporal trends at the county level for demographics, law enforcement coverage, and crime. Further, at the jurisdiction level it identified, for both violent and property crime, periods of highest and lowest relative crime. The overall picture painted is complex. On demographics, different counties were changing in the same direction on some attributes, and in different directions on others. On crime, sub-regions appeared when clusters of jurisdictions were at their safest or their most dangerous relative to the rest of the metro region.

There was some support for Kneebone and Raphael's idea of decreasing primary city violence and increasing exurb violence between 2000 and 2008. But generally, spatiotemporal patterning across sub-regions depended on crime type and did not conform to some of the broader patterns seen for spatial patterning of crime levels. The next chapter digs more deeply into the spatiotemporal patterns of crime.

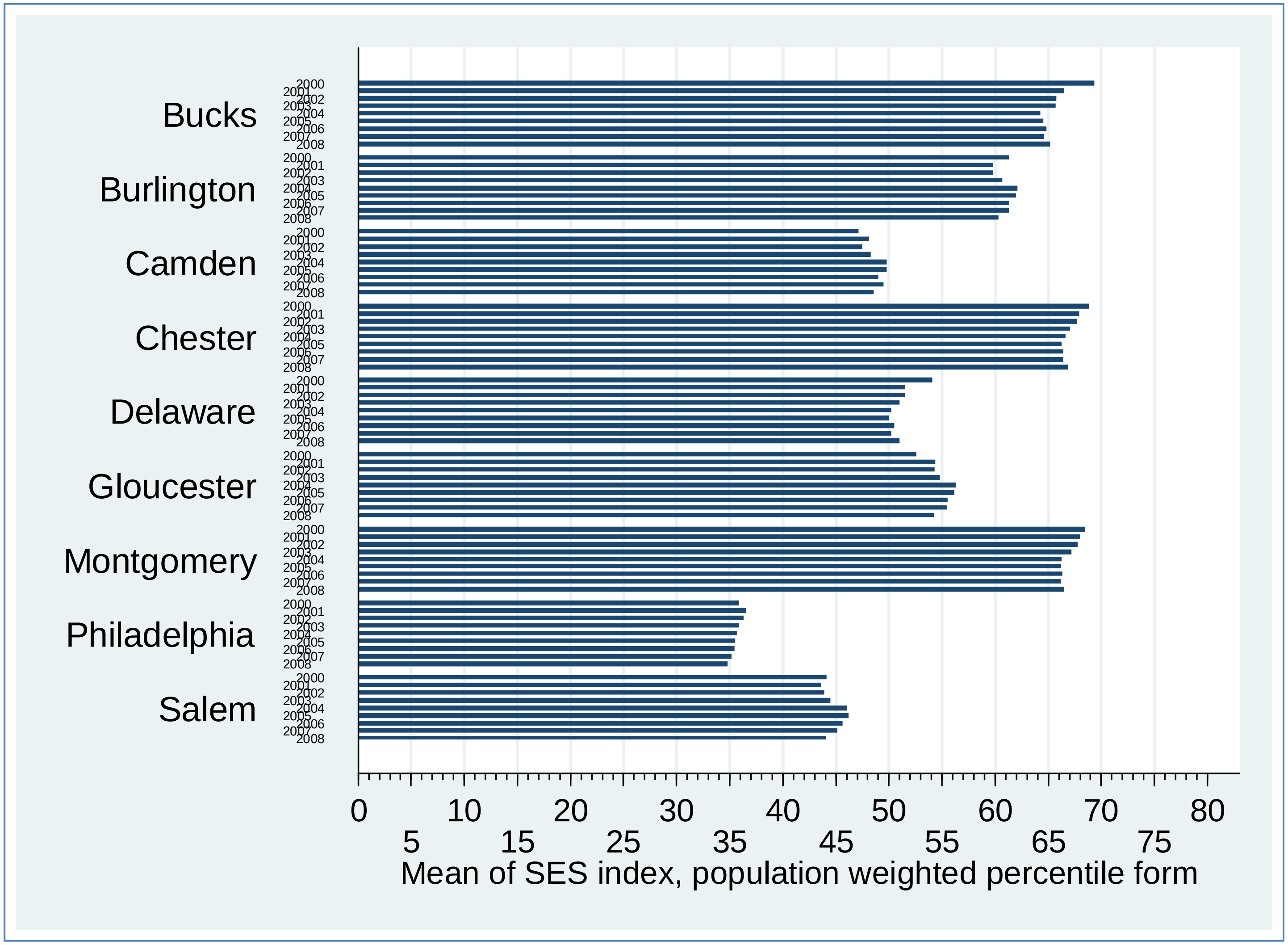

Figure 32. Average jurisdiction SES index shifts, by county, by year, in PWP form.

Note. Units are jurisdictions in Philadelphia MSA. N=355 (354 in 2000).

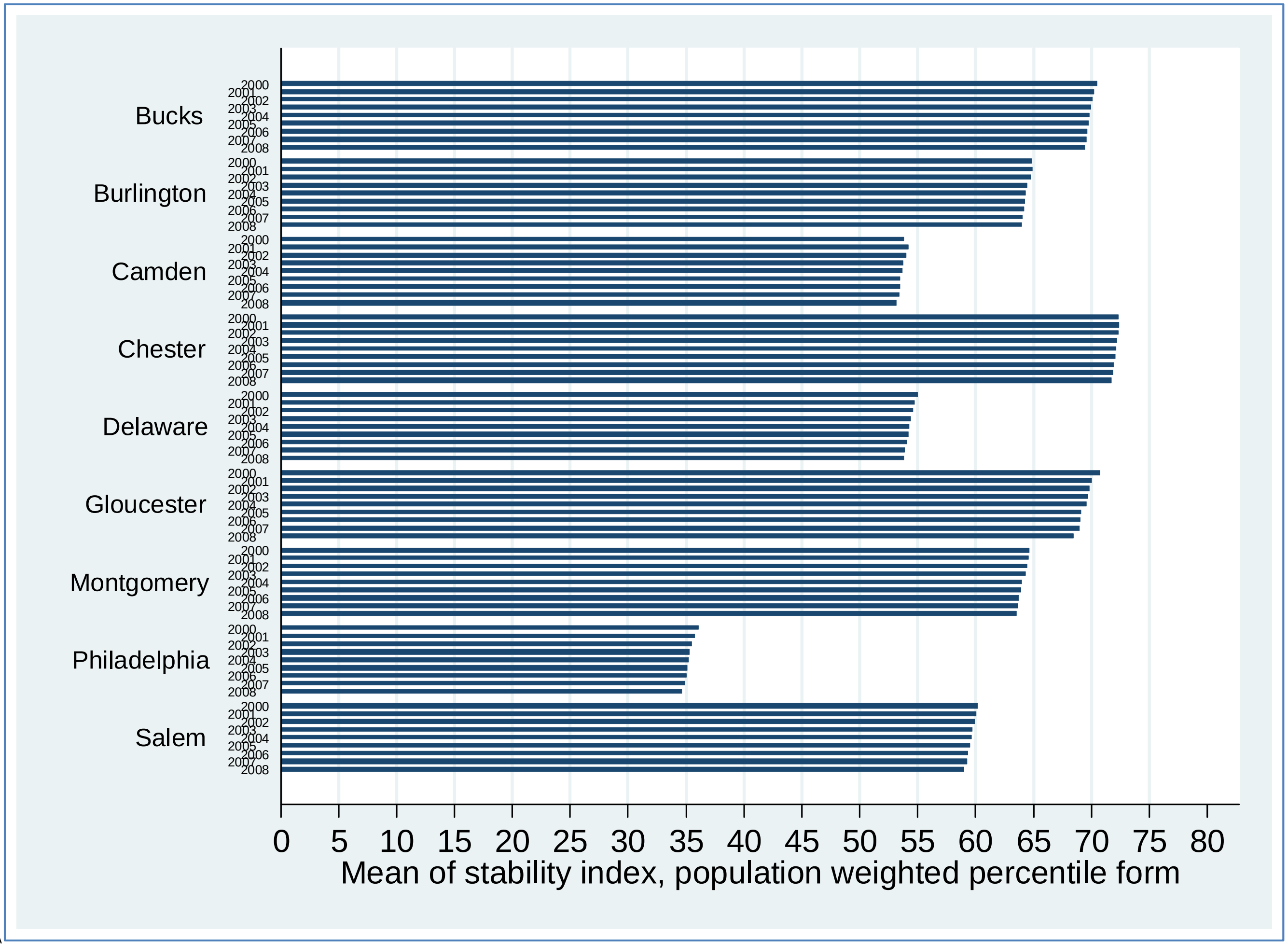

Figure 33. Average jurisdiction stability index shifts, by county, by year, in PWP form.

Note. Units are jurisdictions in Philadelphia MSA. N=355 (354 in 2000). The very slight downward trend in each county average is not a processing mistake.

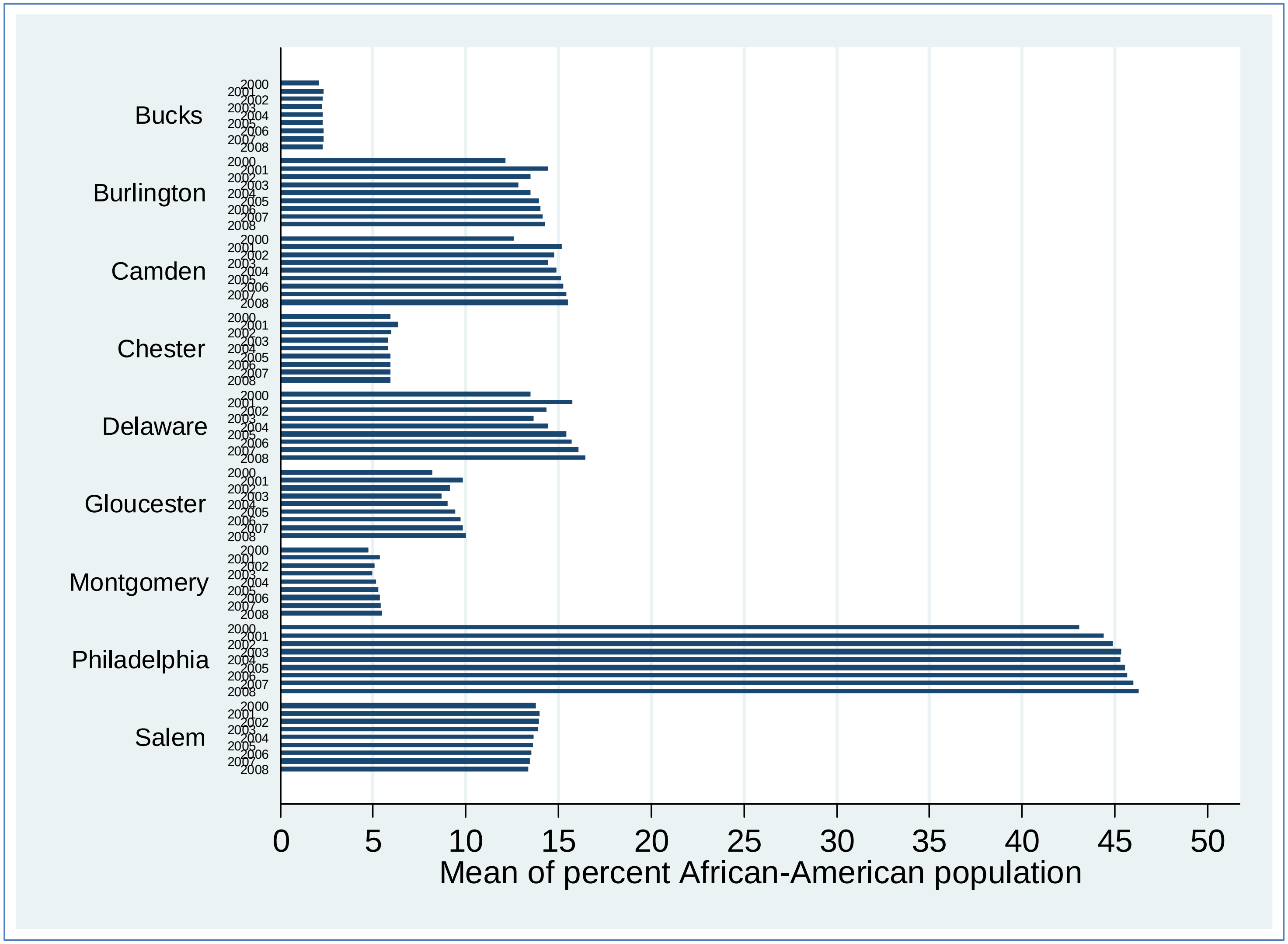

Figure 34. Average jurisdiction-level percent African-American population, by county, by year.

Note. N=355 (354 in 2000).

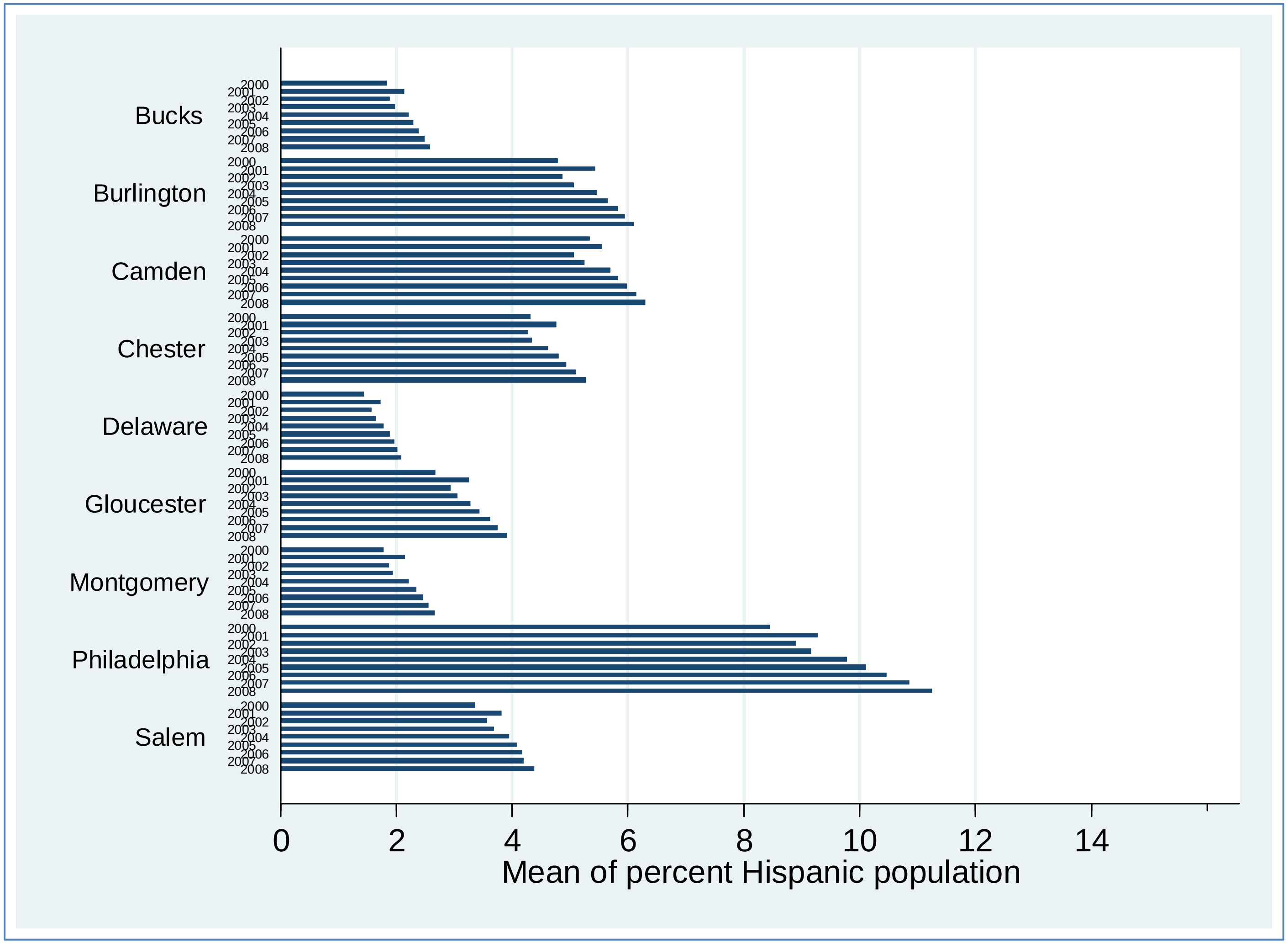

Figure 35. Average jurisdiction-level percent Hispanic population, by county, by year.

Note. N=355 (354 in 2000).

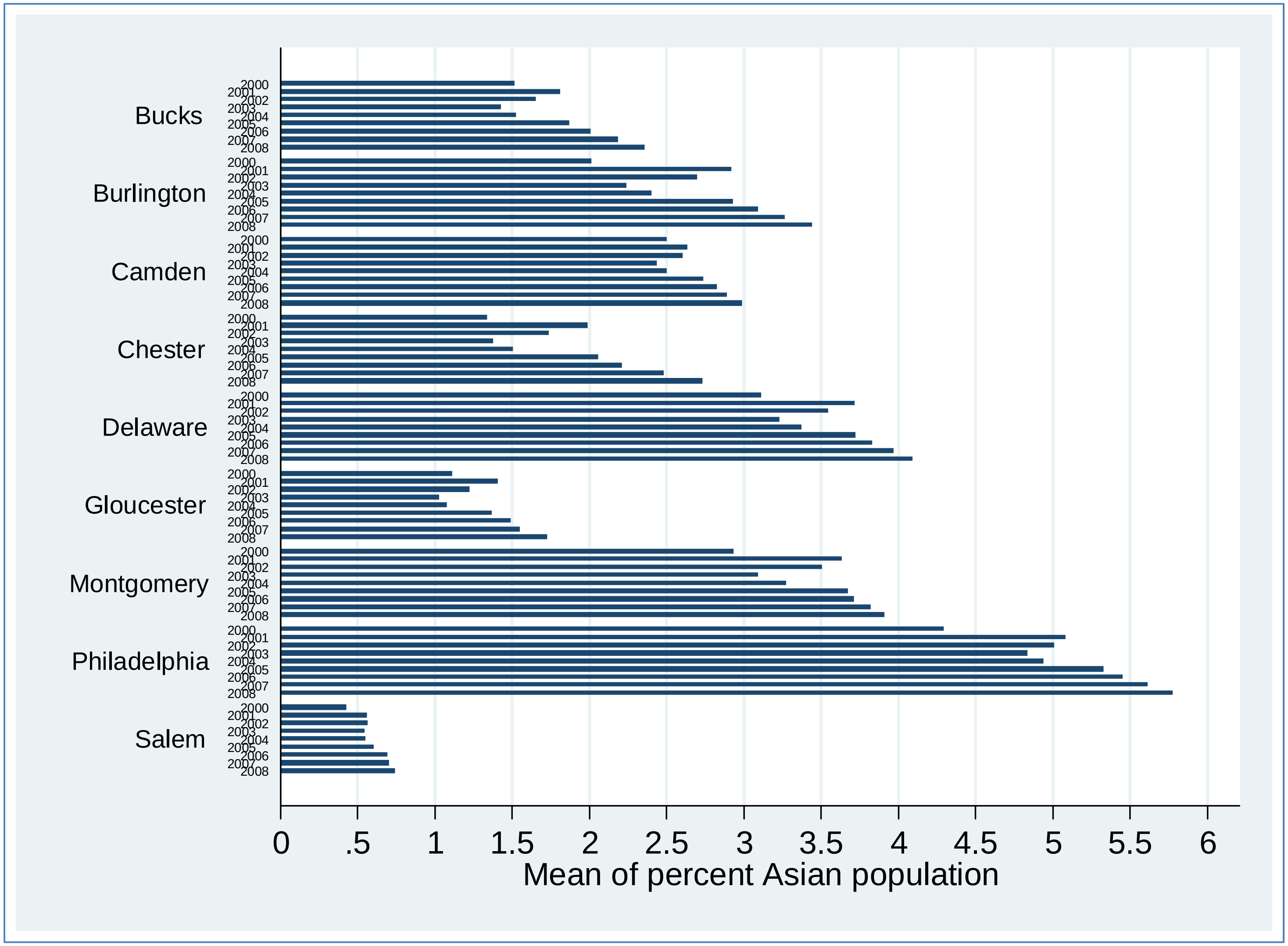

Figure 36. Average jurisdiction-level percent Asian population, by county, by year.

Note. N=355 (354 in 2000).

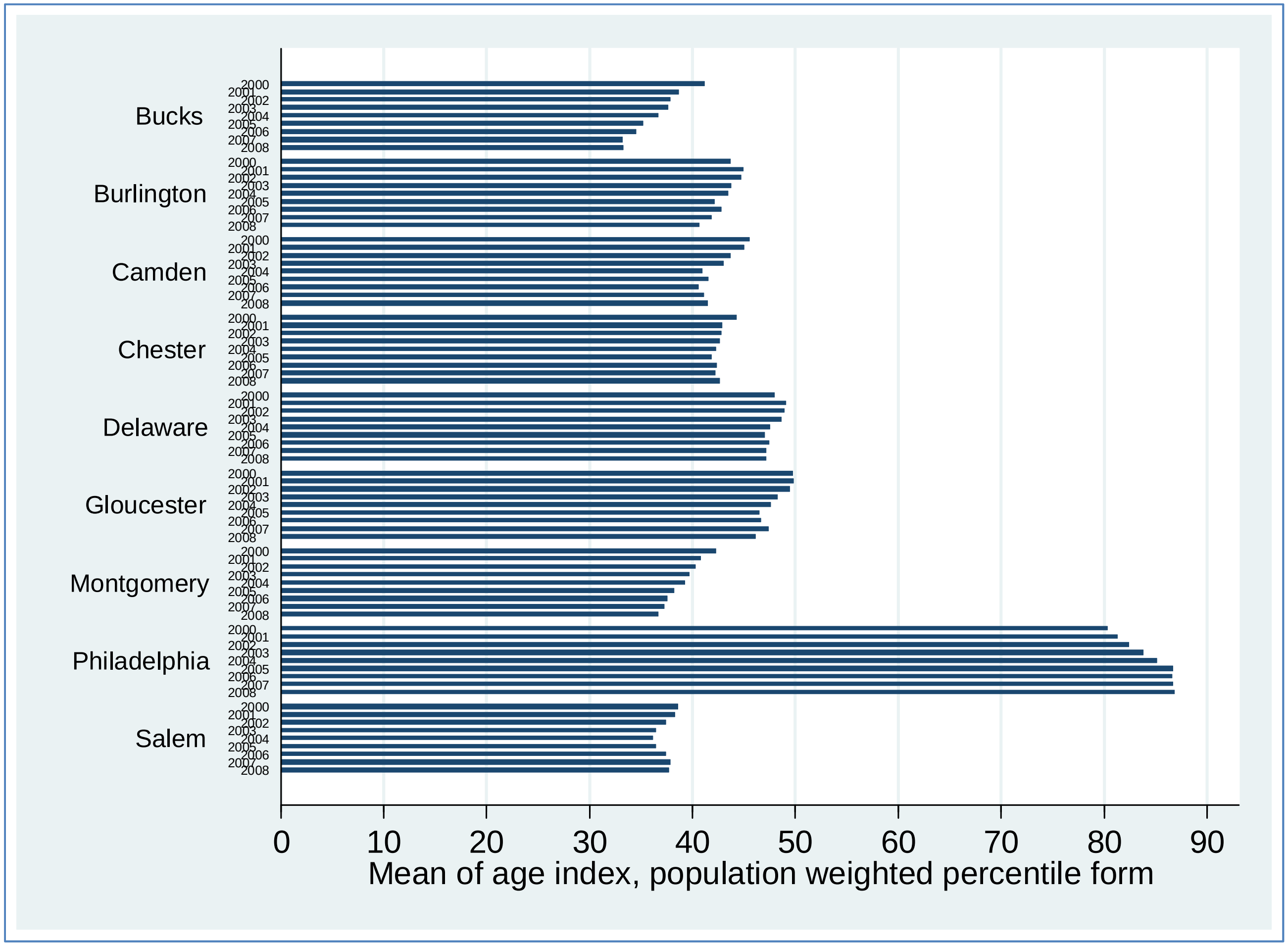

Figure 37. Average jurisdiction age index shifts, by county, by year, in PWP form.

Note. Units are jurisdictions in Philadelphia MSA. N=355 (354 in 2000). A higher score means higher proportions of the population in the age groups 10.14, 15-19 and 20-24; and lower proportions of the population in the age groups 50-54, 55-59, and 60-64.

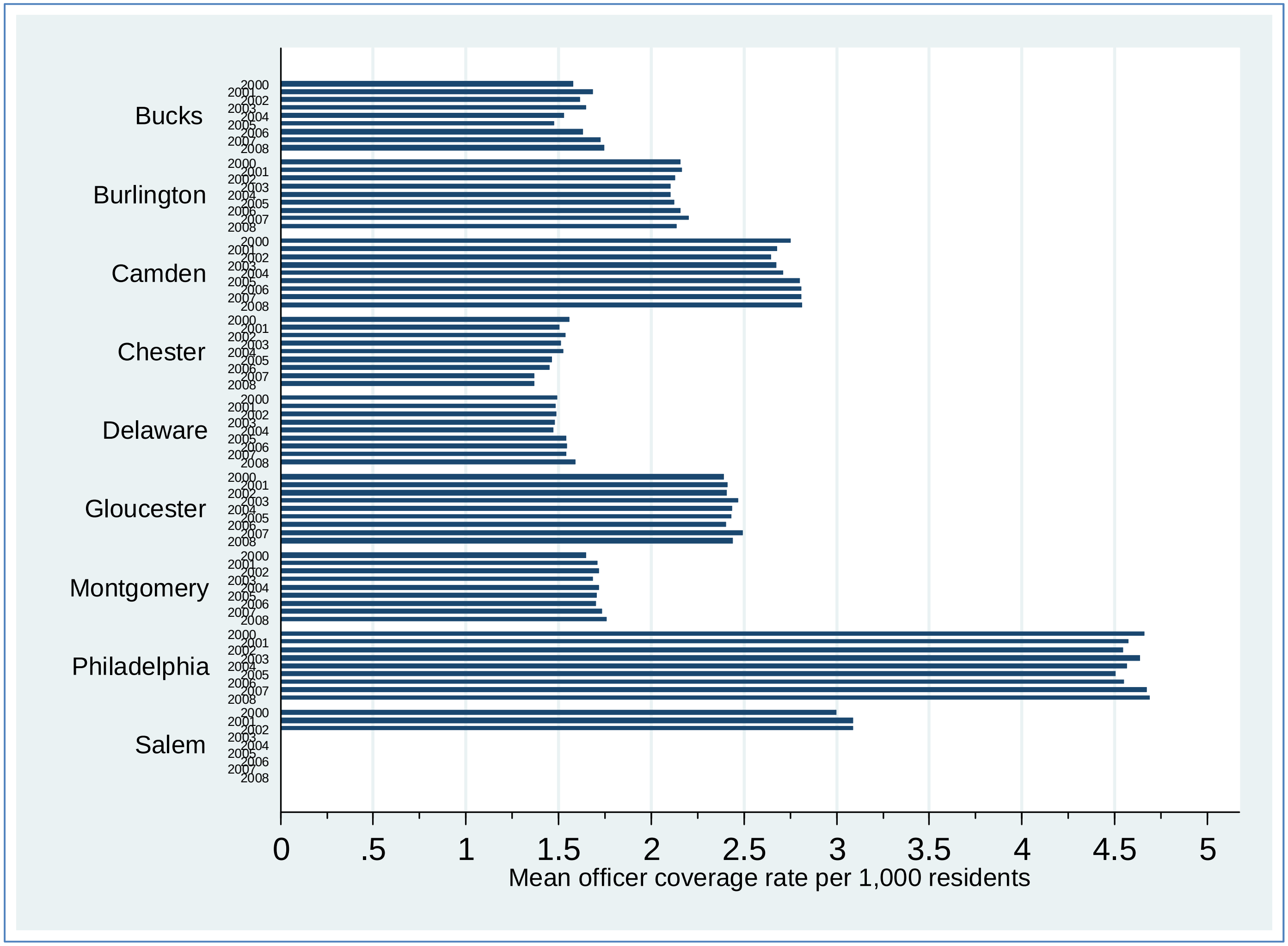

Figure 38. Mean sworn officer coverage rate by county, by year, based on unweighted jurisdiction average.

Note. Jurisdictions included only if they had their own exclusive department and at least one full time sworn officer. Pine valley PD excluded. FBI law enforcement data not available after 2002 for Salem County.

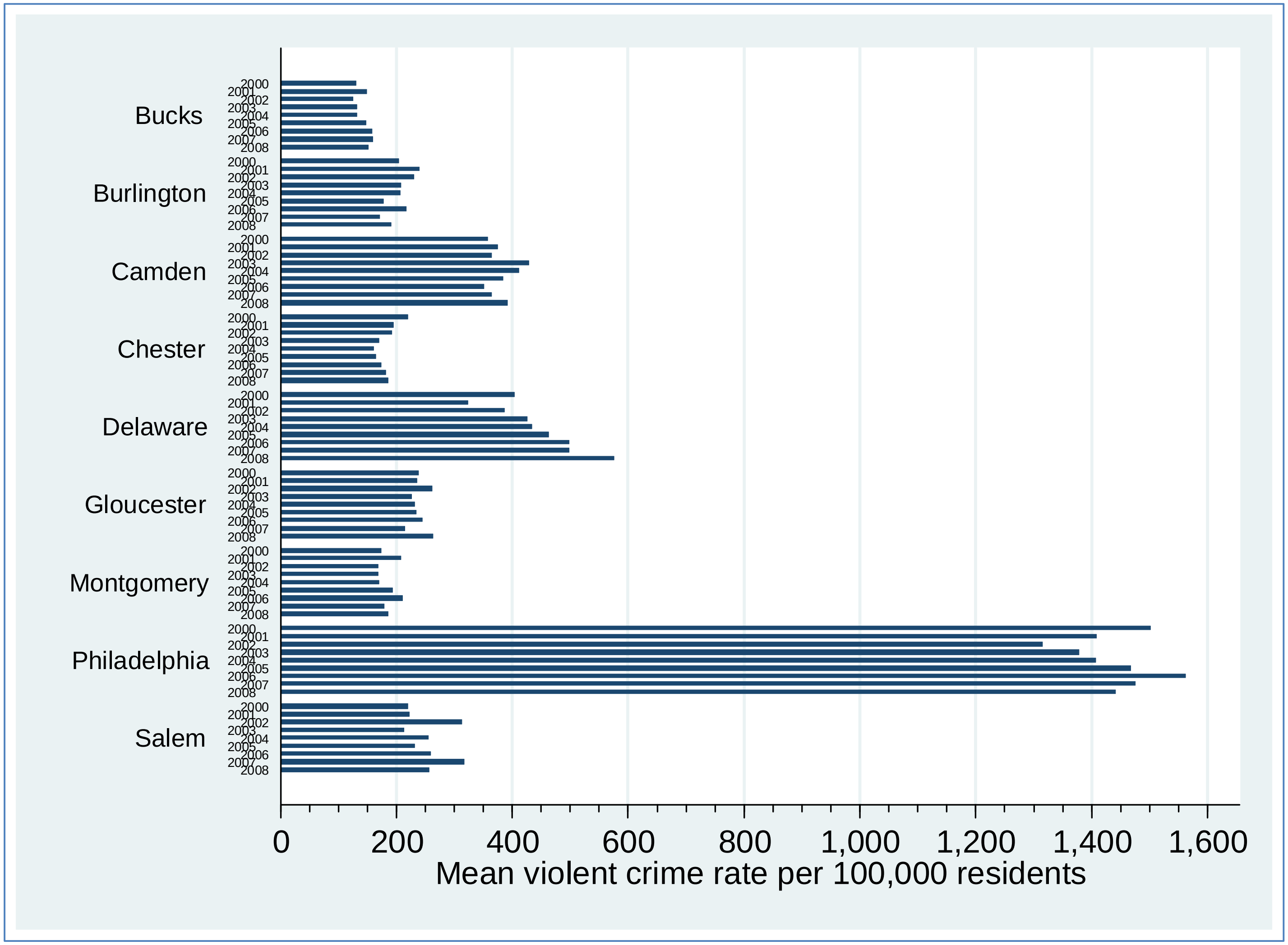

Figure 39. Mean violent crime rate per year.

Note. Based on unweighted jurisdiction average**.** Pine Valley and Tavistock excluded (n=353/year).

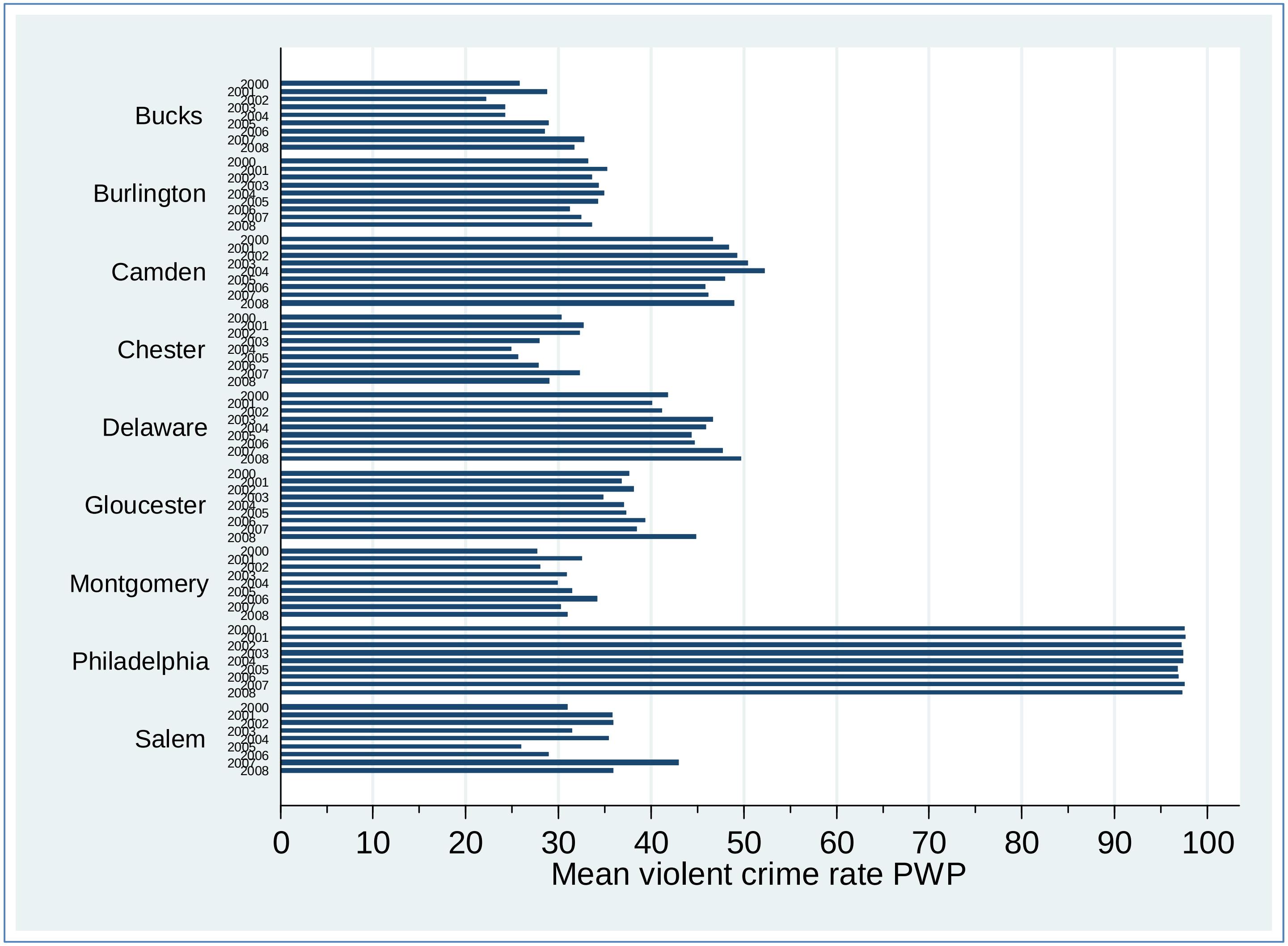

Figure 40. Mean violent crime rate per year, in PWP form

Note. Based on unweighted jurisdiction average. Pine Valley and Tavistock excluded (n=353/year).

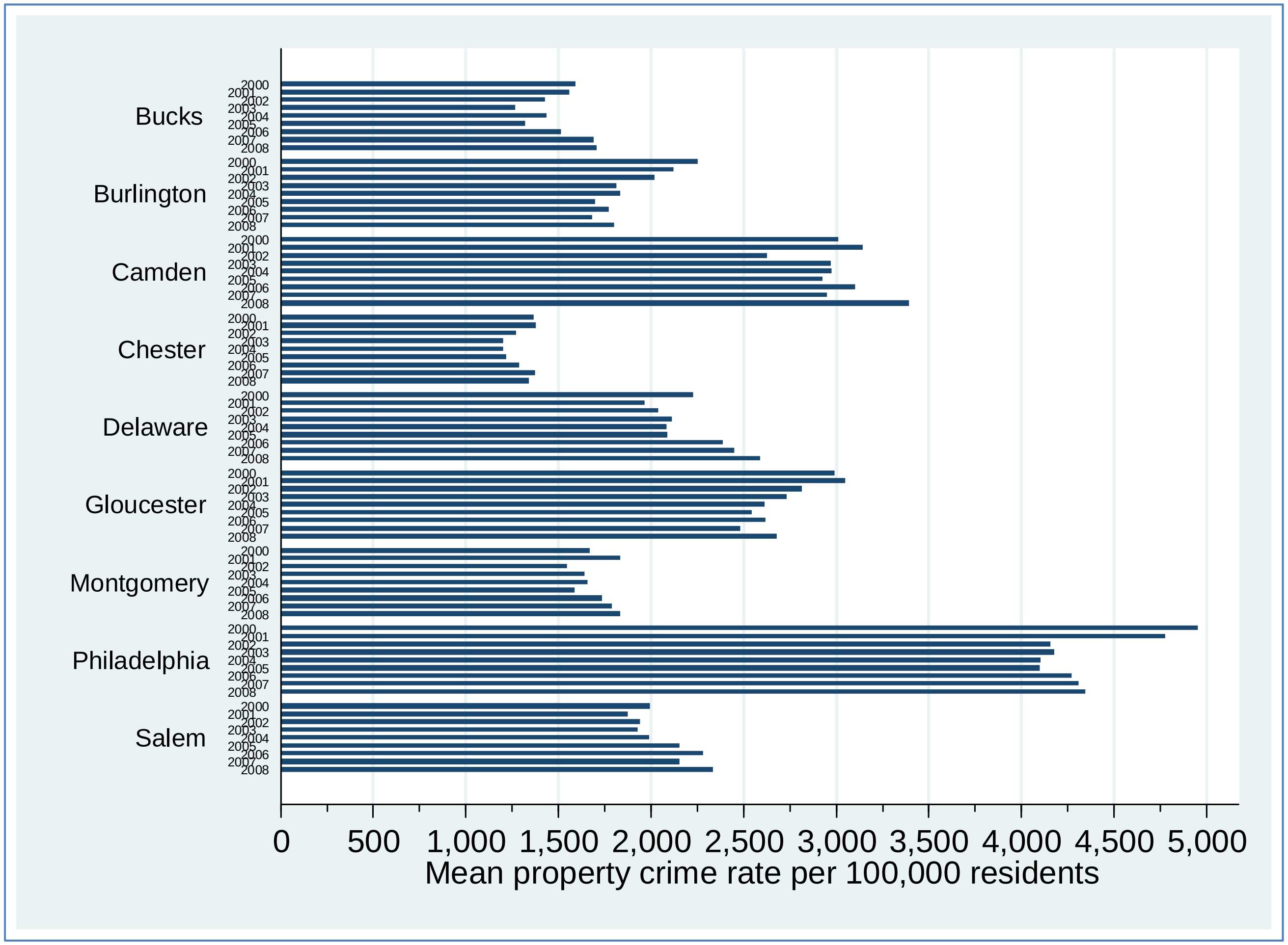

Figure 41. Mean property crime rate per year

Note. Based on unweighted jurisdiction average**.** Pine Valley and Tavistock excluded (n=353/year).

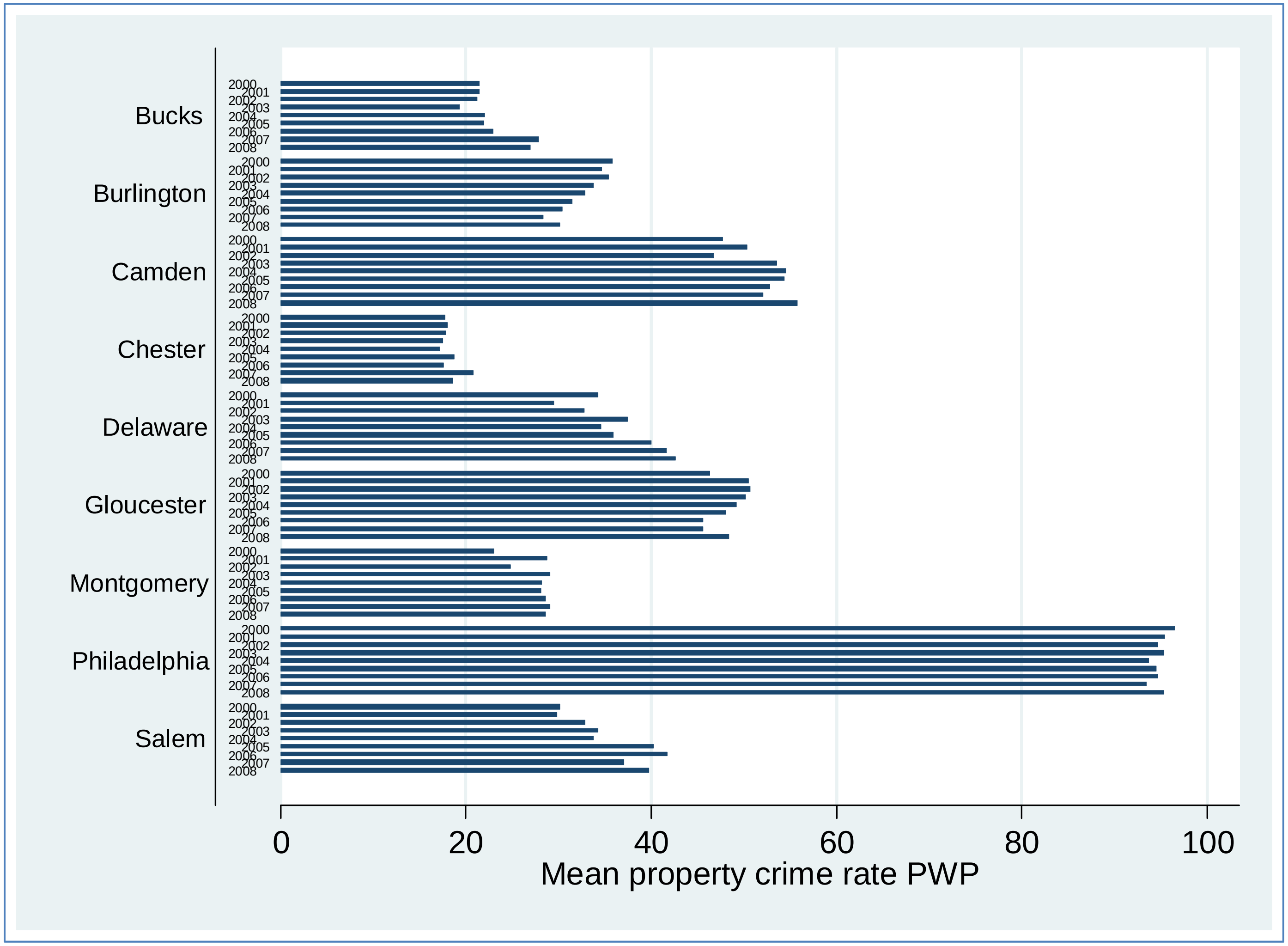

Figure 42. Mean property crime rate per year, in PWP form

Note. Based on unweighted jurisdiction average**.** Pine Valley and Tavistock excluded (n=353/year).

