Western Criminology Review 5(2), 119-130 (2004)

An Excursus on the Population Size-Crime Relationship

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ABSTRACT
The purpose of this exercise is twofold. First, we seek to discern why macro-criminologists prefer to account for the effects of population size on crime through the process of deflation rather than by estimating the effects of population size, along with other predictors, on the number of crimes. Second, we seek to determine the relative efficacy of these competing methodologies for assessing the influence of population size on the level of crime among macro-social units. Our review of the relevant theoretical and empirical literature provides little, if any, rationale for the predilection for the analysis of crime rates in lieu of crime counts. However, our multivariate analyses reveal that while population size has no appreciable effect on violent and property crime rates, it is by far and away the single best predictor of violent and property crime counts. The implications of these findings for the population size-crime relationship are discussed.

KEYWORDS: crime counts; deflators; macro-criminology; population size.

For more than a century scholars, from a variety of disciplines, have debated the wisdom of using ratio variables when conducting correlational or regression analyses of macro-social data. Beginning with Pearson (1897), a number of statisticians have cautioned that correlations between ratio variables that contain common terms can appear to reveal the presence of statistically significant associations when, in fact, none are present (Bollen and Ward 1979; Kronmal 1993; Logan 1982; Schuessler 1974). Yet others reject, with comparable enthusiasm, the assertion that some portion of the correlation among ratio variables is inherently spurious (Firebaugh and Gibbs 1985, 1986; Long 1979; MacMillan and Daft 1980).

Conspicuous in its absence from the ongoing dispute concerning the consequences of utilizing ratio variables in macro-social research is any discussion about whether or not we should be using ratio variables *in the first place*.[1] This omission is particularly evident with respect to macro-level analyses of crime. Specifically, there is a broad consensus among criminologists that the population size of the social unit under investigation should be used to deflate raw counts of crime. To be sure, there is some disagreement about *which* population measure should be used to create crime rates (cf. Chamlin and Cochran 1996; Gibbs and Erickson 1976; Harries 1981; Stafford and Gibbs 1980). However, the fundamental notion that one must control for the effects of population by creating crime rates prior to the estimation of model specifications goes virtually unchallenged.[2]

The purpose of this exercise to twofold. First, we seek to ascertain why macro-criminologists, seemingly without exception, prefer to control for the effects of population size on crime by the process of deflation (the ratio variable approach) rather than by including population size among the other structural predictors of interest and estimating their partial effects on raw counts of crime (the components approach). Second, and more importantly, we seek to better understand the substantive implications of these competing techniques for assessing the influence of population size on the level of crime across macro-social units.

Unstated Assumptions

The practice of dividing raw counts of crime by the population size of the unit of analysis under investigation prior to model estimation is so accepted among macro-criminologists that one is hard pressed to find any justification for it in the empirical literature. Indeed, the only reference to this matter that we could find appears in Gibbs and Erickson's (1976) discussion of the relative merits of deflating a city's crime figures by its population size or that of the larger social aggregation within which it is located. According to their view, macro-criminologists use rates in lieu of raw numbers because more populous social units contain a greater number of potential victims and offenders. Hence, "[w]ithout such control, the incidence of crime is virtually certain to be greater for

California than for, say, Wyoming." (Gibbs and Erickson 1976:606).

There is little doubt that if one wants to make meaningful comparisons about the risk of victimization across social aggregates, or within a social aggregate over time, one must standardize raw counts of crime in some manner. Consider two hypothetical cities. Each experiences 100 felonies within a given time period. Without information about the number of people residing within these cities one could make no reasonable inferences about their relative safety. This, of course, is intuitively obvious and requires little explication. Indeed, the insight that the concentration of large numbers of individuals in one location fosters higher levels of social associations, including criminal victimizations, can be traced to Durkheim's (1933) discussion of the relationship between dynamic density and the division of labor and Spencer's (1972) discourse on the impact of population growth on societal evolution.

What is less clear, however, is why it is necessary, or even advisable, to deflate crime counts by population size when one is trying to estimate the relative effects of population size and other structural predictors on the level of crime. To the best of our knowledge we do this with no other structural variables. For example, not unlike population size, poverty is often hypothesized to be positively related to crime. Yet, in contrast to how we control for the causal influence of population size on crime, we do not deflate crime by poverty and then include poverty among the predictors of a crime-poverty ratio.

