PREVALENCE AND RECIDIVISM IN INDEX ARRESTS: A FEEDBACK MODEL

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It is important for both theoretical and policy reasons to partition aggregate crime rates into measures of prevalence (reflecting breadth of participation) and incidence (reflecting intensity of participation by those who do engage in crime). Prevalence is measured by accumulating over age the probability of first arrest as a function of age. Incidence is estimated by the probability of recidivism in a feedback model. The probability of a male in U.S. cities over 250,000 population ever being arrested for an index crime is estimated as 25 percent, and is quite different for black males (51 percent) and white males (14 percent). The probability of re-arrest for an index crime is estimated as 85 to 90 percent for both whites and blacks. These estimates highlight the breadth of involvement in index-crime arrests, and suggest that the large differences in race-specific arrest rates are predominantly attributable to difference in participation, and not to differences in recidivism for those who do get involved.

I. INTRODUCTION

A principal thrust of contemporary criminology has been directed at identifying the "causes of crime," and a large and diverse set of candidate causal models has been identified.[1] Empirical tests of these theories would search for an association between crime rates and variables serving as proxies for these causes, all of which could legitimately be characterized as manifestations of "social deprivation" and show high correlation with each other.

As long as the dependent variable is an aggregate crime rate, with no distinction between prevalence and incidence, such attempts are bound to be crude. Aggregate crime rate is a product of the prevalence of criminality (i.e., how broad a segment of the population engages in crime) and its incidence (i.e., the rate at which the criminal segment of the population commits crimes, as reflected in the likelihood of recidivism or

[1] Among the "causes" that have been formulated are social control, differential association, negative labeling, symbolic interactionism, objective deprivation, relative deprivation, legitimate-opportunity-strain, oppositional social norms, opportunity theory, and group conflict.

subsequent commission of crime). It is reasonable to expect, for example, that one set of factors distinguishes between those persons who become involved in crime the first time and those who do not, and that a different set of factors distinguishes those who persist in crime, once involved, from those who discontinue criminal activity at an early stage. It is conceivable, for instance, that the value structure in a juvenile's peer group could be a principal factor motivating initial involvement in petty theft, whereas the availability of legitimate employment could be a primary factor facilitating or inhibiting desistance among those who do get involved. If the causes of prevalence and persistence are different, then any attempt to relate causal factors to aggregate crime rates confounds both sets of causes and makes each appear less important than it actually is. On the other hand, if the distinctions could be maintained, then a more sharply focused attribution of cause could emerge.

Furthermore, if information on prevalence and incidence is disaggregated by characteristics associated with differential involvement in criminal activity, that disaggregation helps in the search for theories of criminal behavior. In particular, many criminologists (for example, Sutherland and Cressey, 1974) believe that the disproportionate representation of nonwhites in aggregate arrest statistics reflects both a greater breadth of participation and a greater rate of recidivism for nonwhites. If race-disaggregated information on both prevalence and recidivism were available, then the large difference in the aggregate rates could be partitioned between prevalence (or breadth of involvement) and incidence (or intensity of activity). To the extent that the differences are entirely attributable to prevalence and not to incidence, for example, then the search for factors creating criminal participation would focus on variables that are different across the races, and the search for factors creating incidence would tend to look first at factors that are common across races among offenders (even if they are not common across races in the general population). On the other hand, if prevalence and incidence are equally responsible for the different rates of involvement, then both are more likely to be influenced by common factors.

In addition to the theoretical questions of causation, the same distinction between prevalence and incidence should enter into public policy choices regarding intervention with individual offenders through the criminal justice system. The appropriate response to crime will differ depending on whether the aggregate crime rate is generated by a small number of high-frequency repeaters or by a large number of low-recidivism offenders. Indeed, it is important to know just how many people do get involved in crime. If the numbers are reasonably small, then one can properly think of those individuals as truly deviant; if the numbers are large, however, the sense of "deviance" must be reduced accordingly, and replaced by a concept of "normalcy." In the former case, identification and incapacitation through imprisonment of those rare criminals is quite tenable; in the latter case, such a policy would require unacceptably large resource investments and would be inherently ineffective.

For example, in 1980, there were 13,300,000 index crimes reported to the police (Uniform Crime Reports, 1980: 41). If these were committed by only 133,000 people, each of whom was responsible for 100 crimes, then we would only have to identify those individuals. Our prison system, with a current capacity in excess of 300,000 cells, could easily accommodate them. On the other hand, if there were 13.3 million individual offenders, each of whom commits only a single crime in a year, then no prison system we could reasonably visualize in a democratic society could possibly deal with that volume.

Thus, from both a theoretical and a policy perspective, it becomes crucial to separate the issues of prevalence and incidence in criminal involvement. The fact that this distinction is so rarely made is largely a consequence of the methodological difficulty in doing so. In general, a longitudinal study of cohorts is required to draw such distinctions explicitly, and such studies are difficult to generate, require extensive research-career commitments to pursue, and are in danger of being obsolete by the time they are completed.

Such longitudinal studies could ideally record, for each person in a sampled population, the details of each crime committed. Since offenders do not normally keep accurate logs of their criminal activity, direct information on the extent of participation in the commission of crimes is generally not available. Instead, two surrogate approaches have been used, one involving arrest statistics and the other involving self reports. The concern with arrest statistics relates to the extent to which the "arrest process" is an unbiased sampling of the crime process, and, in particular, the extent to which the demographic differences in arrest statistics reflect actual differences in crime commission rather than a selection bias associated with different arrest vulnerability.

The existence of such bias has been examined by comparing self-reports of criminal activity to arrest statistics. In general, such work, especially that of Gold (Williams and Gold, 1972; Gold and Reimer, 1975), has concluded that demographic differences (e.g., race and sex) in crime have been selectively amplified in arrest data, thereby arguing against the validity of demographic distributions in arrest data as adequate reflections of crime patterns. Hindelang (1978; see also Hindelang *et al.*, 1979), however, in a review of the self-report results, contradicts these conclusions. Using victimization reports in the National Crime Survey as an alternative source of information on actual offenses, Hindelang finds substantial agreement across cities between the demographic characteristics of victim reports and official arrest data, suggesting little bias in the arrest process. He argues further that the disparities between self-reports and arrest reports are largely based on misinterpretation. Self-reports of "crime" from the general population are dominated by trivial offenses, and so their results cannot be reliably compared to arrest reports of the serious crimes. Furthermore, since the populations considered often have very few nonwhites,[2] their reliability in the measurement of racial differences in crime commission is suspect. Hindelang's work thus suggests that the demographic bias in using arrest data may be small.

The prevalence of any specific type of criminal behavior in a population is the fraction of that population who commit those crimes. Presuming that arrest data accurately reflect the demographic characteristics of offenders, a comparable measure of arrest prevalence, or the fraction of the population ever arrested, can serve as a reasonable proxy for crime prevalence. Although this measure ignores the difference between committing a crime and being arrested for that crime, the resulting errors of omission are much larger than those of commission. Arrest prevalence does not include casual offenders who participated in only a few criminal acts and avoided arrest. The number of false arrests is believed to be appreciably smaller than the number who do commit crimes but are never arrested for them. The resulting estimate of prevalence based on arrest is, therefore, likely to be an underestimate of true crime prevalence. Thus, in this paper,

[2] For example, the sample population for Williams and Gold (1972) contained 53 black boys and 48 black girls.

we focus on the fraction of the population ever arrested as both a conservative measure of the prevalence of involvement in criminal activity and a measure of involvement with the criminal justice system.

