CLASSIFICATION, PREDICTION, AND CRIMINAL JUSTICE POLICY

Final Report to the

National Institute of Justice

Stephen D. Gottfredson

Don M. Gottfredson

Justice Policy Research Corporation

June, 1990

This research was supported by grant number 86-IJ-CX-48 from the National Institute of Justice, United States Department of Justice. Opinions expressed are those of the authors and are not necessarily those of the National Institute of Justice or any other agency.

Table of Contents

Table of Contents (Contd.)

Acknowledgments

The authors wish to acknowledge the help of many people who provided support for the research reported here.

The individual background data for the study were collected with help from the prisoners who provided data about themselves; although, for the study described in this report, only "official record" data (extracted from either Department of Corrections case files or from arrest records) were used. Especially, we are indebted to a research team of about 30 prison inmates at the California Medical Facility in Vacaville, California. This team administered tests and questionnaires, scored and coded them, keypunched the data, conducted reliability studies, and performed statistical analyses. Direct supervision of this work crew was provided ably by Kelley B. Ballard, Jr.

Valuable assistance in the original data collection by coding needed data from the case files of the Department of Corrections was given by Dorothy Jaman, Alberta Greeley, Carlen Kreutzer, and Vera Fleming.

A reconstruction of the data file, the follow-up study coding and related work was done with the help of Patricia Harris, Lisa Graff, Doris E. Hunt, Dimitrious Papanikolaou, Myra Culver, and Mary Middlebrook. Research assistance, including the coding of the criminal history data for the follow-up study, was provided by students at the Department of Criminal Justice, Temple University including: Howard Anmuth; Rebecca Brown; Herman Carter; Tim Clark; Bonnie Cox; Robert Dashields; Debra DiGiuseppe; Lisa Freitag; Steven Grabania; Joanne Kelly; Russell Lowe; Theresa Massey; Renee McAlpin; Colleen Murphy; Stephen Morrison; Robert Petrone; Kay Pridgen; Chemtona Scott; Michelle Sralik; Judi Stadler; Anne Sterbenz; Faith Strawley; Jeffrey Skversky; Richard Van Aken; Janice Volpicelli; Kathleen Walsh; and Carol Whitman. Data coding at the California Department of Corrections was done by Karin Garnett, Katherine Gentry, Jay Henry, Jon Josue, and Margaret J. Nelson.

Staff of the California Department of Corrections were gracious and helpful in allowing us to use their archived files to identify data needed for obtaining the follow up arrest records, including Chris Gates, Bernice Faison, Dorothy Metz, and Cynthia Gummert. In the California Bureau of Criminal Statistics we were given all possible assistance by Quint Hegner, Steve Crawford, Charlotte Rhea and Teresa Rooney. Douglas A. Smith and Gary Maggy, of the California Bureau of Criminal Identification, helped us better understand the arrest record system, including the purging process. Appreciation is expressed also to Attorney General John K. Van de Kamp and Deputy Attorney General Brian Taugher, who made it possible to complete the needed record searches, through assignment of staff to overtime work. We have appreciated also the help of Dr. Richard Laymon, our Program Monitor for the National Institute of Justice, and of the Director of the Institute, James Stewart.

CLASSIFICATION, PREDICTION AND CRIMINAL JUSTICE POLICY

Executive Summary

Stephen D. Gottfredson

Don M. Gottfredson

Sentencing proposals emphasizing incapacitation have been met with interest and controversy. Some have promised to reduce the crime rate and prison populations simultaneously. This study examines such policies in the context of a long study of California male prisoners. The first data were collected in prisons in 1962-1963. Criminal records have been followed since. These data permitted a detailed study of classification and prediction issues critical to those policies. The evidence does not support them. It does suggest ways to reduce prison populations without endangering the public.

The most popular proposed strategy is selective incapacitation. Sentence lengths for some types of crime would be set on the basis of how much crime the offender is predicted to commit if not in prison. Predicted high rate offenders would serve more time than now required, predicted low rate offenders less. The net result sought would be reduced crime rates and, through this more selective and hence more efficient use of prison space, reduced prison populations. In this report we examine the technical and ethical problems of incapacitation proposals.

Neither have been resolved. Suggested policies cannot be implemented with acceptable levels of accuracy and fairness.

On the basis of the evidence from our study, we propose an alternative strategy for reducing prison populations. It avoids some of the problems confronting selective incapacitation yet provides a framework for reducing prison populations without appreciably increasing risks to society's stakes in public safety.

Study Results

This long term study of more than 2400 men showed that they continued to have much involvement with the criminal justice system. Only about one in five never were charged with another offense. These men were, on the average, in the community 21 years after prison release and arrested more than once every three years. Offenders who failed did so quickly; nearly a third were confined again within a year. More than half were again incarcerated within three years.

We classified offenses, on the basis of a prior study, according to how people generally group them and how seriously they are regarded. The major categories were called person, property, fraud, serious drug, and nuisance offenses. Person offenses were mainly assaults, murder, manslaughter, kidnapping, rape, and resisting arrest. Property offenses included burglary, robbery attempts, theft, and possessing stolen property. Fraud offenses were forgery or NSF checks, embezzlement, and other fraudulent crimes. The serious drug offense classification included the sale, distribution, or manufacture cf drugs. The nuisance classification included, most often, probation or parole rules violations, drunken driving, possession or use of drugs, and disorderly conduct.

By far, the later charges against these former prisoners were in the nuisance offense category. In the first arrest episode after prison release,the most serious charge was more often than not (56 percent) that of a nuisance offense. This did not change when subsequent charges were studied. In episode after episode, the most frequent, most serious post release charge was a nuisance offense.

In the first post release arrest episode (for all ever arrested) more than a fifth were dismissed or acquitted, but more than half were convicted. Seven percent of charges were for person offenses; one in four was for a property offense, and six percent involved fraud or deception. Fewer than one percent were charges of serious drug offenses. Of those convicted, two fifths were returned to prison, and about one fifth were given jailterms.

The repeated use of prison and jail was found also when later convictions were examined. Half the sample was incarcerated again from one to five times.

Not all failed. About a third were never confined again, and some persons were free for as long as 27 years.

Major resources were used repeatedly to confine the less serious offenders. The 2454 men were charged with many serious crimes: 68 murders, 101 kidnappings, 121 rapes, 885 robberies, 1,1736 non-commercial burglaries, hundreds of auto thefts, larcenies, and forgeries. But it is clear from these data that a large share of jail and prison space is devoted to dealing, over and over again, with the offenses classified as nuisances.

We developed methods for prediction of various outcomes after prison release. These compared favorably with similar studies. Prediction equations were described for the estimation of: the number of arrests to desistance; the number of arrests for nuisance, person, property, and fraud offenses; and the seriousness of the first post-release offense. Methods were described for the prediction of rates of arrest (for all offenders and for all but desistors). Other models were described to predict the number of charges to desistance and the number of charges for person offenses. Generally, the predictive power of the equations was modest. Their utility depends upon the application intended.

A Base Expectancy (risk) Scale developed in an earlier study was found to be as valid for this group of offenders, followed for a much longer period of time, as it was in an earlier validation study. The validity of this scale is modest but well established. Besides predicting return to jail or prison, the scores are related to the probability of arrest, arrest rates, and the number of arrests to desistance.

We examined offense transitions (crime switching) to investigate the extent of specialization and versatility in offending as measured by arrests and charges. We found stronger support for the specialization hypothesis than that reported in earlier studies. Generalization, however, was more pervasive. The analysis showed clearly that the most likely next offense charged, at any point in the sequence of arrest incidents, was a nuisance offense. The next most likely charge was an offense of the last type. The high base rate probability of nuisance offending overwhelmed the specialization effect.

Offense specialization did not increase over time, except slightly for nuisance and property offending. There was some complete specialization: about three out of ten of those re-arrested were charged with only one type of offense. The vast majority of these specialists, however, was arrested for nuisance offenses. And, of the 14,480 arrests counted, the specialist offenders were responsible for a small minority. (Some mixes of offenses were more often found than others: nuisance and property, and nuisance, person, and property. Mixes of person offenses with fraud or property offenses were uncommon.) Arrest rates were inversely related to specialization; the specialists had among the lowest and the generalists had among the highest.

A calculated risk in sentencing an offender requires taking account of both the odds of recidivism and the societal stakes at risk. Therefore, we investigated a classification based on both the probability of new offenses (risk) and the likelihood of serious harms (stakes). The risk measure used was the Base Expectancy Scale, estimating (best) the probability of return to incarceration. The stakes measure was the estimate, from this sample, of the number of arrests for offenses against persons.

The sample was divided into four groups by splitting it at the average scores for these two dimensions. A fourfold typology (High Risk, High Stakes; Low Risk, High Stakes; High Risk, Low Stakes; and Low Risk, Low Stakes) results. It discriminated significantly with respect to the probabilities of arrest and of incarceration and also as to rates of arrest for person, property, and nuisance offenses. It significantly sorted out also the rates of arrest for serious (non-nuisance) offenses.

Thus, the typology sorted offenders into the highest and lowest groups on the Risk X Stakes classification. The two fifths of the sample classified as High Risk / High Stakes offenders had the highest rates of arrest, incarceration, and charges for serious crimes. The one fourth of the sample classified as Low Risk / Low Stakes offenders had the lowest probability of arrest and of incarceration, the lowest arrest rate, and the lowest rates of charges for offenses against persons or property.

Selective Incapacitation

The evidence from these data that would be desirable from the perspective of developing incapacitative policies involve prediction, offense specialization, and characteristics of the arrest rate. The results do not support incapacitation on six counts. First, predictive validity was, as usual, quite modest. Second, specialization was relatively rare; versatility in offending was the norm. Third, specialization did not, in general, increase with greater numbers of transitions. Fourth, the next arrest, from any offense category, was likely to be an arrest for a nuisance offense. Fifth, arrest rates were inversely related to specialization. Sixth, they declined with age.

An examination of ethical issues arising from the concept of selective incapacitation, together with current evidence on the validity of prediction, lead us to conclude that such proposals for radical change in sentencing or correctional policies based on individual level prediction are at best premature.

Selective Deinstitutionalization

Persons may be classified on both the risk and stakes dimensions. Persons classified as high on both would be expected, under the strategy proposed here, to be the candidates for incapacitation if the policy is that prisons are to serve that purpose. They would not, however, serve more prison time than believed to be deserved --- that is, they would not be kept longer in prison simply as a result of the classification. Those classified as low on both dimensions would be expected to be the candidates for deinstitutionalization. The array of possible sanctions, from release with suspended sentences through probation with various levels of supervision and other alternatives with differing levels of custody and security would be graded proportionately to the combination of risk and stakes presented by the offender.

A policy of selective deinstitutionalization --- with identification, for example, of Low Risk, Low Stakes offenders who would be considered for release in population reduction programs or less often considered for incarceration --- may be both technically feasible and ethically sound. This proposal requires no radical changes in current sentencing and imprisonment policies but does require that an incapacitative purpose is regarded as a legitimate concern in decisions aimed at prison population reduction. The selective deinstitutionalization concept, based on a conceptualization and measurement of both stakes and risk, ameliorates some of the ethical concerns and holds promise for reducing prison use (and crowding) without endangering the public.

When many states and the federal government are faced with fast growing prison populations, ever increasing problems of crowding, and a resulting huge economic burden, it should be considered whether the question of who to imprison has been asked in just the right way. Rather than ask who should be incapacitated, it may be more helpful to ask which offenders need not be confined for an incapacitative purpose.

At first, that may seem to be the same question, as in two sides of a coin or the cup half empty or half full. If a modestly valid prediction method is used, however, to help answer the questions, then the ethical issues that arise are different in the two cases. With a selective incapacitation strategy, the aim is to minimize "false negatives" --- that is, we would wish to minimize the failure to select those who in fact pose a substantial risk of continued criminal behavior. Unless predictive accuracy can be increased, reducing false negatives (failing less often to identify those who will do harm) can be done only at the expense of increasing "false positives" (more often confining people unnecessarily). With a selective deinstitutionalization strategy, the aim is to select those offenders who present the least risk of repeated serious harm. It is again the case that "false positives" will be punished more harshly than will those selected for non-confinement (or release) based on the selection criteria. The critical distinction is that they will not be punished more harshly than they would have been had prediction not been used. Rather than treating some persons more harshly than is believed to be justly deserved, this proposal treats no one no more harshly than that but some persons less harshly than that. Moreover, if offense specialization is not very common, if the next offense is likely to be a nuisance offense rather than a serious harm, and if arrest rates decline with age, these circumstances favor a selective deinstitutionalization strategy over a policy of selective incapacitation.

These results should be confirmed by testing the classification and prediction methods on different samples. Also, further examination of the distributions of scores and of optimal cutting points for deinstitutionalization strategies is needed.

The policy maker may seek not only punishment, even if deserved, but may also try to look forward to the consequences of sanctioning policy, considering both societal protection from crime and the differential human and monetary costs of imprisonment and alternative sanctions. The selective deinstitutionalization of offenders presenting lower risk and lower stakes could provide a framework for such a policy.

Tables and Figures

(In Order, Following Text)

Tables

Tables (contd.)

Tables (contd.)

Figures

Figures (contd.)

Figures (contd.)

Figures (contd.)

CLASSIFICATION, PREDICTION, AND CRIMINAL JUSTICE POLICY

Chapter I

Classification, Prediction, and Incapacitation

Policy questions of central importance to the criminal justice system rely, for successful implementation, on the reliable and valid classification of convicted offenders based on predictions of their future behavior. Thus, many critical scientific questions arise from popular but controversial crime control strategies such as selective[1] and collective[2] incapacitation. These have received wide attention in the public press,[3] and have stimulated much scholarly debate about both the scientific and ethical issues involved.[4]

---

1 Greenwood, P., and Abrahamse, A., Selective Incapacitation. Santa Monica, California, Rand Corporation, August, 1982.

2 Cohen, J., "Incapacitation as a Strategy for Crime Control: Possibilities and Pitfalls," 5 Crime and Justice: An Annual Review of Research. Tonry, M. and Morris, N., eds., Chicago: University of Chicago Press, 1983, 1 - 84.

3 To Catch a Career Criminal," Newsweek, November 15, 1982, 77; "Cutting Crime Tied to Jailing of the Busiest Criminals," The New York Times, October 6, 1982; "Key to Criminals' Future: Their Past," U. S. News and World Report, October, 1982; "Making Punishment Fit Future Crimes," The New York Times, November 14, 1982, p. E-9.

4 von Hirsch, A., and Gottfredson, D.M., "Selective Incapacitation: Some Queries About Research Design and Equity," New York University Review of Law and Social Change, 12, 1, 1983 - 1984; Cohen, J., supra note 2; Greenwood, P. and von Hirsch, A., "Selective Incapacitation: Two Views of a Compelling Concept," NIJ Reports, Washington, D.C., National Institute of Justice, December, 1984, 4 - 8; Cohen, J., "Incapacitating Criminals: Recent Research Findings," Research in Brief, Washington, D.C., National Institute of Justice, December, 1983; Gottfredson, S.D. and Gottfredson, D.M., "Selective Incapacitation?," Annals of the American

These concepts of incapacitation provide an illustration of the relevance of classification and prediction topics to criminal justice policy choices; but it should be noted that the concerns addressed are central to any crime control strategy. If we are to be able to control events, we first must be able to predict them. Moreover, issues of classification, often with a predictive intent, lie at the heart of each of the major points of decision that characterize the criminal justice system process.[5]

Efforts to improve criminal justice classification and prediction tools have been impeded seriously by a lack of adequately reliable, comprehensive data on substantial samples of offenders followed long enough to yield the most useful information. Especially lacking are long-range data on outcomes of the criminal justice process. Such data are costly in time, money, and effort; and, if data are collected prospectively in a longitudinal study, patience is required while awaiting the determination of the outcomes.

As a result, much research in classification and prediction has yielded tools that are of questionable validity or subject to myriad other limitations. These often include: severely limited generalizability due to sample selection biases; markedly

---

Academy of Political and Social Science, 478, March, 1985, 135 - 149.

5 For extensive discussion of the relation of classification and prediction methods to decisionmaking at each step in the criminal justice process, see Gottfredson, M.R. and Gottfredson, D.M., Decisionmaking in Criminal Justice: Toward the Rational Exercise of Discretion. Cambridge, Massachusetts: Ballinger, 1980. For a review of these methods, see Gottfredson, D.M. and Tonry, M. (eds.) Prediction and Classification: Criminal Justice Decision Making. Volume 9 of Crime and Justice: A Review of Research. Chicago: University of Chicago Press, 1987.

circumscribed data on the offense, offender, and criminal justice system response; little or no data on the placements of the offender during the sentencing and correctional process; and a short period of data collection after conviction or release.

Despite recent advances in the sophistication of statistical classification and prediction methods, the fundamental problems of data quality and follow-up study of sufficient length still limit seriously the power that should derive from these methods. The potential is there, but practical utility is restricted. Comparisons of available methods for combining predictors show that, with data usually available for prediction studies in criminal justice, simple methods lacking in statistical sophistication may work as well, or nearly so, as their more theoretically apt alternatives.[6] It is plausible that this is due in part to the generally poor quality of available data.

Despite advances in classification,[7] available methods have been little used to define subgroups of offenders for whom

---

6 See, for example, Gottfredson, S.D. and Gottfredson, D.M., Screening for Risk: A Comparison of Methods. Washington, D.C.: National Institute of Corrections, 1979; Gottfredson, S.D. and Gottfredson, D.M., "Screening for Risk," Criminal Justice and Behavior, 1980, 7(3), 315 - 330; Simon, F.H., Prediction Methods in Criminology. London: Her Majesty's Stationery Office, 1971; Solomon, H., "Parole Outcome: A Multidimensional Contingency Table Analysis," Journal of Research in Crime and Delinquency, 1976.

7 Brennan, T., Multivariate Taxonomic Classification for Criminal Justice Research Volumes I, II, and III. Silver Spring, Maryland: National Criminal Justice Reference Service, 1981; Cormack, R.M., "A Review of Classification," Journal of the Royal Statistical Society, 3, 321 et seq.; Brennan, T., "Classification: An Overview of Methodological Issues,: in Gottfredson and Tonry, note 5 supra, 201 - 248.

traditionally used prediction methods may be applied sequentially in a plausible "statistical bootstrapping" procedure.[8]

The power of available prediction methods may be described as "modest at best."[9] It might be improved by better reliability of the predictor information used, with larger samples, longer follow up study, and improved measurement of recidivism.

Despite recent attention to the "criminal career" and to the "career criminal," little is known of long-term patterns of criminal activity.[10] The influential Rand studies were based on the retrospective self-reports of criminal activity by inmates in non-representative samples,[11] with no validation of the predictive utilities claimed. The report of the National Academy of Science's

---

8 Gottfredson, S. D., "Prediction: An Overview of Selected Methodological Issues," in Gottfredson and Tonry, note 5, supra, p. 45; for an early attempt, with some success despite small samples, see Gottfredson, D. M., and Ballard, K.B., Jr., Offender Classification and Parole Prediction. Vacaville, California: Institute for the Study of Crime and Delinquency, December, 1966.

9 Gottfredson, S. D. and Gottfredson, D. M., "Accuracy of Prediction Methods," in A. Blumstein et al, (Eds.), Research in Criminal Careers and "Career Criminals." Vol 2., Washington, D.C.: National Academy Press, 1986.

10 For reviews of that which is known, see Wolfgang, M., Figlio, R., and Sellin, T., Delinquency in a Birth Cohort. Chicago: University of Chicago Press, 1972; Farrington, D., "Longitudinal Research on Crime and Delinquency," in N. Morris and M. Tonry, (Eds), Crime and Justice: An Annual Review of Research. Chicago: University of Chicago Press, 1979; Wolfgang, M., Tracy, P., and Figlio, R., manuscript, 1986.

11 See Peterson, M., Chaiken, J., Ebner, P., and Honig, P., Survey of Prison and Jail Inmates: Background and Method. Santa Monica, California: Rand Corporation, August, 1982; Marguis, K., and Ebner, P., Quality of Prisoner Self-Reports: Arrest and Conviction Response Errors. Santa Monica, California: Rand Corporation, March, 1981; Chaiken, J. and Chaiken, M. Varieties of Criminal Behavior. Santa Monica, California: Rand Corporation, August, 1982; Petersilia, J., Honig, P., and Hubay, C., The Prison Experience of Career Criminals. Santa Monica, California: Rand Corporation, May, 1980.

panel on this subject provided little reason to change Petersilia's 1980 conclusion:

> the data accumulated to date on criminal careers do not permit us, with acceptable confidence, to identify career criminals prospectively or to predict the crime reduction efforts of alternative sentencing proposals.[12]

This study focused on classification and prediction issues for incapacitation strategies as they might be used by the judiciary or by sentencing guidelines commissions in sentencing decisions, or by a paroling authority in deciding whether or when to parole. The concepts used are relevant to both general policy (institutional) decisions and individual (case) decisions.

To set the stage for description of the objectives and procedures used, the concepts of collective and selective incapacitation will be reviewed. Then, the concept of "stakes," which is related to that of "risk" as conventionally used in criminal justice, will be introduced. This concept will be used in devising incapacitative strategies that may provide alternatives to those proposed by others. It is necessary also to discuss measures of crime seriousness, since we used use a novel, multidimensional measure of seriousness in a process aimed at the improved measurement of the "stakes" concept. These considerations will lead, in turn, to a proposed classification and prediction model that is thought to hold promise for practical use.

---

[12] Petersilia, J., "Criminal Career Research: A Review of Recent Evidence," in N. Morris and M. Tonry, eds., Crime and Justice: An Annual Review of Research. Chicago: University of Chicago Press, 1980, 322.

Collective vs. Selective Incapacitation Strategies

Under a collective incapacitation strategy, the same or very similar sanction would be applied to all persons convicted of common offenses; a selective incapacitation strategy involves sentences based on predictions of future rates of offending.[13] Studies of collective incapacitation effects are rare and report widely varying potential effects (ranging in estimated crime reduction effects of from one to 25 percent, depending upon crime rate assumptions and crime types considered).[14] When mandatory terms are considered, expected crime reduction efforts are somewhat larger, but probable impacts on prison populations appear unacceptable given the modest impact on crime.[15]

Studies of selective incapacitation strategies also are rare and also report varying potential impacts on crime and prison populations.[16] In general, selective incapacitation strategies are of two types: those that make use only of information concerning criminal history and current offense (as in the Cohen and Blumstein studies) and those that make use of a wider variety of information thought to be predictive of rates of offending (as in the Greenwood and Abrahamse study). As already noted, the latter has been criticized on ethical and empirical grounds; the former requires complex estimates of average individual arrest and crime rates and

---

13 Cohen, <u>supra</u> note 2.
14 ibid., Table 1.
15 ibid., Tables 2 and 3.
16 Blumstein, A., and Cohen, J., "Estimation of Individual Crime Rates from Arrest Records," <u>Journal of Criminal Law and Criminology</u>, 1979, <u>70</u>, 561 - 585; Greenwood, <u>supra</u> note 1; Cohen, J., <u>Patterns of Adult Offending</u>, unpublished Ph.D. dissertation, Carnegie-Mellon University, 1982.

estimates of average lengths of criminal careers. Either general strategy depends heavily upon (1) questionable assumptions, (2) predictive power, and (3) the accuracy of estimates made. Considerably more research will be required before either may be applied in practice with sufficient predictive validity and with equity. The scientific and ethical problems are intertwined,[17] and both present formidable obstacles to the practical implementation of incapacitation strategies.

Stakes and Risk: Incapacitative Intent in Sentencing Decisions

Studies of sentencing consistently have found some measure of offense seriousness to be an important correlate of the decisions made. This is true both with respect to the decision to incarcerate the convicted offender and the determination of the length of confinement if incarcerated.[18] Although defined differently in various studies, the rated seriousness of the crime for which the person has been convicted appears to provide a strong influence on sentencing decisions. Similar findings obtain with respect to decisions made by prosecutors, magistrates at bail setting, and parole boards.[19]

Similarly, many studies support the contention that offender prior criminal history is influential in decisions at these and other critical steps in the criminal justice process. This variable

---

17 von Hirsch and Gottfredson, supra note 4; Gottfredson, S.D., and Gottfredson, D.M., "Selective Incapacitation?" supra note 4.

18 Gottfredson, M.R. and Gottfredson, D.M., supra note 5.; Blumstein, A., et al, Research on Sentencing: The Search for Reform. Washington, D.C.: National Academy Press, 1983; Gottfredson, S.D. and Gottfredson, D.M., supra note 9.

19 Gottfredson, M.R. and Gottfredson, D.M., idem.

too has been defined variously, and results with it are more mixed; but on the whole the evidence is persuasive that the prior criminal record is influential (though less so, in general, than the offense seriousness) in the determination by a magistrate whether to release an accused person without bail, in the prosecutor's decision whether to charge, in the sentence imposed by a judge, and in the decision by a paroling authority whether or when to release from custody.[20] Thus, concepts of offense seriousness and of prior criminal record help explain decisions throughout the criminal justice system.

For convenience, subsequent discussion will focus on sentencing. The generality of the importance of the concepts of seriousness and prior record for decisions elsewhere in the system of criminal justice, however, should be borne in mind. These findings of the relevance of crime seriousness and prior criminal record to criminal justice decision making are noted not because they are unexpected but because they support the contention that much of sentencing (and other criminal justice decision making) is consistent with a desert theory of punishment.[21] This orientation stands in sharp contrast to current interest in and debates about incapacitation that are based on prediction. Indeed, the fundamental debate, from a perspective of the philosophy of law, is between the desert perspective and a consequentialist orientation. The latter could include not only incapacitation as an aim, but

---

20 Gottfredson, M.R. and Gottfredson, D.M., idem.

21 von Hirsch, A., Doing Justice: The Choice of Punishments. New York: Hill-Wang, 1976; Past or Future Crimes: Deservedness and Dangerousness in the Sentencing of Criminals. New Brunswick: Rutgers University Press, 1985.

also the purposes of rehabilitation and deterrence. Thus, judges may -- and the evidence supports that they do -- have retributive or desert perspectives; but other judicial orientations also may be influential.[22] If so, research on sentencing has not reflected them adequately. It may be contended that judges do make subjective judgments of risk, do have -- at least as one sentencing purpose -- incapacitative intents, and do make selective allocations, with an incapacitative intent, in disposing of cases.[23] Evidence that this is the case, however, has been scarce.

If it is thought that judges seek an incapacitative objective in sentencing decisions, it is important to question why this has not emerged from analyses of those decisions. This may be due in part to the circumstance that judges rarely systematically record either their judgments as to risk (of reoffending) or as to the incapacitative intent (if any) of the sentence at the time it was imposed. It may be due in part also, however, to an inadequate conceptualization of the concept of "risk," failing to differentiate it from the concept of "stakes."

The concept of "stakes," familiar to gamblers, is important to decisions made under uncertainty. This is obvious in games such as roulette or craps, when not only the odds of winning or losing a bet (risk) but also the amount of the wager (stakes) are considered by the prudent gambler. Thus, the expected value of a given bet may

22 The evidence from a study by one author of this report clearly supports this: judges studied indicated their main purposes in a sample of sentences studied, with percentages as follows: Incapacitation (4%); Special Deterrence (9%); Retribution (17%); Rehabilitation (36%); Other Purpose (including General Deterrence) (34%). For details, see Gottfredson, M.R., and Gottfredson, D.M., supra note 5.

23 Greenwood and Abrahamse, supra note 1.

be taken as the product of the probability of winning and the amount at risk (the wager).[24]

If the concept of "risk" is limited to some assessment of the probability of any reoffending (or probation or parole violation) -- as is the case when very limited criteria of recidivism are used (as in most criminological prediction studies with a dichotomous criterion of "success" or "failure") -- then an analysis of the sentencing decision may fail to take account of the concept of "stakes" as it may be considered in the sentencing decision. If the concept of risk is limited to an assessment of the likelihood of membership in a class of "high rate" offenders of a given type, as in the Rand study, then some amount of the variability in the seriousness of subsequent crimes is ignored, reducing the opportunity to find predictive information that may be useful in programs intended to reduce new serious crimes by previously convicted offenders. The latter problem may be exacerbated if, as in the Greenwood study, the search for predictive information is limited to study of a subgroup of imprisoned offenders, such as those convicted of burglary or robbery.

These issues lead to a new way of conceptualizing both the prediction problem and the issue of incapacitation. If the sentencing judge (parole board member or other criminal justice decisionmaker deciding on individual case dispositions) has an incapacitative intent, then it may be assumed that, in a rational

---

24 For a general discussion of mathematical decision theory, see Lee, W. Decision Theory and Human Behavior. New York: Wiley, 1971, or Edwards, W. The theory of decision making. Psychological Bulletin, 51(4):380-417, 1954; Behavioral Decision Theory. Annual Review of Psychology, 12:473-498, 1961.

decisionmaking strategy, information will be sought that is relevant to:

1. The likelihood of new offenses (risk);
2. The degree of seriousness of the harm expected if new offenses are committed (stakes); and
3. the combination of these two concerns (i.e., the conditional probabilities of risk and stakes).

These concerns of risk and stakes are thus conceptually separate, and measures of them may be relatively independent. For example, an offender might be identified as a "good risk" in terms of low probability of (any) new offenses if released from custody but as presenting a high degree of potential harm to the community if the prediction of no new offending proves to have been in error. An example might be an older person, never in prison before, with no known history of drug or alcohol abuse, who has a record of steady employment, and who is classified on the basis of these attributes as a relatively "good risk." The person is, however, to be sentenced for a homicide conviction, and further review of his history shows that one prior conviction, resulting in a jail term, was for assault with a deadly weapon (pistol). Thus, although the probability of a new offense is low, there may be a concern that if a new offense does occur it may involve an offense against a person. It may be said that the risk is low but the stakes are relatively high.

The converse circumstances may obtain. An example might be a younger man who has been convicted repeatedly of minor thefts. His repeated convictions place him in a "poor risk" category; but the absence of evidence of more serious crimes gives little reason to expect worse than continued nuisance behavior. He might be said to be a "high risk, low stakes" offender.

The conceptual model suggested by these assumptions is similar in its general nature to guidelines developed elsewhere for paroling,[25] sentencing,[26] and bail[27] decisions. Central to this model is a matrix, grid, or chart. In the guidelines models cited, it is commonly the case that some measure of "seriousness" is included on one axis, and some "risk" measure is included on the other.[28]

In the paroling and bail decision models cited, the risk dimension is empirically derived and the rationale for its use generally reflects an incapacitative intent. The rationale for including the seriousness measure is more complex; and it may reflect a desire on the part of the decision makers to satisfy simultaneously several (potentially competing) goals. In the paroling example, satisfaction of desert provided partial

---

25 Gottfredson, D.M., Wilkins, L.T., and Hoffman, P.B., Guidelines for Parole and Sentencing: A Policy Control Model. Lexington, Massachusetts: Lexington Books, 1978.

