J Quant Criminol (2015) 31:331–350
DOI 10.1007/s10940-015-9251-z

ORIGINAL PAPER

The Effect of Commuting on City-Level Crime Rates

Brian J. Stults · Matthew Hasbrouck

Published online: 4 February 2015

Abstract
Objective To examine the effect of commuting rates on crime rate estimates in US cities, and to observe potential changes in the effects of other common crime rate correlates after accounting for commuting.
Methods Crimes evaluated include homicide, aggravated assault, robbery, burglary, larceny, and auto theft. The sample includes US cities with a population of at least 100,000. The analysis first compares crime rankings using a rate based on the residential population and an alternative rate that takes into account daytime population changes due to commuting. Next, multivariate random effects panel models are used to evaluate the effect of commuting on crime rates, and to examine the extent to which the effects of other predictors change after controlling for commuting.
Results A city's ranking can vary considerably depending on which denominator is used. Multivariate findings suggest that daily commuting rates are a significant, strong predictor of crime rates, and that controlling for commuting yields important changes in the effects of concentrated disadvantage, concentrated affluence, racial composition and residential instability.
Conclusions The impact of the commuting population on crime rate rankings underscores the importance of viewing crime rankings with great caution. Specifically, the residential crime rate overestimates relative risk for cities that attract a large daily population from outside the city limits. Findings provide support for the routine activities perspective, and suggest that future research examining city-level crime rates should

B. J. Stults (✉)
College of Criminology and Criminal Justice, Florida State University, Eppes Hall, 112 S. Copeland St., Tallahassee, FL 32306-1273, USA
e-mail: bstults@fsu.edu

M. Hasbrouck
State of Florida, Office of Economic and Demographic Research, 111 West Madison Street, Suite 574, Tallahassee, FL 32399-6588, USA
e-mail: hasbrouck.matthew@leg.state.fl.us

control for commuting. Limitations to the study and directions for future research are discussed.

Keywords Crime rate · Routine activities · Commuting · Macro-level · Cities

Introduction

One particularly attractive feature of the conventionally-used crime rate is that it is easy to calculate, requiring only a measure of the number of crimes committed for its numerator, and a measure of the at-risk population for its denominator. While the validity of commonly-used numerators has often been the subject of debate among researchers, the typical denominator for the crime rate—the residential population of the area—has been questioned much less often. This could be a considerable oversight since the crime rate is intended to be a measure of the number of crimes relative to the number of persons at risk, and the population at risk in a given city can be quite different from the population that resides within it.

A considerable portion of the discrepancy between the residential population and the population at risk of crime in a given city is due to daily outbound and inbound commuting for work. In the year 2000, the average American worker traveled 26 min to work, with some states reaching average commuting times over 30 min, and many cities considerably higher (Reschovsky 2004). The nation's largest commercial centers tend to have among the highest rates of inbound daily commuting, and these areas also tend to have among the highest rates of crime. For example, of large US cities in 2000 (at least 250,000 population), Washington, D.C. ranked second in percentage change in daily population due to commuting (71.8 %) and it had the second highest homicide rate. Likewise, Atlanta ranked fourth in daily population change (62.4 %) and it had the highest total crime rate and the 8th highest homicide rate.

There are theoretical and methodological reasons to expect that this apparent link between commuting rates and crime rates is more than coincidental. Routine activities theory argues that crime rates are influenced by routine patterns of activity in people's everyday lives that increase the potential for contact between offenders and suitable targets in the absence of capable guardianship (Cohen and Felson 1979). As a highly patterned routine activity, commuting to work could bring suitable targets into greater contact with potential offenders, and thus variability in rates of commuting across cities could partly explain variability in crime rates. Moreover, any effect of inbound commuting on crime rates will be artifactually increased by the fact that the denominator used in the conventionally constructed crime rate does not include this at-risk population.

Failure to account for this theoretically and methodologically important factor is problematic for at least two reasons. First, the ranking of a given city's crime rate could vary considerably depending on whether changes in its daytime population are accounted for in the calculation. Large central cities and metropolitan commercial centers tend to be heavily represented at the top of such crime rankings, and perhaps not coincidentally, these tend to be areas that have among the highest numbers of daily inbound commuters. Taking into account the daily influx of population due to commuting could provide a very different characterization of crime in many cities. So much local importance and national attention is given to these rankings that tourism, attitudes toward the police, economic health, and the overall image of the city can be at stake.

Second, to the extent that the volume of inbound daily commuting is correlated with other structural characteristics of cities, macro-level empirical research on the causes and correlates of crime may attribute too much explanatory power to the various theoretically specified predictors. Characteristics such as poverty, residential instability, and racial composition have long been identified as strong predictors of city-level crime rates. However, many cities with high concentrations of disadvantage, mobile populations, and minorities, as well as high crime rates, also tend to be central cities where a large portion of the daily workforce returns to homes outside of the city at night. In some cases, these are cities that have experienced considerable suburban growth and flight from central cities. Such broad structural changes may have led to concentrations of the poor and minorities in central cities, while also resulting in longer commutes for workers living outside the city. Failure to account for this large daily influx of population into cities, and its resultant impact on crime rates, may lead to overestimates of the effects of these structural characteristics on crime.

For example, Washington, D.C. had among the highest homicide rates and black percentages in 2000 (second and seventh, respectively), and it had the second highest inbound commuting rate. Miami had the third highest poverty rate in 2000 (23.5 %) and the sixth highest total crime rate of large US cities, and it had the tenth highest inbound commuting rate (37.3 %). These examples illustrate the possibility that part of the observed association between crime and factors such as poverty and racial composition may be due to their relationship with a third factor—daily increases in population due to commuting. Thus, the strength attributed to these ecological predictors in prior research could be partially due to systematic bias in the way crime rates are measured. Of course, this is not to suggest that these ecological factors are wholly spurious and irrelevant. Rather, it points to the importance of accounting for the commuting population in order to generate valid and reliable estimates of the effects of these theoretical predictors on city-level crime rates.

To that end, the purpose of this paper is to examine the effect of daytime shifts in population due to commuting on estimated crime rates. Though there are numerous sources of daily change in the population of cities, this study focuses on data from the US Bureau of the Census that allows for the estimation of levels of daily inbound and outbound commuting to work. The initial descriptive analysis will briefly examine city-level crime rankings and the extent to which they vary depending on whether the calculation of the crime rate is based solely on the residential population as its denominator, or if it also incorporates the commuting population. This will illustrate the magnitude of the impact of commuting on crime rate estimates across cities. The subsequent multivariate analysis will examine whether theoretically-driven empirical research would yield different conclusions depending on whether or not the commuting population is taken into account.