Admittedly, we are somewhat at a loss to understand the predilection among macro-criminologists for "controlling" for differences in the population size by the calculation of crime rates when conducting multivariate analyses. As has been addressed elsewhere, there are no statistical reasons for rejecting, a priori, the practice of including population size, along with the standard array of macro-level predictors, in model specifications to determine its relative impact on the level of crime (Bollen and Ward 1979; Firebaugh and Gibbs 1986; Schuessler 1974).[3]

The only compelling justification that we could envision for opting to study crime rates in lieu of crime counts would be if one could establish that the effect of population size upon crime is either trivial or spurious. If such were the case, then it would make sense to create population-based crime rates to remove the "confounding" effects of structured opportunities for offending before one can assess the impact of more theoretically interesting variables on various forms of crime (Gibbs and Erickson 1976; Harries 1981; Mayhew and Levinger 1976). However, as we explicate in the next section, we doubt that this is so.

THEORETICAL LINKAGES FROM POPULATION SIZE TO CRIME

The potential deleterious effects of living in large social aggregates has long been a subject of concern among urban sociologists (Park and Burgess 1925; Weber 1958; Wirth 1938). At the risk of oversimplification, one can distinguish among three broad intervening causal processes by which population size promotes criminality.

The first, the social control perspective, emphasizes that urbanization and population growth weaken informal mechanisms of social control which, in turn, result in more crime and delinquency. This occurs, in part, because large numbers, regardless of individual proclivities, constrain the *quality* of social interactions. Ostensibly, population growth increases the frequency of more predatory secondary contacts while simultaneously decreasing the frequency of more affective primary ones. Hence, the bonds of solidarity that were once produced by intimate social associations no longer function to inhibit social deviation (Kornhauser 1978; Shaw and McKay 1972; Simmel 1955; Wirth 1938).

The second, the structuralist perspective, focuses on how the size and distribution of population groups within geographic units delimits opportunities for social interactions (see Simmel's [1950] seminal exposition of the relationship between group size and forms of association). Interestingly, little, if any, attention is paid to the content of interpersonal relations. Thus, in contrast to the social control perspective, the structuralist approach centers on the causal impact of population size on the *quantity* of social contacts.

Mayhew and Levinger's (1976) explication of the relationship between population size and generic forms of social interactions typifies the structuralist approach to theory construction. Based on series of observations about the mathematical properties of population elements and the number of potential contacts among population elements within a geographic area, they derive a formal, structural model of social interaction. Specifically, Mayhew and Levinger (1976) postulate that as the population size increases, the frequency of social interactions increases, at an increasing rate. However, Mayhew and Levinger's (1976:94) theoretical presentation offers no clues concerning the likely purpose of any structurally induced associations: "[i]t predicts for example, that as the aggregate size increases additively, both the number of phone calls and the number of homicides will increase multiplicatively."

Blau (1977:160-162), based on the simple assumption that social associations require opportunities for social contacts, also posits a positive relationship between population size and crime. Yet unlike Mayhew and Levinger (1976), Blau (1977) hypothesizes that the population size-crime relationship is likely to be linear. The causal linkages from population size to crime are rather straightforward. Accordingly, population size promotes various social interactions, including criminal victimizations, by reducing the physical distances among members of a community while it simultaneously increases the number of potential associates within a community. However, since the opportunity assumption is silent with respect to the *content* of structurally induced social contacts, one can deduce that population growth is equally likely to lead to an increase in integrative, as well as conflictive, social interactions (Blau 1977:163).

In short, while there may be some debate concerning the functional form of the population size-crime relationship, formal structural theory unequivocally asserts that population growth facilitates all sorts of social contacts - from the most benign to the most pernicious (Mayhew and Levinger 1976; Blau 1977).

Third, the subcultural perspective suggests that the concentration of relatively large numbers of individuals within macro-social units fosters the creation and expansion of deviant subcultures. Urbanization, through the complementary processes of structural differentiation and value diffusion, promotes social support for a multiplicity of behavioral choices. Further, it engenders greater tolerance for nonconformity among the more conventional members of the community. As a consequence, more populous urban areas are expected to experience more criminal activity than less populous ones (Fischer 1975; 1995; Simmel 1955; Tittle 1989).

The implications of the preceding review of the various causal linkages among urbanization, population size, and crime are clear. There are both diverse and compelling theoretical grounds for including population size in any model specification seeking to determine the relative impact of macro-structural conditions on the level of crime. Stated in the context of the present discussion, one cannot conclude that it is preferable to control for the impact of population size on crime by dividing crime figures by population counts because there is reason to believe that the effect of population size is likely to be trivial or spurious.

Unexpected Consequences

By way of compromise, one might be tempted to address this matter by deciding to employ population size as a predictor variable *and* as the denominator in a crime rate measure (see, for example, Blau and Blau 1982; Parker and Pruitt 2000; Sampson 1987). However, this strategy, though normative, may be less expedient than one might think.