26 ibid.; Wilkins, L.T., Kress, J., Gottfredson, D.M., Calpin, J., and Gelman, A., Sentencing Guidelines: Structuring Judicial Discretion. Washington, D.C.: U.S. Government Printing Office, 1978.

27 Goldkamp, J.S. and Gottfredson, M.R., Policy Guidelines for Bail: An Experiment in Court Reform. Philadelphia, Pennsylvania: Temple University Press, 1985.

28 In Minnesota, risk of reoffending was explicitly rejected as a dimension to be used in the model developed and implemented. Minnesota Sentencing Guidelines Commission, Preliminary Report on the Development and Impact of the Minnesota Sentencing Guidelines. St.Paul, Minnesota: Minnesota Sentencing Guidelines Commission, 1982. Items comprising the scale, however, are known to be associated with the risk of reoffending.

justification, but in the bail example, offense seriousness was included, according to the developers of the model, in order:

> specifically to counter the thrust of the risk dimension ...(judges) felt the need for a gauge that allowed them to weigh the differential costs associated with the risks posed by defendants, reasoning, for example, that a high risk numbers runner poses a different cost to the decisionmaker than does a low risk rapist -- should the decision go awry.[29]

Clearly, these judges considered "stakes" as a desired component of the decision process, although the concept was not articulated clearly and was not measured as an independent concern.

Recently, we tested the hypotheses that measures of risk and of stakes, and their interaction, were significantly related to the "in/out" (incarcerate/not) sentencing decision and to the length of confinement served.[30] Data used were a sample of sentences in New Jersey for which judges had provided risk judgments and their purposes in sentencing. The hypothesized relations of both "risk" judgments and a measure of "stakes"[31] to dependent measures of incapacitation were confirmed; and so was the interaction effect (stakes x risk). The explanatory power of equations using only the "risk" and "stakes" measures to account for variation in sentences compared favorably with most studies in the literature using legal variables such as offense and prior record.

---

29 Goldkamp and Gottfredson, 1985, <u>supra</u> note 27, at 39.

30 Gottfredson, D.M., Gottfredson, S.D., and Conly, C. Stakes and Risk: Incapacitative Intent in Sentencing Decisions. <u>Behavioral Sciences and the Law</u>, 1988, <u>7</u>(1), 91-106.

31 These were relatively independent; $r = .29$ with $N > 700$.

Crime Seriousness Measures

A major development in the measurement of recidivism has been the effort to improve upon simple success/failure outcomes through assessment of the seriousness of criminal acts. Measurement of the seriousness of crimes dates from Thurstone,[32] and replications suggest that these judgments remain remarkably stable over time.[33] Others, using similar methods, have developed more comprehensive schemes.[34]

Gottfredson, Warner, and Taylor took a multidimensional approach to the scaling of offense seriousness. Using principal components analyses of 1024 subjects' judgments of the seriousness of hundreds of discrete criminal acts, they observed that six dimensions apparently underlie people's judgments of such acts. Since the resulting method of measurement of seriousness was used in this study, these dimensions will be described briefly.

The first dimension, which represented 11 percent of the variance after rotation, can be interpreted in a number of ways. Many of the offenses which load heavily on this component are

---

32 Thurstone, L.L., "The Method of Paired Comparisons for Social Values, <u>Journal of Abnormal and Social Psychology</u>, 1927, <u>21</u>, 384 - 400.

33 Coombs, C.H., "Thurstone's Measurement of Social Values Revisited, Forty Years Later," <u>Journal of Personality and Social Psychology</u>, 1967, <u>6</u>, 91-92; Krus, D.J., Sherman, J.L., and Krus, P., "Changing Values over the Last Half-century: The Story of Thurstone's Crime Scales," <u>Psychological Reports</u>, 1977, <u>40</u>, 207-211.

34 Sellin, T., and Wolfgang, M., <u>The Measurement of Delinquency</u>, New York: Wiley, 1964; Rossi, P., Waite, E., Bose, C., and Berk, R., "The Seriousness of Crime: Normative Structure and Individual Differences," <u>American Sociological Review</u>, 1974, <u>39</u>, 224 - 237; Gottfredson, S.D., Warner, B.D., and Taylor, R.B. "Conflict and Consensus in Justice System Decisions," in N. Walker and M. Hough, (Eds.), <u>Sentencing and the Public</u>. Cambridge Series in Criminology. London: Gower, 1988.

"nuisance" crimes: prostitution, gambling, use and possession of marijuana, adultery, disorderly conduct, homosexual acts, exposures. It is clear from the standardized item means that in general, people view crimes that loaded on this dimension as relatively non-serious.

The second component (seven percent of the variance after rotation) involves physical assault, personal harm, and interpersonal confrontation. The third component (12 percent of the variance after rotation) equally clearly represents theft, property damage or loss, and property crimes in general.

The fourth dimension, which also accounts for a reasonable portion of the variance after rotation (six percent) seems to represent crimes against the social order. In general, these are either crimes that are committed by an agent or agency in power (an employer, a real estate agent, a police officer, a manufacturer, a producer, a doctor, a public official), or social crimes (i.e., against groups, e.g., racism, the pollution of a water supply, the marketing of contaminated products, price-fixing, false advertising), or both.

The fifth and sixth dimensions, while relatively small (four and five percent, respectively, of the variance after rotation) and defined by relatively few items, were nonetheless readily interpretable. Offenses loading on the fifth dimension (with two exceptions) all involved serious drug offenses: the sale or manufacture of heroin, hallucinogens, or barbiturates and amphetamines. Offenses loading on the sixth (and final) dimension by-and-large involved fraud or deception.

While Gottfredson et al. discovered a clean and clear-cut six-dimensional structure that may underlie people's judgments of offense seriousness, that structure quickly would lose some of its conceptual utility if in fact the dimensions merely represented "ranges" along a single underlying dimension. That is, it clearly would be of little interest simply to know (for example) that people generally judge vice-type offenses as less serious than assaultive, confrontational offenses, and that factor-analytic techniques can demonstrate this fact. In order for a dimensional structure to be theoretically and conceptually heuristic, we would like the distinction among factors or dimensions not to be simply one of relative magnitude. In fact, however, these dimensions substantially overlap one another along the "first-order dimension" of overall judged seriousness.

One power of this dimensional approach to the scaling of offense seriousness is that it allows a ready coding both of the seriousness and of the nature of criminal offenses, thus allowing for a study of transitions, in criminal careers, both across seriousness dimensions and within the overall concept of seriousness. Schemes for coding criminal histories using this novel approach were developed in earlier projects,[35] and the method has been found useful for the prediction of criminal recidivism.

---

[35] Gottfredson, S.D., and Taylor, R.B.,"Person-environment Interactions in the Prediction of Recidivism," In J. Byrne and R. Sampson, (Eds.), The Social Ecology of Crime, New York: Springer Verlag, 1986; Gottfredson, S.D., and Taylor, R.B., Community Context and Criminal Offenders, in T. Hope and M. Shaw (Eds.), Communities and Crime Prevention. London: Her Majesty's Stationary Office, 1988.

Problem Summary

As motivation for our study, we assumed that:

1. There is a need, in classification and prediction research, for follow-up study of a substantial group of offenders over a substantial period of time;
2. Sampling and data quality problems have limited the utility of available data sets for classification and prediction research;
3. Presently available incapacitation strategies, whether for collective or selective incapacitation, have been limited by faulty designs, weak conceptualizations, or inadequate data requiring estimations based on heroic assumptions;
4. The concept of "stakes" should be included in an incapacitative decision policy strategy, as well as that of "risk," but this distinction has not been made previously and the suggested research has not been done;
5. Detailed measures of "crime seriousness," taking account of the multidimensional nature of the concept of seriousness of crime, should be included in assessments of the potential of any proposed models for incapacitative strategies because the concept of crime seriousness is central to the dimension of "stakes" assessments.

Our goal was to extend the theoretical and practical utility of the available research results on classification, prediction, and incapacitation by:

1. Focusing on a large adult population of offenders known to be quite heterogeneous and representative of the California prison population in 1962 -1963, for whom more than 20 years of follow - up after release from prison now could be obtained from official records;
2. Requiring that few, straightforward, estimates of the dangers of reoffending and of the length or seriousness of criminal careers be made (possible because of the available 20 year follow-up period); and
3. Providing a strategy for comparing several selective and collective incapacitative approaches, including current models and a new conceptualization incorporating the concepts of stakes as well as risk.

More specifically, we sought to:

1. Develop a measure of "stakes," on the basis of background information on offenders available at the time of sentencing, that is comprised of demonstrably relevant items related to the seriousness of subsequently committed new offenses. It should be noted that the "stakes" measure described above had, in the previous study, some validity for the prediction of sentencing decisions; there was, however, no evidence of validity in respect to the commission of serious harms in the community. The "stakes" measure seemed to reflect a use of certain data by judges in making their decisions when an incapacitative purpose is involved; but there was yet no evidence of the validity of these data in relation to

that sentencing objective. Thus, an empirical investigation of the relations of the "stakes" items used, and of similar ones, was thought to be needed in order to develop a measure of "stakes" that is demonstrably related to the likelihood of serious person offenses.[36]

2. Compare the relative validities of measures of "risk," such as those proposed by Greenwood for use in selective incapacitation strategies,[37] by Gottfredson (various scales called "base expectancy" measures that have been used extensively in California and after which a number of related prediction methods have been patterned),[38] and the "stakes" measure to be developed in this study. We intended the latter scale to be more directly related to the prediction of levels of seriousness of new offenses, of several types (rather than a dichotomous criterion of "success" or "failure" or membership in a class of "high rate" offenders).

3. Provide a means of comparing incapacitation strategies;

4. Test, in a validation sample, the utility of an incapacitative strategy based on the interaction of "risk" and "stakes" measures. Resource limitations did

---

36 Although this relation obviously must be an important part of the conception of "stakes," there are other factors that may play a role. For example, the probabilities of unfavorable publicity, criticism by superiors or by legislative bodies or by peers, may present "stakes" concerns in decisions.

37 Greenwood, P., 1982, <u>supra</u> note 1, at 50.

38 Gottfredson, D.M., and Bonds, J.A., <u>A Manual for Intake Base Expectancy Scoring</u>. Sacramento, California: California Department of Corrections, mimeo, 1961.

not allow us to meet this final goal during this project period. We intend, however, to complete these validation studies later.

Chapter II

The Class of 1962 -1963

Before describing the procedures used in seeking the objectives described in Chapter I, a further overview of the sample studied, the data collection methods used, and a little more background of several of the scales used is in order. The purpose of this chapter is to provide it.

The Prisoner Sample

This study is about male prisoners of the early 1960s and what became of them so far as revealed by their later criminal records. The data used that are descriptive of their personal histories and the offenses that brought them to prison in California at that time were collected by one of the authors in 1962 - 1963.[39] Their most frequent offenses of conviction were burglary (18 percent) and armed robbery (12 percent). Five percent were sentenced for homicide or manslaughter, nine percent for other violent offenses, and 16 percent for narcotics offenses. Fifteen percent were sentenced for forgery or fraudulent checks; a quarter had been convicted of various other property crimes. A substantial portion (43 percent) had a history of assault, and nearly a fourth had a

[39] These data were collected for research supported by Public Health Service Grant CM 823 from the National Institute of Mental Health. See Gottfredson, D.M., and Ballard, K.B., Jr., Prison and Parole Decisions: A Strategy for Study. final report to the National Institute of Mental Health, 1965: this document includes summaries of most of the reports and articles resulting from the project and citations to them.

record of use of a pistol or gun. One in ten had used knives as weapons. A fourth had used opiate drugs (typically heroin). Fifty-six percent had been in prison before.

Prisoner Data

The descriptions of these data, with detailed definitions, flow charts depicting the processes of data collection, and descriptions of the structures of the files, fill several large binders; and space here permits only the most general description, as provided below. The random process used for sample selection assures that as a whole it may be considered representative of all men in prison in California at the time. General categories of data on hand for these prisoners include: life history data;[40] official institutional record data (for a random subsample of 1,299 persons);[41] inmate questionnaire data (from 3,652 men and most of the women);[42] and psychological test data (from 3,975 persons) collected with unusual attention to reliability.[43]

---

40 Offense, prior criminal record, offense seriousness (various rating scales), type of admission, birthdate, sentence, date of admission, marital status, educational history, work history, grades claimed and measured, intelligence classification, drug use history, Base Expectancy (parole prediction) score, and other items.

41 Custody classification, work assignment, vocational training, education, disciplinary infractions, counseling, therapy, visits and correspondence, and other items.

42 These data include extensive self reports on program participation, attitudes, perceptions, and complaints.

43 A great deal of attention was given in the study to this aspect of the data collection. The file includes the <u>California Psychological Inventory</u> and a variety of scales derived from it, parts of the <u>Minnesota Multiphasic Personality Inventory</u>, scales measuring self esteem, inmate cohesion, self conception, anomie, attitude toward authority, interpersonal maturity, various "faking" scales, and other measures (citations omitted but available upon request). Much of these unusually rich and detailed data were not needed for

Follow-up Data for the Study Sample

Follow-up data were collected for the male offenders in the sample. The analyses presented in this report are limited to a randomly selected half (3,088 men). In order for the California Bureaus of Criminal Statistics and Criminal Identification to succeed in finding the current records on men in this sample, the staff needed as much identifying information as possible. As a result, it was necessary first to code additional data from microfilm records in the California Department of Corrections which usually provided the full name and a date and place of birth and often provided also a CII number. A small portion of the microfilmed records (of five by eight cards with handwritten entries) in the Department of Corrections was missing, but this resulted in the loss of only a few records. Another portion of the sample was men for whom no record was found by the Bureau of Criminal Statistics.[44] Due to a California court order, all references to arrests with alleged offenses involving marijuana were to be removed from the records before they were provided to us, so this exception to the arrest records available for our study should be noted.

---

the study reported here; further studies are in progress investigating the classification utilities of these data linked to the now available follow-up data resource.

44 Some unknown portion of this group may be due to error in the CII system but most most probably is due to a periodic purging of records in which some old cases are removed (discussed subsequently).

The Bureau of Criminal Identification of the California Department of Justice is the state repository for arrest (and applicant) records. In 1973 an automated information system was initiated for the gradual automation of all files. A user's guide describes this system and the data it contains.[45] The Bureau provided us with computerized records for those men in our sample whose files had been entered into this system, and the BCI staff manually prepared records for the rest.

The sample of men for whom records were requested was divided randomly in half, in order to provide a study sample and a potential validation sample. There were 3,088 persons in the first sample. As will be explained later, the study sample was further subdivided in various ways for a potential improvement in predictive efficiency. Typically, equations are solved to define a prediction equation based on the correlation matrix for the entire sample, but the coefficients in such a matrix may not provide adequate estimates of these parameters for identifiable subgroups. Further, there is evidence that more valid prediction may be achieved when demonstrably different such groups are first defined by clustering methods, then equations derived on the basis of the observed relations within them.[46] Research of this last type is still in progress, and is not included in this report.

---

45 Bureau of Criminal Identification, Department of Justice, State of California, Criminal History User's Guide. Sacramento, California: California Department of Justice, March, 1987.

46 See Gottfredson, D.M. and Ballard, K.B., Jr., Offender Classification and Parole Prediction. Vacaville, California: Institute for the Study of Crime and Delinquency, December, 1966.

The limitations of arrest records for the purposes of the study are well known, and we have described the major ones elsewhere.[47] Since, however, the focus of this research was on classification and prediction related to the arrests and convictions subsequently for new serious offenses, these limitations appeared to be acceptable; and in any case it is on the basis of official records that practical implementations of the research may be expected to be designed. Finally, as will be further discussed in a later section, the arrest records provided far more information concerning dispositions for offenses alleged than is common.

Coding forms, associated instructions, and definitions for coding the follow up data from arrest records were based upon procedures developed by one of the authors for a related study.[48] These procedures attend to charges filed, arrests known, and dispositions noted as well as to issues of the nature and seriousness of the offenses recorded. The latter classifications are based on the work cited above concerning the multidimensional nature of criminal events. These procedures have resulted in remarkable reliabilities (interrater agreements) for data coded from arrest records such as those used (no reliability coefficients

---

47 Gottfredson, D.M. and Gottfredson, M.R., "Data for Criminal Justice Evaluation: Some Resources and Pitfalls," in M.W. Klein and K.S. Teilman, (Eds.), <u>Handbook of Criminal Justice Evaluation</u>. Beverly Hills, California: Sage Publications, 1980, 97 - 118.

48 Gottfredson, S.D., and Taylor, R.B., Community Context and Criminal Offenders, in A. Reiss and M. Tonry (eds.), <u>Crime and Justice: An Annual Review of Research</u>. Chicago: Univ. of Chicago Press, 1989; see also Gottfredson, S.D., and Taylor, R.B., "Person-Environment Interactions in the Prediction of Recidivism," in R. Sampson and J. Byrne (eds.), <u>Environmental Criminology</u>. New York: Springer/Verlag, 1986.

less than .90); and the inclusion of information on the seriousness of crimes committed or alleged has been reported to provide advantages to the prediction of those events. The coding form used and associated instructions to coders are available from the authors.

Prisoner Data Included for Study

The data collected on this sample of offenders in 1962 - 1963 included a wide variety of items similar to those used in the development of Greenwood's selective incapacitation proposal,[49] and those included in the Base Expectancy scales developed by one of the authors.[50] Also, the data collected would allow the construction of selective incapacitation prediction tools along the lines of those investigated by Cohen[51] permitting also the improvement of measures of "stakes," of time-to-failure measures,[52] and of the seriousness of subsequent criminal acts.

The several scales developed, or for an already proposed scale, validated, differed in their level of development and should be discussed separately. These are: (1) a variety of risk prediction scales; (2) a "stakes" scale similar in concept to that

49 Greenwood, supra note 1.

50 A number of related scales were developed. For examples of these, for adult men, women, and young offenders, see Gottfredson, D.M. and Beverly, R.F., "Development and Operational Use of Prediction Methods in Correctional Work." Proceedings of the Social Statistics Section. Washington, D.C.: American Statistical Association, 1962.

51 Cohen, supra note 2.

52 Schmidt, P., and Witte, A, "Models of Criminal Recidivism and an Illustration of Their Use in Evaluating Correctional Programs," in L. Sechrest, et al (Eds.), The Rehabilitation of Criminal Offenders: Problems and Prospects. Washington, D.C.: National Academy Press, 1979.

developed by Gottfredson, Gottfredson, and Conly;[53] and (3) one previously developed Base Expectancy scale. Scores for the latter scale already were calculated for the persons in this sample. The individual items were included in the data, so we could use the scales intact or, if warranted by apparent improvement from further analyses, in modified form. In a different sample, the relations of these measures to one another already had been investigated.[54]

Scale Development and Validation

The main tasks of development and/or validation of each of these scales were as follows:

The Risk Scales were developed relative to a number of criteria (e.g., number of arrests to desistance, number of arrests for offenses against persons) using least squares multiple regression.

The Base Expectancy Scale was examined for validity with respect to a dichotomous criterion of "recidivism" similar to that used in the original validations for this instrument, but its validity for prediction of other criteria was investigated also. The validation sample results were compared with the levels of validity achieved in earlier studies, which were based originally

53 Gottfredson, D.M., Gottfredson, S.D., and Conly, C., supra note 30.

54 In the related study of sentencing in New Jersey, we compared a modified Greenwood scale with three of the Base Expectancy scales. The Base Expectancy scales were called forms 61A, 61B, and Burgess. For a sample of 933 persons, the intercorrelations of the Base Expectancy measures (reliability coefficients for equivalent forms) were: 61A with 61B, .86; 61A with Burgess, .86; 61B with Burgess, .84. The correlations with the modified Greenwood scale were: 61A, .57; 61B, .66; and Burgess, .60. Gottfredson, D.M., Gottfredson, S.D. and Conly, C.S., supra note 30.

on only two years of follow - up after release from prison (on parole), and subsequently on an eight year follow-up study.

Because of the centrality of the concept of risk to the conceptualization addressed in this study and since the Base Expectancy Scale used figures prominently in our presentation of results, it should be described further.[55] To differentiate it from related scales developed at about the same time, the scale was named BE 61 B.

The BE scale was developed from study of case files on 873 men. They were selected by a procedure assumed to approximate random selection from all men released from prison to California parole supervision in 1956. A dichotomous outcome criterion was used, defined as the presence or absence of "major difficulty" within two years after release. "Major difficulty" meant: awaiting trial or sentence at the end of two years; absconding, with a felony warrant issued for arrest; sentenced to jail for 90 days or more; or return to prison. The latter category included return for either technical parole violation or for new prison committments. The criterion, scored 0 (unfavorable) or 1 (favorable), was regressed on available predictor candidates in a multiple regression, and items failing to add appreciably to R^2 (arbitrarily, one percent or more) were dropped and the final regression equation was calculated.

---

55 Gottfredson, D. M. and Ballard, K. B., Jr., The Validity of Two Parole Prediction Scales: An Eight Year Follow Up Study, Vacaville, California: Institute for the Study of Crime and Delinquency, December, 1965. A briefer presentation of this scale is given in Gottfredson and Beverley, *supra* note 50.

Based on the unstandardized coefficients, the score is calculated as follows:[56]

TO OBTAIN RAW SCORES:

	If	Add	
A.	Arrest free five or more years	16	_____
	No history of any opiate use	13	_____
	No family criminal record	8	_____
	Not checks or burglary	13	_____
B.	Age at commitment times .6		_____
	21 is added for all persons		21
C.	Subtotal: A + B		_____
D.	Aliases: -3 times number		-_____
E.	Prior incarcerations: -5 times number		-_____
F.	Subtotal: D + E		_____
G.	Score: Subtract F from C		_____

Base Expectancy Form 61B

Score Calculation

The validity coefficient in a second sample of 937 men paroled the same year and followed for two years after release was .29 (point biserial correlation coefficient). A later study extended the follow up study of the same sample to eight years. A similar, but slightly different, criterion definition was used. "Major

56 Definitions of the predictor variables are given in Gottfredson, D. M. and Bonds, J. A., A Manual for Intake Base Expectancy Scoring, Sacramento, California: California Department of Corrections, April, 1961.

difficulty" meant absconding or prison return (with or without a new felony offense). The validity coefficient (point biserial correlation) was .32.

The Stakes Scale was developed in relation to the dimensional typology of offending described earlier. Again, least squares regression methods were used. Equations developed on the basis of data for the study sample were intended to be tested using the validation sample.

The relative power of the various prediction devices is of course an important issue. Although comparisons of predictive utility may appear to be straightforward, they raise complex technical issues, especially when equations or devices to be compared are intended or proposed for practical application. Space precludes a detailed discussion of the issues; the main considerations, aside from issues such as comparability of samples, reliabilities of predictive and criterion information, and potential shrinkage (related, of course, to reliability issues), are complex interactions of base-rate and selection-ratio concerns.[57]

Rates of Offending

We sought to provide more information than presently is available concerning "lambda," the critical estimate of offending rates.[58] Models for estimating lambda were examined for fit to the

---

57 For a detailed discussion, see Gottfredson, S.D. and Gottfredson, D.M., supra note 9.

58 Blumstein, A., Cohen, J., and Nagin, D. (eds.). Deterrence and Incapacitation: Estimating the Effects of Criminal Sanctions on Crime Rates. Washington, D.C.: National Academy Press, 1978.

"actual" rates observed. For examples, we examined the empirical distributions (for the total sample and for various subsamples) to assess whether or not lambda appeared to be constant over offense mixes and age groups.

The results of these analyses are given in Chapter Three.

In the fourth chapter of this report, we summarize the results of these investigations. In the fifth chapter we try to put the observations together and propose some directions for both policy development and research.

Chapter III

Follow up Study Data

Sample Attrition

As noted earlier, arrest records ("rap sheets") for 3,088 men in the construction sample were sought. Thirteen of the "rap sheets" returned were unusable (e.g., pages were missing, or the person identified clearly was incorrect.).[59] Two men were never released from the period of incarceration being served in 1962 - 1963. Record requests for an additional 92 men were returned noting that the man had died (and in most cases, the date and cause of death), but no record was provided. Finally, 527 requests were returned with the notation that the file had been "purged" from the system. Thus, 79.5% of the requested sample is available for analysis. Figure 1 summarizes sample attrition for these various reasons.

Purging

Purging refers to the non-retention of records otherwise maintained by the Department of Justice on persons arrested in California or fingerprinted for licensing and employment purposes. In 1974, when the file was reduced markedly (from about five to three million records), the Department established retention shedules for these records and developed criteria for purging them. In 1987,the purge criteria were changed to extend the retention periods for some types of criminal records.[60]

---

59 Resources did not allow us to resubmit these requests in time for inclusion in this report. We do plan to attempt to add these persons to the data file in the future.

60 The procedures now used are described in Department of Justice, Criminal Record Purge and Sealing Handbook, Sacramento: State of California, Department of Justice, 1989.

The change in purging criteria did not affect the retention rules for the subjects in this sample. All cases were of course convicted felons;[61] and both before and after the 1987 change such records were to be retained until age 70. At age 70, the record could be purged only if there was no activity in the last ten years.

The criteria establish minimum retention periods, and records may be kept longer. The application of the purging criteria apparently have varied over the years and, it was reported to us, has been dependent somewhat on budget availablilities for the purging operation. The basic rule "all entries must meet purge criteria before the record can be destroyed" applies invariably. That rule is important, for example, to the application of some of the exceptions, relating to certain juvenile offenders required to register, records of certain marijuana charges, and records of deceased persons. (The latter may be purged one year and one month after the death, unless the record is of a homicide victim, which may be purged ten years and one month after the death.)

Examples of other exceptions are:

> 1) Records of subjects convicted of offenses which require registration under Penal Code Section 290 will be retained until the individual is 100 years old, or for 10 years from the date of release from supervision, whichever is longer.
>
> 2) Records of subjects for which a handgun purchase has been denied will be retained until the individual is 100 years old.

---

61 For this purpose, felonies are defined as crimes that are punishable by death or imprisonment in the state prison system, regardless of the sentence imposed and whether or not the court deems the offense to be a misdemeanor.

3) Records of subjects sentenced to prison on felony convictions, then paroled for life, will be maintained until the subject has reached age 80. At age 80, the Department will contact the California Department of Corrections regarding the subject's status. Retention will revert to modified life when the subject has been discharged from parole.[62]

Certain marijuana and marijuana related entries should have been removed from all records provided to us. California Health and Safety Code Section 11361.5 requires destruction of these entries within two years of the date of conviction or the date of arrest if there was no conviction. And, pursuant to Health and Safety Code Section 11361.5 (b), certain of these entries are removed upon application by the subject of the record. Moreover, the Department is under court order to remove these entries from any record prior to dissemination. These include possession of marijuana, possession of paraphenalia for using marijuana, visiting or being in a place where marijuana is used, and being under the influence of marijuana.[63]

A substantial decrease in the entry of records for drunk driving arrests occurred about 1979. With the passage of Proposition 13, resources were reduced and the Department stopped entering these records. An effort was begun in December, 1978 to enter cases in a large accumulated backlog, but this operation was terminated (partly because of an arguable duplication of effort with the record keeping of the Department of Motor Vehicles).

---

62 "Modified life" means until age 70. The examples are quoted from the <u>Handbook</u>, page 4.

63 This process appears to have been incomplete, as a substantial number of marijuana-related charges are noted on the rap sheets returned to us.

Potential Purging Bias

Any bias in our data, so far as long term careers is concerned, probably is toward removal of cases with more favorable outcomes (in California) or deaths. The subjects whose records were destroyed would have been those who had reached age 70 with no known arrests in the prior ten years, or else known deaths.

The potential bias is reduced by the policy that the purge rules establish minimal criteria. Thus, records need not be purged -- and may not be -- when resources are scarce for this purpose. Thus, it is likely that some records in our sample met the purge criteria but actually were retained.

The bias in under-reporting of out-of-state arrests, discussed subsequently, is in the opposite direction to the probable bias due to the purging operation.

Potential Bias in the Reporting of Dispositions over Time

There may be a bias in the reporting of dispositions associated with improvement of the process over time. (This,of course, can be examined in the data by looking at trends in the proportions of arrests to dispositions shown.)

Several possible influences on changes in disposition reporting were mentioned by the Bureau of Criminal Identification staff. The Department has a program aimed at improving the recording of dispositions. Also, it is believed that the advent of county computerized systems, beginning in the early 1970s, may have helped increase the reporting of dispositions. And, at about the same time, programs supported by the Law Enforcement Assistance Administration may have helped improve the system.

Potential Bias Associated with Deaths

Deaths are recorded if and only if a fingerprint card is made or the subject was in prison at the time of death. If the death is a coroner's case, and the person is unknown to the coroner, this may happen; but if the subject is known to the coroner, then it is unlikely. Deaths in prison are reported. Otherwise, deaths will not be known from these records. This could tend to inflate the value of time free (exposed to risk) and therefore inflate a decline in arrest rates with age.

Potential Bias Associated with Out-of-State Offenses

Out-of-state records are thought to be far from complete. Over time, the Department has stopped entering these as a result of workload requirements. Thus, there may be some bias associated with time (more out-of-state entries being made earlier). Although the out-of-state entries shown are probably valid, they cannot be regarded as comprehensive. The probable bias in known events due to under-reporting of out-of-state arrests appears to be opposed to the potential bias from purging. Purging would tend to eliminate subjects with relatively good records; lack of complete out-of-state records would exclude crimes done but not recorded in California.

Examinations of Potential Bias

Our first concern, of course, is whether any actual bias resulted from the exclusion of the "purged" cases. We compared characteristics of the 527 men whose files were purged with the remainder of the sample; results are given in Tables 1 and 2.

No statistically significant differences were observed with respect to race, type of admission, completion of testing, whether the instant offense involved illegal economic gain, family criminal record, whether the instant offense involved checks or burglary, measured intelligence, tested grade level, or the Base Expectancy Score calculated in 1962-3. Differences observed were as follows: offenders whose files were "purged" were less likely to have had an arrest-free period of five or more years, more likely to have had a history of opiate use, been incarcerated earlier for the instant commitment offense, have a more serious commitment offense, and had experienced more prior incarcerations (including prison incarcerations). As detailed in Tables 1 and 2, the differences observed, while statistically significant, are not large.

Remaining discussion focuses on the 2,454 men for whom complete information is available.

