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RISK-BASED CRIME STATISTICS: A FORECASTING COMPARISON FOR BURGLARY AND AUTO THEFT

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ABSTRACT

A major criticism of official statistics on crime is that they use inappropriate bases for computing rates. Here we investigate whether computing crime rates that contain in their denominators the number of exposures to risk of a specific event (e.g., residential burglary and auto theft) provides more accurate forecasts than employing the traditional FBI denominators as a base (e.g., the number of auto thefts and burglaries per 100,000 persons living in the United States). Single equation, macro-dynamic structural models are fitted to both the "traditional" and "alternative" forms of computing auto theft and burglary rates over the twenty-seven-year period from 1947–74, in order to determine how well they perform on statistical and substantive grounds over the estimation period. Ex-post forecasts of the 1975–79 observed crime rates, used to gauge the accuracy of these models, reveal few differences between the two kinds of rates in terms of how well they forecast. Both types of rates forecast well with the exogenous variables employed here and lead to similar substantive conclusions. The forecasts of the "traditional" rates are consistently, but only slightly, more accurate than those of the "alternative" rates (in most cases the differences are less than 1 percent). It is argued that the criticism of official data may be overstated and that little benefit accrues from the modification of the rate base for some purposes.

Criminologists, social planners, and the criminal justice community have long been dissatisfied with the quality of data available on the amount of crime and on trends in crime. Criticisms of official statistics are by now very well known and comprise a lengthy list. These criticisms include the facts that many crimes go undiscovered and unreported; that police jurisdictions define particular crimes differently, leading to measurement error in the classification of offenses; and that political motives may influence the accuracy of information (for an excellent summary of these and other criticisms of official crime statistics, see Nettler, 1978:54–64). In addition, the dependence of FBI estimates on voluntary reporting by police agencies leads to systematic over- and undersampling of differentially populated areas of the country. Because many crime rates vary systematically with population density, this phenomenon could have a substantial effect on crime estimates (Cantor and Cohen, 1980:127).

These putative shortcomings have resulted in a search for alternative ways to measure crime, most notably by self-reports of offenders and victims. Dissatisfaction with official statistics has also led to the unfortunate consequence of "freeing" some commentators from the constraints imposed by data, since the data are thought to be questionable. This is so even though official data seem to be as valid as their alternatives, for some measurement purposes—though by no means all (Hindelang, Hirschi, and Weiss, 1981). It seems to have been forgotten that the concept of validity depends on the purpose for which data are used and that validity is always a matter of degree.

A second, less common, response to criticism of official data is research designed to assess the significance of the problems involved in making substantive inferences on the basis of the data. Although these studies do not all have unambiguous outcomes, there is increasing evidence suggesting that for many substantive problems, official and unofficial data yield similar conclusions (Hindelang, Hirschi, and Weiss, 1981 and references used therein). However, many of the measurement questions raised about official data remain uninvestigated. The purpose of this article is to investigate the impact of one common criticism of police data—the inappropriateness of the bases for crime rates. That is, we investigate the possibility that a more rational calculation of crime rates, relative to those now in use by the FBI in the *Uniform Crime Reports* series, would allow us to forecast crime rate trends more accurately. It has long been suggested that the base of any particular crime rate contain information about events for the appropriate exposed population. Crime rates are customarily computed by the FBI as the number of crimes reported in an area (e.g., the United States) relative to a standardized population residing in that area (per 100,000 residents). Following the suggestions of Reiss (1967), Boggs (1965), Sparks (1980), and others, we examined the possibility that a more valid rate—one that considers the risk appropriate for each specific crime category—might lead to more accurate forecasts and, hence, to greater understanding of crime rate trends. Our focus was on burglary and auto theft. The question we asked is whether rates based on the number of residences that were reported burglarized relative to the number of residences that *could have been burglarized* and on the number of automobiles reported stolen relative to the number that *could have been stolen* in any given year, respectively, provide for more accurate forecasts of burglary and auto theft trends than rates using the conventional base (i.e., per 100,000 people living in the United States).

Exposure to Risk and the Opportunity for Crime

The crime rate reported by the FBI is the number of specific crimes known to the police, standardized per 100,000 population. The base (or the denominator) of this rate is supposed to represent the population that is exposed to the occurrence of a certain type of crime. The FBI indicators thus represent crude rates, the interpretation of which is problematic, since they assume that all persons in a given area are equally exposed to the risk of victimization. It would seem that in a more informative rate, the denominator would consist of those individuals or objects in the unit of analysis that have been exposed to risk in some way. That is, the standardization should include those persons or objects for whom there is some chance or risk that the criminal event in question could occur.