Theory and Prior Research

The validity of crime rates has been questioned repeatedly over time, with most attention being directed at the use of Uniform Crime Reporting data as a measure of the volume of criminal offending (Blumestein et al. 1991; Decker 1983; Gove et al. 1985; Kitsuse and Cicourel 1963; O'Brien 1985; O'Brien et al. 1980; Sellin and Wolfgang 1964; Skogan 1974). This literature addresses the validity of the most typical numerator of the crime rate, but much less attention has been directed at the most typical denominator of the crime rate—the residential population. In an early attempt to critically examine the denominator used in calculating crime rates, Boggs (1965) argued that a valid crime occurrence rate should take into account the at-risk population for a given crime, which is likely to be different from the residential population. In her analysis of St. Louis neighborhoods, crime rates were constructed using denominators that captured the at-risk population specific to each particular crime type. For example, the occurrence of larceny was divided by a business-to-residential land use ratio, auto-theft rates were calculated using the amount of space devoted to parking, and "in the absence of a daytime census of population" (p. 901), the number of square feet of streets was used as a denominator for the street robbery rate. The results showed large discrepancies between neighborhood crime rates that used these crime-specific denominators and the traditionally-calculated rates based on residential population.

Researchers have occasionally revisited this issue, though not always as a main focus of their study (Chamlin and Cochran 1996; Gibbs and Erickson 1976; Loftin et al. 2008; Pettiway 1985; Reiss 1967). For example, Gibbs and Erickson (1976) argued that the number of people who might offend or be victimized is potentially different than the residential population of the area, specifically to the extent that the city is part of a broader community such as a metropolitan area. Because central cities provide unique employment and recreational opportunities, they tend to draw persons from the broader metropolis at various times, thus increasing the number of potential offenders and victims. In an analysis of 352 cities with a population of at least 50,000 in 1970, they found a relationship between crime rates and the ratio of metropolitan population to city population, but this held only when the metropolitan area included just one central city. These "singular" cities were assumed to be more dominant attractors of population from the broader metropolis than those in areas where multiple central cities were in competition with one another. However, this highlights one important limitation of the study—the failure to measure the extent to which non-city residents actually traveled into the central city, and were thus exposed to risk of offending and victimization in the city. In a follow-up study, Stafford and Gibbs (1980) acknowledge that it would be desirable to more directly measure the attraction of non-city residents using journey to work data to capture commuting levels, but due to unavailability of data, they ultimately used a proxy measure (the ratio of retail sales dollars in the broader area versus each central city).

Several subsequent studies have examined the impact of the broader metropolitan population, sometimes measured as the suburbanization rate, on crime rates in central cities (Cohen et al. 1985; Farley 1987; Farley and Hansel 1981; Shihadeh and Ousey 1996). Only one of these studies has assessed whether the relevance of standard macro-level predictors of crime varies depending on which method of calculating the crime rate is employed. In an analysis of residential burglary and auto theft, Cohen et al. (1985) used as base populations the number of households that could be burgled and the number of registered automobiles, respectively. They examined trends in these crime rates from 1947 to 1972 and found that the model results were quite similar regardless of which of the alternative rates was used. Thus, though they point to the importance of carefully considering which denominator is most appropriate for different types of crime, they conclude for these crime types that the results of theoretically-derived predictive models are not notably different when using crime-specific denominators instead of the more conventional residential population.

A central theme among many of these studies is the important role of opportunity as an explanation of variability in crime rates across cities. Cohen and Felson (1979) argue that variation in crime rates can be explained by structural differences in the "routine activities" of everyday life. These daily routines can influence the crime rate by affecting the likelihood that the conditions conducive to crime—a motivated offender, a suitable target, and the absence of capable guardianship—will converge in time and space. From this perspective, the influx of population into a city for daily work commuting could increase crime rates in receiving cities by increasing the likelihood of contact between a motivated offender and a suitable victim. As Farley (1987) points out, it may be unreasonable to expect that inbound commuting will substantially increase the pool of offenders in the city, but this daily inbound population is at risk of falling victim to crimes such as shoplifting, robbery, assault, and auto theft while in the city.

The routine activities perspective also implies some reasons to believe that the influence of commuting populations on crime rates may vary across types of crime. Rates for violent crimes such as homicide, rape, and aggravated assault, are likely to be less closely associated with commuting rates since these crimes occur more often between family members or acquaintances than between strangers, and there is little reason to believe that commuting rates would substantially influence the likelihood of interaction between friends and family (Miethe et al. 1991). Also, because perpetrators of property crime tend to travel further to commit crime, such as outside their neighborhood, they are more likely to come into contact with inbound commuters, thus increasing the likelihood of contact between a motivated offender and a suitable target (Farley and Hansel 1981). Prior studies have provided some support for these expectations, finding that the ratio of metropolitan to central-city population was a stronger predictor of variation in property crime rates than violent crime rates (Farley and Hansel 1981; Stafford and Gibbs 1980), and that the influence of daytime and nighttime leisure activities on victimization was only a significant predictor for property crime (Miethe et al. 1987). Of the various property crimes, larceny may be the most affected by inbound commuting populations since it is comprised of crimes such as theft from vehicles, pocket-picking, and purse-snatching, all of which are likely to be elevated in cities with a large daily influx of suitable targets.

While burglary has received considerable attention in routine activities research, with the often-supported expectation that increased activity outside the home will be associated with higher residential burglary rates, the expectations are less clear with regard to the impact of commuting rates. In general, the expectation for other crime types is that cities with a high rate of inbound commuting will have higher crime rates partly due to the increased potential for contact between offenders and targets, but also because the inbound commuting population is not included in the denominator of the crime rate. However, since burglary is a crime committed against homes rather than against individuals, the expectation is just the opposite–cities with higher rates of *outbound* commuting are expected to have higher rates of burglary due to reduced levels of residential guardianship. But burglary is also different from the other crime types considered in this study because the outbound commuters who are victimized by burglary are correctly included in the residential population used in the denominator of the crime rate where the offense occurred, while commuters who are victims of the other crime types are more likely to have been victimized outside the city, and thus would not be included in the denominator of the crime rate where the offense occurred. In other words, routine activities theory does predict an association between commuting rates and burglary, though in the opposite direction of expectations for the other crime types, and less strong because it is not inflated by the use of an underestimated denominator.

To summarize, though a handful of studies have used denominators for the crime rate that are perhaps better indicators of the population that is at risk of offending or victimization, or have indirectly accounted for the influence of surrounding metropolitan populations on central city crime rates, no prior work has directly examined the effect that daytime changes in population size due to commuting may have on crime rate estimates. Failure to account for these regular changes in population size might lead to inaccurate characterizations of crime levels within cities as well as relative levels across cities. If areas that typically rank high in crime also tend to have a large influx of daily work commuters, taking into account that daily surge in at-risk population may result in a notably lower crime rate estimate. This has clear implications for individual cities since crime rates are such a salient factor in the evaluations of current residents, would-be residents, business owners, tourists, etc. Further, the failure to consider such a large source of daily population change in prior city-level analyses of crime rates may have lead researchers to overestimate the predictive importance of various ecological characteristics to the extent that they are also associated with rates of commuting.