Chapter IV

Results

Offense Activity

Only 434 (17.7%) of these men were never charged with another offense. Figure 2 illustrates the distribution of offenses charged against these men during the years subsequent to their release from the period of incarceration they were serving in 1963-1963.[64] The distribution falls off rapidly, but has a very long tail (our busiest offender was charged with 104 offenses during the follow-up period).[65]

Well over half of the offenses charged against these men for any given charge episode was of the "nuisance" variety. Figure 3 gives the distribution of offenses (for major dimensions of offenses) charged in the first post-release charge episode. Seven percent were for crimes falling on the interpersonal harm/confrontation dimension of our typology. One offense in four is a property offense; fewer than one percent were serious drug offenses (e.g., involving the sale, distribution, or manufacture of drugs). Six percent involved fraud or deception. This pattern remains irrespective of the charge episode considered (Figure 4 shows this for the first five post-release charges).[66]

---

64 Note that this figure does not represent the number of arrests subsequent to release, since we coded each charge of each arrest episode. Accordingly, the number of arrests will be fewer than the number of charges.

65 By way of contrast, the offender with the most arrests had only 63. Considering just the first arrest episode, the offender with the most charges experienced thirteen of them.

66 This pattern is the same until very high numbers of episodes are considered, at which point the numbers of offenders/offenses becomes so small that these comparisons are meaningless.

The distributions within the dimensions of person, property, fraud, and nuisance offenses provide the more detailed pictures of the offenses charged that are shown in Figures 4A to 4D. These depict the frequencies of the most serious offense charged in the first arrest episode after release from prison. Within the person offense classification, 72.1 % were charges of assaults (simple assault, 39.3 %, aggravated assault, 32.8 %). Most of the remaining charges were for rape (8.7 %), kidnapping (7.7 %), and murder or manslaughter (6.0 %). On the property dimension, the modal category was burglary (40.2 %). One in five was a robbery or attempted robbery. More than a third were various kinds of thefts. Within the fraud offense group, 80.7 % were charges of forgery or of issuing checks without sufficient funds. Most of the rest were charges of fraud, conspiracy to defraud, or perjury. Of the charges classified as on the nuisance dimension, the modal category was that of probation or parole violations, that is, of the rules violations sometimes called technical violations. The next most popular category shown in Figure 4D was that of disorderly conduct (15.1 %). Drunken driving charges accounted for 11.7 % and possession or use of drugs for 11.2 %. The classification included also a variety of relatively infrequent charges, e.g., sex perversion (3.5 %), illegal possession of a weapon (4.2 %), contributing to the delinquency of a minor (1.1 %), failure to appear or contempt of court (2.6 %), gambling (1.0 %), and other charges. The "Other" category, together with some quite infrequent offenses, includes a substantial proportion --- about 14 % --- of the charges in this category. It includes a wide variety of charges that seem clearly to be named aptly as "nuisance" offenses --- e.g., unlawful assembly, prostitution or pandering, rogue or vagabond, peddling without a license, littering, failure to pay a cab, and telephone misuse.

That the majority of charges are for nuisance offenses is well corroborated when the actual offenses are examined. Considering just the first charge post-release, over one-quarter are for drunken driving (4.6%), disorderly conduct (7.3%), or for a violation of the terms of parole or probation (14.4%).

Many offenses, of course, are substantially more serious. Since release from the period of incarceration served in 1962 - 1963, these 2,454 men have been charged with committing 68 murders, 101 kidnappings, 121 rapes, 885 robberies, and 1,736 non-commercial burglaries. Add to this several hundred assaults, auto thefts, larcenies, and forgeries, and it is clear that the class of 1962 has been active not only in nuisance offending but also in more serious crimes.

The System Response

The records provided by the California Bureau of Criminal Statistics were unusually rich and complete; and they provided far more information concerning the dispositions of offenses charged than is commonly the case (Figure 5). Considering just the first charge post-release, 56.4% of the men were convicted for the offense, 22.7% were acquitted or had the charge dismissed, 2.1% were subject to other action (such as being turned over to some other jurisdiction), and in only 18.7% of the cases was the disposition unknown.

Figure 6 shows that the typical sanction applied is a prison or jail term: 58.7% of those men convicted on their first post-release charge were re-incarcerated. Seven percent were sentenced to a term of probation, and 26.2% were subject to some other sanction.[67] For only eight percent of the cases was a sentence not identifiable given that a conviction was noted. This general pattern of sanctioning is true irrespective of episode (Figure 7).

Although almost one-third of these men were never re-incarcerated (31.3%), most spent additional time under sentences in prison or jail (Figure 8). Nearly one man in five (18.5%) was re-incarcerated at least six times. The average (median) number of re-incarcerations is 1.68. The distribution for the number of incarcerations during the follow-up period mirrors that for the number of charges made against these men (Figure 9). The most often confined offender experienced 28 periods of incarceration during the follow-up period.[68]

---

67 These included (most typically) a suspended sentence, the imposition of fines or restitution orders, etc. but also could include the revocation of parole, or an order such as "jail or fine." Accordingly, the number actually incarcerated may exceed the figures cited here. If a term to prison or jail resulted for whatever reason, that is recorded elsewhere in the data file.

68 See Messinger, S.L., and Berchochea, J.E., "Don't Stay Too Long But Do Come Back Soon: Reflections on the Size and Vicissitudes of California's Prison Population," Paper prepared for the Conference on Growth and its Influence on Correctional Policy, University of California at Berkeley, May 10 - 11, 1990.

Time In/Time Out

Offenders who failed tended to do so quickly: over 30% of these 2,454 men were re-incarcerated within one year of release (Figure 10). Over half of the men were re-incarcerated within three years of release. Others, of course, were free for 10, 15, or over 20 years before experiencing another period of incarceration (Figure 11).

Considering just those men who fail from $time_n$ to $time_{n+1}$, the length of time free in the community decreases monotonically with n (Figure 12). Similarly, considering just those men incarcerated from $time_n$ to $time_{n+1}$, the length of incarceration decreases monotonically with n (Figure 13). Neither of these figures control for possible incapacitation effects, but they are suggestive that the highest rate offenders commit relatively non-serious offenses.

Offending Rates

Table L-1 summarizes arrest rates, time free in the community post-release from the 1962-63 incarceration, and arrests for this sample of men during the follow-up period (all cell entries are means). If all offenders in the sample are considered "active," they experienced an average of .368 arrests per year, were in the community an average of 20.7 years, and were arrested an average of just over six times. Considering just those offenders who experienced at least one arrest during the follow-up period, lambda[69] increases to .447, the men were free just over 20 years in the community, and experienced an average of almost 7.5 arrests.

Restricting the sample just to men who experienced at least one period of incarceration post-release, lambda increases to .515, an average of just over 19 years were spent in the free community, and almost 8.5 arrests were experienced.

Predicting Criminal Careers

Table R-1 summarizes the variables examined for predictive utility relative to the variety of outcomes available to us. In addition to lambda (reported above and in Table L-1), outcome criteria also are reported in Table R-1.

Results of modeling efforts compare favorably with similar studies, and effects are of comparable or greater magnitude than generally found.[70] For example, Table R-2 summarizes efforts to predict the number of arrests to desistance. Significant predictors include the number of prior periods of incarceration experienced, age (at imprisonment in 1962-63), history of opiate use, a rating of the seriousness of behavior of the instant offense,[71] an arrest-free period of five years or more prior the the period of incarceration served in 1962-63, the number of prior periods of prison incarceration experienced, the type of committment to the 1962-63 incarceration, and the number of aliases

---

69 The figures discussed are not lambda in the sense used by Cohen, who adjusts Mu (the rate of arrest) by an estimated likelihood of arrest given the commission of a crime. We do not have those estimators. Hence, our lambda is Cohen's Mu.

70 For a review of many such studies, see Gottfredson, S., and Gottfredson, D. supra note 9.

71 This was a rating scale developed by D. Gottfredson in an unpublished study conducted at the time of the initial data collection. Ratings are of behaviors rather than of legal offense categories. Details are available from the authors.

used by the offender. All independent variables discussed are statistically significant, as is the entire model, which accounts for 16% of the variance in the number of arrests experienced.

Table R-3 summarizes a model intended to predict the number of arrests for nuisance offenses. Age appears not to be predictive of nuisance offending. Significant predictors include prior periods of incarceration, history of opiate use, an arrest free period of five or more years, prior periods of incarceration in prison (negative, interestingly), the seriousness rating of the instant offense (also negative), and whether the instant offense involved illegal economic gain. The model and each independent variable discussed is statistically significant, and accounts for almost 10% of the variance in nuisance offending.

One third of the men whose records were available for study were charged with at least one offense against the person after release from prison on the term served in 1962-1963. Considering just those rearrested at least once during the follow up period, this figure increases to 40 %.

Not surprisingly, we cannot predict violent offending (offending against persons) well. The regression of the number of arrests for offenses against persons on selected predictors is shown in Table R-4. Age (inversely), prior incarcerations, the seriousness of the commitment offense, prior prison incarcerations (negative), and whether the instant offense involved burglary or checks all are statistically significant predictors. But the model, also significant, is weak, accounting for only six percent of the variance in arrests for person offenses.

Despite the modesty of the correlation of scores on this scale to person offense arrests (.24), the relation warrants further consideration for several reasons. First is the importance, for incapacitation strategies, of the problem of prediction of serious harms. Second is the centrality of the issue to the stakes and risk conceptualization that we address in this study. Third, it is well known that predictors with only weak validity coefficients may nevertheless be useful in some applications, depending particularly on the selection ratio (the ratio of those to be selected to all those available for selection).[72]

Moreover, the relation of scores on this scale to those on the Base Expectancy measure is of interest. It would be desirable, in terms of the stakes x risk conceptualization, to have a measure of expected arrests for person offenses that is relatively independent of the measure of risk (such as the Base Expectancy score). This measure of expected arrests for person offenses, however, is substantially related to the BE ($r = -.54$). The BE, though, is only very modestly correlated with the number of arrests for offenses against persons (-.12). Therefore, it is of particular interest to know the relation of the arrest expectancy to the arrest criterion while controlling for the Base Expectancy scores. The partial correlation for scores from the regression equation predicting number of person arrests with that criterion, with Base Expectancy scores "held constant" is .25. This suggests that the two scales in combination, despite the modest correlations with the

[72] Cronbach, L., and Gleser, G. C., Psychological Tests and Personnel Decisions. Urbana: University of Illinois Press, 1957.

criteria, may have some promise for classification in some applications. We therefore pursue this in a later section of this report.

Property offense arrests are considerably more predictable (Table R-5). Prior incarcerations, age, history of opiate use, commitment offense against persons (positive), type of admission (probation or parole violator or not), number of aliases, and commitment offense of the nuisance variety all are significantly associated with later property offends arrests. The model is statistically significant, and accounts for 13% of the variability in property offense arrests (R = .36).

The number of arrests for frauds is only slightly more predictable (R = .26) than offending against persons (Table R-6). Significant predictors include a commitment offense of the property type, the seriousness of the commitment offense, and whether the commitment offense involved illegal economic gain. All effects are in the expected direction, and the overall model is statistically significant, while accounting for about 8% of the variance.

Perhaps most important from a public safety perspective, we cannot predict the seriousness of the first offense committed post-release at all (Table R-7). Although the seriousness score of the committment offense and family criminal record are statistically significant predictors and the model is statistically significant, less than one percent of the variance in seriousness of subsequent offense is accounted for (R = .08).

A slightly stronger (though still modest) correlation is found when the number of charges to desistance is regressed on the various predictor candidates. (The analyses just described were based on the most serious charge for a given arrest episode.) The regression (Table R-2A) accounts for about 17 percent of the variablility in number of charges (R = .41). Prior convictions, age, history of opiate drug use, and arrest free period of five or more years, the seriousness rating of the commitment offense, and prior prison incarcerations are included in the equation. Again, however, the power of the equation is reduced markedly when the number of charges for person offenses is considered the dependent variable. Age, priors, and the offense seriousness rating at commitment are predictive; but the multiple R of .24 accounts for only six percent of the variance in number of person offense charges (Table R-4A).

Can we predict the rate of offending? Table LR-1 summarizes efforts to predict lambda for all offenders in the sample. Significant predictors include the number of prior periods of incarceration, age (with a negative effect -- older offenders have lower lambdas),[73] history of opiate use, number of aliases, and a committment offense of the nuisance variety.

The model accounts for 12% of the variation in lambda and is statistically significant (R = .34).

When desistors are excluded, prediction is not quite so successful (Table LR-2). The model is almost identical to that just described, with the addition only of a small negative effect for a commitment offense of the property type. The model is

[73] As we will show later, lambda decreases monotonically with age.

significant, but accounts for less than ten percent of the variation in lambda.

Finally, if we restrict attention just to those offenders who experienced at least one period of incarceration during the follow-up period, our ability to predict lamda erodes further (Table LR-3). The same variables are predictive, but the model, although statistically significant, accounts for less than eight percent of the variance in lambda (R = .28).

Because the distribution of lambda is positively skewed, we also examined models of its logarithmic transformation. In all cases, this resulted in very modest increases in predictive utility; and in no case did it change the substantive nature of the model.

Validation of the Base Expectancy Scale

The results reported in the previous section have not yet been examined for robustness in validation samples. Although such models generally are relatively stable, some shrinkage is expected. As noted in an earlier chapter, a random half of the available sample has been reserved for validation tests; but these have not yet been done.

The results with the study, or construction, sample of the present research, however, constitute validation data for the Base Expectancy measure, since it was developed on a different sample of men, paroled earlier from California prisons. This section reports on the further evidence of validity found for the sample of 1962-1963 California prisoners.

The associations between the Base Expectancy Scale and a variety of outcome criteria available for the present study are summarized in Table BE-1. The scale is remarkably robust with respect to several important outcome criteria.

The criterion most similar to that used in the original construction and validation of the scale is "any incarceration." The point biserial correlation coefficient of .32 is the same as that found earlier on the basis of the eight year follow-up study cited. Although the offenders in the prior study were paroled at least five years earlier than men in the present sample were released and those in the later sample were followed for a much longer time, the relation of scores to outcomes is the same.

Similar correlations were obtained showing the relation of scores to the number of arrests to desistance ($r = -.34$), the number of property arrests ($r = -.31$), and the logarithmic transformation of arrest rates (lambda). The latter coefficients were -.32 for both all offenders and all arrested offenders. The relations are markedly lower for scores with number of person arrests and with number of fraud arrests.

The validity of the scale is depicted in Table BE-7, which shows, for various groupings of BE scores, outcomes with the two samples. Despite the relatively modest correlations, the percent with more favorable outcomes decreases with BE scores in such a manner as to provide some utility for some applications. As shown for sample 2 (the present sample), the percentage arrested by group decreases with scores, as does the arrest rate. The latter is true whether all arrests are considered or only the more serious (i.e., with arrests in the nuisance classification ignored).

Specialization or Versatility in Offending?

In an earlier section, we stressed that both selective and collective incapacitation strategies rely heavily on predictions of future behavior, and we have sought to improve those predictions and to provide better estimates of lambda than previously have been available. For evaluation, both strategies also depend strongly on the concept of "patterned" criminal activity.[74] By this it is meant that offender criminal activity is not random, but exhibits some degree of consistency. An incapacitation strategy may be based on the assumption, for example, that confining a persistent property offender for a specified time will result in a specified decrease in property crimes committed. Unfortunately, available research evidence does not provide strong support for the specialization assumption.[75] Although some evidence of spe-

74 See, for example, Cohen, J. Research on Criminal Careers: Individual Frequency Rates and Offense Seriousness. Appendix B in A. Blumstein et al., Criminal Careers and "Career Criminals." Washington, D.C.: National Academy Press, 1986, pgs. 292-449.

75 Cohen, op cit., Wolfgang, M., et al., supra note 10, Farrington, D., supra note 10, Farrington, D. Age and Crime. In M. Tonry and N. Morris (Eds.), Crime and Justice: An Annual Review of Research. Volume 7. Chicago: University of Chicago Press, Blumstein, A., Cohen, J., and Farrington, D. Criminal Career Research: Its Value of Criminology. Criminology, 1988, 26, 1-35, Blumstein, A., Cohen, J., and Farrington, D. Longitudinal and Criminal Career Research: Further Clarifications. Criminology, 1988, 26, 57-74, Farrington, D., Snyder, H., and Finnegan, T. Specialization in Juvenile Court Careers. Criminology, 1988, 26, 461-487, Kempf, K. Specialization and the Criminal Career. Criminology, 1987, 25(2), 399-420. The latter reference includes a listing of most of the relevant literature, while the first-listed provides reanalysis of some of the most important studies.

cialization commonly is found, the overwhelming weight of evidence is strongly suggestive of versatility.

The purpose of this section is to investigate whether our dimensional offense typology -- developed to represent a better cognitive reality of the ways in which people think about criminal behavior -- might also better represent behavioral reality and contribute to the empirical work concerning offense transitions.

As noted by Cohen,[76]

> A full treatment of offense switching using transition matrices includes consideration of stationarity, specialization, escalation, homogeneity across population subgroups, and the Markov property.

Each issue raised is of interest, but of particular interest in the current context are evidence first, of specialization, and second, of stationarity.

Just what constitutes evidence of specialization is not entirely clear. In one sense, it is very straightforward: specialization is given by the diagonal cells of a transition matrix, where cell entries are the probability of occurance of offense_j at times t and t+1 (where these are successive). Off-diagonal cells represent versatility, or generalization in offending.

Cohen, following Bursick,[77] examines Adjusted Standardized Residuals for the diagonal (and off-diagonal) cells of the

---

76 Cohen, supra note 66.

77 Cohen, supra note 66, Bursick, R. The Dynamics of Specialization in Juvenile Offenses. Social Forces, 1980, 58, 851-864.

transistion matrix.[78] The ASR is based on deviations from expectency for each cell of the matrix and is distributed as a unit normal variable. Thus, it provides a test of the statistical significance of each cell of the matrix. It does not, of course, have a direct interpretation in terms of the magnitude of the transition effect. Recently, Farrington[79] proposed a "standard summary measure of specialization versus generalization" as follows:

$$\text{Coefficient} = \frac{\text{observed} - \text{expected}}{\text{row total} - \text{expected}},$$

which would equal "zero when there is complete generalization (and hence the observed figure equals the expected one) and one when there is perfect specialization (and hence every conviction offense becomes the same type of reconviction offense)." A related way of looking at the magnitude of the effect (if any), and one that we prefer, is to examine transition probabilities relative to base rate considerations. All three measures are used in the analyses that follow.

Table T-1 gives the transition matrix for the comparison of the offense of conviction for the 1962 - 1963 incarceration and the first post-release charge. All diagonal cells save one (serious drug offense/serious drug offense) are highly statistically significant, supporting a specialization hypothesis. However, the coefficients suggested by Farrington are very low, which suggests that generalization, not specialization, is the norm.

78 For a more complete discussion, see Haberman, S. J., Analysis of Qualitative Data, Vol. 1. London: Academic Press, 1978.

79 Farrington, supra note 75.

Analysis of this particular transition may be misleading, because it compares charges for which the men were convicted and incarcerated with only the first offense charged post-release. It seems highly likely that offenses for which the men were incarcerated in 1962 - 1963 may not be typical of offenses committed or alleged to have been committed; they probably are more serious. Accordingly, we have more confidence in analyses only of charges subsequent to release from that confinement.

Tables T-2 through T-10 give the transition matrices for the first 10 charges post-release.[80] Because the numbers of serious drug offenses and crimes against the social order were so small, they were excluded from the analyses.

All overall Chi-squared tests for independence are highly statistically significant, and Contingency Coefficients for each matrix are on the order of .40. All tests for the significance of diagonal cells (by the ASR) also are highly statistically significant. Moreover, Farrington's coefficients, although by no means large, are substantially larger than found in previous studies of specialization. And, ASR's for all off-diagonal cells either support the null hypothesis (that deviation from expectency is zero) or are significant but negative (suggesting a transition that is significantly <u>not</u> likely to occur).

Evidence presented thus far suggests stronger support for the specialization hypothesis than has been found before, but still shows, we believe, that generalization rather than specialization is the norm.

80 These were actually analyzed for up to twenty charges; these additional tables are available upon request.

More support for this position is given in Figures 14 through 25, which summarize transition probabilities relative to the base rate probabilities of offending of a given type for each successive charge. Figure 14 shows, for example, that given a first charge for a nuisance offense, the probability that the second charge also will be for a nuisance offense is elevated relative to the base rate, and that the transition probabilities for each other offense type is at or below base rate. Similarly, Figure 15 shows that the transitional probability for person offenses is elevated if the first charge was for a person offense, and that the others are depressed. Figures 16 and 17 illustrate this same phenomenon for property and fraud offenses, respectively. The remaining figures in the series report only on the diagonal cells of each successive transition matrix (out to 10 charges).

This is, of course, exactly what must be observed given the remarks made earlier about the diagonal and off-diagonal ASRs. What is most striking about these figures, we believe, is that they show one thing very clearly and dramatically: The most likely transition at time t, given any type of charge at time t-1, is to a nuisance offense. The next most likely occurance is to a charge of the same type, but the extremely high base rate probability associated with nuisance offending simply overwhelms the specialization effect.

Analyses described thus far are based on charges only -- irrespective of arrest episode. From one perspective, this may be seen as generous to the specialization hypothesis (since, for example, arresting authorities may tend to attempt to clear a number of burglaries when a burglar is arrested -- thereby inflating the probability of a "specialization" hypothesis).[81]

Accordingly, these analyses were repeated focusing only on the most serious offense charged for any given arrest episode. Results are given in Tables T-11 through T-19. Adjusted Standardized Residuals remained statistically significant (although smaller in magnitude); and Farrington's coefficients are generally lower. With these exceptions, substantive conclusions remain unchanged.

Does Specialization Change With Transition?

From the perspective of an incapacitation strategy, one would hope that specialization would increase over time, or at a minimum, would remain stable. Figure 26 displays changes in Farrington's Coefficient of Specialization for the first ten charges post-release. No trend is apparent for fraud/fraud or person/person transitions; there is no linear trend with slope other than zero -- that is, attempts to fit a line failed. A modest trend is apparent for nuisance/nuisance and for property/property transitions, and regression analysis bears this out.[82] The trends are statistically significant (Figures 27 and 28), although the slopes are very small.

---

81 Arguing against this is that arresting and prosecuting officials also may charge an offender with many different crimes at once, either so bargaining may take place or in the hope that at least some will "stick."

82 The analysis of variance for regression of nuisance on transition is significant ($R^2 = .631$, $F_{(1,7)} = 11.9$, $p < .01$), as is that for the regression of property on transition ($R^2 = .620$, $F_{(1,7)} = 11.4$, $p < .01$). No line could be fit to person or fraud transitions.

With these analyses carried out through 19 transitions, the substantive conclusions remained unchanged (Figure 29). Only the trends already described remained significant (see, for example, Figure 30). The same remained the case when only the most serious offenses per arrest episode were examined (Figure 31).

The Question of Offense Mix

Another way of considering the specialization vs. versatility question is through examination of the mix of offenses committed. For example, a person who completely specialized in property offenses would commit those and only those types of crimes. Similarly, a person who only offended against persons could be considered to specialize in crimes against the person.

Figure 32 groups offenders in this sample in terms of the mix of offenses they committed subsequent to release from incarceration. Of the 2,002 offenders who were re-arrested, almost 28% were complete specialists -- that is, they were subsequently charged with only one type of offense (columns A - D in Figure 32). Two offense mixes are quite frequent: nuisance and property offending and nuisance, person, and property offending. Other mixes are not likely (e.g., person and fraud, person and property, property and fraud, person, property and fraud).

Figure 33 illustrates that among "specialists," so defined, the vast majority specialize in nuisance offending. These 552 "specialist offenders" were arrested 1,470 times: Figure 34 shows that the nuisance specialists were those predominately active.

Those men experiencing at least one arrest subsequent to release were arrested, in the aggregate, 14,480 times. Figure 35 illustrates clearly that "specialists" were responsible for a small minority of these arrests.

Importantly, and as illustrated in Figure 36, lambda is inversely correlated with specialization: specialists have among the lowest lambdas, and generalists have among the highest.

Lambda and Age

We examined the relation of lambda with the age of the offenders in our sample. Incapacitation strategies would be best served if lambda increased with age -- or at least remained constant over age. But, as illustrated in Figure 37, lambda decreased monotonically with age.

Stakes, Risk, and Incapacitation

In an earlier section we reported on various models designed to predict several behavioral outcomes: the arrest rate (lambda); the logarithm of the arrest rate; the number of arrests to desistance; the number of arrests for nuisance offenses; the number of arrests for offenses against persons; the number of arrests for property offenses; the number of arrests for frauds; the seriousness score of the most serious charge of the first post-release episode; the number of charges to disistance; and the number of charges for person offenses. Also, models were defined for the prediction of arrest rates based only on those offenders who were arrested and, in addition, only on those who were incarcerated. The power of these models was found to be similar to most risk assessment instruments of their type, although some values of R^2 were somewhat larger than typically observed.

The Base Expectancy Scale was found to have some validity for predicting those same outcomes, and it was noted that this scale was developed on a different sample of men released from prison at a different time. In two large samples with long term follow up study, the validity of the scale --- while fairly modest --- was supported and indeed may be regarded as well established. In view of the validity evidence presented, we took the Base Expectancy Scale as our "best" assessment of risk of reoffending for the purpose of the analyses next to be reported.

We took two approaches to the assessment of "stakes." One was based on the number of arrests observed for offenses against persons, since it is these offenses, involving violence and interpersonal confrontations, that most shock the public conscience and may as a group be considered to result in a high degree of harm. The second was based on the number of arrests for offenses classed as nuisances, since all remaining categories in our classification are, on the average, reflective of a greater degree of perceived harm. The method used, the same in each case, will be described along with the results.

For the first of these analyses, we used the model reported in Table R-4, the result of regressing the number of arrests for offenses against persons on various predictors. Scores were assigned for each man in the sample, based on the resulting equation. We then split the group on the basis of the mean predicted score, enabling the assignment of each person to membership in a high or low (expected) stakes group.

The second analysis was based on the model reported in Table R-3, which regressed the number of arrests for nuisance offenses on available predictors. Based on this model, scores again were assigned to each person in the sample, and again the group was divided at the mean. In this case, hovever, we considered those men who scored below average a high risk, on the assumption that if they were offending, the offenses expected were other than nuisance offenses, i.e., more serious harms.

By dividing the sample also on the basis of the mean Base Expectancy Scores, the classification was reduced to a four-fold typology of offenders: High Risk, High Stakes; Low Risk, High Stakes; High Risk, Low Stakes; and Low Risk, Low Stakes. It must, of course, be noted that the "stakes" classification is defined quite differently in the resulting two typologies. We will present the results with both typologies, but note that in the analyses that follow we will use the first one, that is, the stakes classification based on expected offenses against persons.

In considering the results of these analyses it should be borne in mind also that the division of the sample at the mean scores for the scales used is arbitrary, as is the number of categories used. The first point is important, because, since each scale (risk and stakes) provides a continuous measure, various cutting points could be used in defining the classifications. The second also is noteworthy, because the division on each scale into only two groups ignores some potentially useful information.

Bearing these considerations in mind, the simple four-fold classification has the merit of simplicity and was thought useful for an initial examination and explication of the possible utility of the risk / stakes conceptualization.

Various outcomes for men classified under the first scheme are summarized in Figures 38, 39, and 40. This is the classification based on the Base Expectancy Scale scores (Risk) and the Person Offense Expectancy Scale Scores (Stakes). The typology has reasonable discriminating power for a number of important outcomes. It discriminates significantly with respect to the probability of arrest ($F_{(3,2450)} = 51.237$; $p < .001$; Eta = .243) and, somewhat better, with respect to the probability of incarceration ($F_{(3, 2450)} = 76.273$; $p < .001$; Eta = .292). Also, more modestly but still of considerable interest, it discriminates with respect to the rate of arrests for offending against persons ($F_{(3,2439)} = 29.707$; $p < .001$; Eta = .188). The discriminatory power of the classification with respect to arrests for offending against property and for nuisance offense arrests is similar to that for discrimination of overall arrest probabilities. For discrimination of rates of arrests for property offenses the statistics are $F_{(3,2439)} = 53.460$; Eta = .248. Regarding arrest rates for nuisance offenses we found $F_{(3,2439)} = 38.476$; $p < .001$; Eta = .213. The discrimination is statistically significant but at a lower level for arrests for fraud ($F_{(3,2439)} = 5.579$; $p < .001$; Eta = .083). Consistently with the stakes concept, however, the model has somewhat better discriminating power with respect to the the rate of serious offending, that is, of arrests for offenses classified as other than nuisances ($F_{(3,2439)} = 59.011$; $p < .001$; Eta = .260). It may be noted that the discriminatory power described may be a little conservative, since the scales both have been reduced to dichotomies, with some information thereby discarded.

As shown in Figure 41, the largest percentage of these men is found for the High Risk, High Stakes classification (41%), but more than one quarter are classified as Low Risk, Low Stakes offenders. Based on their observed arrest rates (over all classifications of offenses), incapacitating a High Risk, High Stakes offender has almost three times the effect (2.89), in terms of crime reduction, as does incapacitating a Low Risk, Low Stakes offender. If we restrict consideration to non-nuisance offenses, the effect differential is even greater (3.41).

Figures 42 -45 summarize similar results using the second typology described --- that based on expected nuisance offending vs. serious (i.e., non-nuisance) offending. All results shown are statistically significant, and, with one exception, of the same order of magnitude as for the previously discussed typology.[83] The exception noted is that our ability, using this typology, to differentiate those who are charged with offenses against the person is diminished (Eta = .104). Moreover, as shown in Figure 45, the typology does less well in differentiating the groups of most interest. Accordingly, all remaining discussion will focus on the first typology.

83 The analyses are available from the authors on request.

Chapter V

Classification, Prediction, and Criminal Justice Policy

Desirabilities for Incapacitation Strategies

Three related features of the state of nature desirable from the standpoint of incapacitation strategies involve prediction, offense specialization, and characteristics of the arrest rates found when persons are observed over time. If incapacitative strategies are to be effective, the behavior of offenders (and the criminal justice system) must be reasonably predictable. The predictions required are usually of arrests or convictions of specific crime types and therefore could be made more easily and with a greater degree of validity if offenders tend to specialize in the types of crimes committed. Or, at any rate, the nature of "crime switching" (that is, of transistions from one offense type to another) must be reasonably predictable; and it could be helpful if expected transitions are to a more serious crime type. The observed arrest or conviction rates also must be reasonably predictable, and it is desirable (for incapacitative strategies) that these tend to be constant or increasing. It would be helpful to incapacitation strategies if the persons classified correctly as specialists tend to have higher arrest rates than those classified as generalists.

The simplest and most straightforward incapacitation strategy could be formulated if both the termination of offending and the rate of committing crimes (measured, e.g., by arrests) could be predicted with confidence, if the rate of doing crime (or being arrested) were constant or increasing, and if there was a high degree of specialization in crime types committed (or, if the tendency to specialize increases with time). Thus, for implementation of a selective incapacitative intent, it would be helpful if we could identify future high rate specialists in serious offenses, with both specialization and rates of crime commission constant or increasing over time.