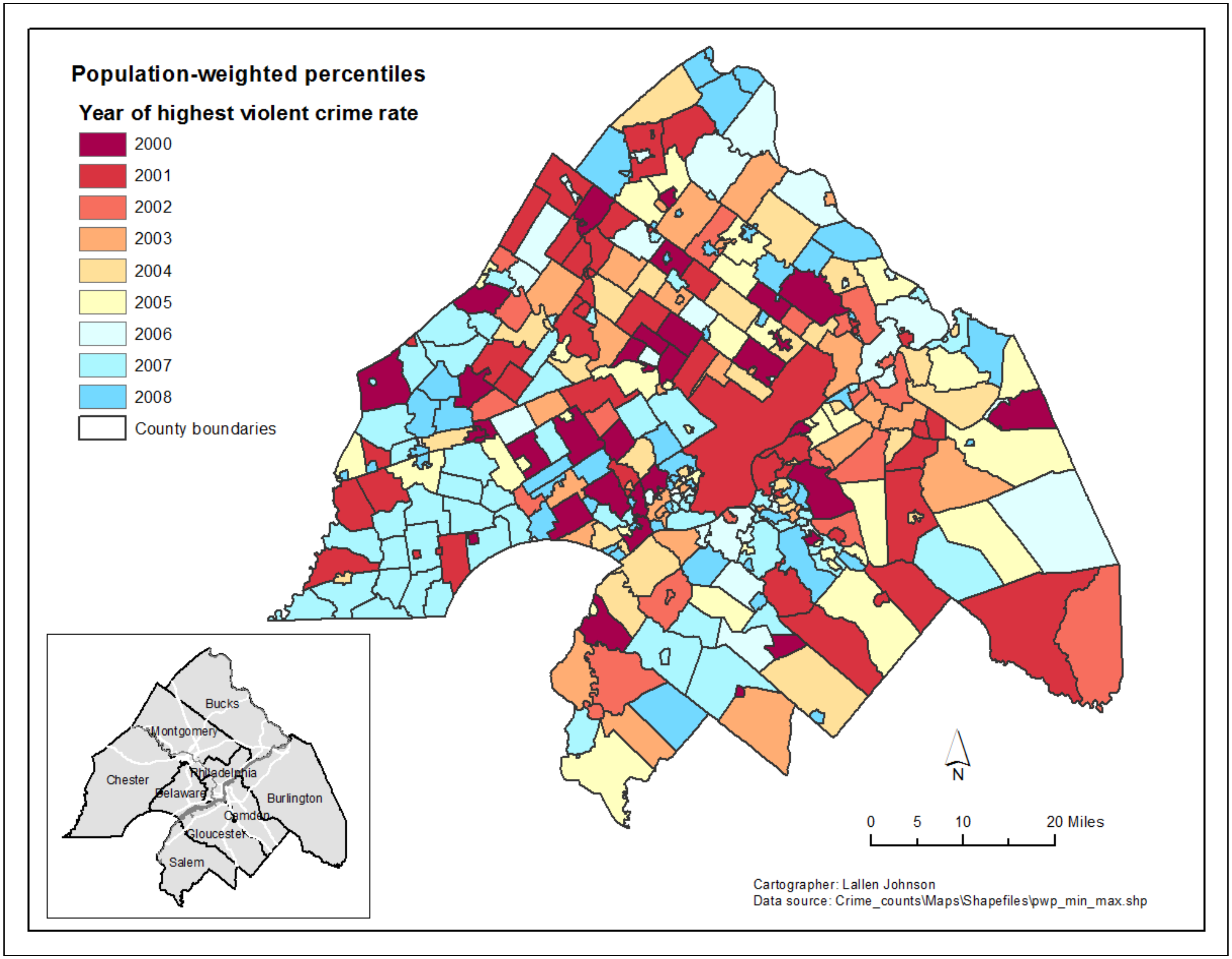

Figure 43. By jurisdiction: Year in period with highest relative violent rate

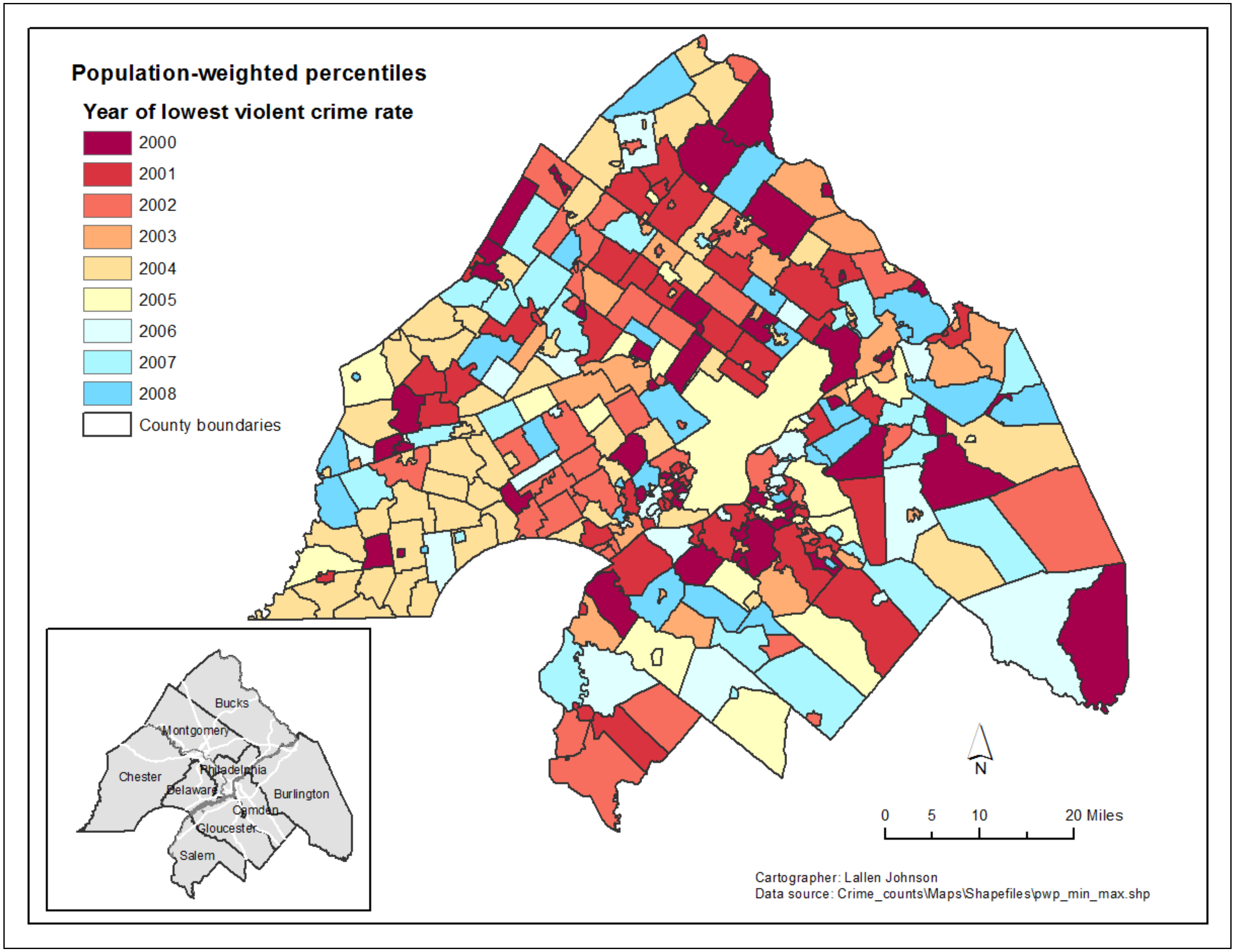

Figure 44. By jurisdiction: Year in period with lowest relative violent rate

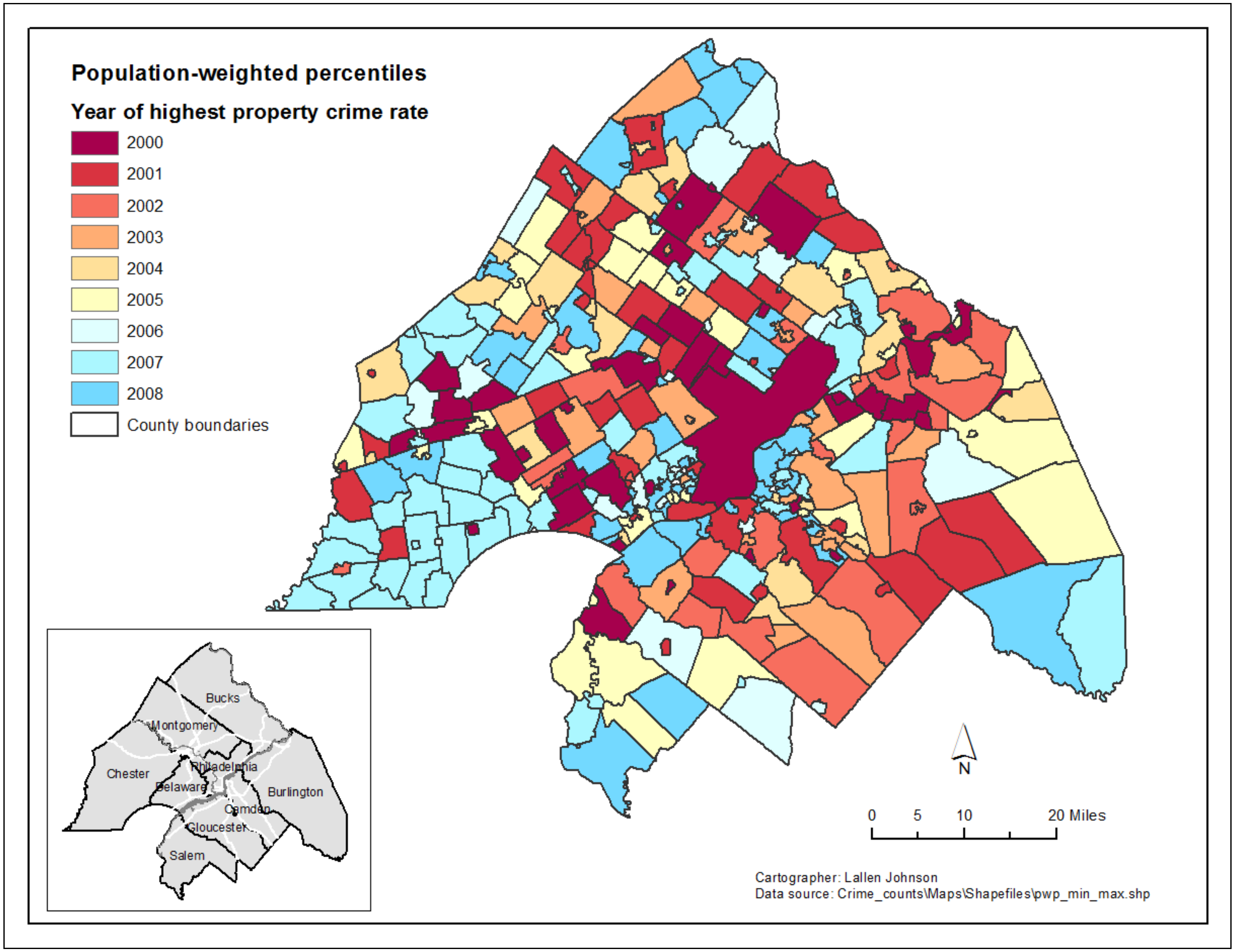

Figure 45. By jurisdiction: Year in period with highest relative property rate

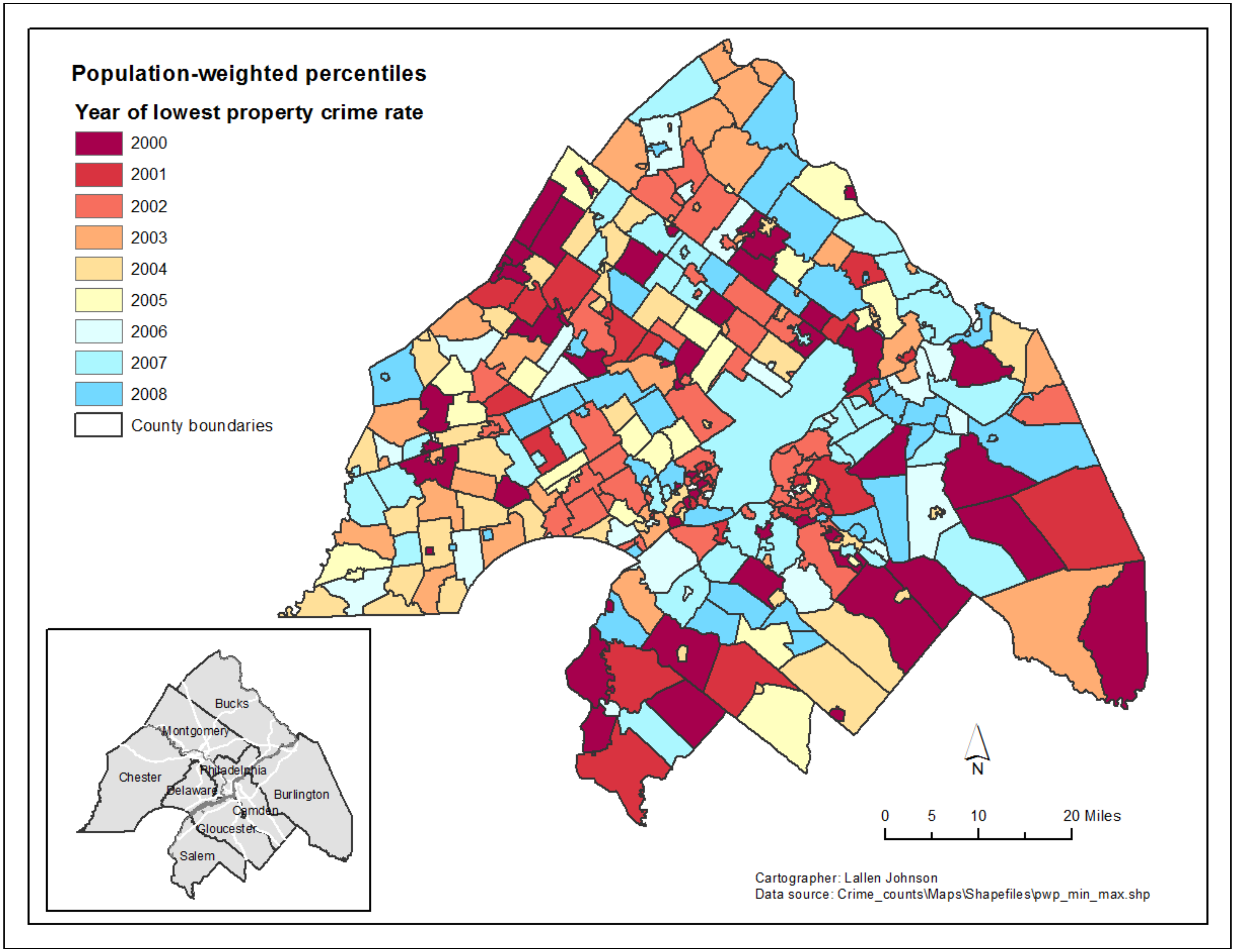

Figure 46. By jurisdiction: Year in period with lowest relative property rate

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4. SPATIOTEMPORAL PATTERNING OF CRIME AND ENFORCEMENT CHANGES

4.1. Overview

This chapter examines the results from cross sectional time series models of violent crime counts, property crime counts, and PWP versions of both variables. From the ecology of crime perspective, the most critical questions addressed are: which structural conditions link most strongly to violent or property crime rates? How do those links reflect on different models about crime structural correlates? These models are cross sectional. Jurisdiction structure and law enforcement levels and arrangements are linked to crime levels in the same year. Spatial dependencies are taken into account in two ways. Spatial dependencies across error terms are explicitly modeled (see below), and spatially lagged crime outcomes are included as predictors.

Also of interest from this perspective is the time question. Controlling for changing features of jurisdictions, was crime increasing or decreasing over the period? Linear and nonlinear trends merit consideration. From the geography of crime perspective, this analysis follows up on the clues provided by the LeBeau charts in the previous chapter about potential spatiotemporal interactions. The more rigorous testing of such interactions here poses a two part question. (a) Do the impacts of time vary significantly across jurisdictions?; and if they do, (b) are those differential time impacts spatially patterned? Such a finding will of course have implications for political economy as well as geography. What would such patterning suggest about shifting inequality across the region and over time?

4.2. Analytic approach

When the term spatiotemporal patterning is used here, it refers to three different but related aspects of how time and space interact when it comes to crime.

The first aspect of spatiotemporal interaction is simply that the effects of time, coded here as years within the study period, has a different impact on crime levels depending on the municipality in question. A multilevel framework is used in this analysis (Snijders & Bosker, 2012). Jurisdiction-years at the lower level (level 1), are nested within jurisdictions (level 2). If the effects of sequential years vary, that is, the average impact of each passing year alters crime levels but does so differently in different places, that would suggest spatiotemporal patterning of crime changes. Over the period, some places were going up (or down) on crime faster or slower than others.

But in doing such testing, spatial relationships among jurisdictions also must be taken into account. This is accomplished with a spatial multiple membership (MM) model (Browne, Goldstein, & Rabash, 2001). More specifically, the outcome variation shared by *sets* of adjoining neighbors is modeled. This permits estimating residual outcome variation for these different sub-regions formed by adjacency patterns. The residual term is broken down into parts, one of which is error variance associated with particular units that share a neighbor (I. H. Langford, Leyland, Rasbash, Goldstein, et al., 1999: 220) (I. Langford, Leyland, Rasbash, & Goldstein, 1999). In effect, there is a third, higher level of grouping in this multilevel model which is based on shared neighbors.

If that error component is significant it is saying: un-predicted portions of crime levels are shared by neighboring jurisdictions. Who is whose neighbor, at the jurisdiction level, contributes to the un-predictable crime portion. The amount of that residual variation shared by neighboring jurisdictions becomes an additional, second aspect of spatiotemporal interaction in crime patterns.

A third aspect of results reflecting spatiotemporal interactions would be in the geographical patterning of the time slopes. If results confirm significant variation in the random effects for linear time, can sub-regional clusters of jurisdictions, sharing similar linear impacts of time, be identified? Stated differently, are similar slopes of linear time in crime change surfacing in specific sub-regions of the metropolitan area? Such clusters can be identified using LISA statistics (Anselin, 1995) such as a Local Moran's *I*. Of course, global patterning of spatially autocorrelated time impacts via a Global Moran's *I* are of interest as well (Bailey & Gatrell, 1995: 280).

A final piece of this model is determining how beginning-of-the-period features of the jurisdictions might link to their differential crime trends. If such links surface they would speak to the conditioning of this aspect of the spatiotemporal interaction on initial jurisdiction attributes. This analysis seeks to predict the varying slopes for time, if that variation proves significant.

Thinking broadly, spatiotemporal interactions in how crime levels shift over time seems likely simply given the charts in the LeBeau previous chapter showing sub-regions of the MSA peaking or bottoming at the same time in their relative crime levels.

Most of the models reported in this chapter will use Markov Chain-Monte Carlo (MCMC) Full Bayesian estimation (Congdon, 2003, 2006; Gelman, Carlin, & Stern, 2003; Gelman & Hill, 2007). MCMC estimation is particularly useful in exactly situations like this where a number of units of analysis are likely to have low counts (Spiegelhalter, Best, Gilks, &

Inskip, 1996). Of course, Full Bayes models have been controversial for decades (Browne & Draper, 2006). Nevertheless, MCMC Full Bayes models have proven quite useful not only in health epidemiology but also in different areas in criminology and criminal justice (Bernardinelli, Clayton, & Montomoli, 1995; Bernardinelli et al., 1995; Bernardinelli, Pascutto, Best, & Gilks, 1997; Gelman, Fagan, & Kiss, 2007; Levine & Block, 2011; Rohde, et al., 2010). Measures of relative model fit will rely on the Deviance Information Criterion (DIC) (Spiegelhalter, Best, Carlin, & van Der Linde, 2002). This fit measure takes into account model fit, and a penalty for model complexity. So accuracy and parsimony are jointly considered. Conceptually and very loosely, it is an adaptation of a Bayesian Information Criterion (BIC) fit measure (Raftery, 1995a).

Results shown here used prior results from the non-MCMC multilevel models as initial prior values for random and fixed components in the MCMC runs. This is a recommended procedure (Leckie & Charlton, 2011). Results for several runs using these for priors were compared with MCMC results using noninformative, diffuse priors. Results generally were the same down to the 3rd if not the 4th decimal place for random and fixed parameters estimated.

As is recommended with MCMC, density charts and trajectory charts were examined after runs. MCMC models with count outcomes, because they generate serially correlated estimates, often required sizable chains in order to generate distributions for fixed and random parameters which were close to normal distributions. Burn-in chains in the tens of thousands, and estimation chains in the hundreds of thousands were sometimes used.

For the violent crime count outcome, it was not possible to run the MCMC models. This is because this outcome required a negative binomial distribution, and the latter was not available for MCMC models. The negative binomial allows "a more complex variance structure" which apparently was needed to generate sensible estimates for this outcome (H. Goldstein, 2003; Rasbash, Steele, Browne, & Goldstein, 2009:190).

4.3. Dependent and predictor variables

The outcomes of interest are yearly violent or property crime counts. The property crime figures do not include arson. These are analyzed with generalized multilevel models expecting either a negative binomial distribution or a Poisson distribution with overdispersion.

Additional analyses using the outcome in population weighted percentile (PWP) format also will be conducted. Since the outcome variable in this form is somewhat normal, these multilevel models will just expect a normally-distributed outcome and will not use generalized models.

Jurisdiction demographic features. For each year in the series, each jurisdiction's score on the three key dimensions of community demographic structure were entered as predictors: community SES, community residential stability, and racial composition. In addition, the Anderson index of your/potential supervisors captured a key feature of age structure. Details on these indicators and index construction appear in Appendix 1.

Linear and quadratic time. In order to separate linear and quadratic effects of time (2000, 2001 … 2008), the linear time variable was centered on 2004 (=0), creating a variable ranging from -4 (2000) to +4 (2008). Quadratic departures from linear time impacts were captured with a variable that squared the centered linear time variable (2000=16, 2004=0, 2008=16).

Population. The natural log of population was entered in specific models either as a predictor whose coefficient was determined in the analyses or as an exposure variable, depending on what produced better fitting models. Of course, there are important interpretation implications of doing it these two different ways.

Policing arrangements. To be sure that fixed and random effects of time passing were not confounded with different types of policing arrangements in different places, it was necessary to control for these arrangements. Several dummy variables were included for this purpose. These included being totally covered by the respective state police (1), or not (0); being partially covered by the respective state police (1), or not (0); being covered by a multi-jurisdiction police department (1), or not (0); and having your own department but with less than one full-time sworn officer (1), or not (0). Some jurisdictions had different arrangements for different years in the study period. A special dummy variable was used for Woodland because its force changed so dramatically during the period. This leaves as the reference string (before excluding the golf boroughs, see below) 2,448 jurisdiction years for years in which jurisdiction had their own single-jurisdiction police department, with at least one full-time sworn officer, not backed up by the respective state police. These 2,448 jurisdiction-years represented 76.6 percent of the 3,195 jurisdiction-years total (355 x 9).

Police coverage/department size. Sworn officers per 1,000 population are used where feasible; in some models it was necessary to include department size captured with the number of full time sworn officers.

Golf boroughs. The two jurisdictions whose area consisted largely of a golf course (Tavistock, Pine Valley) and where, in each case, the population was only in the dozens, were excluded from analyses.

Beginning of the period demographic structure. As mentioned above, if the passage of time affects crime trends differently in different locations, and those differentials are more than sampling error, the connections between demographic structure and these differentials could be of interest. Therefore, *just for predicting this random effect if it proves sizable,* level 2 (jurisdiction-level) predictors included 2000 jurisdiction scores on the socioeconomic status index, the stability index, the needing supervision/supervisors index, and racial composition.

Spatially lagged crime counts. Spatially lagged violent and property crime counts were created as follows. The map was buffered out, and crime information was collected for counties immediately outside the MSA. Crime information, by year, was obtained for those counties. For each jurisdiction, a spatially lagged crime count was created by taking the Empirical Bayes average of surrounding crime levels, with different neighbors being weighted by their relative population. The adjacency rule used was first-order queen contiguity.

Descriptive statistics for variables in these models appear in Table 8.

4.4. Sequence of models

An initial null model learns whether there is significant outcome variation at the jurisdiction and/or the jurisdiction cluster levels. The next model adds all the relevant predictors save the spatially lagged outcome. The final model adds in the latter. Both crime counts also are analyzed in population weighted percentile form.

4.5. Violent crime counts

4.5.1. Distribution of outcome variance across jurisdiction-years, jurisdictions, groups of jurisdictions

Results from the null model controlling only for the population in 100,000s as an offset variable appear in Table 9. The model is a three level multilevel model with years nested within jurisdictions, and jurisdictions nested within groups of neighboring jurisdictions. The typical violent crime rate per jurisdiction, per year, was 240/100,000.

Turning to the random effects, results reveal significantly correlated violent crime rates between adjoining jurisdictions ($\Omega = .22$, $p < .05$; $r_{ICC} = 9.9$ percent). This supports the descriptive patterns seen earlier (see Figure 24) and suggests something theoretically important is happening at the sub-regional MSA level. The multi-year average of jurisdiction-level violent crime rates was another significant source of ecological variation in the outcome ($\Omega = 1.428$, $p < .001$, $r_{ICC} = 64$ percent). Clearly, the bulk of the variation in the violent crime rates arises from average multi-year differences across jurisdictions. Thus there are two significant sources of ecological variation in violent crime levels: jurisdictions, and clusters of neighboring jurisdictions.

4.5.2. Impacts of time: Fixed and random

To gauge the impacts of year-on-year changes on crime levels, fixed and random linear effects of time were included (results not shown). With the random effect of linear time, the average effect of each passing year in the study period was allowed to vary across jurisdictions. This analysis did control for different types of policing arrangements, but not for levels of coverage. Results revealed a modest but significant linear impact of year-on-year changes on violent crime levels (IRR = 1.0115, $p < .05$). It also revealed that linear time affected violence levels differently in different places ($\Omega = .048$, se=.007, $p < .001$). This significant random variation, if it persists after controlling for other factors, would represent spatiotemporal patterning of crime at the intra-metropolitan level. The effects of the passage of time on crime would depend on location.

4.5.3. Cross-sectional model of violent crime counts

The next-to-final cross-sectional model of violent crime counts appears in Table 10. Since this model still appears to have significant clustering of errors among neighboring jurisdictions, an additional model was run controlling for spatially lagged violent crime counts. Those results appear in Table 11. Examining the latter table, and starting with structural linkages, violent crime levels were lower in higher SES jurisdictions (IRR = .87, $p < .05$). Such a result is anticipated by many decades of research on community structure and crime, and by the work on homicide and community structure in the last two decades (Pratt & Cullen, 2005) (Land, et al., 1990; McCall, 2010; McCall, et al., 2010). Each standard deviation increase on the SES index was associated with an expected violence rate about 9.6 percent lower.

The effect of stability proved more powerful (IRR=.66, $p < .001$). Each standard deviation increase in this index was associated with a 29.8 percent drop in the expected violent crime rate. This link certainly aligns strongly with the systemic model of crime, and suggests it may be extensible from the neighborhood level, where it is most widely applied, to the jurisdiction level (Bursik & Grasmick, 1993b).

More predominantly African-American jurisdictions were associated with higher violence levels ($p < .001$). The expected rate was about 9.4percent higher for each standard deviation increase in percent African-American. This finding aligns with earlier reviews of community structure and crime which found that racial composition consistently linked to higher crime (Pratt & Cullen, 2005).

Turning to policing, one coverage variable linked with violence levels. Places covered by a multi-jurisdiction department had expected violence levels about 76 percent higher compared to jurisdictions with their own departments. This result should be treated with caution since for many of these locales, allocations of crime counts were required (see Appendix 1). There was no cross sectional link of law enforcement coverage levels with violence levels.

Turning to time, neither the linear nor curvilinear fixed effects were significant. Across the entire metropolitan region, controlling for community fabric and policing arrangements and levels, *jurisdiction level violent crime rates did not increase over the period*. The Philadelphia metropolitan region, controlling for compositional changes in who lived there and for enforcement changes, was not becoming a more dangerous region when crime rates from each jurisdiction were considered on an equal footing regardless of size.

Evidence of spatiotemporal interactions in violence changes, however, persisted and remained at about the same size ($\Omega = .005$, se = .001, $p < .001$). Although there was no overall change in violence levels across the period, violence was changing at significantly different rates in different jurisdictions during the study period.

The spatially lagged violent crime counts substantially affected focal jurisdiction crime levels ($p < .001$). A one standard deviation increase in the surrounding violent crime count was associated with a focal expected violent crime count that was about 8.8 percent higher. Second, a significant amount of spatially clustered error remained in the models ($\Omega = .045$, $p < .05$). These two results point to extra-jurisdictional effects, some linked to surrounding crime, and some based on unknown factors.

Overall, although the model explains a substantial amount of between-jurisdiction violence levels for the period ((1.428-.262)/1.428) = 74.6 percent), significant crime differences between jurisdictions remains un-modeled ($p < .001$).

4.5.4. Clustering of values of time slope

We now dive a little more deeply into the random effects of linear time. The above results show that these jurisdictions, as a group, varied significantly from the average linear trend for yearly violent crime rate changes (b = .005). Since each jurisdiction's trend, expressed as a deviation from the average trend, can be linked to a confidence interval (+/- 1.96 standard errors), we can see if any *individual* jurisdictions had changing crime trends which were *significantly* different from the average trend. It turned out that approximately two to three dozen jurisdictions did demonstrate crime trends diverging markedly from the average trend. Figure 47 displays the caterpillar plot of jurisdiction departures from the average linear impact of time on violent crime rates. Those deviations whose error bars do not touch the zero line are significantly different from the average linear impact of time.

As can be seen, at the lower left corner of the figure, around a dozen jurisdictions had individual rates that were significantly lower than the average. That is, these jurisdictions' yearly violent crime changes were making them increasingly safe relative to the rest of the region as the first decade of the Twenty-First Century wore on. Conversely, as can be seen at the upper right of the same figure, about a dozen jurisdictions were diverging in the *opposite* way, becoming more dangerous over time relative to the rest of the region. *The broader implication is that jurisdiction-level public safety inequalities across the entire region were increasing during the study period.*

But are those increasing public safety inequalities spatially patterned? It turns out that they were. Looking at all the individual jurisdiction linear temporal trends as a group, these were *not* spatially random. (Global Moran's I = .11, $p < .01$).

To better understand this patterning, two maps are presented. The first simply shows the different change rates and appears in Figure 48. The nine jurisdictions in the highest grouping had yearly increases in their expected crime rate of anywhere from .12 to .34. This translates to yearly expected violent crime rate increases, on average over the nine year period, of anywhere from thirteen percent (exp(.005+.12)) to 41 percent (exp(.05+.34)). The location with the fastest upward shifting violence rate, after controlling for other factors, was Eddystone, located in Delaware County just to the north of the City of Chester.

Next fastest increasing on the violent crime rate after controlling for other factors was West Pottsgrove in Montgomery County. This township of about 4,000 is located right on the northwestern edge of the MSA, just west of the older urban center of Pottstown. West Pottsgrove experienced a net yearly increase in its violent crime rate of about 24.9 percent (exp(.005+.22)).

Also in this fastest increasing violent crime group were three other municipalities bordering an urban center: the township of Chester, just northwest of the City of Chester (expected net annual violent crime increase = 17.1 percent), Darby borough adjacent to southwest Philadelphia (20.2 percent), and Lower Southampton Township in Bucks County, just north of the easternmost arm in the "Y" of Philadelphia (19.3 percent).

These net increases are "net" in that these places were increasing on violent crime rates markedly faster than they "should" have given their beginning of the period structure, their policing levels and arrangements, and surrounding violent crime levels. A few of these in the fastest increasing group were immediately adjacent to urban centers – Chester, Philadelphia, Pottstown – but only on the PA side.

Turning to the opposite temporal dynamic, places where violent crime rates were dropping fastest over the period, also proved interesting. In Plymouth Township in Montgomery County, just one township away from Philadelphia, violent crime rates had a net expected drop of about sixteen percent a year (1-exp(.005-.177)). Springfield Township, in Delaware County, also just one township away from Philadelphia, had an expected net violent crime rate decrease of about the same amount, fifteen percent a year.

Having examined the overall patterning of the rates at which violent crime rates were changing, controlling for other factors, attention turns to whether these rates cluster spatially. Are places increasing faster than average surrounded by other places also increasing faster than average? How about for places decreasing more than average; are they also surrounded by other places where violent crime rates were dropping faster than average? The answer is provided by LISA statistics (Anselin, 1995). The map of significant local clusters appears in Figure 49. The most dominant visual feature of the map is the sizable cluster of jurisdictions where low violent crime rate change jurisdictions were surrounded by other low rate change jurisdictions. This grouping, located in Chester and Delaware counties, included jurisdictions where net violent crime rates held about steady throughout the period, or decreased. This cluster of places that were staying safe or becoming somewhat safer stretches from Charlestown Township in Chester County down to Chadds Ford Township in Delaware County, on the Delaware border. This is a diverse batch of places. Charlestown Township is a mix of farms, newer developments of single family detached housing on one acre lots, and two developments with large numbers of clustered condos. Chadds Ford Township is a historic settlement dating back to the early 1700s. This township straddles US-Route 1 and US-202, the latter dotted with extensive shopping. The township is the home of the historic site of the Revolutionary War Brandywine Battlefield and well-known artists such as Andrew Wyeth (Brower, 2011: 83-85). In the cluster, several jurisdictions have their own departments, so the cluster cannot simply be an artifact of how crime was allocated to jurisdictions covered by the Pennsylvania State Police.

A smaller local cluster of jurisdictions where violence rates were staying steady over the period or dropping appears in outer Montgomery County and includes Lower Frederick, Perkiomen, and Upper Salford.

A cluster of jurisdictions where the net increase in the violent crime rate was higher than the surround is located in Delaware County. The City of Chester is the largest jurisdiction in this grouping. Several in this cluster are small jurisdictions located just southwest of Philadelphia: Darby Borough, Sharon Hill, Collingdale, Aldan, Lansdowne, and Yeadon.

These LISA results demonstrate another facet of the spatiotemporal interaction of crime rates. Not only are the rates at which violent crime rates changing differential depending on the jurisdiction, as was shown in the statistical analyses. In addition, those rate differentials *themselves* are spatially patterned, globally across the entire metro region, and locally, as seen in the LISA clusters.

That spatial patterning of the rate of crime changes seems to reflect both polynucleation and sub-regional dynamics. The polynucleation is reflected in some of the highest net increases in violent crime rates being located immediately adjacent to urban centers like Philadelphia, the city of Chester or Pottstown (Figure 48). The sub-regional dynamics are reflected in a cluster of places just to the southwest of Philadelphia having change rates higher than the surrounding jurisdictions, and two clusters of places, the larger one stretching across central Delaware and Chester counties, the second in outer Montgomery County, having lower violent crime change rates than the surrounding jurisdictions (Figure 49).

4.5.5. Spatial error structure

Residuals from the final cross sectional model were not significantly spatially correlated (Global Moran's I = .04, ns). Examining the LISA map of residuals showed no sizable clusters (n > 3) of low-low or high-high clusters. The features included in the model accommodated all the significant spatial patterning in the outcome.

4.6. Violent crime population weighted percentiles (PWPs)

The violent crime outcome, in population weighted form, had a distribution whose skewness (.33) approximated a normal distribution, but which was flatter than the latter (kurtosis = 2.5). Given the population size of Philadelphia, there was a gap in the scores between 69 and 96. The outcome was analyzed assuming a normal distribution.

4.6.1. Distribution of outcome variance across jurisdiction-years, jurisdictions, groups of jurisdictions

The null model for violent crime in population weighted percentiles form appears in Table 12. There were significant sources of outcome variation both at the level of clusters of adjoining jurisdictions ($r_{ICC} = .25$, $p < .01$) and at the jurisdiction level ($r_{ICC} =.59$, $p < .001$). When the outcome is in PWP form, the estimated amount of outcome variation shared by neighboring jurisdictions is greater than was seen when the outcome was violent crime rates. There is somewhat more similarity among adjoining jurisdictions in their relative position in the MSA violence hierarchy than there is based just on the violent crime levels.

4.6.2. Impacts of time: Fixed and random

Controlling for policing arrangements and jurisdiction population revealed three effects of time (results not shown). Both fixed effects were significant, suggesting an increasing linear trend over time ($b=.28$, $p < .001$), and a significant positive quadratic departure from that trend $b=.09$, $p < .01$). The linear trend arises in part because Philadelphia, whose violence PWP ranged between 96.86 and 97.65, had a larger number of jurisdictions with scores above its score later in the period. The random effects of linear time were significant, suggesting spatiotemporal patterning in violent crime shifts ($\Omega = 2.31$, $z=7.32$, $p < .001$).

4.6.3. Cross-sectional model of violent crime PWPs

The final cross-sectional model with a spatial lag variable included appears in Table 13. The model takes into account policing arrangements, police coverage rates, community structure, fixed and random temporal effects, and spatially lagged violent crime. It also permits residuals among neighboring jurisdictions to be correlated.

Starting with the structural crime correlates, all three of the major dimensions correlate as expected. Jurisdiction-years with higher SES ($p < .01$), more stability ($p < .001$), and a lower fraction of their population which is African-American ($p < .001$) have significantly lower relative scores on violent crime. A one standard deviation increase in each is associated, respectively, with a relative violence score that is 2.5 percentiles lower, 7.7 percentiles lower, and 3.3 percentiles higher.

Other significant correlates were as follows. Jurisdictions with more population had higher violence rates ($p <.001$). Philadelphia, which is so much larger than any other jurisdictions, is clearly having a very strong impact on this relationship. Surrounding violence levels affect relative violence levels in the focal jurisdiction ($p <.001$). Controlling for surrounding violence rates renders the remaining outcome variance shared by neighboring jurisdictions non-significant. Finally, both linear and quadratic temporal trends proved significant.

Turning to the random effects, significant ecological differences in average relative violence levels over the period persisted ($p < .001$). Despite all the factors entered, relative violence levels still differed strongly even though 54 percent (1-(167/362)) of the between-jurisdiction violent crime differences had been accounted for by the model. The impacts of the passage of time on crime continued to vary significantly across jurisdictions ($\Omega = 2.33$, $p < .001$).

4.6.4. Clustering of values of time slope

The slopes capturing the net annual change in violent crime PWPs did not exhibit significant overall spatial autocorrelation (Global Moran's I = .033, ns). These slopes, expressed as departures from the average impact of linear time, appear in Figure 50. As was seen with the net impacts of time on violent crime rates, numerous jurisdictions had change rates significantly lower than the average rate (bottom left corner), and numerous jurisdictions had change rates significantly higher than the average rate (upper right corner).

The slopes, again expressed as departures from the average linear impact of time in years, are mapped in Figure 51. The map uses manual breaks. Places in the lowest grouping had a rate that was at least 2 PWPs less than the average net yearly shift (.5 PWPs), and those in the highest grouping had a rate that was at least 2 PWPs above the average net yearly shift. Some of the same jurisdictions with the highest average yearly increases on the violent crime rate similarly had the sharpest increases on relative violent crime position: Chester Township next to the city of Chester, and West Pottsgrove, next to Pottstown, is each an example.

In general terms, compared to the spatial patterning of the violent crime rate changes, these rate changes seem less clustered. Nevertheless, two groupings of jurisdictions are somewhat discernible. Along the border of Salem and Gloucester counties in New Jersey, it seems that several jurisdictions had yearly rates of crime change that placed them in the upper two change categories. A smaller cluster of jurisdictions toward the northwest corner of Bucks County also were in the upper two categories.

The LISA statistics, however, tell a different story than the manual break map. As shown in Figure 52, a large cluster of low-surrounded-by-low rate change jurisdictions straddles the Delaware County-Chester County border. Jurisdictions in this cluster were maintaining or slightly improving their relative position on violent crime during the study period. Also on the PA side, another smaller cluster of jurisdictions in outer Montgomery County was similarly maintaining or improving its relative safety standing. Other smaller pockets of low-surrounded-by-low rate changes also appear in the region.

Turning to the most rapidly increasing locales on relative violent crime, the influence of older urban centers appears. Coatesville city and South Coatesville borough form a cluster of high change rate surrounded by other high change rate jurisdictions. Upper Pottsgrove Township, next door to Pottstown is in a similar cluster.

In summary, the spatial perspective on the rate of change in violent crime PWPs provides additional insight into how this spatiotemporal interaction is organized. Although there was no overall pattern of global spatial autocorrelation, there were statistically significant pockets of jurisdictions sharing similar impacts of time. Most noticeable was the presence of a handful of jurisdictions in Chester and Montgomery counties that were maintaining or modestly improving their positions of relative safety. Also apparent were impacts of older urban centers like Coatesville on the rates of violent crime change in some immediately neighboring locales.

4.6.5. Spatial error structure

Residuals from the final cross sectional model for violent crime PWPs were still significantly spatially autocorrelated (Global Moran's I = .076, $p < .05$). Although this remaining spatial autocorrelation is troubling, it is understandable to some extent. It was not possible to create a spatial lag variable for the PWP variables that buffered beyond the edge of the MSA. The concept of relative standing only makes sense within the MSA. Consequently, the variable used instead, which did include places beyond the MSA, spatially lagged violent crime rates, only imperfectly captured the impacts of surrounding violence levels. Although the violent crime PWPs are a monotonic transformation of violent crime rates, the two variables are different, as is shown by the different spatial patterning of the variable crime rate changes for the two versions of violent crime.

4.7. Property crime counts

4.7.1. Distribution of outcome variance across jurisdiction-years, jurisdictions, groups of jurisdictions

To analyze property crime counts, negative binomial models were indicated. [11] The first model, equivalent to a null or ANOVA model in multilevel modeling, entered only the log of the population, in 100,000s, as an offset variable. [12] Variance estimates appear in Table 14. Results show significant ecological variation in the property crime rate at two levels. First, there is significant clustering of property crime levels among adjoining jurisdictions (r_{ICC} = .03, p < .001). So before taking temporal trends into account, property crime rates were similar between immediately neighboring jurisdictions, across the entire MSA. Given the descriptive results seen earlier, this is certainly no surprise. Crime levels also vary significantly across jurisdictions ((r_{ICC}

[11] The negative binomial models permit more complex decomposition of covariances and variances. Tests indicated this more complex treatment was warranted here. Using the negative binomial distribution precludes conducting Full Bayes MCMC models in MLwiN. Thus, the results reported here are simply from multilevel negative binomial maximum likelihood models. The entire set of analyses was repeated using Poisson distributions with overdispersion. The less complex modeling permitted with this distribution resulted in results that were markedly different, and counter to considerable communities and crime research.

[12] MLwiN requires entering the offset variable in a count model, also sometimes called an exposure variable, in natural log form (Rasbash, et al., 2009: 182, Eq. 12.1). If the variable is entered in 100,000s, the model becomes, in effect, about predicting crime rates per 100,000 (Raudenbush & Bryk, 2002: 312-315).

= .09, $p < .001$). The most sizable amount of outcome variation arises from yearly variation within jurisdictions, summed across jurisdictions.

Since these models control for population in 100,000s, the exponentiated coefficient is an incident rate ratio (IRR) representing an average (unweighted) property crime rate per 100,000 of 1,869 reported property crimes in an average jurisdiction-year. This expected count is about 7.8 times higher than the typical expected reported violent crime count.

4.7.2. Impacts of time: Fixed and random

Models controlling for jurisdiction population and policing arrangements, and entering three parameters for time (linear, fixed and random, quadratic, fixed only), revealed evidence of spatiotemporal interaction in crime changes (results not shown). The net impacts of linear time on changing property crime levels varied significantly across jurisdictions ($\Omega = .003$, $z = 10.26$, $p < .001$).

Results also showed a significant positive impact of the average quadratic departure from the average linear temporal trend ($p < .001$). This curvilinear effect of time suggests the rate of expected property crime increase was somewhat higher at the beginning and end of the period than in the middle years. This was seen earlier in some of the counties (Figure 41).

4.7.3. Cross-sectional model of property crime counts

The final cross-sectional model for property crime counts appears in Table 15. This model includes policing arrangements, policing department size, demographic structure, temporal trends and a spatially lagged outcome variable. (A model without the spatially lagged variable yielded an identical significance pattern and closely comparable b weights.) The model shown presents both the SES index and the stability index. For this outcome, even though, as described earlier, multicollinearity diagnostics did not suggest a concern, a different significance pattern was obtained if stability was residualised with respect to socioeconomic status. Those differences are mentioned below in the text.

Starting with the impacts of jurisdiction demographic structure, stability linked strongly in the negative direction with expected property crime rates. Each standard deviation increase in the stability index was associated with a reduction in the expected property crime rate of about 12 percent [1-(.85*.774)]. This appears to be the sturdiest demographic correlate of property crime counts. The theoretical implication is that the systemic model of community crime, with its strong emphasis on the important processes set in motion by stability, may be applicable to jurisdiction property crime levels (Bursik & Grasmick, 1993b).

In the model shown, SES has a non-significant impact. But if the overlap between SES and stability is removed from the stability index, the impacts of SES are significant and in the expected direction (results not shown; $b = -.142$, IRR= .868, $p < .001$). Each standard deviation increase in SES was associated with an expected property crime rate about 9.7 percent lower. The portion of stability independent of SES continued to link negatively with property crime rates ($p < .05$). Compared to the results shown in Table 15, there were no other impacts on the pattern of significance for other predictors when residualised stability was used. Given the above, in contrast to the findings with the violent crime counts, with property crime counts it appears that stability is more influential than status.

Turning to department size, jurisdiction-years with larger departments had *higher* expected property crime rates. [13]

The significant impact of the spatial lag predictor ($p <.001$) suggested that higher nearby property crime levels elevated focal jurisdictions property crime levels. Given the clustering of property crime rates seen in earlier descriptive results (Figure 29, Figure 30), this is not surprising.

Turning to time and first its fixed effects: the significant curvilinear effect of year-on-year changes persisted ($p < .001$). As noted earlier (Figure 41) property crime rates seemed to be dropping early in the period, and flattening out or trending upward somewhat later in the period. That shift persists after controlling for shifts in demographic structure and policing coverage.

