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Cities and the larger context: What explains changing levels of crime?

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# **Publication Date**

2017-03-01

# DOI

10.1016/j.jcrimjus.2017.02.001

Peer reviewed

Cities and the Larger Context: What explains changing levels of crime?

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February 15, 2017

Post-print. Published in Journal of Criminal Justice (2017) 49(1): 32-44

Word count: 9,148

Word count (including references): 10,502

Running Head: "Changing crime levels in cities"

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Cities and the Larger Context: What explains changing levels of crime?

Abstract

This study explores whether the broader context in which a city is located impacts the change in

crime levels over the subsequent decade. This study uses a wide range of cities (those with a

population of at least 10,000), over a long period of time (from 1970 to 2010). We test and find

that although cities with larger population and those surrounded by a county with a larger

population typically experience larger increases in crime over the subsequent decade, cities

experiencing an *increase* in population during the current decade experience crime *decreases*.

The study finds that cities with higher average income experience greater subsequent crime

decreases, and those surrounded by counties with larger unemployment increases experience

crime increases. Higher levels of income inequality and racial/ethnic heterogeneity are

associated with increasing crime rates, and increasing inequality and racial/ethnic heterogeneity

in the surrounding county are associated with further increases. Furthermore, this relationship

has strengthened since 1970, suggesting that both scales of inequality are even more important

from a public safety perspective. Finally, we tested the time invariance of these relationships,

and showed that the magnitude of the relationship between city-level inequality and increasing

crime has increased over the study period.

*Keywords*: cities, crime, longitudinal, inequality, racial/ethnic heterogeneity.

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# Bio

John R. Hipp is a Professor in the departments of Criminology, Law and Society, and Sociology, at the University of California Irvine. His research interests focus on how neighborhoods change over time, how that change both affects and is affected by neighborhood crime, and the role networks and institutions play in that change. He approaches these questions using quantitative methods as well as social network analysis. He has published substantive work in such journals as *American Sociological Review, Criminology, Social Forces, Social Problems, Mobilization, City & Community, Urban Studies* and *Journal of Urban Affairs*. He has published methodological work in such journals as *Sociological Methodology, Psychological Methods*, and *Structural Equation Modeling*.

**Kevin Kane**, Ph.D., is a Postdoctoral Research Fellow in the Department of Planning, Policy and Design at the University of California, Irvine. He is an economic geographer interested in the quantitative spatial analysis of urban land-use change and urban development patterns, municipal governance, institutions, and economic development. His research uses land change as an outcome measure – in the form of changes to the built environment, shifting patterns of employment, or the socioeconomic composition of places – and links these to drivers of change including policy, structural economic shifts, or preferences for how we use and travel across urban space.

Cities and the Larger Context: What explains changing levels of crime?

A rich tradition of sociological and criminological studies has focused on the relationship between crime rates and the social and economic environment of macro-level units such as cities (e.g., Chamlin and Cochran 1997; Liska and Bellair 1995). Whereas much of this research has focused on the relationship between key socio-demographic characteristics and levels of crime at a single point in time in cities (Chamlin and Cochran 1997; Sampson 1987), a smaller body of research has explored how the economic environment and levels of crime can co-evolve (Ousey and Kubrin 2009; Stults and Hasbrouck 2015). Nonetheless, a consistent feature of this literature is an almost exclusive focus on very large geographic units such as MSAs, counties, or large cities, typically with at least 100,000 population. Regardless of the size of the units of analysis, a consistent feature of existing research is that it typically does not assess whether the larger context of these units has an additional effect.

An important characteristic of existing macro-level studies is that they have almost never focused on how the broader metropolitan context in which cities are located might impact changes in crime. That is to say, the focus is often placed either on variation in crime across counties or MSAs, or variation in crime across a set of large cities – in both cases omitting the simultaneous relationship between a city's crime rate and the characteristics of both the city and the region in which it is situated. This suggests a needed area of research given that the larger context of a region, and how it is changing, likely has consequences for the level of crime in cities within that region.

In raising the question of the relationship between socio-demographic characteristics and crime rates of cities, and how the larger context may impact these levels of crime, there is an

often implicit assumption that these relationships are time-invariant. Crime patterns across U.S. cities have evolved substantially in recent decades, with a pointed emphasis on how suburbanization is both driven by crime, but also changes its patterns across the broader metropolitan region (Farley 1987; Jargowsky and Park 2009). Given that certain measures are capturing social processes that can strengthen or weaken over time—e.g., the relationships between racial/ethnic composition or income inequality and crime—it is possible that the relationship between some of these measures and crime rates may systematically change over a longer time period. Nonetheless, existing research typically fails to test this, other than rare exceptions such as the classic study of Land et al. qualitatively assessing the consistency of measures across geographic scales and decades (Land, McCall, and Cohen 1990), or more recent studies qualitatively comparing coefficients across decades (McCall, Land, Dollar, and Parker 2013; Stansfield and Parker 2013).

We explore these questions in this study by using data on a wide range of cities (those with a population of at least 10,000), over a long period of time (from 1970 to 2010). We also take into account the characteristics of the county in which these cities are located, and how that context is changing. Furthermore, we account for possible endogeneity between some of these socio-demographic measures and crime rates by estimating models in which the covariates at a point in time are used to predict the change in crime rates over the subsequent decade (Stults and Hasbrouck 2015). Finally, to account for possible macro structural shifts over this long period of time, our analytic technique allows us to assess if these parameters have changed over this time period.

# Literature & Background

Change in the City along Key Socio-demographic Dimensions

A challenge when studying levels of crime in neighborhoods or cities is that there is likely endogeneity between levels of crime and key socio-demographic measures of interest: for example low income levels are thought to drive but also result from high crime. For this reason, cross-sectional analyses that do not account for these likely feedback effects are problematic. Furthermore, research that studies the simultaneous change of the crime rate and the socio-demographic characteristics of the city over some time period (e.g., in the same decade) has this same problem. That is, observing that the change in certain socio-demographic characteristics is related to changes in crime rates does not allow for determining which is causing which. In each of these strategies, instrumental variables are needed to account for these feedback effects (Paxton, Hipp, and Marquart-Pyatt 2011). Alternative strategies sometimes employed in the literature use longitudinal data and predict future crime changes by using either lagged sociodemographic measures, or by measuring socio-demographic change in the prior period. In this study, we use characteristics of the city at the beginning of the decade to explain the change in crime over the subsequent decade.

We are interested in how the level and change of the macro-environment of the city, and the broader area in which it is located, affect subsequent changes in levels of crime. Some existing research has assessed what covariates are associated with the long-term trends in homicide across cities (McCall, Land, and Parker 2011). Other research has used fixed effects or random effects models to assess the contemporaneous change in covariates and crime (McCall, Parker, and MacDonald 2008; Phillips 2006). We instead focus on how city characteristics at the beginning of the decade are associated with changes in crime during the subsequent decade, and argue that, based on the existing literature, there are four key features of structural change that are important for explaining change in crime: 1) the population growth trajectory, 2) levels of

well-being, 3) the level of in/out migration relative to its housing stock, and 4) levels of socioeconomic mixing or inequality amongst residents.

Two key measures of change are the size of the population and population growth. On the one hand, the size of the population is posited to higher rates of crime (Baumer, Lauritsen, Rosenfeld, and Wright 1998; Hipp and Roussell 2013; Kovandzic, Vieratis, and Yeisley 1998; McCall, Land, Dollar, and Parker 2013; McCall, Land, and Parker 2011; Parker 2001). This can occur for various reasons, including Wirth's (1938) notion that large population cities create anomie for residents and therefore increase the number of offenders, or because such cities provide more criminal opportunities for the offenders who live there, and therefore crime rates are higher (Glaeser, Sacerdote, and Scheinkman 1996). On the other hand, a growing population is characteristic of a dynamic city that is economically vibrant. That is, people typically do not move to a city (or region) that is economically moribund (see, e.g. Glaeser, Kallal, Scheinkman, and Shleifer 1992). The evidence is mixed, with some studies finding a positive relationship between changes in population and changes in homicide rates (McCall, Parker, and MacDonald 2008) whereas others have found a negative relationship (Phillips 2006). Furthermore, whereas population growth over a decade is an indicator of a city that is vibrant, the amount of population growth over multiple decades may be a particularly robust indicator of a city's long-term vibrancy. Such long-term population growth contrasts with cities that have a stagnant population level, or even are experiencing shrinking population. Nonetheless, existing research has not considered whether such long-term population growth of a city over multiple decades has consequences for levels of crime.

Hypothesis 1: Cities with more population will experience larger increases in crime

Hypothesis 2: Cities with increasing population will experience larger decreases in crime

Whereas the consequences of population growth for crime rates are uncertain, the next two features we consider more directly capture economic dynamism in cities and have clearer theoretical implications for crime rates. Regarding measures of well-being, scholars have measured this based on characteristics such as levels of growth in average income (Brueckner and Rosenthal 2009) or average home values (Glaeser 2008). Some scholars have also used the unemployment rate, as a high unemployment rate indicates a city or region in which the number of available jobs is lagging behind the number of job-seeking residents, which would presumably act as a brake on in-migration to the region and enhance mobility out of the region (Glaeser 2008). These measures of economic well-being, or how they are changing, should be related to decreases in crime rates. A consistent finding in the literature is that places with higher average incomes have lower crime rates; this has been found at such varying geographic scales as blocks (Boessen and Hipp 2015), neighborhoods (Hipp 2007; Peterson, Krivo, and Harris 2000; Sampson, Raudenbush, and Earls 1997), cities (Beyerlein and Hipp 2005; Byrne 1986; McCall, Land, Dollar, and Parker 2013; Parker, Stults, and Rice 2005), and counties or MSAs (McVeigh 2006; Phillips 2006). However, the relationship between unemployment and crime is more uncertain, with some studies finding a negative relationship (Gibbs and Erickson 1976; Land, McCall, and Cohen 1990) and others finding a positive relationship (Beyerlein and Hipp 2005; Kposowa, Breault, and Harrison 1995; McCall, Land, Dollar, and Parker 2013). As Cantor and Land (1985) discussed, this may be because unemployment has different short-term and longterm effects: a short-term negative effect on crime (due to a routine activities perspective in which unemployed people spend more time around their homes and therefore can thwart crimes) and a long-term positive effect (as economic stress causing persons to turn to crime would take a while to manifest itself) (Phillips 2006).