A possible, but more complex strategy could be formulated if termination and rate of new offenses could be reasonably well predicted, if the distribution of the rate of new crimes (arrests, charges, or convictions) over time were known with some precision, and if, absent a high degree of specialization, the tree of probable crime switching could be defined with a reasonable degree of confidence.

In this section we consider the evidence from this study on these issues, in order to next discuss the feasibility of developing viable incapacitative strategies.[84] This will show that the evidence is at best mixed on each of the three desirabilities: prediction, specialization, and arrest rates. This will lead us to conclude that the evidence is not strong enough to support incapacitative policies as usually proposed but that it shows some promise for the formulation of related, yet quite different, conceptualizations.

---

84 In addressing this topic, we set aside important ethical issues that arise frequently in the discussion in order to consider only the technical aspects of the problem at this moment. Some of the ethical concerns are discussed in the next section.

Prediction

The prediction models developed provide quite modest estimation, for groups of prison inmates, of a variety of outcomes relevant to incapacitative strategies. Most of those discussed in this report have not yet been tested on additional samples to provide better estimates of validity in new samples; but experience shows that similar models usually hold up quite well, usually with a small amount of "shrinkage" of validity coefficients. In the case of the Base Expectancy Scale studied, the evidence for validity of prediction of various outcomes critical to incapacitation strategies is convincing. Indeed, it may be said to be well established. The scale gives valid information about expected reincarcerations and also about the critical outcome of arrest rate. But, the validity of the scale must be described as modest at best.[85]

Specialization

We considered the problem of specialization vs. versatility in terms of our classification of offenses into groups based on how people seem generally to consider crimes to be grouped. It may be assumed that if we had used a finer classification (that is, used more categories of offenses) we would have found less specialization. On the other hand, had we combined groups and used fewer classifications of offenses, we would have found more. If, however, our classifications are accepted as a reasonable and useful middle ground that appears at least to represent cognitive

---

85 In the next section we discuss the consequences of the level of validity of such a scale for errors in prediction.

reality, then four points must be concluded. First, we found specialization in offending; but, the coefficients describing the degree of specialization, although higher than those found in other studies, were (like the predictive validity coefficients) quite modest. Second, we found a high degree of versatility, which seemed to be described aptly as "swamping" the specialization. Third, we found that the most probable next arrest invariably is for an offense in the nuisance category of our classification. And fourth, we found that specialization, in general, does not increase very much with successive transitions; there was a small trend of increasing specialization in nuisance and property offending, but none when the more serious person offenses were considered.

Characteristics of Lambda

The arrest rates in this sample were found to be inversely related to specialization. The specialists had lower arrest rates than did the generalists.

Arrest rates decreased monotonically with age, which was one of the best predictors of those rates in the context of the predictive variables considered in this study. The decline of arrest rates with age is consistent with the results of much other research. For example, Haapanen, from his study of a substantial sample of California Youth Authority wards institutionalized for serious offenses in the 1960s, followed up for 15 to 20 years, found the same result over a variety of classifications of offenders (as well as a decline with age in participation).[86]

[86] Haapanen, Rudy A., Selective Incapacitation and the Serious Offender: A Longitudinal Study of Criminal Career Paterns,

Feasibility of Incapacitation

A strong argument against the feasibility of collective incapacitation strategies based on the offense of conviction is given simply by the transition matrices presented. For example, locking up "burglars" to prevent burglaries may be expected, first of all, to prevent nuisance offenses and only secondarily to prevent burglaries. Confining "robbers" similarly may be reasonably expected to prevent some robberies, but mainly it will prevent nuisance offenses. The expected next offense for any of the classifications of offenses studied is a nuisance offense. Thus, any expected reduction in the targetted crime would have to be considered in the context of large expenditures to prevent nuisance offenses in the hope of capturing some targetted offenders as well. Indeed, the quotation marks around the words "burglar" and "robber" above are well justified, and it is to be hoped that the editor doesn't take them out. If a person convicted of burglary is more apt to be a nuisance offender next time, then it is not very helpful to classify him as a burglar for the purpose of suggesting the form of his next most likely offense. As with offenders in other crime categories, he is more aptly described as a expected nuisance offender. Indeed, the most likely most serious charge for the first post release incident for any offender group was found to be a nuisance offense. It is plausible, of course, that some burglaries and robberies are prevented by incarceration of persons for offenses in the nuisance category; but

---

Sacramento, California: Department of the Youth Authority, September, 1988.

how many cannot be estimated well; and, moreover, the next offense after a nuisance offense must be expected also to be a nuisance offense.

Similarly, the data presented in relation to the predictive requirements of a selective incapacitation strategy provide little support for that orientation. Rates of arrest or of conviction can be predicted, but not well. Rates of arrest for person offenses, a most likely target for selective incapacitation strategies, can be predicted, but even less well. Rates of arrest are inversly related to the degree of specialization, so the small specialist group is less apt to be arrested at a high rate. Specialization increases little with age, and not at all for the most likely targetted groups in a selective incapacitation strategy. And, arrest rates decline with age. For a century and a half it has been known that, for adults, "participation" declines with age:

> Of all the causes which influence the development of the propensity to crime, or which diminish that propensity, age is unquestionably the most energetic.[87]

The data reported here show that arrest rates for active adult offenders also decline with age. (It has been found that arrest rates for offenders age nine through 16 increase with age.)[88]

Taking these results together, it is apparent that the advocate of selective incapacitation as a strategy for more efficient or effective use of criminal justice resources will have

---

87 Quetelet, Lambert A. J., A Treatise on Man and the Development of His Faculties. A Facsimile Reproduction of the English Translation of 1842 with an introduction by Solomon Diamond, Gainsville, Florida: Scholars' Facsimiles and Reprints, 1969, p.92.

88 Loeber, Rolf, and Snyder, Howard N., "Rate of Offending in Juvenile Careers: Findings of Constancy and Change in Lambda," Criminology, 28, 1, 1990, pp. 97 - 109.

many serious obstacles to overcome even when the ethical arguments surrounding the issue are set aside. The state of nature --- of offense behavior and criminal justice response --- is not conducive to the development of such strategies.

Ethical Considerations [89]

The serious ethical questions raised by the selective incapacitation concept are of two types. One set of issues focuses on the consequences of errors of prediction. The other group of concerns addresses more basic questions about the proper purposes of sentencing and correctional practice. Taken together, these issues lie at the heart of a fundamental conflict between values of fairness and equity in sentencing and the values of societal protection.

Since predictions must always be imperfect, two types of errors always will be made; and this is the case regardless of the basis of the predictions. The first type, called false negatives, are persons mistakenly predicted to be good risks. For these persons, a policy of selective incapacitation will fail to provide the public protection sought. False positives, on the other hand, are "false alarms" --- persons mistakenly predicted to be recidivists or to commit crimes at a high rate. Under a selective incapacitation strategy, these persons would be imprisoned for crimes that would in fact never be committed. The resulting dilemma for sentencing policy is posed by the conflict between the

89 Portions of this section are adapted from Gottfredson, Stephen D. and Gottfredson, Don M., "Selective Incapacitation?," Annals of the American Academy of Political and Social Science, 478, March, 1985.

offender's right not to be a false positive --- and kept in prison unfairly and unnecessarily --- and the ordinary citizen's right not to be victimized by a false negative.

The false positive problem has received the most attention from critics on ethical grounds. Given current levels of predictive accuracy, with strategies that select any sizable group for incapacitation, large numbers of persons would be subjected to increased terms of confinement as a result only of their misclassification.

The debate, however, also addresses more fundamental issues of sentencing and correctional treatment. These involve the question whether people should be sent to prison for deserved punishment or for utilitarian (or, more broadly, consequentialist) purposes. The latter include any purposes with a crime control intent. All such purposes, including incapacitation, require predictions. The conflicting ethical theory of just desert, however, asserts that it is unfair to punish for harms expected but not yet done --- that is, for expected crimes that might never be committed. Moreover, this ethical postion requires that punishments must be similar in severity for offenders convicted of similar crimes with similar culpability. The basic focus of this theory is on blameworthiness, and critics of selective incapacitation have pointed out that some predictive information used may have nothing to do with the blameworthiness of the offender; hence, they should not used in determination of the penalty.

These issues are fundamental to policy questions about the applicability of the study results reported here, and we will return to them in a later section. Next, however, some implications of current levels of predictive validity should be discussed.

Is Prediction Accurate Enough?

We have described predictive validity shown in this study, and the level of validity to be expected from each of the models described, as modest. The levels of predictive accuracy in the criminological prediction literature generally are aptly described by that term, or, perhaps more accurately, as rather low.[90] There is no escaping the question of whether statistically based prediction tools such as discussed in this report are accurate enough to justify their use in policy formulation or practice.

Some scholars and practitioners argue against the use of prediction in any case --- whether statistically or subjectively based --- on ethical grounds alone. This is true of a strict just desert argument, in which prediction may be seen as properly irrelevant to decisions made about criminal offenders. If, however, aims of crime control in sentencing are thought ethically permissable, then prediction must be regarded as central to the attainment of those ends. This is the case even if it is believed that crime control purposes may be sought but only within limits of punishments justly deserved.[91] Therefore it may be said that

90 For a detailed review of issues of accuracy in prediction, see supra note 9.

91 See, e.g., Morris, Norval, "Punishment, Desert and Rehabilitation," in U. S. Department of Justice, Equal Justice Under the Law, Bicentennial Lecture Series, Washington, D. C.: U. S. Government Printing Office, 1976; von Hirsch, Andrew, Past and Future Crimes, New Brunswick, New Jersey: Rutgers University Press, 1985.

prediction is a central problem to the extent that crime control objectives are believed to be permissable in formulation of sentencing or correctional policy.

The remaining arguments against the use of statistically based prediction tools all reduce to considerations of their accuracy. The technically sophisticated arguments directly confront the accuracy issue. They cite low proportions of explained variance and resulting high error rates. Commonly, the focus is on false positives, although false negatives may be equally, or more, undesirable depending on the application. Other arguments cite misspecification of prediction models: this too is essentially a complaint about accuracy. Less technically sophisticated critics continue to complain of reducing people to numbers and to observe that human behavior is too complex to allow judgmental decisions to be made on the basis of an equation. This complaint too is essentially one concerning accuracy.

Part of the answer to the question of whether statistical prediction methods are accurate enough to justify their use depends on the use to which the resulting tools will be put. We continue to agree with Petersilia's 1980 assessment quoted earlier and (as even more generally applicable) with Cohen's similar comment with respect to the RAND study, that

> ... for purposes of selective incapacitation, where predicted high rate offenders will be subject to longer prison terms than all other offenders, much better discrimination of the high-rate offenders would seem to be required.[92]

[92] Cohen J., supra note 2.

Proposals for dramatic change in sentencing and incarceration policies based on individual level prediction studies are at best premature. Prediction of such low validity as thus far demonstrated cannot justify the policy changes proposed under the banner of selective incapacitation.

Prediction tools of equal validity can, however, be used appropriately for other purposes. We well try to explicate this argument next. We will focus on the two types of errors to be made in any selection or prediction problem and on ethical considerations involved in the type of policy changes involved in the proposed use of prediction tools.

The Predictive Selection Problem [93]

Predictive selection decisions require the specification of cut-off scores. For example, in selective incapacitation strategies, values of the predictor score at or above which an individual is expected to fail, or commit crimes at a high rate, must be identified. Similarly, values of the criterion variable at or above which a case is considered an actual failure and below which persons are considered to have succeeded must be specified also. Thus, at or above a selected cutting-score on the predictor scale distribution, we predict failure and select accordingly. Below that cutting-point, we predict success. The value decided upon for the predictor cut-off determines what is known as the selection ratio. The selection ratio is the ratio of the number of

93 For a more complete explication of the argument of this section, see Gottfredson, S. and Gottfredson, D. M., supra note 9.

persons to be selected to all persons available for selection. The smaller the selection ratio, the fewer the errors in selection; but, the smaller the selection ratio the smaller the proportion of the population selected for the application.

This situation gives rise, necessarily, to the four potential consequences to any selection decision.[94] There are the two types of errors already discussed; there are also two types of "hits" or correct predictions. There are the persons predicted to succeed (not be convicted again, not commit crimes at a high rate) who in fact do; these are known as negative hits. Some persons predicted to fail will in fact fail; these are called positive hits. In this formulation, the two types of hits (correct predictions) and the two types of errors (misses) exhaust the possibilities.

In selective incapacitation proposals, the cutting score will be selected somewhere above the mean of the risk distribution, or else the high risk cases would not be selected. The criterion cutting score would lie above the mean of the distribution representing subsequent criminal behavior, or else the scheme would call for selectively incapacitating average or below average offenders. The placement of the cutting scores determines the relative numbers of false positives and false negatives. Moving the cutting score up reduces the number of false positives at the expenses of including a smaller proportion of the population,

---

94 Of course, if scores on the predictor scale and/or the criterion measure are continuous, then a large number of classification categories may be used. And, if there are more than two alternative placements, then the situation is yet more complex. The problem is simplified here by considering only dichotomous predictor and criterion classifications for ease of exposition. The principles would be the same in the more complex situation.

capturing fewer positive hits for incapacitation, and an increase in false negatives. Either false positives or false negatives may be increased, but always at the expense of the other; one has only to change the selection ratio.

Clearly, neither error is desirable. False positives must be abhorred from the ethics of desert, false negatives from the ethics of utility. Which error is more important is a question not yet settled in moral philosophy. Moreover, it may well be that the two types of error are not equal in either human or monitary costs.

Selective Deinstitutionalization

Consider, on the other hand, a policy not of selective incapacitation but one of selective deinstitutionalization. Assume the population of interest is that of persons already incarcerated or to be incarcerated under any existing incarceration policy. Suppose that it is desired to reduce the institutional population. Obvious selection criteria for the decision as to who not to incarcerate, or keep confined, could include the risk of recidivism, or the risk of serious harms, or the risk of serious harms to be committed at a high rate.[95]

Now the selection criterion (the cutting-score on the risk measure) would lie below the mean of the distribution of risk scores. That is, we wish to select those inmates, or otherwise prison-bound offenders, who appear to represent the least risk of repeated offending (or for whom the stakes do not appear to be so

95 Other criteria could of course be used. For example, those classified as least deserving of punishment could be released or excluded from incarceration.

great). Since we seek to identify the best risks, the criterion cutting score also likely would lie below the mean. Just as before, the trade-off of false positives and false negatives could be manipulated by moving the cutting-scores for the risk measure up or down. For any given value of the criterion cutting score, the value of the risk cutting-score will determine size of the selected group but also whether more false positive or false negative errors will be made.

Errors, Ethics, and Policy

The ethical consequences of errors made under the strategy of selective incapacitation and that of selective deinstitutionalization are quite different. In a selective incapacitation strategy, the effect of a false positive is to deny liberty based on faulty prediction. The aim is to minimize false negatives; that is, it is sought to minimize the failure to select those who in fact pose a substantial risk of continued criminal behavior. And, unless predictive accuracy can be increased, reducing false negatives can be done only at the expense of increasing false positives.

In the selective deinstitutionalization scenario, it also is the case that false positives will be punished more harshly than will those selected for release or non-incarceration based on the selection device. The critical distinction is that they will not be punished more harshly than they would have been had the device --- and prediction --- not been used. Rather than falsly treating some persons more harshly than is believed to be justly deserved, this proposal treats some persons less harshly than that and treats some persons no more harshly than that.

The selective deinstitutionalization proposal does rely, for its ethical justification, on a permissive rather than positive retributivism. Mackie calls attention to these two types of retributive principles, along with one other: negative retributivism. The principle of negative retributivism asserts that one who is not guilty must not be punished. That of positive retributivism states that one who is guilty ought to be punished. The principle of permissive retributivism posits that one who is guilty may be punished.[96] (One may think that negative retributivism is non-controversial; yet, it is precisely one point of criticism of selective incapacitation proposals that some persons expected to commit crimes will be punished for offenses not yet committed and which might not ever be committed.) A positive retributive theory, however, would assert that the guilty must be punished. This principle is more controversial, particularly when correlative principles are added, as in desert theory.

What then is at issue is whether a guilty person ought to be punished in proportion to that guilt. The "ought" in that sentence is an insistence on positive retributivism and a rejection of the alternative permissive principle. The reasons are that otherwise the principles of equity and of proportionality (of sanctions to harm done and culpability) may be violated. A permissive retributive theory would assert that the guilty may be punished.

96 Mackie, J.L., "Morality and the Retributive Emotions," Criminal Justice Ethics, Winter/Spring, 1982, 3 -10.

The selective deinstitutionalization proposal would not be inconsistent with this ethical view.

A selective incapacitation proposal and a selective deinstitutionalization proposal would differ substantially with respect to proposed policy changes and the consequences of these. Proponents of selective incapacitation suggest clearly that a proper purpose of incarceration is the prevention of crime by removal of offenders from society in order that they can not engage in criminal activity in the community. The suggestion then has been made for a radical change in sentencing and imprisonment policy, based in part on the claims made for the accuracy of prediction. The selective deinstitutionalization proposal relies on no presumption of a need for radical change in sentencing policy in general. The strategy could be adopted even if it is assumed that all purposes for sentencing as currently practices are equally valid. The scheme does propose that risk (and stakes, or risk and stakes) --- and, accordingly an incapacitative purpose --- should be a primary consideration in decisions aimed at prison population reduction.

There is a fundamental difference between the two situations, and this difference requires clarification of our earlier question, is prediction currently accurate enough to be useful? When the question is stated in this way, the answer can only be yes and no. Prediction in criminal justice settings clearly is not sufficiently accurate to form the basis of social policy. Proposals for dramatic changes in policy and practice that rely on the accuracy of prediction are premature at best. Once social policy has been set, however, prediction clearly is sufficiently accurate to be useful, and the decisions made will be more accurate if statistically based prediction tools are used.[97] Even when validity is quite low, it has been demonstrated that such selection devices provide significant improvements in accuracy.[98]

We prefer the selective deinstitutionalization proposal over the selective incapacitation proposal and note that the choice mainly is an ethical one. But the consequences of our proposal are more benign than are those arising from the selective incapacitation concept. Predictive accuracy, while sufficient for the former, is insufficient for the latter. Thus, the selective deinstitutionalization concept is believed to meliorate the ethical concerns discussed and to hold promise for reducing prison crowding without endangering the public. We turn next to a brief example of how the risk X stakes concept might be used in a selective deinstitutionalization formulation.

---

97 For reviews, see Meehl, Paul E., Clinical vs. Statistical Prediction, Minneapolis: University of Minnesota Press, 1954; Goldberg, L. R., "Diagnosticians vs. Diagnostic Signs: the Diagnosis of Psychosis vs. Neurosis from the MMPI," Psychological Monographs, 79 (whole no. 9), 1965; idem, "Seer Over Sign: The First "Good" Example? Journal of Experimental Research in Personality, 3:168-71, 1968; idem, "Man vs. Model of Man: A Rationale, plus Some Evidence of a Method of Improving on Clinical Inference," Psychological Bulletin, 73:422-32, 1970; Sawyer, J., "Measurement and Prediction, Clinical and Statistical," Psychological Bulletin, 66:178-200, 1966; Dawes, Robyn M., "Case-by-case versus Rule-generated Procedures for the Allocation of Scarce Resources," in Human Judgment and Decision Processes in Applied Settings, Martin F. Kaplin and Steven Schwartz, eds., New York: Academic Press, 1975, pp. 83-94; Dawes, Robyn M., "The Robust Beauty of Improper Linear Models in Decision Making," American Psychologist, 34 (7):571-82, 1979.

98 Dunnette, M. D., Personnel Selection and Placement, Belmont, California: Brooks / Cole, 1966, pp. 173-83.

Risks, Stakes, and Selective Deinstitutionalization

Offenders were classified (as discussed in an earlier section) on the basis only of information available when these persons were received into prison into four groups. These were called Low - Risk, Low Stakes; Low Risk, High Stakes; High Risk, Low Stakes; and High Risk, High Stakes. The Low Risk, Low Stakes Group included about one fourth of the sample. The Low Risk, Low Stakes Group subsequently had --- when followed for more than two decades ---

1. The lowest probability of arrest. This must be nevertheless regarded as rather high --- two thirds were arrested at some time after release from prison; but it may be compared with the arrest rate for the High Risk, High Stakes group, which was 91 percent.

2. The lowest arrest rate. The arrest rate for for the High Risk, High Stakes group was nearly three times that of this group. When arrests for nuisance offenses were excluded, the difference was a little larger.

3. The lowest probability of incarceration again after release from prison. This probability must be seen as high: nearly half this group experienced at least one more incarceration. Again, however, this probability may be compared with the High Risk, High Stakes group, four fifths of whom were confined again in jail or prison after release.

4. The lowest rate of arrests for offenses against persons. The rate for this group was .017; that for the High Risk, High Stakes group was .514.

5. The lowest property offense rate and also the lowest nuisance offense rate.

These results should be considered in the context of present widespread concerns about the growth of prison populations in the last decade and the consequent prison crowding and economic costs involved. California, the site of the present study, provides an example. Shortly before the initiation of the data collection used in this study, there were a little more than 23,000 men and women in prison in California. In November, 1989, there were 86,746, with the inmate population expected to grow by 1994 to 136,640.[99] A recent study commission stated:

> [The California Department of Corrections] estimates that it must build approximately 39,000 additional prison beds at an estimated cost of $3.5 billion by 1994 just to stay at what is considers to be a manageable level of overcrowding of 130 percent of capacity. CDC further estimates an annual operational budget of approximately $4 billion by FY 1994-95, approximately $1 billion more than the entire local and state corrections system costs today.[100]

Unless the California offender population has changed markedly, one fourth of the presently confined offenders could be classified as Low Risk, Low Stakes offenders.[101] The study commission cited emphasized, inter alia, as its predominent conclusion that "Judges and parole authorities lack sufficient intermediate sanctions to make balanced public safety decisions" and recommended significant expansion of what they termed intermediate sanctions or punishment options.[102]

It should be emphasized that the classification of offenders here into four groups only, for the purpose of illustration and

---

99 Blue Ribbon Commission on Inmate Population Management, Final Report, Sacramento: Prison Industry Authority, January, 1990.

100 Ibid., p. 3.

101 There is reason to believe that there have indeed been some marked changes. The Blue Ribbon Commission report cited a change in the last decade to a larger proportion of property and felony drug law violators and a smaller proportion of violent offenders (p. 33). This might imply that the proportion of Low Risk, Low Stakes offenders has increased relative to the High Risk, High Stakes group; but this could be determined only by study of the current population.

102 Ibid, pp. 4-7. A recent detailed review and argument for such sanctions has been provided in Morris, Norval and Tonry, Michael, Between Prison and Probation: Intermediate Punishments in a Rational Sentencing System, New York: Oxford University Press, 1990.

exposition, is somewhat arbitrary. It would be quite easy, of course, to classify offenders (using the same scales) into a larger number of groups on both dimensions. Of course, sanctions also may be classified into a larger number of groups than simply "confinement or not." This could suggest a grid not unlike those used in some sentencing or paroling guideline schemes, although with a wider range of sanctioning options.[103]

Implications of a Better Prediction of Lambda

Suppose that the rate of future offending were known at the time of sentence? Or, more realistically, suppose that the information known at the time of sentencing provided improved estimates of those future rates?

Our ability to predict future rates of offending now is quite limited. Our analysis suggested that, using the variables of prior record, age, drug use, aliases and imprisonment for a nuisance offense we might account for about 12 percent of the varibility in future arrest rates. The multiple correlation coefficient, R, in the study sample was .34: comparable to most risk prediction instruments but hardly impressive. Similarly, the Base Expectancy Score, in this case tested on a validation sample, correlated .29 with arrest rates when all offenders were considered.

Data available for the present study did not allow us to calculate arrest or conviction rates for these men prior to their period of incarceration in 1962-1963, as the needed data were not

103 See Morris and Tonry, supra note 102, Chapter 3, "Interchangeability of Punishments in Practice," pp. 37-81 for illustrations.

coded originally.[104] Justice functionaries such as prosecutors, judges, and paroling authorities have access to these offender records before making decisions about them, however; and prior rates of offending could be calculated quite readily.

There is good evidence, however, that prior rates of offending do not provide, by themselves, excellent estimates of later rates, especially as time increases between the period used for the estimation and that period which is the focus of attention. As we have seen, arrest rates decline with age. Moreover, Haapenen[105] found "considerable instability" in rates and that the longer the period from the estimation period, the lower the stability. The correlations of the natural logarithms of ages and rates were small relative to the expected values (given stability) after taking account of unreliability in the data. Nevertheless, he found substantial correlations, varying with offense classifications and age groups as well as time periods studied and the distance in time from the basis of estimate. Despite his conclusion of instability, which was well demonstrated, the correlations found support the conjecture that, when combined with other information, measures of the prior arrest rate may help improve prediction.

This could be very important. Consider Figures 46 - 51, which are based on the Risk/Stakes classification first discussed, but which also classify men as High or Low Rate (based on a split at the mean rate of offending). Discriminatory power is remarkable increased. The typology thus created significantly discriminates

[104] The information is available in the arrest records provided by the California Bureau of Criminal Statistics, but was not coded for this study (nor did available funds permit this).

[105] Haapanen, _supra_ note 86, quote at p. vii.

with respect to the probability of arrest ($F_{(7,2446)}$ = 57.120; $p < .001$; Eta = .375); the probability of incarceration ($F_{(7,2446)}$ = 122.417; $p < .001$; Eta = .509); the rate of offending against persons ($F_{(7,2435)}$ = 75.504; $p < .001$; Eta = .418); the rate of offending against property ($F_{(7,2435)}$ = 162.589; $p < .001$; Eta = .564); the rate of committing frauds ($F_{(7,2435)}$ = 26.449; $p < .001$; Eta = .266); and the rate of nuisance offending ($F_{(7,2435)}$ = 217.267; $p < .001$; Eta = .620). Finally, the typology has discriminatory power with respect to the rate of serious offending (that is, of committing non-nuisance offenses) ($F_{(7,2435)}$ = 214.555; $p < .001$; Eta = .618).

Figure 52 illustrates the relative proportions of the sample falling into the eight cells of the typology. It is not trivial that about 20% fall in each of the extreme groups, especially when it also is noted that the expected incapacitative effect for a High Risk, High Stakes, High Rate offender is approximately 13 times that for a Low Risk, Low Stakes, Low Rate offender.

It is, of course, not surprising that good discrimination of arrest rates are found when the arrest rates, known only after the fact, are included for the classification. The arrest rate classification was not known, and of course could not be known, at the time of incarceration in 1962-1963. The analysis is presented as suggestive only of the value of continuing to seek to improve the estimates of future rates on the basis of information that can be known before the fact. Certainly, it should not be taken as suggesting that this degree of discrimination would be expected to be found if the high rate/low rate classification were based only on the prior rate known at sentencing. It remains to be investigated how much those data will improve predictions of the later rates.

It is quite plausible, however, that the prediction of lambda can be improved. There are three reasons for this confidence. First, several variables found predictive of arrest rates in this study, in linear combination, correlated modestly (R = .30) with arrest rates for those offenders who were arrested and about the same (R = .34) for all offenders. Second, the correlations cited by Haapanen (for the relations of earlier to later arrest rates), while supporting the instability in rates that he reports nevertheless are often substantial. Third, we found that generalization (variability) in types of offending is related to arrest rates. Persons may of course be scored for such variability, which also may improve the prediction of lambda.

Summary and Conclusions

The long term follow-up study of more than 2400 men first studied in 1962-1963 for whom records were available showed that in general they continued to have a great deal of involvement with the criminal justice system. Only 18 percent never were charged with another offense. Nearly a third were confined again within a year; and more than half were incarcerated again within three years.

Not all these prisoners were back in confinement after their release from prison. About a third were never confined again. Some persons were free for as long as 27 years. Indeed, they were, on the average, free in the community for 21 years. Unfortunately, they were, on the average, arrested more than once every three years.

We classified offenses for the purposes of this study into groups according to a method developed in a earlier study. The method groups offenses according to how people generally perceive their nature, and also provides an assessment of how serious they are. The perceived seriousness of offenses differs, on the average, between groups; also, it varies within groups.

The major dimensions of offense seriousness, hence of the classifications used, were called person, property, fraud, serious drug, and nuisance offenses. Person offenses, the interpersonal harm/confrontation dimension of the typology used, included (in this sample) mainly assaults but also murders, manslaughters, arsons (rarely), kidnappings, rapes, and resisting arrest. Property offenses included, most commonly, burglary but included also offenses such as robbery attempts, thefts, and the possession of stolen property. Fraud offenses were mostly forgery or writing checks without sufficient funds, but the offenses of fraud, embezzlement, counterfeiting, conspiracy, false pretenses, and perjury were represented. The serious drug offense classification included the sale, distribution, or manufacture of drugs prohibited by law. The nuisance classification, so named because it is clear that crimes in this category are generally viewed as less serious, on the average, than those in the other crime classifications, included, most often, probation or parole rules violations, drunken driving, possession or use of drugs, and disorderly conduct. To a lesser extent, this group included also offenses of sex perversion, illegal possession of a weapon, contributing to the delinquency of a minor, contempt of court, and gambling. Occasionally it included statutory rape, unlawful assembly, escape, prostitution or pandering, gambling, or offenses called rogue or vagabond. Still more rarely, there were offenses of peddling without a license, trespassing, littering, failure to pay a cab, telephone misuse, or the possession of burglary tools.

Since these groups overlap in the judged seriousness of crimes within categories, we also scored each arrest and charge for seriousness within the appropriate category.

By far, the subsequent charges against these former inmates fell most often into the nuisance offense category. For example, in the first arrest episode after prison release, the most serious charge was, more often than not (56 percent) that of a nuisance offense. Seven percent of offenses were charges of person offenses, one in four was a property offense charge, six percent involved fraud or deception, and less than one percent were serious drug offenses. This general picture did not change when subsequent charges were studied; in episode after episode, the most frequent, most serious post release charge was a nuisance offense.

In the first post release episode, more than a fifth were dismissed or acquitted, but more than half were convicted. Of those convicted, two fifths were returned to prison, and 18 percent were given jail terms. The repeated use of prison and jail did not change when later convictions were examined.

Offenders who failed did so quickly; nearly a third were confined again within a year. More than half were incarcerated, in jails or prisons, within three years.

Major resources were used repeatedly to confine the less serious offenders. The 2454 men were charged with many serious crimes: 68 murders, 101 kidnappings, 121 rapes, 885 robberies, 1,1736 non-commercial burglaries, hundreds of auto thefts, larcenies, and forgeries. But it does not take an astute observer to notice the Grand Canyon, and it does not require an economist to realize that a large share of the costly correctional enterprise was in place to deal, over and over again, with the offenses here classified as nuisances. And, it is clear that a substantial portion of jail and prison space was devoted to confining, again and again, offenders convicted of those offenses.