Turning to time's random effect, the indicator of spatiotemporal interaction noted earlier persisted. The variation, from jurisdiction to jurisdiction, in the rate of year-on–year linear changes in property crime rates remained significant (Ω=.002, z=9.76, $p < .001$). The differential change rates in different locations were not explained away by policing arrangements, department size, or variations in community demographic structure.

[13] Doing an analysis with officer coverage rate rather than department size (results not shown) revealed a non-significant impact of coverage rate. In that model, stability remained influential ($p < .001$), even after removing its overlap with status ($p < .05$). The only other change in patterns of significance that resulted from substituting coverage for department size was a significant impact of racial composition ($p < .05$), in the expected direction, on property crime. This only showed up in models using residualised stability. Runs controlling for boroughs that were golf course boroughs (results not shown) had no impact on the significance pattern when either department size or officer coverage rate were used.

The caterpillar plot of these standardized *departures* from the average linear time slope (b=.002) appears in Figure 53. As in the earlier caterpillar plots, the error bars associated with each slope deviation represent 1.96 times the standard error.

Since the average linear rate (b) of yearly change was almost zero (.002,), this means that a number of jurisdictions on the lower left whose error bars do not cross the zero line had yearly property crime rate changes which were trending down significantly. In these locations, even after controlling for other factors, year-on-year changes in property crime rates were significantly lower than the average yearly change. These places were progressively diverging from the average trend, in the direction of increasing safety, over the period. Conversely, those dozen-plus jurisdictions in the upper right of the plot whose error bars do not cross the zero line were places where property crime on average during the period was increasing significantly faster than average. These places also were progressively diverging over the period, in the direction of becoming more dangerous faster than the typical jurisdiction. The one outlier whose rate of net yearly property crime increase was much higher than other jurisdictions was Eddystone, a small municipality southwest of Philadelphia, right along Interstate 95, and immediately to the north of the city of Chester. It was noted above in the violent crime rate analysis as a rapidly increasing locale. Here, its departure from the average impact of time is twice the nearest yearly change rate. The latter belongs to West Pottsgrove, immediately to the west of Pottstown. Again, the influence of nearby urban centers appears to be at work in both these communities, perhaps as a result of a crime spillover effect.

Turning to the random effects of the outcome, errors among adjoining jurisdictions were no longer significantly correlated. Significant variation ($p < .001$) does remain, however, in property crime rates at the jurisdiction level ($\Omega = .22$, $z=10.76$, $p < .001$). The model has been able to explain about 29 percent (1-.221/.312) of the jurisdiction-level outcome variation in property crime rates.

4.7.4. Clustering of values of time slope

The different change rates, expressed as departures from the average change rate (b=.002, exp(b) = 1, ns), are mapped in Figure 54. Other faster-increasing locales beyond those already mentioned included Norwood, a bit outside southwest Philadelphia, Bristol borough on the Delaware River in Bucks County, and North Wales and Sellersvillle in Montgomery County.

How sizable were the net yearly property crime increases in these locales? West Pottsgrove's linear slope (exp(.002+.12)) suggested its expected property crime rate was increasing by about 1.1 percent a year, for about a ten percent expected rate increase over the period. Eddystone's expected yearly increase was of course the most dramatic. Its expected net property crime rate increase was about 3 percent *a year* (exp(.002+.27)).

On the opposite end, places whose property crime rates were linearly decreasing during the period seemed to be spread throughout the region, although there were a number of jurisdictions in this group toward the southern NJ end of the MSA. Harrison Township in Gloucester County was experiencing the largest drop over time, its expected property crime rate dropping about sixteen percent a year. East Whiteland Township in mid-Chester County experienced a roughly comparable decline, about fifteen percent a year, in expected property crime rates.

Overall, the yearly rates of net property crime changes were not spatially autocorrelated (Global Moran's I = .0048, ns). The LISA statistics, however, did suggest local patterns of spatially auto-correlated crime change rates. The clusters appear in Figure 55. Most notable in the map are three clusters of low-surrounded-by-low jurisdictions: two separate clusters in Gloucester and Burlington counties on the NJ side, and one cluster straddling the Delaware-Chester county border on the PA side. These are statistically identified sub-regions, above the jurisdiction level, where property crime rates were either increasing less, or declining more, compared to those locations outside the sub-region.

4.7.5. Spatial error structure

Residuals from this final cross-sectional model for property crime counts were not significantly spatially correlated (Global Moran's I = -.04, ns).

4.8. Property crime population weighted percentiles (PWPs)

4.8.1. Distribution of outcome variance across jurisdiction-years, jurisdictions, groups of jurisdictions

The distribution of the variance of the property crime outcome, when it was in population weighted percentile form, is described in Table 16. This is a "null" model, with no predictors and no offset variable since the outcome was in PWP form.

The most sizable source of ecological outcome variation arises from the jurisdiction average crime levels (r_{ICC} = 59 percent, $p < .001$). The second most sizable source of ecological variation came from the clusters of neighboring jurisdictions (r_{ICC} = 25 percent, $p < .001$). The dynamics driving this latter source of ecological variation, sub-regional clustering of property crime percentiles, remains to be determined. But the size of this supra-jurisdiction dynamic "makes sense" given the descriptive results seen in the spatial patterning of property crime in this form. Sizable clusters of relatively high rate and relatively low rate jurisdictions were seen (see for example Figure 31). This means that there were clear sub-regions of the MSA where several neighboring jurisdictions had relatively low property crime PWPs, and thus represented sub-regions of relative safety.

4.8.2. Impacts of time: Fixed and random

With property crime rate PWPs as the outcome, does evidence of spatiotemporal interaction surface? This model controls for fixed linear and quadratic effects of time, population, policing arrangements, and nearby crime. Taking these factors into account, do the effects of linear time vary?

The answer is yes (results not shown). The impact of year-to-year linear changes on relative property crime position in the MSA did vary significantly across jurisdictions ($\Omega = 2.71$, $z = 8.88$, $p < .001$).

4.8.3. Cross-sectional model

The results from the final cross-sectional model for property crime PWPs appear in Table 17. The model includes a spatially lagged outcome as a predictor. [14]

Turning first to the demographic correlates, as was seen with property crime count models, when predicting relative property crime levels, stability appears to be the sturdiest

[14] The spatially lagged predictor is based on the property crime rate, not the property crime PWPs, since PWPs make no sense for jurisdictions outside the MSA. The lagged variable did include counties just beyond the MSA as neighbors for jurisdictions right on the boundary of the MSA. The lagged variable, however, is not Empirically Bayes weighted.

demographic correlate ($p < .001$). Each standard deviation increase in the stability index was associated with a relative property crime score that was 9.4 percentiles lower.

In this model another demographic correlate, jurisdiction age structure, proved relevant for the first time, but in a way that was opposite expectation. Recall that this variable reflects the availability of preteens, teens, and young adults needing supervision, *and* the lack of mature adults of supervising ages. Anderson speculated that in African-American communities, more teens and preteens on the street, *and* fewer "old heads" on the street, linked to more violence (Anderson, 1994, 2000). Here, *lower* property crime is associated with more street-age young and fewer adult supervisors ($p < .001$). Each standard deviation increase on this index was associated with a property crime level that was over two percentiles lower. Perhaps the presence of higher fractions of younger persons and fewer adults in their 50s and 60s, changes outside activity patterns in jurisdictions in ways that decrease the chances of property crimes.

It is surprising that SES demonstrated no significant link with property crime at the jurisdiction level. But, as mentioned earlier, this finding links in part to the strong SES-stability correlation. [15]

Returning to Table 17 and other fixed effects, time had a significant fixed average linear impact ($p <.05$). As was explained when discussing violent crime percentiles, this arises in part

[15] These models were repeated (results not shown) using only the portion of the stability index independent of SES; SES demonstrated a strong connection with property crime in the expected direction ($b = -5.05$, $p < .01$), and the impacts of partialled stability became non-significant. The two other changes in the significance pattern with the partialled stability model were as follows. The fraction of the African-American population became significant ($b=.21$, $p <.01$). Further, jurisdictions completely covered by their respective state police had lower relative property crime levels ($b = -9.9$, $p < .01$).

from Philadelphia having slightly lower property crime PWP scores later in the period, thus having more jurisdictions scoring above it later in the data period. Turning to size, jurisdictions with larger populations had higher relative property crime levels ($p < .01$). Finally, jurisdictions surrounded with places with higher relative property crime levels themselves had higher crime levels ($p < .001$). As has been seen numerous times in communities and crime work, nearby crime levels affect focal neighborhoods (Peterson & Krivo, 2010).

Turning to random effects, the spatiotemporal interaction persisted: the effects of linear time varied significantly across jurisdictions ($p < .001$). Relative property crime rates were changing faster in some jurisdictions than others, even after controlling for all other relevant factors. The corresponding caterpillar plot appears in Figure 56. These are deviations from an average linear increase of .28 property crime PWPs per year. Again, as with the earlier caterpillar plots, at both the bottom left and upper right of the figure there are a good number of jurisdictions whose departures from the average change rate were significant. Because the outcome is in PWP form, it is fair to say that jurisdictions in these two end groupings were experiencing shifting property crime niches over the nine year study period. Which jurisdictions were undergoing such shifts?

4.8.4. Mapping the slopes for time

Figure 57 provides clues. It maps the deviations from the average rate of yearly change in property crime PWPs (average = .28). The map uses manual breaks. Table 18 lists jurisdictions, starting with the fastest increasing, whose position on property crime, relative to the rest of the MSA, was moving up fastest during the study period. Three municipalities had net expected increases above the average change, of more than four property crime PWPs a year: Darby borough, right next to southwest Philadelphia; East Lansdowne, just north of Darby; and West Pottsgrove at the western edge of the MSA, just west of Pottstown. Norwood, just two boroughs southwest of Darby borough, also appeared in the fastest increasing group of ten, as did two older urban centers, Bristol borough on the Delaware River in Bucks County, and Coatesville in Chester County. Eddystone also was in the top ten group.

Behind these rapid increases are some substantial rate increases. Darby borough, for example, had property crime rates in the upper 3,000s and lower 4,000s per 100,000 residents early in the study period, but rates in the upper 4,000s and lower 5,000s at the end of the period. West Pottsgrove had some rates in the low 2,000s early in the period, and rates over double that by the end of the period. Other jurisdictions in the ten fastest increasing group saw comparably sized or sometimes even more dramatic increases in their property crime rates. Eddystone provides an example of the latter. Its property crime PWP was increasing on average 2.8 per year. It started the period with a property crime rate of 2,088, then jumped to rates ranging from 6,000 to 8,000 for the next three years, but had rates between 10,000 and 13,000 during the last three years of the period.

When these property crime rate changes moved a jurisdiction from a position in the property crime ordering that was below Philadelphia's rate, to a position above Philadelphia's rate, the PWP change was of course dramatic since Philadelphia's rate applied to about a third of the region's population. This switching from a spot below Philadelphia to above Philadelphia in the property crime ordering happened with several of these jurisdictions in the fastest increasing group including Darby borough, East Lansdowne, Bristol borough, Penns Grove, Coatesville, and others. Even if the jurisdiction scored above Philadelphia for only one year later in the study period, that had a significant impact on the average year-on-year linear impact of time. That artifact of PWPs aside, the actual rates in some of these highlighted places suggest they were experiencing sizable changes in actual property crime rates.

Turning to pockets where the temporal trend was toward decreasing relative property crime levels, the map suggested a couple of spatial groupings of jurisdictions. In Delran, Edgewater Park, and Mount Holly, all in New Jersey, all close to one another in eastern Burlington County, relative property crime rates were dropping as were actual reported property crime rates. Mount Holly, for example, had reported property crime rates per 100,000 around 5,000 early in the period, and these dropped to rates in the low 3,000s by the end of the study period. Changes like this were sufficient to move Mount Holly's relative property crime PWP from the mid 90th percentiles, positioned above Philadelphia in the property crime sorting, to a position below Philadelphia with crime percentiles in the 60s by the end of the period.

The locale with the second fastest-dropping relative property crime level during the period was East Whiteland Township in Chester County, located just south of the already mentioned Charlestown Township in Chester County. East Whiteland's average linear decrease was about 4.1 PWPs a year during the period. Its relative property crime scores were in the 60th percentiles early in the period, and in the 20th and 30th percentiles by the end of the period, corresponding to rate shifts in the 3,000-4,000 range down to around 1,300 by the end of the period. It may be significant that immediately to the west of East Whiteland township is West Whiteland Township, home to the Exton Square Mall. The mall originally opened in 1973, and experienced a modest renovation in the 1980s. The mall was closed for a more major renovation late in the 1990s. After more than two years of renovation, the mall re-opened in May, 2000 with a new anchor store, J.C. Penney, a doubling of retail space, and an additional 48 new stores (Weidener, 2000). Perhaps in the months and years subsequent to the mall's re-opening in mid-

2000, potential property offenders were lured out of East Whiteland Township, towards the denser target opportunities at the expanded, reopened mall next door.

4.8.5. Clustering of values of time slope

Rates of linear net change on property crime PWPs were marginally spatially autocorrelated (Global Moran's I = .051, $p < .07$). This marginal overall level of spatial autocorrelation led us to explore whether significant local clusters of similarly changing rates appeared. The LISA map appears in Figure 58. Although configured somewhat differently, the three clusters of relative safety – low scoring jurisdictions surrounded by other low scoring jurisdictions – seen when property crime rates were examined (Figure 55) reappear. But two new clusters merit mention. Just southwest of Philadelphia, stretching from Upper Darby along US-route 1 down to Clifton Heights and Aldan is a small high-high cluster. That is, this group of jurisdictions, and the jurisdictions immediately adjoining them, were experiencing more sizable increases in relative property crime than those around them. Another high-high cluster emerged on the western edge of the MSA and included Pottstown and two of its neighbors, Upper Pottsgrove and North Coventry.

These LISA statistics for property crime PWPs confirm, albeit with important differences in the patterning, the message from the same map for property crime rates. Statistically identifiable sub-regions in the MSA were experiencing similarly discrepant effects of time on crime changes. With property rates, discrepancies creating sub-regions of maintaining or increasing safety were identified. With property percentile scores, these sub-regions appeared again, as did two sub-regions where relative safety was dissipating faster than elsewhere in the region.

4.8.6. Spatial error structure

Residuals from the final cross-sectional model for property crime percentiles were not significantly spatially autocorrelated (Global Moran's I = -.013, ns).

4.9. Predicting linear rates of change

If crime was changing at different yearly rates in different jurisdictions, did those differential change rates link to any jurisdiction attributes at the beginning of the study period?

To answer this, for each of the four outcomes (violent or property crime, counts or PWPs), spatial regression models were run. Predictors included jurisdiction structural features at the beginning of the period including jurisdiction population, law enforcement coverage rates, and policing arrangements. Both spatial error models and models with a spatially lagged outcome were run.

For both forms of the property crime outcome, the count (transformed to a rate), and the percentiles, higher SES jurisdictions had smaller yearly net crime increases ($p < .01$ for property crime count, $p < .001$ for property percentiles model; results not shown). Results were comparable regardless of whether a spatial error or a spatial lag model was used.

Thus, for property crime, higher initial SES in a jurisdiction helps buffer the locale from more sizable increases in property crime, whether the latter is a rate or a relative measure. This impact of SES is *separate* from its impact on crime levels shown in some of the models.

4.10. Discussion

4.10.1. Limitations

Although the model parameters directly addressing temporal and spatiotemporal variation can be unambiguously interpreted, the cross-sectional impacts of structural features on crime have more ambiguity. This arises because not only does community structure affect crime levels; the reverse also is true (Liska, Logan, & Bellair, 1998; R. B. Taylor, 1995). Crime levels in a jurisdiction in an earlier year in the series could affect structural or law enforcement features (K. Harries, 1974: 92) in a later year in the series. Therefore the safest interpretation of the structural and law enforcement findings of this chapter is that they capture correlates of the crime levels as revealed over almost an entire decade.

4.10.2. Ecology of crime

Table 19 provides a summary of cross-sectional correlates from final models with spatial lag variables included. Starting with fixed effects of jurisdiction demographic structure, it proves illuminating to compare the pattern of findings here with earlier work.

Stability proves the sturdiest structural crime covariate, in that it is the most general, proving highly significant to all four outcomes. As operationalized here, the variable includes aspects of tenure, occupancy, and household structure. Given dramatic declines in marriage rates in the last several decades the link between married households and ownership may strike some as novel. But factorial ecology census studies from the 1960s and before routinely bundled these together in a broader stability dimension (Hunter, 1974b).

Stability's strong linkage with both property and violent crime levels is somewhat surprising given the results of Pratt's and Cullen's meta-analysis of community crime correlates (Pratt & Cullen, 2005). That work (see their Table 1) ranked two SES factors (unemployment, # 2; poverty, #10) and two race factors (percent nonwhite, # 4; percent black, #7) in the top ten.

Residential mobility, the opposite of stability, was ranked # 17 based on its average effect size. Stability was found significant in about half of the studies reviewed. So it has proved a more powerful crime correlate at the jurisdiction level than expected based on this summary of the earlier structural work ranging across a wide array of community units of different sizes.

Of course, the discrepancy in relative importance could have numerous sources. The units of analysis here were not reflected in Pratt and Cullen's categorization (p. 395) of units of aggregation, underscoring the paucity of jurisdiction-level, intra-metropolitan work in community criminology. Further, the stability variable as operationalized here is more than just length of residence or tenure. Stability may have been under-operationalized resulting in weak construct validity in other studies (Messick, 1995).

These points aside, two important implications emerge given the findings seen here for residential stability. First, given the prominent role played by structural stability in the basic systemic model of crime and the powerful roles it plays here for both property and violent crime, that model may be extensible to inter-jurisdictional crime patterns (Bursik & Grasmick, 1993b: 34-35). Second, the only sizable, recent, multi-metropolitan study of intra-metropolitan crime patterning failed to include stability as a predictor (Kneebone & Raphael, 2011). Given the results here, the results from that earlier study, given that exclusion, may have mis-estimated the impacts of other structural factors.

Turning to SES, this is one of the generally strongest correlates of community crime levels. Pratt and Cullen conclude: "based on the results of these analyses, the empirical status of resource/economic deprivation theory is favorable. The perspective appears to be well supported across all macro-level studies of crime" (Pratt & Cullen, 2005: 412).

The results here, however, suggest the jurisdiction-level connection applies most clearly **only to violent crime**. SES's contribution to property crime is less certain. The expected negative association surfaced only after the SES-linked portion of stability had been removed. Pratt and Cullen's conclusion may have been more general than warranted.

SES, however, did have one clear-cut connection with property crime. Net yearly trends in property crime changes were more *positive* in *lower* SES locales. Stated simply, property crime got worse more quickly in lower SES locales. This strong connection appeared regardless of whether property crime rates or relative levels were the outcome of interest, and regardless of whether regression with spatial errors or with a spatially lagged outcome as a predictor was used. The broader point seems plausible: SES buffers jurisdictions from *increasing* property crime vulnerability. How this works is probably worthy of investigation. The political economy implications of this link are explored below.

Turning back to the crime outcomes, the SES results here would seem to align most closely with the work on SES and homicide by Land, McCall, and their associates (Land, et al., 1990; McCall, 2010; McCall, et al., 2010; McCall & Nieuwbeerta, 2007). There are important questions about their invariance thesis (R. B. Taylor, 2010; Ralph B. Taylor, 2015). And their work may have included some mis-specified models by leaving out a sufficient number of stability indicators. Nonetheless, they have linked higher homicide to lower SES using a wide range of units of aggregation. The current work suggests that link applies to violent crime levels more broadly, and at the level of intra-metropolitan jurisdictions. These both may be important extensions of their thesis.

Racial composition, operationalized as percent African-American, also connected only to violent crime. More predominantly African-American locales had higher violence and relative violence levels. No net connection with property crime surfaced. This strong linkage with violence levels agrees with recent cross sectional work by Peterson and Krivo at the census tract level. They found that tract racial composition still linked significantly to violence levels even after controlling for nearby violent crime (Peterson & Krivo, 2010: Table 5.2). [16]

Age structure, built along lines to reflect Anderson's youth/old heads discussion showed only one connection, and that was in an unexpected direction. Property crime rates were lower in places with more youth and fewer old heads. The relevant dynamics are not immediately apparent. Perhaps the presence of large numbers of preteens/teens/young adults alters natural surveillance patterns on streets in ways that depress property offending. The link, however, should be viewed with considerable caution since is appeared only for relative property crime, and not for property crime.

Inspiring somewhat more confidence are the connections between jurisdiction size, measured as population, and higher relative levels for both violent and property crime. In the large scale ecological work there is a long tradition of work on the correlates of a city size/density factor (B.J.L. Berry, 1965; Brian J.L. Berry, 1972; B. J. L. Berry & Kasarda, 1977). Land and colleagues have linked size/density with higher violence levels (Land, et al., 1990). The theoretical basis in urban sociology goes back to Wirth's first statement of his urbanism

[16] We did not replicate their test which examined the impact of surrounding crime after also controlling for surrounding disadvantage and surrounding racial composition.

thesis (Wirth, 1938). [17] The MSA's less populated jurisdictions are certainly the most rural, and its most populated jurisdictions the most urban. Rigorous empirical tests of urbanism, and its offshoot subcultural theory have received considerable empirical support (Fischer, 1975). For example, community size does link to trust of neighbors, with that trust weaker in more populous communities (Fischer, 1982).

Although the link between larger jurisdictions and higher crime aligns with both urbanism and subcultural theory, the responsible dynamics are not yet certain. For example, this could be a reflection of a gradient-periphery, crime-linked dynamic. Also, the responsible conditioning factor might be areal density, not community size, although the two are impossible in practical terms to separate. It also is not clear why the link shows for relative crime but not crime rates. At the least, however, it is clear that size deserves attention.

4.10.3. Geography of crime

The strong influence of the spatially lagged outcome as a predictor speaks to extra-jurisdiction, sub-regional dynamics at work. Crime in focal jurisdictions was affected by what was happening nearby in the same year. Observing such spatially lagged impacts is not especially surprising when the units are relatively compact, like census tracts or census block

[17] Although he was not explicitly concerned with crime, his model has clear implications for crime. When speaking of higher areal density, generally found also in the larger cities, he suggested such a condition "foster[s] a spirit of competition … and mutual exploitation … give[s] occasion to friction and irritation … [and] nervous tensions … are accentuated" (Wirth, 1938: 15-16). Further, the more urban as compared to rural the community, "Personal disorganization, mental breakdown, suicide, delinquency, crime, corruption and disorder might be … more prevalent" (Wirth, 1938: 23).

groups. The work here suggests these adjacency impacts apply even when considering larger ecological units. Despite the larger distances involved, nearby crime still matters.

The spatial lag impact is the first of several ways that the analysis considers extra-jurisdiction dynamics. The models also allowed neighboring jurisdictions to share residual outcome variation. For the violent crime rate model, such shared variation remained significant even after allowing crime changes over time to occur at different rates in different places. Nearby jurisdictions had something in common which was outside the elements included in our model and was shaping violence rates.

Turning to spatiotemporal interactions, for all four outcomes, jurisdictions *as a group* demonstrated significant departures from the average temporal trend. The passing years were affecting jurisdiction crime levels in different ways, even after controlling for surrounding crime, law enforcement, and the structural conditions in the jurisdictions. Trends varied across places.

Switching from the entire region to individual jurisdictions, for most outcomes dozens of them had *individual* places rates of yearly crime change that differed significantly from the average (e.g., Figure 50, Figure 53, Figure 56). This demonstrates a spatiotemporal interaction, at the jurisdiction level, in how crime rates change. Some places were improving significantly faster than average over time, and some places were worsening significantly faster than average over time. This feature of the findings has implications (see below) for the political economy of the region.

Further, as mentioned above, this spatiotemporal interaction, at least for property crime relative levels and rates, was conditioned by jurisdiction SES at the beginning of the period. The rate at which this crime increased was lower in higher SES localities. We turn to this point again when considering implications for political economy.

Finally, spatiotemporal interaction at the sub-region level emerged as reflected in the spatial patterning of the differential time effects. For some outcomes, there appeared to be a spatially non-random pattern to adjusted temporal rates of crime change. Linear trends exhibited significant global spatial autocorrelation for violent crime rates, and marginally significant autocorrelation for property crime percentiles. And for all four outcomes, significant *local* clustering of the rate of crime change appeared. In each instance, clusters of jurisdictions whose change rates were lower than average, and clusters whose change rates were higher than average, were statistically identified. This demonstrates a spatiotemporal interaction in how crime rates change at the *supra*-jurisdiction or sub-regional level. There were identifiable sub-regions where public safety was deteriorating faster than average or improving faster than average across the nine year study period.

Finally, the most important point of the geographic findings here is that they raise questions about previous works which have estimated intra-metropolitan crime patterning but have done so without taking spatial or spatiotemporal patterning into account. The current models observed significant impacts of surrounding crime rates. They also observed significant clustering of model errors at the extra-jurisdictional level. Cross sectional or dynamic models which *fail* to take such features into account may generate mis-estimated links between structure and crime.

4.10.4. Political economy of crime

As noted in chapter 1, Adams and colleagues have been arguing, as have other scholars of the Philadelphia metropolitan region, that inequality in neighborhood quality and services has been increasing in the region over time. The present results depict, for the first time, how inequalities across the region in public safety at the jurisdiction level also have been increasing during the first nine years of the Twenty-First Century.

For both property crime and violent crime, more than a dozen jurisdictions got safer significantly faster, year by year, relative to the rest of the region, even after controlling for jurisdiction residential structure, law enforcement, and surrounding crime. Similarly, more than a dozen places got more dangerous significantly faster, year by year, relative to the rest of the region, after controlling for the same factors. These changes represent increasing inequalities for two reasons.

First, at least in the case of property crime shifts, higher initial SES levels protected jurisdictions against property crime increases in later years. Being well off socioeconomically at the beginning of the decade helped protect against deteriorating safety from property crime later in the decade.

Second, these differential impacts of time were not spatially random but rather seemed to affect sub-regions. Getting better faster seemed to routinely be the story for clusters of jurisdictions straddling mid-Chester and mid-Delaware counties. Getting worse faster seemed to routinely be the story for clusters of jurisdictions stretching from immediately southwest of Philadelphia down to the city of Chester and beyond, and smaller clusters of communities around Pottstown or Coatesville. These crime concentration effects appeared especially strong for violent crime shifts.

Although the increasing inequality is spatially structured, the spatial organization of it follows no simple intra-regional pattern. For example, it was not the case that close in suburbs were getting worse faster than other places throughout the region. Rather, it seemed that certain parts of the region are at higher risk than other places, due to numerous factors. The small jurisdictions between Philadelphia and Chester have experienced significant demanufacturing over the last few decades, and even recently with the closing of the Sunoco Refinery. They are located close to high crime locales like the city of Chester or southwest Philadelphia. They are easily accessible by major interstates, increasing their potential for open air drug market activity (Rengert, Ratcliffe, & Chakravorty, 2005). The communities around Coatesville and Pottstown have suffered due to the strong economic downturns experienced in those cities. In Molotch's term, local history or structuration continues to play out (Molotch, et al., 2000).

4.10.5. Implications for prevention

Law enforcement coverage showed no current link to crime levels. This is not new. At the city level, variations in police coverage rates "do not reflect inter-city crime levels, but more prosaic factors such as differences in fiscal support" (K. Harries, 1974: 92). This appears to be true too, at least cross-sectionally, at the jurisdiction level.

That said, the shared local shifts in crime levels means that in some parts of the metro area, nearby jurisdictions were similarly plagued with rising crime levels. There are implications for police intelligence (Ratcliffe, 2008). If local departments in these afflicted sub-regions can pool intelligence on crime and criminals, they may discover some commonalities in criminals or criminal operations. These matters get discussed more fully in the closing chapter.

Table 8. Descriptive statistics for multilevel time models

Variable	name	N	Min	Max	Mean	SD	Median
N reported violent crimes	n_violto	3,195	0.00	22,884	90.06	1,136.96	9.00
N reported property crimes	n_propto	3,195	0.00	75,188	412.09	3,450.55	96.59
Violent crime rate: PWP form	pwpvio	3,195	0.00	100.00	34.59	21.74	32.66
Property crime rate: PWP form	pwppro	3,195	0.00	100.00	31.23	24.87	26.74
Natural log of population	logpop	3,195	2.83	14.23	8.72	1.14	8.77
Natural log of population in 100,000s	lnp100k	3,195	-8.74	2.72	-2.79	1.14	-2.74
Linear trend for year (2004=0)	yrctr	3,195	-4.00	4.00	0.00	2.58	0.00
Quadratic trend for year (2004=0)	yrctrsq	3,195	0.00	16.00	6.67	5.85	4.00
SES index	sesindx	3,195	-4.16	1.77	0.00	0.72	0.05
Stability index	stabindx	3,195	-2.73	1.79	0.00	0.85	0.07
Age structure (Anderson) index	codeindx	3,195	-3.60	4.29	0.00	0.63	-0.03
Percent population African-American	pblapop	3,195	0.00	93.28	8.97	14.08	3.51
Covered only by state police	sponly	3,195	0.00	1.00	0.15	0.36	0.00
Covered partially by state police	sppart	3,195	0.00	1.00	0.01	0.12	0.00
Part of multi-jurisdiction department	multdept	3,195	0.00	1.00	0.08	0.27	0.00
Coverage: no information	nopdinfo	3,195	0.00	1.00	0.00	0.05	0.00
Coverage: own dept, 0 FT sworn	owndeptze	3,195	0.00	1.00	0.04	0.20	0.00
Spatial lag: property crime count	fEnpro	3,195	-1.52	4.07	0.04	0.65	-0.07
Spatial lag: violent crime count	fenvio	3,195	-0.87	3.86	0.03	0.64	-0.17

Note. Units = jurisdiction years, 355 jurisdictions, 9 years.

Table 9. ANOVA model for number of violent crimes, controlling for population

				95 % CI	
	b	sd	IRR	LCL	UCL
Constant	5.480	0.078	239.845	205.915	279.366
Random effects					
	Variance	se	p <	r(ICC)	
Neighboring jurisdictions	0.221	0.108	.05	0.099	
jurisdiction	1.428	0.137	.001	0.641	
Year-within-jurisdiction					
(1)	0.298	0.068			
(2)	0.280	0.010			

Note. Outcome = yearly violent crime counts at jurisdiction level. Units = jurisdiction-years (n=3,177). Tavistock and Pine Valley excluded. Negative binomial multilevel model. Population, in 100,000s, entered as an offset variable. The constant, in IRR form, can be interpreted as a typical jurisdiction-level violent crime rate, per 100,000 population. Run = 20130422_053

Table 10. Violent crime count, final cross sectional model, no spatial lag

Variable	Label	b	se	IRR	z	p<	95 % CI	
Fixed effects							LCL	UCL
Constant	cons	4.964	0.111	143.103			115.027	178.032
Time: linear	yrctr	0.007	0.006	1.007	1.18	ns	0.995	1.019
Time: quadratic	yrctrsq	0.001	0.001	1.001	1.25	ns	0.999	1.004
Coverage: only state police	sponly	0.086	0.146	1.090	< 1	ns	0.819	1.451
Coverage: partial state police	sppart	-0.548	0.327	0.578	-1.68	ns	0.305	1.097
Coverage: multi-jurisdiction	multdept	0.564	0.168	1.758	3.37	.001	1.266	2.441
Coverage: no information	nopdinfo	0.730	0.712	2.075	1.03	ns	0.514	8.379
Coverage: own dept, 0 FT sworn	owndeptze	0.177	0.126	1.193	1.40	ns	0.932	1.528
Woodland TWP	woodland	-1.179	0.667	0.308	-1.77	ns	0.083	1.137
N sworn officers	lnoff	0.065	0.037	1.067	1.73	ns	0.991	1.148
SES index	sesindx	-0.149	0.064	0.862	-2.31	.05	0.760	0.978
Stability index	stabindx	-0.416	0.055	0.659	-7.50	.001	0.591	0.735
Age index	codeindx	0.072	0.054	1.074	1.34	ns	0.967	1.193
Percent African-American	pblapop	0.011	0.003	1.011	3.73	.001	1.005	1.017

Random effects		Variance	se	p <
Neighboring jurisdictions		0.056	0.029	.05
jurisdiction		0.383	0.038	.001
Year-within-jurisdiction				
	(1)	1.056	0.060	
	(2)	0.058	0.004	
Linear time		0.005	0.001	.001

Note. Outcome = yearly violent crime counts at jurisdiction level. Units = jurisdiction-years (n=3,177). Tavistock and Pine Valley excluded. Multilevel, negative binomial estimation IRR = incident rate ratio. Population, in 100,000s, entered as an offset variable. The constant, in IRR form can be interpreted as a typical jurisdiction-level violent crime rate, per 100,000 population. Run = 055

Table 11. Violent crime count, final cross sectional model, with spatial lag

							95 % CI	
Fixed effects		b	se	IRR	z	p <	LCL	UCL
Constant	cons	4.932	0.107	138.708			4.722	5.143
Time: linear	yrctr	0.005	0.006	1.005	<|1|	ns	-0.006	0.016
Time: quadratic	yrctrsq	0.001	0.001	1.001	1.28	ns	-0.001	0.004
Coverage: only state police	sponly	0.146	0.141	1.157	1.04	ns	-0.130	0.423
Coverage: partial state police	sppart	-0.511	0.315	0.600	-1.62	ns	-1.128	0.107
Coverage: multi-jurisdiction	multdept	0.578	0.162	1.783	3.58	.001	0.262	0.895
Coverage: no information	nopdinfo	0.810	0.681	2.248	1.19	ns	-0.524	2.145
Coverage: own dept, 0 FT sworn	owndeptze	0.199	0.123	1.220	1.61	ns	-0.043	0.441
Woodland TWP	woodland	-1.230	0.650	0.292	-1.89	ns	-2.504	0.045
N sworn officers (+1 logged)	lnoff	0.070	0.036	1.072	1.93	ns	-0.001	0.140
SES index	sesindx	-0.135	0.063	0.874	-2.16	.05	-0.258	-0.012
Stability index	stabindx	-0.407	0.054	0.665	-7.61	.001	-0.512	-0.302
Age index	codeindx	0.056	0.052	1.058	1.08	ns	-0.046	0.159
Percent African-American	pblapop	0.011	0.003	1.011	3.85	.001	0.005	0.016
Spatially lagged crime count	fenvio	0.131	0.036	1.140	3.65	.001	0.061	0.201

Random-effects		Variance	se	p <
Neighboring jurisdictions		0.045	0.025	.05
jurisdiction		0.362	0.035	.001
Year-within-jurisdiction				
	(1)	1.022	0.058	
	(2)	0.057	0.004	
Time: linear		0.005	0.001	.001

Note. Outcome = yearly violent crime counts at jurisdiction level. Units = jurisdiction-years (n=3,177). Tavistock and Pine Valley excluded. Multilevel, negative binomial estimation IRR = incident rate ratio. Population, in 100,000s, entered as an offset variable. The constant, in IRR form can be interpreted as a typical jurisdiction-level violent crime rate, per 100,000 population. Run = 056

Table 12. Violent crime population weighted percentiles (PWP), Null model

			95 % CI	
	b	sd	LCL	UCL
Constant	30.546	1.438	27.737	33.31563
Random effects				
	Variance	sd	p <	r(ICC)
Neighboring jurisdictions	155.05	37.71	.001	0.251
jurisdictions	362.61	34.98	.001	0.588
Years within jurisdictions	99.54	2.64	.001	

Note. Outcome = violent crime in population weighted percentile form. Units = jurisdiction-years. (n=3,177). Tavistock and Pine Valley excluded. Results from MCMC model (burnin=25,000; chains=50,000). B = mean of estimates across chains, sd = standard deviation of b estimates. Bayesian DIC = 24,112.22 (run056)

Table 13. Violent crime PWPs: Final cross-sectional model, with spatial lag

Variable	label	b	sd	p <	95% CI LCL	95% CI UCL
Fixed effects					LCL	UCL
Constant	cons	38.29	2.23		33.91	42.65
Population (in 100,000s, logged)	lnp100k	2.55	0.76	.001	1.08	4.04
Time: linear	yrctr	0.46	0.13	.001	0.21	0.71
Time: quadratic	yrctrsq	0.08	0.03	.01	0.02	0.14
Coverage: only state police	sponly	3.19	2.34	ns	-1.36	7.79
Coverage: partial state police	sppart	-3.71	6.29	ns	-16.08	8.59
Coverage: multi-jurisdiction	multdept	4.25	3.03	ns	-1.72	10.18
Coverage: no information	nopdinfo	-4.20	14.08	ns	-31.86	23.26
Coverage: own dept, 0 FT sworn	owndeptze	-1.28	2.12	ns	-5.41	2.87
Woodland TWP	woodland	8.11	14.86	ns	-20.99	37.14
Sworn officers/1,000 population	offra	-0.10	0.18	ns	-0.45	0.25
SES index	sesindx	-3.79	1.41	.01	-6.58	-1.03
Stability index	stabindx	-8.87	1.12	.001	-11.09	-6.68
Age index	codeindx	1.01	0.92	0.136	-0.79	2.82
Percent African-American	pblapop	0.23	0.06	.001	0.11	0.36
Spatial lag	flrvio	3.85	0.92	.001	2.03	5.65
Random effects	Variance	sd	p <			
Neighboring jurisdictions	6.08	8.75	ns			
jurisdiction	167.19	15.65	.001			
Year-within-jurisdiction	108.65	3.09				
Time: linear	2.33	0.32	.001			

Note. Outcome = yearly violent crime population weighted percentiles at jurisdiction level. Units = jurisdiction-years (n=3,177). Tavistock and Pine Valley excluded. Multilevel, MCMC results (burnin=50,000; chains=150,000). Normal distribution assumed. For fixed effects b/sd = mean estimate of b/sd of those estimates. For random effects variance/sd = mean of variance estimates/sd of those estimates. Spatial lag variable is buffered beyond MSA for jurisdictions on the edge, but not Empirically Bayes weighted based on population, and uses first order queen contiguity. Lag is based on violent crime rates since PWPs cannot be constructed for jurisdictions outside the MSA. Bayesian DIC = 24581.43 (run060_revised)

Table 14. ANOVA model for number of property crimes, controlling for population

				95 % CI	
	b	se	IRR	LCL	UCL
Constant	7.533	0.042	1,868.6	1,721.4	2,028.4
Random effects					
	Variance	se	p <	r(ICC)	
Neighboring jurisdictions	0.104	0.032	.001	0.030	
jurisdiction	0.312	0.031	.001	0.092	
Year-within-jurisdiction					
(1)	2.957	0.223			
(2)	0.038	0.002			

Note. Results from multilevel negative binomial model. Outcome = yearly property crime counts at jurisdiction level. Units = jurisdiction-years (n=3,177). Tavistock and Pine Valley excluded. IRR = incident rate ratio. Population, in 100,000s, entered as an offset variable. The constant, in IRR form can be interpreted as a typical jurisdiction-level property crime rate, per 100,000 population. (run 062)

Table 15. Final cross-sectional model of number of property crimes per 100,000 population (n_propto)

						95 % CI	
Fixed effects		b	se	IRR	p <	LCL	UCL
Constant	cons	7.242	0.074	1397.437		7.098	7.387
Time: linear	yrctr	0.002	0.004	1.002	ns	-0.005	0.009
Time: quadratic	yrctrsq	0.007	0.001	1.007	.001	0.006	0.009
Coverage: only state police	sponly	0.041	0.100	1.042	ns	-0.155	0.237
Coverage: partial state police	sppart	-0.360	0.226	0.698	ns	-0.804	0.084
Coverage: multi-jurisdiction	multdept	0.002	0.118	1.002	ns	-0.229	0.233
Coverage: no information	nopdinfo	-0.211	0.507	0.810	ns	-1.205	0.782
Coverage: own dept, 0 FT sworn	owndeptze	0.212	0.075	1.237	.01	0.066	0.359
Woodland TWP	woodland	-1.178	0.422	0.308	.01	-2.005	-0.351
N sworn officers	lnoff	0.077	0.025	1.080	.01	0.029	0.125
SES index	sesindx	-0.037	0.041	0.963	ns	-0.118	0.043
Stability index	stabindx	-0.256	0.039	0.774	.001	-0.332	-0.180
Age index	codeindx	-0.034	0.035	0.967	ns	-0.102	0.034
Percent African-American	pblapop	0.001	0.002	1.001	ns	-0.003	0.005
Spatial lag	fEnpro	0.195	0.023	1.215	.001	0.151	0.239
Random effects	Variance	se	p <				
Neighboring jurisdictions	0.0107	0.0127	ns				
jurisdiction	0.2210	0.0205	.001				
Year-within-jurisdiction							
(1)	1.8028	0.1306					
(2)	0.0230	0.0014					
Time: linear	0.0021	0.0002	.001				

Note. Outcome = yearly property crime counts at jurisdiction level. Units = jurisdiction-years (n=3,195). Golf boros, Tavistock and Pine Valley, included. Multilevel model assuming negative binomial distribution of the outcome. IRR = incident rate ratio. Population, in 100,000s, entered as an offset variable. The constant in IRR form can be interpreted as a typical jurisdiction-level property crime rate, per 100,000 population. Results using SES residualized with respect to stability provided significant negative impact of SES on property crime rates; significance pattern was otherwise unchanged. (run 064)

Table 16. Property crime in population weighted percentiles (PWP), null model

Fixed effects	b	sd		95 % CI	
				LCL	UCL
Constant	30.5	1.4		27.7	33.3
Random effects	Variance	sd	p <	r(ICC)	
Neighboring jurisdictions	155.0	37.7	.001	.25	
jurisdiction	362.6	35.0	.001	.59	
Year-within-jurisdiction	99.5	2.6	.001		

Note. Outcome = Yearly property crime rates per 100,000, in PWP form at jurisdiction level. Units = jurisdiction-years (n=3,177). Tavistock and Pine Valley excluded. Years = 2000-2008. MCMC estimation (burnin = 25,000; chains=50,000). "Variance" reflects the average of the variance estimates; sd = standard deviation of those variance estimates. Bayesian DIC = 24112.22

Table 17. Property crime in population weighted percentiles (PWP), final cross sectional model

Fixed effects		b	sd	p <	95 % CI	
Variable	label				LCL	UCL
Constant	cons	38.211	3.155		31.916	44.258
Population (logged, 100,000s)	lnp100k	2.634	1.033	.01	0.606	4.652
Time: linear	yrctr	0.284	0.128	.05	0.035	0.535
Time: quadratic	yrctrsq	0.019	0.027	ns	-0.034	0.071
Coverage: only state police	sponly	-4.310	3.040	ns	-10.300	1.588
Coverage: partial state police	sppart	-12.325	8.207	ns	-28.053	3.763
Coverage: multi-jurisdiction	multdept	-3.937	3.954	ns	-11.619	3.698
Golf course borough	golfboro	34.200	18.166	.05	-1.930	68.703
Coverage: no information	nopdinfo	-7.410	18.742	ns	-44.889	29.273
Coverage: own dept, 0 FT sworn	owndeptze	-0.272	2.076	ns	-4.394	3.731
Woodland TWP	woodland	-17.693	20.785	ns	-58.745	22.901
Sworn officers per 1,000 population	offra	0.034	0.293	ns	-0.531	0.614
SES index	sesindx	-0.525	1.573	ns	-3.619	2.570
Stability index	stabindx	-11.030	1.450	.001	-13.905	-8.225
Age index	codeindx	-3.222	0.933	.001	-5.040	-1.404
Percent African-American	pblapop	0.096	0.078	ns	-0.053	0.250
Spatial lag	fLrpro	6.971	0.913	.001	5.174	8.770
Random effects	Variance	sd	p <			
Neighboring jurisdictions	11.208	17.591	ns			
jurisdiction	303.420	28.613	.001			
Year-within-jurisdiction	77.974	2.242				
Time: linear	2.502	0.294	.001			

Note. Outcome = Yearly property crime rates per 100,000, in PWP form at jurisdiction level. Units = jurisdiction-years (n=3,177). Tavistock and Pine Valley excluded. Years = 2000-2008. MCMC estimation (burnin = 25,000; chains=50,000). For random effects" "Variance" reflects the average of the variance estimates; "sd" = standard deviation of those variance estimates. Bayesian DIC = 23568.90 (run 067)

Table 18. Ten jurisdictions with highest yearly rate of increasing property crime population weighted percentiles

Darby borough	4.38
West Pottsgrove	4.33
East Lansdowne	4.31
Bristol borough	3.58
Pennsgrove	3.33
Norwood	3.19
Coatesville	2.91
Parkesburg	2.91
North Wales	2.89
Eddystone	2.78

Table 19. Summary table of cross-sectional impacts

Predictor	Outcome			
	Violent rate	Violent percentile	Property rate	Property percentile
Fixed effects				
Size	na	.001	na	.01
SES	.05	.01	ns	ns
Stability	.001	.001	.001	.001
Age structure	ns	ns	ns	.001
Racial composition	.001	.001	ns	ns
Law enforcement coverage	ns	ns	.01	ns
Spatial lag	.001	.001	.001	.001
Random effects				
Neighboring jurisdictions	.05	ns	ns	ns
Random effect: linear time	.001	.001	.001	.001
Linear time slopes: Global Moran's I	.01	ns	ns	.07

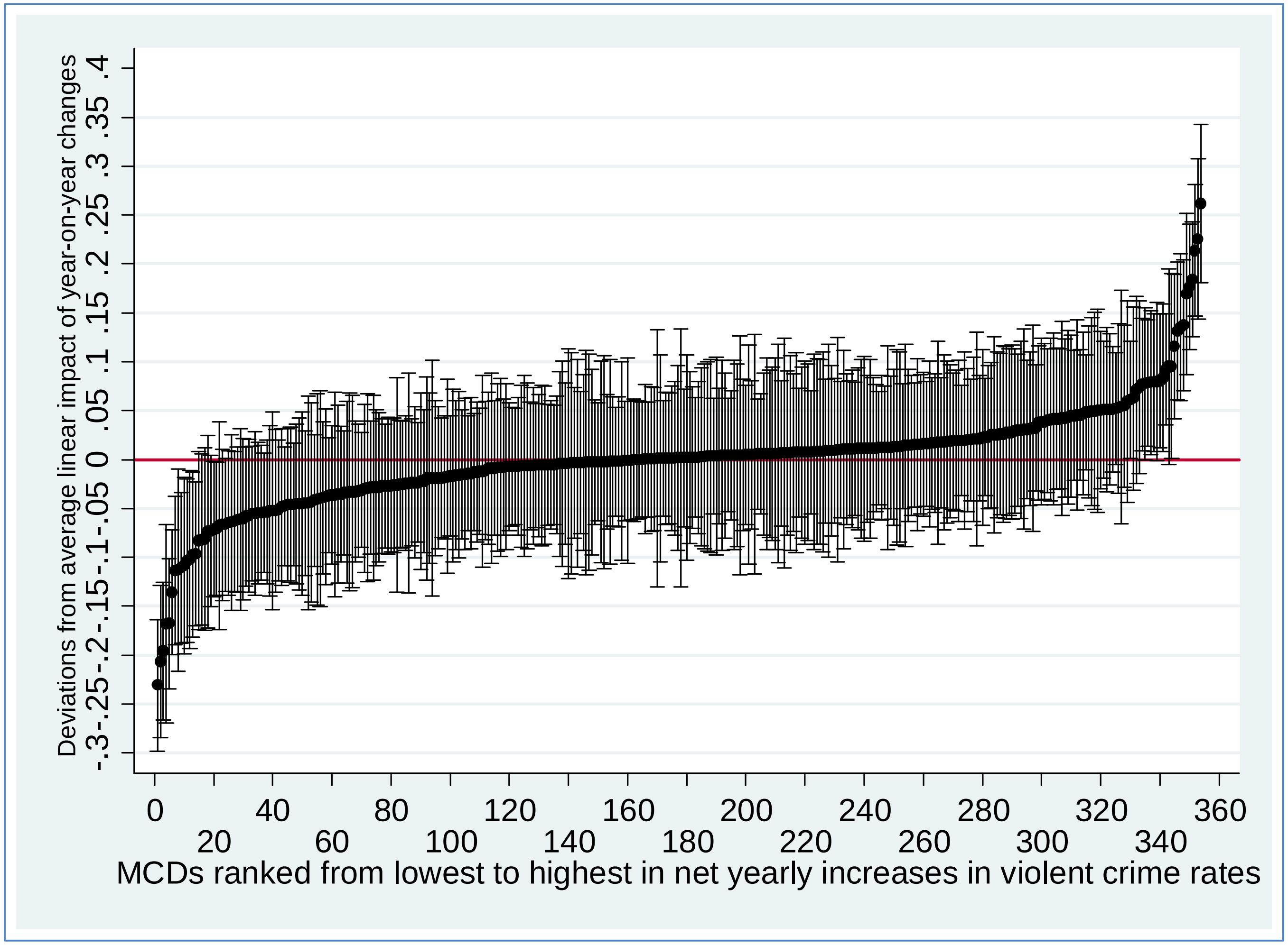

Figure 47. Plot of net departures from average linear impact of time on violent crime counts.