Research Methods

The analysis will begin with an examination of city-level crime rate rankings for several types of crime. This will serve as an illustration of the degree to which crime rates can change across cities when daytime changes in the population due to commuting are taken into account. The next stage of the analysis will involve generating two multivariate regression equations for each crime type—one that includes the standard macro-level predictors but does not account for daytime changes in the population, and one that controls for the percentage change in the population due to in-bound and out-bound commuting. While the effect of the commuting rate is of theoretical interest itself, another purpose of this portion of the analysis will be to compare the effects of the other coefficients across the two models. If the relationship between the crime rate and another structural characteristic of cities, such as concentrated poverty, is confounded by the volume of commuting, it will be evidenced by a reduction in the coefficient for concentrated poverty across the two models. This will allow for an examination of whether conclusions about the effects of typical macro-level predictors of crime are significantly different when we to take into account a considerable source of daily population change that is not captured in prior research.

Data and Sample

This study makes use of data from a variety of sources for the years 1990, 2000, and 2010. Offense counts were drawn from Uniform Crime Reporting data for each respective year (Federal Bureau of Investigation 2002, 2009, 2012). The residential population size as well as indicators of numerous city characteristics identified in prior research as associated with crime rates are drawn from US Census Summary Tape File 3A for 1990 and Summary File 3 for 2000. Because the decennial census no longer included data on socioeconomic characteristics such as poverty, family structure, and residential mobility after 2000, these variables for the latter period are drawn from the 2009–2011 multi-year estimates of the American Community Survey (ACS). The central variable used in this analysis—city-level population change due to commuting—is derived from census and ACS data, as well as information from the Census Transportation Planning Products (CTPP) archive, a set of special census tabulations designed by transportation planners and made available by the Bureau of Transportation Statistics.

The sample used in this study includes US cities that had a population of at least 100,000 and complete data in all three decennial years from 1990 to 2010 (n = 166 cities). Much of the prior city-level crime research has used this sampling criterion (Liska et al. 1985; Krivo and Peterson 2000; McDowall and Loftin 2009; Sampson 1987; Shihadeh and Steffensmeier 1994), and it is relevant for the current study since we are particularly interested in cities that have the potential to attract large numbers of persons on a daily basis who reside outside the city. Cities with populations of at least 100,000 are often commercial centers for their respective regions, employing city residents as well as people from the broader metropolitan area and beyond.

Dependent Variables

The dependent variables used in this study are offense rates per 100,000[1] persons for homicide, aggravated assault, robbery, burglary, larceny, and auto theft. These particular crime types were chosen for several reasons. First, they are all Part I index crimes, and occur with sufficient frequency for analysis in all cities in the sample. Second, the volume of some of these crime types is likely to be influenced by a large influx of daytime population, such as commuting flows. Aggravated assault and robbery are interpersonal crimes that require the presence of both the victim and the offender at the time of occurrence. Inbound commuters are unlikely to contribute in large numbers to assault and robbery counts as offenders, but they are potential victims of these crimes, so it is reasonable to expect that a large presence of daytime commuters in a city could increase the frequency of these crimes. Likewise, in most cities, a large number of inbound commuters results in a marked increase in the number of automobiles in the city during the day, which could yield higher rates of motor vehicle theft. Because of the influx of persons and the large number of stores that cater to the daytime population, these areas will also have more potential targets for larceny crimes such as shoplifting, pick-pocketing, and purse-snatching. Homicide and burglary are also included, largely because of the attention they have received in prior research, but as noted above, the expectations are less clear for these crime types.

Independent Variables

A key concept used in this analysis is the change in daily population due to inbound and outbound commuting, referred to as the commuter-adjusted daytime population by the Census Bureau (http://www.census.gov/hhes/commuting/data/calculations.html). This daytime population is calculated using the following components from the CTPP and the Census or ACS:daytime population = resident population + workers working in city − workers living in city.

By adding to the residential population the number of workers working in the city less workers living in the city, we simultaneously include the number of people who work in the city but live elsewhere, as well as remove the number of people who live in the city but work outside of it. When generating crime rate rankings that account for this daytime population, a decision must be made about how to weight the residential and daytime populations in the denominator. One option would be to weight them equally, essentially using the average of the two populations. This seems reasonable with regard to the number of hours in the work day, since commuting and working hours could be considered to be

[1] Homicide rates are expressed per 1 million persons to make the coefficients more readable.

from roughly 6 am to 6 pm, or 7 am to 7 pm. However, this would not take into account the fact that most of the businesses where out-of-city commuters are employed are likely to be closed on Saturday and Sunday. To adjust for these weekend days when calculating the denominator of the crime rate, the daytime population is given a weight of 5/14ths to represent the daytime portion of the five work days, and the residential population is given a weight of 9/14ths to represent the nighttime portion of the five work days plus the full weekend days. Potential limitations of this strategy, as well as alternatives that could be explored in future research, are discussed in the conclusion. The mean for the percentage change in population due to commuting across this sample of cities is 13.9, with a high of 72.4 and a low of −18.3. Negative values indicate that the city loses population during the day due to net levels of commuting. The variable approaches normality, with only mild levels of skewness and kurtosis.[2]

The other independent variables used in the regression analysis include predictors that have been consistently used in macro-level studies of crime (Land et al. 1990; Ousey 1999; Sampson et al. 1997). Ten census variables were submitted to factor analysis to determine if they loaded on a smaller number of common factors as previous research has shown. Three dominant factors emerged from a principle components analysis with promax rotation, all with eigenvalues of at least 1.0 and a cumulative explained variance of at least 0.82 in every year. Nearly every variable had a uniqueness of <0.20, with a maximum uniqueness of 0.30. The first factor score, referred to as *concentrated disadvantage*, is comprised of the percentage of families below poverty, percentage of families receiving public assistance, percentage unemployed, and percentage of households headed by a female with children. The second factor score, referred to as *concentrated affluence*, consists of the percentage of households with an income of $100,000 or greater, the percentage of persons 25 and older with a bachelor's degree, and the percentage of persons in the civilian labor force who are employed in professional and managerial occupations. The third factor score, referred to as *immigrant concentration*, is comprised of percent Hispanic, percent foreign-born, and percentage of persons who immigrated in the last 10 years. Additional variables used in the multivariate analysis include the percentage of persons who lived in a different house 1 year prior[3], referred to as residential instability, percent non-Hispanic black, percentage of the population that is male and between the ages of 15 and 24, and population density.[4] Finally, year dummy variables are included to model time-specific effects, taking into account the fact that most areas across the country experienced a considerable crime drop across these decades.[5]

2 Skewness and kurtosis were 0.77 and 4.04, respectively, using Stata's "summarize" command which centers skewness and kurtosis on values of 0 and 3. No severe outliers were found for this variable using Stata's "iqr" command.

3 In the 1990 and 2000 decennial censuses, respondents were asked whether they lived in a different house 5 years ago, while the 2009–11 ACS asked about one year ago. To make the measures more comparable, the percentage measures for 1990 and 2000 were divided by five to generate estimates of the percentage of people who moved in the past year.