Recall that the ratio variable approach contends that by dividing the number of crimes within a social aggregate by the number of people residing within that social aggregate one can effectively remove the linear effect of population size on crime prior to conducting statistical analyses of interest (Bollen and Ward 1979; Mayhew and Levinger 1976). Let us assume, for the sake of discussion, that this procedure is efficacious. Let us further assume that the relationship between population size and crime is linear. If both conjectures are valid, then one cannot simultaneously control for the effects of population size by the process of deflation *and* the inclusion of population counts among a set of predictors. One would invariably find that population size has no impact on crime.

There can be no doubt that subjecting crime counts to the arithmetic operation of division by population counts reduces its variance. What remains to be seen, however, is the extent to which the decision to deflate crime figures by population counts prior to the estimation of multivariate equations tempers the impact population size on the level of crime. The proceeding analyses are designed to address this matter.

RESEARCH DESIGN

In order to discern the effects of deflating crime counts by the number of inhabitants residing within macro-social units, we compare the relative influence of linear and non-linear measures of population size on crime and crime rates.

Sample

The sample is part of a sample of 354 U. S. cities, originally selected for another project because it contained information concerning charitable contributions. Missing data, primarily for the crime measures, yield a final sample size of 271. These cities are distributed with a mean population of approximately 211,000 and a standard deviation of 53,000.

We decided to employ this sample for two reasons. First, larger social aggregations, such as metropolitan areas or states, are probably too heterogenous to allow for an assessment of the differential effects of population size on crime. Second, the selection of a large sample of cities assuages several statistical concerns. That is to say, it increases the likelihood that there will be substantial variation in population size, decreases the likelihood of encountering harmful collinearity, and allows one to specify the requisite control variables without worrying about the loss of degrees of freedom (Hanushek and Jackson 1977).

Measures

Crime counts and ratios.

The present investigation examines the effects of alternative measures of population size, as well as a number of other structural predictors on property crime rates, violent crime rates, the simple count of property crimes, and the simple count of violent crimes. Following convention, burglaries, larcenies, and motor vehicle thefts are designated as property offenses (1990), while homicides, robberies, aggravated assaults, and forcible rapes are classified as violent offenses (1990). The rate measures are deflated by the city population in units of 100,000.

Population size.

To foster a comparison of the ratio and components approaches to crime measurement, population size is estimated using three alternative functional forms of the total number of inhabitants in each city (1990): the simple count (a linear model), the simple count and the count squared (a quadratic model), and the natural log transformation of the simple count (a semi-log model).

Control variables.

Following previous research (Blau an Blau 1982; Liska and Bellair 1995; Sampson 1987), nine control variables are included in the model specifications to account for the predictions of motivational, opportunity, and subcultural macro-level theories of crime.

A number of motivational theories contend that economic deprivation has a substantial impact on the level of crime across macro-social units. For example, traditional Marxist theory (Bonger 1916) and anomie theory (Merton 1938) suggest that blocked opportunities produce frustration and thereby motivate the disadvantaged to engage in crime to satisfy their material needs. Given the ongoing debate concerning the relative importance of absolute and relative deprivation as predictors of crime (Kovandzic, Vieraitis, and Yeisley 1998), the models contain measures of both dimensions of economic deprivation. Absolute deprivation is measured as the percentage of families below the poverty level (1990). Relative economic deprivation is measured by the Gini index of economic concentration (1989).

Opportunity theories of crime focus on the relationships among the physical and social structures of ecological units, informal social control, and crime. For instance, urbanism theory, including the social disorganization approach, suggests that structural conditions that impede communication and the formation of affective interpersonal relationships foster high rates of crime. Neighborhoods, as well as larger social areas, that have large, heterogenous populations and that possess few economic resources have difficulties creating and maintaining social institutions that discourage criminal victimizations (Bursik and Grasmick 1993; Fischer 1975; Kornhauser 1972; Sampson, Raudenbush, and Earls 1997; Shaw and McKay 1972; Wirth 1938). To take into account the predictions of urbanism theory, the model specifications include three measures of population heterogeneity and an estimate of residential mobility. The first indicator of population heterogeneity, racial heterogeneity, is measured as the percentage of the population that is black (1990). The second, ethnic heterogeneity, is measured as the percentage of the population that is foreign born (1990). The third, age structure, is measured as the percentage of the population aged 18 to 24 (1990). Lastly, residential mobility is measured as the percentage of persons five years of age and older living in different locations in 1990 than in 1985.