Note. Units = jurisdiction-years, 2000-2008. Tavistock and Pine Valley excluded. Outcome = number of violent crime rates (violent crime count, controlling for log of population in 100,000s as an exposure variable). Bars = +/- 1.96 standard errors Results after controlling for police arrangements, police coverage, demographic structure, and spatially lagged outcome. (run 046)

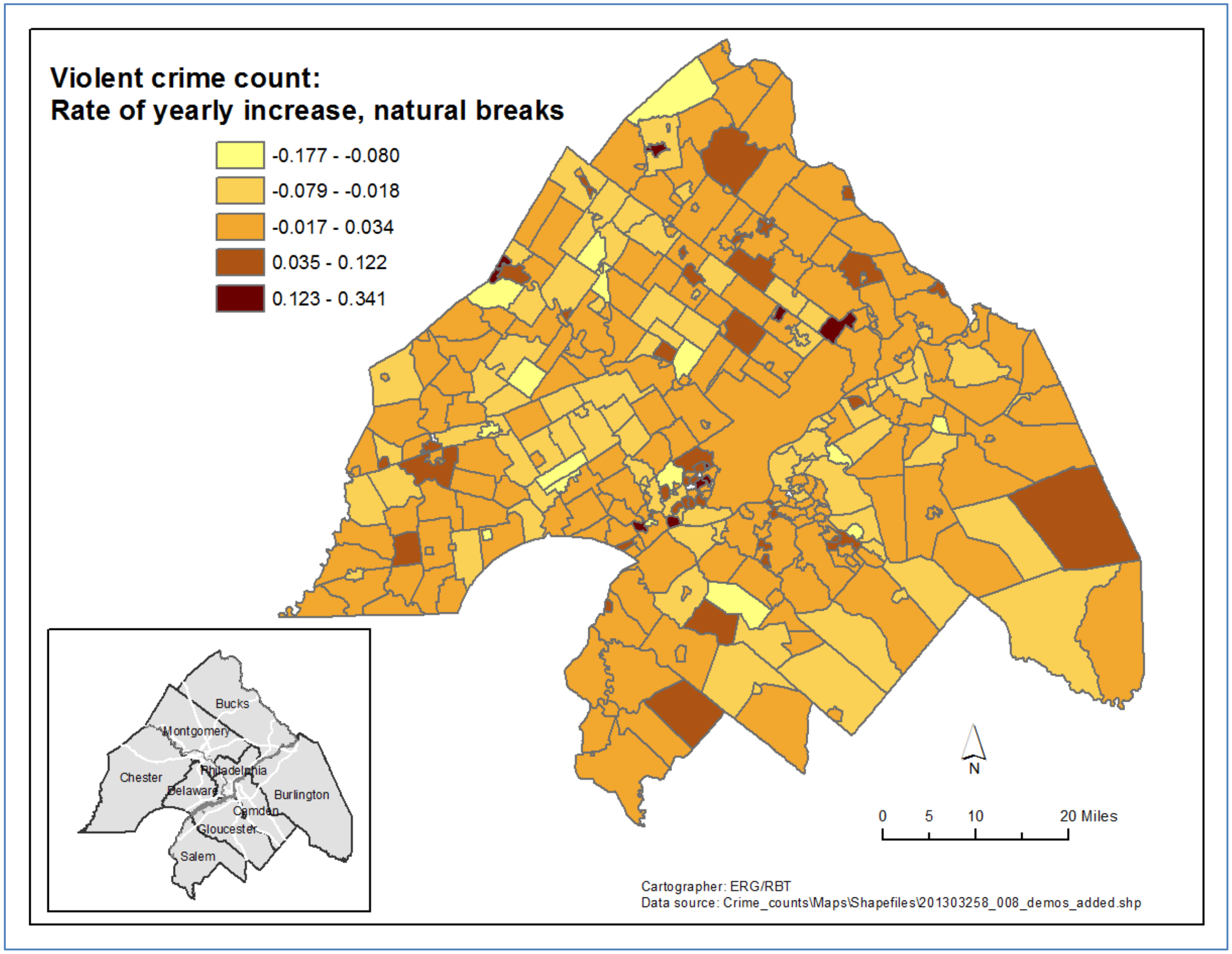

Figure 48. Natural break map of annual linear rate violent crime rate change

Note. Annual violent crime change rate is after controlling for demographic structure, policing arrangements, coverage rates, and jurisdiction size. Rates expressed as deviations from the average slope. Slopes from multilevel model.

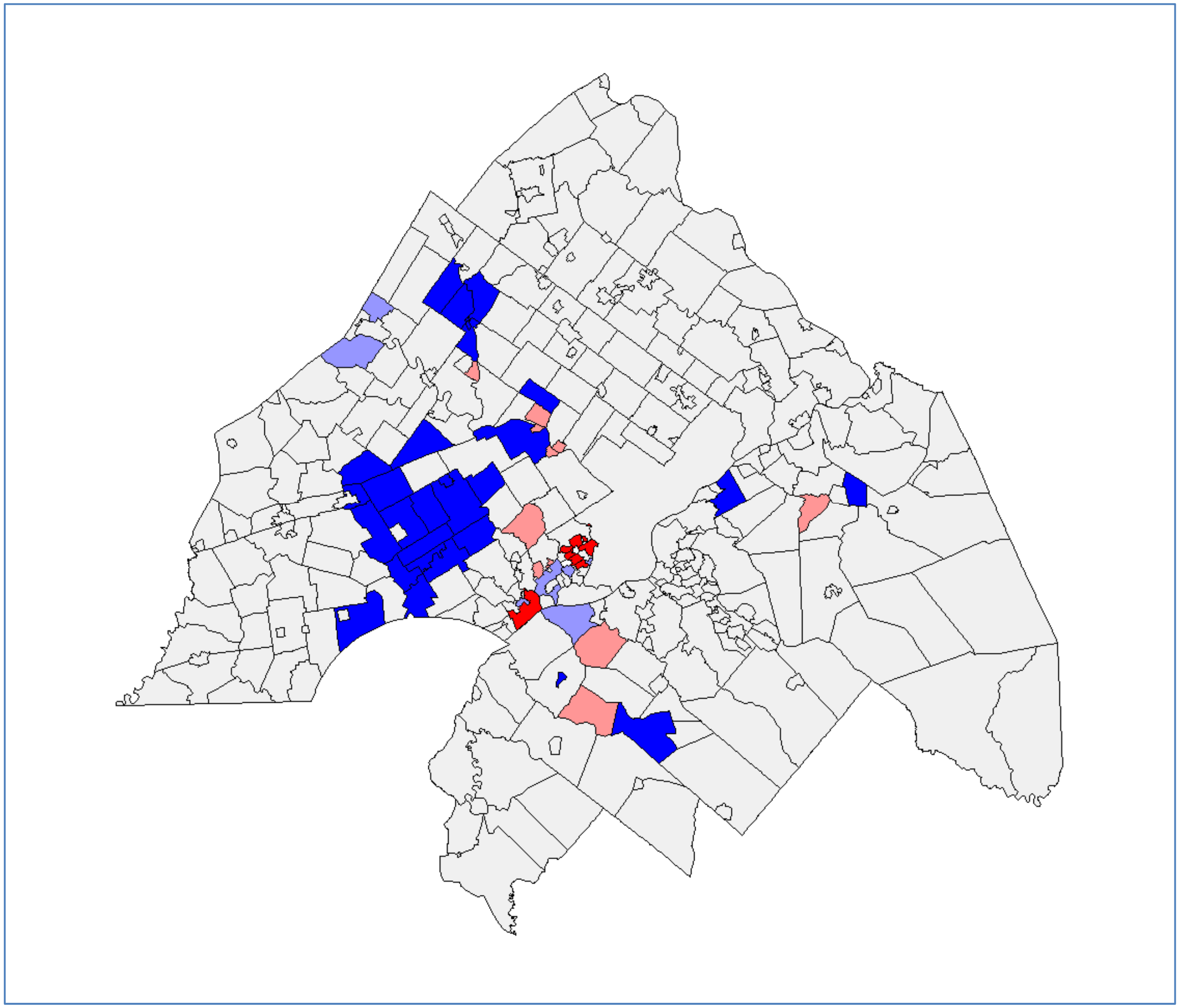

Figure 49. LISA statistics, annual net linear rate of violent crime rate change.

Note. Dark blue = low-low; dark red = high-high; light blue = low surrounded by high; pink = high surrounded by low.

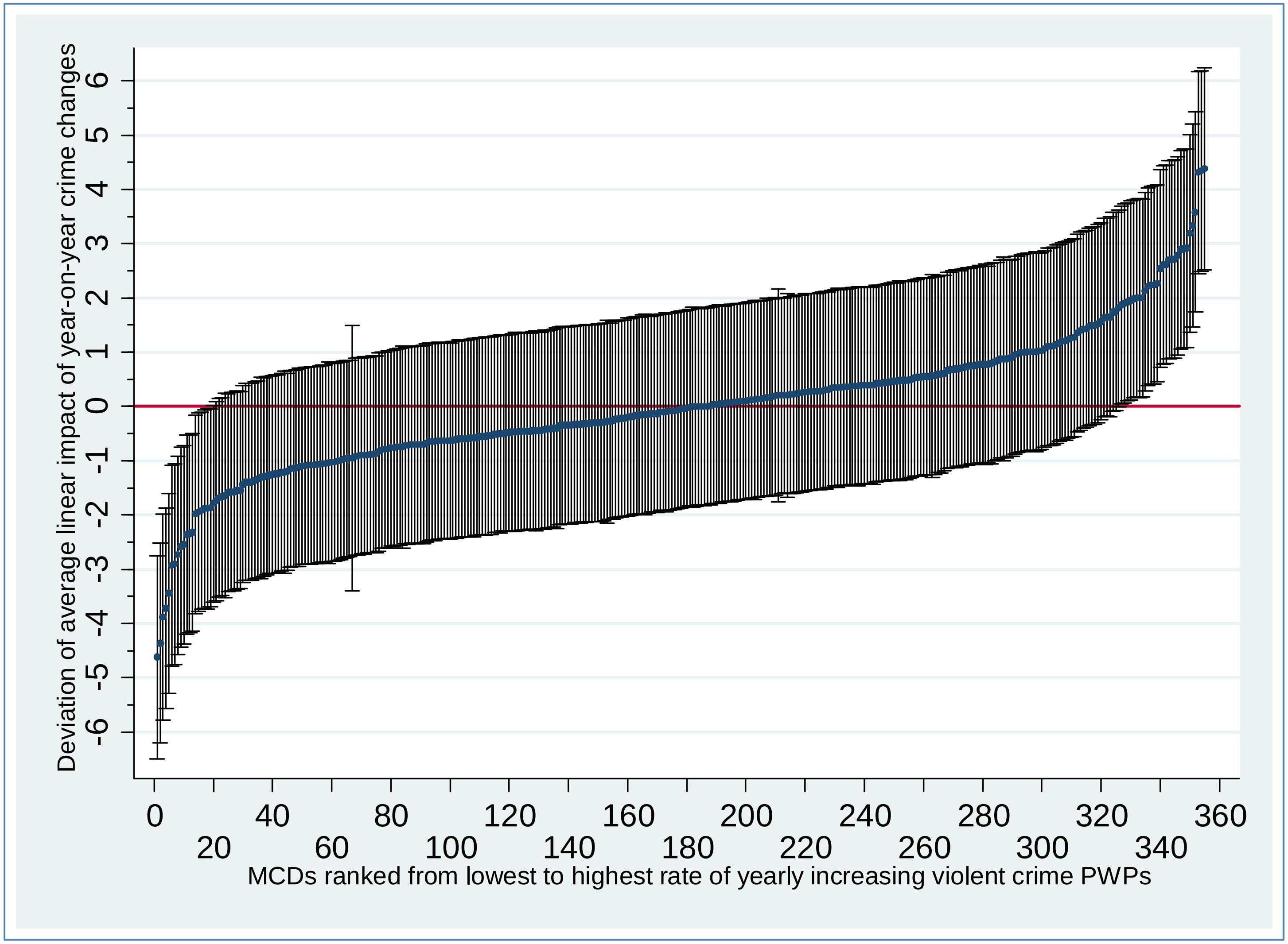

Figure 50. Plot of departures from average linear impact of time on violent crime population weighted percentiles (PWPs).

Note. Units = jurisdictions. Outcome = violent crime PWPs. Bars = +/- 1.96 standard errors Results after controlling for police arrangements, police coverage, demographic structure, and spatial lag. (run067)

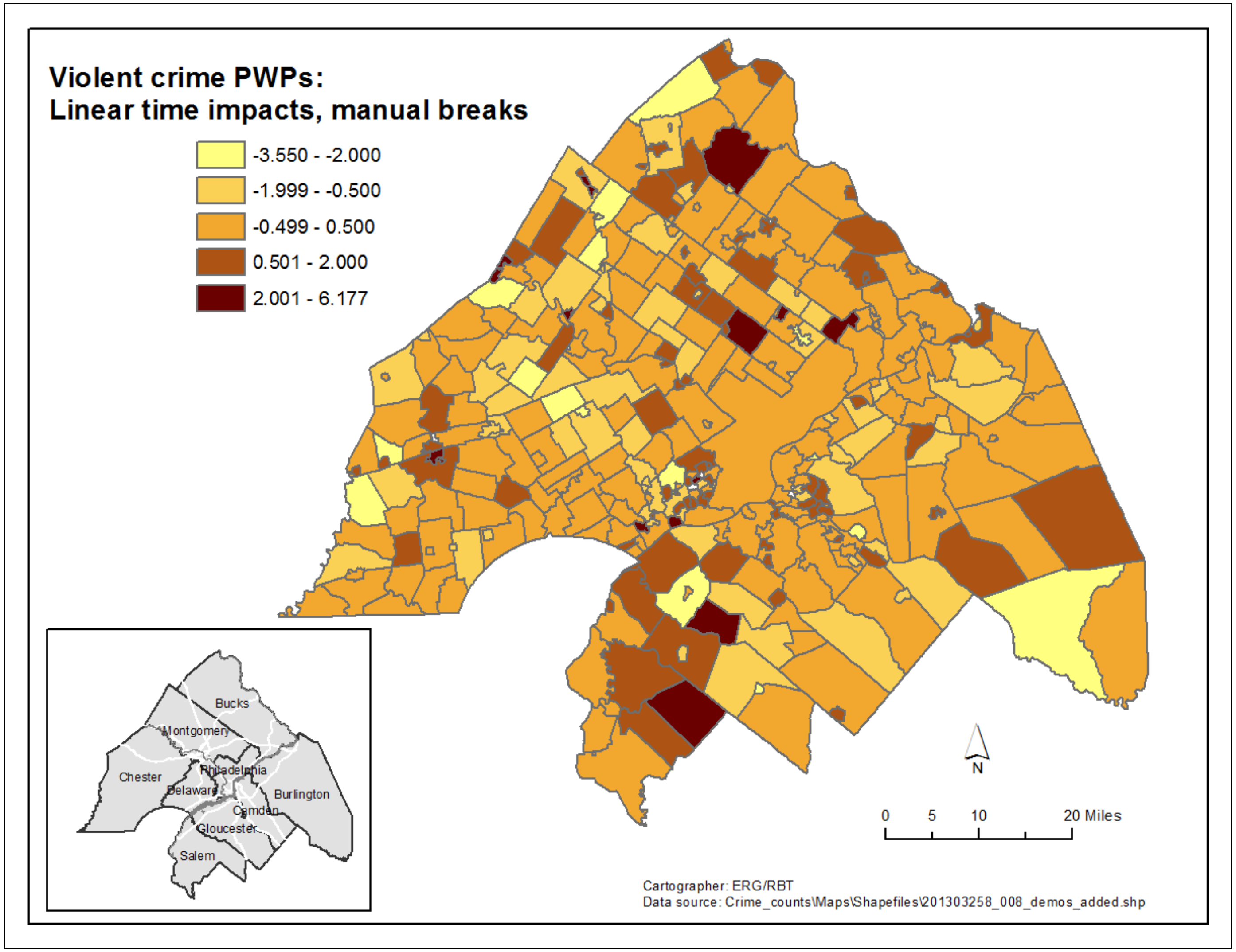

Figure 51. Natural break map of annual linear rate of violent crime PWP change.

Note. After controlling for demographic structure, policing arrangements, coverage rates, spatial lag, and jurisdiction size. Rates expressed as deviations from the average slope. Slopes from multilevel MCMC model.

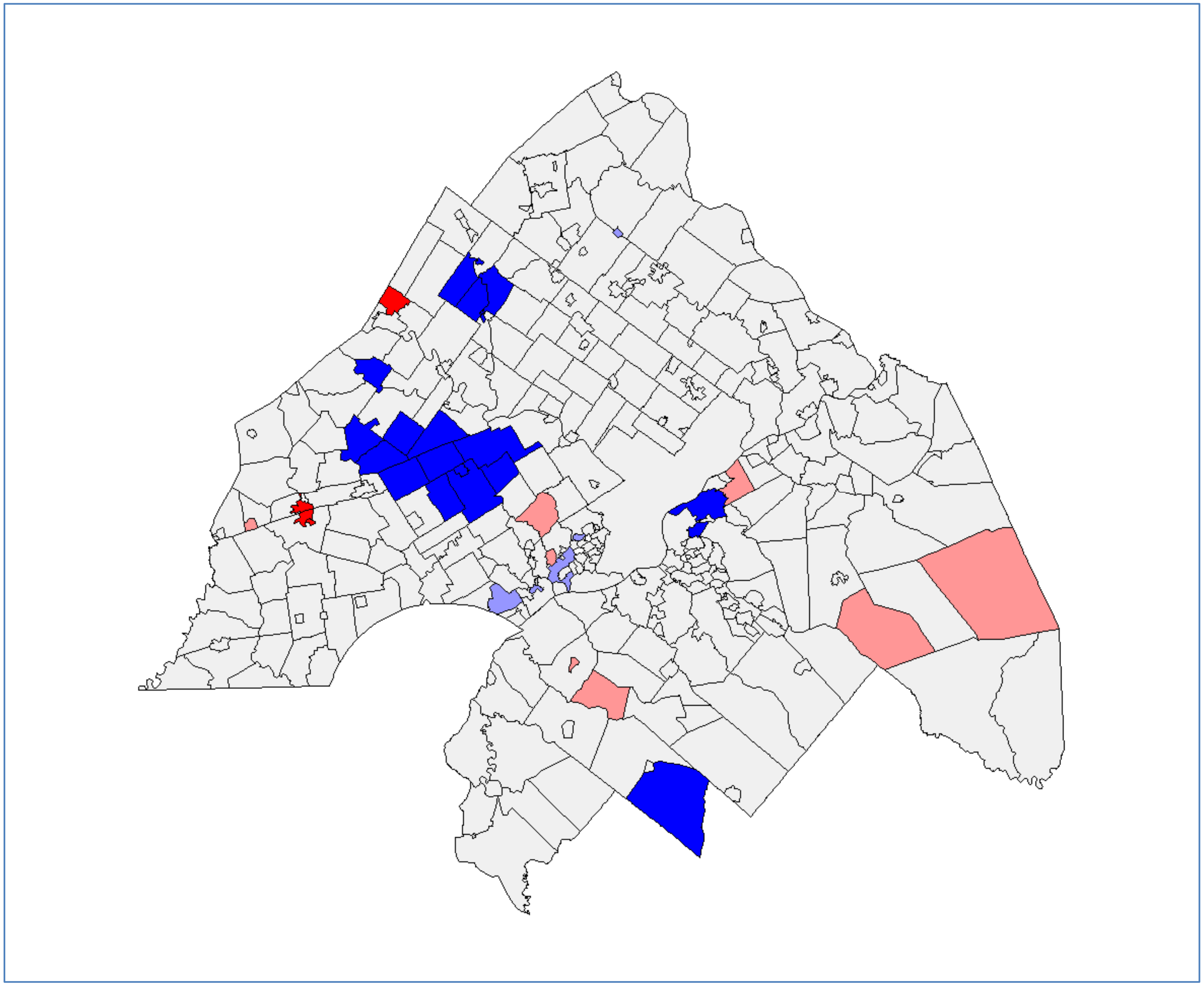

Figure 52. LISA statistics, annual net linear rate of violent crime PWP rate change.

Note. Dark blue = low-low; dark red = high-high; light blue = low surrounded by high; pink = high surrounded by low.

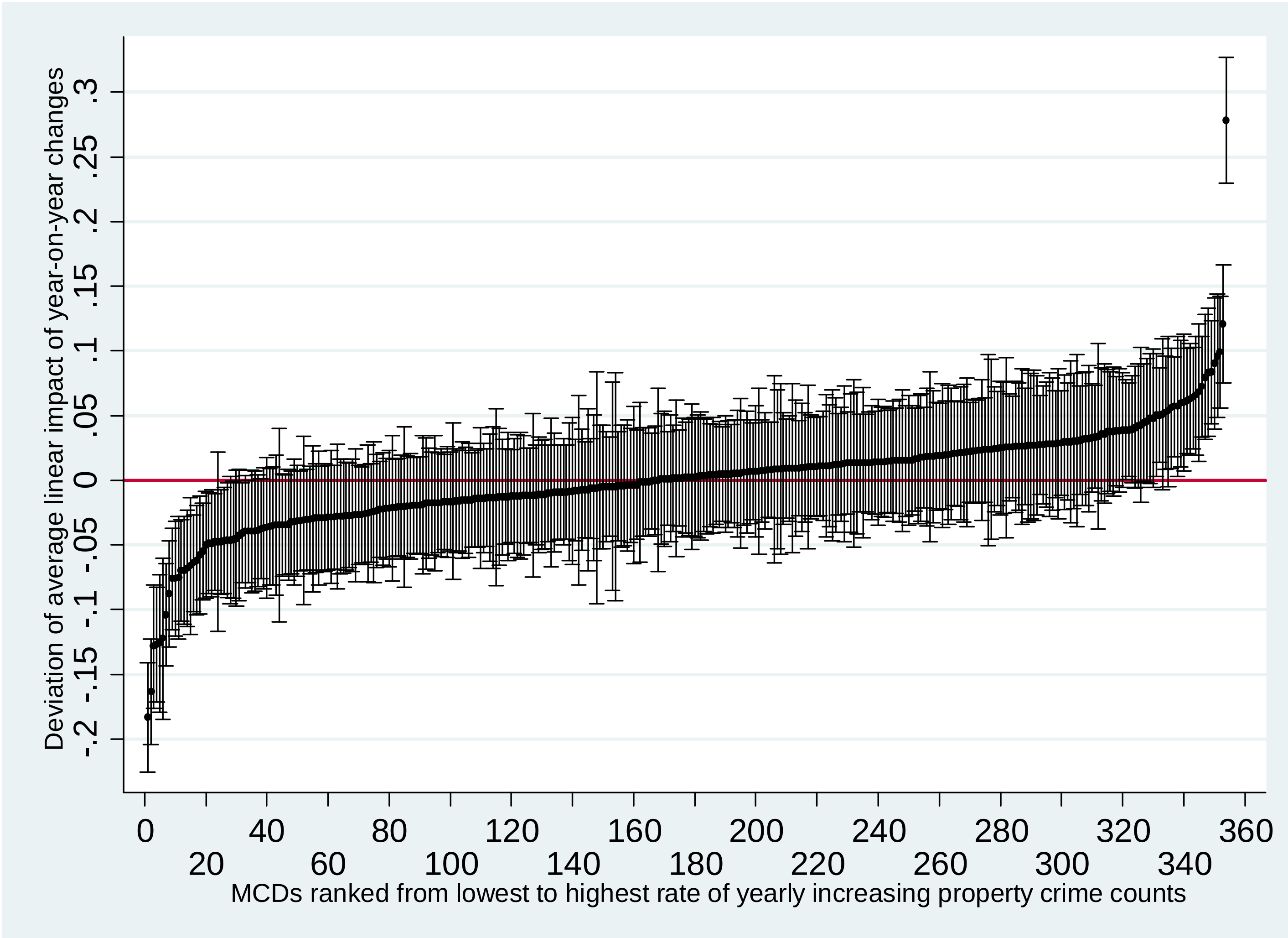

Figure 53. Plot of departures from average linear impact of time on property crime counts.

Note. Units = jurisdiction-years. Outcome = number of property crimes. Bars = +/- 1.96 standard errors Results after controlling for police arrangements, police coverage, and demographic structure. (run064)

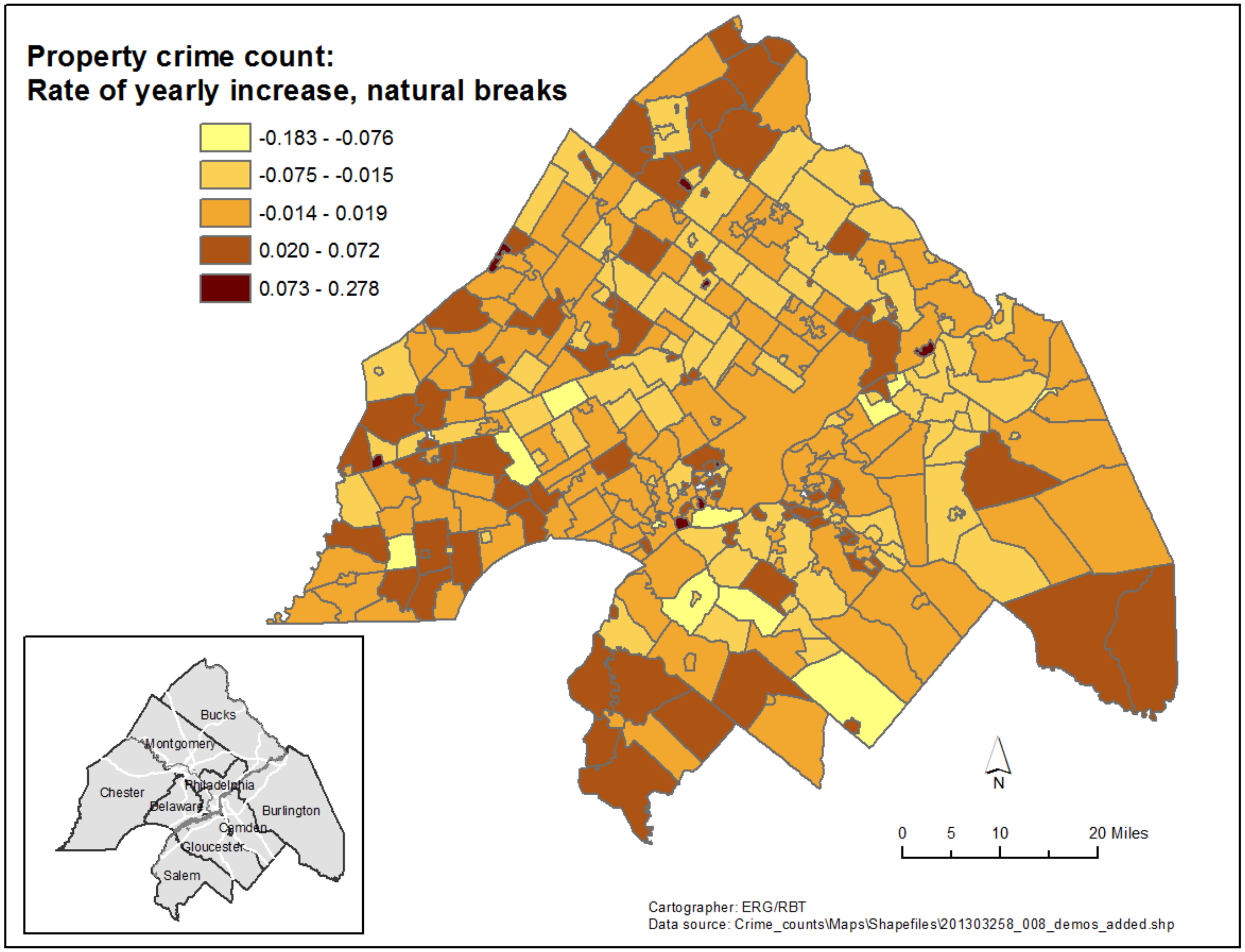

Figure 54. Natural break map of annual linear rate of property crime rate change

Note. After controlling for demographic structure, policing arrangements, coverage rates, spatial lag, and jurisdiction size. Rates expressed as deviations from the average slope. Slopes from multilevel model.

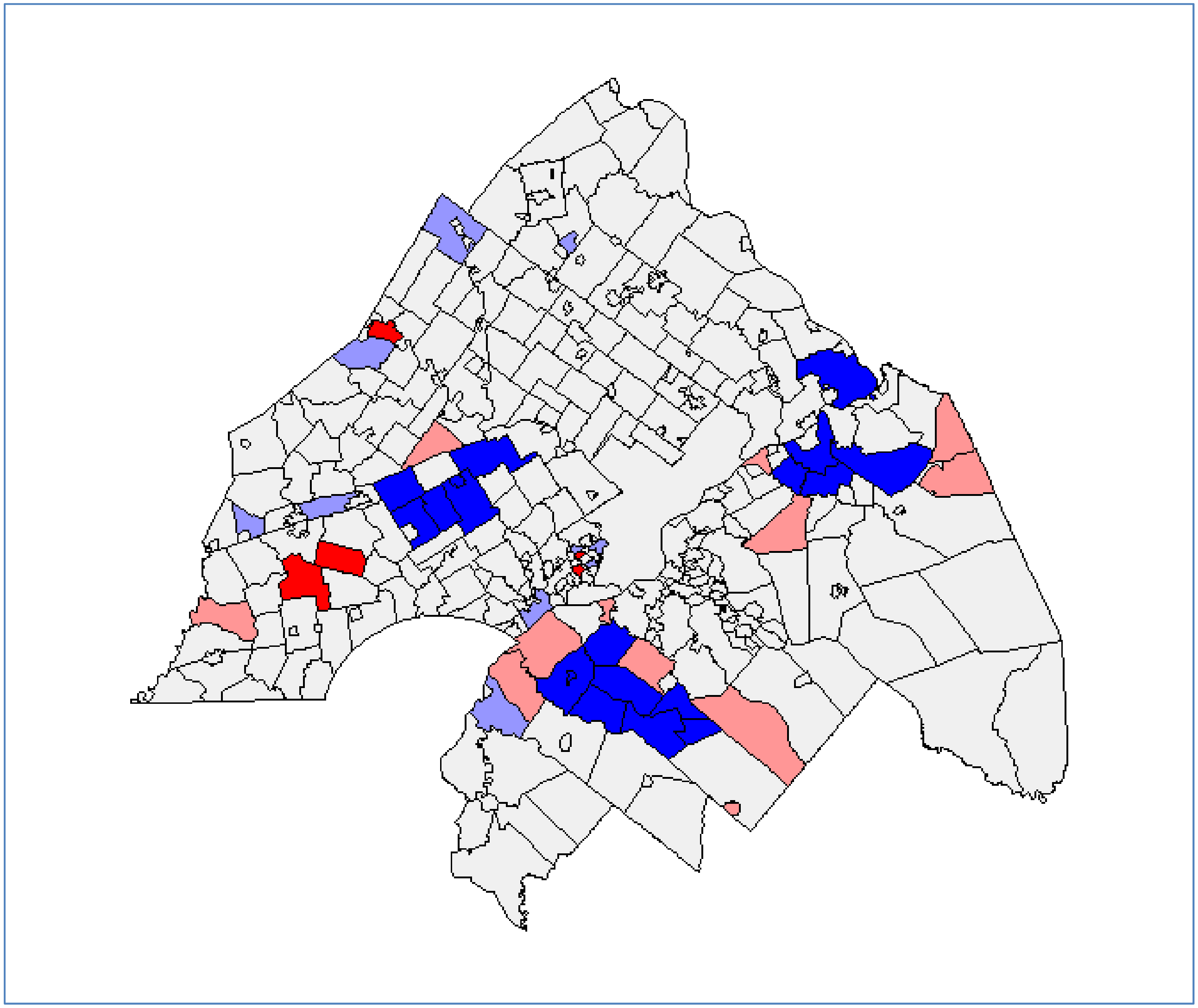

Figure 55. LISA statistics, annual net linear rate of property crime rate change.

Note. Dark blue = low-low; dark red = high-high; light blue = low surrounded by high; pink = high surrounded by low.

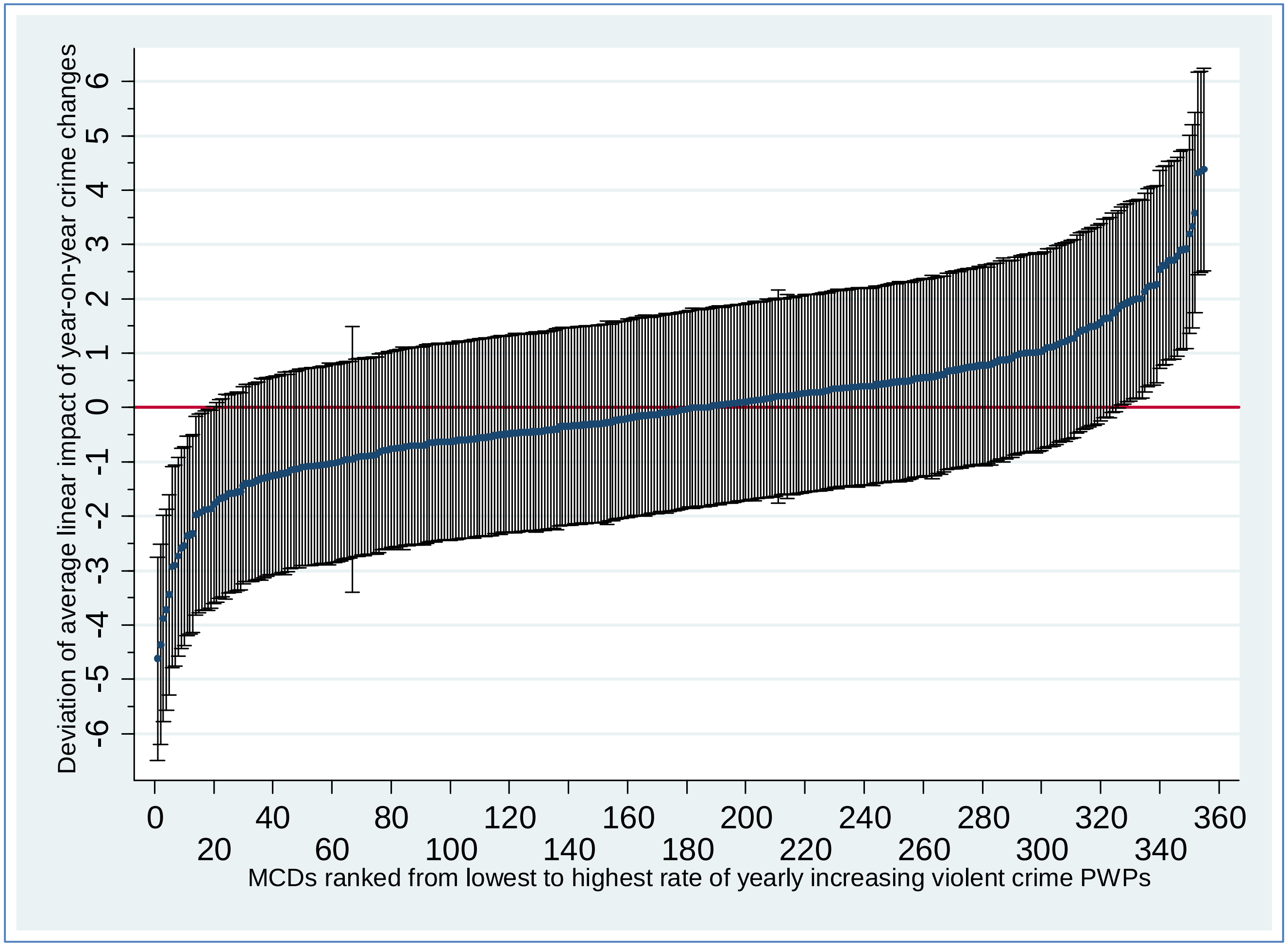

Figure 56. Plot of departures from average linear impact of time on property crime population weighted percentiles (PWPs).

Note. Bars = +/- 1.96 standard errors. Units = jurisdiction-years. Outcome = property crime PWPs. Results after controlling for police arrangements, police coverage, demographic structure and surrounding crime.

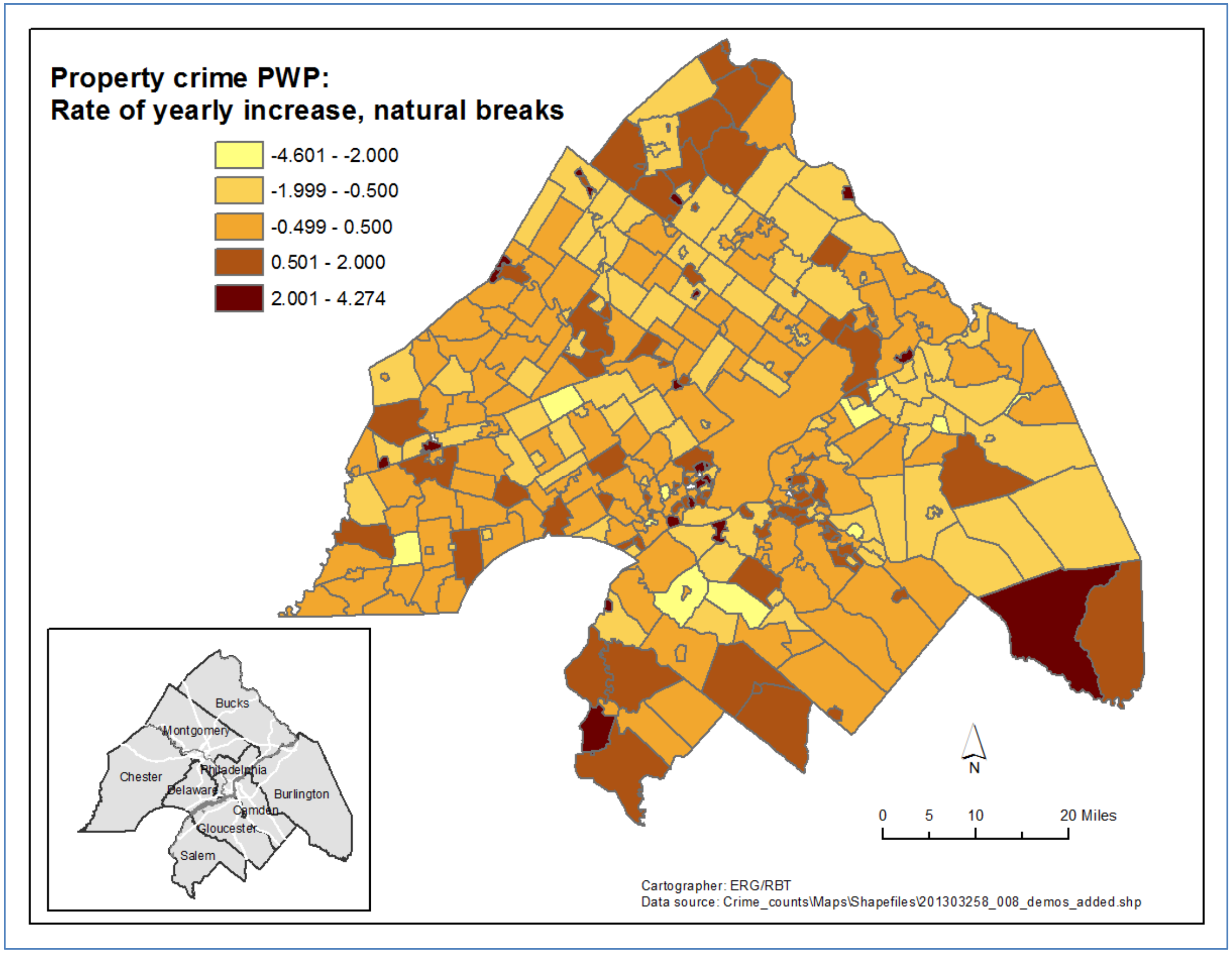

Figure 57. Map of net rate of yearly change on property crime population weighted percentiles

Note. After controlling for demographic structure, policing arrangements, coverage rates, spatial lag, and jurisdiction size. Rates expressed as deviations from the average slope. Slopes from multilevel MCMC model. Manual breaks. Rates shown here are deviations from the average rate of linear yearly change (b=.28).