It is apparent, moreover, that some people cannot, logically, be the victims of certain types of crime; that is, they lack absolute exposure (Gottfredson, 1981). For example, it follows that if one does not own an automobile, he or she does not share the same risk of victimization from auto theft as one who owns one or more. And if the number of automobiles varies differently over time than do population figures, or if it varies over geographic areas, then person-based rates may mislead. A more informative rate would seem to be one that considers auto thefts relative to the number of registered autos. With respect to the burglary rate, we are presented with a similar problem in interpretation. Calculating a burglary rate per 100,000 residents does not accurately reflect the exposed population. A more informative rate would take the number of households and/or businesses in a given area as its base, depending on whether one was interested in residential or commercial burglary (or both) as the unit of analysis (Reiss, 1967:10–11). According to long-standing criticism, the FBI's method of calculating indicators of crime, at least for some of its rates, does not consider the logical base of exposure.

This argument can be extended to other index offenses as well. For example, it is apparent that males and females do not face the same risk of being victimized either by forcible rape or by purse snatching. By assuming that all members of a given population face the same risk of crime victimization, we obtain crime rates that are quite different in magnitude from those that would be obtained if our denominator contained only those elements of the population exposed to risk (Reiss, 1967).

The latter way of designating the population at risk is closely intertwined with the concepts of exposure to risk and criminal opportunity. Exposure to risk, as we use the concept here, refers to the physical visibility and accessibility of people and/or objects to potential offenders at any given time or place. We assume here that, all other things being equal, an increase in exposure leads directly to an increase in victimization risk, due to the fact that in order for an index offense to occur, an offender must come into direct physical contact with a potential victim and/or his or her property (Hindelang, Gottfredson, and Garofalo, 1978; Cohen and Felson, 1979). The more frequently such contact occurs, the greater the opportunity for a motivated offender to act against a potential victim or his/her property. Similarly, an increase in the size of the population at risk also increases the extent of criminal opportunity and, hence, the rate of crime. Thus when forecasting crime trends, it seems desirable to consider the interrelationships among exposure to risk, the population at risk, and criminal opportunities, because changes in these factors lead to changes in the opportunity to commit crimes and, hence, can have a profound effect on individual offense rates (Cohen, Felson, and Land, 1980).

Exogenous Factors

The purpose of this investigation is to compare the forecasting abilities of traditional and alternative denominators in computing burglary and auto theft rates. In order to accomplish our objectives, we needed to employ a suitable set of exogenous variables in our forecasts. Here we make use of a set of exogenous factors recently found by Cohen, Felson, and Land (1980) to provide reasonably accurate forecasts for property crimes. Our interest is purely methodological, and we make no claims to theory testing. A brief description of the rationale behind the selection of exogenous variables employed in the present study follows.

Using an "opportunity" framework to forecast crime rate trends for robbery, burglary, and auto theft, Cohen, Felson, and Land (1980) employed stochastic difference equations containing various exogenous variables for changes in criminal opportunities—variables such as the residential population density ratio, total consumer expenditures, and the number of automobiles per capita—as well as two control variables long considered relevant to the causation of crime—age structure (percentage of fifteen- to twenty-four-year-olds in the population) and the unemployment rate. The models specified on the basis of this opportunity approach exhibited a good statistical fit with official crime rates between 1947–72. When these models were used to generate ex-post forecasts of the observed rates for the five-year period from 1973–77, they provided reasonably accurate forecasts. In addition, Cohen, Felson, and Land found that introducing a dummy variable in their auto theft equation, to incorporate the improved ignition security systems made mandatory in the United States for new cars sold after 1970, significantly improved the basis for forecasting this crime.

The main theorem derived from the opportunity approach tested by Cohen, Felson and Land (1980) was that, other things being equal, a decrease in the density of the population in physical locations that are normally sites of primary groups should lead to an increase in criminal opportunities and, hence, in crime rates. Corollaries to the main theorem were presented and tested after operationalizing relevant independent and control variables (e.g., residential population density ratio, the unemployment rate, age structure, total consumer expenditures, and automobiles per capita).

We employed the same exogenous variables in our analysis. Our strategy was to report the empirical results obtained by fitting single equation, macrodynamic structural models to both the traditional and alternate methods of computing burglary and auto theft rates over the twenty-seven year period from 1947–74, in order to determine how well these methods performed, on statistical grounds, over the estimation period. We then employed the observed burglary and auto theft occurrence rates over the five-year period from 1975–79, for use in the ex-post forecasting analysis of our models. Since these are years for which observed values of the predetermined (exogenous and lagged dependent) variables in our estimated equations were available, we could compare the two methods of computing crime rates for each offense and evaluate which, if any, appeared to lead to more accurate projections.