4 Prior research has often included black percentage as one of the components in a concentrated disadvantage index (Sampson et al. 1997; Steffensmeier and Haynie 2000). However, because racial composition has been an important factor in both the theoretical and empirical literature, percent black is included separately in the current study. Percent black and the concentrated disadvantage factor score were only moderately correlated (no more than $r = 0.61$). All VIFs were less than 4 in each year, with average VIFs of around 2.5, and a condition number <30 in each year.

5 Prior research on auto theft suggests that opportunity, in the form of more vehicles available to steal, may be particularly relevant for explaining variation in offense rates (Copes 1999). In supplementary auto theft models (not shown), the inclusion of a measure of vehicles per square mile did not yield substantive changes

Results

Crime Rate Rankings

Table 1 presents city rankings for offense rates calculated using two different denominators. The first set of rankings listed under each crime type is based on rates calculated in the conventional manner with residential population as the denominator, and the cities in the table are sorted according to this ranking. The second set of rankings listed for each crime type is based on rates calculated with a denominator that combines the residential and commuter-adjusted daytime populations as described above. Comparing these two sets of figures allows us to observe how evaluations of crime rates and the relative dangerousness of cities might be different if we used a calculation of the crime rate that takes into account daytime changes in the at-risk population due to commuting. The subsequent regression models will use data from 1990, 2000, and 2010 for all six crime types, but to conserve space here, crime rankings are provided only for cities in the year 2010, and only for homicide, robbery, and larceny. Moreover, only the 25 highest ranked cities for each crime type are listed, though particularly notable cases from the remainder of the cities will be discussed in the text.

Looking first at the rankings for homicide in Table 1, we see that the top of the list includes cities that are typically discussed as being among the most dangerous in the US, such as New Orleans, St. Louis, Detroit, and Baltimore. Indeed, several of the top ten cities have been designated as either the murder capital of the US or the most dangerous city at some point in the past two decades. A comparison of the residential and daytime rankings shows that, overall, the homicide rate rankings do not change much; cities tend to have similar rankings regardless of which denominator is used. In fact, the rankings for the top ten cities either do not change at all, or they change by only one position. However, more sizable changes occur for cities further down on the top 25, and given the level of attention paid to such rankings and the consequences that can result from being among the most dangerous cities in the country, even a small change in these rankings can be significant for an individual city.

Looking at some specific cities, we see that when the commuting population is included in the denominator, Washington, D.C., experiences the most sizable drop among these 25 cities, moving from a rank of 14th to 23rd. Atlanta and Pittsburgh also experienced notable changes, each of them dropping seven ranks when the commuting population is included in the estimate. Other cities experienced comparable changes, but in the opposite direction, due to the fact that these cities experience a net daytime population loss due to commuting. These include Philadelphia which increased by five ranks, and Inglewood, CA, which moved up seven positions.

One way of characterizing the overall level of change between the two sets of rankings is by looking at the mean absolute difference between the two, which indicates the average amount of movement in the rankings, either up or down, when comparing the residential rate to the alternative rate. The mean absolute difference in the homicide rate rankings is just 4.18, meaning the average city moved up or down by about 4 ranks when comparing the residential rate to a rate calculation that includes the commuting population. Though many of these changes are relatively small, dropping into or out of the top 25 can be

Footnote 5 continued
to the results. In order to maintain model comparability across crime types, this variable is not included in the reported models.

Table 1 Comparison of crime rankings for US cities in 2010 using residential and commuter-adjusted populations

Homicide			Robbery			Larceny		
City	Res. rank	Adj. rank	City	Res. rank	Adj. rank	City	Res. rank	Adj. rank
Flint, MI	1	1	Cleveland, OH	1	3	Springfield, MO	1	1
New Orleans, LA	2	2	Detroit, MI	2	1	Salt Lake City, UT	2	13
St. Louis, MO	3	4	Oakland, CA	3	2	Everett, WA	3	5
Detroit, MI	4	3	Cincinnati, OH	4	4	St. Louis, MO	4	6
Baltimore, MD	5	5	St. Louis, MO	5	7	Knoxville, TN	5	12
Newark, NJ	6	6	Flint, MI	6	6	San Antonio, TX	6	2
Baton Rouge, LA	7	7	Washington, DC	7	16	Little Rock, AR	7	11
Dayton, OH	8	9	Jackson, MS	8	8	Spokane, WA	8	4
Jackson, MS	9	10	Elizabeth, NJ	9	5	Mcallen, TX	9	9
Oakland, CA	10	8	New Haven, CT	10	9	Columbus, GA	10	7
Cincinnati, OH	11	13	Newark, NJ	11	11	Independence, MO	11	3
Kansas City, MO	12	11	Buffalo, NY	12	13	Chattanooga, TN	12	22
Atlanta, GA	13	20	Dayton, OH	13	17	Brownsville, TX	13	10
Washington, DC	14	23	Philadelphia, PA	14	12	Springfield, IL	14	16
Buffalo, NY	15	14	Baltimore, MD	15	15	Austin, TX	15	14
Hartford, CT	16	21	Chicago, IL	16	14	Glendale, AZ	16	8
Richmond, VA	17	17	Paterson, NJ	17	10	Orlando, FL	17	40
Cleveland, OH	18	19	Atlanta, GA	18	22	Columbia, SC	18	32
Richmond, CA	19	12	Memphis, TN	19	20	Topeka, KS	19	17
Philadelphia, PA	20	15	Milwaukee, WI	20	18	Atlanta, GA	20	38
Peoria, IL	21	18	Stockton, CA	21	19	Cincinnati, OH	21	25
Rochester, NY	22	22	Miami, FL	22	28	Norfolk, VA	22	20
Inglewood, CA	23	16	Hartford, CT	23	29	Amarillo, TX	23	15
Pittsburgh, PA	24	31	Houston, TX	24	24	Tempe, AZ	24	43
New Haven, CT	25	26	Little Rock, AR	25	27	Jackson, MS	25	28
Mean absolute difference	4.18			4.63			8.75	
Largest decline	23			30			55	
Largest increase	19			18			35	

important symbolically and could have a meaningful impact on the perceived safety and desirability of a given city.

Table 1 shows that there are also few dramatic changes in the rankings of the top 25 cities with regard to the robbery rate. Cleveland moves out of the top ranking down to a rank of 3rd, while Washington, D.C., again experiences a sizable drop from 7th to 16th. Both of these changes are particularly notable because they involve symbolically important moves, either out of the 1st position or out of the top 10 cities. The largest changes in the robbery rate ranking occur outside the top 25, and thus are not shown in the table. For example, Orlando, FL, drops from 61st to 96th, and Yonkers, NY, increases from 83rd to 64th. The average rank movement for robbery is 4.63, which is somewhat higher than what was observed for the homicide rate.