A third dimension we focus on is the inward and outward flow of households at the housing unit level, which is another measure of the economic vibrancy of a city or region. Cities in which a relatively high number of households are leaving while fewer are entering will experience an increasing vacancy rate. These vacancy rates indicate that the city is relatively undesirable and may be struggling economically. In contrast, in a city in which residents are relatively satisfied with their circumstances, there will be relatively less residential movement out of units; a consequence is that in such cities residential stability based on the average length of residence will be higher, reflecting residents' willingness and desire to remain in the city rather than engaging in out-migration. Vacant units can act as crime generators (Boessen and Hipp 2015; Roncek 1981), and therefore it follows that cities or regions with high vacancy rates would be expected to have higher crime rates (Hipp 2011a). The prototypical example of this is the city of Detroit in recent years, in which high vacancy rates have coincided with increasing crime rates (Galster 2012; Raleigh and Galster 2014). Likewise, residential stability is posited to increase cohesion in neighborhoods and the ability to control disorder and crime; research has found that neighborhoods with higher levels of residential stability typically have lower crime rates (Bellair 1997; Hipp 2010; Warner and Pierce 1993), and this has also scaled up to larger geographic units (Beyerlein and Hipp 2005; Hipp 2011a; Hipp, Bauer, Curran, and Bollen 2004). Hypothesis 4: Cities with more residential stability will experience larger decreases in crime

Whereas the structural characteristics of cities that we have been discussing generally reflect economic dynamism in some fashion, the fourth structural characteristic of importance for understanding the ecological distribution of crime concerns the economic and racial/ethnic mixing in a city. Specifically, scholars have repeatedly found that areas with high levels of

income inequality have higher crime rates (Blau and Blau 1982; Kovandzic, Vieratis, and Yeisley 1998; McCall, Land, Dollar, and Parker 2013). Studies have also found that larger areas with high levels of racial/ethnic heterogeneity have higher levels of crime (Hipp, Bauer, Curran, and Bollen 2004; McCall, Land, Dollar, and Parker 2013; McVeigh 2006). Various mechanisms have been posited for explaining these relationships. Wirth (1938) argued that heterogeneity in a city leads to anomie, which would be expected to increase the number of offenders and hence crime. Another argument is that high levels of inequality foster enmity among the poorest residents, which can result in them resorting to criminal acts (Blau and Blau 1982). In the routine activities and crime patterning perspectives, low income residents will perceive more criminal opportunities given a relatively larger number of nearby residents with more income. Social disorganization theory posits that higher levels of racial/ethnic heterogeneity or inequality can reduce the ability of residents to work together to address problems (Hipp 2007). In the group threat model (Blumer 1958), members of one group perceive members of other groups as a threat to their own resources, which can lead to more crime in locations with more racial/ethnic heterogeneity. Regardless of the mechanism, inequality and racial heterogeneity are expected to result in more crime.

Hypothesis 5: Cities with more inequality or racial/ethnic heterogeneity will experience larger increases in crime

What is a City?

Although a number of studies have explored the general question of why some cities have higher rates of crime than others, or why some cities experience greater increases, a surprising lacuna in this literature is how to define a city? Peterson (1981) describes how "city borders are not economic borders," emphasizing that while a city government can use zoning to control to a

certain extent the activities that take place within its borders, a regional economy and labor market are often a more substantive economic unit that matters for individuals. In particular, suburbanization and municipal fragmentation have, since the middle of the 20<sup>th</sup> century, gradually changed the meaning of what a city or a region is (Carruthers 2003; Judd and Swanstrom 2008). Furthermore, most crime research focuses on a very small subset of cities generally very large cities that have at least 100,000 population (Liska and Bellair 1995; McCall, Land, and Parker 2011; McCall, Parker, and MacDonald 2008; Shihadeh and Ousey 1996; Stansfield and Parker 2013)—with the effect being that smaller metropolitan regions or suburbs of large central cities are often omitted. This approach avoids the question of how to define a city but instead raises the problem of a sample that does not necessarily generalize to *all* cities. For one thing, very large cities may have important structural differences from mid-sized and smaller cities, and therefore presuming that the ecological processes observed operate similarly over all sized cities may not be justified. Another issue is that for a city to be very large, it is typically going to be an older city—and sometimes much older—that is therefore more established. Such cities may have older industries or other characteristics that may make them fundamentally different from new cities. All these considerations imply that simply focusing on one very small subset of cities—very large cities—may not be advisable for better understanding ecological processes. We therefore study a broader range of city sizes.

Impact of the Larger Context and how it is Changing

Is what's good for a city good for the region? While the responsibility of social programs like Medicaid or public housing sometimes falls to county-level governments, cities themselves are the main local policymaking entities and are more likely to share spatial boundaries as well as financing mechanisms with police departments themselves. Tiebout (1956) describes an

efficient sorting mechanism whereby residents self-select into cities that match their preference for levels of public service. His system of cities might be described as a uniformly suburban landscape, i.e. very different from a large central city that stands out from surrounding municipalities. A notable shortcoming of Tiebout's model is that cities also exist in a regional context whereby some services, amenities, and disamenities occur at the regional scale. Peterson (1981) in particular notes that "economic borders are not city borders" which can lead to bifurcated objectives between city and county or regional governments. For example, cities can restrict industrial or commercial land uses within their borders in order to mitigate negative externalities, though residents can still commute to them for work. Similarly, poverty alleviation programs may not be considered efficient expenditures for cities though they may bring wellbeing to the region.

A natural extension of this lies in the study of crime. The "suburban exodus" reorganized space in US metropolitan regions beginning in the middle of the twentieth century (Judd and Swanstrom 2008; Teaford 1979), one principal reason being increasing crime rates in central cities. Municipal incorporation became a mechanism to formalize separation between upperstatus residents who desired spatial and fiscal separation from blight, crime, or unwanted groups. Central cities became "the receptacles for public service functions that suburbs did not want to support" (Wood 1958). The historical trajectory and even formation of cities – which are the units of analysis in this paper – are largely a reaction to social outcomes including crime. Since it can be argued that a labor market area – and its economic integration – is a more natural or exogenous delineation of urban space, this paper's approach of separating the city-level and county-level contextual effects can help to understand the relationship between a city and its larger context.

Extant literature has considered some facets of the relationship between suburbanization and crime patterns. Mills and Price (1984) suggest that racial composition rather than crime is a strong driver of suburbanization, while Farley (1987) finds that even controlling for socioeconomic conditions, more suburbanized metropolitan areas have higher crime rates in their central cities and Shihadeh and Ousey (1996) link this relationship closely to the undermining of central-city black communities. Jargowsky and Park (2009) go further in linking aggregated measures of suburbanization to *metropolitan*, not just central city crime.

However, the dichotomy offered by central city/suburbs is increasingly a deficient conceptualization of modern urban regions. Studies of polycentric employment (Giuliano and Small 1991) and so-called "Edge Cities" (Garreau 1991) challenge the relevance of a central job or population center, while the suburbanization of racial minorities and lower-income populations (Ehrenhalt 2012)— typically conceived of as existing in the "city center" in some fashion — further weakens the relevance of studies operating in this binary. While the focus of this paper is not specifically suburbanization's relationship with crime, our analysis of cities as discrete entities existing within metropolitan regions is more realistic as suburbs proliferate and municipal incorporation continues, in both mature and new metropolitan regions. In other words, rather than asking how suburbanization is driven by central city crime rates, we analyze each city's level of crime within its own socioeconomic context and that its metropolitan area.

The question addressed here is what impact, if any, this larger context has on how crime changes within the cities located in this broader context. One manner in which this can differ depends on the relative population density of this broader context: a city that is surrounded by a relatively rural environment may differ in levels of crime compared to a city that is situated within a larger urban area, even if the two cities appear similar based on socio-demographic

characteristics. Another manner in which cities can differ depends on the socio-economic characteristics of the broader environment, and how they are changing. Two cities both situated in relatively urban environments may have their crime levels impacted differently depending on what changes are occurring in the broader social context surrounding them.

To demonstrate how the city and its broader context may or may not move in parallel, Figure 1 presents stylized examples of four city-county pairs based on the population growth rate of the city and the county from 2000-2010. Florence, Arizona, on the far outskirts of the Phoenix metropolitan area, is a high growth city in a high growth county, while Pittsburgh, Pennsylvania is a shrinking city in a shrinking county. Cities and counties can also display opposite trends: North Royalton, Ohio, just outside of Cleveland, is a high growth city in a shrinking county, whereas Grand Haven, on Michigan's western lakeshore, is a shrinking city in a high growth county. Our analyses will assess the relationship between these different patterns and city crime rates over time.