Another variant of opportunity theory, the routine activity approach, suggests that household structure affects levels of capable guardianship and target suitability. Specifically, household structure is hypothesized to simultaneously decrease guardianship, but increase target attractiveness, thereby increasing rates of crime, especially those involving theft (Cohen and Felson 1979). The models include two indicators of household structure: the percentage of single-person households (1990) and the percentage of persons 15 and older who are divorced (1990).

Lastly, the subculture of violence thesis maintains that the South, as a result of idiosyncratic historical processes, has developed a value system that condones the use of violence to settle interpersonal disputes (Gastil 1971; Hackney 1969). To control for the impact of regional variations in normative orientations on the level of crime, especially that of a violent nature, a measure of southern location is included in the model specifications. The regional dummy variable is coded 1 for cities located in the South and 0 for those located elsewhere.

Sources

Information concerning the official count of violent and property offenses was obtained from the *Uniform Crime Reports* (Federal Bureau of Investigation 1991). With the exception of residential mobility and the percentage of divorcees, data for each of the structural predictors, as well as the income distributions used to calculate the Gini index, were obtained from the *County and City Data Book* (Bureau of the Census 1994). Residential mobility was calculated from data ascertained from Table 172 of the *Census of Population: Social and Economic Characteristics* (Bureau of the Census 1993). The percentage of divorcees was calculated from data gathered from Table 64 of *The Census of Population: General Population Characteristics* (Bureau of the Census 1992).

RESULTS

Preliminary Data Analyses

While the specification of a comprehensive array of statistical controls assuages fears about omitted variable bias, it simultaneously increases the risk of multicollinearity among the predictors. And while the analysis of raw counts of crime is essential if we are to evaluate our contention that the use of crime rate measures obscures the nature of the relationship between population size and crime, it simultaneously increases the likelihood that the disturbance terms will be heteroskedastic. Hence, we performed a number of diagnostic tests to determine whether or not the final equations are affected by either of these potential problems.

Although high zero-order correlations between predictor variables do not, in and of themselves, indicate that multicollinearity is present (Hanushek and Jackson 1977:90), the zero-order correlations between percent black and poverty (.64), percent black and the Gini index (.52), poverty and the Gini Index (.60), and percent 18-24 and residential mobility (.61) are large enough to warrant concerns about this issue.[4] To assess the extent to which collinearity among the exogenous variables affects the parameter estimates collinearity diagnostics were examined (Belsley, Kuh, and Welsch 1980). Experiments conducted by Belsley et al. (1980) reveal that a condition index threshold of 30 is indicative of potentially harmful collinearity and a variance-decomposition proportion threshold of 0.5 should be used to identify dependencies among the predictor variables. As expected, inspection of the collinearity diagnostics for the each of the equations suggests that there are strong linear dependencies among the Gini index, poverty, and percent black.

One solution to the problem of muliticollinearity that has emerged from the literature is the use of principal components analysis to reduce the number of predictors prior to the estimation of any regression equations (Land, McCall, and Lawrence 1990; Morenoff and Sampson 1997). However, both Greene (1993:273) and Maddala (1992:285) warn that this approach has a number of limitations, chief among them is that it often combines predictors into principal components that possess little, if any, substantive meaning. Consequently, we decided to modify the principal components procedure by rotating the final solution using the varimax option to make the factors more coherent and easier to interpret.

Table 1 presents the results of the final principal component factor analysis with varimax rotation. Two of the nine control variables, the dummy variable for southern location and percent foreign born, were excluded from the analyses. The former was excluded because it is a nominal variable, while the latter was excluded because it did not load on any of the factors. As is clear from inspection of Table 1, the remaining seven control variables can be combined into three latent constructs. The first appears to capture the racial and economic structure of the sample. Three variables: the Gini index, poverty, and percent black load on this factor. The second, which is not as readily interpretable as the first, seems to tap a dimension of the population structure. Two variables, the percentage of the population aged 18 to 24 and residential mobility, load on this factor. The final principal component measures household structure. Two variables, the percentage of single person households and percent divorced, load on this factor. In sum, the three factor solution reduces the number of control variables from nine to five. More importantly, the revised models reveal no evidence of multicollinearity.

We also explored the possibility that the error terms are heteroskedastic. We calculated the Breusch-Pagan test statistic, which is distributed as chi-square, to evaluate the null hypothesis that the model residuals are homoskedastic. Unfortunately, the residual analyses clearly indicate that the disturbance terms produced by each of the violent crime rate, the number of violent crimes, and the number of property crimes, equations are heteroskedastic.