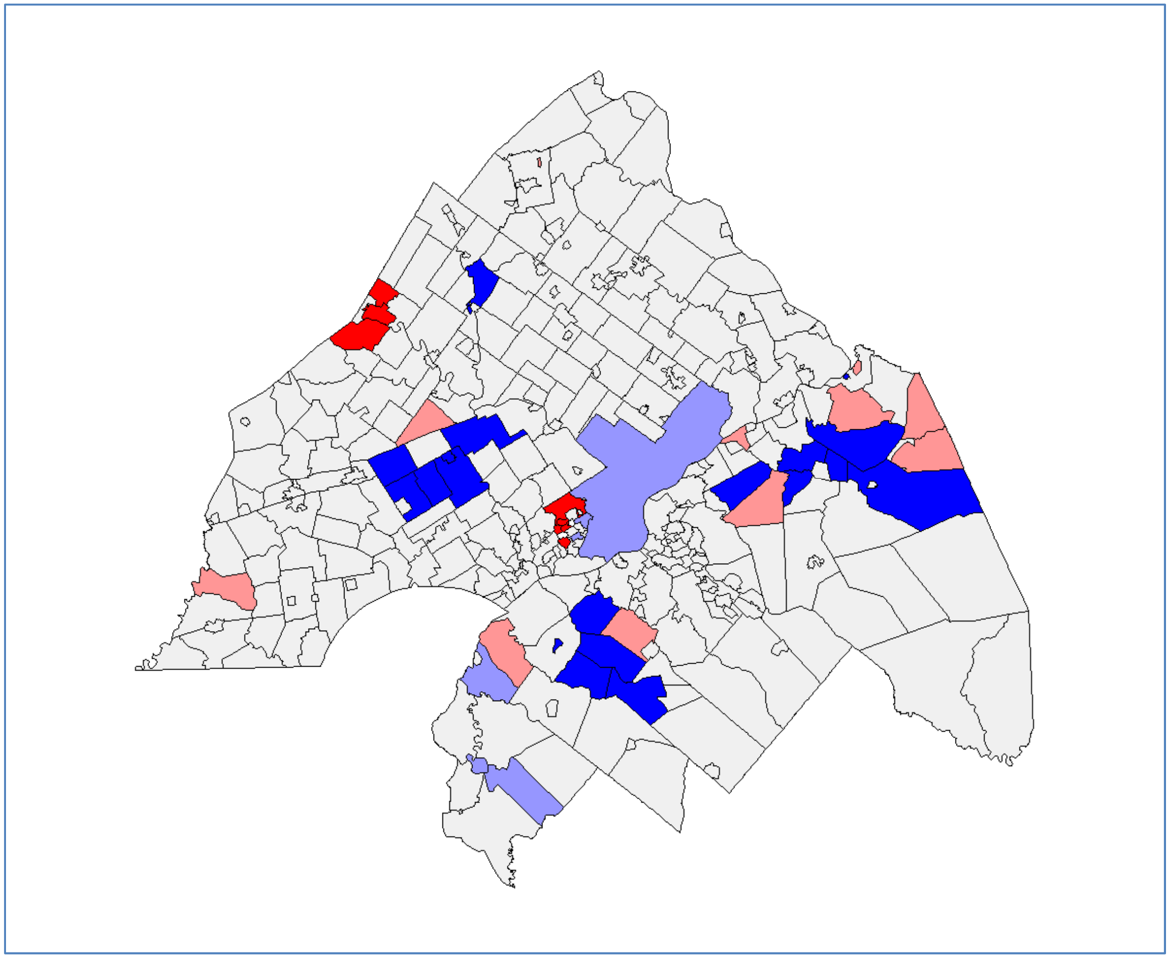

Figure 58. LISA statistics, annual net linear rate of property crime PWP changes.

Note. Dark blue = low-low; dark red = high-high; light blue = low surrounded by high; pink = high surrounded by low

5. UNEXPECTED CRIME CHANGES ONE YEAR LATER

5.1. Overview

The last chapter examined average cross-sectional relationships between jurisdiction demographic structure and policing, and crime. Because crime affects law enforcement and structure, those results contain some inherent causal ambiguity. The crime consequences might not manifest in one specific year, but could be operative within a multiyear series. That causal ambiguity can be reduced somewhat if we ask: What are the impacts of *earlier* community structure and *earlier* coverage rates on *later unexpected* changes in violence and property crime levels? That question is addressed in this chapter. It examines temporally lagged relationships with crime as the outcome, while controlling for earlier crime. These two steps reduce the causal ambiguity to a considerable extent. The variation contained in the outcome is associated with a later period than the variation contained in the predictors.

The current series of analyses presupposes a particular structure to these cross – year impacts. More specifically, it assumes that impacts of demographic structure and law enforcement coverage levels in one year are reflected in unexpected crime changes in the following year. Of course, it is possible that the lagged impacts on crime changes unfold over a different timeframe, for example, shaping unexpected crime changes two years hence. Nevertheless, lacking specific theoretical guidance about the structure of temporally lagged impacts for the units of analysis under consideration here, and desiring to use the greatest fraction possible of the available data, the one-year timeframe for lagged impacts on crime to surface was adopted.

5.2. Analytic approach and rationale

In keeping with the ecological perspective, the change focus in the current chapter is on shifts in crime niches, that is, examining shifts in jurisdiction crime position relative to other jurisdictions in the metro region. Consequently, crime rates in population weighted percentile (PWP) form are of interest. For details on their construction, see Appendix 1.The crime outcome in this form reflects the specific ecological crime niche occupied by a specific jurisdiction in a specific year. The goal is to learn whether these year-to-year shifts in relative position can be predicted from earlier structural and law enforcement features. Unexpected changes emerging in the following year will be calculated (see below) to capture these shifts in crime rates.

Conceptually there are three scenarios of interest when focusing on unexpected crime changes emerging in the next year. (A) One possibility is that a jurisdiction's relative crime level in the next year is linked only to its relative crime level in the current year. If this is the case, once next year's relative crime levels are residualised with respect to this year's relative crime levels, there is nothing left that is predictable. If so, unexpected changes in relative crime levels will not link to current community structure or enforcement levels. Further, the size of the residualised crime changes would be quite small. This scenario would suggest extreme durability of relative crime levels over time at the jurisdiction level in the metropolitan area, and a crime ordering of communities across the MSA which is relatively static over time.

(B) A second possibility is that the unexpected changes in relative crime levels over the next year are somewhat predictable from features of current demographic structure, law enforcement coverage, or both. Should temporally lagged impacts of current demographic structure on crime shifts surface, it would prove particularly intriguing in light of the connections observed in the previous chapter. There, results showed cross-sectional links between jurisdiction demographic structure and crime. If the current analysis focuses solely on unexpected crime changes, and finds links with demographic attributes, such a pattern would suggest a second connection between demography and crime. The links from the previous chapter suggest how current crime levels reflect current community makeup. If the expected pattern emerges here, it would provide evidence of a link between current structure and **future** crime shifts. Stated differently, such results would underscore how the current makeup of the community is conditioning it or preparing it for forthcoming shifts in that community's crime niche in the broader metropolitan region.

A third possibility (C) is that the year-to-year changes in crime niches occupied by jurisdictions are sizable and largely unpredictable from earlier structure of law enforcement. This would suggest an extremely "noisy" crime ecosystem with communities rapidly and sizably shifting their functional crime niches from year to year in ways that are largely unrelated to the broader demographic structure of the region.

5.2.1. Unexpected changes: Single level framework

The current chapter removes the dynamics associated with crime as a cause by doing two things. First, the outcome, next year's crime rate in PWP form, is transformed into unexpected changes in relative crime levels. This is accomplished using the regression framework to define unexpected changes. In a single-level model, the outcome becomes the residual that remains after controlling for this year's crime level (Bohrnstedt, 1969; Bursik, 1986b). Conceptually, the outcome becomes portions of relative crime levels in any given year that could not be predicted by either a) a municipality's relative crime level in the immediately previous year or b) overall changes affecting the entire set of municipalities from the current year to the next year. Second, the outcome is temporally lagged; unexpected crime changes are matched with structural and enforcement predictors from the year prior to the unexpected crime changes. So, for example, unexpected crime changes recorded for the year 2001, i.e., taking place between the end of calendar year 2000 and the end of calendar year 2001, are matched with demographics and law enforcement data from the year 2000. The 2001 unexpected crime changes are what remain after predicting 2001 crime levels with 2000 crime levels. Consequently, only eight years of outcome data are available because there is no unexpected change outcome for the year 2000. This lag structure is shown below.

Predictor year	2000	2001	2002	2003	2004	2005	2006	2007
Outcome year: Unexpected crime changes surfacing by the end of	2001	2002	2003	2004	2005	2006	2007	2008

5.2.2. Unexpected changes: Multilevel context

The multilevel organization of the current data, however, has important conceptual and operational implications for the change analysis. The nature of multilevel residuals is such that if this year's relative crime level is used to predict next year's relative crime level the resulting residuals have a three-level structure: level 3 residuals (g_{0k}) for each cluster of adjoining jurisdictions, level 2 residuals (u_{0jk}), one for each jurisdiction, and level 1 residuals (e_{ijk}), one for each jurisdiction-year of unexpected change within each jurisdiction.

The two ecological portions of the residuals – jurisdiction-level residuals and adjoining-jurisdiction-level residuals – refer to the extent to which a particular jurisdiction or jurisdiction cluster, across all the years predicted, tended to have a below average or above-average unexpected crime shift. These two residuals reflect the *spatial* patterning of unexpected changes. There is also a time specific portion of the residuals, the year-within-jurisdiction residuals (e_{ijk}). These refer to the extent to which a jurisdiction's crime change in a specific year was above or below *that* jurisdiction's average unexpected change across the entire study timeframe. These year-within-jurisdiction residuals control for spatial differences. Each jurisdiction averages zero on these residuals. So these level 1 residuals reflect *only* the temporal, or intra-jurisdiction portion of unexpected crime change.

In a single level regression framework, of course, "unexpected" change is straightforward as described above. The shifts are unrelated to initial scores, and unrelated to the overall change from Year 0 to Year 1 that affected all the ecological units.

But this idea of unexpected change requires some adjustment given the multilevel structure of residuals capturing crime change. More specifically, as will be seen below, the ecological (spatial) portions of relative crime level shifts (g_{0k}, u_{0jk}) are *not* completely independent of initial crime levels. Stated more simply, relative crime changes in some jurisdictions over the entire study period tend to be above average, and in other places below average; further, that average change over several years links with initial crime levels. This should not be surprising given the findings in the last chapter showing that the linear effects of time on crime were stronger in some sub-regions of the MSA compared to others.

Thus, when both ecological portions and the temporal portion of unexpected change are all included ($g_{0k} + u_{0jk} + e_{ijk}$), the outcome does not reflect *totally* unexpected changes; those changes still correlate noticeably with initial crime scores. [18] What this means is that an additional, not yet modeled factor, but one that correlates with current crime levels, is affecting remaining outcome variation.

By contrast, the year-within-jurisdiction portion of unexpected crime changes (e_{ikj}), which reflects *only* temporal variation in unexpected change, *is* completely independent of initial crime levels. This portion represents *completely* unexpected crime changes. This is because they represent within-jurisdiction yearly variations around the average jurisdiction-level unexpected change, and each jurisdiction's set of level 1residuals (e_{ijk}s) averages zero. There is no spatial component in these unexpected changes because the average is the same for each locale.

Given the different structure of these different components of relative crime change -- the overall changes, which have spatial and temporal components, and the intra-jurisdiction, year-to-year changes, which have only a temporal component -- two analyses will be conducted. The first will predict *both* the overall (spatial + temporal) unexpected crime change in the following year ($g_{0k} + u_{0jk} + e_{ijk}$). Predictors include current year: relative crime, community structure, enforcement structure, coverage rates, and a spatially lagged outcome.

The second analysis will concentrate solely on the temporal component of unexpected crime change (e_{ijk}), i.e., within-jurisdiction yearly variations in unexpected relative crime

[18] For example, for violent crime, initial percentile scores correlate .45 with unexpected changes in those percentiles in the following year. Examination of the scatterplot shows this is a linear relationship.

changes. Since these changes correlate 0 with current year relative crime levels, this intra-jurisdiction outcome represents *ecologically discontinuous* crime changes. Predictors are as in the first analysis series except current relative crime is excluded.

5.2.3. Outcome functional form

An analysis was conducted for violent crime population weighted percentiles, and then property crime population weighted percentiles. The distribution of each of these variables is somewhere between a uniform and a normal distribution. The functional form assumed in the multilevel models was a normally distributed outcome.

5.2.4. Model sequence

The first analytic approach entered current relative crime level, current structure, current law enforcement arrangements and levels, jurisdiction population size, linear and curvilinear effects of time, and surrounding spatially lagged current crime rates. All these were used to predict the next year's relative crime level. After controlling for current crime rate, the remaining predictors are predicting spatial-plus-temporal unexpected crime changes. Crime changes at the jurisdiction-cluster, jurisdiction, and year-within-jurisdiction levels are combined. As in the last chapter, these analyses allow for spatially clustered errors among adjoining jurisdictions, and linear temporal trends that vary by jurisdiction.

One additional random effect was introduced in these models. It was not seen in the models in the previous chapter, because the relevant predictor was not included there. The impacts of current year crime PWP were allowed to vary across clusters of adjoining jurisdictions. Incorporating this parameter reflects the idea that relative crime levels were more volatile from year to year in some sub-regions of the MSA than others. Stated more broadly, the idea is that crime ecological continuity might be differential across sub-regions of the MSA. Given what was seen in previous chapters with spatiotemporal crime patterning, this seems a reasonable elaboration. Adding this parameter, however, sometimes rendered the jurisdiction-level random effect of linear time non-significant or did not allow it to be estimated. These tradeoffs across different models are footnoted when they occurred.

The second analysis focused solely on intra-jurisdiction unexpected changes (e_{ijk}s). This is just the temporal portion of unexpected changes. For each jurisdiction, the "average" jurisdiction level and jurisdiction-cluster level unexpected deviations (u_{0jk}, g_{0jk}), are both discarded, leaving only year-to-year variation *around a jurisdiction's average change*. In a multilevel framework, only the level 1 (years-within jurisdictions) residuals are retained. These level 1 residuals *are* completely independent (r=.00) of initial crime levels, and are normally distributed. So this outcome reflects temporal ecological discontinuity, the a-spatial portion of each jurisdiction's year-to-year crime niche shifts which were unrelated to its previous year relative crime level.

The outcome capturing this intra-jurisdiction, temporal variation was created as follows. Next year's crime PWP (e.g., 2001) was brought into the current year (e.g., 2000) and then estimated in a model using corresponding current year crime PWP as the only predictor. Three-level multilevel models were run (clusters of adjoining jurisdictions, jurisdictions, years-within-jurisdictions) and errors were allowed to correlate within clusters of adjoining jurisdictions. Impacts of current crime PWP were allowed to vary across jurisdiction clusters. The level 1 residuals were retained, thus creating the outcome.

5.2.5. Implications of lagged impacts for specific predictors

Turning to specific predictors, it will be informative to learn how specific structural and law enforcement attributes drive later crime shifts, if indeed they do. Starting first with structure, in the last chapter stability and socioeconomic status (SES) emerged as the strongest structural cross-sectional correlates of crime levels and of relative crime levels. It will be interesting to see if they demonstrate temporally lagged impacts in the current analysis. Should they do so, it would speak to crime impacts of fundamental features of community fabric unfolding over time. It would mean that there is something about current structural conditions, *quite apart from their connection with current crime conditions*, that shapes where relative crime levels are headed in the future in that jurisdiction. These would be the kind of impacts expected by several different theoretical models, but especially by Molotch's perspective on structuration (Molotch, et al., 2000). Such a finding would have significant political economy implications.

Turning to law enforcement, it will be interesting to learn whether *local* officer coverage rates in one year are associated with lower relative crime levels in the next year. Work on the impacts of police coverage rates (officers per thousand population), as noted earlier, has been mixed from the beginning (K. Harries, 1974: 91). The work providing the clearest evidence of deterrence has relied on more specific indicators of department efficacy than are used here. For example, Sampson and Cohen examining large city robbery rates used the rate of arrests per officer for (disorderly conduct plus DUI) as a predictor (Sampson & Cohen, 1988b). Kubrin's recent work supports and extends that finding (Kubrin, et al., 2010).

But, despite these works, and despite supportive evidence from studies of geographically focused policing activities, important questions about *municipality-wide* ecological deterrence across a range of crimes remain (Corsaro, Hunt, Hipple, & McGarrell, 2012; Jang, Lee, & Hoover, 2012; Paternoster, 2010; Ratcliffe, Taniguchi, Groff, & Wood, 2011).

Unfortunately, precise indicators like those used in the best multi-city work on proactive policing cannot be used here. Although it is possible to construct indicators for some crimes like arrests per officer, or clearance rates more broadly, *it is not possible to do so for the entire set of jurisdictions in the metropolitan region*. Many jurisdictions, because of the different policing arrangements, do not report separate figures to the FBI. See Appendix 1 for details. We were able through various state police data sources to get at the crime counts for departments not included in the UCR files (Appendix 1). But arrest data were not available through those same state police data sources. As already seen in the previous chapter, and as will be explored further here, because of geographic dependencies, policing indicators for *an entire geographic surface* are required. At least in the case of crime, those numbers could be estimated from available state police reports.

Further, *because* of these different policing arrangements in different MSAs, ratios used in other studies like arrests in a specific category, e.g., DUI arrests *per local officer,* do not make sense. There are two reasons. So many jurisdictions do not have their own dedicated department with at least one full time sworn officer. In addition, many departments are supplemented by their respective state police, creating a complex mix of local and state enforcement levels.

Stated broadly, work on *municipality wide* proactive policing across a complex metropolitan area, like this one, with different types of policing arrangements and police reporting arrangements, will need to come up with an indicator of proactive policing that is applicable across the entire region. The earlier work, by limiting its focus to large cities, has sidestepped this challenge.

Nevertheless, as seen from earlier results, coverage rates vary dramatically across the metropolitan region. So too does department size. Therefore, at the least, coverage indicators need to be taken into account. Further, if impacts of local department coverage or size are observed, it will be worthwhile seeing which types of crimes are affected and how this might align with either the proactive policing work or the crime spillover work. As noted earlier, there are challenges in interpreting the meaning of local coverage rates and department size, and these indicators have a long and complicated history.

5.3. Changes in violent crime property weighted percentiles

5.3.1. Overall unexpected changes

This outcome includes all three residual components; the jurisdiction cluster, jurisdiction, and year-within-cluster residuals summed.

5.3.2. Describing patterns of year-to-year relative crime shifts

To get a descriptive sense of what these lagged crime relationships look like, current and next-year relative crime levels are plotted for three pairs of years in the data series: 2000-2001 (Figure 59), 2003-2004 (Figure 60), and 2007-2008 (Figure 61). Several features of these relationships are noteworthy.

The connections are both similar and different for different pairs of years. For each year pair, there is a strong, positive, generally linear relationship between the two crime levels. At the same time, the strength of that relationship appears to depend on the specific pairs of years examined. For example, it seems strongest for crime shifts from 2003-2004 because there appear to be fewest residuals scattered far from the regression line, and no jurisdictions which switched from a very high percentile score (95+) in one year to a moderate score (60-70) in the other year. As explained in the last chapter, these shifts from very high to moderately high, or vice versa, arise from jurisdictions switching their position relative to Philadelphia's position in the PWP ordering. Another "constant but shifting" feature of the lagged crime relationships is the number of jurisdictions scoring close to zero in one year, and showing a substantially higher score for the other year. This feature of the pattern arises from relatively small jurisdictions being crime free or almost crime free in one year, but having some crime and a low to moderate PWP in the other year. The number of jurisdictions switching from/to a zero or near-zero position seems to vary somewhat from one year-pair to another.

To gain a clearer picture of the overall and time-varying lagged relationship between this year's relative crime level and the next year's, a three level (clusters of adjoining jurisdictions, jurisdictions, years-within-jurisdictions) multilevel model with MCMC estimation was run. The only predictor is current year crime. Table 20 displays the variance of the outcome (relative violent crime level for predicted year) and the residual (the portion of next year's relative violent crime level not predicted). [19] The portion not predictable ($1-R^2$) ranged from .64 to .57, and averaged .59 across the year pairs. These numbers describe variations in the unpredictability of next year's relative violent crime across year-pairs, when only current relative violent crime levels are taken into account. To put the point somewhat more generally, ongoing year-to-year ecological continuity in violent crime niches at the jurisdiction level explains, depending on the

[19] The residual includes both ecological portions (jurisdiction cluster and jurisdiction) and the temporal portion (years-within-jurisdictions).

year, anywhere from about a third to slightly less than half of the variation in those violent crime niches. On average over the period, ecological continuity accounts for a sizable portion of violent crime niche variation.

5.3.3. Predicting overall unexpected changes

Fixed effects

Table 21 displays the results predicting next year's violent crime population weighted percentiles. The outcome is transformed into unexpected change (2 spatial components + temporal component) because current crime is a predictor. On average current year violent crime percentiles link strongly ($b = .30$, $p < .001$) with next year's violent crime percentiles, underscoring ongoing temporal ecological continuity in relative crime positioning across the metro area, as already seen in the variance decomposition table (Table 20).

Temporal fixed impacts, both linear and curvilinear, were positive and significant ($ps < .001$). Relative crime changes a year ahead tended to be more positive and more substantially positive later in the period. This arises from Philadelphia moving down somewhat in the ordering later in the period, and fewer jurisdictions of substantive population scoring at the very bottom of the ordering later in the period. On the temporally lagged outcome Philadelphia started (2001) at the 97.6th percentile, and moved down over the next few years to the 96.9th percentile (2005), then recovered to the 97.3rd percentile by the end of the period. Even though these shifts in the relative crime ordering are slight, the shifts link to a number of communities "jumping" in the ordering each time Philadelphia shifts down or up in the ordering. Since these "jumps" in other communities' scores link to a difference of at least 30 percentiles, such shifts are sizable. These shifts of Philadelphia in the ordering are relevant both for the linear and quadratic temporal trends.

Three structural features demonstrated sizable lagged impacts on later unexpected crime changes. Relative violent crime was more likely to increase in lower SES jurisdictions ($b = -5.43$, $p < .001$), less stable jurisdictions ($b = -5.78$, $p < .001$), and in more predominantly African-America jurisdictions ($b=.14$, $p < .01$). The SES and race lagged impacts on later changes in relative crime align with the work to date on cross-sectional impacts of community features on crime (Pratt & Cullen, 2005). But at the same time they extend that earlier work by pointing out how structural effects on crime *continue to play out at later points in time.* The impact of stability is less expected given its mixed results in earlier research

The surrounding crime rate had a significant negative impact ($p < .05$). Relative crime was *less* likely to increase later in the focal jurisdiction if crime rates were higher at the beginning of the change period in immediately surrounding jurisdictions. This represents a somewhat unusual impact pattern for a spatially lagged outcome. The relevant dynamic is not apparent.

Random effects

Turning to random effects, as was seen in the cross-sectional models (previous chapter), linear impacts of time varied across jurisdictions ($p < .05$). Thus, spatiotemporal interactions in crime patterning apply when upcoming crime *changes* are investigated, as well as when cross-sectional links with crime are examined. Examination of the caterpillar plot, however, showed that none of the *individual* departures from the average effect of linear time were beyond two standard errors from that average linear temporal effect (results not shown).

But stronger evidence of a different sort appeared supporting the idea of spatiotemporal interactions around crime changes. The model allowed the impacts of current crime on future crime to vary by adjoining jurisdiction clusters (level 3 in the multilevel model). Those impacts did indeed vary significantly ($p < .001$). The caterpillar plot (results not shown) of these differential current crime impacts showed six clusters with significantly ($p < .05$) above average impacts of current crime, and six with significantly ($p < .05$) below average impacts of current crime on later crime changes.

The spatial patterning of these varying impacts of current relative violent crime on future relative violent crime at the jurisdiction cluster level is shown in Figure 62. The lightest colored jurisdictions are those where current and future relative violence levels were most loosely linked. Not surprisingly given how small scale will link to rates fluctuating more widely, many of the very small jurisdictions throughout this region were in this most volatile group (e.g., the borough of Narberth in Lower Merion). Some mid-to-outer region more sizable jurisdictions, in Montgomery County, lower Salem County, and in a few other places around the region, also demonstrated loose relative crime linkages.

Some of these places demonstrating a loose linkage were relatively rural, and with relatively small populations. Lower Alloways Creek Township in lower Salem County is a case in point. With a population of fewer than 2,000, its violent crime PWP ranged from .1 to 40 over the entire study period. Douglass Township in outer Montgomery County is another case in point. A township of about 9,000 residents, its violent crime PWP ranged from 4 to 50 over the entire study period. Others in this loose linkage group, however, had more sizable populations, were not rural, and just had widely fluctuating relative violence levels. Whitemarsh Township, just outside northwestern Philadelphia, is a case in point. With a population of more than 16,000, its relative violence level shifted between 3 and 39.

The conceptual opposite end, places where current relative crime levels had the strongest impact on future relative crime levels, is reflected in jurisdictions with the darkest coloring. A grouping of these appears just to the west of Philadelphia (Lower Merion, Upper Darby, Springfield, and Marple Townships). Upper Darby is moderate on relative violence, with scores ranging from 44 to 66 over the period, while Lower Merion and Marple townships were relatively safer and fluctuated less in relative safety. Springfield Township's relative violence score, however, ranged between 17 and 60 over the period, despite the township having a sizable population of over 20,000.

A second and more sizable cluster of jurisdictions with strong links between current and future relative violence levels appeared in southern Delaware County north of the Delaware state line, extending west into lower Chester County. These locales are more populous than the jurisdictions with the loosest crime linkage. Further, in all of these jurisdictions, there was less of a discrepancy between the lowest and highest relative violence levels. Although their minimum relative violence levels varied, their maximum relative levels were rarely above 30.

The conceptual midpoint is captured by jurisdictions in the middle category. Here, the impact of current relative violent crime level on future relative violent crime level closely approximated the average impact. It is interesting that Philadelphia, the cities of Camden and Chester, and many of the immediate neighbors of each of these cities demonstrated cross-year relative violent crime links of average strength.

Overall

For the overall model, the variance of the residuals (1-R^2) was about 41 percent of the total variation in the outcome, suggesting that overall about 59 percent of the outcome was explained by the current model.

Examining the relationship between model residuals and current relative violence level (results not shown) revealed that heteroscedasticity was not a problem. There was of course, a gap in residuals between initial violence scores of about 70 and about 95. More problematic was the sizable correlation between initial violence and the residuals (r=.33), suggesting some additional, un-modeled factor linked with initial relative violence level was shaping the outcome.

5.3.4. Predicting intra-jurisdiction, year-to-year unexpected changes

Attention turns now to relative violence changes that are *totally* unexpected, that is, they correlate zero with current relative violence levels. These outcomes are the year-within-jurisdiction (level 1) residuals of each jurisdiction when current relative violence was used to predict next-year's relative violence. Within each jurisdiction these residuals average zero. Conceptually, they represent purely temporal variation, since spatial variation is discarded by setting each jurisdiction's average on the outcome to zero. These intra-jurisdiction unexpected changes are normally distributed, with minimal skewness. Their distribution is shown in Figure 63. Because cluster-level and jurisdiction-level outcome variation was essentially zero, it was not possible to model random effects of time or any other predictors and use MCMC full estimation. So these models include only fixed effects of predictors.

As with the overall unexpected changes, these intra-jurisdiction unexpected changes were analyzed using two different lag variables and either officer coverage rate or sworn officer department size. Regardless of which predictor combination is used, the fit measures were closely comparable. The four Bayesian DICs differed by less than one.

Further, regardless of the predictor combination, the significance pattern was the same (results not shown). Results using the officer coverage rate and the Empirical Bayes spatially lagged variable based on violent crime rates appear in Table 22. As seen in the model predicting all portions of unexpected changes, both linear and quadratic temporal effects had a significant impact (ps < .001). Beyond the time effects, however, only one other variable demonstrated a significant impact in all four models. Later intra-jurisdiction increases in relative violent crime were *less* likely if stability was *higher* in the previous year (b = -.568, p < .05).This impact was about 1/10th of the stability impact (b = -5.782) seen in the models predicting all components of unexpected change (Table 21). Here, for each standard deviation increase in stability (1 sd = .85), in the following year the violent crime PWP would be about a half a percentile (.48) lower. Stated differently, about 9/10th of the stability impact seen predicting all portions of change arose from a jurisdiction level spatial relationship, and 1/10th from a temporal relationship.

Overall, despite the significance of the temporal effects and stability, intra-jurisdiction, year-to-year shifts were not that predictable using the current lagged model. The model explained only about 1.3 percent of the outcome.

In sum, these intra-jurisdictional temporal shifts in relative violence levels, which are truly unexpected changes correlating zero with initial relative violence levels, had some predictability but at the same time were largely unpredictable. The predictability arises from two temporal trends within the period, and a lagged impact of temporal shifts in jurisdiction stability. Years when a jurisdiction's stability is above average linked to a downward shift in relative violence a year later. This connection speaks perhaps to the relevance of the basic systemic model of communities and crime to temporal intra-jurisdictional crime dynamics (Bursik & Grasmick, 1993b). A jurisdiction's shifts over time in the crime niches it occupies are not completely random, but rather link with one earlier structural condition. At the same time, these shifts, albeit not completely random, are substantially random. The model here captured only about one percent of the variation in these unexpected changes. When spatial location is completely ignored, and between-jurisdiction differences on the outcome discarded, it proves tough to predict intra-jurisdictional purely temporal changes in relative violent crime levels.

5.4. Changes in property crime property weighted percentiles

5.4.1. Overall unexpected changes

Describing patterns of year-to-year relative crime shifts

A descriptive overview of the relationship between current year property crime population weighted percentiles, and corresponding percentiles in the year ahead is provided by looking at three figures where these lagged relationships are plotted for three different year pairs in the series (Figure 64, Figure 65, Figure 66). As was seen with the violent crime lagged relationship, here too the connection varies depending upon the year–pair examined. For example, in year-pair 2000-2001 there are a larger number of jurisdictions with moderate initial crime scores switching to zero or almost zero in the follow-up year, compared to 2007-2008. At the same time there are notable differences between the relative property crime lagged relationship and the relative violent crime lagged relationship. For the latter as compared to the former, for example, it appears that there are a larger number of jurisdictions switching into or out of a relative score close to zero. Given generally much lower violent crime rates compared to property crime rates, this is understandable.

Another way to describe the year-to-year changes is to look at the variance of unexpected change relative to initial levels. This information appears in Table 23. On average, across the year-pairs, about 26 percent of the following year's relative property crime level was left unexplained by the score from the year previous. This, on average, appears to be markedly smaller than the unexpected changes in relative violent crime (see Table 20), where on average about 59 percent of next year's crime level was not explained by the current level. In short, there is a lot more ecological continuity for property crime niches, year to year, than for violent crime niches year to year. But the two unexpected outcomes are similar in that the predictability of next year's crime varies somewhat from year to year. For relative property crime, the level in the coming year seemed to be most predictable in the middle year pairs (2004 predicting 2005, 2005 predicting 2006), and somewhat less predictable in the earlier and later year pairs.

In sum, at least descriptively, the ecological continuity of jurisdiction-level crime niches in the MSA depends both on crime type, being markedly stronger for property than violent crime. It also depends, to a lesser extent, on the specific pair of years considered within the overall time frame.

5.4.2. Predicting overall unexpected changes

As with violent crime percentile scores, four different models were run using police department size or coverage rate and the spatially lagged property crime rate either with or without Empirical Bayes weighting. Fit (Bayesian DIC) was better with models using the "plain" spatially lagged property crime rate (results not shown). The impacts of policing, however, depended on whether department size or coverage rate was used. Results are reported therefore for two models: one with the coverage rate, and one with police department size (logged) in sworn officers. [20]

<u>*Using officer coverage rate*</u>

Fixed effects. Results appear in Table 24. Starting with community structure, as was seen in the models predicting shifts in violent crime, here too impacts in the theoretically expected direction appeared for socioeconomic status ($p < .01$) and stability ($p < .001$). Jurisdictions one standard deviation higher on SES in one year could anticipate a relative property crime score in the next year that was 1.8 percentiles lower. The corresponding later shift for being one standard deviation higher on stability was 2.8 crime percentiles lower. Again, such results may speak to the potential applicability of the basic systemic crime model to intra-metropolitan, municipality-level crime dynamics. Implications for political economy emerge as well and are discussed later.

Turning from structure to enforcement, jurisdictions with higher law enforcement coverage rates in one year were more likely ($p < .001$) to experience a decline in relative property crime in the year following. Jurisdictions with a police/population ratio one standard deviation higher in a given year could anticipate property crime being 2.8 percentiles lower in the following year. The temporally lagged impact of enforcement coverage rate presents a marked contrast with the findings for lagged violent crime where enforcement failed to demonstrate a significant impact.

[20] Models would not estimate with random effects both for linear time and for jurisdiction-cluster crime (results not shown). Thus the time random parameter was excluded.

Another contrast with the relative violent crime results was seen in the impacts of spatially lagged property crime. Here, the connection was positive ($p < .01$) rather than negative.

Turning to time, there was a significant ($p < .01$) average linear trend. Later in the time frame more jurisdictions were likely to have higher relative property crime scores. As was seen with relative violent crime levels, here again this trend arose substantially from the way Philadelphia's relative ranking on property crime shifted during the time frame. It started out (2001) at the 95.4th percentile, trending downward in subsequent years to a score in the 93.5th percentile (2007), then almost fully recovering by the end of the series (2008) to its original 95.3rd percentile position. During the years it was moving down in the ordering, other smaller communities were shifting upward substantially in their position; thus, the average positive linear trend.

Finally, it is notable that municipalities with larger populations were more likely to experience later increases in relative property crime levels ($p <.01$). Each additional increase in a hundred thousand population (logged), was associated with an unexpected crime increase of a little over one percentile per year.

Random effects. Even after entering all the predictors shown, significant ecological variation in the outcome remained to be explained at both the jurisdiction and the neighboring-jurisdictions levels (ps < .001). Of greater interest, however, were the significantly ($p < .001$) varying impacts, at the jurisdiction-cluster level, of current relative property crime on later relative property crime. The strength of the linkage between current and future relative crime varied across sub-regions of the MSA. Since this was a temporally lagged connection, these results suggest another aspect of spatiotemporal interactions in crime patterning. Ecological continuity in relative property crime niches also depended on sub-region within the MSA. The same type of connection was seen with the temporally lagged model of relative violent crime changes.

The varying impacts of current crime on future crime are mapped in Figure 67. The values mapped represent deviations from the average slope (b=.59) and are grouped into five categories using manually defined intervals, centered on the average slope. The middle category captures jurisdictions where the lagged crime impact was close to the average impact. As was seen in the lagged violent crime model, in Philadelphia and several of its immediate neighbors, relative property crime levels had average impact on future changes in property crime levels. But what's different here is which immediate neighbors join Philadelphia and Camden (city) in this average crime link over time. For relative property crime compared to relative violent crime, many more of Philadelphia's neighboring municipalities in Montgomery County immediately to its North and West are included for the average temporal crime impact. What's also different is the inclusion in this average impact group of a large number of municipalities in outer Montgomery County and wrapping around counterclockwise to upper Chester County and mid-Delaware County. Turning to the lightest colored category in the map, these are the places where current relative property crime was most loosely linked to future relative property crime levels. We find in this volatile group several jurisdictions whose locations by now should be familiar to the reader: several small localities in a string just southwest of Southwest Philadelphia, and several just southeast of the city of Camden in New Jersey. Because many of these are small municipalities with relatively high property crime rates, some of this temporal volatility arises from them switching places in the crime ordering with Philadelphia over time. Turning to the next-to-darkest shaded municipalities, places where property crime niches were a little bit more stable than average, two interesting clusters appear. In the upper part of the metro area, many of the jurisdictions in Bucks County are in this more stable than average property crime impact grouping. In the lower portion of the metro area we see a band of relatively stable crime impact locales ranging from the westernmost portion of Gloucester County, westward to lower Delaware County, and central Chester County. Connected to this band is another group of jurisdiction's extending up into northern Delaware County (Marple Township and Haverford Township) and lower Montgomery County (lower Merion Township). A rough cluster of jurisdictions in Gloucester County appear in the most stable property crime niche group.

It appears that the strength of the year-to-year property crime link may or may not covary significantly with the strength of the year-to-year violent crime link. It depends on how that tie is modeled. Spatial regressions (results not shown) predicting violent crime year-to-year link strength using the strength of the property crime year-to-year link showed a non-significant connection ($p < .10$) when a spatial lag model was used, but the lagged predictor itself was highly significant ($p < .001$). If a spatial error model was used, the strength of the property crime slope significantly predicted the strength of the violent crime slope ($p < .05$), and the spatial error parameter (lambda) was highly significant ($p < .001$). The only point being suggested here, and it is put forward tentatively, is that even though the spatial patterning of relative property crime and relative violent crime are markedly different, and even though they shift over time in different ways, there may be a cross-crime type connection in the following way: places that are more stable over time in their relative property crime niches may also be more stable over time in their relative property crime niches. The two types of ecological crime continuity may be somewhat related.

Overall, the current model explained 74.3 percent of the temporally lagged outcome, leaving 25.7 percent unexplained. Winsorizing the data, recoding unexpected change values more extreme than |40|, did not alter the pattern of significance (results not shown).

Using department size

The results predicting relative property crime changes using police department size rather than law enforcement coverage rate appear in Table 25. Because police department size correlates so strongly with municipality population ($r = .73$), department size was first examined without municipality population included. Of course, this creates a challenge for interpreting the department size impacts.

Using department size rather than law enforcement coverage rates generates results which replicates several key findings (Table 25). As before, higher socioeconomic status and higher stability were associated with smaller property crime increases later. The positive significant impact of the spatially lagged outcome reappeared, as did the positive linear impact of time. Turning to random effects, the significance pattern was identical.

The new information here is the positive impact of department size on later changes in relative property crime levels. Places with larger departments were more likely to experience significant later increases in relative property crime ($p < .001$). Interpretation problems arise because the places with bigger departments were also bigger municipalities. A question arises about the impact of Philadelphia. Because its department is literally an order of magnitude larger than the next largest department, was it having undue influence? The same impact of police department size was seen, if the analysis was repeated without Philadelphia included (results not shown).

In models which also included the log of the municipality population as well as department size, the latter continued to have a significant impact with a closely comparable b weight (results not shown). Excluding Philadelphia (results not shown) had no effect on the significance pattern seen in the model. The implication of all this would seem to be that the places where relative property crime was going up over time were also places with larger departments, while places with smaller departments which in general tend to be located toward the outer zone of the metropolitan region were less likely to be unexpectedly increasing on relative property crime.

5.4.3. Predicting intra-jurisdiction unexpected changes

As happened when predicting violent crime shifts with enforcement coverage rate, so too when predicting property crime shifts: the residuals were somewhat correlated with the crime predictor (r=.271) In other words, there were some places were average unexpected change over the years were somewhat above zero, and these places tended to have slightly higher initial relative crime levels. Consequently, an additional analysis predicted just the intra-jurisdictional, year-to-year unexpected shifts in relative property crimes (level 1 residuals after controlling for earlier relative crime levels). These residuals indeed were completely "unexpected" correlating zero with previous crime level (r=.00). They also were normally distributed. Their distribution is shown in Figure 68.

<u>*Using officer coverage rate*</u>

Results using law enforcement coverage rate appear in Table 26. There were several similarities with results predicting intra-jurisdiction unexpected changes in relative violent crime (Table 22). There was a positive linear effect of time ($p < .05$). Intra-jurisdiction changes on relative property crime were more likely to be positive later in the period. There also was a negative impact of stability ($p < .05$). When a jurisdiction was more stable than its average in a year, it was more likely to experience lower than average relative property crime in the following year. For each additional standard deviation on stability, relative property crime the year following was likely to be about half a percentile lower (-.55). Contrasting the b weight for stability in this model with the one in the full change model suggested that about 4/5th of the stability impact arose from spatial covariation, and about 1/5th from temporal covariation.

But a result not seen when predicting intra-jurisdiction violent crime was a deterrent impact of the law enforcement coverage rate on intra-jurisdictional property crime changes. Jurisdictions a standard deviation higher were likely to experience a later unexpected relative property crime drop of one percentile. The size of the lagged deterrent impact seen here (b=-.21) relative to the deterrent impact seen when examining total unexpected change (b=-.63; Table 24) suggest that about 2/3 of the lagged deterrent impact of enforcement arose from spatial patterning, and about 1/3 from temporal patterning. A year when a jurisdiction had a coverage rate that was higher than its average coverage rate for the entire period was likely to experience a relative property crime level in the *next* year that was lower than its average property crime level during the entire period. The two sets of results together suggest temporal lagged impacts of both average coverage differences across jurisdictions, and year-to-year shifts in coverage. We return to this in the discussion.

Despite having some significant impacts, the model overall did not do well predicting intra-jurisdiction shifts in relative property crime. Explained variation in the outcome was 9/10th of a percent.

<u>*Using department size*</u>

Results (not shown) using police department size and municipality population continued to show significant impacts of stability (b = -.54, p < .05). Neither department size nor municipality population had a significant impact on the outcome. The only other significant impact in this model was a significant positive impact of linear time (b=.20, p < .05) Overall, the model with department size fit less well than the model with law enforcement coverage rate (Bayesian DIC = 20956.98 vs. 20945.73). A DIC difference of at least 3-7 is considered a notable difference in fit (Spiegelhalter, et al., 2002).

5.5. Discussion and implications

5.5.1. Ecology of crime

The table immediately below summarizes the fixed impacts of three classes of predictors: community structure, coverage, and spatially lagged crime.

Outcome	Violent crime change: full	Violence change: temporal only	Property crime change: full	Property change: temporal only
Predictor				
SES	-		-	
Stability	-	-	-	-
African-American	+	+		
Law enforcement coverage			-	-
Spatially lagged crime	-		+	

Note. Pattern of significance for specific predictors, across outcomes. Blank = no significant impact.

5.5.1. Impacts of specific predictors

Stability was the structural factor demonstrating the most consistent lagged impact on later crime changes. Current stability levels shaped later changes in both property and violent crime. Comparing the size of the b weights in the different models suggested that for later violent crime changes about 9/10 of the stability impacts were spatially-based and 1/10 were temporally based. For property crime the corresponding ratios were 4/5 spatial and 1/5 temporal.

The consistency of the impacts of stability on later crime shifts perhaps supports applying Bursik and Grasmick's basic systemic model of crime to longitudinal jurisdiction–based crime models (Bursik & Grasmick, 1993b). In Bursik & Grasmick's model residential stability plays key roles shaping later social dynamics and local control patterns. Whether and how jurisdiction-level stability sets in motion the local social patterns and parochial control dynamics as postulated in that model, remains to be learned. In that model stability also links indirectly to *public* control, the ability of the locale to garner external resources. Given the size of the units considered here, it may be these links between stability and public rather than parochial control that are more relevant.

The case can be made that importance of stability for understanding crime changes at the community and municipality levels has been overlooked given the long shadow cast by studies at the city level and higher underscoring the importance of socioeconomics for understanding homicide levels and violent crime more broadly (McCall, 2010). It would appear from the current work that stability deserves at least as much attention as socioeconomics when considering crime patterning at the municipality level within a metropolitan area.

Of course, socioeconomics also proved relevant here. Higher SES places improved their crime standing over time and/or lower SES places experienced deteriorating relative safety. This link is discussed below from a political economy perspective.

Turning to racial composition, the percentage of the municipality composed of African Americans proved relevant to the spatial but not the temporal component of later violent crime shifts. Places that were more African American in composition had higher average unexpected violence changes. Racial composition appeared more relevant to these crime shifts than it did to the cross-sectional crime links seen in the previous chapter.

5.5.2. Geography of crime

Spatiotemporal interaction: Geographic variation in year-to-year crime links

The current analyses incorporated spatiotemporal patterning in the analyses of the full set of changes that contained both spatial and temporal. It did this by allowing impacts of current crime on future crime to vary across clusters of adjoining jurisdictions. This is basically saying that the bond between current and future crime may depend on where the jurisdiction is positioned in the broader metro area. In other words, the ecological continuity of crime niches might vary across sub-regions of the metropolitan area.

Results showed this to be the case (Table 21, Table 24, Figure 62, Figure 67). With violent crime, current crime niche was most determinative of future crime niche for clusters of municipalities immediately west of Philadelphia, and just north of the Delaware border. Current violent crime niches appeared least determinative of future crime niches for a cluster of jurisdiction's in Salem County and lower Gloucester County, and a small group of municipalities in Montgomery County near Northwest Philadelphia. Crime niche stability was average for

Philadelphia, Camden, and many of their immediate neighbors. Property crime niche stability was patterned differently. It appeared moderately strong in an arc of communities stretching across the lower third of the metropolitan area, and moderately strong as well in most of Bucks County. Both violent and property variations in niche stability proved significant. Whether and how the two patterns themselves link depended upon how that connection was modeled.

What are the implications of these two spatiotemporal patterns for these two crime types? Most importantly and most broadly, there is something sub – regional going on with both of these. The global Moran's I for the violent crime slope was a significant ($p < .001$) .28. The LISA map (Figure 69) shows where the sub-regional patterning was statistically significant. Violent crime niches were most unstable from year-to-year in the western portion of Salem County, in a string of communities in the northwestern corner of the metro area spanning jurisdictions in outer Montgomery and Chester counties, and in a small group of Montgomery County jurisdictions just west of northwest Philadelphia. The most sizable sub–region where violent crime niches were most stable year-to-year was located in a swath of communities stretching from southernmost Delaware County westwards through Chester County. The LISA pattern provides statistical underpinning for the descriptive patterns noted.

The global Moran's I for the property crime slope was a significant ($p < .001$) .18. Local clustering also was significant for this slope. The LISA map (Figure 70) for the property crime slopes showed significant local clustering. So there was statistical support for the idea of sub – regional patterning of ecological continuity in property crime niches as well.

The following take away points seem warranted about the spatiotemporal features of the intra- metropolitan crime patterning. First, adjacency dynamics for the entire metropolitan area, and sub-regional dynamics for particular clusters of municipalities, were both at work. The ongoing ecological continuity of crime niches at the municipality level linked to both the niche continuity of a jurisdiction's immediate neighbors, and the jurisdiction's spatial positioning within the broader metro area. Second, the sub-regional dynamics were specific to crime type. The clustering of places with stronger continuity between current and future crime levels were different depending on whether property or violent crime was examined. The reasons behind crime type dependency of the spatiotemporal patterning needs to be explored. Third, no immediately obvious over-arching schematic seems relevant as an explanation for how these patterns played out across the region. It is tempting for example to think about the role of rural texture. Is this relevant to the high degree of ecological property crime niche continuity seen in segments of Gloucester, Chester, and Bucks counties? Perhaps. But this explanation is called into question by the failure of other heavily rural locations, such as eastern Burlington County, to have high ecological continuity in their property crime niches (Figure 67). Further, for neither crime is there an obvious center-to-periphery gradient in ecological crime continuity. Nor is it clear how broader road network features apply. At present, probably the best that can be said is that this aspect of spatiotemporal crime patterning demands further investigation into its causes.