We sought to develop methods for prediction of a variety of outcomes after prison release. The models developed, although not yet validated on independent samples, compared favorably with similar studies. Thus, prediction equations were described for the estimation of number of arrests to desistance, number of arrests for nuisance, person, property, frauds, and seriousness of the first post-release offense. Similarly, methods were described for the prediction of rates of arrest (for all offenders and for offenders excluding desistors). Other models were described to predict the number of charges to desistance and the number of charges for person offenses. Generally, the predictive power of the equations must be described as modest; yet they may be of some utility, depending upon the application intended.

A Base Expectancy (risk) Scale developed in an earlier study was found to be as valid for this group of offenders, followed for a much longer period of time, as it was in earlier validation studies. The validity of this scale, although still described as modest, is well established. Besides its validity in respect to the criterion of re-incarceration, the scores on this scale are related to both the probability of arrest and to the arrest rate.

We examined offense transitions (crime swithching) to investigate the extent of specialization and versatility in offending as measured by arrests and charges. For this purpose, we used the offense classifications described earlier. We found stronger support for the specialization hypothesis than that reported in earlier studies; but, in general, generalization was more pervasive. The anaysis showed clearly that the most likely transition, at any point in the sequence of arrest incidents, is to a nuisance category offense. The next most likely occurance is to an offense of the same type, but the very high base rate probability associated with nuisance offending overwhelms the specialization effect.

Specialization did not increase over time, except slightly for nuisance to nuisance and for property to property transitions. Generally, there was little evidence that offenders tend over time to increasingly specialize in the types of crimes they commit. That there is some specialization was supported by the fact that about 28% of those re-arrested were charged with only one type of offense. (Also, although the next most likely offense is a nuisance offense, if it is not then it tends to be an offense of the same type as the last.) The vast majority of the charges against these specialists, however, were for offenses of the nuisance variety. And, of the 14,480 arrests counted, the specialist offenders were responsible for a small minority.

Some mixes of offenses were more often found than others: for example, nuisance and property offending seemed to go together, as did nuisance, person, and property offending. Mixes of person offenses and fraud, person and property, property and fraud, or person, property and fraud were not frequent. The arrest rates were found to be inversely related to specialization; the specialists had among the lowest arrest rates and the generalists had among the highest.

We investigated the applicability of our Risk X Stakes conceptualization to problems of incapacitation. The risk measure used was the Base Expectancy Scale. The stakes measure (Stakes Expectancy) was the equation related in this sample to the number of arrests, after release from prison, for offenses against persons.

The sample was divided into four groups by splitting it at the mean scores for these two dimensions. This resulted in a fourfold typology (High Risk, High Stakes; Low Risk, High Stakes; High Risk, Low Stakes; and Low Risk, Low Stakes). The typology discriminated significantly with respect to the probability of arrest, the probability of incarceration, the person offense arrest rate, and rates of arrests for property and nuisance offenses. It discriminated significantly the rates of arrest for serious (non-nuisance) offenses.

It was noted that the "states of nature" that would be desirable from the perspective of developing incapacitative policies involve prediction, offense specialization, and characteristics of the arrest rate. Current levels of predictive validity are regarded as quite modest. Specialization, as measured in this study, is relatively rare, and versitility in offending is more the norm. Specialization does not, in general, increase with increasing numbers of transitions. The next arrest, from any offense category, is likely to be an arrest for a nuisance offense. Arrest rates are inversely related to specialization and decline with age.

It was concluded that the "states of nature" as revealed by these data are not conducive to the development of either collective or selective incapacitation strategies. The evidence does not support collective incapacitation strategies based on offenses of conviction, if only on the basis of the offense transitions observed. Neither does it support selective incapacitation strategies, given the modest levels of prediction that can at present be expected, the lack of strong support for specialization, the inverse relation between specialization and arrest rates, and the decline of arrest rates with age.

Ethical issues surrounding the concept of selective incapacitation, together with the current evidence on validity of prediction, lead us to conclude that proposals for radical change in sentencing or correctional policies based on an incapacitative intent and on individual level prediction are at best premature.

It was concluded, however, that a policy of selective deinstitutionalization --- with identification, for example, of Low Risk, Low Stakes offenders who would be less often considered for incarceration --- may be both technically feasible and ethically sound. The proposal requires no radical changes in current sentencing and imprisonment policies, does require that an incapacitative purpose is regarded as a legitimate concern in decisions aimed at prison population reduction, and does require an acceptance of a permissive rather than positive retributive theory of sentencing.

Limitations of the study are set most notably by the single jurisdiction studied and by specific issues related to the follow-up arrest records. These are discussed in the report. The results presented should be confirmed by testing the classification and prediction methods on other samples. Also, further examination of the distributions of scores and of optimal cutting points for deinstitutionalization strategies is needed. Although, as with any such official record data, there are some unanswered questions concerning possible bias in the data used, it is believed that the records used were unusually carefully compiled by the state agencies concerned and that potential biases may tend to offset one another.

Most research reports end with a recitation of needs for further study, and that could be appropriate here. Some such needs are noted throughout the report. Among them, the need for improved prediction of arrest rates is highlighted, and specific next steps that appear promising for that are noted.

It is believed that the selective deinstitutionalization concept, based on a conceptualization and measurement of both risk and stakes, ameliorates the ethical concerns discussed and holds promise for reducing prison use and prison crowding without endangering the public.

Table 1

Comparison of "Purged" and Returned Cases

	Returned	Purged
Testing:		
Incomplete	15.7%	18.3%
Complete	52.5	50.9
Not Tested	18.2	18.5
Refused	13.7	12.2
($X^2_{(3)}$ = 2.875; n.s.)		
Race:		
White	54.0%	53.9%
Other	46.0	46.1
($X^2_{(1)}$ = 0.001; n.s.)		
Type of Admission:		
Parole Violator	25.1%	27.6%
New Commitment	74.9	72.4
($X^2_{(1)}$ = 1.322; n.s.)		
Instant Offense Involved Illegal Economic Gain:		
Yes	65.0%	60.5%
No	35.0	39.5
($X^2_{(1)}$ = 3.423; n.s.)		
Arrest-Free Period of Five or More Years:		
Yes	78.0%	71.8%
No	22.0	28.2
($X^2_{(1)}$ = 8.603; $p < .01$)		
History of Opiate Use:		
Yes	25.1%	33.8%
No	74.9	66.2
($X^2_{(1)}$ = 15.546; $p < .001$)		
Family Criminal Record:		
Yes	43.7%	40.7%
No	56.3	59.3
($X^2_{(1)}$ = 1.422; n.s.)		
Committment Offense of Checks or Burglary:		
Yes	34.4%	32.8%
No	65.6	67.2
($X^2_{(1)}$ = 0.470; n.s.)		

Table 2

Comparison of "Purged" and Returned Cases

Variable	N	Mean	S.D.
Measured Intelligence:[1]			
Returned	1,570	3.95	1.05
Purged	334	3.89	1.14
($t_{(1,902)}$ = 0.349; n.s.)			
Year of Commitment:			
Returned	1,592	60.00	3.08
Purged	347	59.54	4.48
($t_{(1,937)}$ = 2.307; p = .02)			
Tested Grade Level:			
Returned	2,405	3.34	3.16
Purged	474	3.31	3.12
($t_{(2,877)}$ = 0.168; n.s.)			
Seriousness Score of Commitment Offense:[2]			
Returned	2,378	64.18	24.33
Purged	455	60.34	23.90
($t_{(2,831)}$ = 3.093; p = .002)			
Number of Prior Incarcerations:[3]			
Returned	2,506	2.52	1.46
Purged	479	2.88	1.38
($t_{(2,983)}$ = 4.978; p < .001)			
Number of Prior Prison Incarcerations:[4]			
Returned	2,506	1.07	1.26
Purged	479	1.40	1.41
($t_{(2,983)}$ = 5.139; p < .001)			
Base Expectency Raw Score:			
Returned	2,500	510.99	179.12
Purged	479	525.26	201.94
($t_{(2,977)}$ = 1.564; n.s.)			

1 Seven point scale; four equals Normal (90 - 109).
2 Thirty-four point scale; scores range from 0 - 103.
3 Four equals four or more.
4 Four equals four or more.

Table L-1

Summary of Aggregate Individual
Arrest Frequencies and Other Outcome Criteria
by Type of "Active Offender"

Outcome Criterion	Type of "Active Offender": All Considered Active (N = 2,443)	At Least One Arrest (N = 2,019)	At Least One Conviction (N = 1,678)
Lambda	.368	.447	.515
Years Free	20.653	20.065	19.318
Arrests	6.131	7.455	8.466

Table LR-1

Regression of Lambda (All Offenders) on Selected Predictors (Minimum N = 2,432)

Predictor	B	Beta	t
Priors	0.790	.229	11.13***
Age	-0.012	-.206	-10.23***
Drugs	-0.151	-.129	- 6.37***
Alias	0.032	-.050	2.49**
InstN	0.054	.044	2.20*
Constant	0.626		14.99***

$R^2 = .116$; $F_{(5,\ 2416)} = 63.62$, $p < .001$.

Notes: *** p < .001.
** p < .01.
* p < .05.

Table LR-2

Regression of Lambda (Arrested Offenders) on Selected Predictors (Minimum N = 2,012)

Predictor	B	Beta	t
Priors	0.066	.184	7.96***
Age	-0.011	-.182	- 8.05***
Drugs	-0.135	-.112	- 4.92***
Alias	0.040	.062	2.74**
InstN	0.064	.050	2.19*
InstPr	-0.071	-.045	-2.03*
Constant	0.699		14.41***

$R^2 = .090$; $F_{(6,\ 1986)} = 32.66$, $p < .001$.

Notes: *** p < .001.
** p < .01.
* p < .05.

Table LR-3

Regression of Lambda (Incarcerated Offenders) on Selected Predictors (Minimum N = 1,678)

Predictor	B	Beta	t
Drugs	-0.131	-.103	- 4.12***
Age	-0.011	-.174	- 6.95***
Priors	0.056	.149	5.84***
InstPr	-0.098	-.059	-2.41*
Alias	0.050	.074	2.94**
InstN	0.078	.059	2.36*
Constant	0.783		14.02***

$R^2 = .078$; $F_{(6,\ 1654)} = 23.16$, $p < .001$.

Notes: *** p < .001.
** p < .01.
* p < .05.

Table R-1

Descriptive Statistics of
Variables Included in Regression Analyses

Name	Description	N	Mean	S.D.
Type	Type of Admission, Instant Offense (0 = Parole Violator, 1 = Original Commitment)	2,432	.75	.43
Age	Age at Current Commitment	2,432	29.79	8.37
Serious	Offense Seriousness Scale (0 = Walkaway, 103 = Criminal Circumstances Resulting in Death)	2,432	63.54	23.84
Gain	Commitment Offense Involved Illegal Economic Gain (0 = Yes, 1 = No)	2,432	.35	.48
Priors	Prior Periods of Incarceration (0 = 0, 4 = 4 or More)	2,432	2.51	1.46
PriorsP	Prior Periods of Prison Incarceration (0 = 0, 4 = 4 or More)	2,432	1.05	1.25
Free	Arrest Free Period of Five or More Years (Between First Arrest and Arrest Resulting in Instant Commitment (0 = Yes, 1 = No)	2,432	.22	.41
Drugs	History of Opiate Use (0 = Yes, 1 = No)	2,432	.75	.43
Family	Family Criminal Record (0 = Yes, 1 = No)	2,432	.56	.50
Checks	Commitment Offense Burglary or Checks (0 = Yes, 1 = No)	2,432	.65	.48
Alias	Number of Aliases (0 = None, 9 = Nine or More)	2,432	.49	.81
InstN	Commitment Offense, Nuisance (0 = No, 1 = Yes)	2,455	.21	.41
InstP	Commitment Offense, Person (0 = No, 1 = Yes)	2,455	.48	.50

Table R-1 (Contd.)

Descriptive Statistics of
Variables Included in Regression Analyses

Name	Description	N	Mean	S.D.
InstPr	Commitment Offense, Property (0 = No, 1 = Yes)	2,455	.12	.33
Ser1	Seriousness Score, Most Serious Charge, First Arrest Episode (1 = Murder First)	2,021	34.46	16.67
Desist	Number of Arrests To Desistance	2,455	6.13	6.04
NuisT	Number of Arrests For Nuisance Offenses (To Desistance or to 20th Arrest Episode; Nuisance Offense Most Serious Charge/ Arrest Episode)	2,455	3.30	3.88
PersT	Number of Arrests For Person Offenses (To Desistance or to 20th Arrest Episode; Person Offense Most Serious Charge/ Arrest Episode)	2,455	.58	1.07
PropT	Number of Arrests For Property Offenses (To Desistance or to 20th Arrest Episode; Property Offense Most Serious Charge/ Arrest Episode)	2,455	1.72	2.60
FraudT	Number of Arrests For Fraud Offenses (To Desistance or to 20th Arrest Episode; Fraud Offense Most Serious Charge/ Arrest Episode)	2,455	.31	.81
Cdesist	Number of Charges To Desistance (Or to 20th Charge)	2,455	8.11	7.21
CnuisT	Number of Nuisance Charges to Desistance (Or to 20th Charge)	2,455	4.56	4.72
CpersT	Number of Person Charges to Desistance (Or to 20th Charge)	2,455	0.69	1.33
CpropT	Number of Property Charges to Desistance (Or to 20th Charge)	2,455	2.10	2.95

Table R-1 (Contd.)

Descriptive Statistics of
Variables Included in Regression Analyses

Name	Description	N	Mean	S.D.
CfraudT	Number of Fraud Charges to Desistance (Or to 20th Charge)	2,455	.46	1.32
CdrugsT	Number of Serious Drug Charges to Desistance (Or to 20th Charge)	2,455	.14	.59
Arrest	Any Subsequent Arrest (0 = No, 1 = Yes)	2,455	.82	.38
Incar	Any Subsequent Incarceration (0 = No, 1 = Yes)	2,455	.69	.46
Tarest1	Time to First Arrest (Days)	2,455	729.58	1182.75
Tinc1	Time to First Reincarceration (Days)	2,455	854.38	1223.70
Cser1	Seriousness Score of First Charge Post-Release (1 = Murder First)	2,021	35.33	16.23

Table R-2

Regression of Number of Arrests to Desistance on Selected Predictors (Minimum N = 1,998)

Predictor	B	Beta	t
Priors	1.115	.270	11.02***
Age	-0.104	-.144	- 6.39***
Drugs	-2.155	-.154	- 7.94***
Serious	-0.015	-.058	- 2.92**
Free	-0.899	-.062	- 3.18**
PriorsP	-0.413	-.085	- 2.37**
Type	-0.706	-.050	- 2.31*
Alias	0.343	.046	2.31*
Constant	9.976		15.51***

$R^2 = .159$; $F_{(8, 2423)} = 57.14$, $p < .001$.

Notes: *** p < .001.
** p < .01.
* p < .05.

Table R-2A

Regression of Number of Charges to Desistance
on Selected Predictors
(Minimum N = 1,998)

Predictor	B	Beta	t
Priors	1.470	.298	12.35***
Age	-0.157	-.183	- 8.24***
Drugs	-2.299	-.138	- 7.19***
Free	-1.195	-.069	- 3.28**
Serious	-0.015	-.049	- 2.49**
PriorsP	-0.297	-.051	- 2.03*
Constant	12.340		16.71***

$R^2 = .168$; $F_{(6,\ 2425)} = 81.83$, $p < .001$.

Notes: *** $p < .001$.
** $p < .01$.
* $p < .05$.

Table R-3

Regression of Number of Arrests for Nuisance Offenses
on Selected Predictors
(Minimum N = 1,998)

Predictor	B	Beta	t
Priors	0.592	.223	8.85***
Drugs	-1.215	-.135	- 6.55***
Free	-0.819	-.087	- 4.33**
PriorsP	-0.271	-.087	- 3.59**
Serious	-0.010	-.059	- 2.87**
Gain	0.355	.044	2.16*
Constant	3.677		11.10***

$R^2 = .096$; $F_{(6, 2425)} = 43.09$, $p < .001$.

Notes: *** p < .001.
** p < .01.
* p < .05.

Table R-4

Regression of Number of Arrests for Person Offenses on Selected Predictors (Minimum N = 1,998)

Predictor	B	Beta	t
Age	-0.023	-.182	-8.43***
Priors	.136	.186	7.49***
Serious	0.002	.053	2.53*
PriorsP	-0.059	-.068	- 2.56*
Checks	0.110	.049	2.41*
Constant	0.767		6.83***

$R^2 = .058$; $F_{(5,\ 2426)} = 30.06$, $p < .001$.

Notes: *** $p < .001$.
** $p < .01$.
* $p < .05$.

Table R-4A

Regression of Number of Charges for Person Offenses on Selected Predictors (Minimum N = 1,998)

Predictor	B	Beta	t
Age	-0.034	-.212	-10.57***
Priors	.115	.127	6.10***
Serious	0.005	.089	4.33***
Constant	1.092		8.10***

$R^2 = .056$; $F_{(3, 2428)} = 48.35$, $p < .001$.

Notes: *** $p < .001$.
** $p < .01$.
* $p < .05$.

Table R-5

Regression of Number of Arrests for Property Offenses on Selected Predictors (Minimum N = 1,998)

Predictor	B	Beta	t
Priors	0.349	.196	9.24***
Age	-0.056	-.180	-8.89***
Drugs	-0.887	-.147	-7.28***
InstP	0.708	.136	6.08***
Type	-0.301	-.050	-2.48*
Alias	0.144	.044	2.21*
InstN	0.290	.046	2.05*
Constant	2.927		11.35***

$R^2 = .131$; $F_{(7,\ 2424)} = 52.12$, $p < .001$.

Notes: *** $p < .001$.
** $p < .01$.
* $p < .05$.

Table R-6

Regression of Number of Arrests for Fraud Offenses on Selected Predictors (Minimum N = 1,998)

Predictor	B	Beta	t
InstPr	0.452	.184	8.54***
Serious	-0.004	-.113	-5.39***
Gain	-0.133	-.078	-3.91***
Constant	0.541		10.34***

$R^2 = .076$; $F_{(3, 2428)} = 66.62$, $p < .001$.

Notes: *** $p < .001$.
** $p < .01$.
* $p < .05$.

Table R-7

Regression of Seriousness Score of Most Serious Charge, First Post-Release Arrest Episode, on Selected Predictors (Minimum N = 1,998)

Predictor	B	Beta	t
Serious	-0.045	-.065	-2.90**
Family	-1.699	-.051	-2.27*
Constant	38.285		33.67***

$R^2 = .007$; $F_{(2, 1999)} = 6.81$, $p < .01$.

Notes: *** $p < .001$.
** $p < .01$.
* $p < .05$.

Table BE-1

Correlation of Base Expectancy (BE)

Scores and Various Outcomes

Outcome	Correlation
Any Arrest	-.260
Any Incarceration	-.318
Number of Arrests to Desistance	-.344
Time to First Arrest	.209
Time to First Reincarceration	.125
Number of Nuisance Arrests	-.249
Number of Person Arrests	-.120
Number of Property Arrests	-.306
Number of Fraud Arrests	-.122
Lambda (All Offenders)	-.289
Lambda (Offenders Arrested)	-.248
Lambda (Offenders Incarcerated)	-.217
Ln(Lambda) (All)	-.328
Ln(Lambda) (Arrested)	-.328
Ln(Lambda) (Incarcerated)	-.277

Table BE-2

Probability of Arrest
By
Base Expectency Subgroup

Base Expectancy Subgroup	Probality of Arrest
A (N = 56)	.393
B (N = 248)	.669
C (N = 284)	.732
X (N = 925)	.829
D (N = 548)	.903
E (N = 345)	.925
F (N = 21)	.952

Note: $F_{(6,2420)} = 32.030$; $p < .001$; $r_{pb} = .254$; $p < .001$.

Table BE-3

Probability of Incarceration
By
Base Expectancy Subgroup

Base Expectancy Subgroup	Probability of Incarceration
A (N = 56)	.232
B (N = 248)	.415
C (N = 284)	.539
X (N = 925)	.694
D (N = 548)	.808
E (N = 345)	.844
F (N = 21)	.857

Note: $F_{(6,2420)} = 45.723$; $p < .001$; $r_{pb} = .310$; $p < .001$.

Table BE-4

Lambda
By
Base Expectency Subgroup

Base Expectancy Subgroup	Lambda
A (N = 56)	.069
B (N = 248)	.142
C (N = 283)	.201
X (N = 922)	.347
D (N = 543)	.459
E (N = 344)	.606
F (N = 21)	.582

Note: $F_{(6,2410)} = 36.492$; $p < .001$; $r_{pb} = .285$; $p < .001$.

Table BE-5

Lambda for Serious Offenses
By
Base Expectency Subgroup

Base Expectancy Subgroup	Lambda
A (N = 56)	.021
B (N = 248)	.055
C (N = 283)	.082
X (N = 922)	.154
D (N = 543)	.203
E (N = 344)	.277
F (N = 21)	.278

Note: $F_{(6,2410)} = 31.304$; $p < .001$; $r_{pb} = .266$; $p < .001$.

Table BE-6

Average Number of Offenses Against Persons
By
Base Expectancy Subgroup

Base Expectancy Subgroup	Average Offenses
A (N = 56)	.125
B (N = 248)	.307
C (N = 284)	.489
X (N = 925)	.620
D (N = 548)	.641
E (N = 345)	.733
F (N = 21)	.476

Note: $F_{(6,2420)} = 6.495$; $p < .001$; $r_{pb} = .113$; $p < .001$.

TABLE BE-7

Validity of the Base Expectancy Scale (61B)
in Two Follow-up Studies of Different Samples
of Released California Prisioners*

		Sample 1: Eight Year Follow-Up; Validation Sample, Offenders Paroled in 1956		Sample 2: Offenders in Prison in 1962-1963; Follow-Up to 1988 (variable release dates)			
Base Expectancy Score	Group	Number	Percent Not Arrested or Incarcerated	Number	Percent Not Incarcerated	Percent Arrested	Arrest Rate All/Serious Only
A	92-112	30	87	56	77	39	.07/.02
B	73-91	120	63	248	58	67	.14/.16
C	63-72	137	51	284	46	73	.20/.08
X	44-62	345	39	925	31	83	.35/.15
D	34-43	165	32	548	19	90	.46/.20
E	15-33	133	21	345	16	92	.61/.28
F	0-14	7	0	21	14	95	.58/.28
ALL		937	41	2427	32		

*Score gropus were defined in the initial study sample as follows:
A = 2 S.D.; B 1 S.D, 2 S.D.; C .5 S.D., 1 S.D.; x -5 S.D., .5 S.D.; -5 S.D., 1 S.D.; E -1 S.D., -2 S.D.; F -2 S.D..

Table SE-1

Probability of Arrest
By
Stakes Expectency Subgroup

Stakes Expectancy Subgroup	Probability of Arrest
A (N = 21)	.857
B (N = 363)	.931
C (N = 398)	.887
X (N = 954)	.838
D (N = 332)	.762
E (N = 290)	.676
F (N = 74)	.595

Note: $F_{(6,2425)} = 20.942$; $p < .001$; $r_{pb} = -.215$; $p < .001$.

Table SE-2

Probability of Incarceration
By
Stakes Expectency Subgroup

Stakes Expectancy Subgroup	Probability of Incarceration
A (N = 21)	.762
B (N = 363)	.840
C (N = 398)	.779
X (N = 954)	.697
D (N = 332)	.596
E (N = 290)	.500
F (N = 74)	.378

Note: $F_{(6,2425)} = 26.274$; $p < .001$; $r_{pb} = -.243$; $p < .001$.

Table SE-3

Lambda
By
Stakes Expectancy Subgroup

Stakes Expectancy Subgroup	Lambda
A (N = 21)	.508
B (N = 360)	.616
C (N = 398)	.475
X (N = 948)	.340
D (N = 331)	.248
E (N = 290)	.184
F (N = 74)	.123

Note: $F_{(6,2415)} = 33.352$; $p < .001$; $r_{pb} = -.269$; $p < .001$.

Table SE-4

Lambda for Serious Offenses
By
Stakes Expectancy Subgroup

Stakes Expectancy Subgroup	Lambda
A (N = 21)	.243
B (N = 360)	.290
C (N = 398)	.222
X (N = 948)	.144
D (N = 331)	.103
E (N = 290)	.070
F (N = 74)	.043

Note: $F_{(6,2415)} = 33.809$; $p < .001$; $r_{pb} = -.269$; $p < .001$.

Table SE-5

Average Number of Offenses Against Persons
By
Stakes Expectency Subgroup

Stakes Expectancy Subgroup	Average Offenses
A (N = 21)	.952
B (N = 363)	1.003
C (N = 398)	.802
X (N = 954)	.533
D (N = 332)	.419
E (N = 290)	.169
F (N = 74)	.149

Note: $F_{(6,2425)} = 24.688$; $p < .001$; $r_{pb} = -.236$; $p < .001$.

Table T-1

Offense Transition Matrix
Commitment Offense and First Charge Post-Release
(N = 1,946)

Commitment Offense Dimension	First Charge Offense Dimension: Nuisance	Person	Property	Fraud	Serious Drug	Totals
Nuisance	275 239.0 .661	24 30.4 .058	95 118.0 .228	14 24.8 .034	8 3.8 .019	416 C_F = .203 ASR = 4.0
Person	128 118.9 .618	29 15.1 .140	42 58.7 .203	6 12.3 .029	2 1.9 .010	207 C_F = .072 ASR = 3.9
Property	502 564.7 .511	72 71.7 .073	354 278.8 .360	49 58.6 .050	6 9.1 .006	983 C_F = .107 ASR = 7.6
Fraud	146 144.2 .582	12 18.3 .048	49 71.2 .195	44 15.0 .175	0 2.3 .000	251 C_F = .123 ASR = 8.3
Serious Drug	67 51.1 .753	5 6.5 .056	12 25.2 .135	3 5.3 .034	2 0.8 .022	89 C_F = .014 ASR = 1.3
Totals	1118 .575	142 .073	552 .284	116 .060	18 .009	1946

Note: $X^2_{(16)} = 154.47$; $p < .001$; C = .271.

Table T-2

Offense Transition Matrix
First and Second Charges Post-Release
(N = 1,747)

First Charge Dimension	Second Charge Offense Dimension: Nuisance	Person	Property	Fraud	Totals
Nuisance	700	78	192	31	1,001
	625.7	89.9	235.5	49.8	$C_F = .198$
	.699	.078	.191	.031	ASR = 7.4
Person	71	35	19	4	129
	80.6	11.6	30.3	6.4	$C_F = .199$
	.550	.271	.147	.031	ASR = 7.5
Property	268	38	189	20	515
	321.9	46.3	121.2	25.6	$C_F = .172$
	.520	.074	.367	.039	ASR = 8.4
Fraud	53	6	11	32	102
	63.8	9.2	24.0	5.1	$C_F = .278$
	.520	.059	.108	.314	ASR =12.6
Totals	1,092	157	411	87	1,747
	.625	.090	.235	.050	

Note: $X^2_{(9)} = 281.50$; $p < .001$; C = .373.

Table T-3

Offense Transition Matrix
Second and Third Charges Post-Release
(N = 1,599)

Second Charge Dimension	Third Charge Offense Dimension				
	Nuisance	Person	Property	Fraud	Totals
Nuisance	688 611.1 .695	74 89.2 .075	179 223.5 .181	49 66.3 .049	990 C_F = .203 ASR = 8.1
Person	81 90.7 .551	37 13.2 .252	24 33.2 .163	5 9.8 .034	147 C_F = .178 ASR = 7.2
Property	193 263.4 .504	31 34.5 .081	143 86.5 .373	16 25.6 .042	383 C_F = .191 ASR = 7.9
Fraud	25 48.8 .316	2 7.1 .025	15 17.8 .190	37 5.3 .468	79 C_F = .430 ASR =14.6
Totals	987 .617	144 .090	361 .226	107 .067	1,599

Note: $X^2_{(9)}$ = 329.09; $p < .001$; C = .413.

Table T-4

Offense Transition Matrix
Third and Fourth Charges Post-Release
(N = 1,435)

Third Charge Dimension	Fourth Charge Offense Dimension: Nuisance	Person	Property	Fraud	Totals
Nuisance	616 529.1 .694	69 86.0 .078	174 220.3 .196	29 52.6 .033	888 $C_F = .242$ ASR = 9.6
Person	57 75.1 .452	42 12.2 .333	26 31.3 .206	1 7.5 .008	126 $C_F = .262$ ASR = 9.4
Property	152 192.4 .471	19 31.3 .059	132 80.1 .409	20 19.1 .062	323 $C_F = .214$ ASR = 7.6
Fraud	30 58.4 .306	9 9.5 .092	24 24.3 .245	35 5.8 .357	98 $C_F = .317$ ASR = 12.9
Totals	855 .596	139 .097	356 .248	85 .059	1,435

Note: $X^2_{(9)} = 329.14$; $p < .001$; C = .432.

Table T-5

Offense Transition Matrix
Fourth and Fifth Charges Post-Release
(N = 1,317)

Fourth Charge Offense Dimension	Fifth Charge Offense Dimension: Nuisance	Person	Property	Fraud	Totals
Nuisance	523 457.2 .679	53 71.3 .069	159 185.3 .206	35 56.1 .045	770 C_F = .210 ASR = 7.5
Person	69 74.8 .548	35 11.7 .278	21 30.3 .167	1 9.2 .008	126 C_F = .204 ASR = 7.5
Property	165 201.9 .485	33 31.5 .097	121 81.8 .356	21 24.8 .062	340 C_F = .155 ASR = 5.8
Fraud	25 48.1 .309	1 7.5 .012	16 19.5 .198	39 5.9 .481	81 C_F = .441 ASR =14.6
Totals	782 .594	122 .093	317 .241	96 .073	1,317

Note: $X^2_{(9)} = 312.11$; $p < .001$; $C = .438$

Table T-6

Offense Transition Matrix
Fifth and Sixth Charges Post-Release
(N = 1,215)

Fifth Charge Dimension		Sixth Charge Offense Dimension: Nuisance	Person	Property	Fraud	Totals
	Nuisance	485 406.7 .682	51 69.6 .072	158 196.6 .222	17 38.0 .024	711 C_F = .257 ASR = 9.2
	Person	54 63.5 .486	35 10.9 .315	22 30.7 .198	0 5.9 .000	111 C_F = .241 ASR = 8.1
	Property	129 175.0 .422	30 30 .098	133 84.6 .435	14 16.4 .046	306 C_F = .219 ASR = 7.1
	Fraud	27 49.8 .310	3 8.5 .034	23 24.1 .264	34 4.7 .391	87 C_F = .356 ASR =14.5
	Totals	695 .572	119 .098	336 .277	65 .053	1,215

Note: $X^2_{(9)} = 341.83$; $p < .001$; $C = .469$.