# <<<Figure 1 about here>>>

For these reasons, the characteristics of the larger context of the county and how they are changing may have consequences for levels of crime within its cities. The same four dimensions that we earlier discussed regarding the city context are arguably also important when measured in the larger context. These measures also likely contain the same possibly dual meanings as those at the city level, in that they can in part reflect the economic vibrancy of the metropolitan region, but can also have crime-specific implications. Thus, increasing levels of population in the larger county indicate a vibrant region, but they also indicate more potential offenders that might impact crime rates within cities in the region. An increasing unemployment rate indicates a lack of economic vibrancy, and also indicates potential offenders due to economic stress on

inhabitants. And whereas income inequality and racial/ethnic heterogeneity are posited to impact crime rates, an open research question is the proper scale at which these operate. If it is only the level of inequality and heterogeneity within a city that matters for levels of crime, then measuring these constructs at the larger region level will have no relationship with city-level crime rates. On the other hand, existing theory is not clear on the proper scale at which inequality and heterogeneity operate, and therefore we test here whether higher levels of these types of mixing at the broader geographic scale impact levels of crime within individual cities in the region controlling for levels of inequality and heterogeneity within the cities.

Hypothesis 6: The larger context of the county will impact crime in the same fashion as the

Hypothesis 6: The larger context of the county will impact crime in the same fashion as the characteristics of the city

Change in these processes over 40 years

A final consideration that we address here is whether the strength of these relationships are stable over a long study period of 40 years. That is, whereas studies often estimate a model using data from a single point in time, or data over a single decade, a question is whether the relationships of these various structural characteristics with changing levels of crime are indeed invariant over time. On the one hand, a perspective that desires to detect scientific regularity (Kuhn 1970) would expect the coefficients for these various measures to remain constant over decades. Indeed, the classic study of Land et al. (Land, McCall, and Cohen 1990) not only compared the consistency of measures across geographic scales, but also qualitatively assessed their consistency across three decades and found relative consistency. A replication study found general consistency, although the effect of concentrated disadvantage appeared to decrease (McCall, Land, and Parker 2010). More recent studies have also qualitatively compared coefficients across decades, but their results qualitatively detected differences across decades

(McCall, Land, Dollar, and Parker 2013; Stansfield and Parker 2013). On the other hand, given that these measures capture social characteristics, there is at least the possibility that the social meaning of these measures, and therefore their relationships with crime rates, may change over time. This is particularly relevant given changing perspectives on inner-city crime rates over our study period, 1980-2010. For example, whereas studies have found that higher levels of racial/ethnic heterogeneity or racial minorities are associated with higher levels of crime or greater increases in crime (Hipp 2011a; McVeigh 2006), a question is whether this relationship is weakening or strengthening over time, and one study showed suggestive evidence that it may be decreasing (McCall, Land, Dollar, and Parker 2013). Likewise, the increasing levels of inequality in the country raise the question of whether the relationship between inequality and crime is also changing over this period. And given the changing patterns in population density given various smart growth and New Urbanism perspectives, we will address whether the relationship between levels of population and crime has changed. In this study, we address these possibilities by testing whether the coefficients for our structural measures of interest demonstrate a linear change in magnitude over the four decades of the study period, which allows us to explicitly test for changes over time.

Hypothesis 7: The coefficients for the models will remain invariant over the study period

#### **Data and methods**

Data

We use data for all cities in the U.S. over the period from 1970 to 2010 in each year in which they have at least 10,000 population in a particular year and reported crime data to the Uniform Crime Reporting (UCR) program. The FBI's UCR program provides data on crime

events reported by police agencies across the U.S. The socio-demographic data come from the 1970, 1980, 1990, and 2000 U.S. Census and the American Community Survey (2008-2012 5-year estimates). The data is stacked long such that each observation is a city decadal point. Given that our outcome measure is the change in crime over the decade, there are four decades of change in our data. There are therefore four observations for each city that was present at all five waves (that is, the city existed in the UCR data as a police agency reporting crime and had at least 10,000 population in a given year).

Given the social and spatial evolution of a city over time, defining a "city" over a long time period becomes complicated. A straightforward approach would use the date of incorporation to indicate when a city comes into existence. However, a limitation is that a geographic area can sometimes function in a manner similar to a city for a relatively long period of time without actually incorporating. The US Census Bureau's "Census-Designated Place" represents an effort to define a unit that is city-like without incorporation; however, its function is fundamentally different since it is not likely to have powers of home rule, taxation, or in some cases a police department similar to its incorporated counterparts. At the other extreme, some cities incorporate very early in the growth process when they have a very small population and in some instances will remain very small. Thus, a researcher could possibly make the peculiar decision of excluding a relatively large populated area that is not incorporated from an analysis, but including a very small area that is in fact incorporated. Given that much of the literature considering cities typically considers them to be ecological units of at least some particular size, we argue that using a particular population cutoff value is the most justifiable approach. We therefore include both incorporated cities as well as census designated places that reported crime data to the Uniform Crime Reporting program. We use a 10,000 population cutoff, given that

this matches the value used by the Census for cities worth listing their demographic information through much of the 20<sup>th</sup> century, and because we believe that a city should contain at least two neighborhoods (i.e., census tracts are typically about 4,000 population). By using all cities we capture a wider range of types of cities than most existing research. For example, in 2010 the Census reported 279 cities with at least 100,000 population, but over ten times as many (2,923) with at least 10,000 population. Studies have rarely used smaller cities: one studied the pattern of homicide in a broad sample of cities (McCall, Land, Dollar, and Parker 2013), another focused on cities in 14 recently developing areas (Hipp 2011a) and another focused on seasonal patterns in crime (Hipp, Bauer, Curran, and Bollen 2004). Notably, none of these took into account the broader area around these cities.

### Dependent variable

The outcome variable is the change in the crime rate (logged) over the decade. We constructed measures of each of the six Part 1 crimes: aggravated assaults; robberies; homicides; burglaries; motor vehicle thefts; and larcenies. We computed the average number of crimes over the three-year period at each decadal point and the two years surrounding it. We log transform these variables, and then compute the difference over the decade.

# Independent variables

# City-level variables

We included several city-level variables, all measured at the beginning of the decade. First, we directly account for the *population* (*logged*) of the city. We account for the long-term population growth of the city with a measure of the *change in city population since 1950*,

measured as  $\frac{(pop_t - pop_{50})}{pop_{50}}$ , where  $pop_t$  is the population in the current year and  $pop_{50}$  is the

population in 1950. We capture the economic vibrancy of a city with measures of the *average household income* (*logged*), and the *unemployment rate*. To capture city vibrancy based on change at the housing unit level, we included two measures: *residential stability* (the average length of residence) and the *percent occupied units*. The fourth dimension we measure is racial and economic mixing, which is measured as the levels of inequality or racial heterogeneity in a city. We constructed a measure of *income inequality* (based on the Gini coefficient)<sup>1</sup>, and a measure of *racial/ethnic heterogeneity* (based on a Herfindahl index of five racial/ethnic groups: percent white, black, Asian, Latino, and other race).

We also included city-level control variables to minimize the possibility of obtaining spurious results. We accounted for the presence of racial/ethnic minorities with measures of *percent black* and *percent Latino*. Given the rich body of research focusing on the potential role of immigrants in crime levels, we included a measure of *percent immigrants*. Finally, we account for the percent of the population in the prime crime-prone ages by including a measure of the *percent aged 16 to 29*.

# County-level variables

We accounted for the same four dimensions at the county-level. We capture the level of population in the area by including a measure of the *county population*. We capture the economic vibrancy with a measure of the *unemployment rate*. We measure turnover at the housing unit level with the *percent occupied units*. We capture income and racial/ethnic mixing with measures of *income inequality* and *racial/ethnic heterogeneity* that are constructed similarly to the city-level ones.

Change at the city- or county-level variables

<sup>1</sup> Given that the Census data are reported in income bins, we compute the Gini coefficient using the prln04.exe program provided by Francois Nielsen at the following website: <a href="http://www.unc.edu/~nielsen/data/data.htm">http://www.unc.edu/~nielsen/data/data.htm</a>.

We included several measures that capture change in various characteristics of the county during the same decade. Although potential endogeneity issues can be introduced by including measures of the socio-demographic change in the city during the same decade, there is less reason to expect such issues when including measures of the socio-demographic change of the broader county during the same decade. We included measures of change at the county level during the current decade in five measures capturing our four dimensions: *change in population, change in unemployment rate, change in percent occupied units, change in income inequality,* and *change in racial/ethnic heterogeneity.* Finally, we included a single measure of simultaneous change at the city level as the *change in city population* during the decade to capture the possibility that large increases in city population can impact the level of crime.<sup>2</sup> The summary statistics for the variables included in the analyses are shown in Table 1. In our study, 51% of the cities appear in all four waves, 13.5% appear in three waves, 18.9% appear in two waves, and 16.6% appear in one wave.