Adjoining property crime rates

If a jurisdiction in a year was surrounded by higher property crime rate communities, it was more likely in the next year to see its own relative property crime rate elevate. This link was inter-jurisdictional and spatial, not intra-jurisdictional and temporal. The most immediately plausible interpretation here is that a jurisdiction surrounded by other communities where more property offenders are active, or active at a higher rate, will likely experience more attention from those offenders operating nearby in the immediate future. Whether this spatially and temporally lagged impact arises from offender-based shifts in offending patterns, or from crime spillover effects as policing ramps up in these nearby locations, cannot be determined (Hakim, Ovadia, Sagi, & Weinblatt, 1979; Hakim & Rengert, 1981). It is not possible to include both nearby and focal enforcement levels in one model due to their high degree of collinearity. It is not possible calculate enforcement differentials between adjoining communities, as has been done in some previous work (Mehay, 1977). This is for two reasons: incomplete coverage by *local* police across the metro area, and edge effects.

The spatially lagged crime impact seen here for property crime also contrasts with Brown’s analysis of suburban property crime around Chicago (M. A. Brown, 1982). She found no significant spatial autocorrelation of property crime rates for these suburban locales before or after controlling for structure. She concluded that property crime rates were substantially intra-jurisdictional, driven by qualities of the place, not the surround. Important differences between that study and the current one may be the size of the municipalities examined, the different types of crime indicator, or the longitudinal orientation of the current study.

5.5.3. Political economy of crime

By temporally lagging the relationship between the crime changes and the predictors, causal ambiguity was reduced compared to the cross-sectional models in the previous chapter. It was literally not possible for the outcomes to influence the predictors because the variation in the outcomes is occurring after the predictors are measured. At least that's the way it's supposed to work following the Bohrnstedt/Bursik approach to separating ecological change from ongoing ecological continuity (Bohrnstedt, 1969; Bursik, 1986b). Initial crime levels are controlled, leaving only subsequent crime changes which are completely orthogonal to initial crime levels but which also take into account overall changes affecting the entire set of communities. In this instance, however, when these unexpected crime shifts were constructed -- earlier crime levels predicted later crime levels and residuals were retained – something different was seen. Modest positive correlations remained between the initial crime level and the amount of unexpected crime change.

Methodologically, the explanation is straightforward. The unexpected changes have multiple components because multilevel models were used. There were two spatial components: one was arising from clusters of jurisdictions (the level 3 portion of the residuals, g_{0k}), the other arising from individual jurisdictions (the level 2 portion of the residuals, u_{0jk}). And there was a third temporal component capturing year-to-year unexpected changes *within* a particular jurisdiction, pooled across jurisdictions (the level 1 portion of the residuals, e_{ijk}).

Stated different, spatial components of unexpected change were not "totally" unexpected. Rather, places with higher initial relative crime levels were more likely to experience later increases in relative crime levels. This meant that there were spatial dynamics, linked to a jurisdiction's cluster average (i.e., sub-region average) on the outcome being above or below the study period average for the region, and linked to a jurisdiction's multiyear average being above or below the period average for its sub-region; these spatial dynamics correlated with higher initial relative crime levels. Given that the total changes were somewhat but not totally unexpected relative to initial crime levels, and that only the intra-jurisdiction temporal chances were totally unexpected, the two types of changes were each analyzed independently.

What the ecological connections illustrate are deepening spatially-linked inequalities in public safety in the broader metropolitan region during the first decade of this century. The ecological patterning of relative crime differences in a year, across sub-regions of the metropolitan area, and within sub-regions, drive later relative crime changes. More dangerous sub-regions, and more dangerous jurisdictions within a sub-region, become even more dangerous later. The implication for the entire region, and sub-regions, is that spatially linked public safety disparities continue to intensify over time.

As importantly, these increasing spatially-linked safety inequalities over time are also structurally driven. Impacts of earlier SES emerged only when both inter- (spatial) and intra- (temporal) jurisdictional change components were considered, and not when purely temporal changes were considered. Spatial inequalities in residential quality drive later discrepancies in public safety. The same impact pattern was seen for residential stability, another indicator of residential quality.

Adams and colleagues have described how long-term pattern of increasing spatial inequality in the Philadelphia metropolitan region build substantially on historically grounded residential, street network and land-use differences across jurisdictions and sub-regions (Adams, et al., 2008). The results here extend their argument in the following ways. They show that these inequalities exist for public safety, are spatially based, and emerge on a year-to-year basis from earlier differences in residential quality in terms of socioeconomic status and residential stability. The current work is the first to document the increasing intra-regional inequality in *relative* crime disparities for the Philadelphia metropolitan area. It also is the first to show how the place-linked components of these increasing safety differentials are structurally driven.

The fact that the connection between earlier SES and later relative crime shifts appears to be spatial and not temporal also might reflect Molotch's (2000) structuration. The historical patterns mentioned just above are less likely to shift substantially on a year-to-year basis. Over a decade or a quarter century, such shifts in relative ordering on prestige and its corollary exchange value seem somewhat more likely (Logan & Molotch, 1987). Purely temporal impacts of shifting socioeconomics on later shifting relative crime levels may require longer temporal cycles than examined here.

5.5.4. Prevention

The most notable practical result here for prevention is the finding that initial department coverage levels link to lower relative property crime levels in the next year, across the period. This connection has both a spatial component and a temporal component. The temporal component is particularly important because it suggests that jurisdictions with higher than average (for them) coverage levels in a year will experience lower than average property crime (for them) in the next year. This temporally lagged impact of coverage speaks to the extensive work on police deterrence and crime conducted largely at the city level (Kubrin, et al., 2010; Sampson & Cohen, 1988a). Using a far less precise indicator than employed in those works, it nonetheless suggests a deterrent impact across a broader set of crimes than seen in some of that work which has concentrated on a particular subset of crimes. Here the impact is seen for property crime in general. The finding here also extends that deterrence impact beyond cities to a broader range of municipality types.

Although the link between higher coverage and lower property crime later generally aligns with the economic spillover work, it is hard to speak more definitively because key works in that vein were cross sectional, and used differentials in coverage rates or different policing indicators than are used here(Hakim, et al., 1979; Mehay, 1977).

Turning to officer/population coverage ratios, the current results align with earlier city-level work on proactive policing and robbery, using a very different policing indicator and a broader outcome (Kubrin, et al., 2010; Sampson & Cohen, 1988a). The current findings suggest an impact of coverage on a broader outcome, and an impact that has both spatial and temporal components. Based on the different b weights it appears that about two thirds of the law enforcement coverage impact was spatial and about one third temporal.

What that coverage variable reflects, however, is open to interpretation (McCarty, Ren, & Zhao, 2012; Zhao, et al., 2012). Does it simply reflect better resourced jurisdictions? Or does it reflect different types of government structures? Or does it reflect something more broadly about jurisdiction priorities? For interpreting the purely temporal linkage, only the first and last dynamic seem plausibly relevant. Jurisdictions in some years as compared to others have more resources; further, from one year to the next perceptions of needs can shift in the locale leading to reallocating available resources.

The spatial component of this deterrent impact could be linked to cross-department differences in policing styles (Wilson, 1968). The current data set provides no information on police cultures and the associated "varieties of police behavior." 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). Nevertheless, all these cautions notwithstanding, there may be substantial policy implications linked to the current property crime deterrent impacts of law enforcement coverage. These will be addressed more fully in Chapter 12.

5.6. Looking ahead

The work so far has described spatial patterns of crime and crime changes, geographic patterns for these, and spatiotemporal patterns for these. Links with structure and law enforcement have been demonstrated. Now we ask, given all of the above, how predictable is future crime? The next chapter turns to this purely practical forecasting question. Once a relationship between current conditions, crime and non-crime, and future crime conditions has been established, what happens when that relationship is "rolled forward" to a period outside of the forecast construction period?

Table 20. Variance of violence population weighted percentiles (PWP): Outcome vs. unexpected change

Predictor-outcome year pair	Variance: Violence PWP for outcome year	Variance: Unexpected change in outcome	Variance ratio: unexpected change as fraction of outcome
2000-2001	439.5	281.0	0.64
2001-2002	475.8	299.3	0.63
2002-2003	472.0	267.0	0.57
2003-2004	488.8	277.8	0.57
2004-2005	494.3	280.4	0.57
2005-2006	471.5	269.8	0.57
2006-2007	465.4	281.3	0.60
2007-2008	496.1	294.2	0.59
Average variance ratio			0.59

Note. In each year, n=355 jurisdictions. Unexpected change is what remains after predicting next year's violent crime PWP score with current year's corresponding score, using 3 level (adjoining jurisdictions, jurisdictions, years-within-jurisdictions) multilevel model with MCMC estimation (burnin = 25,000; estimation = 150,000). Model allowed impact of this year's crime level on next year's crime level to vary by cluster of adjoining jurisdictions. Impact did vary significantly by these clusters (Ω = .051, sd = .012, $p < .001$). Numbers in middle columns are variances. Numbers in last column reflect the coefficient of alienation ($1 - R^2$), the fraction of next year's relative violent crime level not predictable from this year's relative violent crime level.

Table 21. Predicting next year's violent crime population weighted percentiles

					95 % CI	
Fixed effects		b	sd	p <	LCL	UCL
Constant	cons	27.434	2.103		23.390	31.644
Violence PWP: Current	pwpvio	0.305	0.032	.001	0.242	0.367
Population (in 100,000s, logged)	lnp100k	2.106	0.574	.001	0.985	3.238
Time: linear	yrctr	0.585	0.123	.001	0.344	0.827
Time: quadratic	yrctrsq	0.151	0.045	.001	0.063	0.239
Coverage: only state police	sponly	2.637	1.663	ns	-0.623	5.886
Coverage: partial state police	sppart	-1.793	4.417	ns	-10.466	6.880
Coverage: multi-jurisdiction	multdept	2.652	2.217	ns	-1.631	7.053
Coverage: no information	nopdinfo	0.816	9.881	ns	-18.563	20.191
Coverage: own dept, 0 FT sworn	owndeptze	-1.261	1.820	ns	-4.848	2.292
Woodland TWP	woodland	-1.838	12.925	ns	-27.318	23.472
Sworn officers/1,000 population	offra	-0.078	0.152	ns	-0.375	0.222
SES index	sesindx	-5.425	1.200	.001	-7.775	-3.068
Stability index	stabindx	-5.782	0.869	.001	-7.526	-4.105
Age index	codeindx	0.377	0.740	ns	-1.081	1.826
Percent African-American	pblapop	0.138	0.048	.01	0.044	0.233
Spatial lag	fervio	-2.122	1.043	.05	-4.161	-0.065
Random effects		Variance	sd			
Neighboring jurisdictions		54.195	16.457	.001		
jurisdictions		63.621	10.129	.001		
Year-within-jurisdiction		114.864	3.907			
Time: linear (jurisdiction level)		0.392	0.224	.05		
Current crime (neighboring jurisdiction level)		0.035	0.009	.001		

Note. Outcome = violent crime PWP, following year at jurisdiction level (n=355). Units = jurisdiction-years (n=2,485). Predictor years = 2000-2007; outcome years = 2001-2008. MCMC estimation (burnin = 25,000; chains=150,000). For random effects "Variance" reflects the average of the variance estimates; "sd" = standard deviation of those variance estimates. Bayesian DIC = 21921.75 (run 081)

Table 22. Lagged prediction, next year's violent crime PWP, intra-jurisdiction portion only.

					95 % CI	
Fixed effects	e0_075	b	sd	p <	LCL	UCL
Constant	cons	-0.369	0.647	ns	-1.636	0.887
Population (in 100,000s, logged)	lnp100k	0.169	0.208	ns	-0.238	0.576
Time: linear	yrctr	0.344	0.097	.001	0.155	0.534
Time: quadratic	yrctrsq	0.138	0.042	.001	0.056	0.220
Coverage: only state police	sponly	0.309	0.618	ns	-0.901	1.519
Coverage: partial state police	sppart	-0.259	1.682	ns	-3.557	3.016
Coverage: multi-jurisdiction	multdept	0.340	0.810	ns	-1.248	1.932
Coverage: no information	nopdinfo	2.343	4.598	ns	-6.662	11.390
Coverage: own dept, 0 FT sworn	owndeptze	-0.244	0.976	ns	-2.165	1.669
Woodland TWP	woodland	-5.840	8.146	ns	-21.816	10.146
Sworn officers/1,000 population	offra	-0.009	0.049	ns	-0.105	0.088
SES index	sesindx	-0.611	0.481	ns	-1.553	0.334
Stability index	stabindx	-0.568	0.321	.05	-1.198	0.060
Age index	codeindx	-0.029	0.360	ns	-0.736	0.679
Percent African-American	pblapop	0.009	0.018	ns	-0.025	0.044
Spatial lag	fervio	-0.716	0.559	ns	-1.810	0.382
Random effects						
Level	Variance	sd				
Neighboring jurisdictions	0.024	0.041	ns			
jurisdictions	0.020	0.034	ns			
Year-within-jurisdiction	103.967	2.767				

Note. Outcome = following year unexpected intra-jurisdiction changes in violent crime PWP (e0_075). 355 jurisdictions, 2,485 jurisdiction-years. Predictor years = 2000-2007; outcome years = 2001-2008. MCMC estimation (burnin = 25,000; chains=150,000). For random effects "Variance" reflects the average of the variance estimates; "sd" = standard deviation of those variance estimates. Bayesian DIC = 21,266 (run 082; outcome = e0_075)

Table 23. Variance of property crime population weighted percentiles (PWP): Outcome vs. unexpected change

Predictor-outcome year pair	Variance: Property PWP for outcome year	Variance: Unexpected change in outcome year	Variance ratio: unexpected change as fraction of outcome
2000-2001	576.4	176.4	0.31
2001-2002	600.9	151.0	0.25
2002-2003	646.7	185.2	0.29
2003-2004	685.1	179.1	0.26
2004-2005	652.5	130.8	0.20
2005-2006	627.1	128.2	0.20
2006-2007	594.7	175.9	0.30
2007-2008	626.3	164.8	0.26
Average variance ratio			.26

Note. In each year, n=355 jurisdictions. Unexpected change is what remains after predicting next year's property crime PWP score with current year's corresponding score, using 3 level (adjoining jurisdictions, jurisdictions, years-within-jurisdictions) multilevel model with MCMC estimation (burnin = 25,000; estimation = 150,000). Model allowed impact of this year's crime level on next year's crime level to vary by cluster of adjoining jurisdictions. Impact did vary significantly (Ω = .031, sd = .009, $p < .001$) Numbers in middle columns are variances. Numbers in last column reflect the coefficient of alienation ($1 – R^2$), the fraction of next year's relative property crime level not predictable from this year's relative property crime level.

Table 24. Predicting next year's property crime population weighted percentiles: Using law enforcement coverage rate

					95 % CI	
Fixed effects		b	sd	p <	LCL	UCL
Constant	cons	17.976	2.131	.001	13.820	22.204
Property PWP: Current	pwppro	0.589	0.040	.001	0.513	0.670
Population (in 100,000s, logged)	lnp100k	1.185	0.476	.01	0.272	2.146
Time: linear	yrctr	0.344	0.105	.01	0.140	0.549
Time: quadratic	yrctrsq	0.020	0.040	ns	-0.058	0.099
Coverage: only state police	sponly	-2.512	1.384	.05	-5.269	0.166
Coverage: partial state police	sppart	-4.935	3.822	ns	-12.584	2.468
Coverage: multi-jurisdiction	multdept	-1.497	1.738	ns	-4.942	1.893
Golf borough	golfboro	35.607	8.020	.001	20.177	51.723
Coverage: no information	nopdinfo	-7.816	8.210	ns	-23.922	8.360
Coverage: own dept, 0 FT sworn	owndeptze	-2.050	1.546	ns	-5.088	0.981
Woodland TWP	woodland	45.965	11.075	.001	24.238	67.745
Sworn officers/1,000 population	offra	-0.625	0.128	.001	-0.877	-0.374
SES index	sesindx	-2.529	0.988	.01	-4.493	-0.620
Stability index	stabindx	-3.333	0.768	.001	-4.891	-1.878
Age index	codeindx	-0.558	0.633	ns	-1.800	0.685
Percent African-American	pblapop	0.031	0.036	ns	-0.039	0.102
Spatial lag	fLrpro	3.235	0.668	.01	1.935	4.555
Random effects						
Level		Variance	sd	p <		
Neighboring jurisdictions		52.008	11.670	.001		
jurisdictions		35.258	9.467	.001		
Year-within-jurisdiction		92.974	3.367			
Neighboring jurisdictions: Property crime slope		0.030	0.006	.001		

Note. Outcome = property crime PWP, following year at jurisdiction level (n=355). Units = jurisdiction-years (n=2,485). Predictor years = 2000-2007; outcome years = 2001-2008. MCMC estimation (burnin = 25,000; chains=150,000). For random effects "Variance" reflects the average of the variance estimates; "sd" = standard deviation of those variance estimates. Bayesian DIC = 21498.47 (run 084)

Table 25. Predicting next year's property crime population weighted percentiles: Using police department size

					95 % CI	
		b	sd	p <	LCL	UCL
Constant	cons	9.026	1.727		5.682	12.436
Property PWP: Current	pwppro	0.532	0.034	.001	0.466	0.600
Time: linear	yrctr	0.385	0.106	.001	0.177	0.592
Time: quadratic	yrctrsq	0.021	0.040	ns	-0.057	0.098
Coverage: only state police	sponly	3.303	1.975	.05	-0.521	7.222
Coverage: partial state police	sppart	-6.388	4.165	ns	-14.673	1.678
Coverage: multi-jurisdiction	multdept	4.517	2.193	.05	0.208	8.820
Golf borough	golfboro	7.857	6.551	ns	-4.820	20.845
Coverage: no information	nopdinfo	-5.946	8.954	ns	-23.400	11.557
Coverage: own dept, 0 FT sworn	owndeptze	4.002	1.984	.05	0.129	7.907
Woodland TWP	woodland	-4.171	7.490	ns	-18.889	10.497
Total sworn officers (logged)	lnoff	2.422	0.564	.001	1.333	3.542
SES index	sesindx	-2.904	1.067	.01	-5.001	-0.804
Stability index	stabindx	-3.464	0.812	.001	-5.094	-1.912
Age index	codeindx	-0.458	0.662	ns	-1.754	0.838
Percent African-American	pblapop	0.025	0.041	ns	-0.055	0.104
Spatial lag	fLrpro	3.013	0.709	.001	1.626	4.406
Random effects						
Level		Variance	sd	p <		
Neighboring jurisdictions		46.624	11.422	.001		
jurisdictions		49.909	9.567	.001		
Year-within-jurisdiction		90.396	2.953			
Neighboring jurisdictions: Property crime slope		0.029	0.006	.001		

Note. Outcome = property crime PWP, following year at jurisdiction level (n=355). Units = jurisdiction-years (n=2,485). Predictor years = 2000-2007; outcome years = 2001-2008. MCMC estimation (burnin = 25,000; chains=150,000). For random effects "Variance" reflects the average of the variance estimates; "sd" = standard deviation of those variance estimates. Bayesian DIC = 21187.51. jurisdiction population not included in model because it correlates strongly with police department size (run 087)

Table 26. Lagged prediction, next year's property crime PWP, intra-jurisdiction portion only

					95 % CI	
		b	sd	P	LCL	UCL
Fixed effects						
Constant	cons	0.584	0.635		-0.663	1.825
Population (in 100,000s, logged)	lnp100k	0.077	0.200	ns	-0.315	0.471
Time: linear	yrctr	0.201	0.091	.05	0.020	0.379
Time: quadratic	yrctrsq	0.012	0.040	ns	-0.065	0.090
Coverage: only state police	sponly	-0.425	0.595	ns	-1.591	0.746
Coverage: partial state police	sppart	-1.205	1.593	ns	-4.321	1.919
Coverage: multi-jurisdiction	multdept	-0.161	0.789	ns	-1.707	1.391
Golf borough	golfboro	10.860	3.735	0.002	3.525	18.168
Coverage: no information	nopdinfo	-5.431	4.342	ns	-13.918	3.096
Coverage: own dept, 0 FT sworn	owndeptze	-0.665	0.931	ns	-2.486	1.166
Woodland TWP	woodland	21.496	8.114	.01	5.566	37.374
Sworn officers/1,000 population	offra	-0.210	0.061	.001	-0.330	-0.089
SES index	sesindx	-0.406	0.468	ns	-1.325	0.509
Stability index	stabindx	-0.642	0.313	.05	-1.258	-0.029
Age index	codeindx	-0.065	0.354	ns	-0.758	0.628
Percent African-American	pblapop	0.006	0.017	ns	-0.026	0.039
Spatial lag	fLrpro	0.404	0.328	ns	-0.239	1.047
Random effects		Variance	sd			
Neighboring jurisdictions		0.022	0.036	ns		
jurisdictions		0.024	0.040	ns		
Year-within-jurisdiction		92.837	2.474			

Note. Outcome = following year unexpected intra-jurisdiction changes in property crime PWP (e0_088). 355 jurisdictions, 2,485 jurisdiction-years. Predictor years = 2000-2007; outcome years = 2001-2008. MCMC estimation (burnin = 25,000; chains=150,000). For random effects "Variance" reflects the average of the variance estimates; "sd" = standard deviation of those variance estimates. Bayesian DIC = 20,945 (run 090) (outcome=e0_088)

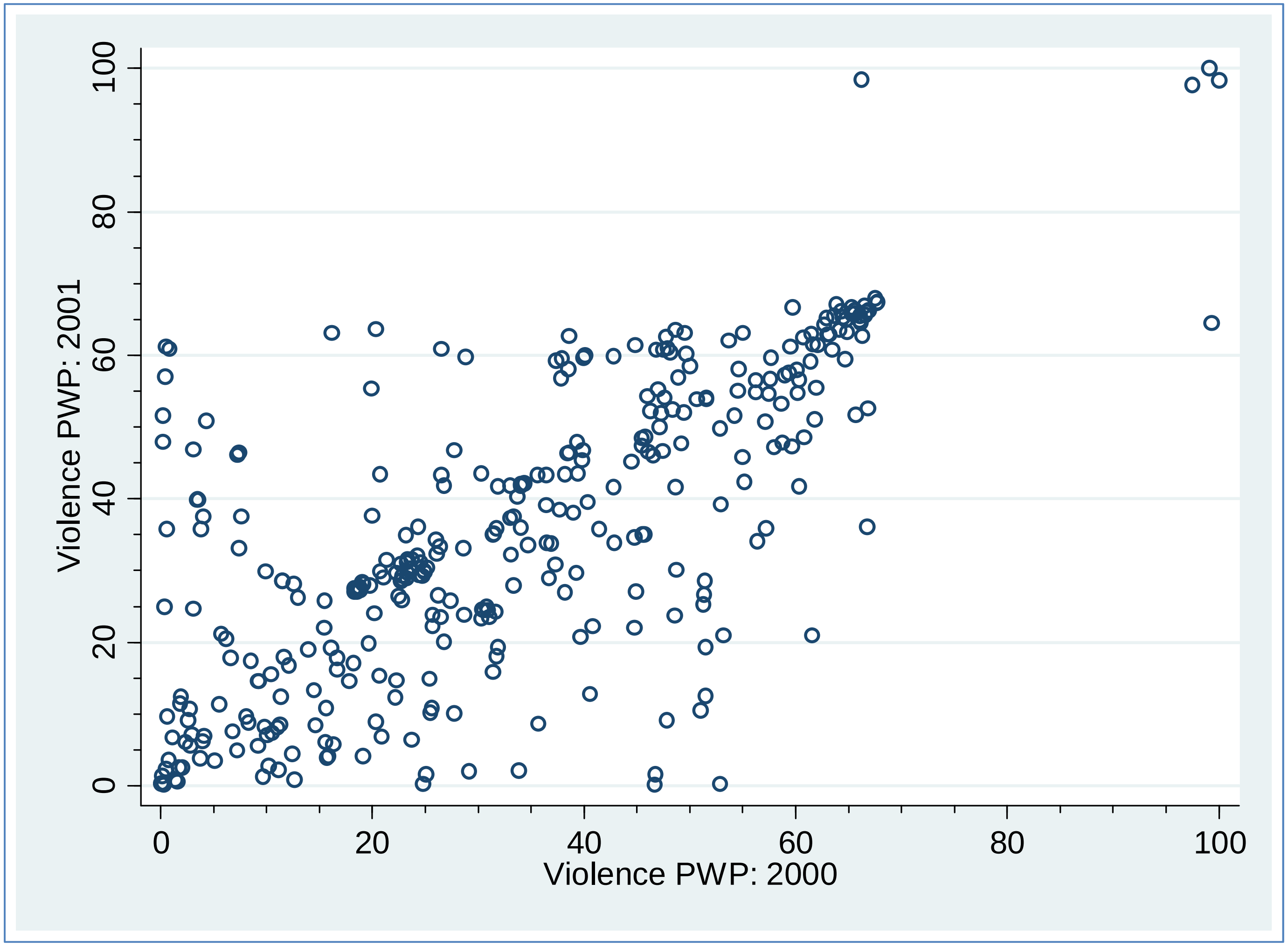

Figure 59. Relationship between violent crime rate PWPs in two consecutive years: 2000-2001

Note. Units = jurisdictions (n=355).

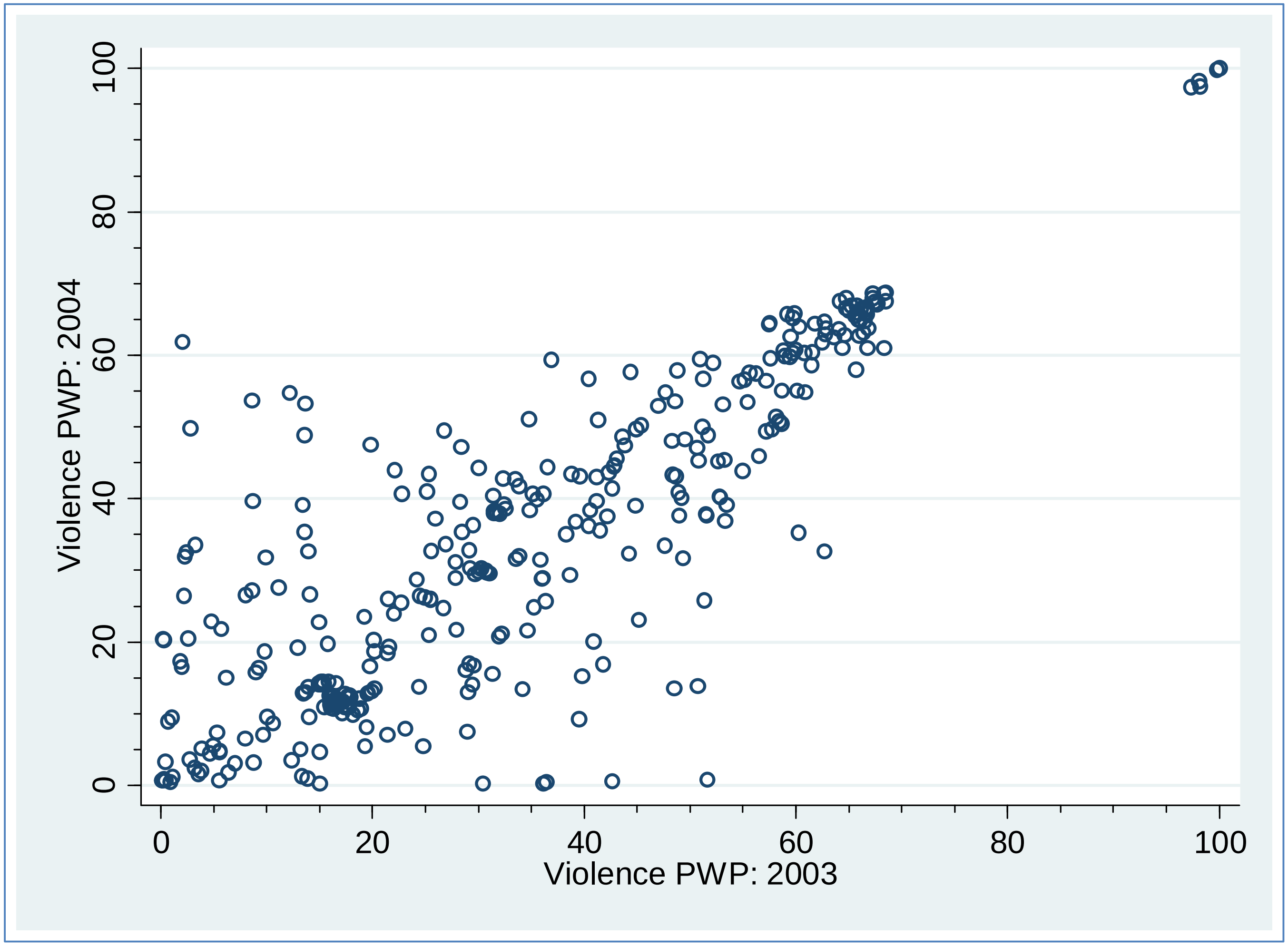

Figure 60. Relationship between violent crime rate PWPs in two consecutive years: 2003 - 2004.

Note. Units = jurisdictions (n=355).

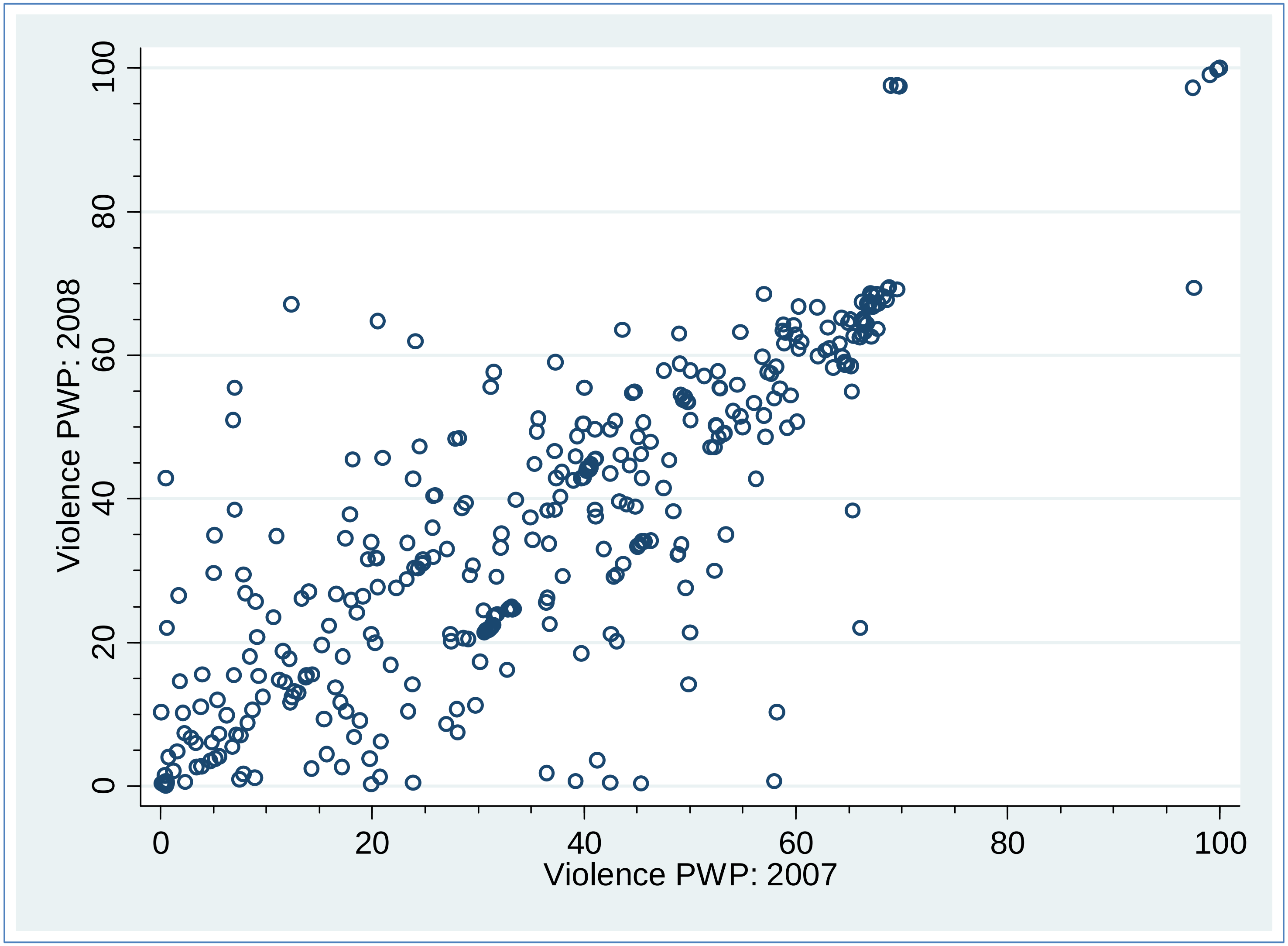

Figure 61. Relationship between violent crime rate PWPs in two consecutive years: 2007-2008.

Note. Units = jurisdictions (n=355).

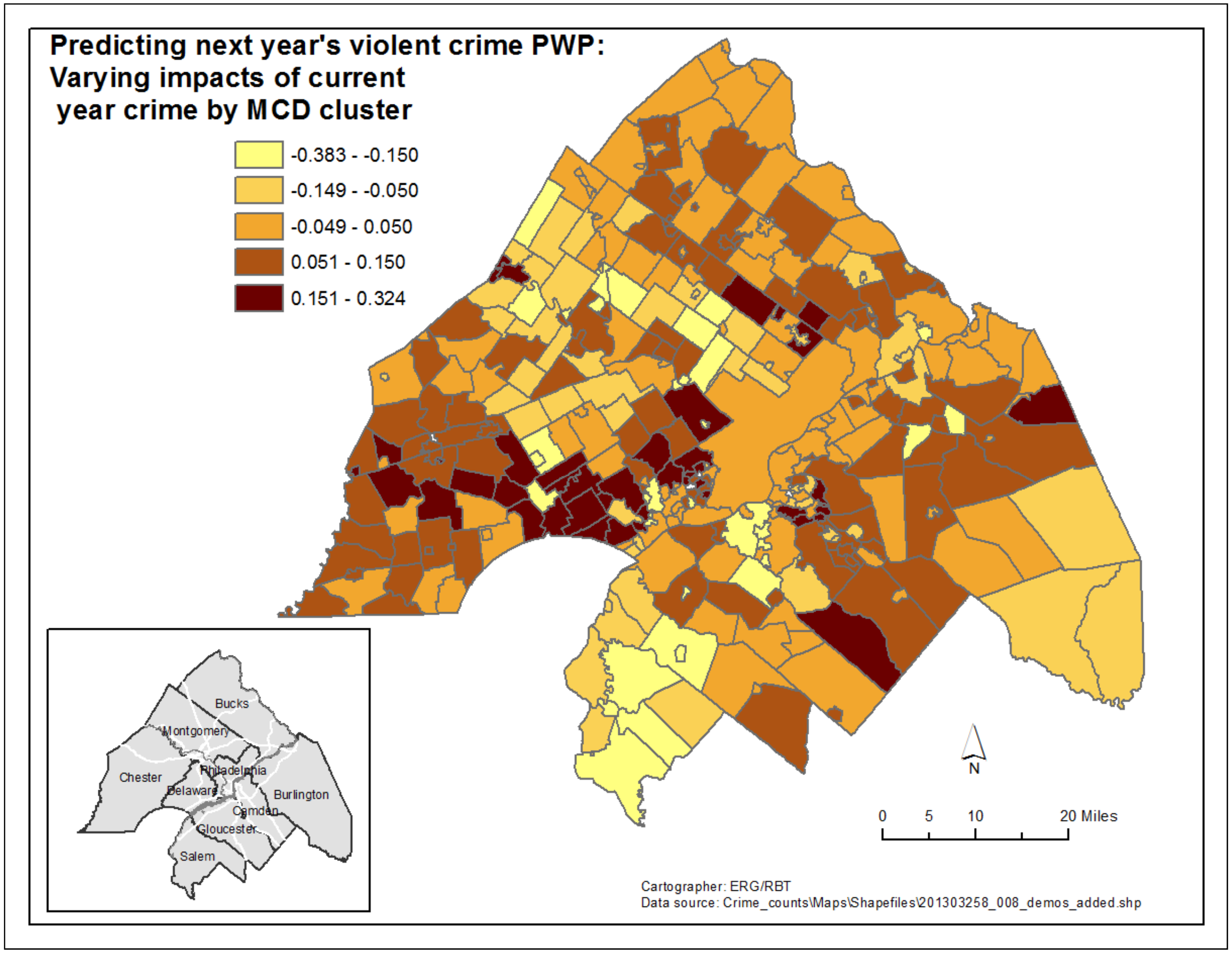

Figure 62. Varying impacts of current year violent crime population weighted percentile on next year's violent crime PWP.

Note. Outcome years = 2001-2008; predictor years=2000-2007. Impact was allowed to vary at the jurisdiction cluster level. B weights shown are the deviations from the average b weight (.305). These random effects control for other predictors and other random effects in the model (Table 21). Manual breaks.

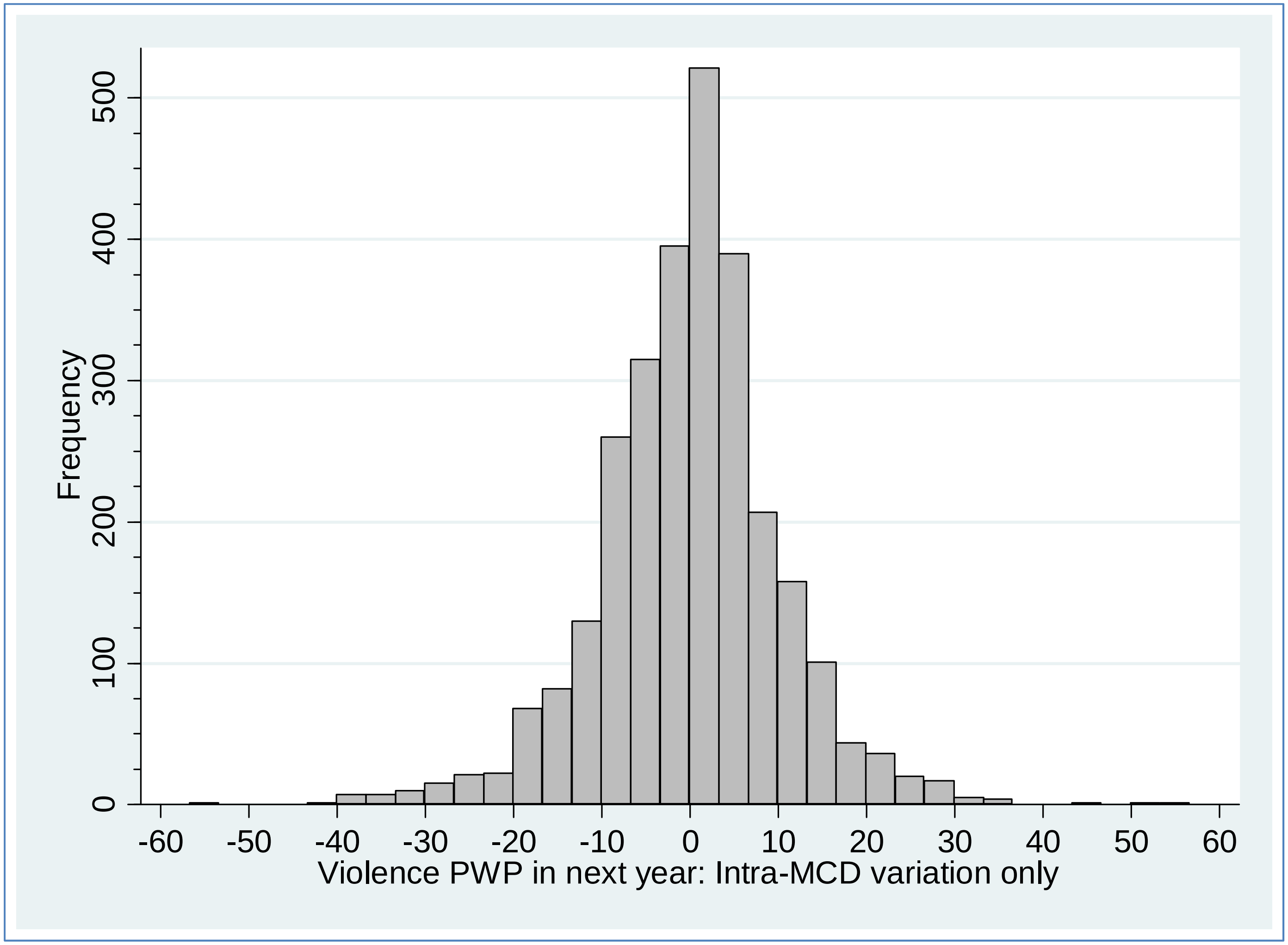

Figure 63. Distribution of intra-jurisdiction unexpected changes, violent crime property weighted percentiles.

Note. Units = jurisdiction-years. Data for years 2001-2008.

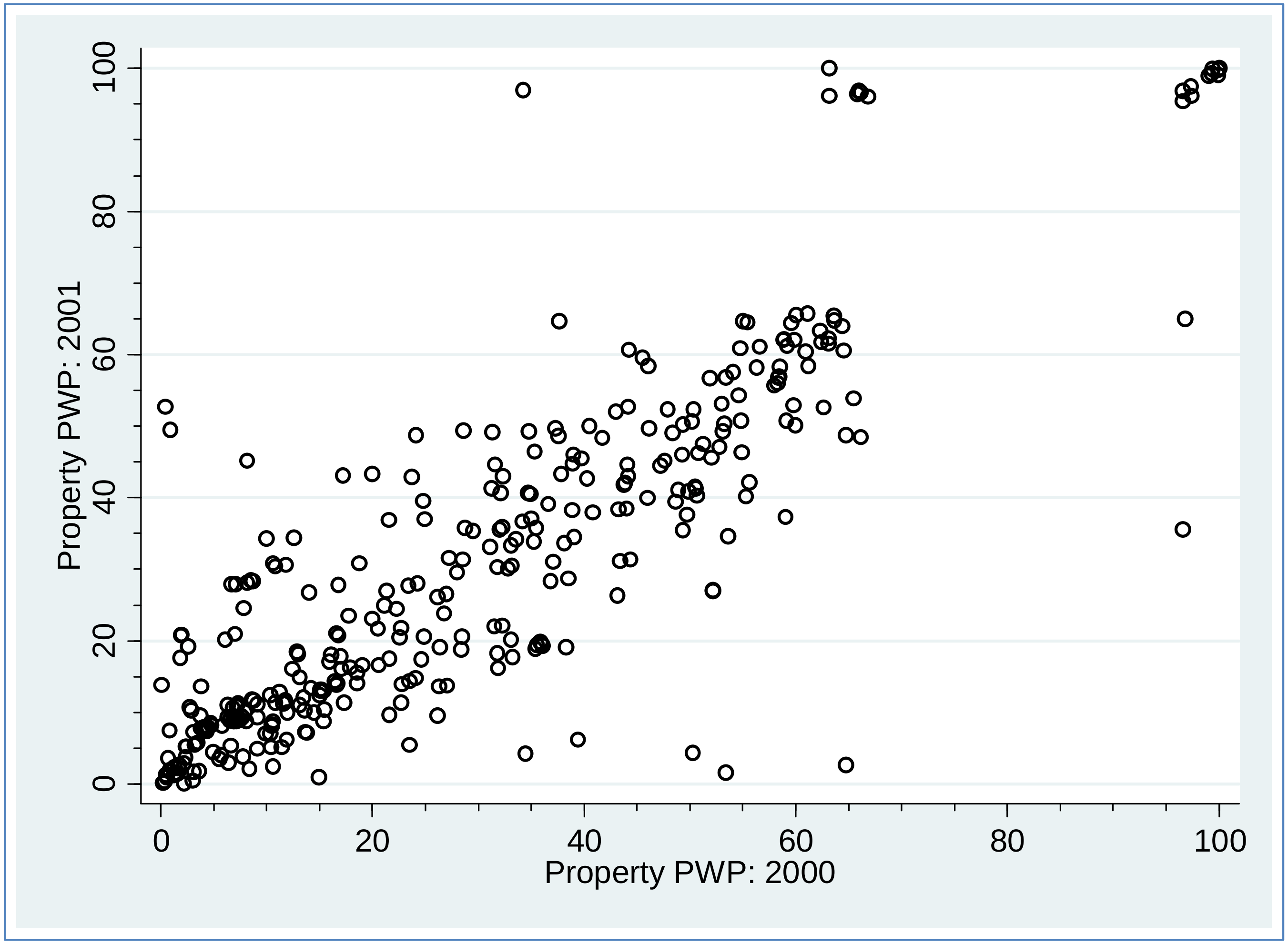

Figure 64. Relationship between property crime rate PWPs in two consecutive years: 2000- 2001.

Note. Units = jurisdictions (n=355).