Table T-7

Offense Transition Matrix
Sixth and Seventh Charges Post-Release
(N = 1,125)

Sixth Charge Dimension	Seventh Charge Offense Dimension: Nuisance	Person	Property	Fraud	Totals
Nuisance	444 377.9 .685	50 59.3 .077	130 172.2 .201	24 38.6 .037	648 C_F = .245 ASR = 8.1
Person	55 60.1 .534	22 9.4 .214	24 27.4 .233	2 6.1 .019	103 C_F = .135 ASR = 4.5
Property	139 183.1 .443	29 28.7 .092	131 83.5 .417	15 18.7 .048	314 C_F = .206 ASR = 7.2
Fraud	18 35 .300	2 5.5 .033	14 15.9 .233	26 3.6 .433	60 C_F = .397 ASR =12.6
Totals	656 .583	103 .092	299 .266	67 .060	1,125

Note: $X^2_{(9)} = 239.20$; $p < .001$; C = .419.

Table T-8

Offense Transition Matrix
Seventh and Eighth Charges Post-Release
(N = 1,020)

Seventh Charge Offense Dimension	Eighth Charge Offense Dimension: Nuisance	Person	Property	Fraud	Totals
Nuisance	421 353.7 .705	34 48.1 .052	123 161.9 .206	22 36.4 .037	600 C_F = .277 ASR = 8.7
Person	43 53.6 .473	28 7.3 .308	15 24.6 .165	5 5.5 .055	91 C_F = .247 ASR = 8.4
Property	120 160.3 .441	18 21.8 .066	123 73.4 .449	11 16.5 .040	272 C_F = .250 ASR = 7.9
Fraud	19 35.4 .317	2 4.8 .033	15 16.2 .250	24 3.6 .400	60 C_F = .362 ASR =11.4
Totals	603 .589	82 .080	276 .270	62 .061	1,023

Note: $X^2_{(9)} = 266.13$; $p < .001$; C = .454.

Table T-9

Offense Transition Matrix
Eighth and Ninth Charges Post-Release
(N = 937)

Ninth Charge Offense Dimension

Eighth Charge Dimension	Nuisance	Person	Property	Fraud	Totals
Nuisance	357 297.4 .644	40 46.1 .072	136 175.0 .245	21 35.5 .038	554 C_F = .232 ASR = 7.9
Person	34 39.7 .459	23 6.2 .311	16 23.4 .216	1 4.7 .014	74 C_F = .248 ASR = 7.4
Property	95 135.8 .375	15 21.1 .059	127 79.9 .502	16 16.2 .063	253 C_F = .272 ASR = 7.5
Fraud	17 30.1 .304	0 4.7 .000	17 17.7 .304	22 3.6 .393	56 C_F = .351 ASR =10.4
Totals	503 .537	78 .083	296 .316	60 .064	937

Note: $X^2_{(9)}$ = 226.16; $p < .001$; C = .441.

Table T-10

Offense Transition Matrix
Ninth and Tenth Charges Post-Release
(N = 862)

Ninth Charge Offense Dimension	Tenth Charge Offense Dimension: Nuisance	Person	Property	Fraud	Totals
Nuisance	333 266.6 .710	33 39.7 .070	91 130.6 .194	12 32.1 .026	469 C_F = .328 ASR = 9.2
Person	28 40.4 .394	22 6.0 .310	17 19.8 .239	4 4.9 .056	71 C_F = .246 ASR = 7.1
Property	111 152.9 .413	15 22.8 .056	122 74.9 .454	21 18.4 .078	269 C_F = .243 ASR = 7.7
Fraud	18 30.1 .340	3 4.5 .057	10 14.8 .189	22 3.6 .415	53 C_F = .372 ASR =10.3
Totals	490 .568	73 .085	240 .278	59 .068	862

Note: $X^2_{(9)} = 233.18$; $p < .001$; C = .461.

Table T-11

Offense Transistion Matrix
First and Second Arrests Post-Release
(Most Serious Charge Dimensions Only)
(N = 1,660)

First Charge Dimension	Second Charge Offense Dimension: Nuisance	Person	Property	Fraud	Totals
Nuisance	619 561.0 .662	88 91.8 .094	197 227.0 .211	31 55.2 .033	935 C_F = .155 ASR = 5.9
Person	79 85.2 .556	30 13.9 .211	25 34.5 .176	8 8.4 .056	142 C_F = .126 ASR = 4.7
Property	245 289.8 .507	36 47.4 .075	169 117.3 .350	33 28.5 .068	483 C_F = .141 ASR = 6.5
Fraud	53 60.0 .530	9 9.8 .090	12 24.3 .120	26 5.9 .260	100 C_F = .214 ASR = 8.8
Totals	996 .600	163 .098	403 .243	98 .059	1,660

Note: $X^2_{(9)} = 151.001$; $p < .001$; C = .289.

Table T-12

Offense Transistion Matrix
Second and Third Arrests Post-Release
(Most Serious Charge Dimensions Only)
(N = 1,450)

Second Charge Dimension	Third Charge Offense Dimension: Nuisance	Person	Property	Fraud	Totals
Nuisance	570 502.2 .643	80 93.6 .090	180 223.9 .203	57 67.3 .064	887 C_F = .176 ASR = 7.4
Person	61 76.4 .452	35 14.2 .259	33 34.1 .244	6 10.2 .044	135 C_F = .172 ASR = 6.1
Property	162 198.2 .463	33 36.9 .094	134 88.3 .383	21 26.6 .060	350 C_F = .175 ASR = 6.4
Fraud	28 44.2 .359	5 8.2 .064	19 19.7 .244	26 5.9 .333	78 C_F = .279 ASR = 8.8
Totals	821 .566	153 .106	366 .252	110 .076	1,450

Note: $X^2_{(9)} = 163.591$; $p < .001$; C = .318.

Table T-13

Offense Transition Matrix
Third and Fourth Arrests Post-Release
(Most Serious Charge Dimensions Only)
(N = 1,252)

Third Charge Dimension		Fourth Charge Offense Dimension				
		Nuisance	Person	Property	Fraud	Totals
	Nuisance	458 404.3 .651	56 72.4 .080	161 190.3 .229	28 35.9 .040	703 C_F = .180 ASR = 6.2
	Person	66 73.0 .520	34 13.1 .268	26 34.4 .205	1 6.5 .008	127 C_F = .183 ASR = 6.4
	Property	153 188.1 .468	29 33.7 .089	129 88.5 .394	16 16.7 .049	327 C_F = .170 ASR = 5.9
	Fraud	43 54.6 .453	10 9.8 .105	23 25.7 .242	19 4.9 .200	95 C_F = .156 ASR = 6.9
	Totals	720 .575	129 .103	339 .271	64 .051	1,252

Note: $X^2_{(9)} = 127.610$; $p < .001$; C = .304.

Table T-14

Offense Transition Matrix
Fourth and Fifth Arrests Post-Release
(Most Serious Charge Dimensions Only)
(N = 1,095)

Fourth Charge Dimension	Fifth Charge Offense Dimension: Nuisance	Person	Property	Fraud	Totals
Nuisance	397 350.2 .624	61 68.0 .096	154 184.1 .242	24 33.7 .038	636 C_F = .164 ASR = 5.8
Person	53 59.5 .491	26 11.5 .241	26 31.3 .241	3 5.7 .028	108 C_F = .150 ASR = 4.7
Property	139 164.1 .466	25 31.8 .084	119 86.3 .399	15 15.8 .050	298 C_F = .154 ASR = 4.9
Fraud	14 29.2 .264	5 5.7 .094	18 15.3 .340	16 2.8 .302	53 C_F = .263 ASR = 8.3
Totals	603 .551	117 .107	317 .289	58 .053	1,095

Note: $X^2_{(9)} = 123.879$; $p < .001$; C = .319.

Table T-15

Offense Transition Matrix
Fifth and Sixth Arrests Post-Release
(Most Serious Charge Dimensions Only)
(N = 946)

Fifth Charge Dimension	Sixth Charge Offense Dimension: Nuisance	Person	Property	Fraud	Totals
Nuisance	334 291.9 .630	47 52.7 .089	131 151.8 .247	18 33.6 .034	530 C_F = .177 ASR = 5.5
Person	47 51.2 .505	21 9.2 .226	19 26.6 .204	6 5.9 .065	93 C_F = .141 ASR = 4.3
Property	122 154.2 .436	23 27.8 .082	111 80.2 .396	24 17.8 .086	280 C_F = .154 ASR = 4.9
Fraud	18 23.7 .419	3 4.3 .070	10 12.3 .233	12 2.7 .279	43 C_F = .231 ASR = 5.9
Totals	521 .551	94 .099	271 .286	60 .063	946

Note: $X^2_{(9)} = 89.578$; $p < .001$; C = .294.

Table T-16

Offense Transition Matrix
Sixth and Seventh Arrests Post-Release
(Most Serious Charge Dimensions Only)
(N = 835)

Sixth Charge Dimension		Seventh Charge Offense Dimension: Nuisance	Person	Property	Fraud	Totals
	Nuisance	299 262.9 .636	45 41.7 .096	106 142.4 .226	20 23.1 .043	470 C_F = .174 ASR = 5.1
	Person	33 41.4 .446	18 6.6 .243	18 22.4 .243	5 3.6 .068	74 C_F = .169 ASR = 4.9
	Property	113 135.9 .465	11 21.5 .045	115 73.6 .473	4 11.9 .016	243 C_F = .244 ASR = 6.9
	Fraud	22 26.8 .458	0 4.3 .000	14 14.5 .292	12 2.4 .250	48 C_F = .211 ASR = 6.6
	Totals	467 .559	74 .089	253 .303	41 .049	835

Note: $X^2_{(9)} = 120.142$; $p < .001$; C = .355.

Table T-17

Offense Transition Matrix
Seventh and Eighth Arrests Post-Release
(Most Serious Charge Dimensions Only)
(N = 738)

Seventh Charge Dimension	Eighth Charge Offense Dimension: Nuisance	Person	Property	Fraud	Totals
Nuisance	258 230.4 .607	39 38.6 .092	110 137.1 .259	18 19.0 .042	425 C_F = .142 ASR = 4.1
Person	32 31.4 .552	11 5.3 .190	13 18.7 .224	2 2.6 .034	58 C_F = .108 ASR = 2.7
Property	96 119.2 .436	17 20.0 .077	103 70.9 .468	4 9.8 .018	220 C_F = .215 ASR = 5.5
Fraud	14 19.0 .400	0 3.2 .000	12 11.3 .343	9 1.6 .257	35 C_F = .222 ASR = 6.2
Totals	400 .542	67 .091	238 .322	33 .045	738

Note: $X^2_{(9)} = 79.610$; $p < .001$; C = .312.

Table T-18

Offense Transition Matrix
Eighth and Ninth Arrests Post-Release
(Most Serious Charge Dimensions Only)
(N = 651)

Eighth Charge Dimension	Ninth Charge Offense Dimension: Nuisance	Person	Property	Fraud	Totals
Nuisance	227 191.9 .629	42 41.0 .116	82 112.0 .227	10 16.1 .028	361 $C_F = .208$ ASR = 5.6
Person	27 27.6 .519	13 5.9 .250	10 16.1 .192	2 2.3 .038	52 $C_F = .154$ ASR = 3.2
Property	79 112.1 .374	17 24.0 .081	105 65.5 .498	10 9.4 .047	211 $C_F = .271$ ASR = 7.2
Fraud	13 14.4 .481	2 3.1 .074	5 8.4 .185	7 1.2 .259	27 $C_F = .225$ ASR = 5.5
Totals	346 .531	74 .114	202 .310	29 .045	651

Note: $X^2_{(9)} = 93.228$; $p < .001$; C = .354.

Table T-19

Offense Transition Matrix
Ninth and Tenth Arrests Post-Release
(Most Serious Charge Dimensions Only)
(N = 567)

Ninth Charge Dimension	Tenth Charge Offense Dimension: Nuisance	Person	Property	Fraud	Totals
Nuisance	203 169.4 .672	26 30.9 .086	65 91.6 .215	8 10.1 .026	302 C_F = .253 ASR = 5.7
Person	25 34.2 .410	17 6.2 .279	16 18.5 .262	3 2.0 .049	61 C_F = .197 ASR = 4.8
Property	78 100.4 .436	14 18.3 .078	83 54.3 .464	4 6.0 .022	179 C_F = .230 ASR = 5.6
Fraud	12 14.0 .480	1 2.6 .040	8 7.6 .320	4 .8 .160	25 C_F = .132 ASR = 3.6
Totals	318 .561	58 .102	172 .303	19 .034	567

Note: $X^2_{(9)}$ = 72.489; $p < .001$; C = .337.

Figure 1
Sample Attrition
(N = 3,088)

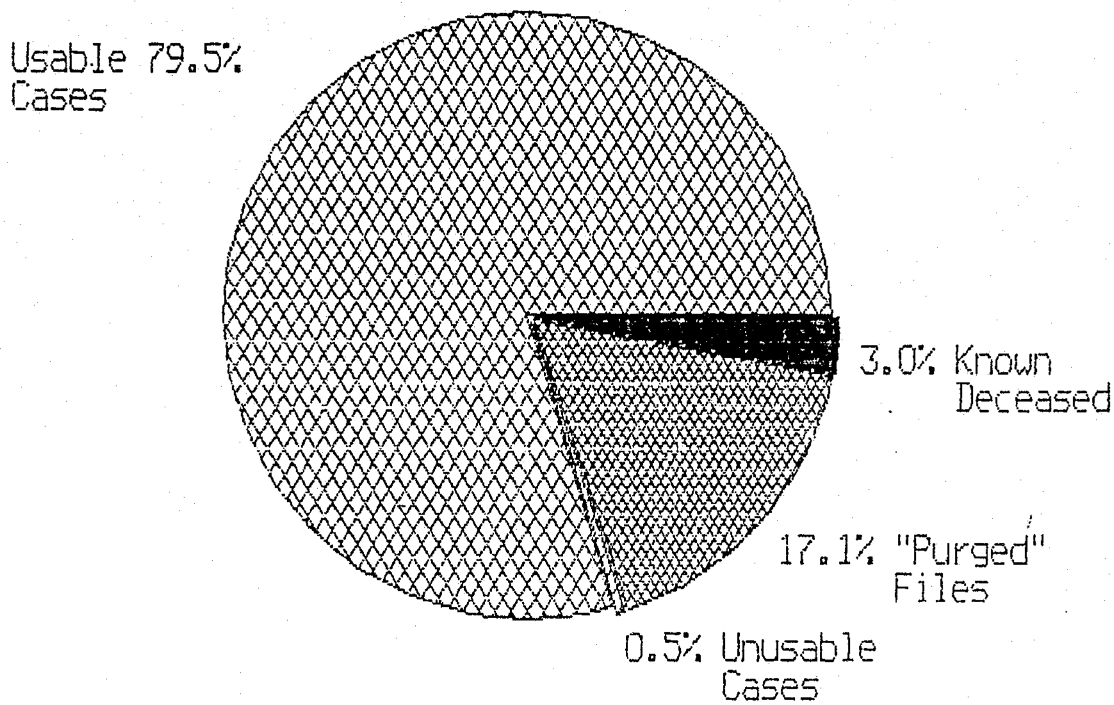


Figure 2
Number of Charges Post-Release
(N = 2,454)

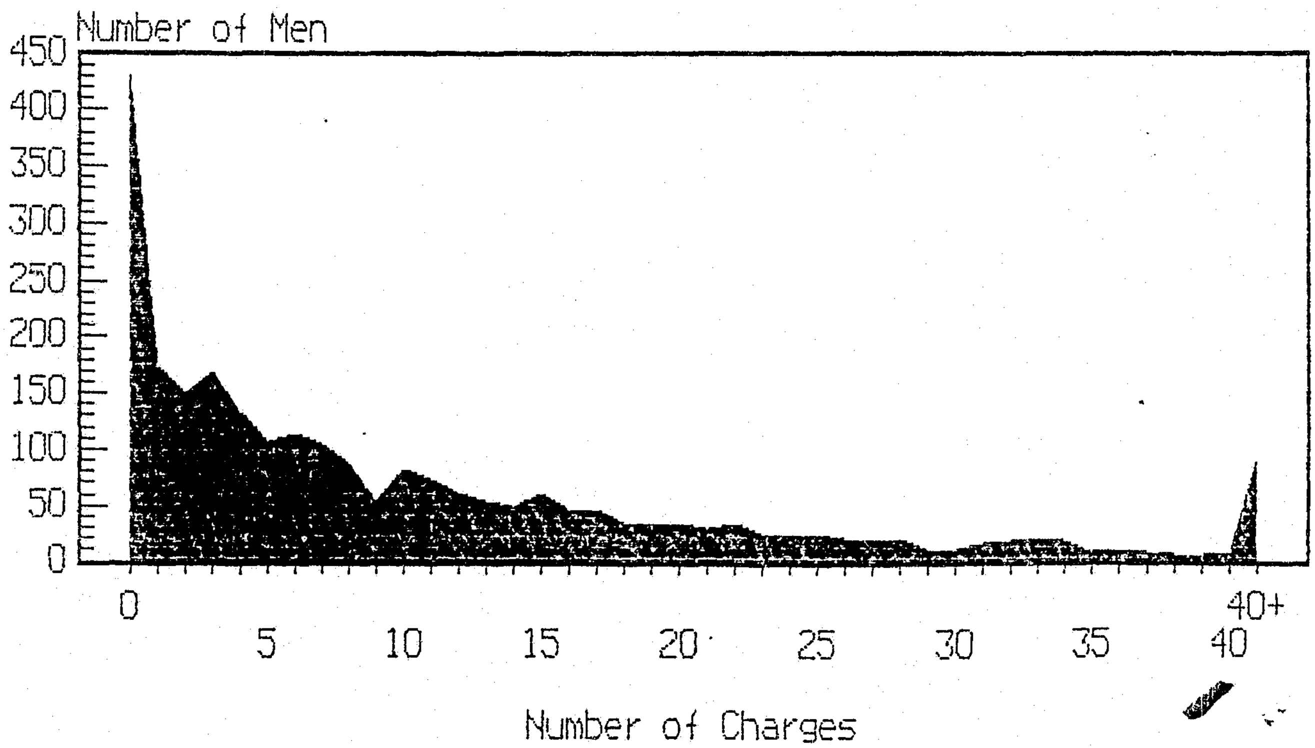


Figure 1
Sample Attrition
(N = 3,088)

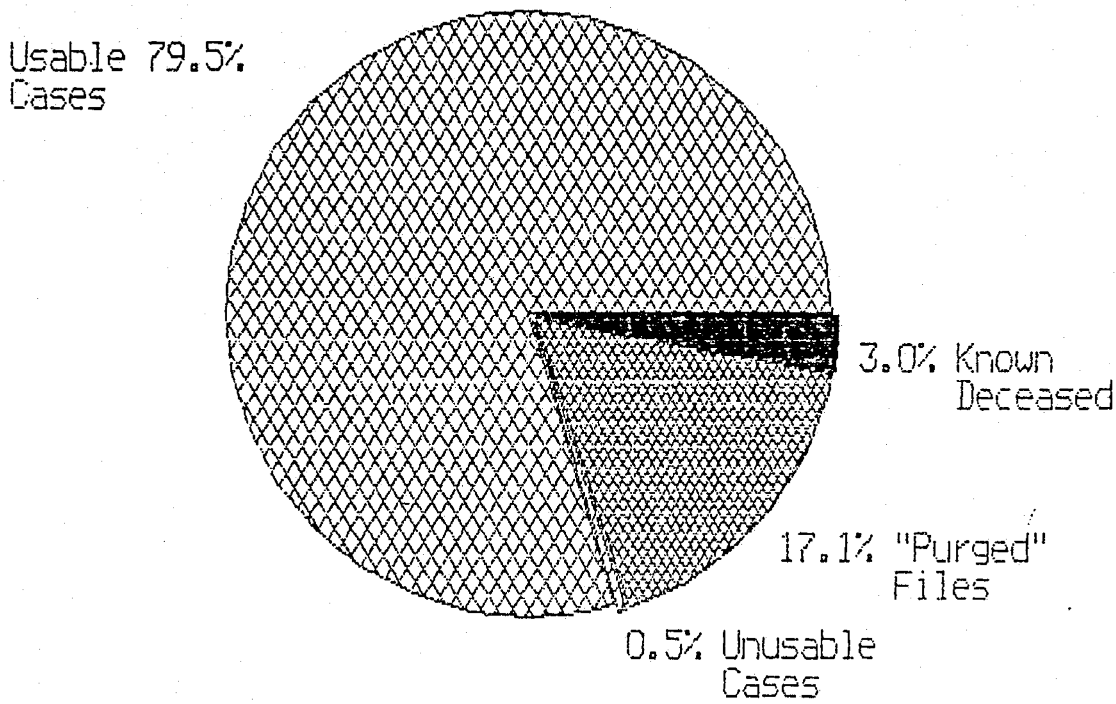


Figure 2
Number of Charges Post-Release
(N = 2,454)

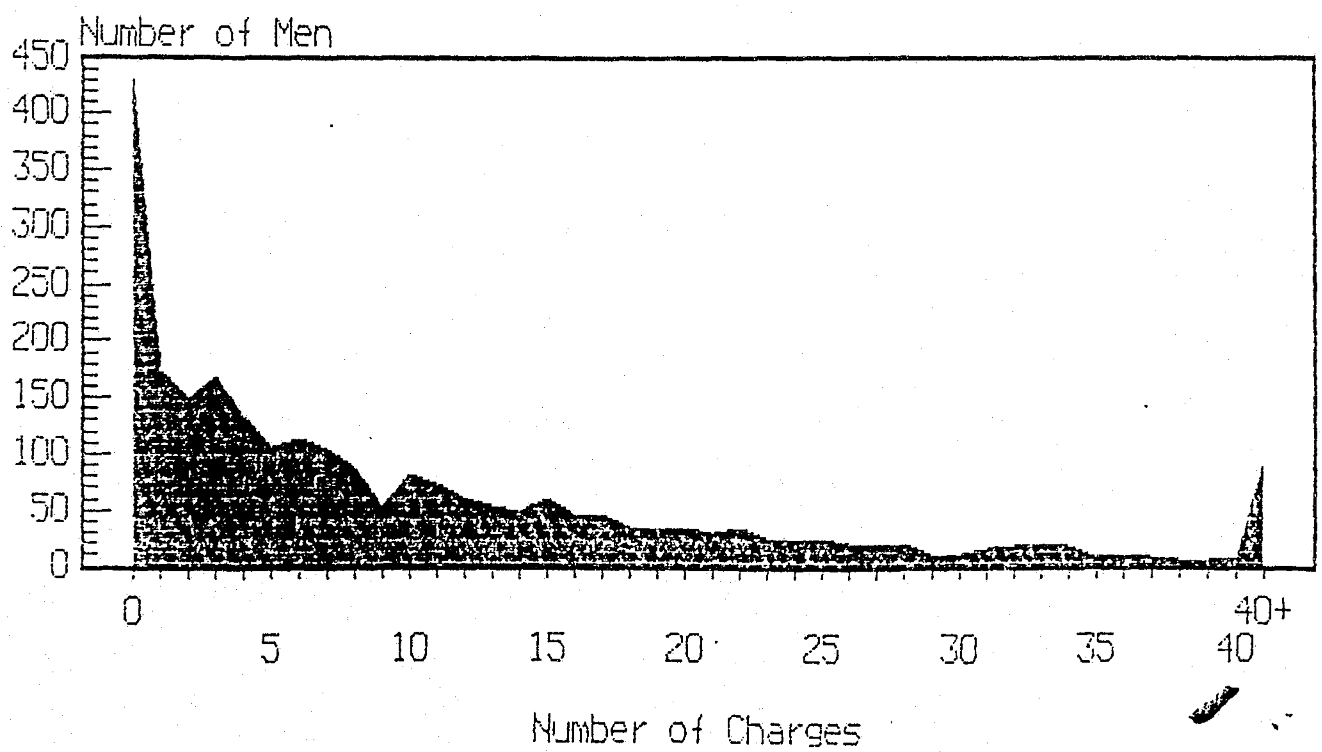


Figure 3
Offenses of First Post-Release Charge
By Dimension (First Arrest Episode)
(N = 2,019)

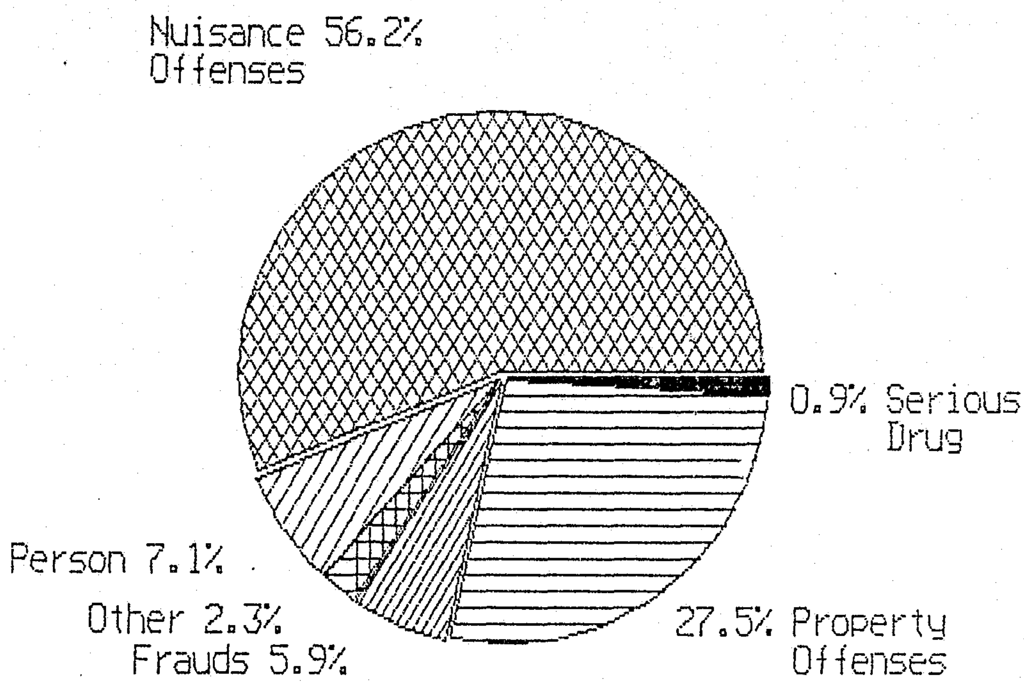


Figure 4
Percent of Post-Release Arrest Offenses
By Dimension of Offense
(First Five Charges Post-Release)

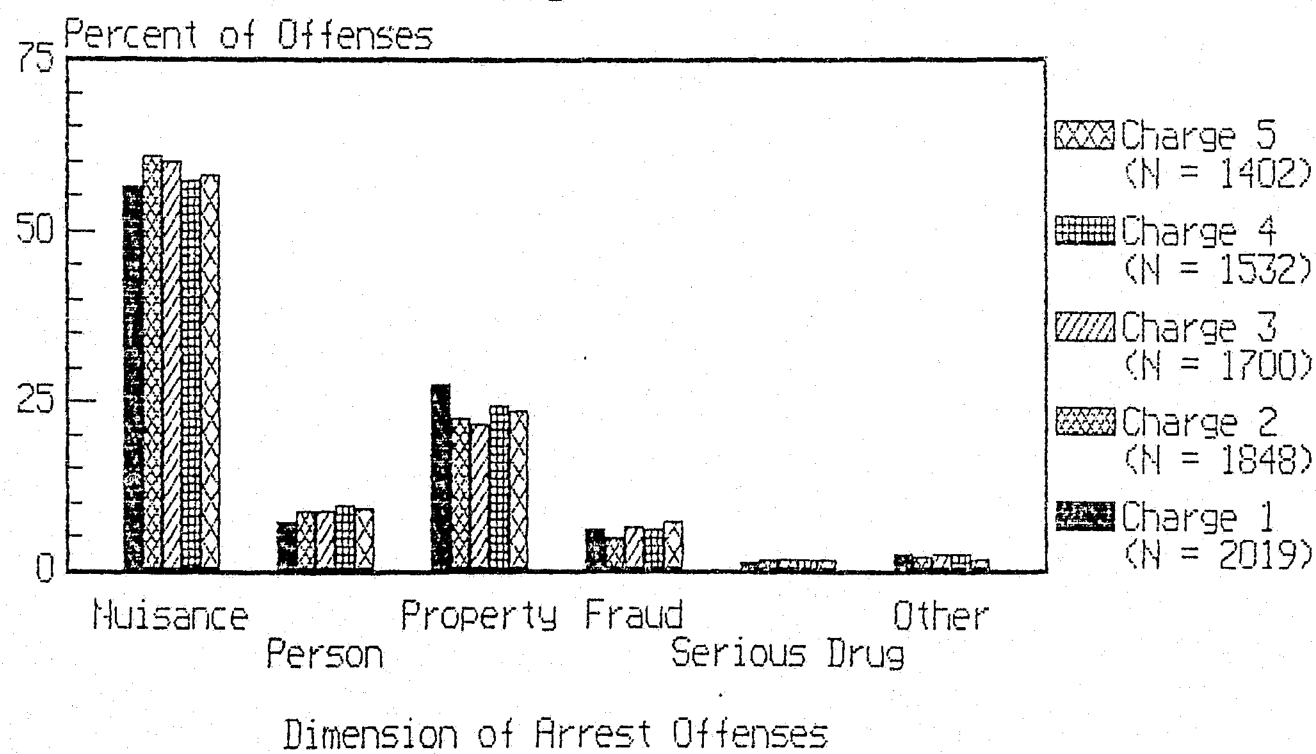


Figure 4A
Most Serious Offenses Charged
(First Arrest Episode): Person Dimension
(N = 183)