DATA AND METHODOLOGY

In order to compare the different definitions of the *population at risk* for auto theft and burglary, we needed two different computations of each crime rate. The traditional crime rate computation gives rates per 100,000 persons for both crimes. The alternate crime rate computation gives rates per 100,000 (registered) automobiles for auto theft and rates per 100,000 households for burglary. Our measurement of burglary rates also differs from most previous studies by restricting attention to residential burglaries. The exclusion of nonresidential burglaries makes conceptual sense, since the discussion of the effects of many of the exogenous variables specified by the opportunity approach refers almost exclusively to residential physical. locales rather than to nonresidential physical locales.

Two sources of official crime reports were used to produce the time series data on number of auto thefts and total number of burglaries: *Social Indicators:1973* (Office of Management and the Budget, 1974) and the *Uniform Crime Report* (FBI, 1948–1980). The former source was used for the years 1947 to 1972, while data from the latter source were adjusted and used for the years 1973 to 1979 (see Cohen, Felson, and Land, 1980 for details). For each year, the number of residential burglaries was estimated by multiplying the number of total burglaries for the year by the estimated proportion of residential burglaries for that year. This estimated proportion is reported in the *Uniform Crime Report.* To create the traditional and alternate crime rates, we used the time series data on total resident population and total number of households from the *Current Population Reports* (U.S. Bureau of the Census, 1974) and the *Statistical Abstract of the United States* (U.S. Bureau of the Census, 1976, 1977, 1980).

We followed Cohen, Felson, and Land (1980) exactly in our definition and operationalization of exogenous variables, and the interested reader should consult this article for more details. Our measure of the density of the population in residential locations was the number of non-husband/wife households plus the number of female labor-force participants with husband present—this sum divided by the total number of households. The higher the values for this ratio, the lower the residential density. The unemployment rate is also an index of the residential population density, but it indexes the degree of criminal opportunity in transit locations as well. We used the proportion of the U.S. population aged fifteen to twenty-four as our offender-related indicator. We also used measures of the availability of property targets for each crime. For burglary we used the amount of consumer durable expenditures (excluding automobiles) in year t–2, and for auto thefts we used the number of registered automobiles per capita.[1] It should be noted that the automobiles per capita variable was used only in the traditional auto-theft-rate equation, since the alternate measure of our auto theft rate was formulated precisely to take account of the number of automobiles at risk. Finally, we also included in the auto theft equation a dummy variable contrasting the pre- and post-1971 eras, as suggested by Cohen, Felson, and Land (1980). This variable was included to take account of the introduction of ignition security systems on new automobiles in 1971—systems that make auto theft more difficult for relatively unskilled thieves. The dummy variable was coded 1 for the years post-1970 and 0 for the years pre-1971.

Following previous work by Cohen, Felson, and Land (1980), we fitted single equation, macrodynamic structural models to the time series of auto theft rates for the period 1947 to 1974 and of burglary rates for the period 1948 to 1974[2]. The general form of our models was:

$$(1) R_t/R_{t-1} = e^{\alpha} \cdot R_{t-1}^{\beta-1} \cdot X_{1t}^{\gamma 1} \cdot X_{2t}^{\gamma 2} \cdots \cdot X_{kt}^{\gamma k} \cdot \varepsilon t,$$

or, equivalently, in the natural log form that we estimate:

$$(2) \ln R_t = \alpha + \beta \ln R_{t-1} + \gamma_1 \ln X_{1t} + \gamma_2 \ln X_{2t} + \ldots + \gamma_k \ln X_{kt} + \ln \varepsilon_t.$$

R_t and R_{t-1} are the crime rates for years t and $t-1$, respectively; $X_{1t}, X_{2t} \ldots X_{kt}$ are the k exogenous variables measured at year t; εt is a stochastic disturbance in year t; and α, β, γ_1, $\gamma_2 \ldots \gamma_k$ are the coefficients to be estimated.[3] For more discussion of the appropriateness of this functional form in this situation and for the interpretation of coefficients, see Cohen, Felson, and Land (1980), Land (1979), and Land (1970).[4]

In estimating equations of the form presented in equation (2), several statistical issues must be kept in mind. Most of the equations that we estimate contain lagged values of the dependent variable. In this situation, OLS (ordinary least squares) does not provide unbiased estimates of the coefficients, nor does any other known procedure. But OLS estimates are consistent as long as the disturbances are not autocorrelated. The presence of autocorrelated disturbances would have a substantial impact on the ease of estimating our equations.