Whereas prevalence is concerned with breadth of involvement, individual persistence reflects another dimension of concern. Persistence can be measured by the recidivism probability or the proportion of those released from the criminal justice system (CJS) who return with a new arrest. Because of its importance in measuring the effects of the CJS on its clients, considerable effort has been expended on measuring individual recidivism rates. Most often, experiments or quasi-experiments are undertaken by tracking individual offenders released from some stage of the CJS and then observing the proportion that re-enter at a later time with a new arrest, conviction, or confinement. The resulting recidivism measures are often the subject of considerable controversy. In part, the controversy arises because different investigators measure recidivism at different re-entry points (e.g., arrest, conviction, confinement), and the resulting recidivism probabilities are not directly comparable.[3]

Experimental measurement of the recidivism probability is also subject to variation in the exposure times over which the measurements are taken, and this variation can generate different estimates of the recidivism probability.[4] An additional source of undesired variation in recidivism measurement results from the use of different seriousness thresholds for determining whether recidivism has occurred—e.g., counting a rearrest (or reconviction) for disorderly conduct in one analysis, while excluding it as too trivial in another, will lead to a higher recidivism probability in the former case.

Results from an experimental paradigm are also unique to the particular experimental situation being tested; generalization, therefore, is often difficult. Finally, experimentation involves problems of cost, time, access to the experimental situation and its data, and the inevitable errors in

[3] See Blumstein and Larson (1971) for an exploration of the issues involved in such comparisons of inconsistent measures of recidivism.

[4] Recognizing this problem, Stollmack and Harris (1974) used a failure rate analysis to compare the recidivism rates of different groups of released arrestees. The probability that an individual would "fail," i.e., be rearrested, in some time period was assumed to be distributed as a negative exponential with parameter λ. An underlying assumption of such a model is that all would ultimately fail. In order to avoid this unreasonable assumption, Maltz and McCleary (1977) proposed a two-parameter model in which there is a finite probability, ψ, of not failing; among those who do fail, time to failure is again distributed with a negative exponential distribution.

data collection. It would thus be desirable to have alternative analytical approaches for estimating aggregate recidivism probabilities.

One such analytical approach was introduced by Belkin, Blumstein, and Glass (1972). They used a positive-feedback model of the criminal justice system in which all arrests are accounted for by either first-time arrestees or recidivist arrestees. Their model enabled them to generate an estimate of the arrest recidivism probability for all nontraffic offenses, and they found that probability to be strikingly high: 87.5 percent of persons arrested had a subsequent arrest. They also estimated prevalence as the probability of a male ever being arrested for a nontraffic offense over his lifetime. This value was found to be 60 percent, also a very high value. Even though these estimates are surprisingly high, both cannot be overestimates. Since the total actual reported arrests must be accounted for either by recidivist arrestees or by first-time arrestees, a decrease in either of these estimates must be compensated by an increase in the other.

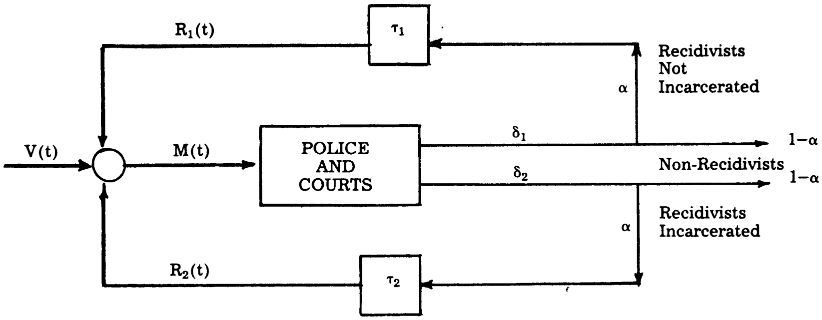
These results were based on arrests for all types of nontraffic offenses and considered all offenders across the United States. The types of offenses considered ranged from truancy to homicide and so included many minor offenses that are not of great concern to society. It would be important to determine the degree to which these findings apply to more serious offenses. The FBI index crimes (homicide, rape, robbery, aggravated assault, burglary, larceny, and auto theft) represent an appropriate group of serious offenses. Such crimes are of particular concern in urban areas, and since arrest reports from cities are likely to be more reliable than those from nonurban agencies, it would be appropriate to focus on the large cities. Since the 56 cities with populations greater than 250,000 comprise 21 percent of the U.S. population, an analysis of the recidivism characteristics of their populations certainly represents an important component of the national picture.

Also, it is known that there is a large disproportionality between white and nonwhite representation in the arrestee population. Thus, it would be very desirable to disaggregate any analysis of arrest by race, a dimension that Belkin *et al.* did not explore. This might help to indicate the degree to which this disproportionality reflects a higher prevalence of arrest, a higher rearrest probability, or both. In this paper, therefore, we extend the Belkin *et al.* analysis by focusing on the FBI index offenses in the large U.S. cities and disaggregating the analysis by race.

II. DEVELOPMENT OF THE MODEL

The positive-feedback model of the criminal justice system formulated by Belkin *et al.* is presented in Figure 1.

Figure 1. Feedback Model of the Criminal Justice System



where $V(t)$ = first arrests per unit time at t
$M(t)$ = total arrests per unit time at t
α = proportion of individuals rearrested after release
δ_1 = probability of all dispositions other than incarceration
δ_2 = probability of incarceration $(1 - \delta_1)$
τ_1 = mean time between arrest for those not incarcerated
τ_2 = mean time between arrest for those incarcerated
$R_1(t)$ = recidivist arrests of individuals whose last arrest did not result in incarceration per unit time at t
$R_2(t)$ = recidivist arrests of individuals who were incarcerated as a result of their last arrest per unit time at t

Persons arrested for the first time are the external input to the system. The recidivists are generated as a function of the system parameters: the recidivism probability (α), the mean time between arrest for those not incarcerated (τ_1) and those incarcerated (τ_2), and the probability of incarceration (δ_2), $\delta_1 = 1 - \delta_2$. Total arrests, $M(t)$, at any time t are simply the sum of the first-time arrestees, $V(t)$, plus the recidivist rearrestees, $R_1(t)$, representing those last released without incarceration, and $R_2(t)$, representing those whose last arrest resulted in incarceration.

The system of differential equations that describes the flow in this model can be formulated using Laplace transforms (see appendix). The calculation of $M(t)$ is straightforward given the input $V(t)$ and the system parameters indicated in Figure 1. Alternatively, if $M(t)$ and $V(t)$ are known the model can be used to estimate the values of those parameters that gave rise to the observed values of M and V. We will use the latter approach to obtain estimates of α and τ.

III. DATA SOURCES

In order to develop estimates of α (the probability of rearrest for an index crime given an earlier arrest) and τ (the mean time between index arrests) using the model described in the previous section, data on first index arrests and total index arrests are required over some time period. Unfortunately, the number of new index arrests is not generally available. Most arrest records do not distinguish first and recidivist arrests, and arrest histories rarely contain juvenile records. Given these data problems, it is necessary to synthesize these values from other data. Christensen (1967) estimated the number of first arrests by considering p(a), the probability that a person is arrested for the first time for an index offense at age a.

$$p(a) = \frac{\text{number of individuals arrested for the first time at age a}}{\text{total population at age a}}$$

If p(a) is stationary, then the number of first-time index arrestees in some year t, V(t), can be calculated as follows:

$$V(t) = \Sigma_a [p(a)][U(a,t)] \qquad (1)$$

where U(a,t) is the number of persons a years old in year t.