Table 1. Principal Components Analysis with Varimax Rotation

Indicator	Factor Loadings
Racial and Economic Structure	
Gini Index	.82
Poverty	.86
Percent Black	.83
Eigenvalue	2.36
Population Structure	
Percent 18 to 24	.91
Residential mobility	.82
Eigenvalue	1.86
Household Structure	
Percent single person household	.73
Percent divorced	.82
Eigenvalue	1.21

Various remedies have been proffered in the literature to correct for the problems that arise from the presence of heteroskedastic errors. We decided to employ White's (1980) correction of the standard error to the OLS regression solutions for the violent and property crime equations to address this matter. Unlike other approaches, which entail making assumptions about the underlying processes that are responsible for the production of heteroskedastic errors (e.g., Weighted Least Squares regression, log transformations of the data), White's correction requires no such conjectures to generate unbiased estimates of the variance of the least squares estimator (Greene 1992:391).

Table 2. OLS Regression Estimates for Violent Crime Rates, with White's Correction for Heteroskedasticity

	Linear Equation			Quadratic Equation			Semi-log Equation		
Indicators	b	β	*t*	b	β	*t*	b	β	*t*
Racial & Economic Structure	80.95	.68	10.46***	80.40	.68	10.93***	78.79	.66	10.46***
Population Structure	0.72	.01	0.13	0.62	.01	0.12	0.65	.01	0.13
Household structure	42.98	.15	4.05***	42.15	.15	3.94***	39.98	.14	3.72***
% Foreign Born	35.79	.28	6.63***	32.95	.27	6.13***	32.43	.25	5.64***
South	-164.26	-.09	-1.67	-164.46	-.09	-1.66	-160.49	-.09	-1.61
Population	0.00	.02	0.75	1.4E-4	.08	0.85			
Population Squared				-1.7E-11	-.06	-0.83			
Population Natural Log							75.53	.08	1.59
Constant	-1101.34**			-1083.61***			-1851.09***		
Adjusted R^2	.52			.52			.53		
Breusch-Pagan test[A]	17.71			18.19			18.33		
N	271			271			271		

Note: [A] Reject the null hypothesis that the disturbance terms are homoskedastic at p<.05
* p<.05; ** p<.01; *** p<.001

Multivariate Analyses

Violent and property crime rates.

Tables 2 and 3 present the OLS regression estimates of the effects of the structural predictors and the alternative measures of population size on the violent and property crime rates, respectively. Each table contains the results of three analyses, which differ only with respect to how we estimate the functional form of population size-crime relationship. The first equation estimates the linear effect of population size on crime. The second equation also includes a quadratic term to capture a change, if any, in the slope of the relationship between population size and crime. Lastly, the third equation includes the natural logarithmic transformation of the population size in lieu of the original measure to estimate the semi-log effects of population size on crime.

Two patterns of interest emerge from these analyses. First, the structural predictors, both the composite factors and individual variables, have a substantial impact on violent and property crime rates. Moreover, with the exception of the effects of southern location, these effects are virtually identical across all six equations. Consistent with a variety of theoretical perspectives, the racial and economic composition factor, the household structure factor, and percent foreign born positively affect violent and property crime rates. Contrary to the predictions of subcultural theory, southern location has no appreciable impact on rates of violent crime, but is positively related to the rate of property crime. Second, the effect of population size on each of the crime rate measures is small and insignificant. This result holds for both the linear and non-linear models.

Table 3. OLS Regression Estimates for Property Crime Rates

	Linear Equation			Quadratic Equation			Semi-log Equation		
Indicators	b	β	*t*	b	β	*t*	b	β	*t*
Racial & Economic Structure	132.89	.40	7.24***	130.74	.39	9.02***	123.59	.37	6.55***
Population Structure	10.94	.02	.51	10.54	.02	.49	14.40	.03	.67
Household structure	238.74	.30	6.12***	236.04	.30	6.02***	229.38	.29	5.79***
% Foreign Born	130.53	.36	6.86***	127.62	.35	6.55***	109.70	.30	5.64***
South	1093.79	.21	4.01***	1094.74	.21	4.01***	1125.79	.22	4.11***
Population	-4.E-4	-.10	-1.90	-1.2E-4	-.03	-.21			
Population Squared				-6.2E-11	-.08	-.70			
Population Natural Log							102.53	.04	.73
Constant	-939.95			-877.21			-1883.99		
Adjusted R^2	.39			.39			.39		
Breusch-Pagan test[A]	11.06			12.24			12.60		
N	271			271			271		

Note: [A] Reject the null hypothesis that the disturbance terms are homoskedastic at p<.05.
* p<.05; ** p<.01; *** p<.001

Table 4. OLS Regression Estimates for Violent Crimes, with White's Correction for Heteroskedasticity.