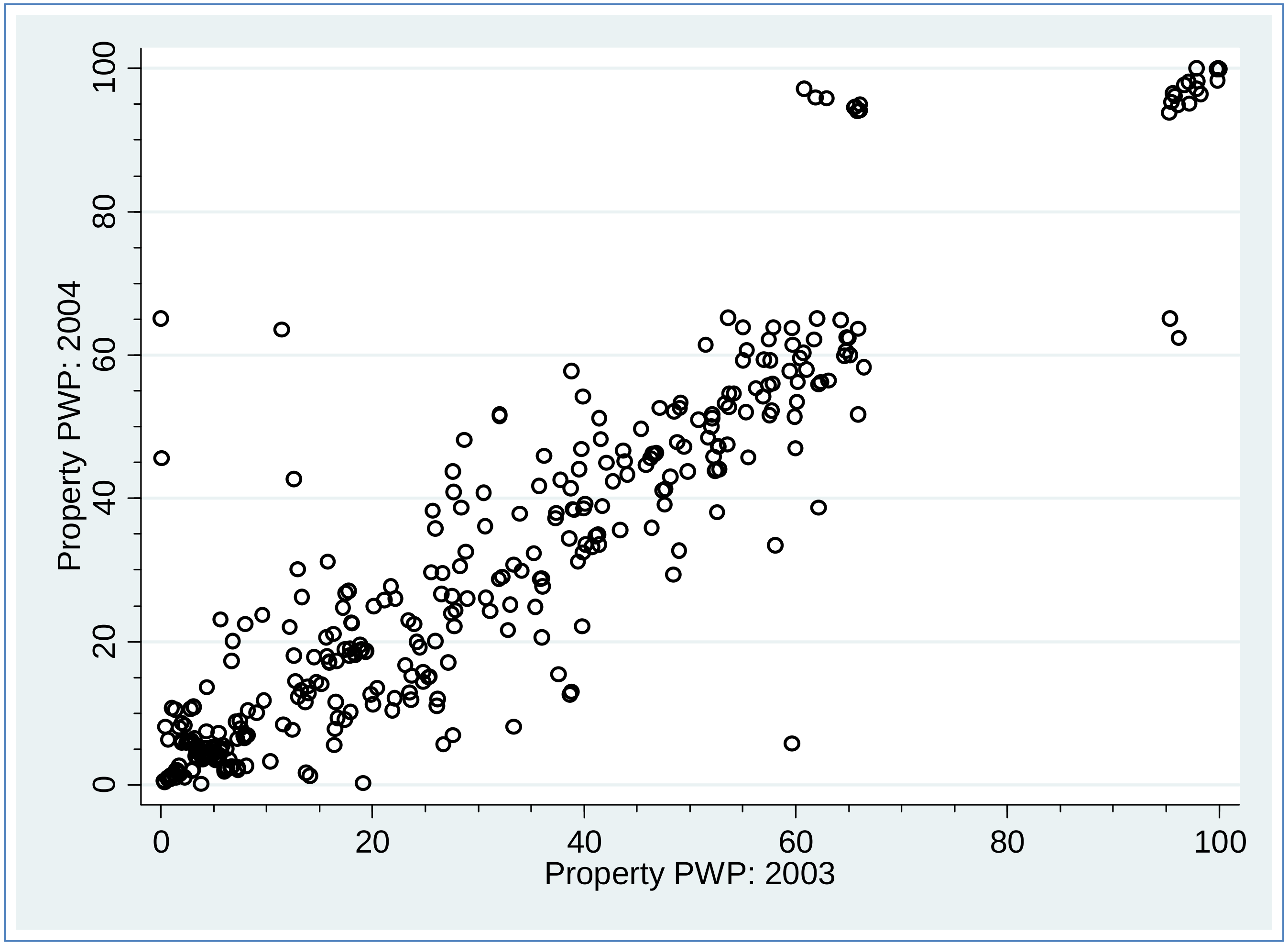

Figure 65. Relationship between property crime rate PWPs in two consecutive years: 2003-2004.

Note. Units = jurisdictions (n=355).

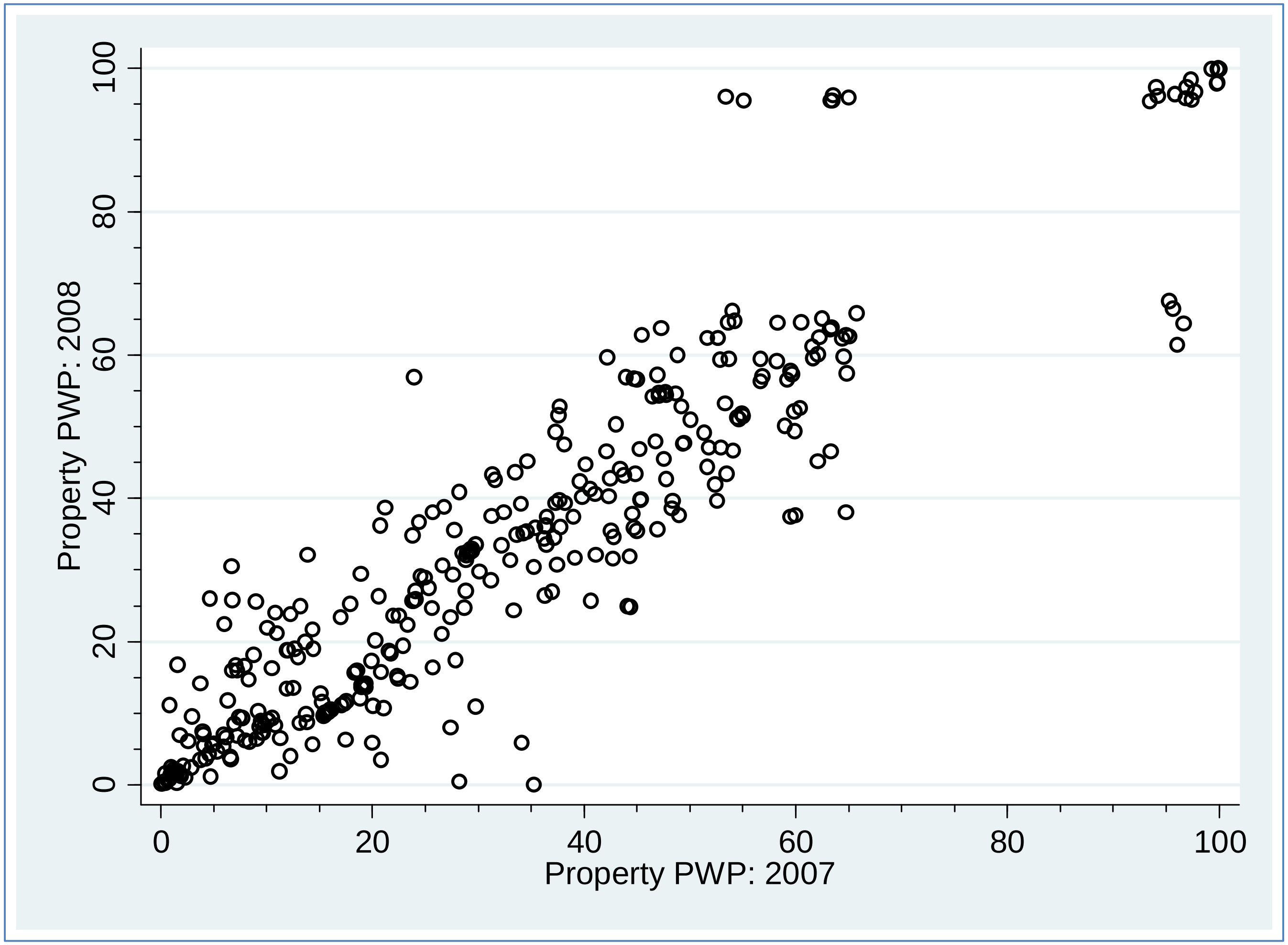

Figure 66. Relationship between property crime rate PWPs in two consecutive years: 2007-2008.

Note. Units = jurisdictions (n=355).

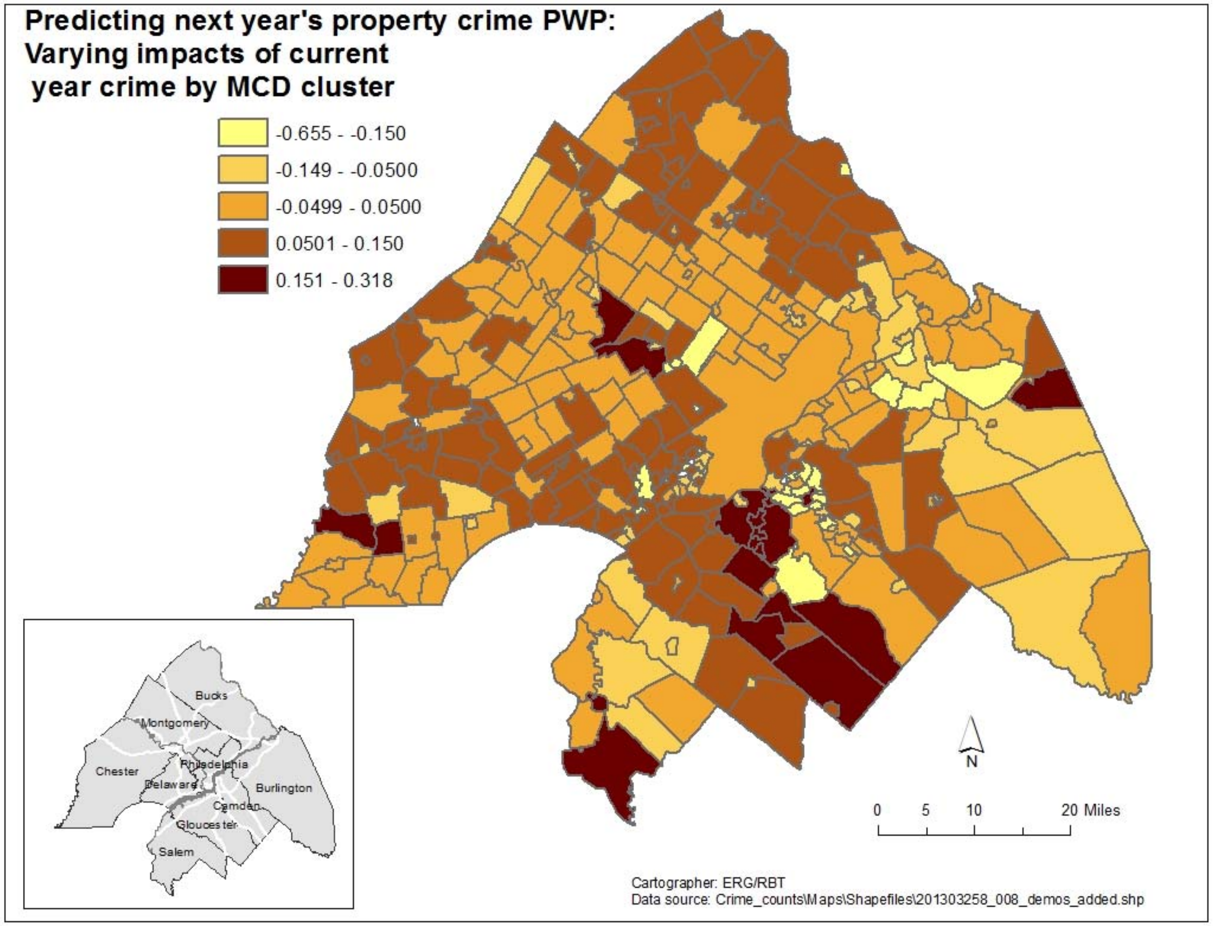

Figure 67. Varying impacts of current year property crime PWP on next year's property crime PWP.

Note. Outcome years = 2001-2008; predictor years=2000-2007. Impact was allowed to vary at the jurisdiction cluster level. B weights shown are the deviations from the average b weight (.589). These random effects control for other predictors and other random effects in the model (Table 24). The darkest shaded locales are places where current and future relative property crime levels are most strongly linked.

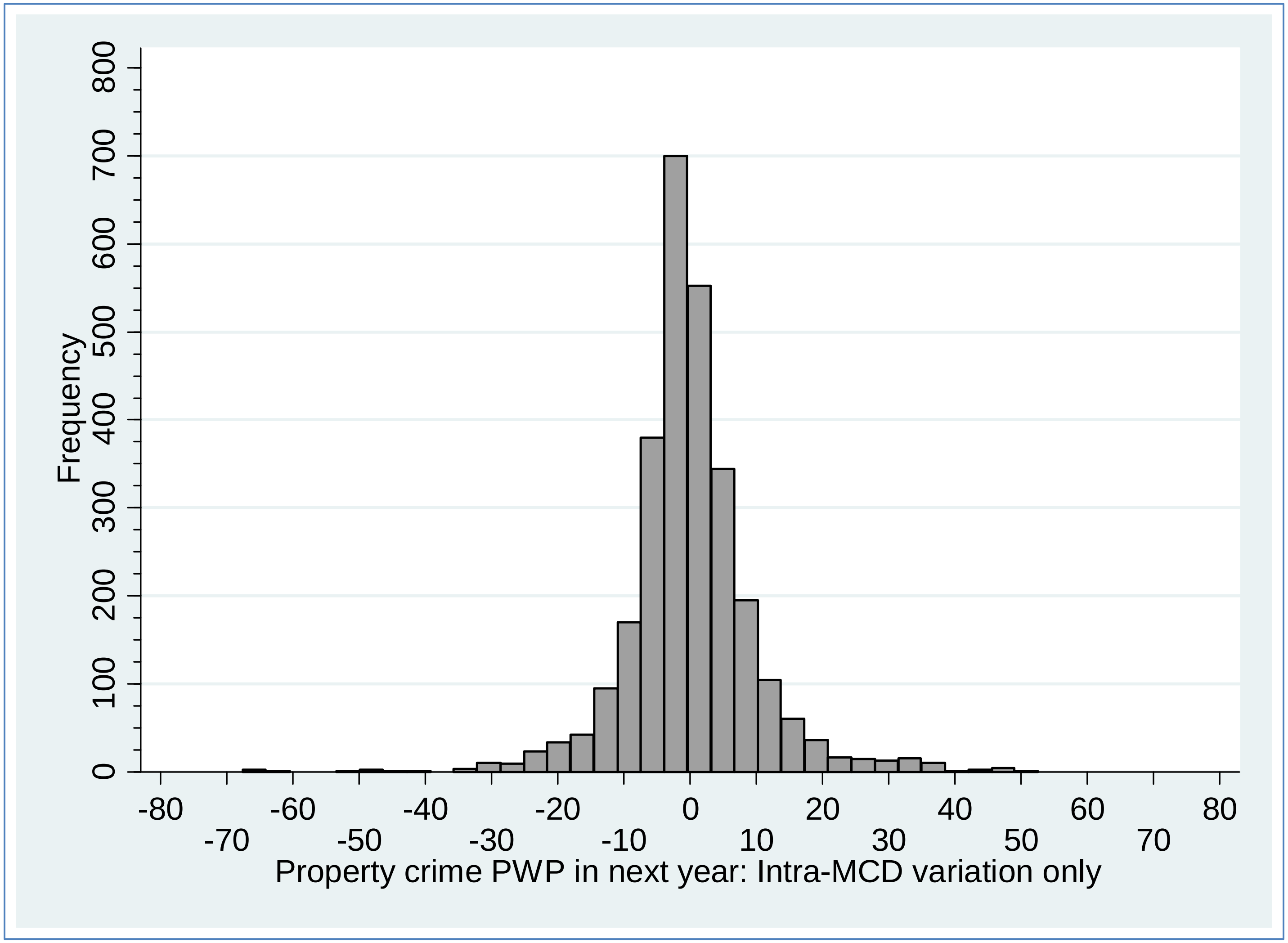

Figure 68. Distribution of intra-jurisdiction unexpected changes, property crime PWP

Note. Units=jurisdiction-years. Data for years 2001-2008.

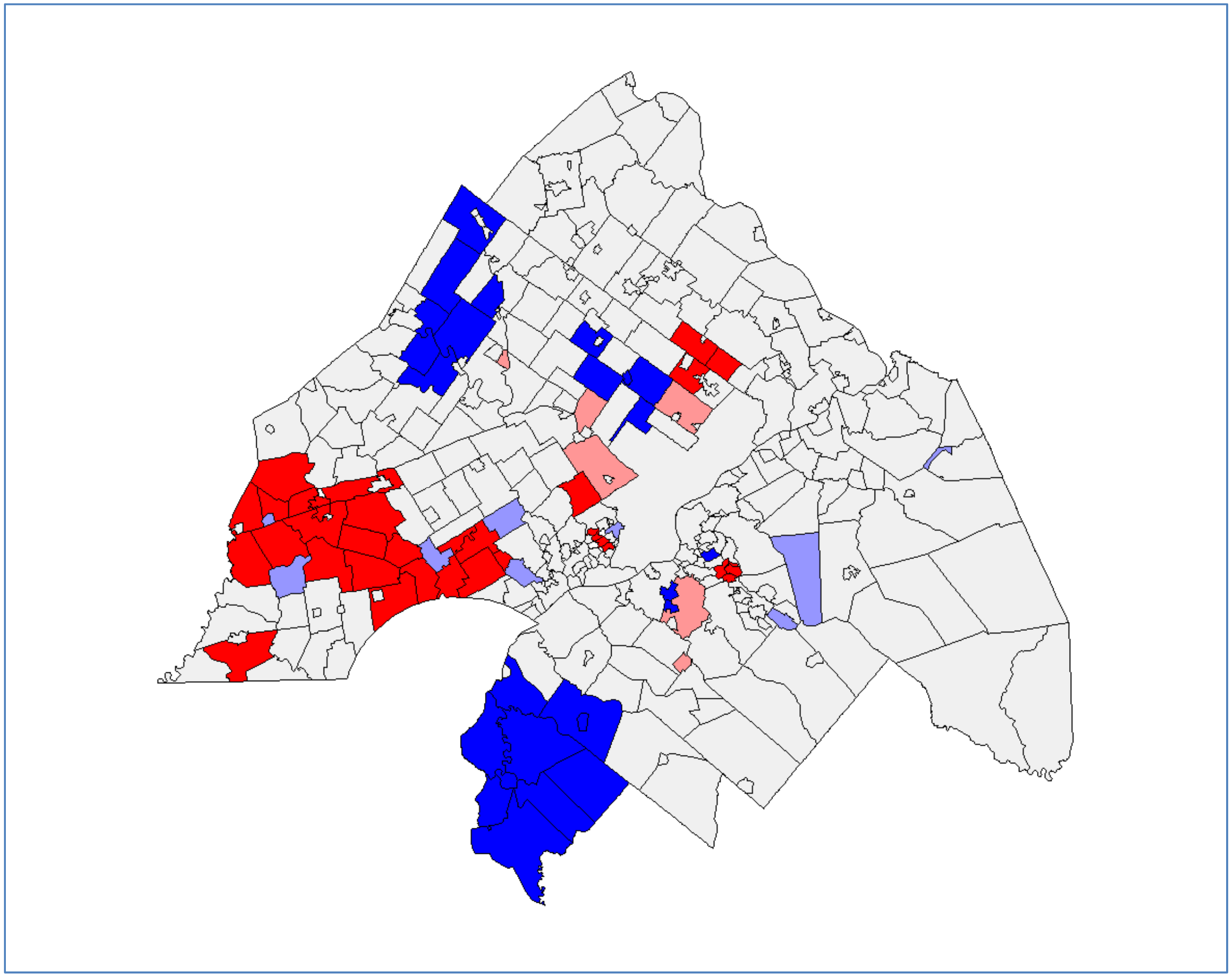

Figure 69. LISA map of clusters based on variations in violent crime (PWP) slope.

Note. Dark red equals high surrounded by high, i.e., clusters where the jurisdiction's share high levels of ecological continuity in their relative violent crime rates. Dark blue equals low surrounded by low, i.e., Clusters where the jurisdiction's share high levels of ecological instability in their relative violent crime rates. Pink equals high surrounded by low. Light blue equals low surrounded by high.

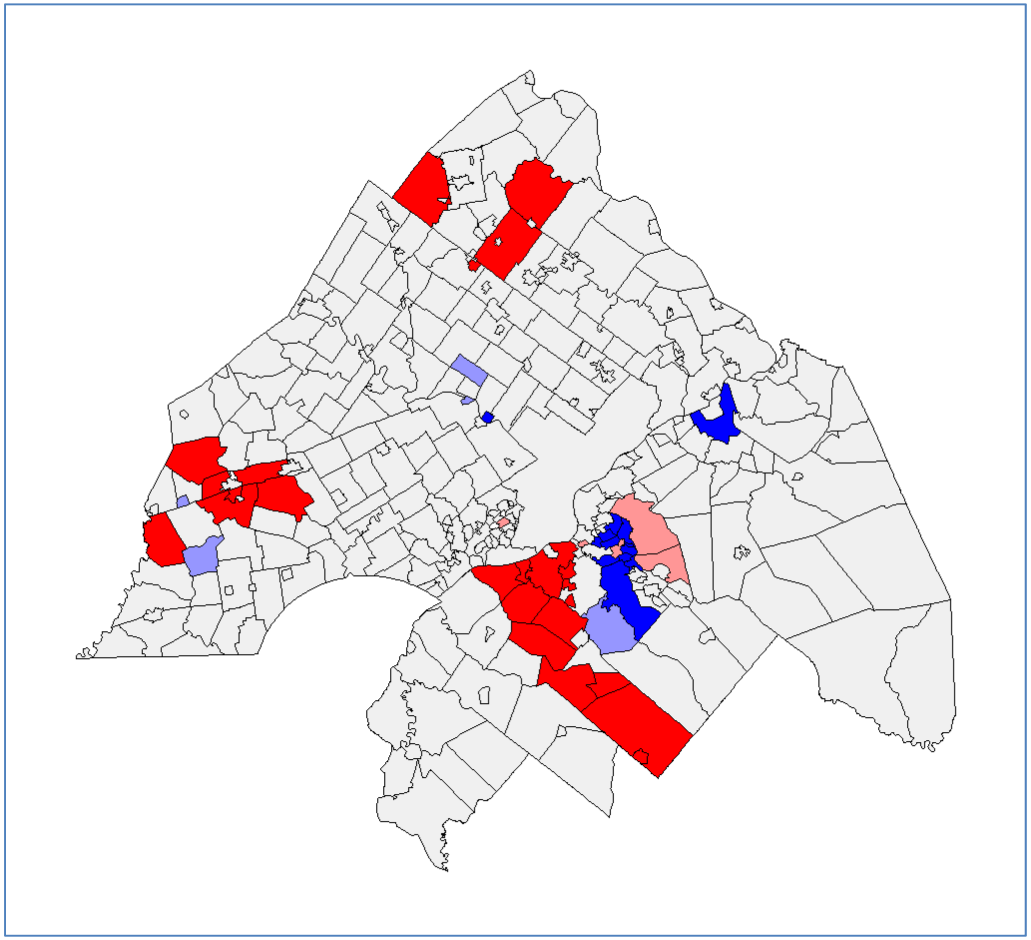

Figure 70. LISA map of clusters based on variations in property crime (PWP) slope.

Note. Dark red equals high surrounded by high, i.e., clusters where the jurisdiction's share high levels of ecological continuity in their relative property crime rates. Dark blue equals low surrounded by low, i.e., Clusters where the jurisdiction's share high levels of ecological instability in their relative property crime rates. Pink equals high surrounded by low. Light blue equals low surrounded by high.

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6. FORECASTING CRIME

6.1. Overview and implications

Previous chapters have highlighted complexities in the spatial and spatiotemporal patterning of jurisdiction level crime and crime changes in the metropolitan area. The work on unexpected crime changes observed an ecological deterrence effect of police coverage rates on later shifts in property crime levels. The current chapter investigates a second practical aspect of the crime rate patterning: the extent to which crime levels prove predictable.

Chapter 1 provided background on crime forecasting. As mentioned there, the focus of the current effort is to see how well three different types of forecast models perform: those based only on current crime levels, those based only on current demographic data, or those based on both.

There are enormous practical implications of differences in sufficiency, or a lack of difference in sufficiency, across the three models. For example, if the crime only models do as well as the two other types, then crime analysts need *not* concern themselves with acquiring and organizing census demographic data. This would greatly simplify the forecasting process.

In an effort to learn about the generalizability of one type of model over another, the current work will do forecasts for two periods: one year look-ahead forecasts and three year look-ahead forecasts. If one model type proves superior over both forecast periods, that would speak to its robustness.

The one year look-ahead forecasts first build a relationship between current year crime and demographics and crime a year later. Stated differently, the predictor-outcome relationship is lagged by one year, and just this one year of lagged prediction is used to build the model. The specifics of the resulting model are then rolled forward one year; i.e., the results from the model are applied to the predictors one year later. This is the scenario shown in Figure 71.

In the three year look-ahead forecasts, there is again a one-year lagged relationship between predictors and crime outcomes. But the one-year lagged relationship is estimated over a three year window rather than a one year window. The specifics of that relationship are then rolled forward to the next three year window and those specific coefficients applied to the scores on the predictors in that next three year window. This scenario is shown in Figure 72.

Forecasting could be stronger or weaker using three year as compared to one year windows. The three year windows could document a statistical relationship that is more stable because it is based on a longer time frame; thus, forecast results might be stronger. On the other hand with the three year windows there is a bigger time gap between the model building years and the model validating years; thus, forecast results might be weaker when they are applied to the validating data.

With the one year windows, there are four model building periods and four corresponding model validating periods one year later. With the three year windows, there is just one combined model-building period (2000➔2001; 2001➔2002; and 2002➔2003) and one combined model validation period (2004➔2005; 2005➔2006; 2006➔2007).

The next section complements the general background on forecasting provided in Chapter 1 by describing how the current forecasting effort maps onto a recent investigation of city-level crime forecasts.

6.2. Three Types of approaches and conceptual implications

Three types of lagged scenarios with different combinations of predictors are investigated. Within each type, variations are possible depending on what assumptions are made about time. These three types are situated within Pepper's recent investigation of city crime forecasting.

6.2.1. Based on past lagged crime relationships, how well can future crime be predicted? (Model A)

Pepper has called this Model A in his work, and that label is adopted here, even though his work did not include controls for law enforcement coverage and arrangements (Pepper, 2008). Say you are looking at the crime level or crime rate in year Y1 as your outcome. You are interested in the degree to which the crime level or rate in that year simply reflected a continuation of the crime level or rate in the previous year, Y0. In Hawley/Bursik terms, you are gauging the degree of ecological continuity of crime. You run a regression model usingY0 crime to predict Y1 crime. The overall strength and accuracy of the relationship observed gives you a sense of the year-to-year consistency in crime rates or crime levels across locations analyzed. Say you are now interested in what the crime count or rate will be in the upcoming year, Y2. With data from year Y1 in hand, you could apply the relationship observed when you used Y0 crime to predict Y1 crime, but just roll the relationship forward one year. Assuming a simple regression model, you would apply the intercept and b weight to the observed Y1 crime to predict Y2 crime. To account for shifts in levels from one year to the next, you could allow an additional constant.

So the crime prediction equation for the validation model would be as follows

$$Y2_{predicted} = A2 + (A1 + B1*Y1) \qquad \text{(Eq. 6.1)}$$

Where

$Y2_{predicted}$ = predicted crime rate in year Y2

A2 = a constant added when switching to the validation window

A1 = the constant from the model building window

B1 = the b weight from the model building window, originally applied to crime in year Y0

Y1 = crime rate in year Y1

Conceptually, this approach embodies a short-term, bivariate autoregressive relationship. (In the models, law enforcement levels and arrangements will be controlled, so the relationship is technically speaking multivariate. But the conceptual focus is just on the crime predictor.) Implicit is the idea that this relationship might be shifting over time; therefore of most interest is the autoregressive relationship in the immediately preceding time period. Figure 71 below displays the relationship graphically.

A modified version of this approach would use lagged relationships over multiple years to develop the prediction model for future years. The presumption here is that there is an autoregressive relationship, but that it might prove more stable over a longer period. Therefore using multiple years to estimate the one-year lagged relationship might result in more overall accuracy. Ecological crime continuity is again assumed, but it is assumed to be more temporally durable.

Say one decides to use three year prediction and outcome windows. A lagged panel model could have crime in years Y0 through Y2 as the predictors and the same crime in years Y1 through Y3 as the outcome. If one then sought to test the model using data which were entirely independent of the development data, the window would be rolled forward three years. Crime in years Y4-Y6 would be used to predict crime in years Y5-Y7. This model development and validation scheme is shown in Figure 72. Three year prediction and outcome windows are shown. Here there is no overlap between *any* of the model construction years and any of the model validation years.

Of course a two year model development time frame, or a four year time frame, also could be used. The size of the multiyear prediction and outcome window, with a one year lag in between, depends on what one assumes about stability of the autoregressive relationship. The size of the multiyear window also may depend on the practical purposes being pursued. For example, a regional agency may be interested in forward budgeting for the next three years, or only the next year.

In addition to the one-year, look-ahead models, the current work uses a three year window for estimating the lagged relationship, and then a three year window for validating the model. The current data structure, with completely separated model construction and validation years, permits one three year model validation period. Using a three year window and one-year lagged relationships, the validation model is as follows

$$[Y5\text{-}Y7]_{\text{predicted}} = A2 + (A1 + B1^{*}[Y4\text{-}Y6]) \qquad \text{(Eq. 6.2)}$$

Where

$[Y5\text{-}Y7]_{\text{predicted}}$ = predicted average crime rate in years Y5-Y7

A2 = a constant added when switching to the validation window

A1 = the constant from the model building window

B1 = the b weight from the model building window, originally applied to crime predictors in years Y0-Y2, predicting crime in years Y1-Y3; B weight represents the average impact of the predictor across the three years.

[Y4-Y6] = crime rates in years Y4-Y6, used as predictors for crime rates in years Y5-Y7

To be clear, the number of years in the model estimation period is separate from the temporal lag assumed between predictors and outcomes. Throughout, only a one year lag is assumed. It is just that in the first version of Model A, only one pair of years is used to estimate the lagged link, while in the second version, three pairs of years are used to estimate the lagged link.

6.2.2. Based on lagged demographic impacts on crime, how well can future crime levels be predicted? (Model B)

This parallels Pepper's (2008) Model B. It focuses exclusively on municipality demographic structure, again assuming a temporally lagged relationship of one year. The underlying assumption here is that demographic conditions in the preceding year "set the stage" for the expected crime level in the following year.

A time lagged etiological relationship is presumed. There is something about preceding demographic conditions that is strongly shaping later crime levels. In the Hawley/Bursik framework, it is presumed that ecological continuity as well as ecological discontinuity in relative crime levels each arises from demographic structures and changes.

In such a model there is no attempt to separate threads of continuity from threads of discontinuity. The focus is simply forecasting. The relative influence of continuity versus change is not of interest because the overriding purpose is a practical one: how well are future crime levels predicted?

The setup shown in Figure 71 is relevant if the researcher assumes that the links between structure and later crime levels shift somewhat over time. If so, a one year lagged relationship is built using one year of demographics and one year of crime, and then tested using data starting one year later. Then the entire relationship is re-estimated moving forward yet another year, and that re-estimated relationship validated by moving forward yet another year. The relevant equation for model validation is as follows.

$$Y2_{predicted} = A2 + (A1 + [B_1*D_{1(Y1)} + \dots B_d*D_{d(Y1)}]) \qquad \text{(Eq. 6.3)}$$

Where

$Y2_{predicted}$ = predicted crime rate in year Y2

A2 = a constant added when switching to the validation window

A1 = the constant from the model building window

$B_1 \dots B_d$ = the b weights from the model building window, for demographic predictors 1– d in year Y0 when predicting crime in year Y1.

$D_1 \dots D_d$ = scores on demographic predictors 1-d in year Y1.

Again, the researcher might assume the link between demographic structure and later crime levels is somewhat more stable over time. Under this assumption, a multiyear year window could be used to gauge the lagged relationship. This is the setup shown in Figure 72, but now earlier demographics are the predictors, not earlier crime levels. The multiyear window is three years. Of course, shorter (two year) or longer (four year) windows also could be used. For the validation model, the equation is as follows:

$$[Y5\text{-}Y7]_{predicted} = A2 + (A1 + [B_{1(0\text{-}2)} * D_{1(4\text{-}6)} + \dots + B_{d(0\text{-}2)} * D_{d(4\text{-}6)}]) \qquad \text{(Eq. 6.4)}$$

Where

$[Y5\text{-}Y7]_{predicted}$ = predicted average crime rate in years Y5-Y7

A2 = a constant added when switching to the validation window

A1 = the constant from the model building window

$B_{1(0\text{-}2)} \ldots B_{d(0\text{-}2)}$ = the b weights from the model building window, for demographic predictors 1– d in years 0-2 when predicting crime in years 1-3.

$D_{1(4\text{-}6)} \ldots D_{d(4\text{-}6)}$ = scores on demographic predictors 1-d in years 4-6.

- Based on past lagged crime relationships *and* lagged demographic impacts, how well are future crime levels predicted? (Model C)

This model parallels Pepper's Model C which includes both earlier crime and earlier demographics. This last approach combines the first two. Including both earlier crime and demographic structure provides greater conceptual clarity because it shifts our interpretation of earlier community demographic structural impacts in two ways.

In Model B, it is possible that the lagged predictor of crime in year Y2, for example socioeconomic status in year Y1, *itself* could have been shaped by even earlier crime levels, e.g., violence levels in year 0. Crime can shape community structure (R. B. Taylor, 1995). Therefore, the conceptual interpretation of the b weights associated with the impacts of earlier demographics on later crime is clouded. Some of the lagged demographic impacts captured in the b weight might have reflected indirect crime impacts, e.g., year Y0 violence levels shaping year Y1 socioeconomic status, and these in turn shaping year Y2 violent crime levels. Consequently, in this third type of model (C) the impacts of demographic structure on later crime cannot be carrying an impact of earlier crime because earlier crime levels are explicitly controlled.

But the clarification goes further. Because earlier crime levels are explicitly controlled, the only outcome variation remaining after controlling for earlier crime are unexpected crime changes. Granted these crime changes may not be "totally" unexpected because they may not correlate zero with earlier crime levels. But they do have a considerable fraction of ongoing ecological crime continuity removed. Consequently, to a greater degree than was true in Model B, the impacts of demographic factors describe how earlier demographics set in motion later crime *changes*. This is an important conceptual shift from model B to C. It also may have practical import, depending on agency purposes.

As with Models A and B so too with C: different time frames can be chosen for model construction and validation. As with the previous models, one year windows (Figure 71) and three year windows (Figure 72) will be used.

The model being estimated combines Models A and B. For the version with three year build and validation windows, the model being estimated is as follows:

$$[Y5\text{-}Y7]_{predicted} = A2 + (A1 + [B_{1(0\text{-}2)} * D_{1(4\text{-}6)} + \ldots B_{d(0\text{-}2)} * D_{d(4\text{-}6)}] + B_{y(0\text{-}2)}*[Y4\text{-}Y6]) \quad \text{(Eq. 6.5)}$$

Where:

$[Y5\text{-}Y7]_{predicted}$ = predicted average crime rate in year Y5-Y7

A2 = a constant added when switching to the validation window

A1 = the constant from the model building window

$B_{1(0\text{-}2)} \ldots B_{d(0\text{-}2)}$ = the b weights from the model building window, for demographic predictors 1– d in years 0-2 when predicting crime in years 1-3.

$D_{1(4\text{-}6)} \ldots D_{d(4\text{-}6)}$ = scores on demographic predictors 1-d in years 4-6.

$B_{y(0\text{-}2)}$ = the b weight for crime predictor from years 0-2 when predicting crime in years 1-3

[Y4-Y6] = scores on crime predictor in years 4-6

6.2.3. Model metrics, comparing models, modeling features

Metrics

Once forecast models are developed and tested, how does one gauge the adequacy of model forecasts? Further, if multiple metrics describing the accuracy of the forecast models are available, which one might be preferable and why? And finally, if multiple models forecasting the same outcome are of interest, how does one compare the metrics arising from different forecasts to determine which of the competing forecasts might be significantly better?

Broadly speaking, forecast metrics can seek to gauge three concerns: accuracy or degree of fit, unbiasedness, and model complexity. The latter is taken into account as a penalty since simpler models are more desirable. Since parsimony and accuracy are both desirable in models, an ideal metric would take both of these into account.

Typically used metrics to gauge accuracy include, in addition to the well-known explained variance (R^2), root mean square error (RMSE) or root mean square error of prediction (RMSEP), mean absolute error (MAE), and mean absolute percentage error (MAPE). These accuracy metrics are themselves not without controversy, and some have suggested superior alternative indicators (Hyndman & Koehler, 2006). The current work relies on some of these most widely used indicators of accuracy, bearing these cautions in mind while doing so.

RMSE is one of the most widely used in physical and social sciences (Faber, 1999). Error terms ($Y_{observed} – Y_{predicted}$) are squared, the mean determined, and then the square root of the latter is calculated. MAE takes the average of $|(Y_{observed} – Y_{predicted})|$. In turn, MAPE expresses the MAE as a percentage of Yobserved. “Most textbooks recommend the use of the MAPE” (Hyndman & Koehler, 2006: 684).

There is controversy about which accuracy indicators to prefer because each of these different accuracy indicators has different strengths and weaknesses. Whether MAE or MAPE is preferred depends on the outcome in question (Boiroju, Yerukala, Rao, & Reddy, 2011). Further, “Often, the RMSE is preferred to the MSE as it is on the same scale as the data. Historically, the RMSE and MSE have been popular, largely because of their theoretical relevance in statistical models. However, they are more sensitive to outliers than MAE or MdAE (median absolute error), which has led some authors to recommend against their use in forecast accuracy evaluation" (Hyndman & Koehler, 2006: 682).

Metrics and model adequacy comparisons

Deciding which model is "better" relies in part on differences in model accuracy indicators. One could look for *significant* differences in accuracy indicators. Not only are there controversies about the relative strengths of these specific accuracy indicators relative to one another, and relative to other accuracy indicators; there are also a variety of ways to estimate whether the accuracy differences are significant (Faber, 1999; Harvey, Leybourne, & Newbold, 1997). The analytic and conceptual complexities in this area are considerable. And, again, there are surrounding controversies.

An alternative approach is to simultaneously consider both model fit and model complexity. "A different approach to assessing the fit of a model and for comparing competing models is based on measures of information" (Long, 1997: 109). "Within the classical modeling framework, model comparison generally takes place by defining a measure of fit, typically a deviance statistic, and complexity, the number of free parameters in the model. Since increasing complexity is accompanied by a better fit, models are compared by trading off these two quantities" (Spiegelhalter, et al., 2002: 584). A range of information-based indicators are available here as well. These include the Akaike Information Criterion (AIC) and different versions of the Bayesian Information Criterion (BIC, BIC') (Raftery, 1995a, 1995b). Such indicators, however, encounter problems when applied to "complex hierarchical models" (Spiegelhalter, et al., 2002: 584). Spiegelhalter has proposed a Deviance Information Criterion (DIC), which also can be derived in Bayesian form for MCMC models, for assessing complex multilevel models (Spiegelhalter, et al., 2002). The DIC is "a classical estimate of fit, plus twice the effective number of parameters" (Spiegelhalter, et al., 2002: 603). Differences of 3-7 in the Bayesian DIC suggest that one model may be deserving of more support than another. As with BIC, a lower DIC score indicates better fit.

Of course, fit or accuracy indicators should not be the sole focus for deciding which models are preferable. "An overformal approach to model 'selection' is inappropriate since so many other features of a model should be taken into account before using it as a basis for reporting inferences, e.g., the robustness of its conclusions and its inherent plausibility" (Spiegelhalter, et al., 2002: 602). Also relevant when forecasting an outcome like crime are questions of ease of implementation.

Model conceptual, practical comparisons

How to frame model comparisons probably depends on whether the purpose is theoretical or practical. The comparisons between model types A, B, and Care of interest theoretically given Pepper's forecasting work (see above) focusing on city-level crime rates from 1980-2004 (Pepper, 2008). Using homicide, robbery, burglary, and motor vehicle theft crime rates for 101 cities with populations above 200,000, he constructed models based on 1982-2000 crime. He then constructed look-ahead forecasts for 1, 2, 4 and 10 years ahead.

His Model A included just the outcome crime level from the year before. His Model B included law enforcement coverage from two years prior (logged), drug arrest rates from two years prior (logged), incarceration rates from two years prior (logged), population from two years prior (logged), and the percent of young persons from two years prior. He used a two year lag to better separate his temporally lagged covariates from the temporally lagged (by one year) crime predictor. His Model C included the above plus the crime indicator from Model A.

There are numerous differences between Pepper's models and the models here. (1) His models included only demographics for age. Here SES, stability, race, and age structure are all considered. (2) His models included dummy variables for "unobserved city level fixed effects" (Pepper, 2008: 191). Those are not included here given the low ratio of years (1 or 3) to municipalities. (3) Pepper included population and law enforcement coverage variables only in his models B and C. Here they are included in all three model types. (4) His models B and C included incarceration and drug arrest rates; those are not used here. Incarceration rates are not readily available at the jurisdiction level, and data on arrests are incomplete because of the FBI reporting issues (see Appendix 1). (5) Pepper estimated two types of models; those where each predictor had the same impact across the different units (homogeneous panel data model), and those where each predictor was allowed to have a different impact for each different city (heterogeneous panel data model). Here only the homogeneous models will be estimated. This is for three reasons. Pepper's results suggested the heterogeneous models provided no advantage when moving to out of sample forecasts. In the multilevel models these introduce substantial complexity. And, finally, although there are conceptual points of interest in forecasting using heterogeneous predictors whose impacts vary across units, the primary focus here is a practical one.

Bearing those points in mind, the three model types are similar conceptually to his, except that these models control throughout for law enforcement coverage and arrangements, and for population. Model A highlights the utility of earlier crime. Model B highlights the utility of earlier community structure. Model C highlights the joint utility of both. Of interest will be whether the out of sample forecasts replicate Pepper's results.

Pepper's model comparisons produced complex results which depended on the crime, whether it was a short or long term forecast, and model specifics. Of interest here are shorter-term forecasts. He found "for shorter run forecasts" that "the restricted [homogeneous] Model A seems to do at least as well as the unrestricted [heterogeneous] Model C" (Pepper, 2008: 202). His analysis, however, failed to conduct statistical tests of differences in model adequacy. Further, his model comparisons failed to control for differences in model complexity.

If the results here show that Model A does better in the one-year look-ahead and three-year look ahead forecasts, and if this difference is statistically significant bearing in mind both accuracy and model complexity, such a finding would suggest the broader application of Pepper's conclusion. Here, differences in Bayesian DIC values will be used to decide which differences are significant.

From a practical perspective, minute model differences in either accuracy or accuracy and complexity combined may not be especially relevant. Most important is whether relatively simple models provide a relatively high degree of unbiased accuracy. Consequently, R^2 and MAPE values for the forecast and the ability of the model to generate relatively unbiased predictions for relatively high crime rates will be the primary features of interest. To gauge the latter, plots of predicted values against residuals are considered.

Additional modeling considerations

Also in keeping with the practical focus, the forecast models used will be relatively naïve spatially. No spatially lagged predictors or spatial modeling of error components will be included. Typically, forecasting is applied to logged crime rates, so the analysis will use that outcome. As has been done throughout, violent crime and property crime will be separated.

Another practical question arises given the population variation across jurisdictions. Constructing crime rates for extremely low population jurisdictions seems unwise because so many of these are likely to have zero crime counts, and because the small denominator will produce wildly fluctuating crime rates from year to year. Therefore, extremely low population jurisdictions need to be excluded. What population cutoff should be used? In 2000, seventeen jurisdictions (4.79 percent of jurisdictions) had populations of less than 1000. Initial models will exclude jurisdictions with populations in that range. Some sensitivity analyses will be conducted using different cutoffs such as a population of less than 1500 (n=35, 9.86 percent of jurisdictions) to see if that appreciably alters the pattern of findings. Finally, for three years Woodland (Burlington County) had an officer rate of about 66 per thousand officers. After dropping places with less than 1,000 in population in 2000, the next nearest coverage rate was less than seven. These three Woodland observations with the extreme score on this coverage predictor were dropped from the analysis. As has been done in city-level research, the natural log of (1+ the crime rate) will be used as a predictor.

6.3. Results

6.3.1. Outcome distributions

Histograms of each outcome, for a middle year (2005) in the series, appear in Figure 73 (property crime rates) and Figure 74 (violent crime rates). The skewness statistic (-.48) suggests a normal distribution for the property crime rates. The small number (n=10) of places with violent crime rates of zero contribute to a slightly non-normal skewness statistic (-1.37) for the violent crime rates. Choosing a slightly higher population cutoff (2000 population >= 1,500) does not "solve" this non-normality issue. There are still eight jurisdictions with violent crime rates of zero.

6.3.2. Property crime

Property crime out-of-sample forecast validation results appear in Table 27. The top half contains forecasts using a one year build period that is validated by rolling the data window forward one year. The bottom half contains models using a three year build period that is rolled forward three years for out-of-sample validation.

One-year forecasts

Looking first at the one year forecast validation results, two points seem clear. First, model success depends to some extent on the year predicted, but is affected even more strongly by model type.

Regarding the specific year, all forecasts regardless of model type seem less adequate for the first forecasted period (validating with 2001 predictors and 2002 outcomes). Within each model type, MAPEs are highest for this period, and R^2 values are lowest. Regarding model type, deciding which is "best" based solely on accuracy indicators suggests that models A (crime only) and C (crime and demographics) are equally preferable if we examine MAPE and R^2 values. The average MAPE for both A and C models was 3.1 percent, contrasted with 5.6 percent for the B (demographics only) models. The average R^2 was comparable for A (76 percent) and C (75.4 percent) models, and markedly better than the average (33.6 percent) for the B models. So Models A and C look preferred.