Estimation of U(a,t)

Thus, data are required for U(a,t) and p(a). Since we wish to focus on arrestees in large U.S. cities, we calculate U(a,t) for the 56 cities in the U.S. with populations greater than 250,000 in 1970.[5] The analysis was conducted for the period 1968 to 1977, the most recent decade for which arrest data for these cities were available. Census data with the necessary race,[6] sex, and age disaggregation were available for 1960 and 1970, and so an estimation process was necessary for the noncensus years. For the years 1961 to 1969, a simple linear interpolation was used

[5] These cities were: Birmingham, Phoenix, Tucson, Oakland, Long Beach, Los Angeles, Sacramento, San Diego, San Francisco, San Jose, Denver, Washington, D.C., Miami, Jacksonville, Tampa, Atlanta, Chicago, Indianapolis, Wichita, Louisville, New Orleans, Baltimore, Boston, Detroit, Minneapolis, St. Paul, Kansas City, St. Louis, Omaha, Newark, Jersey City, Albuquerque, Buffalo, Rochester, New York, Charlotte, Cincinnati, Cleveland, Columbus, Toledo, Oklahoma City, Tulsa, Portland, Philadelphia, Pittsburgh, Memphis, Dallas, Houston, San Antonio, El Paso, Ft. Worth, Austin, Norfolk, Seattle, Milwaukee, Honolulu.

[6] In keeping with 1960 census definitions, the race categories used were white (including Hispanics) and nonwhite, which includes all others, but is predominantly black.

between the endpoints 1960 and 1970. For the 1970's a slightly more complex process was needed. Single-age populations were estimated from known total city populations and known race-grouped age proportions of total central city populations.[7] We were thus able to develop reasonable estimates of the single-age populations of large U.S. cities — U(a,t) — disaggregated by race and sex.

Estimation of p(a)

The calculation of p(a) was problematic for Christensen and for adults in the Belkin study. Fortunately, the longitudinal study by Wolfgang, Figlio, and Sellin (1972) of the social and arrest histories of Philadelphia boys born in 1945 provides data with which p(a) can be estimated for males to age 30. The basis for inclusion in the original study was residency in Philadelphia for at least the ages 10 to 18. The cohort of 9945 boys included 7043 whites and 2902 nonwhites, and these boys generated 10,214 total arrests (or "police contacts"). This data provided an estimated p(a) to age 18. In 1977, Wolfgang (1977) completed a follow-up study of a 10 percent sample of the original cohort, providing the data for p(a) to age 30. The sample included 693 whites and 278 nonwhites.

Even though Philadelphia is not wholly representative of all large U.S. cities, the p(a) based on Philadelphia is attributed to the other cities in this analysis. Any bias resulting from this assumption may distort the results somewhat, although the correspondence between the index arrest rate for Philadelphia (1111.7 per 100,000) and all cities with populations greater than 250,000 in 1970 (1240 per 100,000) provides encouragement that this distortion is not serious. Disaggregated by race and sex,

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[7] The procedure was to first estimate grouped ages, then the needed single age populations.

Using data on:

T_{zt} = total population in cites of size z, year t (Current Population Reports, P25)

P_{rztg} = proportion of persons of race r and age group g in central cities of size z, year t (Current Population Reports, P23)

the value

G_{rztg} = total population in all cities of size z, race r, year t, age group g where z differentiated city populations of less than or greater than 1 million; r, white or nonwhite males; g, eight age groups ranging from less than 5 to greater than 65.

was estimated by

$$G_{rztg} = P_{rztg} * T_{zt}$$

Single ages were estimated from grouped ages by calculating group means, then interpolating linearly between those means.

the 1970 index arrest rates for white males was 720.1 per 100,000 in Philadelphia and 1218 per 100,000 for all large cities; for nonwhite males, 4816.3 per 100,000 in Philadelphia, and 5031.7 per 100,000 in large U.S. cities. Thus, arrest rates in Philadelphia are certainly no higher than for our sample of large U.S. cities, and appear to be appreciably lower for whites.

Since the Philadelphia data terminate at age 30, another data base was needed for the later ages. A sample of arrest histories was available from Washington, D.C., for individuals who were arrested for an index crime other than larceny at least once in 1973 in the District of Columbia.[8] Once this criterion was met, the offender's entire arrest history from age 18 to late 1975 was included. There were 5364 offenders, predominantly male (4811) and nonwhite (4927). In this group, 161 whites and 1151 nonwhites had their first arrest in 1973. There are three potential problems with the use of this data: the absence of juvenile records, the exclusion of larceny arrests, and the extent to which D.C. is representative of other large U.S. cities.

First, the D.C. arrest histories do not include juvenile records. It is, therefore, possible that a first adult arrest for those who were arrested as juveniles could be incorrectly assumed to be a first arrest, and the number of first arrests would, consequently, be overestimated. Since we are only using the D.C. data for ages greater than 30, this issue is not of major concern. A person experiencing a first adult index arrest after age 30 who had no index arrest from ages 18 to 30 might reasonably be assumed not to have had an index arrest prior to age 18.

Second, there is no information available in the D.C. data on first larceny arrests. This is less problematic than one might initially believe, since few persons are arrested for the first time after age 30. At worst, this would bias $p(a)$ downward for total index arrests for $a > 30$. To explore this issue, $p(a)$ was calculated for both total index arrests and for the subset of the six index arrests other than larceny for $a < 30$. Subsequent analyses considered the distinction between these two groups, where the nonlarceny group (which includes personal offenses as a greater proportion of the total) might be regarded as a better indicator of the behavior of more serious criminals. In addition, the nonlarceny group provided a means with which to test the sensitivity of the model.

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[8] The arrest-history data used are described in Blumstein and Cohen (1979).

Third, as with Philadelphia, there is some question of the degree to which the age- and race-specific arrest experience is representative of the other 55 cities considered.[9] Since the data sources from Philadelphia and Washington overlap for ages 21 to 30,[10] these years were examined to discern at least the consistency between the experiences of these two cities. The estimates of p(a) for nonwhites were very similar in both cities: Σ_{21}^{30} p(a) for the nonlarceny group was .0828 in Philadelphia and .0748 in D.C. For whites the corresponding Σ_{21}^{30} p(a) values were .013 in Philadelphia and .0257 in D.C. It is thus possible that the estimate of p(a) in D.C. may be overestimating p(a) for whites. However, the total probability of a first arrest for an index offense for all ages greater than 30, i.e., Σ_{31}^{∞} p(a), is only .0219 for whites. This represents less than 20 percent of the total white nonlarceny p(a), Σ_{0}^{∞}p(a). One would thus not expect any bias in p(a) for $a > 30$ to significantly affect any of our results.

The focus of this analysis will be limited to male arrestees. This stems primarily from two considerations. First, the Wolfgang study is of males only, and little can be reasonably inferred about the behavior of young female arrestees. Second, males comprise the vast majority of index arrestees in the U.S. (82 percent total index and 93 percent non-larceny in 1970).