Looking to larceny, some larger changes begin to appear among the top 25 cities. For example, three cities—Salt Lake, Knoxville, and Little Rock—drop out of the top 10 after accounting for the commuting population. Orlando experiences an even greater drop of 23 rankings from 17th to 40th, and several other cities drop well out of the top 25. Examples of large upward movements in the larceny rankings include Arlington, TX, which moves from 40th up to 18th, and Glendale, AZ, which increases from 16th into the top 10 at the 8th position. This examination of the rankings reveals somewhat larger changes for larceny compared with homicide and robbery, and this is confirmed by the larger average absolute change of 8.75, indicating that the average city moves up or down the larceny rankings by about 9 positions when the commuting population is accounted for in the denominator.

The purpose of examining these rankings was to determine whether characterizations of the dangerousness of cities would vary notably when the inbound and outbound commuting populations are accounted for in the denominator rather than using just the residential population. The general conclusion is yes, the crime rankings do change somewhat, and often in important ways. The greatest overall changes were for larceny, but even homicide and robbery exhibited some sizable differences between the rankings. Overall, these rankings provide a descriptive illustration of the notable impact that net commuting flows have on crime rate calculations, suggesting that this may be an important characteristic to consider when evaluating the predictors of crime rates in cities, a task to which we now turn.

Multivariate Analysis

The second portion of the analysis addresses whether population change due to commuting is a significant predictor of city-level crime rates as expected by the routine activities

Table 2 Correlation coefficients among predictor variables

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	Commuting Rate	1.000							
(2)	Conc. Disadv.	0.179**	1.000						
(3)	Conc. affluence	0.285**	−0.473**	1.000					
(4)	Immigrant Conc.	0.254**	0.067	−0.101*	1.000				
(5)	% Black	0.328**	0.582**	−0.113*	−0.367**	1.000			
(6)	Pop. density	0.105*	0.357**	−0.066	0.529**	0.090*	1.000		
(7)	Res. instability	0.177**	−0.068	0.101*	−0.089*	−0.037	−0.139**	1.000	
(8)	% Young male	0.028	0.081	−0.084	0.111*	−0.009	0.067	0.474**	1.000

* $p \leq .05$; ** $p \leq .01$

Table 3 Random effects panel model regressions of crime rates with and without commuting population change as a predictor

	Homicide		Aggravated assault		Robbery	
	(1)	(2)	(1)	(2)	(1)	(2)
Commuting rate	—	0.5* (0.2)	—	5.0** (1.0)	—	2.9** (0.6)
Conc. Disadv.	20.4** (4.9)	18.6** (4.9)	**87.6** (22.6)**	**73.1** (22.3)**	**68.7** (13.7)**	**55.1** (13.5)**
Conc. affluence	−0.8 (3.9)	−4.3 (4.2)	**−33.7 (18.4)**	**−69.4** (19.0)**	**−6.9 (10.7)**	**−27.1* (11.1)**
Immigrant Conc.	12.3* (5.0)	13.3** (5.0)	0.2 (23.8)	9.2 (23.0)	42.0** (13.0)	46.5** (12.4)
% Black	**4.3** (0.3)**	**4.1** (0.3)**	**6.6** (1.4)**	**5.2** (1.4)**	**8.5** (0.8)**	**7.8** (0.7)**
Pop. Density	−0.004 (0.01)	−0.002 (0.01)	−0.0002 (0.04)	0.01 (0.04)	0.1** (0.02)	0.1** (0.02)
Res. instability	−0.5 (1.1)	−1.1 (1.1)	4.6 (5.0)	0.1 (5.0)	**6.1* (3.1)**	**3.4 (3.3)**
% Young male	2.4 (1.9)	2.1 (1.9)	−10.9 (8.8)	−13.5 (8.7)	4.6 (5.8)	2.2 (5.6)
Year 2000	−71.0** (13.4)	−69.0** (13.3)	**−262.7** (61.1)**	**−243.6** (60.1)**	**−222.1** (40.8)**	**−206.1** (39.9)**
Year 2010	**−71.7** (13.5)**	**−65.4** (13.7)**	**−383.1** (61.9)**	**−327.1** (61.9)**	**−314.9** (40.642)**	**−272.0** (40.4)**
Constant	72.7** (14.8)	72.6** (14.8)	641.7** (68.53)	639.9** (66.9)	185.8** (43.4)	188.3** (42.3)
R-squared	0.6639	0.6692	0.4413	0.4769	0.6346	0.6567

	Burglary		Larceny		Auto theft	
	(1)	(2)	(1)	(2)	(1)	(2)
Commuting Rate	—	7.8** (1.6)	—	26.8** (4.2)	—	2.8* (1.5)
Conc. Disadv.	**192.2** (35.2)**	**170.3** (34.7)**	**173.5* (87.1)**	**117.7 (84.2)**	163.1** (33.9)	150.9** (34.4)
Conc. Affluence	−2.8 (28.8)	−50.4 (29.7)	75.5 (74.3)	−71.8 (74.0)	−42.7 (26.8)	−61.8* (28.6)
Immigrant Conc.	−38.9 (37.4)	−24.5 (36.1)	−282.3** (99.4)	−233.5* (93.5)	107.9** (33.3)	112.5** (33.4)
% black	**11.9** (2.2)**	**9.8** (2.2)**	8.8 (5.8)	0.6 (5.6)	**10.0** (2.0)**	**8.1** (2.0)**
Pop. Density	−0.3** (0.1)	−0.3** (0.1)	−0.7** (0.2)	−0.6** (0.2)	0.04 (0.1)	0.05 (0.1)
Res. Instability	2.3 (7.8)	−4.0 (7.8)	**−26.9 (18.2)**	**−43.1* (18.1)**	1.17 (8.0)	−1.9 (8.1)
% Young Male	27.8* (13.7)	22.5 (13.5)	77.9*@@@32.211	63.3* (31.5)	14.8 (13.9)	13.6 (13.8)
Year 2000	**−1,021.7** (94.8)**	**−984.8** (93.5)**	**−1,778.6** (221.8)**	**−1,671.5** (217.6)**	−476.4** (97.1)	−467.6** (96.9)

Table 3 continued

	Burglary		Larceny		Auto theft	
	(1)	(2)	(1)	(2)	(1)	(2)
Year 2010	**−1,065.6**** (**96.3**)	**−977.6**** (**96.4**)	**−2,388.9**** (**227.8**)	**−2,154.1**** (**226.1**)	−811.8** (97.4)	−777.2** (98.9)
Constant	1,800.7** (106.9)	1,792.0** (104.4)	5,350.2** (264.2)	5,276.4** (253.3)	892.8** (105.0)	894.7** (104.8)
R-squared	0.5763	0.6064	0.4164	0.4947	0.4989	0.502

Bold results indicate a statistically significant difference in coefficients after controlling for population change due to commuting, and at least one of the coefficients in the pair is statistically significant

* $p \leq .05$; ** $p \leq .01$

perspective, and whether the inclusion of commuting rates in a typical city-level model of crime rates yields changes in the effects of predictors that are suggested by other theories. The bivariate correlations among the predictors presented in Table 2 show that the commuting rate is positively correlated with each of the other predictor variables, and these correlations are statistically significant for all variables except the percentage of young males. These consistently positive correlations, along with significant, positive correlations between the commuting rate and each crime rate (not shown), indicate the potential for confounding effects.