#### <<<Table 1 about here>>>

# **Analytical Methods**

Given that the data are stacked long such that there are up to four observations for each city, as well as the fact that cities are nested within counties, we estimated three-level linear multilevel models (decades nested in cities nested in counties). We constructed our outcome variables as the change in the logged crime rate over the decade, which exhibited a normal distribution allowing use of a linear multilevel model. Note that a Poisson model is not appropriate given that there can be negative values for cities in which the number of crime events decreased over the decade. The models also include a variable that captures time as a linear

<sup>2</sup> There may be concern that this measure is endogenous to crime. We therefore estimated ancillary models that did not include this variable, and the pattern of results was very similar.

variable measured in years (this variable is centered around the mid-point of the study, thus observations have values of -15, -5, 5 or 15 in years 1980, 1990, 2000, or 2010 respectively). We tested for random parameters of our key measures over years, and allowed each that was statistically significant to be random. Rather than assume that the coefficient for each variable of interest is invariant over the waves of our study, we also included interactions of each of our variables with the year variable to capture possible change in the coefficient estimate over the study period. Given that we only have four time points, a linear trend is more appropriate than more complicated functional forms. Given how we have centered the year variable, the main effect of each variable is capturing the effect of the variable of interest at the mid-point of the study period (or the average), and the interactions capture how the parameter changes over the decades (for a discussion of time coding and the implications for interpreting parameters, see Biesanz, Deeb-Sossa, Papadakis, Bollen, and Curran 2004). There is no evidence of multicollinearity in our study as the highest variance inflation factor is 4.4, well below common guidelines. We assessed possible influentional with Cook's D measures, and found no evidence that the results are sensitive to dropping cases with the largest values.

#### **Results**

Population and Growth Trajectory

The model results are displayed in Table 2, and in this section we focus on the main effects coefficients. The coefficients capturing parameter change over decades will be discussed later. We begin with the variables measuring the population of the city and county. We find evidence that the size of the city population at the beginning of the decade consistently has a positive relationship with the increase in crime across the subsequent decade for all crime types.

This relationship is strongest for the three violent crimes, as a one standard deviation larger population is associated with a 12%, 10%, or 21% increase over the subsequent decade in aggravated assault, robbery, or homicide, respectively (for all calculations the coefficient is multiplied by the variable's standard deviation: e.g., for robbery (.1094\*.88)-1=.101). And if the population in the county surrounding the city is larger, the city experiences, on average, additional increases in most crime types during the decade (with the exception of larcenies); this relationship is particularly strong for robberies and motor vehicle thefts as cities with a one standard deviation larger county population at the beginning of the decade experience increases of 20.5% and 11.9% in these two crime types, respectively, compared to other cities. Note that the "parameter change over decades" coefficient tracks how the coefficient differs over time: we ignore these for now and will return to them later.

#### <<<Table 2 about here>>>

We find a different effect for how population is *changing*. Cities with increasing population during the decade experience *decreases* in all of these crime types, consistent with the idea that this captures city dynamism. A city experiencing one standard deviation greater population increase during the decade has a 7.2% and 4.7% greater decrease in aggravated assault and robbery, respectively, and about 2-4% fewer property crimes. The long-term change in the city population—what we have proposed as a long-term measure of city vibrancy—also has a consistently negative relationship with subsequent crime rates for all types. Cities that have experienced one standard deviation greater population growth since 1950 experience about 2-3 percent lower crime increase over the subsequent decade. In contrast, greater population *increases* in the county during the same decade is robustly associated with *increasing* crime rates. A city in which county population is increasing one standard deviation more experiences

from a 5% to 9% greater increase in crime rates during the decade, holding constant the city's population. Thus, there is a distinction between the consequences of population growth of the city itself and that of the surrounding area: a shrinking city situated in a growing context experiences the largest increases in crime.

Residents' material well-being

Turning to the two measures capturing the economic state of the city, we observe that whereas the unemployment rate has an unexpected negative relationship with certain types of crime, average household income has a strong negative relationship with the subsequent change in crime. Cities with one standard deviation higher average household income at the beginning of the decade experience about 40% less aggravated assault and robbery increases than other cities, 20% lower larceny increase, and about 30% less increase in the other crime types. Surprisingly, cities with a one standard deviation higher unemployment rate actually have between 2.3 and 3.9% lower rates of robbery, burglary, or larceny at the end of the decade (but higher rates of the other crime types). Nonetheless, these are much smaller effects than for the household income measure.

We do see that our measure of the economic deprivation in the broader area—the county unemployment rate—is associated with greater increases in robbery, burglary, and larceny. A city surrounded by a county with one standard deviation higher unemployment experiences 3% to 4% greater increases in these crime types. Cities in which the economic environment in the broader area is worsening during the decade also experience increases in their own crime rates. A city in which the unemployment rate in the surrounding county is increasing one standard deviation greater than the mean experiences between 3% and 6% greater increases in robbery, burglary, and homicide.

Our two measures of residential unit stability exhibit more modest effects. The presence of a higher percentage of vacant units in the city is associated with more aggravated assaults, homicides, and burglaries at the end of the decade (about 2 to 5% more for a one standard deviation increase in percent vacant units). And greater residential stability in the city is associated with decreases in aggravated assaults, burglaries, and larcenies at the end of the decade (between 2 and 6.5% less for a one standard deviation increase), consistent with hypothesis 4.

The change in the broader context also matters, as cities in which the vacancy rate is increasing in the surrounding county experience rising crime rates for four of the crime types (although the vacancy rate at the beginning of the decade has no relationship). Cities located in counties in which the vacancy rate is increasing at a rate one standard deviation above the average during the decade experience about a 5-6% greater increase in crime rates during the same decade.

*Inequality and heterogeneity* 

The two measures of mixing—based on income and race/ethnicity—exhibit robust positive relationships with changes in crime. A city with a one standard deviation higher level of income inequality at the beginning of the decade experiences between 4 and 10% greater increase in all crime types except motor vehicle thefts. Cities in which the level of inequality is increasing in the surrounding county experience 7% and 4% greater aggravated assault and homicide, respectively. However, higher levels of income inequality in the broader area at the beginning of the decade do not increase crime rates in the subsequent decade beyond the effect of inequality in the city itself.

Cities with higher levels of racial/ethnic heterogeneity experience sharp increases in violent crime. Cities with a one standard deviation higher level of racial/ethnic heterogeneity at the beginning of the decade experience an 8% greater increase in burglary by the end of the decade; and they experience 13%, 21%, and 22% greater increases in robbery, homicide, and aggravated assault, respectively. Cities in which there is one standard deviation more racial/ethnic heterogeneity in the surrounding county at the beginning of the decade have 6% more motor vehicle thefts and 4% more homicides in the subsequent decade. Likewise, cities in counties that are experiencing a greater increase in racial/ethnic heterogeneity during the decade also experience greater increases in crime during the same decade: one standard deviation greater increase results in between 2.5% and 5.6% greater increase in all crimes except larcenies and aggravated assaults.

We also assessed which spatial scale had a greater effect on crime: the city and its characteristics, the county and its characteristics, or the joint impact of city and county characteristics. To do this, we compared the explanatory power of separate models using R-squared values: 1) a model with no variables, 2) city variables only, 3) county variables only, and 4) all variables (Table 3). This is done in two steps. First we compare the increase in explanatory power that individually adding city variables in model (2) and county variables in model (3) offers. This increased explanatory power is then compared with the increase offered by the full model (4), and this value is subtracted from 100% to gauge the share of explanatory power of the *other* unit of analysis, e.g. if city-level factors explain 90% of the total variance increase then county-level factors explain 10%, with the remaining share belonging to the joint effects of the city and county. The results are shown in Table 3, and overall city-level factors explain more of the variation in crime than county-level factors. The difference in impact varies

by crime type: city-level factors explain roughly ten times more variation than county-level factors for homicide, burglary, and larceny, and 2-5 times more variation than county-level factors for robbery and motor vehicle theft. However, the combined effect is also substantial - for burglary and larceny, county plus joint city/county effects actually explain a majority of the variation in city-level crime rates. This suggests that what happens outside a city border can matter even more than what is happening inside. Alongside the consistently significant (and sometimes opposite results) for county-level factors, these results are even more meaningful since the city-level variables are direct effects (i.e. a city factor impacting city-level crime) whereas the county-level variables are contextual effects (county factor impacting city crime).

Moderating effect of the larger context characteristics

Although we have shown that the county context has important consequences for changes in city-level crime rates, we next asked whether the county context has a moderating effect on the relationship between the city-level measure and changes in crime. For example, whereas low population cities have lower crime rates, this advantage is considerably reduced in high population counties. This pattern is shown in Figure 2a for robbery, and was similar also for burglary and larceny. However, although *increasing* county population is associated with increasing crime rates, this effect is accentuated in cities with *decreasing* population (not shown). This pattern was evident for all crimes except homicide and burglary.

We also found that the level of inequality and heterogeneity in the city and county exhibit interaction effects. Whereas cities with higher levels of racial heterogeneity have higher robbery rates, this effect is accentuated if it occurs in a *low* heterogeneity county, as shown in Figure 2b.

A similar pattern was detected for all crime types except homicide. And whereas a city with low racial heterogeneity but in a county with decreasing racial heterogeneity has lower property crime rates, the same city in a county with *increasing* racial heterogeneity will experience larger increases in property crime (not shown). The pattern was very similar for inequality: the highest rates of crime occur in high inequality cities located in low inequality counties (not shown). *Are these relationships time-invariant?* 

Beyond the average effects over the study period that we have just discussed, an advantage of our modeling strategy is that it provides insight on the extent to which parameter estimates have changed in a linear fashion over this time period. Given that most parameters showed inconsistent, or insignificant, changes over this period, we focus here only on the ones that showed the most consistent parameter changes.