The approach outlined above was thus used to estimate p(a), the probability of a first arrest for an index offense at age a, for white and nonwhite males. Table 1 presents the resulting estimates of p(a). The value of p(a) grows in the early teenage years and declines in later years, both because of a decline in criminal participation and because most of those who will ever be arrested have already had their first arrest. These patterns can be seen most readily in the graphic representation[11] of p(a) with age in Figures 2 and 3 for total index arrests and non-larceny index arrests respectively.

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9 D.C.'s nonwhite percentage of population in 1970 was 71 percent, while center cities with populations greater than 250,000 were 24 percent nonwhite. This disproportionality is troublesome only if the age- and race-specific arrest rates differ because of this sharply different population mix.

10 Although data were available in the D.C. histories for ages 18 to 20, they could not be considered as reliable first-arrest data since juvenile records were not included.

11 These displays are smoothed to avoid the erratic fluctuations that occasionally occur in the raw values of p(a). A three-year smoothing was used, i.e., $p'(a) = (p(a-1) + p(a) + p(a+1))/3$.

Table 1. Total Index Offenses p(a)

Age	p(a) white males	p(a) nonwhite males
6	0	.0007
7	.0004	.0014
8	.0011	.0041
9	.0017	.0090
10	.0026	.0121
11	.0034	.0252
12	.0075	.0289
13	.0067	.0379
14	.0098	.0369
15	.0192	.0438
16	.0172	.0376
17	.0129	.0317
18	.0043	.0432
19	.0101	.0360
20	.0029	.0252
21	.0029	.0108
22	.0043	.0108
23	.0072	.0108
24	.0014	.0252
25	.0014	.0072
26	.0014	.0072
27	.0025	.0072
28	.0021	.0036
29	.0011	.0072
30	.0012	.0036
31	.0013	.0038
32	.0007	.0034
33	.0008	.0043
34	0	.0042
35	.0009	.0037
36	.0010	.0029
37	0	.0037
38	.0022	.0031
39	0	.0021
40	.0021	.0024
41	0	.0010
42	.0011	.0010
43	.0021	.0021
44	0	.0025
45	.0011	.0025
46	0	.0004
47	.0023	.0011
48	0	.0011
49	0	.0011
50	.0011	.0015
51	0	.0004
52	.0011	.0008
53	.0021	.0018
54	0	.0009
55	.0010	.0010

The p(a) function varies markedly by race. For both white and nonwhite males, p(a) peaks at age 15; for whites this peak probability is .019; for nonwhites, it is .044, more than twice as large. The spread at the peak is also broader for nonwhites

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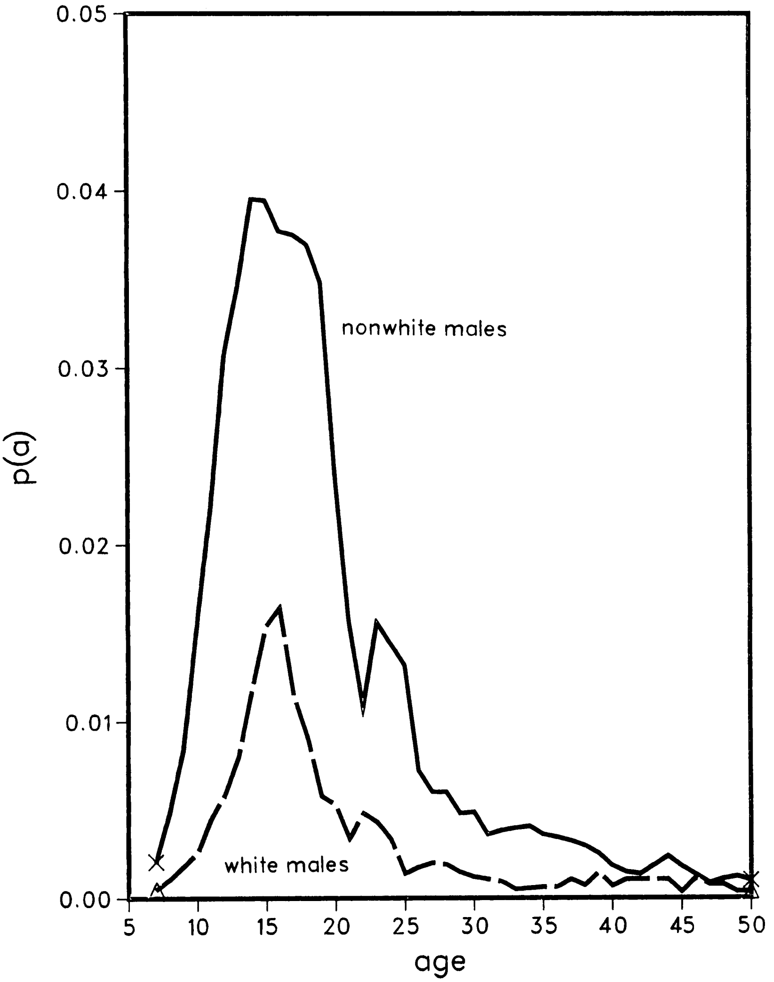
Figure 2. Probability of a First Index Arrest at Age a [p(a)]

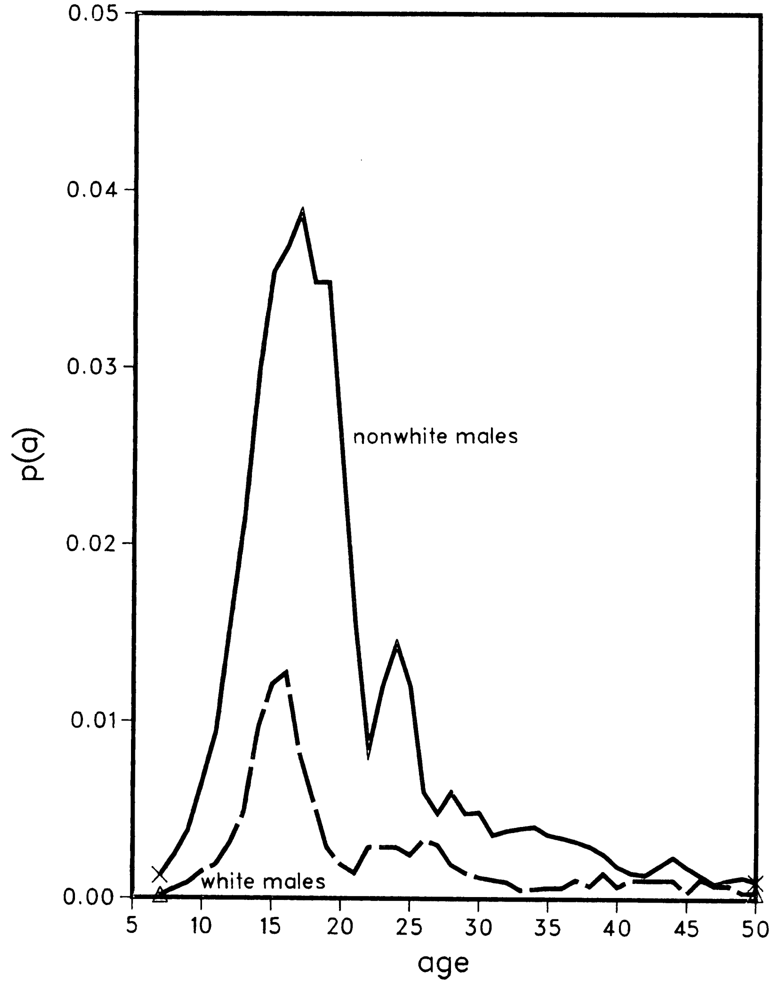


than for whites, another factor indicating the greater breadth of participation by nonwhites.