Our approach to testing for autocorrelation among the disturbances was to use a variety of statistical tests, since any single test statistic is flawed for our purposes. Both the familiar Durbin-Watson statistic and the Von Neumann ratio are known to be biased towards the acceptance of the null hypothesis of no autocorrelation if the regression equation contains a lagged dependent variable. While Durbin's h-statistic was formulated precisely for the situation involving a lagged dependent variable as a regressor, computer simulation studies suggest that the small sample properties of the h-statistic are questionable relative to the upper level of the Durbin-Watson statistic (see Taylor and Wilson, 1964; Kenkel, 1974). Durbin (1970) also suggests an alternative to his h-statistic that can be used when h cannot be calculated (that is, when $nV(B_1) \geq 1.0$) and that is asymptotically equivalent. This alternative is an F test based on a regression of the observed OLS residuals on the explanatory variables and on a lagged residual term. The small sample properties of this alternative statistic are as yet unknown. Since none of these statistics is clearly superior for testing for autocorrelation, we calculated and included all of them in the estimation results presented below. We accepted the null hypothesis of zero autocorrelation only if none of these statistics was significant at the .01 level.[5]

RESULTS

Before looking at the results of our analysis, it may be useful to see what differences in trends over time were revealed by the two different sets of rates. In order to compare trends in the two rates, which are in different metrics, each rate was scaled as a percentage increase over the minimum value of the rate. Figures 1 and 2 present these rescaled rates for auto theft and burglary, respectively. From figure 1 it is obvious that depending on one's purpose,