One notable finding is that the positive relationships of income inequality with subsequent changes in crime are generally increasing over this time period. For example, the coefficient for aggravated assault of .0079 captures the average relationship for a one unit increase in inequality over the study period, whereas the positive "parameter change over decades" coefficient of .0006 indicates that this effect becomes this much stronger over each year in the study period. Figure 3a plots the estimated coefficients at each time point for the relationship between city income inequality and the change in various types of crime. As seen there, the parameters are increasing for all of the crime types, indicating an even stronger positive relationship between inequality and subsequent crime increases in more recent years. For motor vehicle theft, the coefficient was somewhat negative in 1980 but has become positive in more recent decades. The increasing strength of the coefficient for aggravated assault is

Changing crime levels in cities particularly notable, as it has gone from effectively zero in 1980 to almost .02 in 2010 (implying a 13.6 percent increase for a standard deviation change in inequality).

### <<<Figure 3 about here>>>

The relationships of population in the city or the broader area with crime rates are generally becoming more negative over time. The effect of changing city population over the decade on changes in crime in the same decade is becoming more negative over the study period (see Figure 3b). Thus, growing cities are experiencing even stronger drops in crime in recent decades. Likewise, the positive relationship between county population and aggravated assault, robbery, and burglary is weakening over the study period. And the positive relationship for the growth in county population is weakening for aggravated assault and robbery over this period.

The effect of increasing percent occupied units in counties shows a routinely weaker negative relationship with most crime types, as seen in Figure 3c. Whereas in 1980 cities in which the percent occupied units in the county was increasing during the decade experienced falling crime rates for most types of crime, by 2010 this negative relationship had weakened considerably and even become slightly positive for certain crime types. Thus, increasing vacancies in the surrounding county no longer appear to have strong negative consequences for cities.

It is also the case that the effect of the economy on these crime rate changes has changed over time differently at various scales. The strong negative parameter for city-level average household income has weakened over the study period for all crime types except motor vehicle theft (Figure 3d). The stress effect of city-level unemployment has worsened over this period as the coefficients increased positively for robbery and burglary.

Finally, as shown in Figure 3e, whereas the average effect of the presence of a higher percentage of African Americans in a city at the beginning of the decade is associated with larger increases in all crime types in the subsequent decade, these parameter estimates demonstrate a notable drop over the study period for all crime types except homicide. Thus, the estimated parameter value for percent black in 2010 is just 65% or 54% the size of that in 1980 for aggravated assault and robbery, respectively. The drops for the property crimes are even more dramatic, as the 2010 estimated parameters are 40%, 40%, and 8% the size of the 1980 parameters for burglary, motor vehicle theft, and larceny, respectively. Only the parameter for the homicide rate has slightly increased over the study period.

# Sensitivity Analyses

Given that our analytic sample is distinct from most existing research that limits their analyses to cities with at least 100,000 population, we assessed the sensitivity of our results by testing whether the results differ between large and small cities. We assessed this by reestimating the models in Table 2 but including an indicator variable if a city had at least 100,000 population, and including interactions between this measure and each socio-demographic variable in the model. We then compared the Bayesian Information Criterion (BIC) from each of these models to each model in Table 2 to assess if the model fit was improved. In each case, nearly all of the interaction variables were nonsignificant, and the BIC preferred the simpler model from Table 2, indicating that there are not significant differences in the models whether estimated on small or large cities.<sup>3</sup>

# **Discussion**

<sup>3</sup> The BIC was smaller for the initial model for each crime type: 15491.2 vs. 16080.1 for aggravated assault, 11867.7 vs. 12405.6 for robbery, 15126.6 vs. 15751 for homicide, 6257.9 vs. 6791.6 for burglary, 10176.6 vs. 10715.3 for motor vehicle theft, and 5224.7 vs. 5838.1 for larceny.

This study has emphasized the importance of not only studying how crime rates change in cities, but taking into account the broader county context in which these cities are located and how it is changing along key dimensions. Existing criminological research has generally not considered whether this broader context might matter for the cities within this context; nonetheless, there is considerable reason to suspect it likely does given the research on regional economies (Glaeser 2008), and we found that it indeed does matter. We also extended the existing literature by moving beyond a focus only very large cities (with at least 100,000 population), and studied a much wider variety of city population sizes (including all those with at least 10,000 population). We focused on four dimensions of the city and county context, and how they help in explaining changes in crime rates over the subsequent decade. We next discuss the key findings. Finally, we assessed whether the parameters capturing these relationships have changed over the 40-year period of this study (1970-2010), and found some evidence of change.

First, we found that the level of population and how it is changing have different consequences for changes in crime. Consistent with hypothesis 1, cities with larger populations typically experience larger increases in crime compared to smaller cities, and there is an additional boost in most crime types if the surrounding county has a larger population (consistent with hypothesis 6). Thus, the larger number of potential targets and offenders in an area does indeed seem related to greater increases in crime in the cities within that area (Glaeser and Sacerdote 1999; Glaeser, Sacerdote, and Scheinkman 1996). This implies that a broader population beyond that of just the city impacts city crime rates (Stults and Hasbrouck 2015). On the other hand, increasing population in the city—either during the current decade or over a much longer period of time—is actually associated with crime *decreases*. This was consistent with hypothesis 2 that city population growth serves as a proxy for vibrancy, and therefore may

be associated with less crime. It also echoes the findings of Phillips (2006) studying homicide in large counties in the U.S. Notably, in our results population growth in the county was associated with *increases* in city crime; and the combination of county population growth with decreasing city population resulted in particularly large spikes in crime in these cities, suggesting that a city's relative lack of vibrancy compared to the larger area has particularly negative consequences.

Second, we found that the economic vibrancy of both the city and county mattered for how crime rates change over time. A particularly robust pattern detected was that cities with the lowest average income at the beginning of the decade experienced the sharpest increases in crime over the subsequent decade. These results are consistent with a broad swath of literature demonstrating the relationship between economic disadvantage and crime at various spatial scales (Hipp and Wickes 2016; Liska, Logan, and Bellair 1998; Sampson, Raudenbush, and Earls 1997; Weisburd, Groff, and Yang 2012), and our hypothesis 3. However, we also found that the economic health of the broader context impacted crime rate changes: cities located in counties with higher unemployment rates at the beginning of the decade, or counties that experienced unemployment increases during the decade, or counties experiencing increasing vacancy rates, suffered from increasing levels of almost all types of crime. Thus, consistent with hypothesis 6, it is not enough to simply focus on the economic context of the city itself, but rather that the economic context of the broader region can impact city crime levels even if the city itself is not suffering economic woes.

Third, a related point is that whereas city inequality and racial/ethnic heterogeneity impact changing crime rates, consistent with hypothesis 5, there is an additional effect from inequality and heterogeneity in the broader area. Thus, it is not enough for cities to reduce the

level of inequality within their own boundaries, as increasing levels of inequality in the region will spill over into increasing levels of violence for the city itself. Likewise, cities within counties experiencing increasing levels of racial/ethnic heterogeneity experienced increasing levels of most crime types, regardless of the level of heterogeneity in the city itself. Thus, it appears that it is not just inequality and heterogeneity at a particular scale that matters, but rather that their presence across multiple scales has important consequences for crime. Furthermore, there were moderating effects in which a city with high inequality or high racial/ethnic heterogeneity experienced particularly large increases in crime if it was located in a county with *low* levels of inequality or heterogeneity. Thus, a city's *relative* level of inequality or heterogeneity compared to the region has consequences for how crime rates change, a possibility that has not been explored previously in the literature.

A final key point is that the long time period of our study allowed us to test the time invariance of these relationships, and whereas many of them were stable, in contradiction to hypothesis 7, certain ones showed distinct trends over this 40 year period (Land, McCall, and Cohen 1990). We found that not only is city-level inequality at the beginning of the decade related to greater increases in crime over the subsequent decade, the magnitude of this relationship has increased over the study period. Thus, not only are there increasing levels of inequality observed in the U.S. since 1970<sup>4</sup>, but the positive relationship between this inequality and crime rates has increased as well. The implication is that addressing inequality in communities appears even more important from a safety perspective. The fact that the protective effect of high average income in cities is also weakening over this time period may also be indicative of a broader scale inequality effect playing out between cities. Thus, the benefits of higher average income in cities will be diminished if it results in higher inequality in the larger

<sup>4</sup> http://eml.berkeley.edu/~saez/TabFig2015prel.xls

region. And whereas we found that increasing population in a city seems to capture a particular dynamism of a city that is related to subsequent falling crime rates, this negative relationship is even more pronounced in recent decades. This may speak to a residential mobility pattern in which safer cities are perceived as more attractive, resulting in population growth, which then translates into even lower crime rates. Although speculative, this suggests a direction for future research.

Finally, it is worth highlighting that the positive relationship between the percentage of the black population in the city and crime increases has weakened over the study period. There are many possible explanations for this pattern, including the possibility of lessening housing constraints that otherwise limited African Americans to moving to the highest crime neighborhoods (Hipp 2011b; Xie and McDowall 2010), or the possible suburbanization of the black population that reduces the concentration in disadvantaged inner-city neighborhoods in certain cities. Nonetheless, this is an intriguing observation worthy of additional research.

We acknowledge some limitations to this study. First, it would be ideal to have point-level crime data across the entire U.S. to avoid aggregation issues. This is of course not feasible, and therefore we have had to trade-off using larger units of analysis (cities rather than neighborhoods or street segments) in order to gain more generality across all cities. It is notable that even when using these larger units, we still detected important effects of the larger context on crime levels within these cities. Second, we used counties as the measure of the larger area, which is not ideal. We tested our same models using 2010-defined metropolitan statistical areas and the results were very similar, which enhances confident in our results; however, since MSA boundaries change between census decennials, we felt that using a consistent unit such as counties was more appropriate for interpreting longitudinal results. Nonetheless, it would be

preferable to use a more flexible approach when aggregating to larger units in future research (e.g., Hipp and Roussell 2013). Third, we were not able to measure the actual proposed mechanisms. Thus, similar to many other research studies, we were only able to view how certain socio-structural measures are related to changes in crime, and unable to explain exactly *why* such relationships exist.