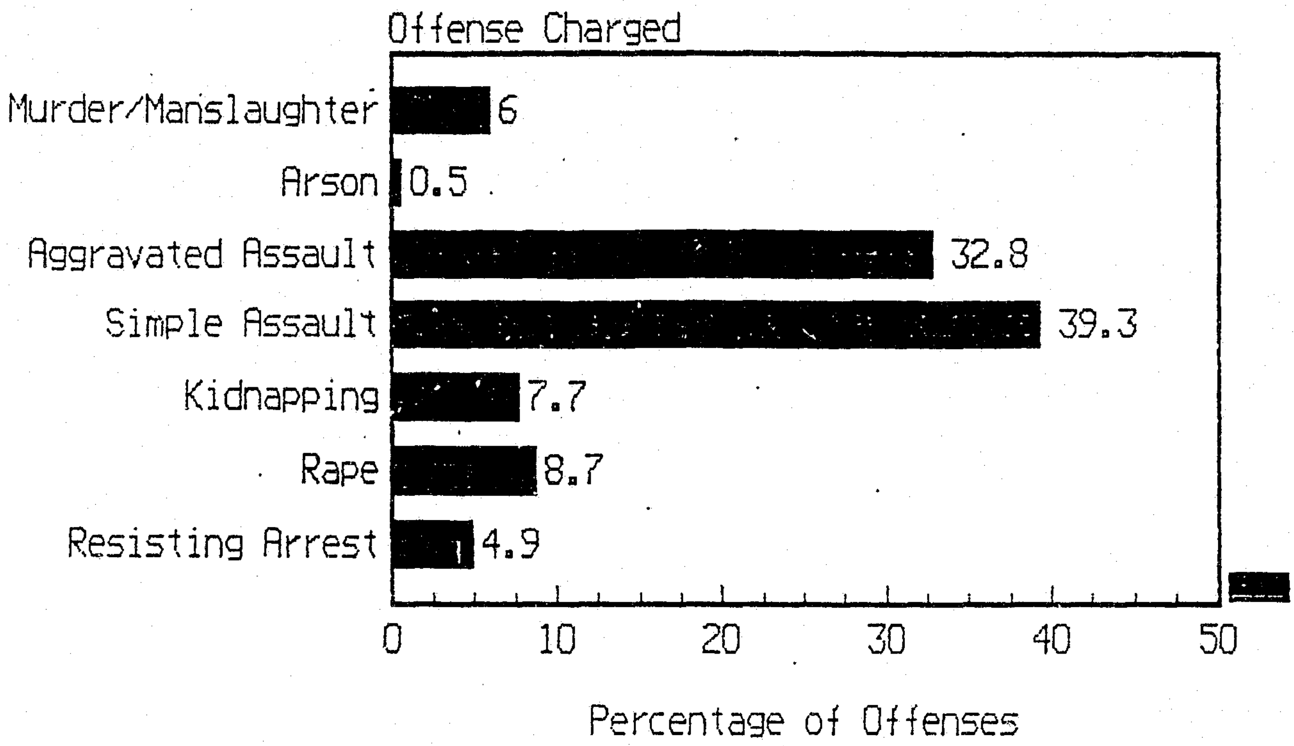


Figure 4B
Most Serious Offenses Charged
(First Arrest Episode): Property Dimen.
(N = 550)

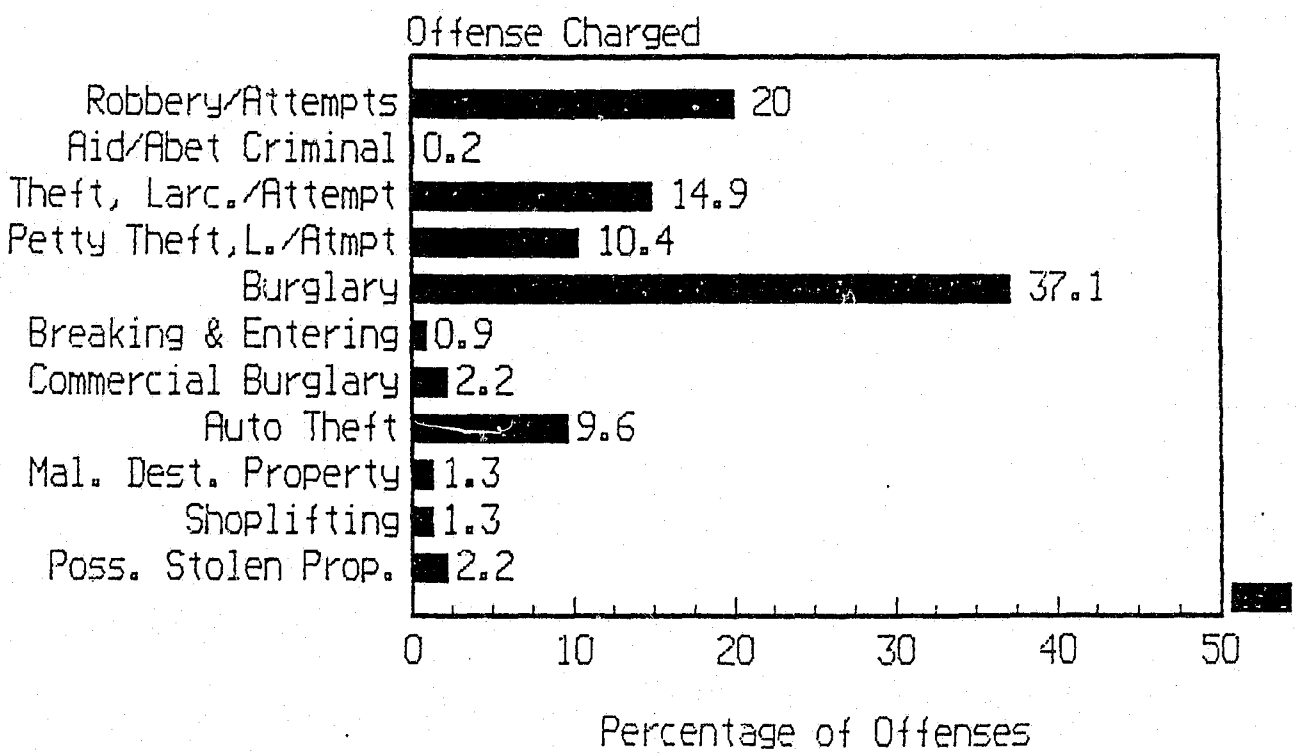


Figure 4C
Most Serious Offenses Charged
(First Arrest Episode): Fraud Dimension
(N = 119)

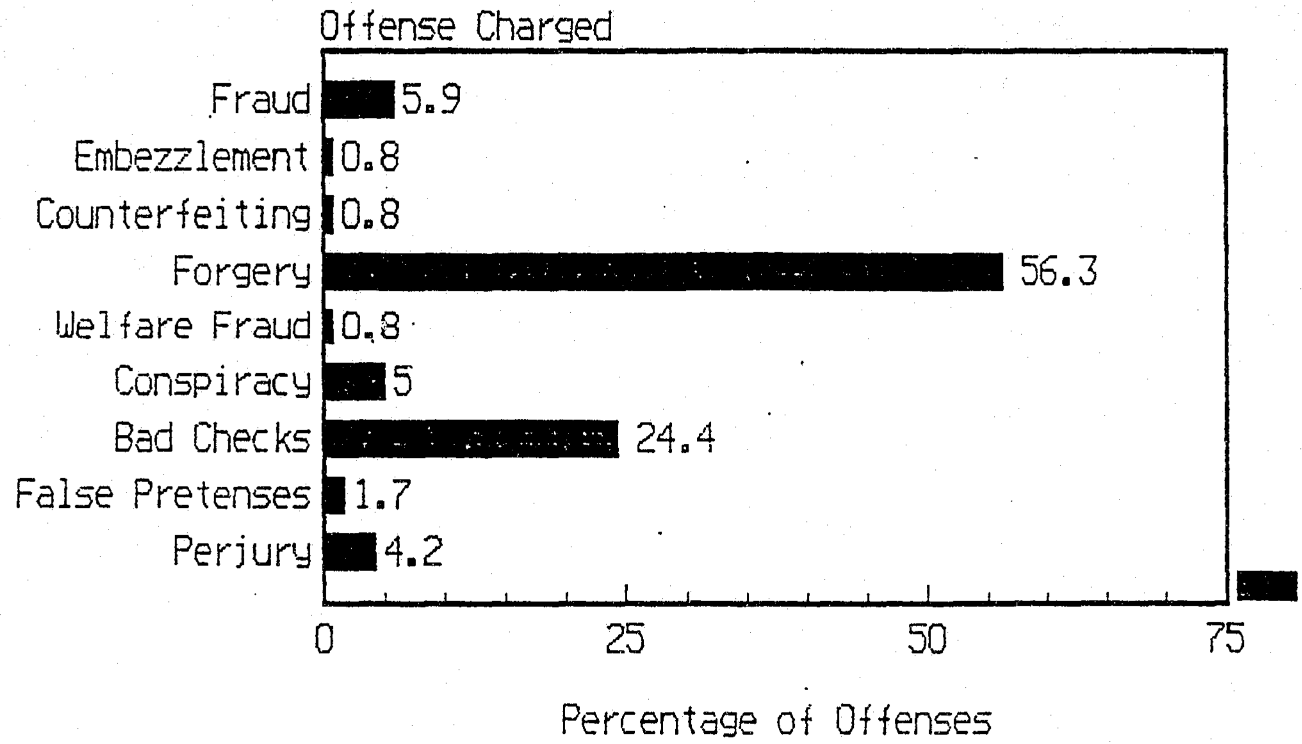
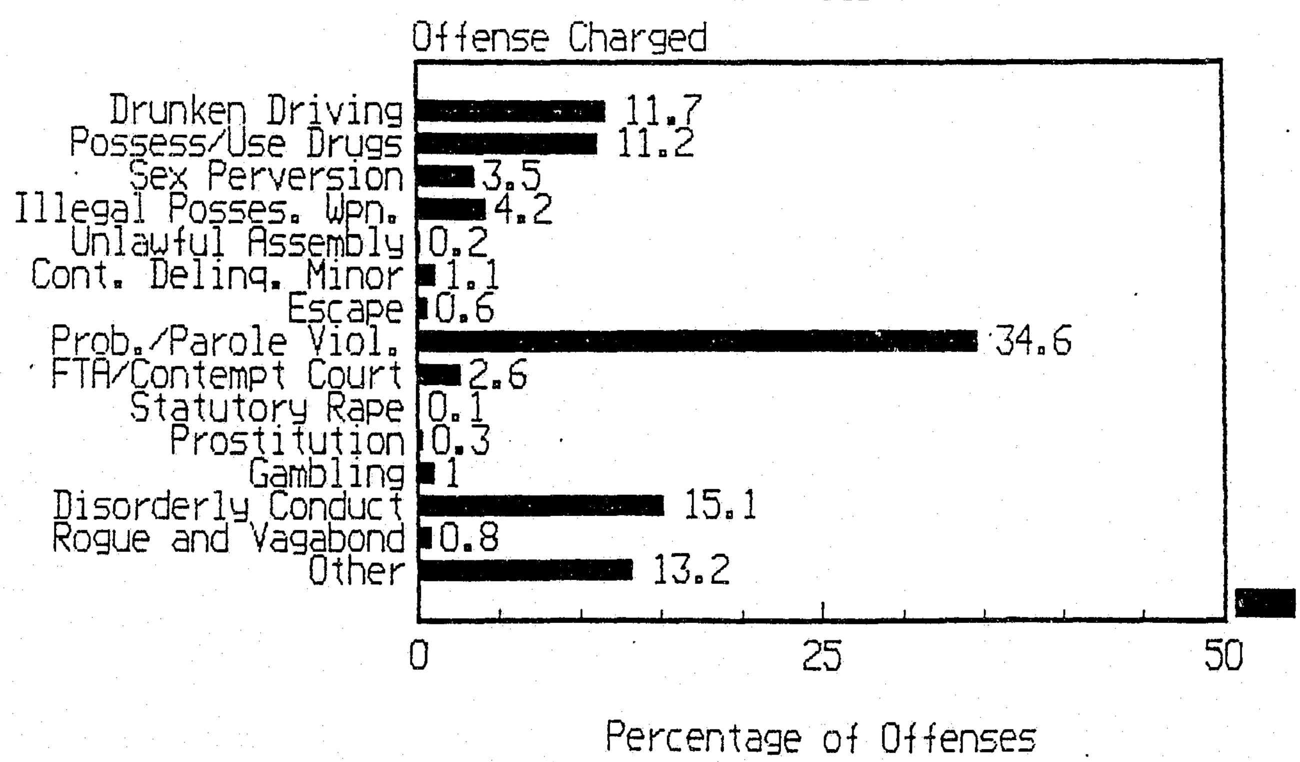


Figure 4D
Most Serious Offenses Charged
(First Arrest Episode): Nuisance Dimen.
(N = 1094)



Note: Examples of "Other" include: peddling without a license, trespassing, littering, failure to pay a cab, telephone misuse, and possession of criminal tools.

Figure 5
Dispositions of First Post-Release Charge (First Charge, First Arrest)
(N = 2,019)

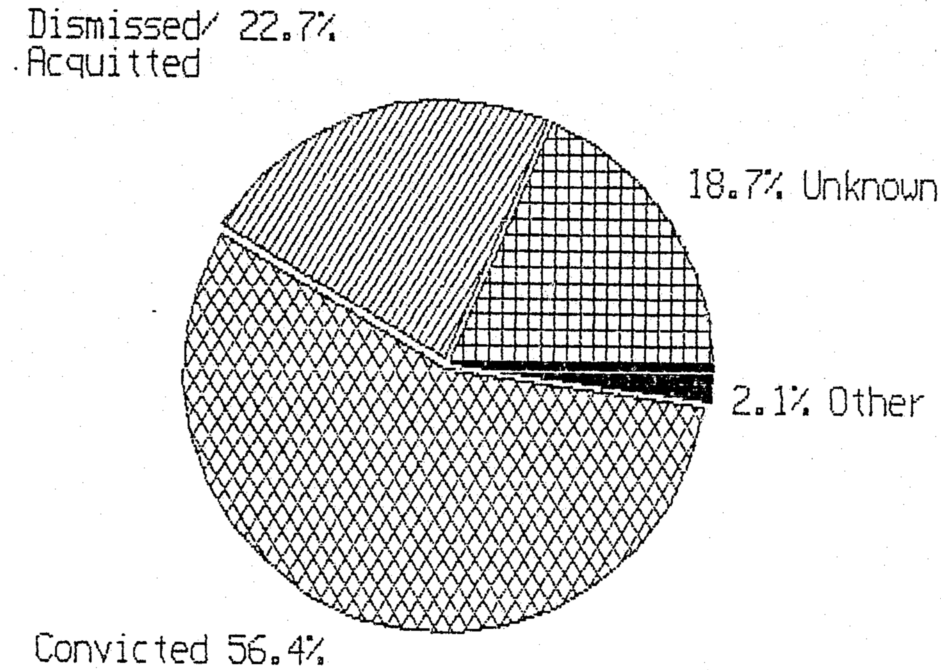


Figure 6
Sentence for First Post-Release Conviction
(N = 1,180)

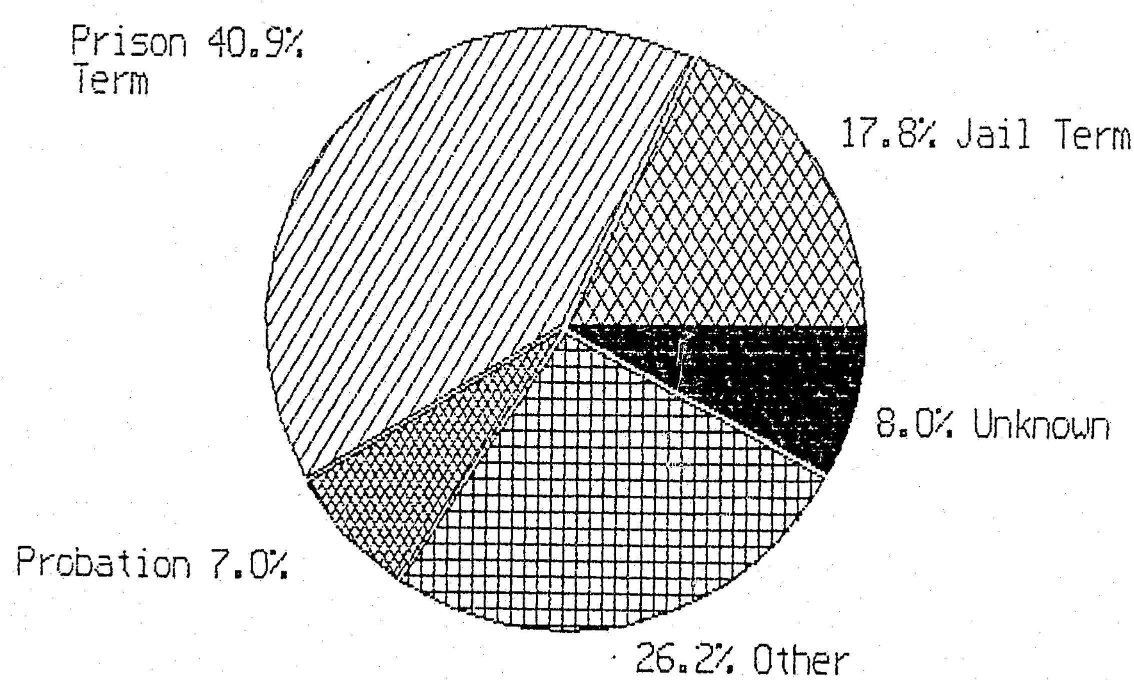


Figure 7
Sentence Imposed
First Five Convictions
Post 1962 - 1963 Release

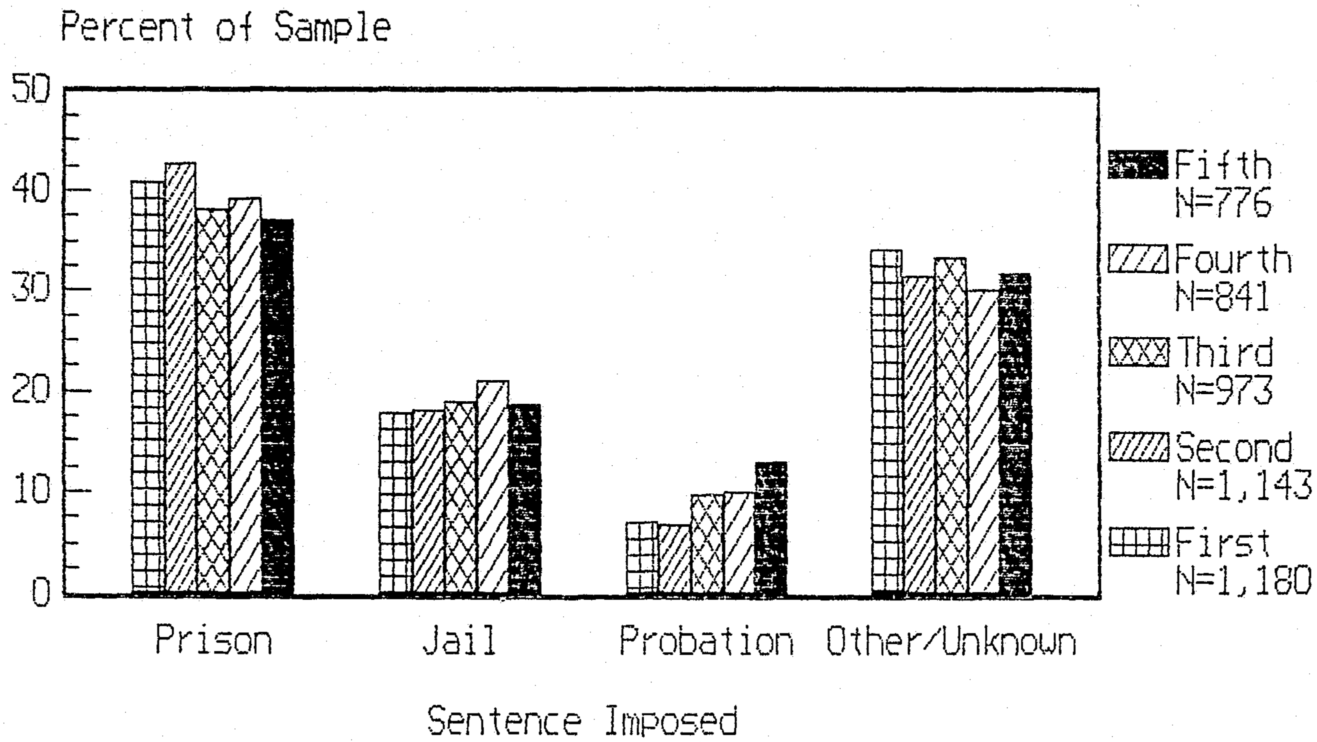


Figure 8
Number of Times Incarcerated
Post-Release (Prison or Jail)
(N = 2,454)

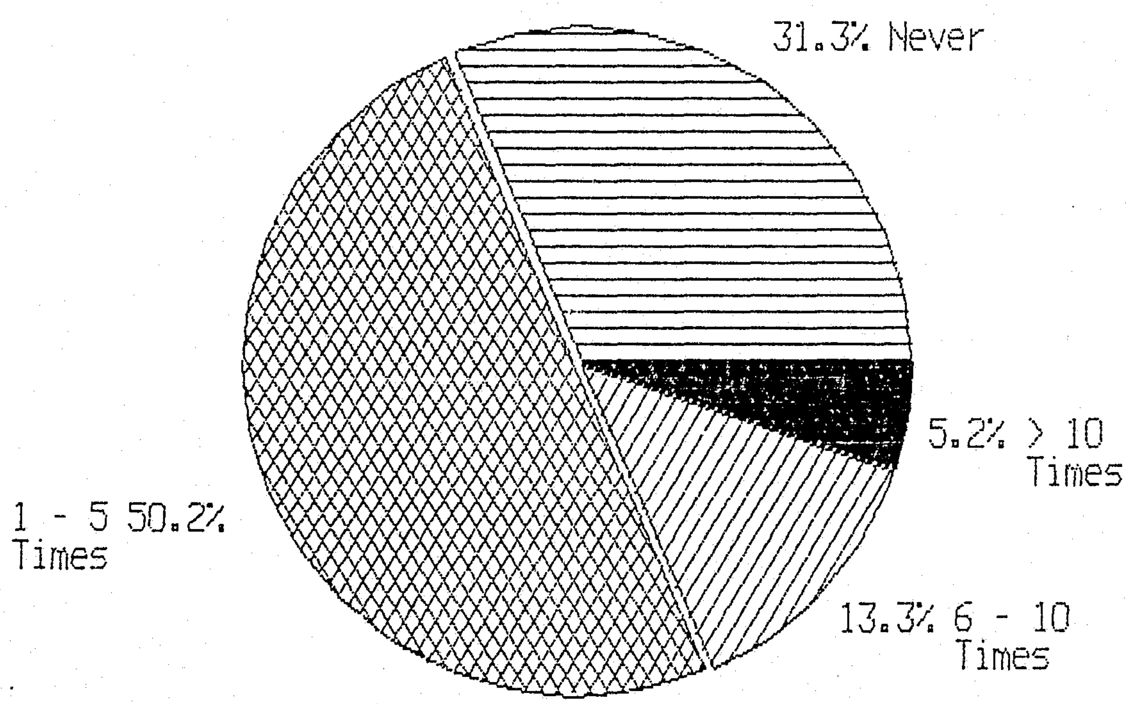


Figure 9
Number of Times Incarcerated
Post-Release (Prison or Jail)
(N = 2454)

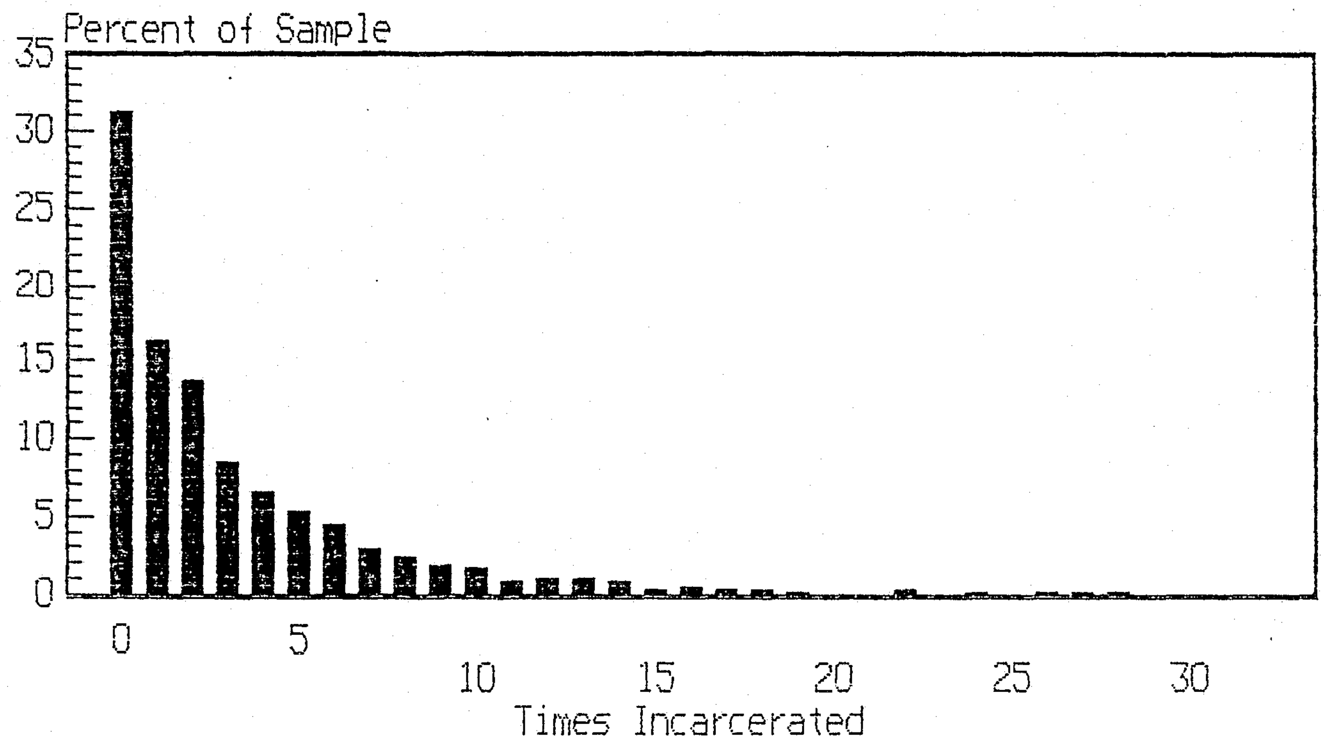


Figure 10
Time to First Incarceration (In Years)
Post-Release From 1962-63 Incarceration
(N = 2,454)

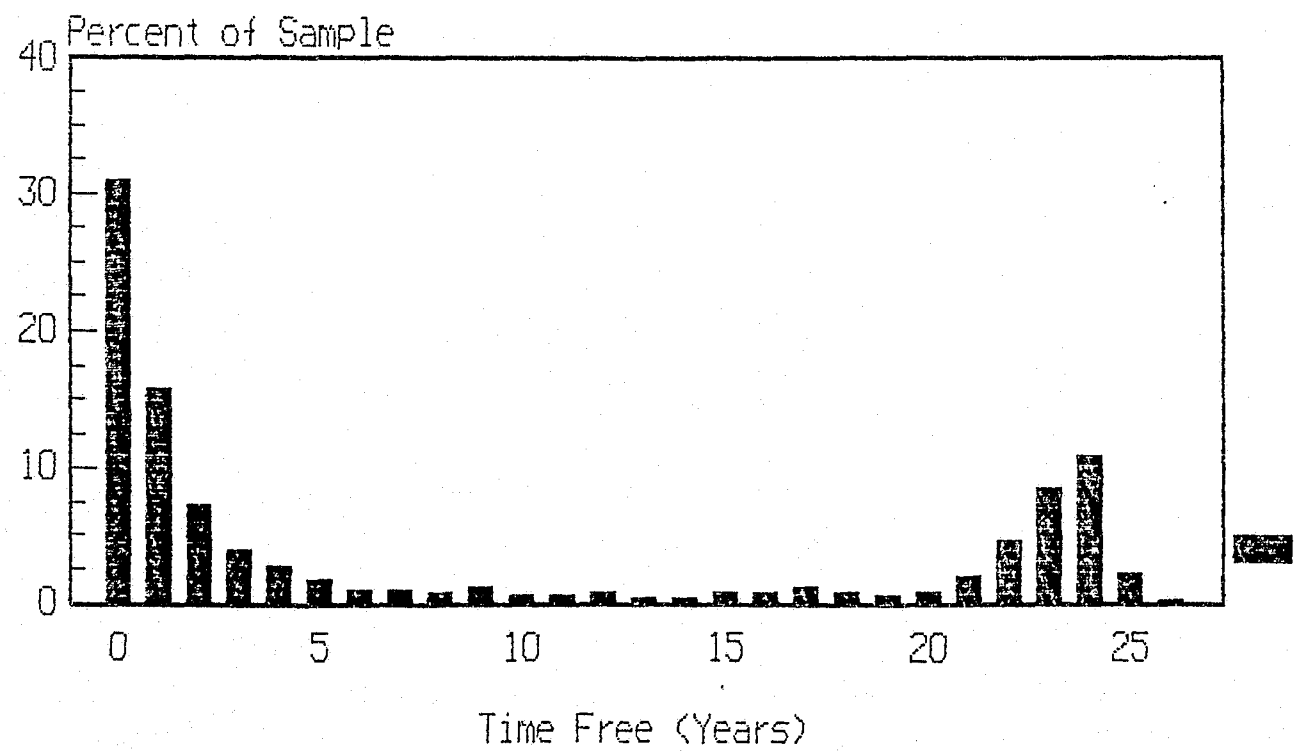


Figure 11
Total Time Free (In Years)
Post-Release From 1962-63 Incarceration
(N = 2,442)

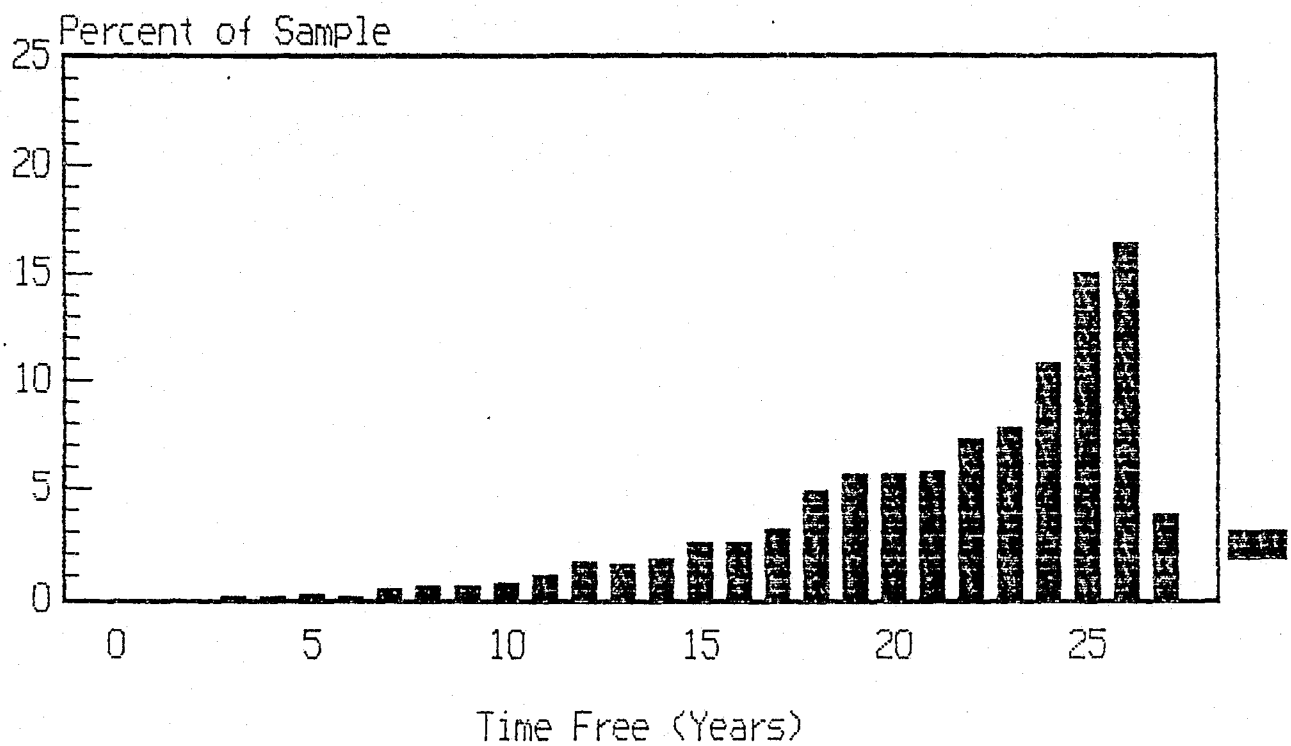


Figure 12
Median Length of Time Free
After Successive Periods of
Incarceration (Failures Only)