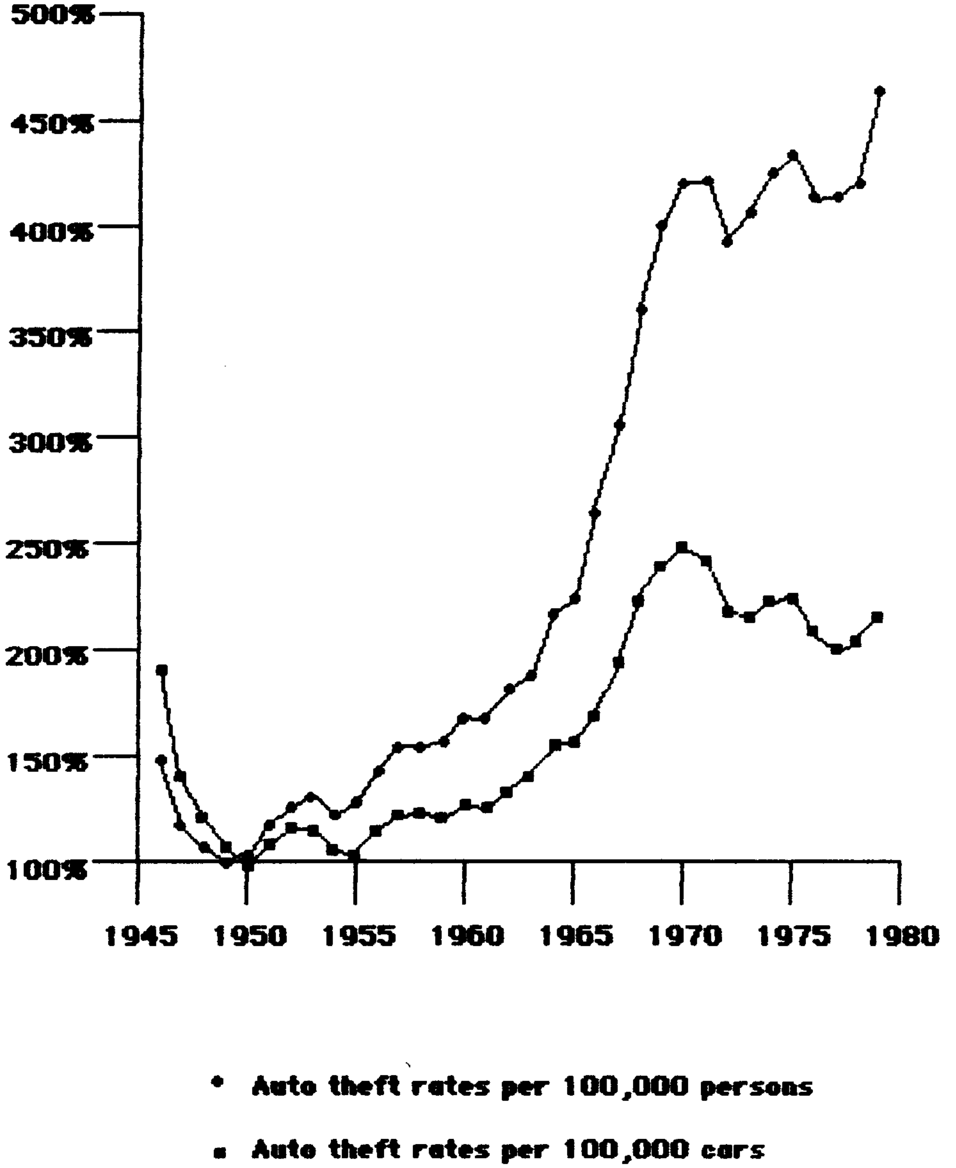

Figure 1. Auto theft rates per 100,00 persons and per 100,000 cars 1946–1979, scaled as a percentage of the minimum rate.

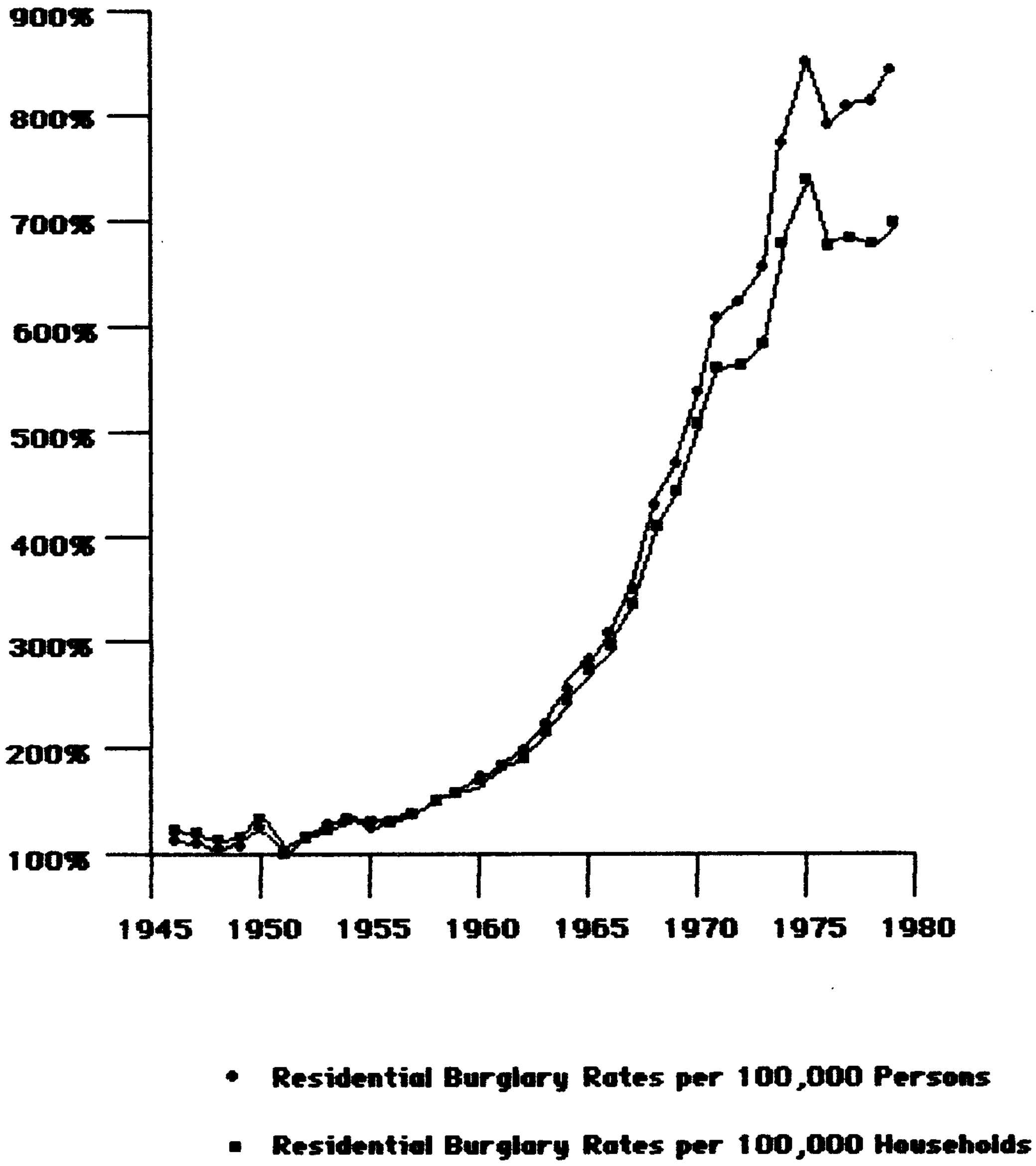

Figure 2. Residential burglary rates per 100,000 persons and per 100,000 households 1946–1979, scaled as a percentage of the minimum rate.