In conclusion, this study has demonstrated that the spatial scale for understanding crime is important even when studying relatively larger units such as cities. Not only is it important to explore the growth in crime rates across cities with a large range of population sizes, but this study demonstrated that the context of the broader region impacts levels of crime in the cities within a region. Although socio-economic resources are important for cities, the socio-economic vibrancy of the larger region also impacts crime levels within cities. And whereas levels of inequality or racial/ethnic heterogeneity in a city are related to increases in crime, the level of inequality or heterogeneity in the broader region, and particularly how it is changing, also impacts levels of crime within the cities in that region. It is clear that the socio-demographic context and change in the context occurring at the larger spatial scale of the region has consequences for the level of crime that occurs at smaller geographic scales within the region.

#### References

- Baumer, Eric, Janet L. Lauritsen, Richard Rosenfeld, and Richard Wright. 1998. "The Influence of Crack Cocaine on Robbery, Burglary, and Homicide Rates: A Cross-City, Longitudinal Analysis." *Journal of Research in Crime and Delinquency* 35:316-340.
- Bellair, Paul E. 1997. "Social Interaction and Community Crime: Examining the Importance of Neighbor Networks." *Criminology* 35:677-703.
- Beyerlein, Kraig and John R. Hipp. 2005. "Social Capital, Too Much of a Good Thing? American Religious Traditions and Community Crime." *Social Forces* 84:995-1013.
- Biesanz, Jeremy C., Natalia Deeb-Sossa, Alison A. Papadakis, Kenneth A. Bollen, and Patrick J. Curran. 2004. "The Role of Coding Time in Estimating and Interpreting Growth Curve Models." *Psychological Methods* 9:30-52.
- Blau, Judith R. and Peter M. Blau. 1982. "The Cost of Inequality: Metropolitan Structure and Violent Crime." *American Sociological Review* 47:114-129.
- Blumer, Herbert. 1958. "Race Prejudice as a Sense of Group Position." *Pacific Sociological Review* 1:3-7.
- Boessen, Adam and John R. Hipp. 2015. "Close-ups and the scale of ecology: Land uses and the geography of social context and crime." *Criminology* 53:399-426.
- Brueckner, Jan K. and Stuart S. Rosenthal. 2009. "Gentrification and Neighborhood Housing Cycles: Will America's Future Downtowns be Rich?" *The Review of Economics and Statistics* 91:725-743.
- Byrne, James M. 1986. "Citizens, and Crime: The Ecological/Nonecological Debate Reconsidered." Pp. 77-101 in *The Social Ecology of Crime*, edited by J. M. Byrne and R. J. Sampson. New York: Springer-Verlag.
- Cantor, David and Kenneth C. Land. 1985. "Unemployment and Crime Rates in the Post-World War II United States: A Theoretical and Empirical Analysis." *American Sociological Review* 50:317-332.
- Carruthers, John I. 2003. "Growth at the fringe: The influence of political fragmentation in United States metropolitan areas." *Papers in Regional Science* 82:475-499.
- Chamlin, Mitchell B. and John K. Cochran. 1997. "Social Altruism and Crime." *Criminology* 35:203-228.
- Ehrenhalt, Alan. 2012. *The Great Inversion and the Future of the American City*. New York: Random House LLC.
- Farley, John E. 1987. "Suburbanization and Central-City Crime Rates: New Evidence and a Reinterpretation." *American Journal of Sociology* 3.
- Galster, George C. 2012. *Driving Detroit: The Quest for Respect in the Motor City*. Philadelphia: University of Pennsylvanie.
- Garreau, Joel. 1991. Edge City. Doubleday: New York.
- Gibbs, Jack P. and Maynard L. Erickson. 1976. "Crime Rates of American Cities in an Ecological Context." *American Journal of Sociology* 82:605-620.
- Giuliano, G. and K. A. Small. 1991. "Subcenters in the Los-Angeles Region." *Regional Science and Urban Economics* 21:163-182.
- Glaeser, Edward L. 2008. Cities, Agglomeration and Spatial Equilibrium. New York: Oxford.
- Glaeser, Edward L., Hedi D. Kallal, Jose A. Scheinkman, and Andrei Shleifer. 1992. "Growth in Cities." *Journal of Political Economy* 100:1126-1152.
- Glaeser, Edward L. and Bruce Sacerdote. 1999. "Why Is There More Crime in Cities?" *The Journal of Political Economy* 107:S225-S258.

- Changing crime levels in cities
- Glaeser, Edward L., Bruce Sacerdote, and Jose A. Scheinkman. 1996. "Crime and Social Interactions." *The Quarterly Journal of Economics* 111:507-548.
- Hipp, John R. 2007. "Income Inequality, Race, and Place: Does the Distribution of Race and Class within Neighborhoods affect Crime Rates?" *Criminology* 45:665-697.
- —. 2010. "A dynamic view of neighborhoods: The reciprocal relationship between crime and neighborhood structural characteristics." *Social Problems* 57:205-230.
- —. 2011a. "Spreading the Wealth: The Effect of the Distribution of Income and Race/ethnicity across Households and Neighborhoods on City Crime Trajectories." *Criminology* 49:631-665.
- —. 2011b. "Violent crime, mobility decisions, and neighborhood racial/ethnic transition." *Social Problems* 58:410-432.
- Hipp, John R., Daniel J. Bauer, Patrick J. Curran, and Kenneth A. Bollen. 2004. "Crimes of Opportunity or Crimes of Emotion: Testing Two Explanations of Seasonal Change in Crime." *Social Forces* 82:1333-1372.
- Hipp, John R. and Aaron Roussell. 2013. "Micro- and Macro-environment Population and the Consequences for Crime Rates." *Social Forces* 92:563-595.
- Hipp, John R. and Rebecca Wickes. 2016. "Violence in Urban Neighborhoods: A Longitudinal Study of Collective Efficacy and Violent Crime." *Journal of Quantitative Criminology* Forthcoming.
- Jargowsky, Paul A. and Yoonhwan Park. 2009. "Cause or Consequence?: Suburbanization and Crime in U.S. Metropolitan Areas." *Crime & Delinquency* 55:28-50.
- Judd, Dennis R and Todd Swanstrom. 2008. *City Politics: The Political Economy of Urban America*, vol. 6th. New York: Pearson.
- Kovandzic, Tomislav V., Lynne M. Vieratis, and Mark R. Yeisley. 1998. "The Structural Covariates of Urban Homicide: Reassessing the Impact of Income Inequality and Poverty in the Post-Reagan Era." *Criminology* 36:569-599.
- Kposowa, Augustine J., Kevin D. Breault, and Beatrice M. Harrison. 1995. "Reassessing the Structural Covariates of Violent and Property Crimes in the USA: A County Level Analysis." *British Journal of Sociology* 46:79-105.
- Kuhn, Thomas. 1970. *The Structure of Scientific Revolutions*. Chicago: University of Chicago. Land, Kenneth C., Patricia L. McCall, and Lawrence E. Cohen. 1990. "Structural Covariates of Homicide Rates: Are There Any Invariances across Time and Social Space?" *American Journal of Sociology* 95:922-963.
- Liska, Allen E. and Paul E. Bellair. 1995. "Violent-Crime Rates and Racial Composition: Convergence Over Time." *American Journal of Sociology* 101:578-610.
- Liska, Allen E., John R. Logan, and Paul E. Bellair. 1998. "Race and Violent Crime in the Suburbs." *American Sociological Review* 63:27-38.
- McCall, Patricia L., Kenneth C. Land, Cindy Brooks Dollar, and Karen F. Parker. 2013. "The Age Structure-Crime Rate Relationship: Solving a Long-Standing Puzzle." *Journal of Quantitative Criminology* 29:167-190.
- McCall, Patricia L., Kenneth C. Land, and Karen F. Parker. 2010. "An Empirical Assessment of What We Know About Structural Covariates of Homicide Rates: A Return to a Classic 20 Years Later." *Homicide Studies* 14:219-243.
- —. 2011. "Heterogeneity in the rise and decline of city-level homicide rates, 1976-2005: A latent trajectory analysis." *Social Science Research* 40:363-378.