When one removes larceny from the crime set, the pattern changes only slightly; the peak for whites occurs again at age 15 with a value of .017 for nonwhites at age 18 with .043. These peaks in Figure 3 are within 10 percent of the peaks of Figure 2 that do count larceny arrests, reflecting the fact that even though larceny comprises half of the index arrests, very few individuals are arrested *only* for larceny.

Quite obviously, nonwhite males have a greater probability of arrest for an index offense than do white males. This is true for all ages, but is most apparent in the teenage years.

Figure 3. Probability of a First Non-Larceny Index Arrest



A different perspective on arrest involvement is offered by the cumulative value, P(a):

$$P(a) = \Sigma_{a=0}^{a} p(a)$$

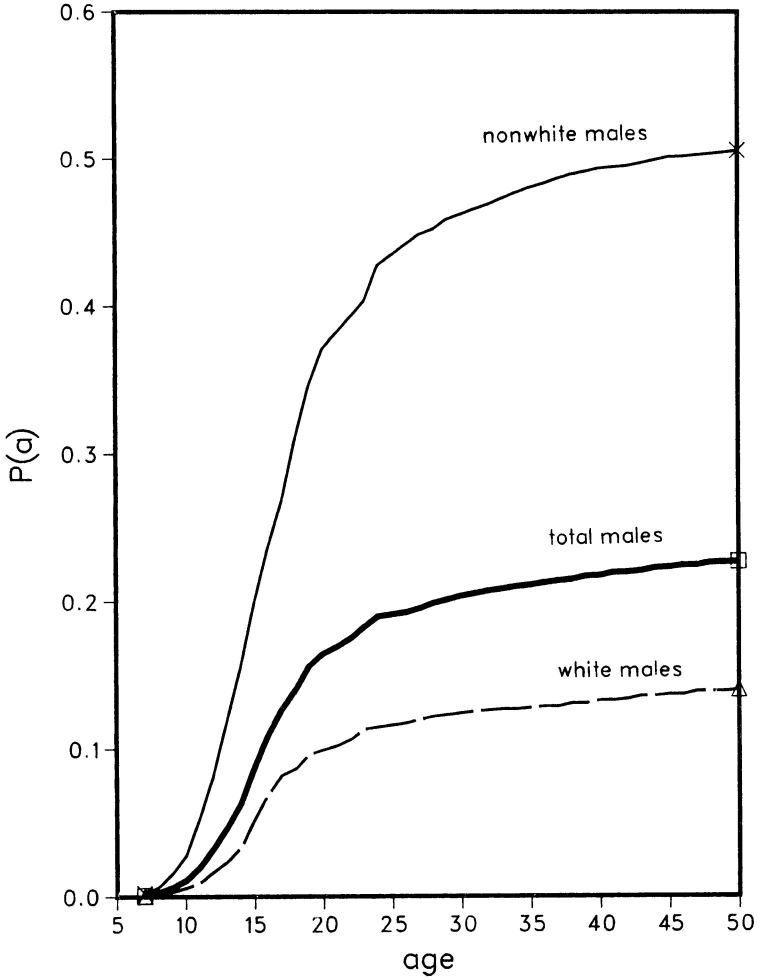
or, to correct for mortality effects, by:

$$P(a) = \Sigma_{a=0}^{a} p(a) \; L(a)$$

where L(a) is the probability of a five-year-old surviving to age a.

P(a) represents the probability of ever having been arrested for an index crime by a given age, a, and is presented in Figure 4 for whites and nonwhites.

Figure 4. Probability of an Index Arrest by a Given Age



Arrest is found to be surprisingly prevalent for the limited set of offenses included in the index crimes. The probability that a male has been arrested for an *index offense* by age 55 is 0.23. One in every four males living in a large U.S. city can expect to be arrested for an index crime some time in his lifetime. Belkin *et al.* (1972) found the cumulative probability of ever being arrested for *any offense* to be 0.58.[12] Thus, the widespread involvement in arrest shown by Belkin *et al.* is reduced by 60 percent if we limit attention to the index crimes. Even though arrests for index crimes represent about 20

12 The difference between the two values results partly from the fact that Belkin *et al.* (1972) applies to the entire U.S. whereas our analysis is limited to large U.S. cities with their higher arrest rates. The index arrest rate for the U.S. was 840 per 100,000 in 1970 and 1202 for cities greater than 250,000 (Uniform Crime Reports, 1970: 120).

percent of total arrests,[13] almost half of all arrestees get arrested at least once for an index offense.[14]

The racial difference in P(a) is striking. At age 55, the probability that a nonwhite male has been arrested for an index offense is approximately 0.51; for a white male, this probability is 0.14. Thus a nonwhite male is 3.6 times as likely to have had an index arrest in his lifetime as a white male: one in every two nonwhite males in large U.S. cities can expect to have at least one index arrest.

Estimation of V(t)

With estimates of p(a) and U(a,t), the calculation of V(t), the number of first index arrests at time t, was straightforward using equation (1). The resulting estimate of V(t) for total index crimes is displayed in Figure 5. The V(t) curve is flat for whites and sharply increasing for nonwhites. This results primarily from the changing racial mix of these 56 cities during the period considered. During the period from 1960 to 1977, the white male population as a percentage of the total male population in cities with population greater than 250,000 dropped 10 percent, while the nonwhite males increased 41 percent. In addition, there was a shift in the age distribution within races. The number of white males in the first-arrest-prone ages of 10 to 18 decreased 7 percent, while the number of nonwhite males in this age group increased 100 percent.

Similar estimates of V(t) can be developed for the reduced set of offenses comprising the nonlarceny index offenses. The effect of examining this reduced set of more serious offenses is to shift the V(t) curves downward, but to leave their shapes unchanged. Since all other results for the nonlarceny offenses are similar, the subsequent analysis is presented only for the total set of seven index offenses.

By augmenting these estimates of V(t) with data on actual total index arrests, N(t), the parameters of the feedback model can be estimated. Although the FBI publishes index arrests for