the two types of rates may present quite different pictures of auto theft. Although the general pattern of increases and decreases are similar, the magnitudes of the changes over time are radically different. Using the traditional measure of the auto theft rate, it appears that during the 1970s this rate was about four times greater than the minimum rate in 1949. Using the alternate rate, however, it appears that the auto theft rate had barely doubled by the 1970s. Thus both sets of rates show rather dramatic increases in the auto theft rate, but the real extent of this increase is much less if we use a more realistic definition of population at risk; that is, if we define *population at risk* in terms of the total number of registered automobiles.

From figure 2 we can see that the two sets of burglary rates are much more similar than are the auto theft rates. Indeed, the increases and decreases relative to the minimum are practically identical for many years. But the magnitudes of increase during the 1960s and 1970s are much less for the alternate rate than for the traditional rate, though not as dramatically different as for the comparable auto theft rates.

It should be noted that our results are not directly comparable to Cohen, Felson, and Land's (1980) analysis, even if we restrict attention to the traditional rate equations. In our analysis of auto theft rates, we included a dummy variable for the pre- to post-1971 period that they did not employ for the major portion of their analysis. In addition, our measurement of burglary does not include nonresidential burglaries. Indeed, this may explain one of the biggest differences between their results and ours. While Cohen, Felson, and Land (1980) found a positive, but marginally significant, coefficient for the unemployment rate in their burglary rate equation, the effect of unemployment was not significant in our equations. It seems likely that when attention is restricted to residential burglaries, the unemployment rate is almost solely an indicator of the presence of guardians. But in the case of total (residential plus nonresidential) burglaries, the unemployment rate might index both guardianship as well as the motivation to commit burglaries.

Turning now to our analytical results, two different comparisons of the use of traditional and alternate rates are undertaken. In Tables 1 and 2 we present the estimated macrodynamic equations for auto theft and burglary, respectively, using both sets of rates. These results allow us to compare the two types of rates in terms of differences in the effects of the exogenous variables. We also compare the two types of rates on more pragmatic grounds, by comparing the forecast errors for each rate. Table 3 presents ex-post forecasts of the auto theft and burglary rates for the years 1975–1979 and a comparison of the forecast error for the traditional and alternate rate computations.

Starting with the auto theft equations presented in Table 1, we can see that the substantive results achieved by using both the traditional rates and the alternate rates are largely similar. Four of the same exogenous variables enter into each equation, and each has a similar sign and relative magnitude. The only real difference between the two equations appears to be that the effect of the residential population density ratio is insignificant in the traditional auto-theft-rate equation while it is significant in the alternate auto-theft-rate equation. It is reasonable to assume that this difference results solely from the conceptual exclusion of autos per capita from the alternate auto-theft-rate equation and the fact that autos per capita and the residential population density ratio are highly correlated over time ($r = .991$). As the summary statistics show, we can accept the null hypothesis of no autocorrelation, since none of the four test statistics is significant at the .01 level.

The substantive results for burglary rates presented in Table 2 are also basically similar. Three of the same exogenous variables enter each equation, and each has the same sign and a similar relative magnitude. The only (though an important) difference is that the effect of the lagged dependent variable is marginally significant in the traditional burglary rate equation but not in the alternate burglary rate equation. Thus, the former equation suggests that the effects of the exogenous variables are distributed out partially over a number of years, while the latter equation suggests that the burglary rate responds rapidly to changes in the exogenous variables. As the summary statistics show, we can again accept the null hypothesis of zero autocorrelation for both equations.