In order to explore this further, random effects panel models (Table 3) are estimated to take advantage of the three periods of data—1990, 2000, and 2010—and to evaluate both within-unit and between-unit variation[6]. Two models are estimated for each crime time, with both models using as their dependent variable the residential crime rate that is typically used in macro level research, and including predictor variables that have been used in many previous analyses of crime rates for cities, neighborhoods, and metropolitan areas. The difference between the two models for each crime type is that the second model also includes as a predictor the percentage change in the daytime population due to inbound and outbound commuting. A significant positive effect of the commuting measure indicates support for routine activities theory, and the notion that residential crime rates may be inflated by failing to include this additional daytime population in the denominator. Also, by comparing coefficients across models for each of the other predictors, we can assess whether some of the effects observed in prior research for variables such as concentrated disadvantage and residential instability may be confounded by the fact that cities with these characteristics also tend to be ones where there is a large net change in daytime population due to commuting.

One consistent finding evident in the regression analysis in Table 3 for all six crime types is that cities with net increases in population due to commuting tend to have higher crime rates, as expected. This is exhibited in the significant, positive coefficient for the commuting variable for every crime type. For example, an increase of one percentage point in population size due to commuting is predicted to increase the assault rate by 5.0 and the larceny rate by 26.8 (per 100,000). Standardized coefficients (not shown) reveal that, aside from the year-specific effects, the commuting rate is the strongest predictor for assault and larceny, and it is the second and third strongest predictor for burglary and robbery, respectively. These results clearly show that it is important to account for the size of the commuting population when examining city-level variation in crime rates, but the question remains as to whether the failure to account for it in past research has generated misleading results. This question will be addressed by comparing coefficients between the two models for each crime type.

Looking first at the violent crimes of homicide, assault, and robbery, we see in Model 1 for each crime type that the effects of concentrated disadvantage and % black are statistically significant and in directions consistent with expectations. Immigrant concentration is also positively related to the homicide rate and robbery rate, concentrated affluence is inversely associated with the assault rate, and residential instability is positively associated

[6] Hausman tests were significant for robbery, burglary, and larceny. However, the relatively small number of cases, and the relatively low within-unit variation in the key predictor—the commuting rate—relative to the dependent variables, lead to a preference for random effects models for all crime types. A “hybrid” random effects model was also estimated for each crime type to decompose the predictors into their between- and within-unit components, and the coefficients for both components were highly consistent for all predictors (Allison 2005; Gaspera et al. 2010; Raudenbush and Bryk 2002). As this type of model complicates the mediational analysis, again, the simpler random effects model was chosen.

with the robbery rate. These results are not surprising, and largely consistent with prior work. Of greatest interest to the current study is whether the effects of these variables change significantly after introducing the commuting variable. Bold face is used in Table 3 to highlight pairs of coefficients that change significantly, but only when at least one of the effects is significantly different from zero.[7] For homicide, the effects of the other variables change very little after including the commuting variable. The only significant decline in coefficients is for % black, but it declines by only about 3.5 %, a difference that is significant largely due to the very small standard errors. However, there are more sizable changes in the models for aggravated assault and robbery. For example, the effect of concentrated disadvantage on aggravated assault declined by over 16 % after controlling for the commuting population, and it declined by nearly 20 % in the robbery model. The effect of % black on the assault rate declined significantly by 21 %, though only by about 8 % for robbery. The effect of concentrated affluence changed sizably for both aggravated assault and robbery, though surprisingly the introduction of the commuting variable led these coefficients to become larger and emerge as statistically significant. The single largest change in coefficients was for the effect of residential instability on robbery. The effect was initially statistically significant and positive, but after including the commuting variable, the effect of residential mobility declined by almost 44 % and was no longer significant.

We turn now to the results for the three property crimes in the bottom panel of Table 3. It was expected, for reasons explained above, that the effect of the commuting population on crime rates would be stronger for property crimes than for violent crimes, but we have already seen that its effect was strong for all crime types. It was also expected that in the property crime models we would see greater changes in the effects of the other variables after introducing the commuting variable. Though the pattern of differences across the two burglary models is somewhat similar to the results for aggravated assault and robbery, there were very few significant coefficient changes in the models for larceny and auto theft. For burglary, again we see significant declines in the effects of concentrated disadvantage and % black, while the only significant change in the effects on the auto theft rate was for % black, which declined by about 19 %.

To summarize, two general findings emerge from this analysis. First, population change due to commuting appears to have a strong, positive effect on all crime types. This was expected, at least in part, due to the fact that the commuting population represents a group of persons who are at risk of offending and especially victimization when they travel to the city for work, yet they are not included in the denominator of the crime rate. Thus, cities with a high volume of inbound commuting will have higher and artificially inflated crime rates, which would yield the strong, positive effects of commuting observed in the preceding analysis. Second, the comparison of regression models before and after controlling for population change due to commuting shows that several variables that have been identified in prior research as important predictors of city-level crime rates display attenuated effects after accounting for the commuting population.

[7] Three tests were used to evaluate the confounding effect of the commuting population via the 'sgmediation' command (adapted by the authors to accommodate panel models) in Stata 12.1—the Sobel first-order solution, the Arolian second-order exact solution, and the Goodman unbiased solution (Baron and Kenney 1986; MacKinnon et al. 2002). These tests are commonly used to evaluate mediation, but they are also appropriate for evaluating confounding effects since there is no statistical difference between mediation and confounding. The statistic suggested by Paternoster et al. (1998), for testing the equality of coefficients across models is widely used in criminology, but it is designed to test coefficients across independent samples, which is not the case when evaluating mediating or confounding effects.

The most consistent changes in coefficients across pairs of models were for the effect of % black, which changed significantly in five of the models, and for the effect of concentrated disadvantage which changed in four of the models. In every case, these effects declined after including the commuting variable, but they were still statistically significant. One interpretation of these findings is that cities with high black percentages and a high degree of concentrated disadvantage also tend to be areas that attract a large number of daily work commuters. These cities may be places where many people find work but are not willing to reside, in which case the residential crime rate would systematically underestimate the number of potential offenders and especially victims, thus artificially inflating the estimated crime rate. This suggests that the effect of these variables on crime rates that has been consistently observed in prior research may be partly spurious, due to the association between levels of disadvantage and rates of commuting to work.

Significant changes in the effect of concentrated affluence were also found for two crime types, but in this case the commuting rate acted as a suppressor. For assault and robbery, there was initially no significant effect of concentrated affluence, but it emerged as a significant predictor after controlling for population change due to commuting. Recent scholarship has argued that concentrated affluence is an important and conceptually distinct predictor of crime and deviance due to the positive influence that concentrations of socioeconomic resources can have on individuals' risk of offending (Brooks-Gunn et al. 1993). Bivariate correlations for the sample used in this analysis indicate that cities with a high degree of concentrated affluence do, indeed, have significantly lower crime rates, but these cities also have significantly higher levels of net population change from commuting. Thus, it was only after taking into account the suppressing effect of the commuting population that we observed the expected effect of concentrated affluence.