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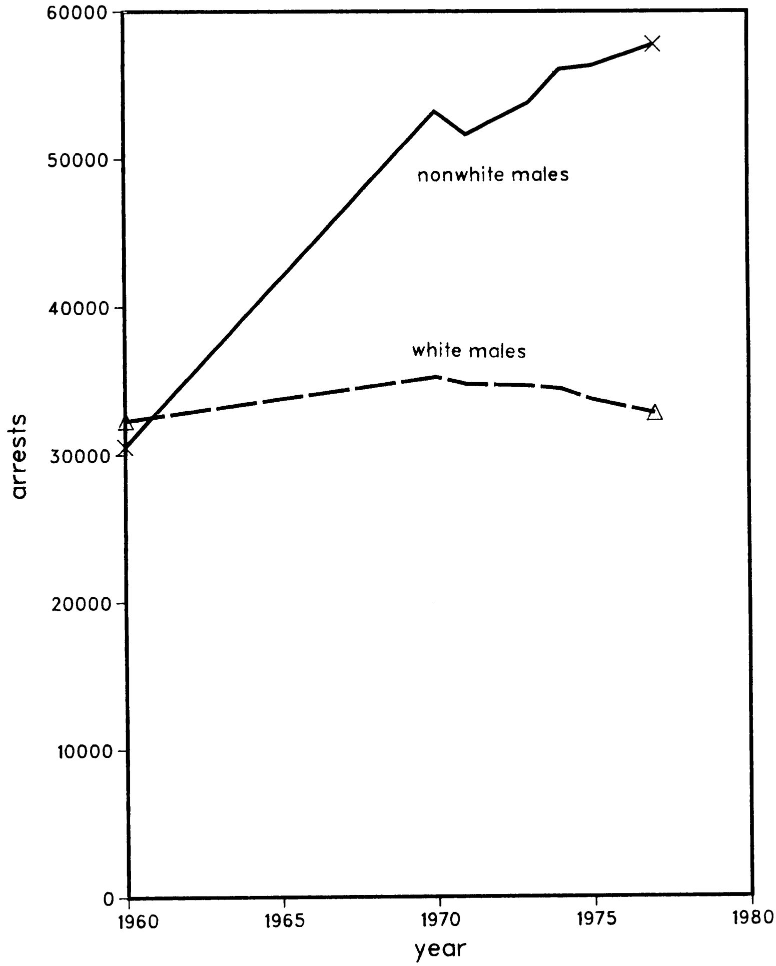
[13] In 1978, 2,284,400 of the estimated 10,271,000 arrests in the U.S. were for index offenses (Uniform Crime Reports, 1978: 186).

[14] Arrest prevalence, P(a), is strongly influenced by the p(a) values generated by the 1945 cohort. In view of the growth in arrest rates since the cohort reached age 18 in 1963, any movement in p(a) is probably associated with a uniform increase in p(a) for all ages or a shift to earlier ages. In the latter case, there would be no significant influence on P(a). In the former case, estimates of P(a) would be even higher.

Figure 5. Number of First Arrests for Index Offenses



cities with populations greater than 250,000 in the UCR, the published estimate is composed of reports from a varying number of cities each year, and so does not represent a consistent series. In addition, and more important, these reports are not disaggregated by race. We were able to obtain from the FBI the individual city arrest reports for each year in the 1968-77 period.[15] These data provided total arrests disaggregated by sex and by race for each of the 56 cities. The joint race and sex arrest counts (e.g., the number of black males) were estimated as the product of the marginal

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15 The assistance of Paul Zolbe of the FBI in providing these data is greatly appreciated.

proportions (i.e., implicitly assuming that race and sex are independent in arrest).[16]

IV. EMPIRICAL RESULTS

The parameters to be estimated with the model described in Section II are the probability of rearrest (α) and the mean time between arrest for individuals not incarcerated (τ_1) and for those incarcerated (τ_2). It is assumed that the time between arrests, $T - t$, is distributed as a negative exponential with mean τ, where T is the current time and t, the previous arrest time. This implies that the total number of arrests at some time T, M(T), is:

$$M(T) = V(T) + \int_0^T \alpha\delta_1 M(t)\ (1/\tau_1)\ \exp\ [(t-T)/\tau_2]\ dt + \int_0^T \alpha\delta_2 M(t)\ 1/\tau_2\ \exp\ [t-T]/\tau_2\ dt$$

An estimate of the value of δ_2, the probability of incarceration given an index arrest, was obtained from Blumstein and Cohen (1979) and set at .15.[17] Obviously, $\delta_1 = 1 - \delta_2 = .85$. With this parameter established, a sensitivity analysis was performed on the effect of the relationship between τ_1 and τ_2 on estimates of α and τ_1. For a reasonable range of values of $\tau_2 - \tau_1 = \Delta$ (including the value of $\Delta = 0$), the estimates of α and τ_1 are insensitive to this difference. Thus, for simplicity, we now assume that $\tau = \tau_1 = \tau_2$.[18]

With these parameter assumptions and the first arrest estimates, we can calculate $M(t,\alpha,\tau)$ for any combination of α, τ. We then seek those values of α and τ that provide the closest fit between the calculated values, M(t), and the actual values, N(t). The measure of fit chosen is the average percent deviation (APD)[19] used by Belkin:

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[16] Even though one cannot assume that white women are the same proportion of white arrestees as nonwhite women are of nonwhite arrestees, all women arrestees are such a small percentage of total index arrestees that the possible bias that might result from this approximation is small.

[17] The President's Commission on Law Enforcement and Administration of Justice's *Task Force Report: Science & Technology* (Christensen, 1967: 55) found the probability of incarceration for an index arrest to be between .10 and .20, which is consistent with this point estimate.

[18] Belkin *et al.* (1972) assumed a fixed relationship between τ_1 and τ_2, $\tau_2 = 1 + \tau_1$, implicitly assuming that the mean times until rearrest were displaced by an average of one year spent in prison by those incarcerated. One could argue, however, that those incarcerated are a different sector of the criminal population and recidivate more quickly than others. Thus, τ_2 could equal τ_1 or, considering the short amount of time usually served in prison, might even be smaller. To explore the model's sensitivity to this issue, we considered four alternative specifications of the relationship between τ_1 and τ_2: $\tau_2 = \tau_1 + \Delta(\Delta = 0,.5,1,1.8)$. All produced the same estimates of α and τ_1, implying that the model is insensitive to τ_2.

[19] Steven Garber has pointed out that this estimator is a maximum likelihood estimator if errors are normal, independent, and identically distributed over the observations. The consistency and efficiency of maximum likelihood estimators are asymptotic properties, however, and our small sample size (n = 9) limits our ability to invoke these properties.

$$APD = 1/T \sqrt{\Sigma_t (M(t) - N(t))^2} \div 1/T\, \Sigma_t N(t)$$

where $N(t)$ = actual total index arrests in period t
$M(t)$ = predicted index arrests in period t
T = total number of time periods

The numerator provides a measure of the deviation of the variable's predicted and actual values. The ratio is a measure of the magnitude of this deviation as compared to the average size of the variable.[20]

A grid-search technique was used to find the best fit. The initial search was coarse over the entire (0,1) interval for α with τ bounded above at 2.5 years. Successively smaller intervals of α values were used to minimize the APD value. The resulting set and point estimates of parameter values with the lowest average percent deviation were:

	α	τ	APD
White	.87 – .89	1.6 – 2.1	<3.0%
	.88	1.9	2.9%
Nonwhite	.81 – .82	.2 – .6	<4.5%
	.81	.4	4.4%

The fit for both whites and nonwhites was reasonably good (less than 5 percent deviation in both cases), although the fit for whites was somewhat better than for nonwhites. The reason for this difference is suggested by the display of the predicted $M(t)$ versus the actual $N(t)$ series in Figure 6, where one can observe the sharper fluctuations in the $N(t)$ series for nonwhites.