	Linear Equation			Quadratic Equation			Semi-log Equation		
Indicators	b	β	*t*	b	β	*t*	b	β	*t*
Racial & Economic Structure	101.61	.06	4.26***	140.68	.09	7.03***	142.85	.09	3.36***
Population Structure	-2.55	-.01	-.14	4.82	.01	.37	-144.65	-.07	-1.16
Household structure	36.66	.01	.73	95.12	.03	2.20	12.43	.01	.10
% Foreign Born	41.63	.02	1.01	10.02	.06	3.38***	364.43	.21	1.99*
South	-407.68	-.02	-.99	-393.46	-.02	-1.20	-952.49	-.04	-1.15
Population	.02	.96	17.30***	.01	.63	6.44***			
Population Squared				1.2E-9	.34	4.41***			
Population Natural Log							5563.11	.45	2.81**
Constant	-3508.92*			-4762.15***			-60664.12***		
Adjusted R^2	.95			.97			.35		
Breusch-Pagan test[A]	96.60			147.24			31.23		
N	271			271			271		

Note: [A] Reject the null hypothesis that the disturbance terms are homoskedastic at p<.05.
* p<.05; ** p<.01; *** p<.001

Table 5. OLS Regression Estimates or Property Crimes, with White's Correction for Heteroskedasticity.

	Linear Equation			Quadratic Equation			Semi-log Equation		
Indicators	b	β	*t*	b	β	*t*	b	β	*t*
Racial & Economic Structure	184.06	.03	2.89**	124.88	.02	1.95	136.11	.02	.90
Population Structure	28.62	.01	.68	17.53	.01	.44	-466.91	-.07	-1.35
Household structure	402.71	.03	2.80**	328.15	.03	2.38*	1.02	.00	.00
% Foreign Born	343.97	.02	4.01	263.73	.05	3.33***	1018.43	.17	2.01*
South	2861.32	.03	2.57*	263.73	.03	2.89**	322.06	.01	.11
Population	.07	.96	35.57***	.08	1.09	13.30			
Population Squared				-1.7E-9	-.14	-2.08***			
Population Natural Log							26409.11	.63	4.99***
Constant	-13867.22*			-12137.59**			-281751.99***		
Adjusted R^2	.97			.98			.52		
Breusch-Pagan test[A]	48.44			116.83			31.92		
N	271			271			271		

Note: [A] Reject the null hypothesis that the disturbance terms are homoskedastic at p<.05.
* p<.05; ** p<.01; *** p<.001

In sum, our conventional, multivariate analyses of violent and property crime rates are fairly consistent with prior city-level research (cf. Carroll and Jackson, 1983; Loftin and Parker, 1985). We find that variations in violent and property crime are best accounted for by the structural antecedents of intergroup conflict and/or disorganization. In contrast, the effects structured opportunities for social interaction, as approximated by population size, are negligible.

The number of violent and property crimes.

Tables 4 and 5 contain OLS regression estimates of the effects of the structural predictors and the alternative measures of population size on the number of violent and property crimes, respectively. As with Tables 2 and 3, each table contains the results of three analyses, which differ only with respect to how we estimate the functional form of population size-crime relationship. The first equation estimates the linear effect of population size on crime. The second equation also includes a quadratic term to capture a change, if any, in the slope of the relationship between population size and crime. Lastly, the third equation includes the natural logarithmic transformation of the population size in lieu of the original measure to estimate the semi-log effects of population size on crime.

Inspection of tables 4 and 5 leaves little doubt as to the influence that a priori measurement decisions can have on subsequent data analyses. In stark contrast to analyses of the rate measures, the examination of the count measures suggests that variations in the level of crime across cities are primarily determined by opportunities for social contacts.

This is not to say, of course, that the more substantive macro-level predictors have no influence on crime counts.

Somewhat akin to what we found for the rate measure equations, the racial and economic structure, the household structure, and percent foreign born positively affect both the number of violent and property crimes. However, unlike what we reported above, these effects are not invariant across model specifications (compare tables 2 and 3 with table 4 and 5). Similarly, southern location continues to exhibit positive partial effects on property crime in the linear and quadratic equations, but not in the semi-log equation. Nonetheless, compared to the impact of the population size, the magnitudes of these effects are trivial.

Indeed, regardless of the functional form specified, population size is, by far and away, the strongest predictor of the number of violent and property crimes. One should not infer, of course, that there are no important differences across equations. Based upon a comparison of the variance explained by the competing models, it is clear that the quadratic equations provide the best fit to the counts of violent and property offenses.