We can also compare the two types of rates on how well they forecast the observed crime rates for the years 1974 to 1979. Recall that these five years were not included in the earlier analysis (presented in Tables 1 and 2), so that we could construct ex-post forecasts. That is, the ex-post forecasts use the actual values of the exogenous variables for the forecast year applied to the

TABLE 1

ESTIMATED AUTO THEFT RATE EQUATIONS BASED ON THE YEARS 1947–1974

	Dependent Variable	
Predictors	*Rate per 100,000 Persons*	*Rate per 100,000 Cars*
Constant	−2.2100	4.5135
	(0.3146)	(0.7618)
ln auto theft rate, lagged (t−1)	0.6214	0.5475
	(0.0587)	(0.0729)
Year dummy variable	0.1091	0.0959
	(0.0273)	(0.0306)
ln unemployment rate (t)	−0.1243	−0.1410
	(0.0300)	(0.0343)
ln proportion aged 15–24	0.4490	0.4066
	(0.1333)	(0.1621)
ln residential population density ratio (t)	*NS*	0.9978
		(0.0842)
ln autos per capita (t)	0.8919	excluded
	(0.0866)	
$\bar{R}^2$	0.9955	0.9839
Standard error of estimate	0.0341	0.0387
Durbin-Watson statistic	1.9482[a]	1.9594[a]
Von Neumann's ratio	2.0204[a]	2.0320[a]
Durbin's h	0.1442[a]	0.1164[a]
df	22	22

Note: Results presented only for equations with significant (p < .10) predictors.
[a] Fail to reject null hypothesis of no autocorrelation (α = .001).

equation estimated on the basis of the pre-1975 data. For each of the four sets of forecasts (traditional and alternate rates for both auto theft and burglary), we can compute the forecast error by subtracting the ex-post forecast from the observed crime rate. In order to compare the traditional and alternate rates, which are measured in different metrics, we computed the forecast errors as a percentage of the observed rate. The forecasting results shown in Table 3 reveal little difference between the two kinds of rates in terms of how well they forecast the observed rates, although the forecasts for the traditional rates are consistently slightly better than those for the alternative rates. The differences in results for the two methods of computing auto theft and burglary rates are, in most cases, less than 1 percent. Both sets of equations for each of the two crimes provide accurate ex-post forecasts with the exogenous variables used by Cohen, Felson, and Land (1980), as would be expected on the basis of their accurate forecasts of the 1973–1977 period.

CONCLUSION

Our objective has been to investigate a common criticism of official data—that is, that the base for the rates of residential burglary and auto theft used by the FBI in their *Uniform Crime Reports* substantially detracts from our ability to measure crime

TABLE 2

ESTIMATED BURGLARY RATE EQUATIONS BASED ON THE YEARS 1948–1974

Predictors	*Dependent Variable*	
	Rate per 100,000 Persons	*Rate per 100,000 Households*
Constant	4.7629	9.8834
	(2.5742)	(1.5522)
ln burglary rate, lagged (t–1)	0.3696	*NS*
	(0.2045)	
ln unemployment rate (t)	*NS*	*NS*
ln proportion aged 15–24 (t)	0.8110	2.6505
	(0.4603)	(0.3458)
ln residential population density ratio (t)	1.6880	1.4331
	(0.6774)	(0.2900)
ln consumer durable expenditures except automobiles, lagged (t–2)	0.4149	0.4060
	(0.2525)	(0.2413)
R^{-2}	0.9881	0.9873
Standard error of estimate	0.0720	0.0700
Durbin-Watson statistic	2.3794[a]	2.1433[a]
Von Neumann's ratio	2.4709[a]	2.2258[a]
Durbin's h	—[b]	—[b]
df	22	23

Note: Results presented only for equations with significant ($p < .10$) predictors.
[a] Fail to reject null hypothesis of no autocorrelation ($\alpha = .001$).
[b] Durbin's h cannot be calculated.

rates and to account for crime rates. Our forecasts, using alternative rates, demonstrate that two sets of equations using different denominators provide very similar estimates, although the traditional method provides for slightly, but consistently, more accurate forecasts. Why this occurs is not entirely clear. One possibility is that creating a ratio of the number of crimes to the size of the population with traditional measures indirectly standardizes out, or removes the effects of, the size of the offender population. This is not so clearly the case with the alternate measures of auto theft and burglary, where the denominator of the ratio is the size of the target population at risk.