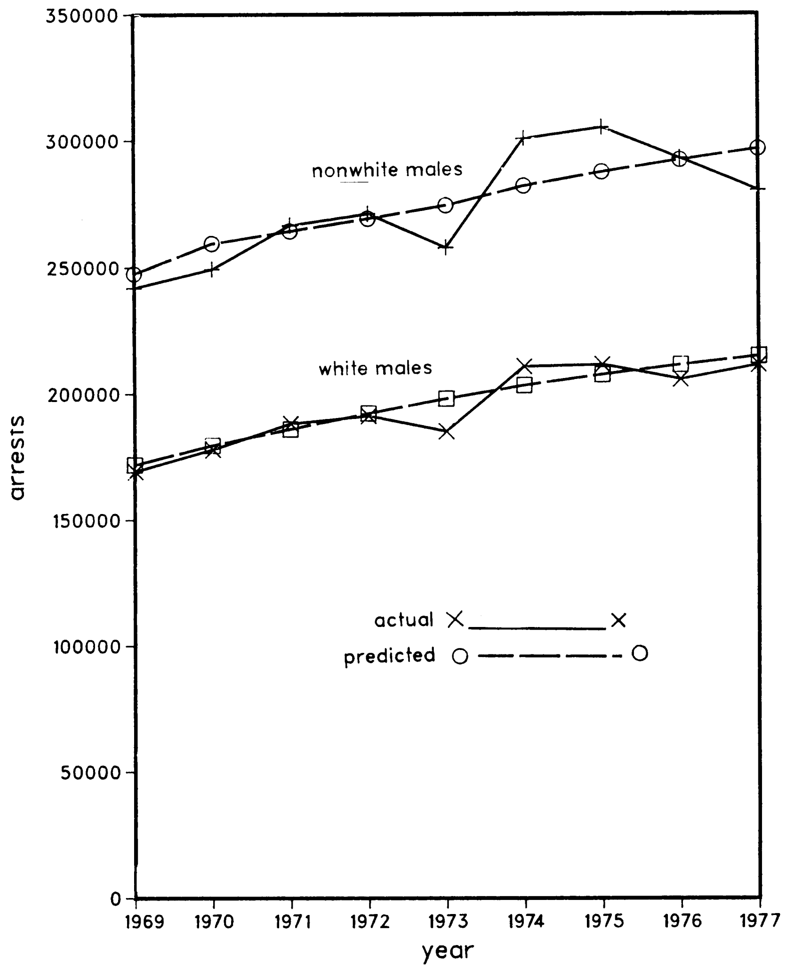
One apparent anomaly in the results is the large difference in τ between whites (1.9 years) and nonwhites (0.4 years). This is largely a technical issue. It results from the much more erratic oscillations in the nonwhite arrests, requiring a shorter time constant (τ) in the model as it attempts to track those oscillations. In addition, it is quite possible that the proportion of those incarcerated varies by race. The model could be lowering the nonwhite τ to compensate for the effect of a true higher incarceration proportion for nonwhites. Sensitivity

20 To test the sensitivity of the results to the use of this particular measure of deviation, a second measure, the total percent deviation (TPD), was considered:

$$TPD = \Sigma_t \mid M(t) - N(t) \mid / \Sigma_t N(t)$$

The basic difference in the two criteria is that APD penalizes large individual errors more heavily than TPD. Both criteria produced the same set estimates for α and τ.

Figure 6. Comparison of Actual and Predicted Total Index Arrests



analyses indicate that the estimates of α are not very sensitive to the values of τ. If τ for nonwhites is set at 1.9 (the value for whites), the best estimate of α is .87, resulting in a slightly higher APD value, 6.1 percent. Thus, because the difference in τ (and especially the low τ for nonwhites) might have resulted from an artifact, we re-evaluated the α estimates when τ was constrained to be equal between races. In all cases the α estimates for whites and nonwhites were almost identical. If τ is indeed the same for both races (and the observed differences in τ are attributable to the erratic fluctuations in N(t)), then we can reasonably conclude that α does not vary by race, i.e., the probability of rearrest given an index arrest is not substantially different for whites and nonwhites. There is, however, a possibility that τ *is* significantly lower for nonwhites. This

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would imply a somewhat lower α as well, suggesting that although fewer nonwhites recidivate, those who do recidivate return with a rearrest much more quickly than do their white counterparts. In either case, one feels less confident drawing conclusions about τ than about α.

Summarizing these considerations, then, we conclude that the recidivism rate for index offenses is approximately .85-.90 for both whites and nonwhites, and that the mean time between arrests is approximately 1.5 to 2.0 years. The important observation here rests with the estimates of α, the recidivism probability. The value of .88 is strikingly high, especially when compared to the value of .875 found by Belkin *et al.* (1972) for all offenses for the U.S. One might have anticipated that a focus on a restricted set of offenses would have resulted in an appreciably lower value of α. The high value results partly from the fact that the estimate here is based on males in large cities, whereas the Belkin study is based on the entire U.S. population. In addition, the restricted set of offenders who do engage in index offenses could well be more committed to continuing criminal activity. In that case, their α could be higher than the associated α for all offenders and all offenses.

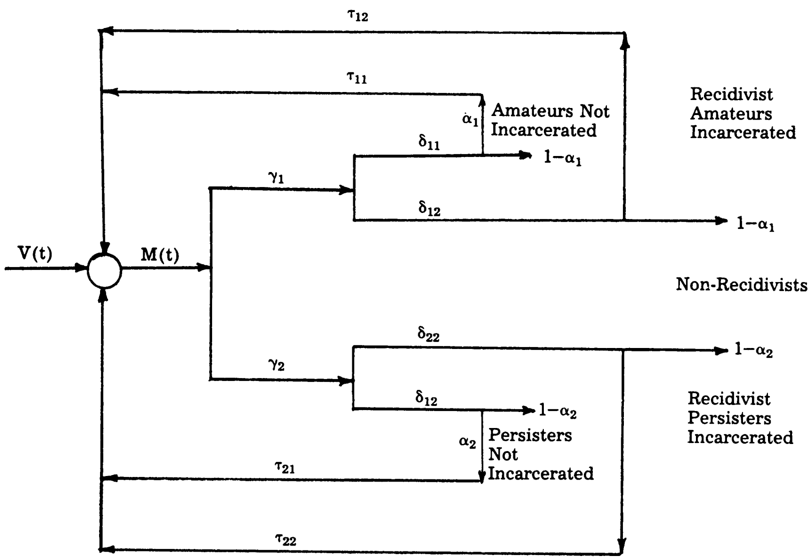
It is also rather surprising that the value of α for nonwhites is so close to that for whites. In view of the large discrepancy between white and nonwhite aggregate arrest rates,[21] one might have expected to see these differences reflected in the respective values of α; that is not the case. As indicated earlier in the consideration of P(a), there is a marked difference in prevalence between the two racial groups (.14 for whites, .51 for nonwhites), but no comparable difference exists in rates of recidivism *among those who do become involved*. Thus, the large racial differences in aggregate arrest rates must be attributed primarily to differences in involvement, and not to different patterns among those who do participate.

V. A TWO-GROUP MODEL

In the previous analysis, all individuals have been viewed as recidivating at a common rate α. The inherent underlying variability in recidivism rates might be better represented by considering two or more groups of arrestees who recidivate at different rates. It was found in the Wolfgang birth cohort

21 Although nonwhites represented only 12 percent of the U.S. population, nonwhite arrests were 38 percent of all index arrests in 1970.