Consistent with Mayhew and Levinger's (1976) thesis, the effect of population size on the number of violent crimes is positive, with an increasing slope. However, contrary to their expectations, the shape of the population size-property crime relationship approximates that of an inverted U. Admittedly, we did not anticipate that the functional form of the population-crime relationship would vary across offense types. Nonetheless, we are reluctant to attribute these findings to some methodological deficiency. As we discussed above, the collinearity and other diagnostics reveal no statistical problems with the final equations. Moreover, we are not attempting to analyze rare events that occur within small social aggregates. Hence, there is no reason to believe that Gaussian-based regression models are inappropriate (Osgood 2001; Osgood and Chambers 2000).

Therefore, if we can conclude that these findings do not arise from some statistical error, then we are forced to deduce that the effects of racial, economic, and social structural characteristics of cities pale before the influence of population size on variations in *the number of crimes*. Put in the larger context of this exercise, it would appear that the decision whether or not to measure crime as a rate or as a simple count has substantial ramifications for the appraisal of macro-social theory.

DISCUSSION

In the introduction to this manuscript we posited two questions concerning the manner in which macro-criminologists study the relationship between population size and crime. First, we sought to discover why the vast majority of macro-criminologists have come to accept, with virtually no debate, the conventional practice of accounting for the influence of population size on crime through the process of deflation. Second, we sought to discern the consequences of following this procedure for the evaluation of competing theoretical perspectives.

To be frank, we are still uncomfortable about making any strong statements concerning why the ratio variable approach has come to dominate the empirical literature. Initially, we speculated that the penchant for deflating the number of crimes by the number of inhabitants of a geographic unit of interest arises from the perception that the effects of population are spurious or trivial. We now think that this is unlikely. As we explicated above, there is ample theory to support the contention that the influence of population size on crime is substantively interesting. Urban (Wirth, 1938), formal macro-structural (Blau 1977; Mayhew and Levinger 1976), and subcultural (Fischer 1975; Tittle 1989) theories, albeit for different reasons, posit a causal relationship between population size and crime.

To be sure, part of the answer probably rests with the desire to control for victimization risk. Indeed, we are in total agreement with Gibbs and Erickson's (1976:606) observation that the incidence of crime is going to be greater in more, rather than in less, populated communities. Nonetheless, the recognition that cross-jurisdictional comparisons should take into account opportunities for criminal events does not necessarily require investigators to study crime rates. As has been demonstrated elsewhere, one can just as easily account for the risks of victimization associated with differences in the number of potential offenders and victims by including population size as an additional predictor in models of crime counts (Bollen and Ward 1979; Firebaugh and Gibbs 1986; Schuessler 1974). Moreover, this method of addressing the issue, the components approach, has the advantage of allowing one to assess the relative impact of population size on crime without having to worry whether or not some portion of this effect has been removed by the process of deflation (Chamlin and Cochran 1996).

Admittedly, we can offer no definitive explanation for the overwhelming preference among macro-criminologists for modeling the structured opportunities for criminal victimizations associated with population size by the process of deflation. Regardless, we suspect that there is a relatively simple answer to our question. At the risk of appearing naive, we speculate that most criminologists study crime rates, in lieu of crime counts, because their teachers, colleagues, and peer reviewers study crime rates. That this to say, this 'convention' has become so reified that it no longer invites much scholarly interest or debate.

Independent of how the practice of deflation became normative, it is abundantly clear that it can affect the analysis of the population size-crime relationship. In an effort to delineate the consequences of a priori measurement decisions for assessing the influence of population size on crime, we conducted two, complementary analyses. The first set of equations estimated the linear and non-linear partial effects of population size on violent and property crime rates (per 100,000 population); while the second set of equations estimated the linear and non-linear partial effects of population size on the number of violent and property crimes, respectively. As we reported above, two patterns of interest emerge from these analyses. First, population size exhibits null effects in each of the crime rate equations. However, regardless of the functional form examined, population size significantly affects the number of violent and property crimes. Second, the results from the crime rate equations indicate that the racial and economic structure composite variable and, to a lesser extent, the percentage of foreign-born have the largest impact on the level of crime. In contrast, the results from the count equations indicate that population size is, by far and away, the single best predictor of the level of violent and property crime.

What are we to infer from all this? At a minimum, our analyses reveal that how one decides to "control" for the influence of population size on the level of crime across macro-social units has a substantial impact on the findings one is likely to generate. Consequently, we think it is time that macro-criminologists revisit the how best to model the influence of population size on crime.