In general, there are two alternate ways to standardize out the effects of an exogenous factor. The first is to include the factor as a control variable in the analysis. The second is to divide the measure by the exogenous factor. Thus when we employ the traditional measures of burglary and auto theft, we take a ratio of the number of observed crimes to the size of the population, standardizing out the effects of population change over time. The problem here is that this procedure may be roughly equivalent to standardizing for the differential size of the offender population over time. For example, suppose that the size of the offender population is, approximately, a constant proportion of the total population over time. Then dividing by the size of the total population is equivalent to standardizing out the effects of the size of the offender population. We would not expect there to be such a relationship between the size of the offender population and the size of the

TABLE 3

COMPARISON OF ACTUAL CRIME RATES TO EX-POST FORECASTS FOR THE YEARS 1975–1979

						Forecast errors as % of actual				
	1975	*1976*	*1977*	*1978*	*1979*	*1975*	*1976*	*1977*	*1978*	*1979*
ln auto thefts per 100,000 persons	6.1515	6.1005	6.1038	6.1189	6.2116					
Forecast of ln auto thefts per 100,000 persons	6.1261	6.1728	6.1924	6.2212	6.2496	0.41	−1.19	−1.45	−1.67	−0.61
ln auto thefts per 100,000 cars	6.8428	6.7721	6.7320	6.7411	6.8142					
Forecast of ln auto thefts per 100,000 cars	6.8265	6.8655	6.8561	6.9130	6.9095	0.24	−1.38	−1.84	−2.55	−1.40
ln burglaries per 100,000 persons	6.8798	6.8061	6.8230	6.8330	6.8717					
Forecast of ln burglaries per 100,000 persons	6.8964	6.9446	6.9069	6.9239	6.9533	−0.24	−2.03	−1.23	−1.33	−1.19
ln burglaries per 100,000 households	7.9769	7.8866	7.8940	7.8874	7.9177					
Forecast of ln burglaries per 100,000 households	8.0027	8.0352	8.0412	8.0846	8.1205	−0.32	−1.88	−1.86	−2.50	−2.56

target population at risk. Thus, the population-size ratio removes variation that is not removed when the target at risk is used as the denominator of the ratio.

On the basis of our empirical assessment, it is apparent that use of the traditional calculations of auto theft and burglary rates appear preferable when the goal of one's projections is to estimate future resources and service needs as accurately as possible. However, the differences in the accuracy of the two sets of measures is small (in most cases less than 1 percent difference). An inspection of figures 1 and 2 demonstrates that the real extent of the post–World War II increase in residential burglary and auto thefts, when a more realistic definition of the population at risk is employed, is much less than that depicted in FBI calculations. In our judgment, studies employing the traditional measures of auto theft and burglary have greater potential for misinterpreting the scope of this change. In addition, a more careful specification of the denominator in crime rates for burglary and auto theft (provided by the alternative methods proposed here and elsewhere) may be more useful to policy makers in the adoption of strategies to combat crime or in targeting the areas most in need of resources. Knowledge of the population at risk may be useful for the rational concentration and manipulation of manpower and other resources to more effectively combat crime. However, it appears that if one's goal is forecast accuracy, the traditional measures of burglary and auto theft are slightly superior to the proposed, "rational-alternative" measures. Either way, however, the gross correlates of these rate changes are not substantively altered.

Our research suggests that forecasting ability is not likely to be greatly improved by changes in the rate base. It may very well be that crime rates and crime rate major correlates are sufficiently robust to withstand such modifications. If so, then criminologists, social planners, and the criminal justice community may become less sensitive to common criticisms about the definition of crime rates than they have been in the past. This conclusion is consistent with much recent research on the measurement properties of crime data (Hindelang, Hirschi, and Weiss, 1981). We are not suggesting that such data are error-free; on the contrary, ample evidence exists suggesting they are not. We are suggesting, however, that some of the common complaints about the use of these data ignore the robustness in the data and the maxim that validity depends on purpose.

NOTES

[1] For a theoretical justification of a two-year lag term and an excellent analysis of how consumers change and maintain their current stock of consumer durables, see Juster, 1961.

[2] We could use only the data for the years 1948 to 1972, instead of for the years 1947 to 1972, for the burglary rates because one of the exogenous variables in the burglary rate equation (consumer durable expenditures) has a two-year lag.

[3] While no social science theory is precise enough to predict the exact form of nonlinearity, the choice can be made on the basis of previous knowledge of the variables under study. Previous research has shown that larger values of crime rates tend to be more variable than smaller variables. Snedecor and Cochran (1967) recommend logarithmic transformation in this situation.

[4] While a sample size of twenty-five is problematic for regression estimates with individual-level data, this problem is less acute in macro-level time series where individual variability is averaged out in the aggregate averages (Theil, 1971).

[5] Durbin's h is defined as $h = (1.0 - 1/2\ DW) \sqrt{\frac{n}{1-nV(b_1)}}$, where DW is the Durbin-Watson statistic for the equation, n is the sample size, and $\hat{V}(b_1)$ is the estimated variance of the coefficient for the lagged dependent variable. Further, h is distributed as a standard normal random variable.

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