Figure 7. Feedback Model of the Criminal Justice System — Two-Group Model



where $V(t)$ = first arrests per unit time at t
$M(t)$ = total arrests per unit time at t
γ_1 = proportion of amateurs in total arrests
γ_2 = proportion of persisters in total arrests
α_1 = probability of recidivism for amateurs
α_2 = probability of recidivism for persisters
δ = incarceration probabilities, subscripted: 11=unincarcerated amateurs, 12=incarcerated amateurs, 21=unincarcerated persisters, 22=incarcerated persisters
τ = mean time between arrests (subscripted as δ)

(1972) that the recidivism probability for those with one arrest was .54, whereas the rate for those with more than three arrests was constant at .72. This suggests an extension of the above model which characterizes two groups of arrestees, each of which has its own characteristic recidivism probability: "amateurs" with a relatively low recidivism probability and "persisters" with a higher one (see Blumstein and Moitra, 1980). Each group of first-time arrestees contains some proportion γ_1 of amateurs and the complementary proportion, $\gamma_2 = 1 - \gamma_1$ of persisters. The persisters recidivate at some rate α_2 which is larger than α_1, the recidivism rate for amateurs. This model presented in Figure 7 enables us to examine this multi-group proposition. The number of total arrests under this model is then given by:

$$M(T) = V(T) + \int_0^T \gamma_1\alpha_1\delta_{11}\, M(t)\, 1/\tau_{11}\, e^{(t-T)/\tau_{11}}\, dt + \int_0^T \gamma_1\alpha_1\delta_{12}\, M(t)\, 1/\tau_{12} e^{(t-T)/\tau_{12}}\, dt + \int_0^T \gamma_2\alpha_2\delta_{21}\, M(t)\, 1/\tau_{21}\, e^{(t-T)/\tau_{21}}\, dt + \int_0^T \gamma_2\alpha_2\delta_{22}\, M(t)\, 1/\tau_{22}\, e^{(t-T)/\tau_{22}}\, dt$$

The two-group model requires an estimate of the proportion of amateurs, γ_1, in a first-arrest cohort. If an independently generated estimate of γ_1 were available we could estimate α_1, the recidivism rate for amateurs and α_2, the recidivism rate of persisters using the same approach as in the one-group model. Alternatively, if we had an independent estimate of α_2, we could use the previous approach to estimate γ_1 and α_1.[22] Neither of these approaches was possible with the data available, and so the two-group model was not pursued further.

VI. CONCLUSION

This analysis has provided significant new information about the characteristics of criminal participation and recidivism. The breadth of participation of males in large U.S. cities in index crimes is quite large. One in every four males living in a large city can expect to be arrested for an index offense in his lifetime, with the majority of such first involvements occurring before age 18. Although the great majority of these teenage boys stop their criminal activities, the cessation process is more gradual than sharp. Participation this broad severely limits a general strategy of crime control based on incapacitation.[23] Indeed, when such involvement is as pervasive as a full quarter of the male population, a common perception of a vast law-abiding population and a tiny band of "criminals" must be reconsidered.[24]

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[22] This would be possible using the Wolfgang cohort data for a model of all offenses, since it was observed that α_2 was constant at a value of .72 for all arrests after the third, and progressively lower for each of the earlier arrests, which contained a larger proportion of amateurs. In focusing on the index offenses, however, no such clear progression to a stationary asymptote was discerned. Rather, the aggregate recidivism probability was fairly stationary, and fluctuated about a constant value for all arrests.

[23] To the extent that one could identify the persisters (rather than the short-duration participants) in criminal activity, incapacitation might be more feasible. However, an examination of this issue by Blumstein and Moitra (1980) revealed that juvenile persisters were not identified with prior-record information alone.

[24] However surprising these results may be, they are consistent with Farrington's (1981) prevalance estimates for England and Wales. The cumulative probability of conviction for a standard-list offense for a male in his lifetime based on 1977 data was .436. In addition, Farrington demonstrated an upward trend over time; the equivalent probability in 1965 was .313. This latter estimate is larger than that found by Little (1965) who estimated the prevalence of arrest for indictable offenses in England and Wales of persons prior to age 21 as .1125. Little's estimate is for males and females combined and so reflects the much lower arrest rate of females. Both these studies are based

Among those who have been arrested for an index offense, the probability of rearrest is also quite high, about .88. This is very close to the recidivism rate of .875 found by Belkin *et al.* (1972) for all persons arrested for all offenses, across the entire United States. The expectation that restricting consideration to only the serious offenses would result in a significantly lower recidivism probability has not been realized. The offenders who commit the more serious crimes display a higher recidivism probability which offsets the reduction induced by the smaller set of offenses for which recidivism is counted. In addition, the higher arrest rates of the larger cities could have influenced the higher recidivism probability.

The race-disaggregated analysis revealed a disproportionately high involvement of nonwhites in the population ever arrested for index crimes—51 percent of nonwhite males can expect to be arrested, compared to 14 percent of white males. This ratio of about 3.5 is consistent with the ratio of about 3 in the aggregate arrest rates by race. The surprising finding, however, is the consistency between whites and nonwhites on the rearrest probability for those who do get involved. Both are well within the range of 85 to 90 percent. This states that the large differences between races in aggregate arrest statistics is primarily a consequence of differences in participation rather than differences in recidivism. Most discussions of racially different involvements in crime fail to distinguish between these very different aspects. If there were an important difference in recidivism, for example, that might stimulate a differential incapacitation response. The findings here suggest that there is no such difference, and aside from the equity considerations which must be dominant in any event, they suggest no utilitarian basis for racially based differentiation.

APPENDIX

$M(T) = V(T) + R_1(T) + R_2(T)$

$M(T) = V(T) + \alpha\delta_1/\tau_1 \int_0^T M(t)\, e^{(t-T}/\tau_1)\, dt + \alpha\delta_2/\tau_2 \int_0^T M(t)\, e^{(t-T)}/\tau_2)\, dt$

Let $c1 = \alpha\delta_1/\tau_1$, $c2 = \alpha\delta_2/\tau_2$

Recall $L[M(T)] = L[V(T)] + L[R_1(T)] + L[R_2(T)]$, where L represents the Laplace transform.

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on a country which is generally perceived as having a level of criminal activity appreciably lower than that of the United States.

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Taking Laplace transforms and simplifying:

$m(s) = [L(V(T)) (s + 1/\tau_1)(s + 1/\tau_2)] / [(s + 1/\tau_1)(s + 1/\tau_2) - c1(s + 1/\tau_2) - c2(s + 1/\tau_1)]$

Assume $V(t) = V(0) + Gt$, where G is approximated from the first-arrest data, then:

$L(V(T)) = [sV(0) + G]/s^2$

$m(s) = [(sV(0) + G)(s + 1/\tau_1)(s + 1/\tau_2)] / [s^2[(s + 1/\tau_1)(s + 1/\tau_2) - c1(s + 1/\tau_2) - c2(s + 1/\tau_1)]]$

Now m(s) is in terms of initial conditions and model parameters. Using partial fractions to find linear factors and re-transforming, we find:

$M(t) = A0t + A1 + [(F0 + F1*r1)/(r1 - r2)] e^{r1t} - [(F0 + F1*r2)/(r1 - r2)] e^{r2t}$

where

$$n0 = G/\tau_1\tau_2$$
$$n1 = V(0)/\tau_1\tau_2 + G(1/\tau_1 + 1/\tau_2)$$
$$n2 = G + V(0)(1/\tau_1 + 1/\tau_2)$$
$$n3 = V(0)$$
$$g0 = 1/\tau_1\tau_2 - c1/\tau_2 - c2/\tau_1$$
$$g1 = 1/\tau_1 + 1\tau_2 - c1 - c2$$
$$A0 = n0/g0$$
$$A1 = (n1 - A0*g1)/g0$$
$$F0 = n2 - A0 - A1*g1$$
$$F1 = n3 - A1$$
$$r1 = [-g1 + g1^2 - 4*g0] / 2$$
$$r2 = [-g1 - g1^2 - 4*g0] / 2$$

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