Discussion and Conclusions

Many cities, and particularly large commercial centers, attract large numbers of persons during the day who return to their homes outside of the city at night. The routine activity of daily commuting to work puts this group at higher risk of crime while within the city boundaries, and any crimes they commit or that are committed against them are included in reported levels of crime for the city. However, this population is not included in the denominator when calculating the city's crime rate since the traditional method of calculation includes only the residential population. For cities that attract large numbers of people during the day, this leads to a higher and overestimated crime rate. The purpose of this paper was to assess the theoretical and methodological impact that commuting might have on the empirical analysis of crime in US cities.

The first portion of the analysis compared crime rate rankings based on the traditional residential crime rate with rankings that use an alternative crime rate that takes into account daily changes in the population. The results showed that a city's ranking can vary considerably depending on which denominator is used to calculate the crime rate. Though many warnings have been issued against the use of crime rankings, they are common employed by a variety of groups and individuals to assess the relative dangerousness of cities, and a city's reported crime ranking can have profound consequences on population change, tourism, and civic pride. The results presented above suggest that the most commonly cited rankings—those that use the residential population to calculate the crime rate—are somewhat flawed in that they overestimate crime rates for cities that attract a large non-residential population during the day, and thus rank them too high relative to other cities. Though there were either small changes or no change across the rankings for many cities, some cities experienced larger moves up or down the rankings, and in ways that could have a symbolic impact on perceptions about the city's level of safety or dangerousness.

The second portion of the analysis examined whether net change in daily population due to commuting to work significantly affects city crime rates, and whether failing to account for the effect of daily commuting on crime rates may yield invalid estimates of the strength of commonly-used macro-level predictors in explaining variation in crime rates across cities. One clear finding that emerged from this analysis is that commuting has a strong, consistent, positive effect on a variety of crime types. For each of the three forms of property and violent crime, it was found that cities with a net increase in population due to commuting tend to have higher rates of crime. This finding is expected by routine activities theory, since the patterned and regular activity of traveling to work can increase one's risk of criminal victimization to the extent that it brings suitable targets into greater contact with potential offenders. This effect should be especially pronounced where the net influx of population is large, particularly since this at risk population is not included in the denominator of the crime rate. As mentioned above, many cities more than double their population during daytime hours because of commuting, and this highly routine activity appears to have a sizeable impact on levels of crime in US cities.

Another key finding to emerge from the analysis is that several city characteristics that have been identified in prior research as key predictors of crime rates are less strongly associated with crime after accounting for population change due to commuting. This was particularly evident for racial composition and concentrated disadvantage, the effects of which declined significantly and substantially for many crime types. It is also noteworthy that the positive effect of residential instability on robbery was statistically significant initially, but it dropped to non-significance after controlling for the commuting population. Though it is not possible in this study to directly assess the source of this confounding, one possible explanation is that many of these cities have experienced population decline, out-migration, and suburban growth, which leads to higher rates of commuting from outside the city. These commuters are at risk of victimization within the city, but they are not included in the denominator of the crime rate, thus resulting in overestimates.

In general, these results show that different assessments may be reached about the size and statistical significance of the effects of many structural characteristics on crime depending on whether the analysis accounts for the influence of the commuting population. Fortunately, data on inbound and outbound commuting are readily available to the public. Including a measure of population change due to commuting as a predictor in models of city-level crime rates results in a better specified theoretical model, and it allows researchers to worry less about the validity problem associated with failure to include this important at-risk population in the denominator of the residential crime rate.

Still, differences between models with and without the commuting population should not be overstated. Though some effect sizes do change significantly, many do not, and the pattern of effects remains similar in many ways across pairs of models for each crime type. The signs of coefficients do not change direction, and the effects of immigrant concentration, population density, residential instability, and the presence of young males, are largely unaffected by the inclusion of the commuting population as a predictor. Thus, although the effects of some variables are overestimated in the original models, and the effects of concentrated affluence are underestimated, the two models tell essentially the same story with regard to the other variables.

There are several ways in which this analysis should be expanded in future research. There are many sources of daily population change in cities that should be considered in addition to commuting for work. For example, cities also attract people from outside the city for entertainment and recreation (Messner and Blau 1987). Since this form of population influx occurs largely outside of business hours, it may be particularly relevant for inter-personal crimes and auto theft, which also occur in large part at night. Moreover, the method used above to generate the weighted denominator used in the crime rankings has some shortcomings, and alternatives could be developed. For example, the same weighting procedure was used for all crime types, yet data from NIBRS and NCVS show that some forms of crime occur more commonly at night, or on certain days of the week. This information, along with data on other sources of population change in cities, could be used to generate a more complex weighting scheme that might result in a more valid crime rate.

The current analysis focused on cities with a population of at least 100,000 population because this sample criterion has been used in much of the previous city-level crime research, and because these are likely to include the cities that employ residents from the broader metropolitan area. Future research might examine the effect of daily changes in population size for other smaller geographic areas such as small towns and commuter suburbs. These areas are more likely to lose a significant portion of population during the day as their residents travel to work in nearby cities. For these smaller areas, failure to take *outbound* commuting into account may lead to *underestimated* crime rates since the denominator of the crime rate includes people who are not in that area for a large portion of the day. Further, with continued annual releases of data from the American Community Survey, it will be possible to compile a longitudinal database with more frequent measurements than every 10 years. Using non-overlapping three-year pooled ACS estimates would allow for as many as four measurement points per decade, which would be better able to capture any shorter term trends that may occur.

Another useful avenue for future research would be to conduct a similar analysis of daytime population shifts at the neighborhood level. Certain areas within the city experience dramatic changes in population throughout the day. Highly commercial and industrial areas of the city may have very small residential populations, but very large daytime populations, resulting in discrepancies between the residential and daytime populations that are much greater than those found at the city level. These types of neighborhoods often appear as extreme outliers in neighborhood-level studies of crime, and failing to account for these large population shifts could severely undermine attempts to understand the factors that influence levels of crime across neighborhoods. Likewise, local context at both the city and the neighborhood level could condition the influence of commuting rates on crime rates. For example, the presence of a large daily commuting population may be more likely to influence rates of victimization in areas where public transportation is readily available and widely used, as this may increase the confluence of offenders and potential victims.

Finally, future research should attempt to further our understanding of the causal mechanisms through which commuting rates may influence crime rates. The current paper draws on the routine activities perspective, yet other explanations may be equally plausible. For example, commuting rates might affect crime rates via their influence on levels of informal social control, much like prior research has argued for the effect of residential mobility. Also, high rates of commuting in commercial centers may contribute to a sense of relative deprivation, and associated increases in stain and stress, which may in turn yield higher rates of crime. The unavailability of data sources for measuring these characteristics for a large number of cities may preclude this sort of analysis at the city level, but this is another example of how incorporation of commuting rates may greatly enhance research at the neighborhood level, a level at which measures of these intervening mechanisms are more likely to be available.