To the extent that one wants to determine the relative impact of various macro-level variables, once the "opportunity" effects of the population size have been removed from the amount of crime, then one should probably examine crime rates. However, careful attention should be given to who is included, and excluded, from the denominator of a particular rate of crime. As demographers have long recognized, for comparisons across time and space to be meaningful they must take into account the risk of experiencing the behavioral outcome of interest (Shryock and Siegel 1976). For example, population of origin is often used to control for the number of people that can move from one place to another in the calculation of migration rates (Haenszel 1967), while sex- and age-specific population distributions are typically used to calculate marriage rates (Hajnal 1953).[5]

We encourage those who decide to control for the "opportunity" effects of population size by the calculation of rate measures to explicitly consider which individuals are likely to comprise the pool of victims and offenders for the crime category under investigation. One can envision a number of situations where the gross population of a place might over- or under-estimate the number of potential victims or offenders.

Consider, for purposes of illustration, the problem of inanimate victims of crime. The supposition that total population size accurately measures the number of potential victims assumes that only humans can be the targets of crime. Clearly, for property crimes this is not the case. For example, it appears self-evident that the appropriate risk denominator for burglary rates should be the number of commercial and residential buildings (Boggs, 1965). Similarly, the number of motor vehicles is likely to be a better deflator for motor vehicle theft than total population size. To be sure, the quantity of physical targets in a social aggregate is likely to be highly correlated with the quantity of individuals. However, to the extent that the use of population-based and target-based denominators produce inconsistent rankings of crime rates within, and across, political units (Phillips, 1973; Boggs, 1965; Harries, 1981), grounding the selection of the denominator in either theory or logic becomes critical.

Alternatively, if one is interested in ascertaining the relative partial effects of population size, we advocate abandoning the conventional methodology, because we believe that it underestimates the partial effects of population size on the level of crime among macro-social units. Deflating the number of crimes by the population counts removes a substantial portion of the variance in the level of crime, which would be attributable to the size of the populace, prior to the estimation of the multivariate models. In the present case, the process of deflation removed approximately 92% of the variance in the amount of violent crimes and approximately 94% of the variance in property crimes.

In short, we believe that the process of deflation, by *partially* controlling for the effects of population size on crime prior to the estimation of any multivariate models, misspecifies the causal relationship between population size and macro-level indicators of crime. It tends to overestimate the effects of the social, economic, and political conditions, while it simultaneously underestimates the importance of opportunities for social contacts (the number people in a geographic area) on variations in the level of crime. We recognize, as we discussed above, that the analysis of crime counts (the components approach) is not without its problems (e.g., heteroskedasticity). However, as we also discussed above, these limitations are not fatal and, depending on the source of the problem, can be addressed in a number of ways (Greene 1993; Osgood 2000; White 1980).

NOTES

1. Some proponents of ratio variable approach do consider whether or not the proportions are "theoretically meaningful." However, the interest here is not so much with the thinking that led to the creation of a particular rate, but rather with the belief that "theoretically meaningful" ratios that contain common terms are less likely to be spuriously related to one another (Kasarda and Nolan 1979; MacMillan and Daft 1980).

2. Recently, concern about the use of ratio measures of crime has expanded to consider the relative efficacy of OLS, Poisson, and negative binomial regression analyses of crime rates among small social aggregates. In brief, this exchange focuses on the limitations associated with the use of OLS techniques for the purpose of studying rare events (Gardner, Mulvey, and Shaw 1995; Osgood 2000). For example, Osgood (2000) provides persuasive evidence that supports the conclusion that Poisson-based regression models of count data can (and should) be used in lieu of OLS regression techniques to analyze per capita offense rates when the number of crimes approaches zero. Interestingly, this *statistically-motivated* discussion of the benefits accrued from the use of Poisson-based regression to model crime rates in sparsely populated places (not unlike the statistically-motivated discussion of the correlation between ratios with common terms) fails to consider the *theoretical issues* that inform the decision whether or not to deflate raw counts of crime. In contrast, our investigation focuses on the substantive, rather than the statistical, implications of how one elects to account for the influence of population size on the level of crime across macro-social units.

3. It is true that statistical models of crime count data are more likely than similar analyses of crime rate data to produce heteroskedastic disturbance terms. It should be recognized, however, that rate models are not immune to this problem (see, for example, Sampson and Groves 1989).

4. By construction, the various population measures are, of course, highly collinear. However, the addition of a quadratic term to an equation that includes a linear term (the only situation where the collinear population variables will appear in the same equation) has no effect on the unstandardized coefficients for the linear or quadratic terms or their respective significance tests (Allison 1977).

5. We would like to thank an anonymous reviewer for calling our attention to the contributions of demographers with respect to discerning and estimating populations at risk.

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