But a slightly different vantage on the preferred model is suggested when both accuracy and complexity are jointly considered, as they are with the Bayesian DIC statistic. Here it is not appropriate to consider the average but rather to do comparisons within each outcome, i.e., each forecasted year within crime type, to determine which model generated the lowest DIC and whether it was significantly lower than the next lowest value. For forecasted year 2002, Model A generated a DIC significantly lower than Model C (411 < 421). This also was true for forecasted years 2006 (112 < 131) and 2008 (162 < 177). But for forecasted year 2004, Model C was significantly better than Model A (228 < 235). So for three out of the four forecasted periods, the crime only model (A) provided the best combination of accuracy and simplicity. The implication of the pattern is that one-year out-of-sample forecasts, based only on a previously estimated lagged crime relationship, generally provided the best combination of accuracy and parsimony. Adding information about lagged demographic relationships generally did not improve the out-of-sample forecasts.

Three year forecast

The bottom half of Table 27 displays validation metrics when one year lagged relationships, averaged over a three year window, are rolled forward to a new three year out-of-sample validation window. With these forecasts, different metrics tell different stories. The R^2 values clearly suggest either crime only (A) or crime and demographics (C) models provide the best forecasts. But all the other metrics, including the Bayesian DIC, point to the demographics only model (B) as the best performing. MAPE is close to 2 for B, and close to 3 for A and C. If one bases selection on accuracy and parsimony, thus paying most attention to the Bayesian DIC metric, then the demographic model (B) is strongly preferred. The DIC is substantially lower for this model relative to crime only (B vs. A: 577 < 713) and crime and demographics (B vs. C: 577 < 687).

Looking ahead three years vs. one year

Why are the results so different depending on the size of the model building and look-ahead periods? Why do the three year model results favor the demographics only model while the one year models favor the crime only models?

There are two possibilities. First, it could just be a sample data issue. Perhaps there is something about the *particular* three year validation period that favors the demographics only model. Because there is only one data validation period within the overall study period, this idea cannot be ruled out. A second possibility is that the strength of the link between demographics and later crime is clearer than the crime-later crime link when each relationship is averaged over a three year period.

Unbiasedness

Scatterplots of predicted scores vs. residuals (not shown) suggested that all three model types were equally unbiased. All model types did a good job of generating a roughly equal number of positive vs. negative residuals at different levels of predicted crime.

Chapter 6:

Summary

Although validation performance varied depending on the size of the look-ahead window and model type, the property crime forecast models performed moderately well overall. Error levels (MAPE) for the three year models were quite low, with values of two to three percent. The one-year models had error levels between two and six percent. Again, such values seem acceptable.

That said, there were sizable differences across some of the models, and those differences have theoretical implications. Most notably, despite the lower R^2 of the crime-and-demographics model (B) for the three year look-ahead forecasts, this version seemed to provide the best combination of accuracy and parsimony. If this performance difference is not due to just sample data peculiarities during the validation period, the implication is that community conditions are shaping later crime *changes*, and those influences can be observed for a trio of years going forward.

From a practical perspective, which type of forecast to use depends on the size of the look-ahead window. For one year forecasts, the crime-only models seemed to provide the best combination of accuracy and simplicity (lowest DIC). These models also have the advantage that crime analysts would not need to acquire and master the intricacies of census demographic data. For the three year look-ahead windows, choosing the crime-only model also seems defensible given ease of implementation by crime analysts, and MAPE values that were closely comparable across the three model types.

6.3.3. Violent crime

Validation forecast results for violent crime models appear in Table 28. One year look-ahead model results appear in the top half, and the three year look-ahead model results in the bottom half.

One year forecasts

The one year look-ahead violence forecast models reveal differences between the three model types (A vs. B. vs. C). But the patterning of these variations is quite different from the property crime results. For violent crime, out-of-sample forecast results were the strongest for the crime-plus-demographics models (C). Their DIC values were always significantly lower than the corresponding values for the other model types for each specific year. Their R^2 values were the highest; the average = 49.4 percent for C vs. 47 for crime only (A) and 28.7 for demographics only (B). MAPE values were comparable for crime-plus-demographics (C: average = 10.8) and crime only (A: average=11) models. MAPE values for demographic models seemed noticeably higher (B: average = 13.9).

These results seem to contradict Pepper's finding that city-level forecast models with just crime did as well as models with crime and demographics. Perhaps, as will be discussed further below, crime forecasts for big cities behave in different ways than crime forecasts for a complex mix of urban, suburban and semi-rural localities.

The violence one-year forecast models generally did more poorly than the property crime one-year forecast models. The amount of error, reflected in the MAPE values, was generally two to three times higher. In part this higher error level reflects the inclusion of a small number of jurisdictions with violent crime rates of zero.

Three year forecast

The comparative picture proves more complex when the forecast period is three years ahead. These discrepancies mimic what was seen for property crime rates in the following way. First, the best combination of accuracy and simplicity, i.e., the lowest Bayesian DIC value, was generated by the demographics only model (B). Further, this model also produced the lowest percentage error (7.33 vs. 10.21 (C) and 10.64 (A)). Finally, this model produced the worst R^2 of the three types.

To get a more detailed sense of how Model B is behaving, Figure 75 plots predicted scores against observed scores. Save for a) the jurisdiction-years with observed violent crime rates of zero strung out along the bottom of the plot, b) a tendency for predicted scores above about 6.25 to be consistently underestimated, and a c) smaller variance of the outcome at extremely high values, the results seem somewhat presentable.

Looking ahead three years vs. one year

The same problem presents itself with violent crime forecasts as was seen with the property crime forecasts. The size of the forecast window makes a difference in which model seems the strongest. Looking ahead just one year demonstrates the virtues of taking both demographics and crime into account. Looking ahead three years suggests predictions based only on demographics may generate the most acceptable forecasts. As noted above, because there is only one three year validation window, it is hard to draw general inferences about the underlying reasons for the difference depending on look-ahead window. As with property crime, the important point is simply that the size of the forecast window matters.

Unbiasedness

Plots of predicted scores against residuals revealed a generally presentable distribution of positive and negative residuals at different levels of the predicted outcome save for two features. Figure 76 is a scatterplot based on Model B (demographics only) for the three year validation window. Residuals generally seem to be evenly distributed between positive and negative values. The exceptions are as follows. (1) At very low predicted values (predicted log of 1+ violent crime between 3 and 4), almost all of the residuals are positive. (2) Further, there is a string of extremely negative residuals extending from predicted values of about 3.75 to about 5.5. These arise from jurisdiction-years scoring zero on violent crime which were predicted to have non-zero violent crime rates.

Summary

The violent crime forecasts presented some challenges. Despite those, some points seem warranted.

Based on the one-year validation forecasts it looks like the best estimates of near-term future violence incorporate both earlier crime levels reflecting ecological crime continuity, and community conditions creating later ecological discontinuities in crime rates. Models (C) with both earlier crime and earlier community structure outperformed violence one-year look-ahead forecasts based on only one of these (Models A or B). Because Model C controlled for earlier violent crime levels, the included demographics inform about upcoming unexpected violent crime shifts. Community conditions lay the groundwork for later crime shifts. Turning for a moment to specific predictors, when either stability or SES was significant, the link with future violence shifts was always in the direction seen in decades of work in the communities and crime literature; higher stability and higher SES linked to lower future violence rates.

The relevance of *both* earlier demographics and earlier crime to short-term violent crime forecasting is a result at variance with Pepper's conclusion based on crime rate forecasts for the largest cities in the US. As noted earlier, his conclusion was that modeling future city-level crime as a function of earlier crime seemed to "provide somewhat more accurate forecasts for one and two year time horizons" (Pepper, 2008: 207).

The discrepant results seen here could be due to any number of factors: a different mix of localities in the two different studies, different data years, different lag structures, or other factors. The main point to be gleaned from the current work is that his conclusion that forecasts based on earlier-crime-only models do somewhat better perhaps should not be taken as a broadly generalizable conclusion. The current results for this period, for these units, jurisdictions, in one location, the Philadelphia MSA, for one crime class, violence rates, suggest both earlier crime and earlier demographics are needed for the "best" predictions.

That said, from a practical perspective crime analysts who can only comfortably fold crime variables into their predictions will only do somewhat worse by leaving out demographics. For the three year models, the MAPE for crime only (A) versus crime-plus-demographics (C) was less than a percentage point higher. This may be an acceptable tradeoff for analysts with little experience working with census data. For the one year look-ahead models, the average MAPE values for these two model types were almost identical. Consequently, from the practitioners' vantage, ignoring demographic structure when making violent crime forecasts for jurisdictions in a single region may not substantially compromise the quality of their efforts.

6.4. Discussion

Although Pepper (2008) found crime-only models superior for some forecasts, his overall pattern of results showed that forecast quality depended on the crime type, the model type, and the forecast period. Generally, the present results confirm those complexities. Here, model superiority, at least based on accuracy (MAPE) or accuracy-controlling-for-complexity (DIC) metrics, depended on all these as well. Different types of models did better depending on whether the look-ahead period was one or three years and whether the outcome was property or violent crime rates. These complexities are summarized in Table 29. Which model type was "best" in terms of the combined accuracy-controlling-for-parsimony metric, depended on crime type and prediction window. With one-year look-ahead predictions, and a property crime outcome, crime only models performed significantly better (DIC) in three out of the four out-of-sample validation tests. This result confirms Pepper's conclusion that crime-only models showed modestly better accuracy than other model types. But if we switch to property crime three-year look-ahead predictions, demographics-only models proved strongest on the DIC combined metric. This model type also looked strongest for violent crime three-year look-ahead predictions. Further, for violent crime one-year look-ahead predictions, the model combining crime and demographics turned in the best performance. Relative forecast performance differentials depended here, as they did in Pepper's work, on numerous factors.

From a theoretical perspective, the superior validation performance of Model C (crime-plus-demographics) for at least one forecast situation – one year look-ahead, violent crime – and the relevance of Model B for both three year predictions, all confirm the general idea, seen in several different ways in earlier chapters, that earlier structural conditions shape later crime levels (Model B) or later crime changes (Model C). Demographics literally serve as setting conditions for later safety levels and shifts. These results and the associated benchmarks such as MAPE help benchmark how far one gets with such an assumption.

From a practical perspective, however, demographics can be ignored with only modest reductions in forecast accuracy. Looking at MAPE values for different model types suggested in several situations that forecasts were only modestly impaired if they were based on models using only earlier crime.

Of course the current chapter, by design, overlooks spatial dependencies and spatiotemporal interactions across jurisdictions affecting crime levels and changes. Given the overall policy-relevance intended from these models, they were kept relatively simple.

Numerous important theoretical and practical questions lie ahead. Most importantly, as Pepper has said, this area needs "a well-developed research program on the problem" and since "social processes evolve over time [it] would [also] seem to require a scientific process that evolves as well" (Pepper, 2008: 208).

The current efforts around micro-scale predictive policing may not be a good template for a forecasting program focused on city-level or jurisdiction-level crime rates for two reasons. Since different police departments collect some crime data using different categories and recording protocols, and these vary from department to department, relying on forecasting programs that identify what kinds of non-serious crimes surface as temporal and spatial precursors to more serious crimes may not be a viable approach for large numbers of municipalities across the country. Second, moving away from crime precursors, as Blumstein and Rosenfeld have previously pointed out, the relevant precursors of later crime changes vary depending on the size of the units considered (Blumstein & Rosenfeld, 2008). What proves useful for predicting small scale crime changes may not be helpful for crime changes at larger scales.

What types of information are broadly available that should form the basis for crime forecasting? At the current juncture, Part 1 crime monthly counts reported to the FBI, and lagged census data released as part of the American Community Survey are the only two data sources that approach universal availability in the US. And, as noted earlier, even these crime data are incomplete. Nonetheless, these three sources seem for numerous reasons to represent the best data frames for grounding a large scale crime forecasting research effort at the jurisdiction level.

Step one in moving a jurisdiction-level crime forecasting research effort forward is learning more about the crime data issues, especially the missing data patterns and implications for imputation that are associated with these data at this level (see Appendix 1). A systematic investigation of jurisdiction crime data properties, parallel to Maltz's careful examination of the limitations of county-level UCR data, is required (Maltz & Targonski, 2002, 2003). Most importantly, imputation strengths and weaknesses deserve systematic consideration.

The obligatory list of study limitations is substantial. The current study is in essence a case study of jurisdictions in one MSA for one multi-year data window. Only one type of forecasting methodology was used. There are numerous other ones, which could lead to different conclusions. As noted earlier, the models are, by design, spatially naïve in order to keep the focus relatively practical. Only one lag structure was used: crime or demographics in one year affecting crime levels in the next year. Different lags may tell different stories. Further, the violent crime forecast models did not do well with jurisdictions whose earlier violent crime levels were nil.

Such limitations are partially offset by some study strengths. A performance metric that combines accuracy while controlling for model parsimony, Spiegelhalter's DIC, was employed. Its ranking of the models from more to less preferred sometimes agreed with more conventional forecast metrics, but other times did not. In addition to being a combined metric, the DIC is useful because significant differences between different models of the same outcome are straightforwardly determined by subtraction. For the one-year look-ahead crime forecasts, multiple out-of-sample validation periods were available. Finally, overall model accuracy in terms of MAPE, was generally strong.

The "take away" lesson from these forecasts is threefold. First, for the practitioners, using earlier crime levels to predict upcoming crime levels in the next year or so generally works well. Of course this approach is limited, as Pepper has noted, because it misses sharp transitions in crime rates. It also does not work well if jurisdictions have had earlier violent crime rates of zero. As long as practitioners are aware of these issues, the approach should be serviceable. Turning to theory, the strong performance of crime-only models in terms of overall forecast accuracy underscores the strength of ecological continuities in crime rates at the jurisdiction level and thus more broadly across the MSA. Third, the relevance of demographics net of earlier crime in some models confirms how these setting conditions shape later crime changes. This lagged impacts seem more relevant for violent than property crime. The relevant underlying processes remain to be determined.

Table 27. Forecast results: Property crime rate

Outcome / Model		Build years	Validate years			Validation results		
Property crime rate (logged) (lproranx)				DIC	RMSE	MAE	MAPE	R^2
One year lag: one year build	A	2000=>2001	2001=>2002	410.8	0.44	0.30	4.15	61.3
	A	2002=>2003	2003=>2004	235.4	0.34	0.21	2.84	76.8
	A	2004=>2005	2005=>2006	111.8	0.28	0.17	2.30	82.9
	A	2006=>2007	2007=>2008	162.4	0.30	0.21	2.93	82.9
	B	2000=>2001	2001=>2002	614.3	0.60	0.43	5.93	29.2
	B	2002=>2003	2003=>2004	551.5	0.54	0.39	5.43	40.9
	B	2004=>2005	2005=>2006	554.9	0.54	0.39	5.30	36.6
	B	2006=>2007	2007=>2008	650.2	0.63	0.42	5.74	27.5
	C	2000=>2001	2001=>2002	420.6	0.45	0.31	4.24	60.2
	C	2002=>2003	2003=>2004	228.4	0.34	0.21	2.91	77.3
	C	2004=>2005	2005=>2006	131.1	0.29	0.18	2.44	81.9
	C	2006=>2007	2007=>2008	177.5	0.31	0.22	2.95	82.1
One year lag: three year build	A	2000=>2001	2004=>2005	712.9	0.33	0.22	3.01	74.9
		2001=>2002	2005=>2006					
		2002=>2003	2006=>2007					
	B	2000=>2001	2004=>2005	576.9	0.23	0.16	2.18	30.6
		2001=>2002	2005=>2006					
		2002=>2003	2006=>2007					
	C	2000=>2001	2004=>2005	687.2	0.32	0.21	2.92	75.3
		2001=>2002	2005=>2006					
		2002=>2003	2006=>2007					

Note. Outcome = natural log of (1+property crime rate). Jurisdictions included only if: population 1000 or greater in 2000, officer coverage rate less than 10 in 2000 (n=337). DIC = Bayesian Deviance Information Criterion, from multilevel MCMC models. RMSE = root mean square error. MAE = mean absolute error. MAPE = mean absolute percentage error. MODEL A = crime. MODEL B = demographics (socioeconomic status, stability, percent African-American, age structure). MODEL C = crime plus demographics. ALL models also control for law enforcement coverage rate (offra), law enforcement arrangements (sppart, sponly, multdept), and population (lnp100k) With one year build: prediction model built on a one-year, lagged relationship, then rolled forward one year. With three year build: prediction model built on a one-year, lagged relationship averaged over three years, then rolled forward to the next three year period.

Table 28. Forecast results: Violent crime rate

Outcome / Model		Build years	Validate years	Validation results				
				DIC	RMSE	MAE	MAPE	R^2
One year lag: one year build	A	2000=>2001	2001=>2002	911.5	0.93	0.58	11.76	38.1
	A	2002=>2003	2003=>2004	885.0	0.89	0.51	10.49	52.6
	A	2004=>2005	2005=>2006	889.0	0.89	0.51	10.46	42.0
	A	2006=>2007	2007=>2008	901.7	0.91	0.55	11.24	55.3
	B	2000=>2001	2001=>2002	992.5	1.05	0.67	13.59	21.2
	B	2002=>2003	2003=>2004	1,016.3	1.08	0.70	14.33	30.0
	B	2004=>2005	2005=>2006	944.0	0.97	0.65	13.13	31.8
	B	2006=>2007	2007=>2008	1,043.2	1.12	0.71	14.45	32.0
	C	2000=>2001	2001=>2002	888.6	0.90	0.56	11.32	42.1
	C	2002=>2003	2003=>2004	871.6	0.87	0.51	10.42	54.4
	C	2004=>2005	2005=>2006	872.9	0.87	0.50	10.17	44.7
	C	2006=>2007	2007=>2008	893.9	0.90	0.54	11.11	56.3
One year lag: three year build	A	2000=>2001	2004=>2005	2,622.5	0.87	0.52	10.64	48.8
		2001=>2002	2005=>2006					
		2002=>2003	2006=>2007					
	B	2000=>2001	2004=>2005	2,433.9	0.61	0.36	7.33	30.1
		2001=>2002	2005=>2006					
		2002=>2003	2006=>2007					
	C	2000=>2001	2004=>2005	2,553.3	0.84	0.50	10.21	52.1
		2001=>2002	2005=>2006					
		2002=>2003	2006=>2007					

Note. Outcome = natural log of (1+violent crime rate). Jurisdictions included only if: population 1000 or greater in 2000, officer coverage rate less than 10 in 2000 (n=337). DIC = Bayesian Deviance Information Criterion, from multilevel MCMC models. RMSE = root mean square error. MAE = mean absolute error. MAPE = mean absolute percentage error. MODEL A = crime. MODEL B = demographics (socioeconomic status, stability, percent African-American, age structure). MODEL C = crime plus demographics. ALL models also control for law enforcement coverage rate (offra), law enforcement arrangements (sppart, sponly, multdept), and population (lnp100k) With one year build: prediction model built on a one-year, lagged relationship, then rolled forward one year. With three year build: prediction model built on a one-year, lagged relationship averaged over three years, then rolled forward to the next three year period.

Table 29. Summary of out-of-sample validation results for crime forecast models

Prediction window	Feature	Property crime	Violent Crime
1 year	Error (MAPE range)	2-6 percent error	10-14 percent error
	Model type yielding best (accuracy + parsimony)	Crime only (Model A)	Crime and demographics (Model C)
3 year	Error (MAPE range)	2-3 percent error	7-11 percent error
	Model type yielding best (accuracy + parsimony)	Demographics only (Model B)	Demographics only (Model B)

Note. Jurisdiction-level forecast model summary. Jurisdictions with populations less than 1,000 in 2000 excluded. All models constructed using one year lag between predictor(s) and crime rate outcome. For one year prediction window, MAPE range based on four validation periods and three model types. For three year prediction window, MAPE range based on one validation period and three model types. Model types were crime only (A), demographics only (B), and crime plus demographics (C). All models controlled for law enforcement coverage rate and coverage arrangement. Best (accuracy + parsimony) based on having significantly lower Bayesian DIC (Deviance Information Criterion) values.

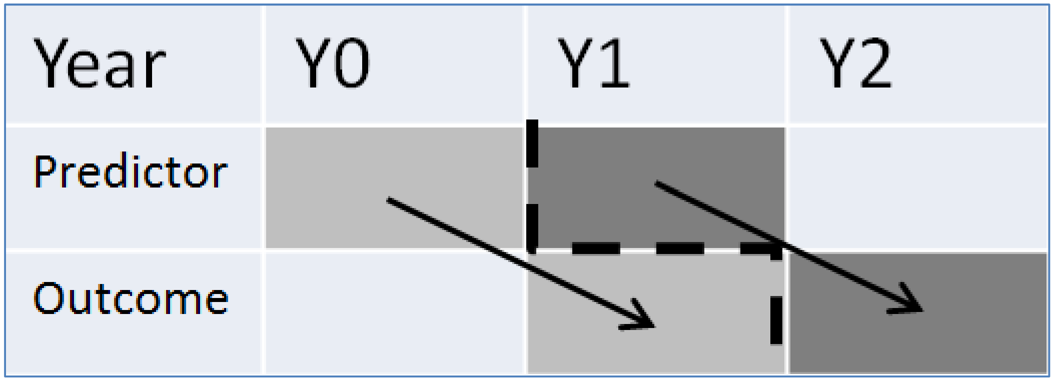

Figure 71. Short term autoregressive relationship with lag of one.

Note. Dashed line separates model development data from out-of-sample model test data.

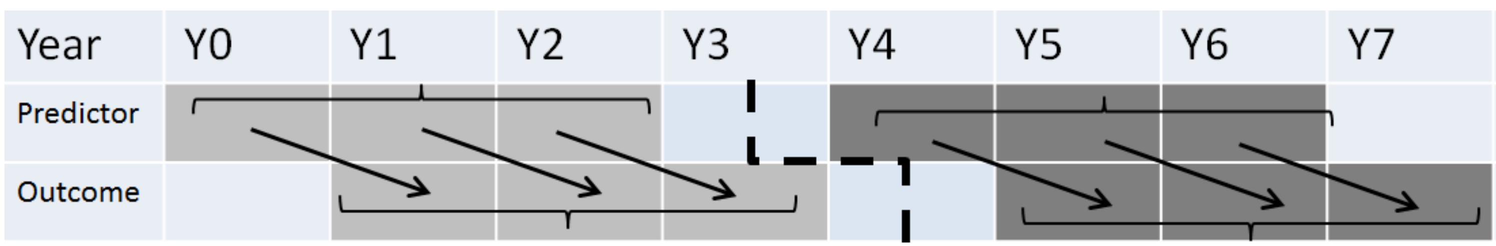

Figure 72. Autoregressive relationship with a lag of one, but presumed stable over a longer period.

Note. Dashed line separates model development data from out-of-sample model test data. Each of the three arrows reflects the *same* statistical relationship.

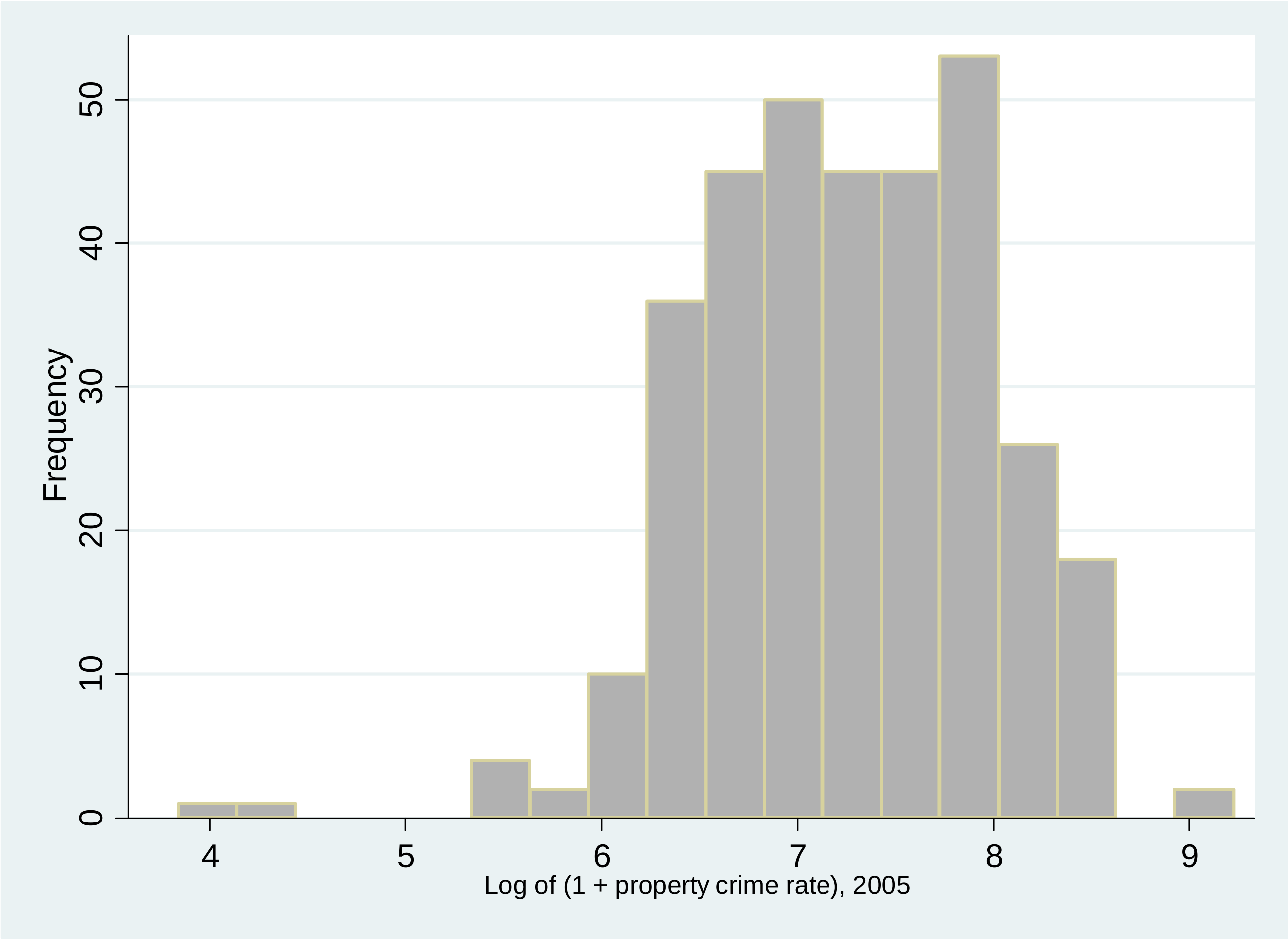

Figure 73. Histogram, jurisdiction-level property crime rate, natural logged, 2005.

Note. (n=338). Jurisdictions with population less than 1000, or officer coverage rate > 60 excluded.

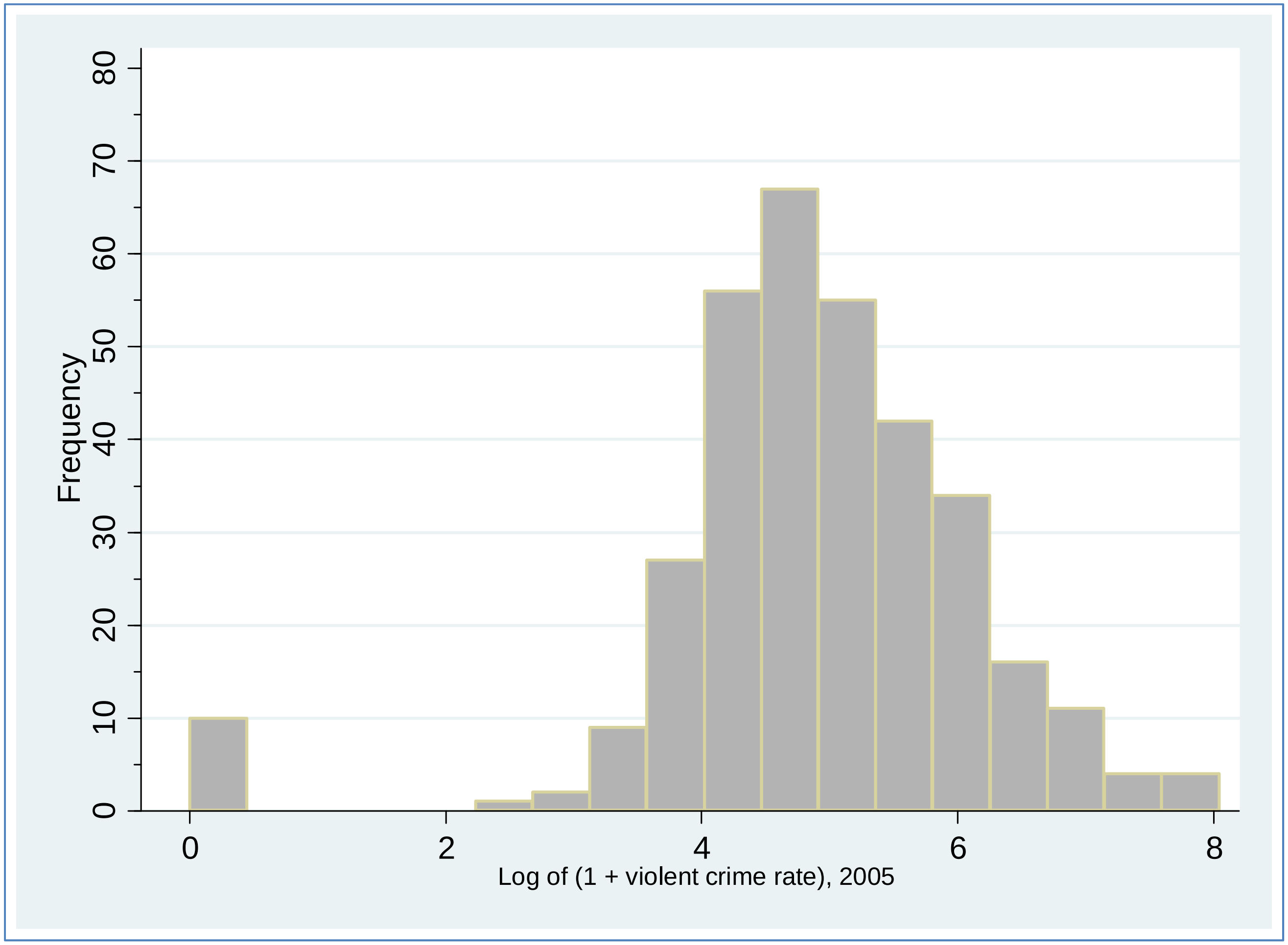

Figure 74 Histogram, jurisdiction-level violent crime rate, natural logged, 2005. (n=338).

Note. Jurisdictions with population less than 1000, or officer coverage rate > 60 excluded.

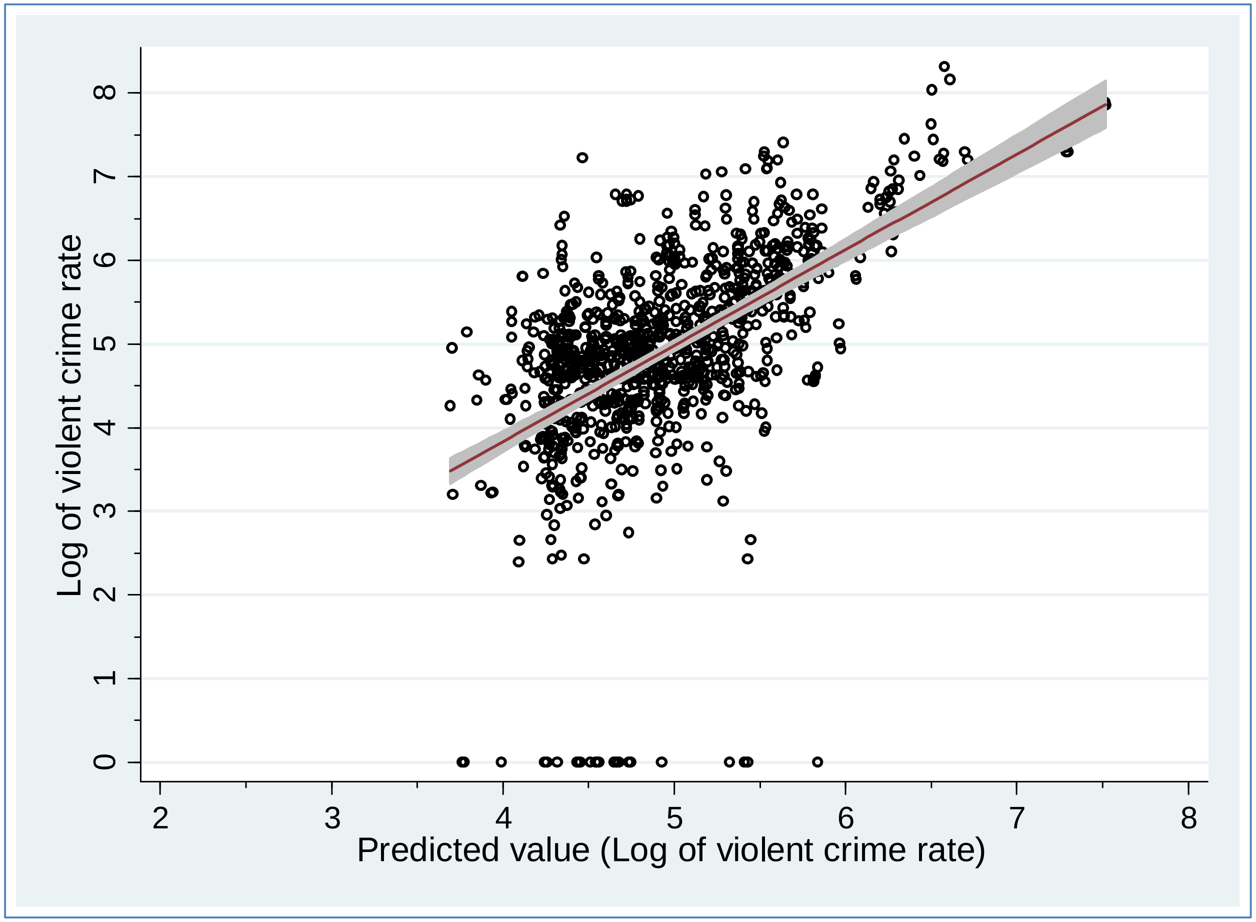

Figure 75. Log of violent crime rate, three year forecast window.

Note. Predicted values from Model B (demographics only) appear on X axis. Observed log of violent crime rate on Y axis. Line = linear regression of y on x with 95 percent confidence interval shown. (run = 126)

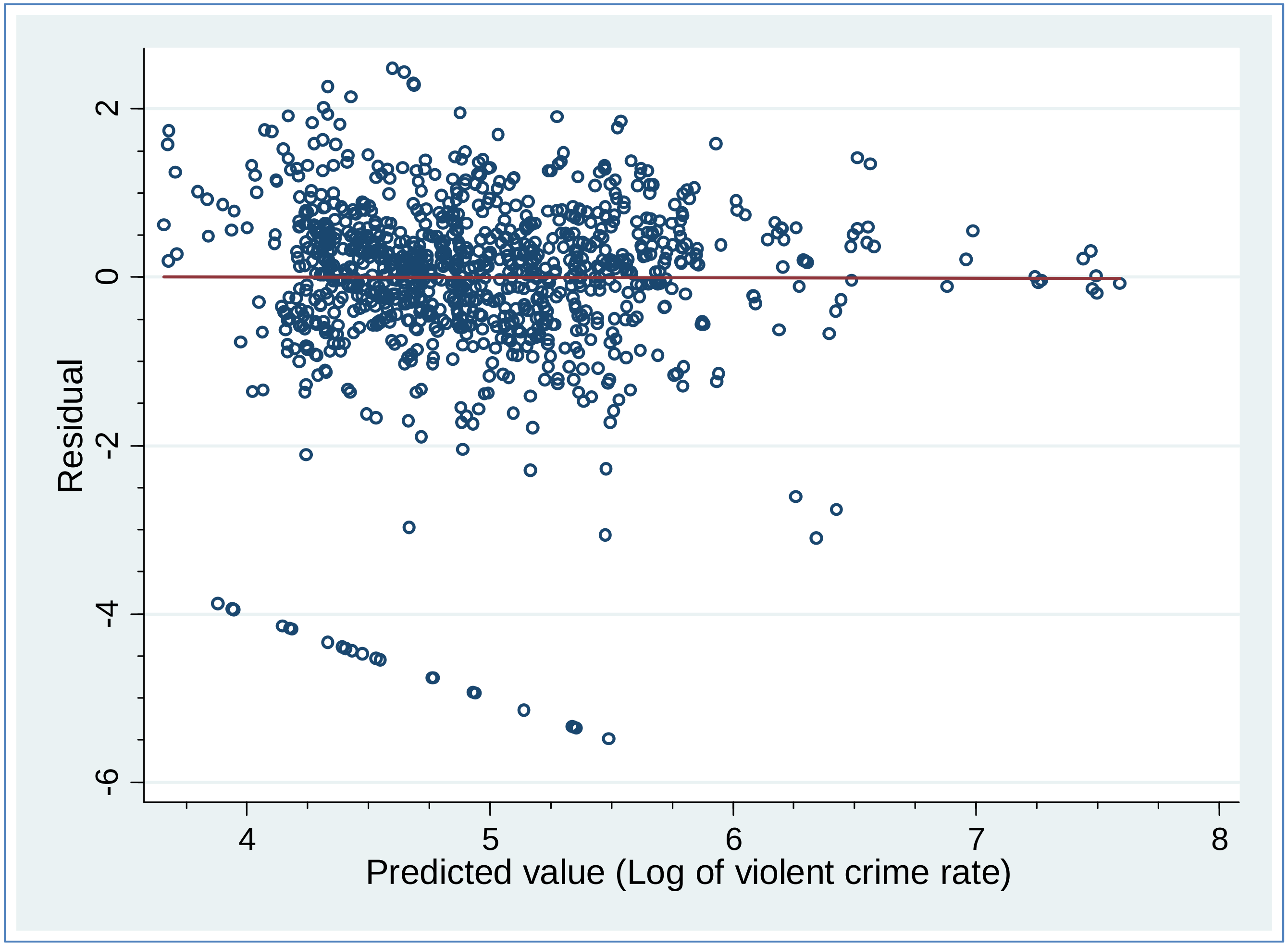

Figure 76. Log of violent crime: Predicted scores and residuals.

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.

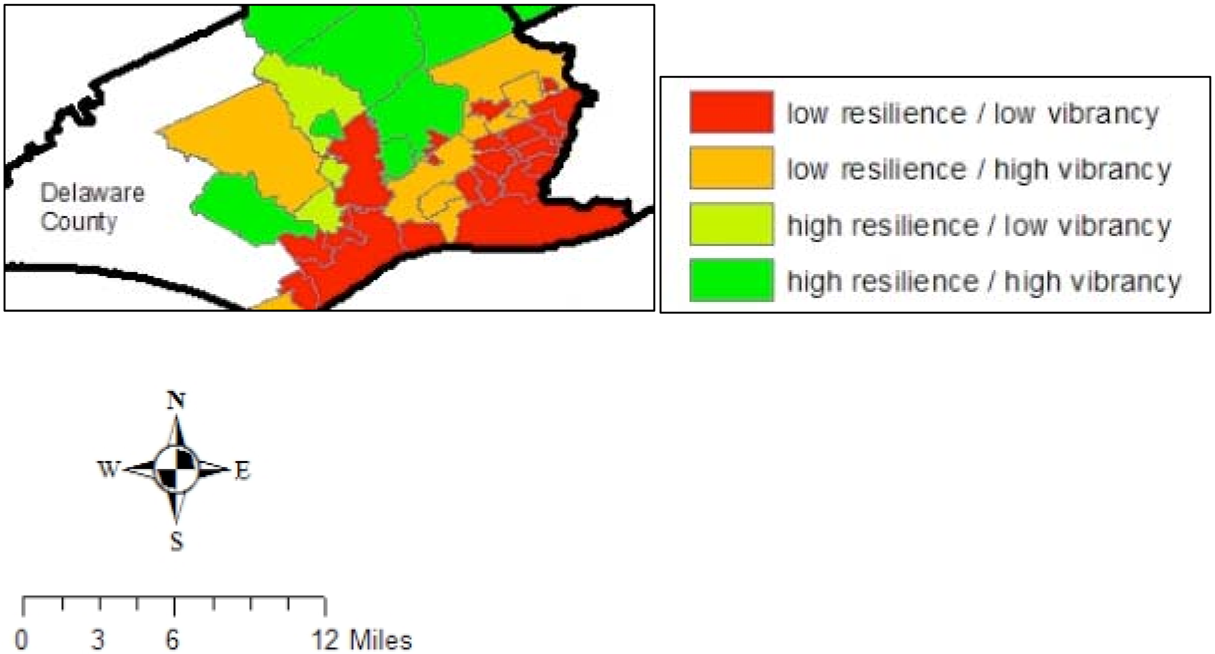

Figure 77. Jurisdictions classified by resilience and vibrancy.

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

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.

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[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.

Appendix 1

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

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		95.30			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

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		94.47			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			

Appendix 1

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			

Appendix 1

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.

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

Appendix 1

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

Appendix 1

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.

Appendix 1

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.

Appendix 1

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.

Appendix 1

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

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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	7.21	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

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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	6.69	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

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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%

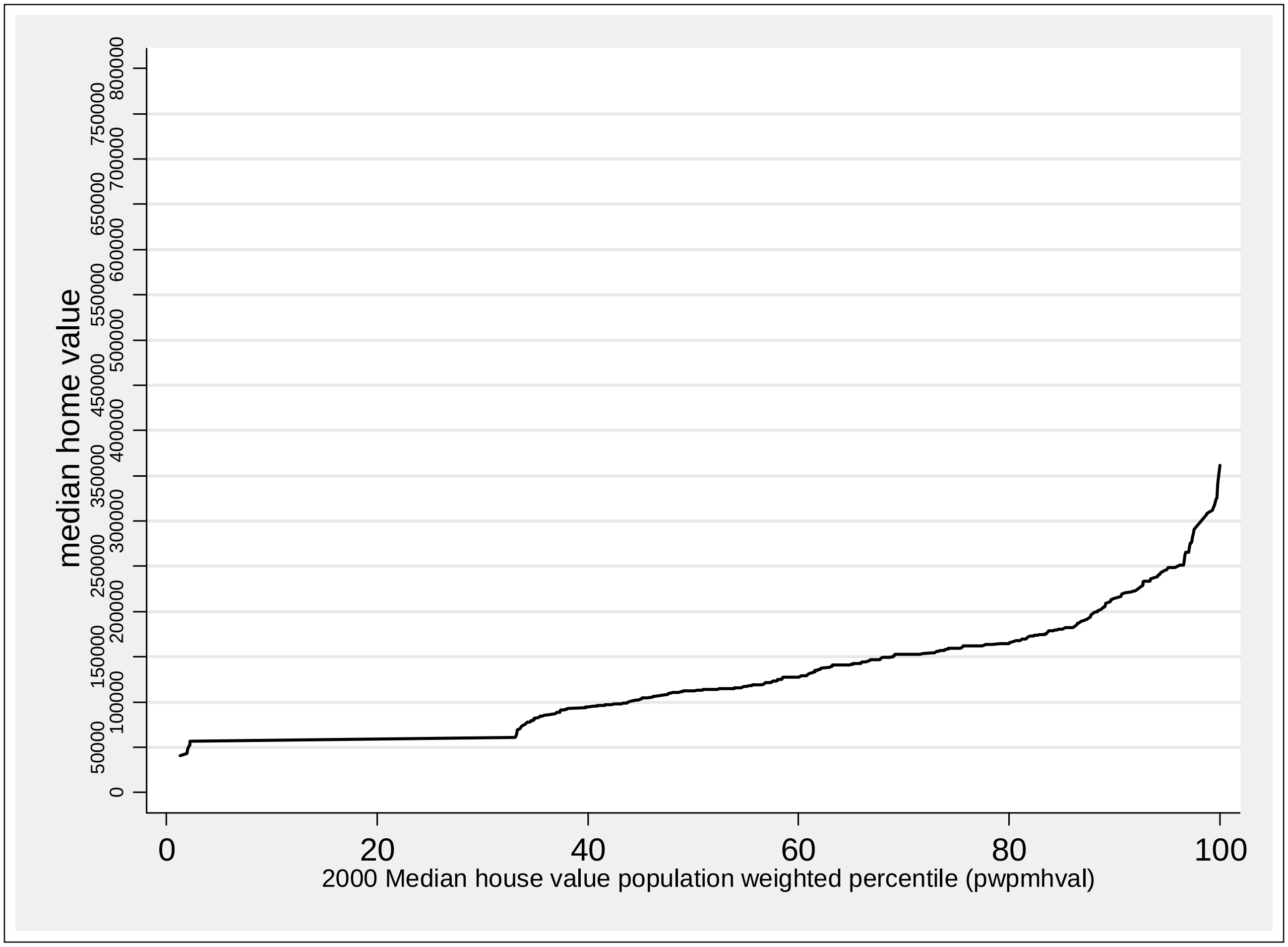

Figure 78. Relationship between population weighted percentile scores for median home value, and median home value.

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

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