The purpose of this paper was to highlight the importance of considering population shifts due to daily commuting when evaluating city-level crime rates. A more general recommendation for future research is to consider the use of any alternative denominator that may be more appropriate than the residential population for the type of crime being studied. As described above, researchers have occasionally employed denominators such as the business-to-residential land use ratio for larceny, and the number of registered automobiles for auto theft. Similar to the current study, the findings from these studies have often diverged from what would have been found if the traditional rate was used. While it is often the case that the residential population is the only readily available proxy for measuring the population at risk, the results of this study suggest that, when possible, alternative measures should always be considered.

References

Allison PD (2005) Fixed effects regression methods for longitudinal data using SAS. SAS Institute, Cary

Baron RM, Kenney DA (1986) The moderator–mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. J Pers 51:1173–1182

Blumestein A, Cohen J, Rosenfeld R (1991) Trend and deviation in crime rates: a comparison of UCR and NCS data for burglary and robbery. Criminology 29:237–263

Boggs SL (1965) Urban crime patterns. Am Sociol Rev 30:899–908

Brooks-Gunn J, Duncan GJ, Kato P, Sealand N (1993) Do neighborhoods influence child and adolescent behavior? Am J Sociol 99:353–395

Chamlin MB, Cochran JK (1996) Macro social measures of crime: toward the selection of an appropriate deflator. J Crime Justice 14:121–144

Cohen LE, Felson M (1979) Social change and crime rate trends: a routine activity approach. Am Sociol Rev 44:588–608

Cohen LE, Kaufman RL, Gottfredson MR (1985) Risk-based crime statistics: a forecasting comparison for burglary and auto theft. J Crime Justice 13:445–457

Copes H (1999) Routine activities and motor vehicle theft: a crime specific approach. J of Crime and Justice 22:125–146

Decker S (1983) Comparing victimization and official estimates of crime: a re-examination of the validity of police statistics. Am J Police 2:193–201

Farley JE (1987) Suburbanization and central-city crime rates: new evidence and a reinterpretation. Am J Sociol 93:688–700

Farley JE, Hansel M (1981) The ecological context of urban crime: a further exploration. Urban Aff Rev 17:37–54

Federal Bureau of Investigation (2002) Uniform crime reporting program: offenses known and clearances by arrest, 2000 [data file]. http://www.icpsr.umich.edu/cocoon/ICPSR/STUDY/03447.xml

Federal Bureau of Investigation (2009) Uniform Crime Reporting Program Data [United States]: 1975–1997 9 [data file]. http://www.icpsr.umich.edu/cocoon/ICPSR/STUDY/09028.xml

Federal Bureau of Investigation (2012) Uniform crime reporting program: offenses known and clearances by arrest, 2010 [data file]. http://www.icpsr.umich.edu/cocoon/ICPSR/STUDY/33526.xml

Gaspera J, DeLucaa S, Estacion A (2010) Coming and going: explaining the effects of residential and school mobility on adolescent delinquency. Soc Sci Res 39:459–476

Gibbs JP, Erickson ML (1976) Crime rates of American cities in an ecological context. Am J Sociol 82:605–620

Gove WR, Hughes M, Geerken M (1985) Are uniform crime reports a valid indicator of the index crimes? An affirmative answer with minor qualifications. Criminology 23:451–502

Kitsuse JI, Cicourel AV (1963) A note on the uses of official statistics. Soc Probl 11:131–139

Krivo LJ, Peterson RD (2000) The structural context of homicide: accounting for racial differences in process. Am Sociol Rev 65:547–559

Land KC, McCall PL, Cohen LE (1990) Structural covariates of homicide rates: are there any invariances across time and social space? Am J Sociol 95:922

Liska AE, Chamlin MB, Reed MD (1985) Testing the economic production and conflict models of crime control. Soc Forces 64:119–138

Loftin C, McDowall D, Fetzer MD (2008) A comparison of SHR and vital statistics homicide estimates for US cities. J Contemp Crime Justice 24:4–17

MacKinnon DP, Lockwood CM, Hoffman JM, West SG, Sheets V (2002) A comparison of methods to test mediation and other intervening variable effects. Psychol Methods 7:83–104

McDowall D, Loftin C (2009) Do US city crime rates follow a national trend? The influence of nationwide conditions on local crime patterns. J Quant Criminol 25:307–324

Messner SM, Blau JR (1987) Routine liesure activities and rates of crime: a macro-level analysis. Soc Forces 65:1035–1052

Miethe TD, Stafford MC, Long JS (1987) Social differentiation in criminal victimization: a test of routine activities/lifestyle. Am Sociol Rev 52:184–194

Miethe TD, Hughes M, McDowall D (1991) Social change and crime rates: an evaluation of alternative theoretical approaches. Soc Forces 70:165–185

O'Brien RM (1985) Crime and victimization data. Sage, Beverly Hills

O'Brien RM, Shichor D, Decker DL (1980) An empirical comparison of the validity of UCR and NCS crime rates. Sociol Quart 21:391–401

Ousey GC (1999) Homicide, structural factors, and the racial invariance assumption. Criminology 37:405–426

Paternoster R, Brame R, Mazerolle P, Piquero A (1998) Using the correct statistical test for the equality of coefficients. Criminology 36:859–866

Pettiway LE (1985) The internal structure of the ghetto and the criminal commute. J Black Stud 16:189–211

Raudenbush SW, Bryk AS (2002) Hierarchical linear models: applications and data analysis methods. Sage, Thousand Oaks

Reiss AJ (1967) Measurement of the nature and amount of crime, field surveys iii, studies in crime and law enforcement in major metropolitan areas, President's common on law enforcement and administration of justice. United States Government Printing Office, Washington

Reschovsky C (2004) Journey to Work: 2000. US Department of Commerce, Economics and Statistical Administration, US Census Bureau, http://www.census.gov/prod/2004pubs/c2kbr-33.pdf

Sampson RJ (1987) Urban black violence: the effect of male joblessness and family disruption. Am J Sociol 93:348–382

Sampson RJ, Raudenbush SW, Earls F (1997) Neighborhoods and violent crime: a multilevel study of collective efficacy. Science 277:918–924

Sellin T, Wolfgang ME (1964) The measurement of delinquency. Wiley, New York

Shihadeh ES, Ousey GC (1996) Metropolitan expansion and black social dislocation the link between suburbanization and center-city crime. Soc Forces 75:649–666

Shihadeh ES, Steffensmeier DJ (1994) Economic inequality, family disruption, and urban black violence: cities as units of stratification and social control. Soc Forces 73:729–751

Skogan WG (1974) The validity of official crime statistics: an empirical investigation. Soc Sci Quart 55:25–38

Stafford MS, Gibbs JP (1980) Crime rates in an ecological context: extension of a proposition. Soc Sci Quart 61:653–665

Steffensmeier DJ, Haynie D (2000) Gender, structural disadvantage, and urban crime: do macrosocial variables also explain female offending rates? Criminology 38:403–438