- Changing crime levels in cities
- McCall, Patricia L., Karen F. Parker, and John M. MacDonald. 2008. "The dynamic relationship between homicide rates and social, economic, and political factors from 1970 to 2000." *Social Science Research* 37:721-735.
- McVeigh, Rory. 2006. "Structural Influences on Activism and Crime: Identifying the Social Structure of Discontent." *American Journal of Sociology* 112:510-566.
- Mills, Edwin S. and Richard Price. 1984. "Metropolitan suburbanization and central city problems." *Journal of Urban Economics* 15:1-17.
- Ousey, Graham C. and Charis E. Kubrin. 2009. "Exploring the Connection between Immigration and Violent Crime Rates in U.S. Cities, 1980–2000." *Social Problems* 56:447-473.
- Parker, Karen F. 2001. "A Move toward Specificity: Disadvantage and Race- and Relationship-Specific Homicide Rates." *Journal of Quantitative Criminology* 17:89-110.
- Parker, Karen F., Brian J. Stults, and Stephen K. Rice. 2005. "Racial Threat, Concentrated Disadvantage and Social Control: Considering the Macro-Level Sources of Variation in Arrests." *Criminology* 43:1111-1134.
- Paxton, Pamela, John R. Hipp, and Sandy Marquart-Pyatt. 2011. *Nonrecursive Models: Endogeneity, Reciprocal Relationships, and Feedback Loops*. Los Angeles: Sage.
- Peterson, Paul. 1981. City Limits. Chicago: University of Chicago Press.
- Peterson, Ruth D., Lauren J. Krivo, and Mark A. Harris. 2000. "Disadvantage and Neighborhood Violent Crime: Do Local Institutions Matter?" *Journal of Research in Crime and Delinquency* 37:31-63.
- Phillips, Julie A. 2006. "Explaining Discrepant Findings in Cross-sectional and Longitudinal Analyses: An Application to U.S. Homicide Rates." *Social Science Research* 35:948-974.
- Raleigh, Erica and George Galster. 2014. "Neighborhood Disinvestment, Abandonment, and Crime Dynamics." *Journal of Urban Affairs*:online.
- Roncek, Dennis W. 1981. "Dangerous Places: Crime and Residential Environment." *Social Forces* 60:74-96.
- Sampson, Robert J. 1987. "Urban Black Violence: The Effect of Male Joblessness and Family Disruption." *American Journal of Sociology* 93:348-382.
- Sampson, Robert J., Stephen W. Raudenbush, and Felton Earls. 1997. "Neighborhoods and Violent Crime: A Multilevel Study of Collective Efficacy." *Science* 277:918-924.
- Shihadeh, Edward S. and Graham C. Ousey. 1996. "Metropolitan Expansion and Black Social Dislocation: The Link Between Suburbanization and Center-City Crime." *Social Forces* 75:649-666.
- Stansfield, Richard and Karen F. Parker. 2013. "Teasing out the effects of macro-conditions on race-specific male homicide rates: Do distinct predictors vary by racial group and over time?" *Social Science Research* 42:633-49.
- Stults, Brian J. and Matthew Hasbrouck. 2015. "The Effect of Commuting on City-Level Crime Rates." *Journal of Quantitative Criminology* 31:331-350.
- Teaford, John C. 1979. *City and Suburb: The Political Fragmentation of Metropolitan America*. Baltimore: Johns Hopkins University Press.
- Tiebout, Charles M. 1956. "A Pure Theory of Local Expenditures." *Journal of Political Economy* 64:416-424.
- Warner, Barbara D. and Glenn L. Pierce. 1993. "Reexamining Social Disorganization Theory Using Calls to the Police as a Measure of Crime." *Criminology* 31:493-517.
- Weisburd, David, Elizabeth Groff, and Sue-Ming Yang. 2012. *The Criminology of Place*. New York: Oxford.

Wirth, Louis. 1938. "Urbanism as a Way of Life." *American Journal of Sociology* 44:1-24. Wood, R.C. 1958. *Suburbia: Its people and their politics*. Boston: Houghton Mifflin. Xie, Min and David McDowall. 2010. "The Reproduction of Racial Inequality: How Crime Affects Housing Turnover." *Criminology* 48:865-896.

# Changing crime levels in cities **Tables and Figures**

	198	30	1990	)	2000	)	2010	0
Aggravated assault rate (logged)	5.14	1.05	5.57	1.01	5.24	1.02	5.14	1.0
Robbery rate (logged)	4.53	1.07	4.43	1.23	4.26	1.11	4.19	1.10
Homicide rate (logged)	1.60	1.01	1.46	1.03	1.21	0.94	1.20	0.9
Burglary rate (logged)	7.24	0.54	6.93	0.62	6.47	0.64	6.42	0.72
Motor vehicle theft rate (logged)	5.87	0.67	5.87	0.86	5.60	0.85	5.07	0.8
Larceny rate (logged)	8.15	0.46	8.15	0.48	7.90	0.55	7.68	0.60
	All ye	ears						
City population (logged)	10.27	0.88						
Change in city population during decade	0.09	0.19						
Change in city population since 1950	54.41	212.03						
County population	12.49	1.51						
Change in county population	0.10	0.13						
City average household income (logged)	0.27	0.16						
City unemployment rate	5.86	3.03						
County unemployment rate	5.82	2.45						
Change in county unemployment rate during decade	1.21	2.94						
City percent occupied units	93.90	3.97						
City residential stability	51.15	10.50						
County percent occupied units	92.79	4.42						
Change in county percent occupied units during decade	-1.12	2.90						
City income inequality	39.16	6.38						
County income inequality	41.37	3.63						
Change in county income inequality during decade	0.96	2.68						
City racial/ethnic heterogeneity	26.63	19.03						
County racial/ethnic heterogeneity	29.87	18.87						
Change in county racial/ethnic heterogeneity during deca	5.62	4.96						
Percent black	9.08	14.06						
Percent Latino	8.55	15.69						
Percent immigrants	7.13	8.37						
Percent aged 16 to 29	22.46	6.91						

Table 2. Multilevel linear regression models of city level crime rates over four decades (1970=80, 1980-90, 1990-2000, 2000-2010) for cities with at least 10,000 population

	Aggravated				Motor	
	assault	Robbery	Homicide	Burglary	vehicle theft	Larceny
Logged crime rate beginning of decade	0.2986 **	0.5459 **	0.1503 **	0.4612 **	0.5529 **	0.5065 **
	(30.79)	(63.29)	(13.63)	(46.27)	(58.84)	(55.67)
Population change						
City population (logged)	0.1256 **	0.1094 **	0.2191 **	0.0743 **	0.1037 **	0.0486 **
	(9.41)	(10.66)	(18.26)	(10.29)	(11.43)	(6.89)
Parameter change over decades	-0.0004	0.0002	-0.0002	-0.0011 *	0.0029 **	-0.0008
	-(0.41)	(0.24)	-(0.23)	-(1.97)	(4.20)	-(1.64)
Change in city population during decade	-0.3858 **	-0.2476 **	-0.0968 +	-0.1990 **	-0.1167 **	-0.1814 **
	-(6.49)	-(5.33)	-(1.70)	-(6.06)	-(2.82)	-(6.20)
Parameter change over decades	-0.0128 *	-0.0082 *	-0.0039	-0.0123 **	-0.0126 **	-0.0092 **
	-(2.45)	-(1.98)	-(0.76)	-(4.23)	-(3.38)	-(3.56)
Change in city population since 1950	-0.0002 **	-0.0001 **	-0.0001 **	-0.0002 **	-0.0001 **	-0.0001 *
	-(2.80)	-(3.85)	-(3.00)	-(5.48)	-(3.60)	-(2.12)
Parameter change over decades	0.0000 †	0.0000	0.0000	0.0000	0.0000 **	0.0000
	(1.75)	-(0.68)	-(0.21)	-(0.59)	-(2.65)	-(0.16)
County population	0.0115	0.1234 **	0.0169 +	0.0224 **	0.0743 **	-0.0219 **
	(1.14)	(15.65)	(1.86)	(4.09)	(10.62)	-(4.18)
Parameter change over decades	-0.0016 *	-0.0012 *	-0.0004	-0.0021 **	-0.0002	0.0020 **
	-(2.17)	-(2.06)	-(0.59)	-(5.06)	-(0.28)	(5.31)
Change in county population	0.5950 **	0.6256 **	0.4024 **	0.3455 **	0.6612 **	0.3084 **
	(6.09)	(8.30)	(4.37)	(6.42)	(9.76)	(6.23)
Parameter change over decades	-0.0224 **	-0.0311 **	-0.0040	-0.0033	-0.0087	0.0024
	-(2.96)	-(5.15)	-(0.56)	-(0.79)	-(1.60)	(0.65)

Socio-economic status change						
City average household income (logged)	-3.4870 **	-2.9765 **	-2.3752 **	-2.6922 **	-2.3977 **	-1.4681 **
	-(20.01)	-(22.31)	-(14.79)	-(25.64)	-(18.37)	-(16.30)
Parameter change over decades	0.0645 **	0.1037 **	0.0912 **	0.1132 **	0.0113	0.0371 **
	(6.61)	(13.38)	(9.55)	(20.99)	(1.63)	(7.54)
City unemployment rate	0.0154 **	-0.0103 **	0.0153 **	-0.0076 **	0.0097 **	-0.0133 **
	(3.10)	-(2.66)	(3.16)	-(2.85)	(2.84)	-(5.31)
Parameter change over decades	0.0000	0.0015 **	0.0007	0.0013 **	-0.0001	0.0002
	(0.06)	(4.14)	(1.46)	(5.40)	-(0.23)	(0.73)
County unemployment rate	0.0090	0.0117 **	0.0040	0.0156 **	0.0013	0.0134 **
	(1.53)	(2.59)	(0.70)	(5.04)	(0.33)	(4.49)
Parameter change over decades	-0.0010	-0.0007	-0.0004	-0.0004	0.0007 +	-0.0004
	-(1.64)	-(1.53)	-(0.60)	-(1.24)	(1.74)	-(1.28)
Change in county unemployment rate during decade	-0.0147 **	0.0122 **	0.0109 **	0.0194 **	0.0035	0.0043 +
	-(3.23)	(3.56)	(2.74)	(8.25)	(1.17)	(1.87)
Parameter change over decades	0.0001	-0.0003	-0.0004	0.0000	-0.0002	-0.0007 **
	(0.21)	-(1.01)	-(1.30)	(0.13)	-(0.85)	-(3.82)
Housing unit change						
City percent occupied units	-0.0134 **	0.0030	-0.0121 **	-0.0052 **	0.0021	-0.0004
	-(3.82)	(1.09)	-(3.58)	-(2.75)	(0.87)	-(0.25)
Parameter change over decades	0.0005	-0.0003	0.0001	-0.0002	0.0001	-0.0002
	(1.58)	-(1.37)	(0.48)	-(1.41)	(0.66)	-(1.56)
City residential stability	-0.0064 **	0.0011	-0.0004	-0.0030 **	0.0000	-0.0022 **
	-(5.13)	(1.11)	-(0.32)	-(4.42)	(0.02)	-(3.46)
Parameter change over decades	0.0000	0.0001	0.0000	0.0001	-0.0003 **	-0.0001
	-(0.36)	(1.12)	-(0.12)	(1.06)	-(4.25)	-(1.10)

Changing Chine icvers in clues	II.	1			1		
County percent occupied units	0.0012		-0.0035	0.0036	-0.0030 †	-0.0048 *	-0.0024
	(0.37)		-(1.35)	(1.13)	-(1.68)	-(2.09)	-(1.39)
Parameter change over decades	-0.0002		0.0002	0.0003	0.0003 †	0.0011 **	0.0003 *
	-(0.59)		(1.06)	(1.02)	(1.78)	(5.51)	(2.27)
Change in county percent occupied units during decade	-0.0143	**	-0.0013	-0.0135 **	-0.0122 **	0.0005	-0.0058 **
	-(4.25)		-(0.46)	-(3.97)	-(6.07)	(0.17)	-(2.65)
Parameter change over decades	0.0015	**	-0.0002	0.0008 *	0.0003	0.0006 *	0.0005 *
	(4.40)		-(0.64)	(2.53)	(1.39)	(2.41)	(2.44)
Income inequality							
City income inequality	0.0079	**	0.0149 **	0.0128 **	0.0114 **	0.0027	0.0060 **
	(3.22)		(7.89)	(5.68)	(8.22)	(1.56)	(4.83)
Parameter change over decades	0.0006	**	0.0004 *	0.0002	0.0003 **	0.0004 **	0.0004 **
	(3.33)		(2.48)	(0.96)	(2.95)	(3.09)	(4.50)
County income inequality	0.0042		-0.0042	0.0029	0.0004	0.0028	0.0000
	(0.98)		-(1.29)	(0.76)	(0.18)	(0.96)	(0.00)
Parameter change over decades	-0.0004		-0.0002	-0.0009 **	0.0003 +	-0.0011 **	0.0000
	-(1.03)		-(0.88)	-(2.68)	(1.67)	-(4.41)	-(0.11)
Change in county income inequality during decade	0.0255	**	-0.0013	0.0149 *	-0.0009	-0.0056	-0.0020
	(4.20)		-(0.27)	(2.51)	-(0.27)	-(1.31)	-(0.67)
Parameter change over decades	-0.0011	*	-0.0003	-0.0012 *	0.0005 †	-0.0022 **	-0.0002
	-(2.24)		-(0.89)	-(2.56)	(1.86)	-(6.58)	-(0.83)
Racial/ethnic heterogeneity							
City racial/ethnic heterogeneity	0.0104	**	0.0064 **	0.0102 **	0.0040 **	0.0003	0.0006
	(10.52)		(8.42)	(10.69)	(7.67)	(0.50)	(1.13)
Parameter change over decades	-0.0002	*	0.0000	-0.0004 **	0.0000	0.0000	0.0000
	-(2.45)		-(0.40)	-(4.88)	(0.69)	(0.38)	(0.50)

Changing chine levels in clues				1	Transition of the second	1		1
County racial/ethnic heterogeneity	0.0011		0.0010	0.0021 *	-0.0004		0.0031 **	-0.0002
	(1.18)		(1.39)	(2.36)	-(0.79)		(4.75)	-(0.31)
Parameter change over decades	0.0001		-0.0001	-0.0001	0.0001	**	0.0002 **	0.0000
	(0.68)		-(0.99)	-(1.30)	(2.62)		(4.16)	(0.51)
Change in county racial/ethnic heterogeneity during deca	0.0028		0.0111 **	0.0067 **	* 0.0049	**	0.0072 **	-0.0006
	(1.36)		(6.75)	(3.34)	(4.20)		(4.86)	-(0.51)
Parameter change over decades	0.0002		-0.0002	-0.0004 *	-0.0004	**	0.0001	-0.0002 **
	(1.37)		-(1.24)	-(2.26)	-(4.02)		(0.67)	-(2.61)
City level control variables								
Percent black	0.0071	**	0.0111 **	0.0165 **	* 0.0046	**	0.0053 **	0.0032 **
	(6.43)		(13.16)	(15.74)	(7.99)		(7.19)	(5.57)
Parameter change over decades	-0.0001		-0.0002 **	0.0002 +	-0.0001	**	-0.0002 *	-0.0002 **
	-(1.15)		-(3.15)	(1.79)	-(2.71)		-(2.42)	-(4.09)
Percent Latino	0.0034	**	-0.0005	0.0062 **	* 0.0019	**	0.0001	-0.0005
	(3.43)		-(0.65)	(5.98)	(3.68)		(0.13)	-(0.87)
Parameter change over decades	0.0001		0.0001	0.0001	0.0000		0.0001 *	0.0000
	(1.45)		(1.31)	(0.97)	(0.16)		(2.22)	(0.21)
Percent immigrants	-0.0038	†	-0.0009	-0.0111 **	* -0.0114	**	0.0047 **	-0.0077 **
	-(1.87)		-(0.60)	-(5.75)	-(10.54)		(3.41)	-(7.15)
Parameter change over decades	-0.0004	*	-0.0002 †	0.0001	0.0000		-0.0007 **	-0.0001
	-(2.51)		-(1.90)	(0.66)	-(0.28)		-(6.30)	-(0.96)
Percent aged 16 to 29	-0.0132	**	-0.0045 **	-0.0142 **	* -0.0102	**	-0.0072 **	-0.0053 **
	-(7.12)		-(3.04)	-(8.18)	-(10.09)		-(5.67)	-(5.78)
Parameter change over decades	-0.0003	+	0.0000	-0.0001	0.0000		-0.0005 **	-0.0001
	-(1.79)		(0.20)	-(0.50)	-(0.14)		-(4.53)	-(1.58)
Year	0.0026		-0.0052	-0.0243	-0.0293	†	-0.0985 **	-0.0419 **
	(0.08)		-(0.21)	-(0.70)	-(1.71)		-(4.41)	-(2.68)
Intercept	3.9017	**	-0.6810 *	-0.8898 *	3.5894	**	0.9638 **	4.3034 **
	(10.24)		-(2.35)	-(2.53)	(16.75)		(3.73)	(20.69)

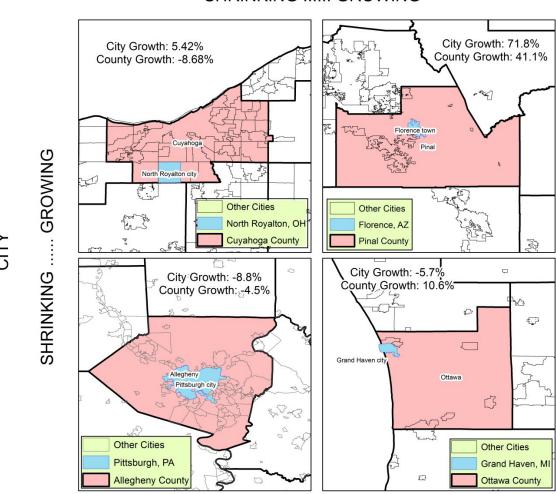
Changing crime levels in cities

Table 3. Share of variance explained at each level

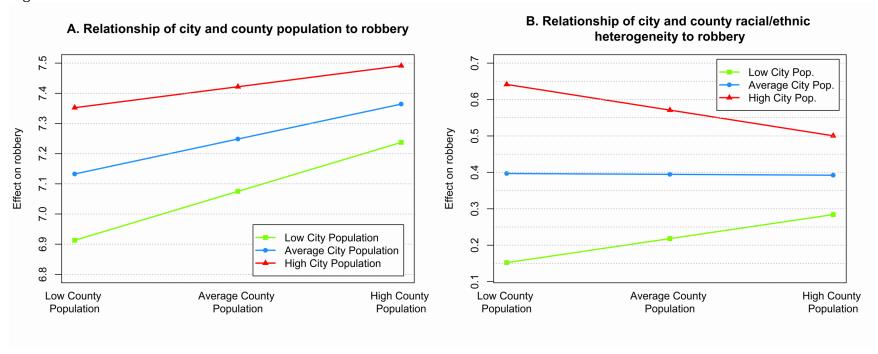
City	County	Both
share	share	share
73.0%	5.8%	21.3%
58.2%	20.2%	21.6%
77.4%	5.1%	17.5%
41.4%	5.3%	53.3%
62.9%	27.0%	10.1%
44.4%	9.6%	45.9%
	share 73.0% 58.2% 77.4% 41.4% 62.9%	share         share           73.0%         5.8%           58.2%         20.2%           77.4%         5.1%           41.4%         5.3%           62.9%         27.0%

#### **REGION**

#### SHRINKING ..... GROWING



## Changing crime levels in cities Figure 2.



## Changing crime levels in cities Figure 3.