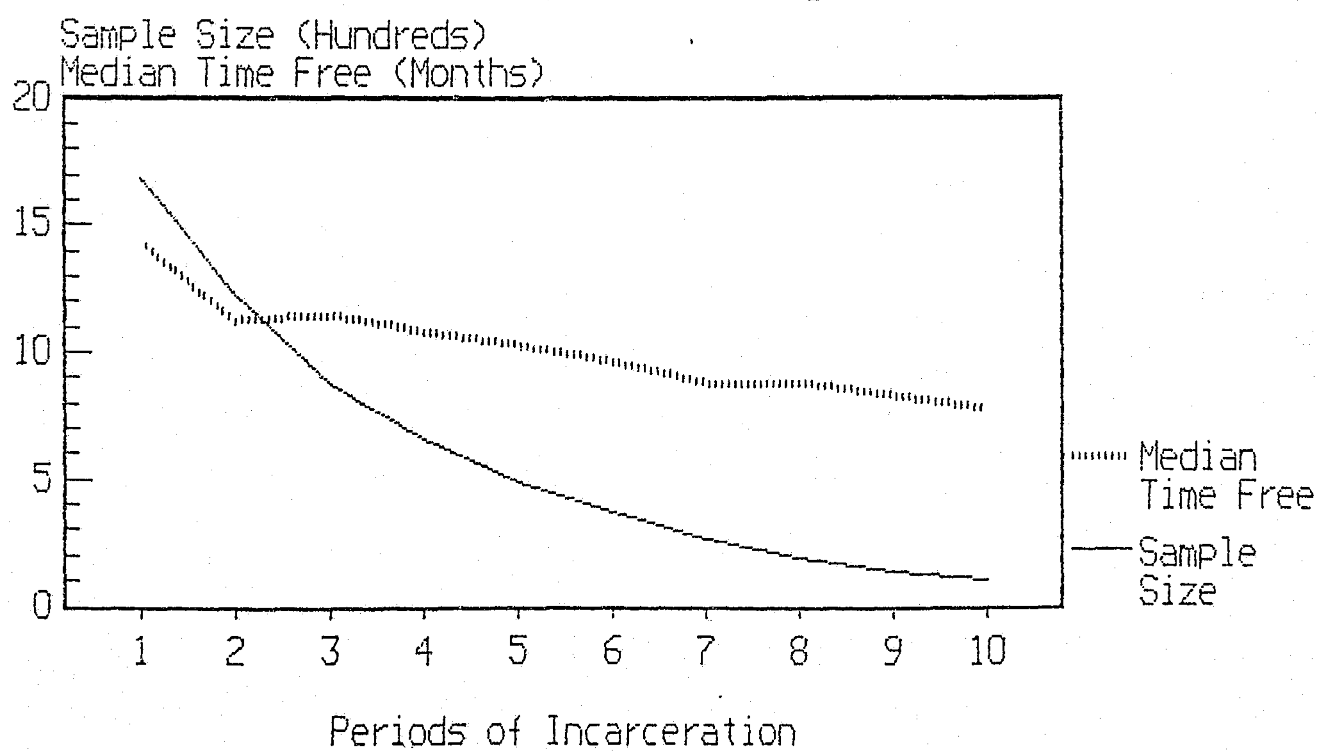


Figure 13
Median Length of Imprisonment
As a Function of Number of Times
Incarcerated

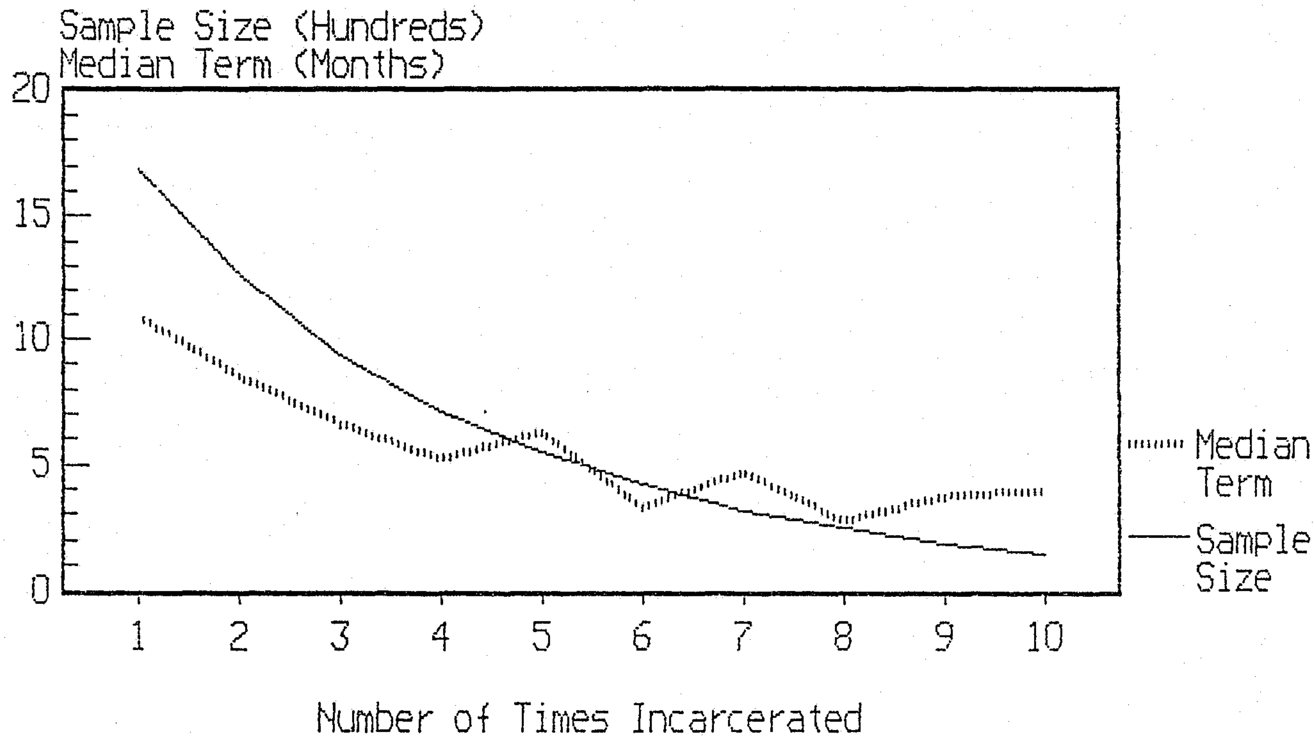


Figure 14: Transition Probabilities
First Two Charges Post-Release
(Charge Two Base Rates For Comparison)
First Charge: Nuisance Offense

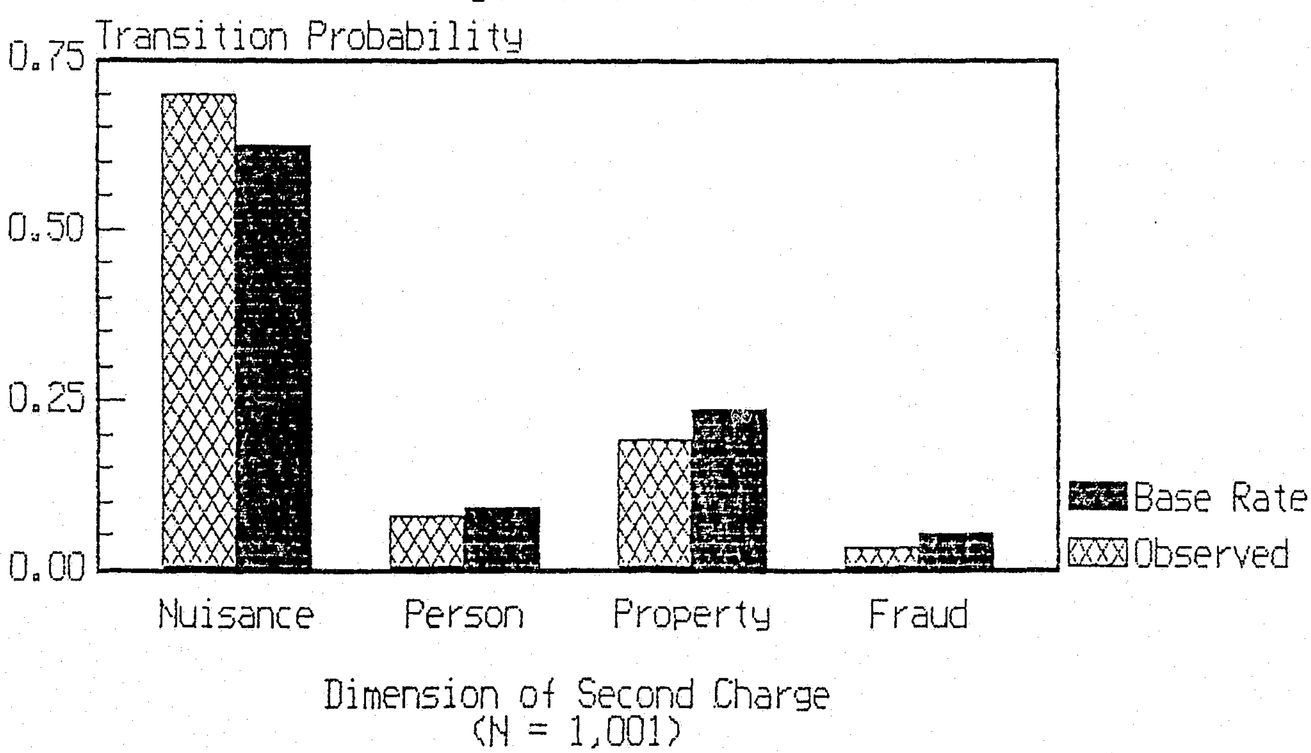


Figure 15: Transition Probabilities
First Two Charges Post-Release
(Charge Two Base Rates For Comparison)
First Charge: Person Offense

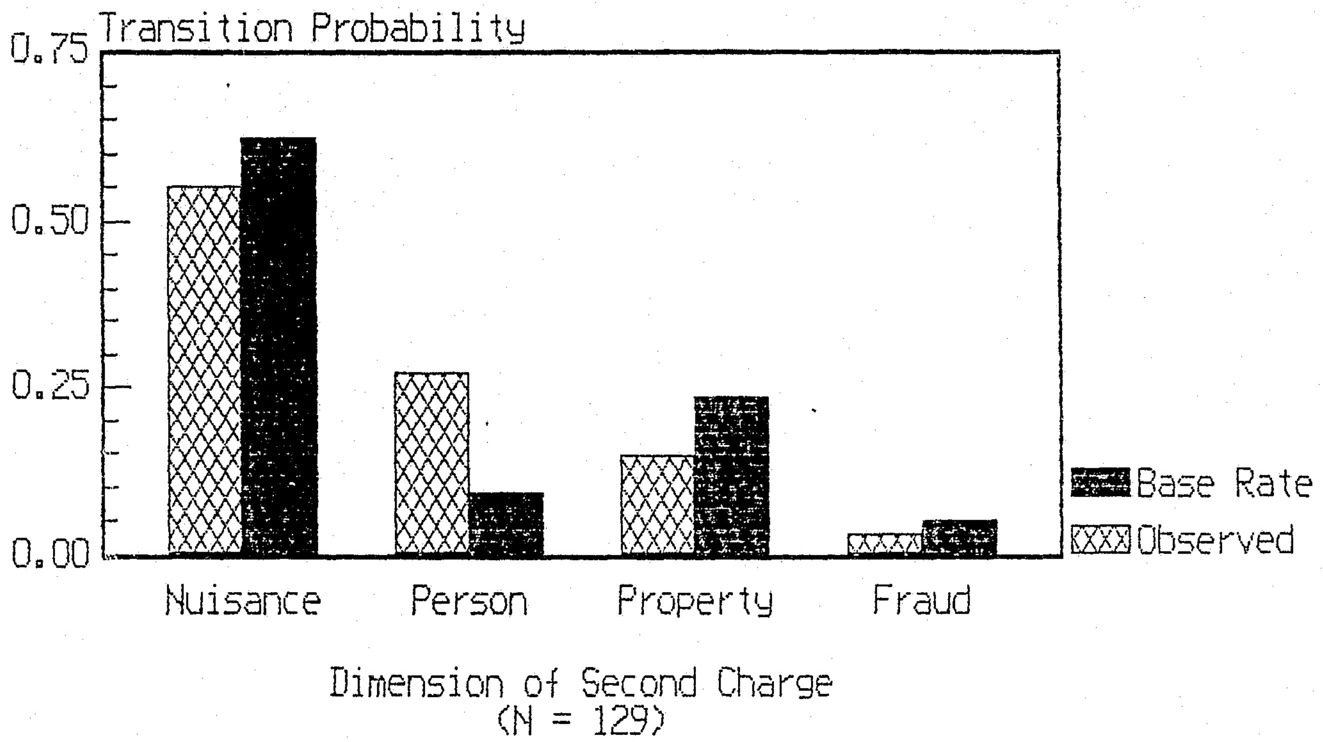


Figure 16: Transition Probabilities
First Two Charges Post-Release
(Charge Two Base Rates For Comparison)
First Charge: Property Offense

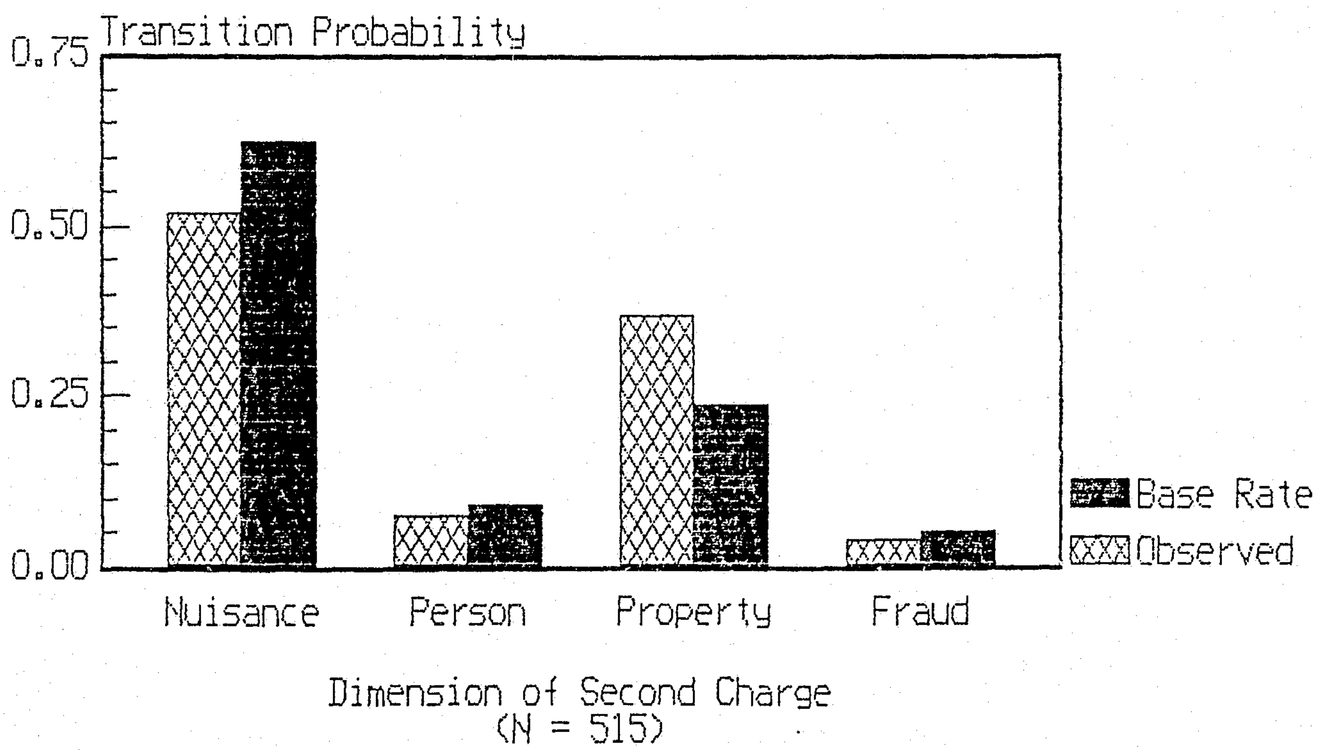


Figure 17: Transition Probabilities
First Two Charges Post-Release
(Charge Two Base Rates For Comparison)
First Charge: Fraud Offense

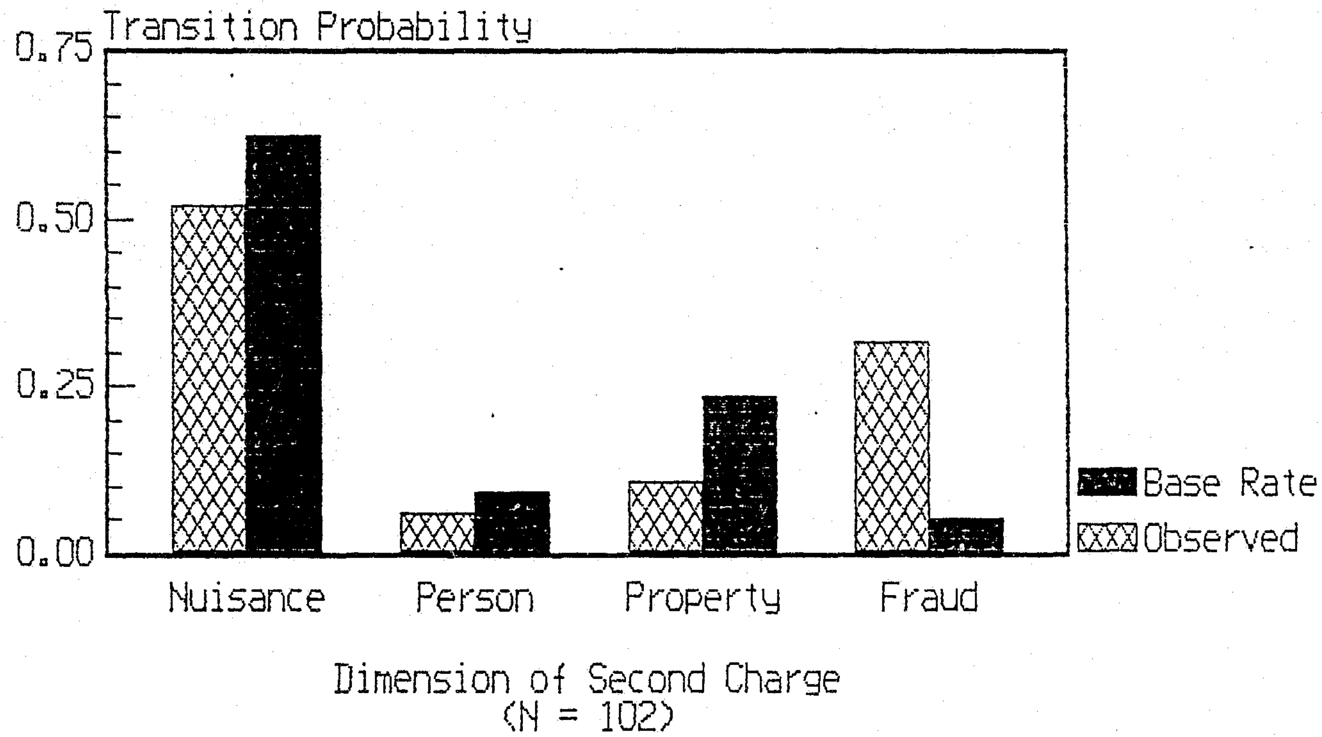


Figure 18: Transition Probabilities
Charges Two and Three
Diagonal Cells Only
(Charge Three Base Rates For Comparison)

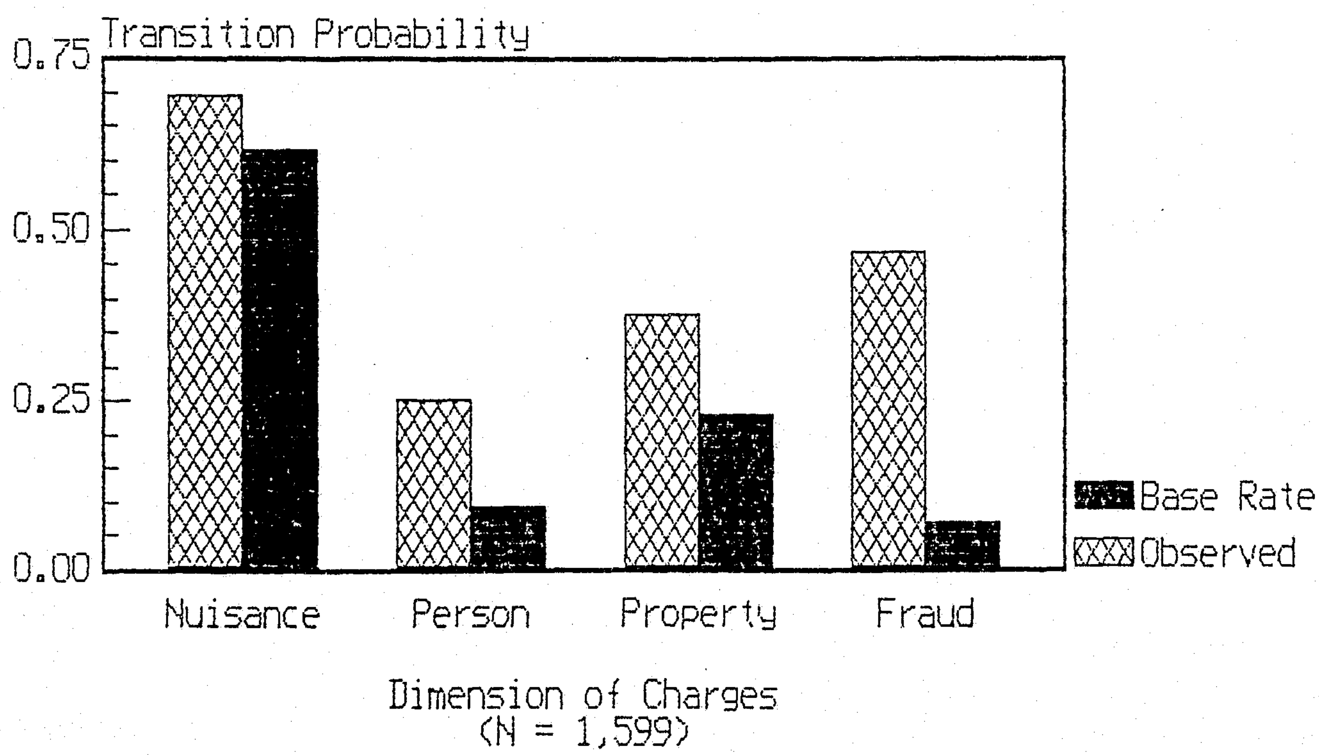


Figure 19: Transition Probabilities
Charges Three and Four
Diagonal Cells Only
(Charge Four Base Rates For Comparison)

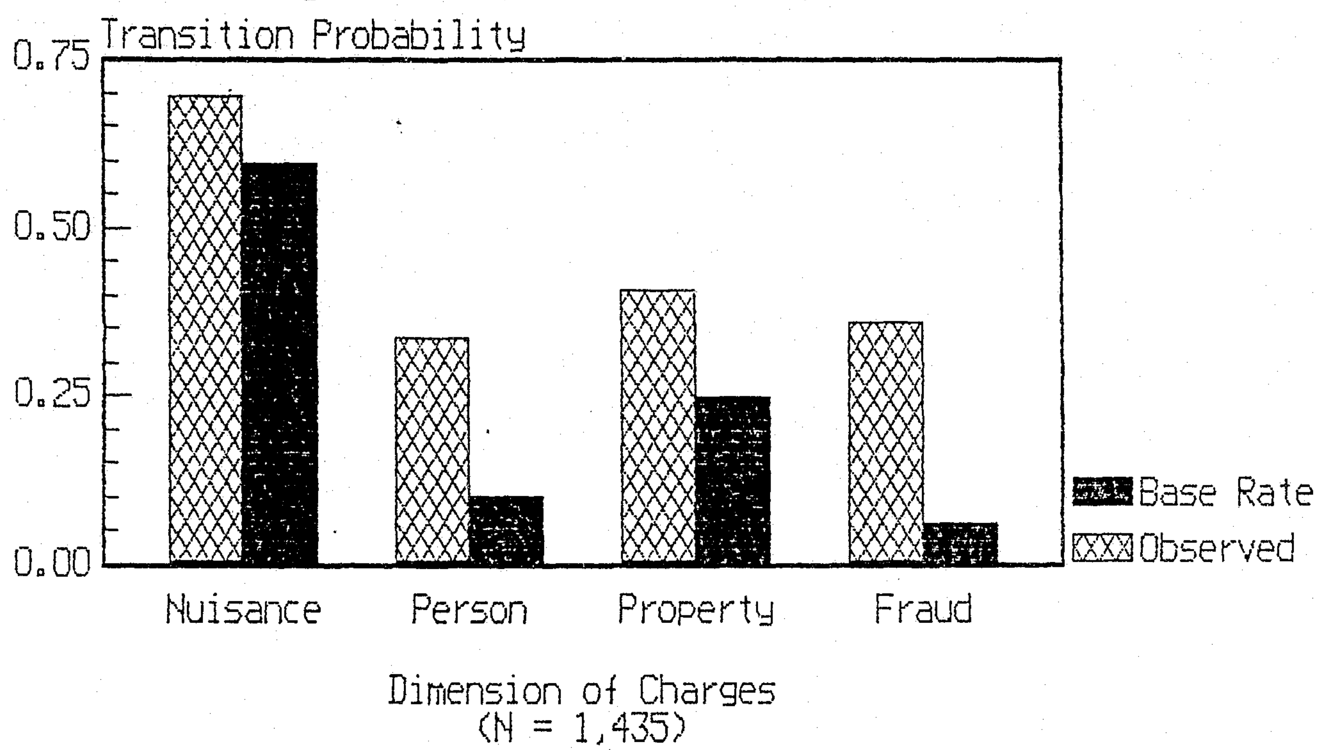


Figure 20: Transition Probabilities
Charges Four and Five
Diagonal Cells Only
(Charge Five Base Rates For Comparison)

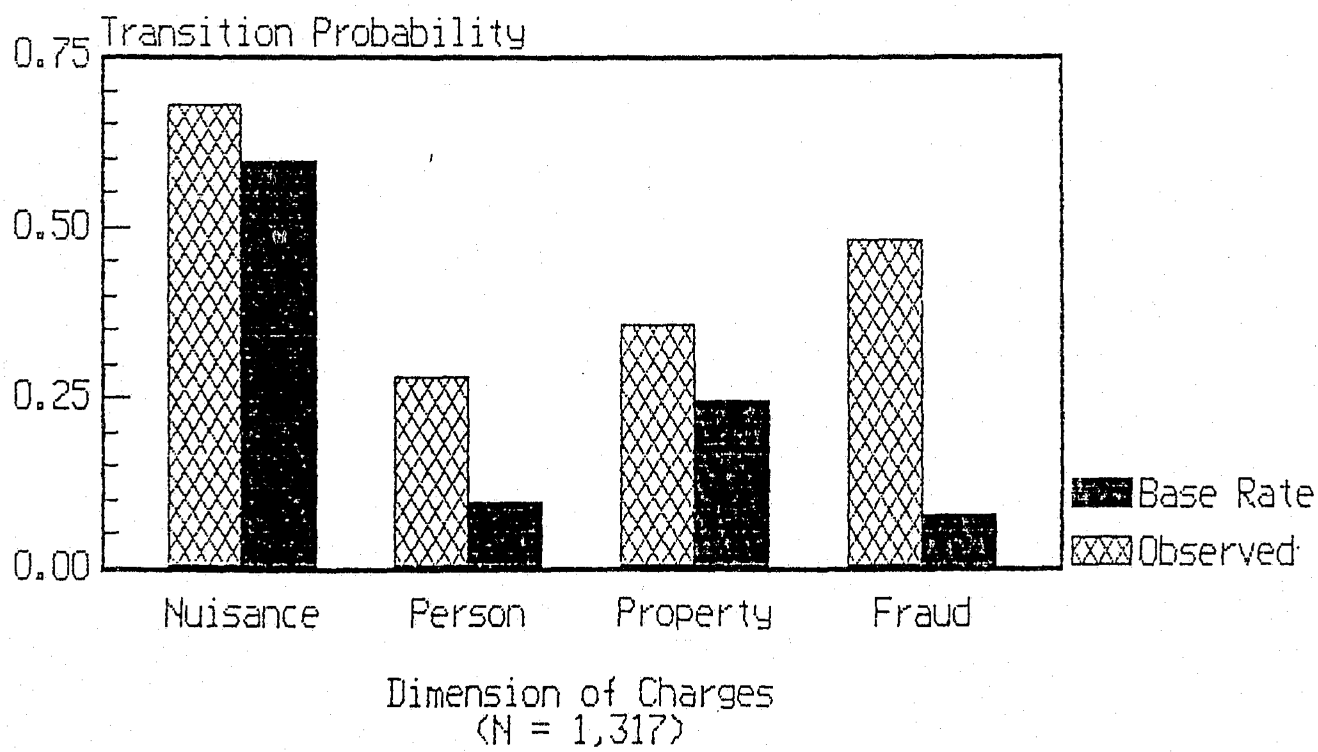


Figure 21: Transition Probabilities
Charges Five and Six
Diagonal Cells Only
(Charge Six Base Rates For Comparison)

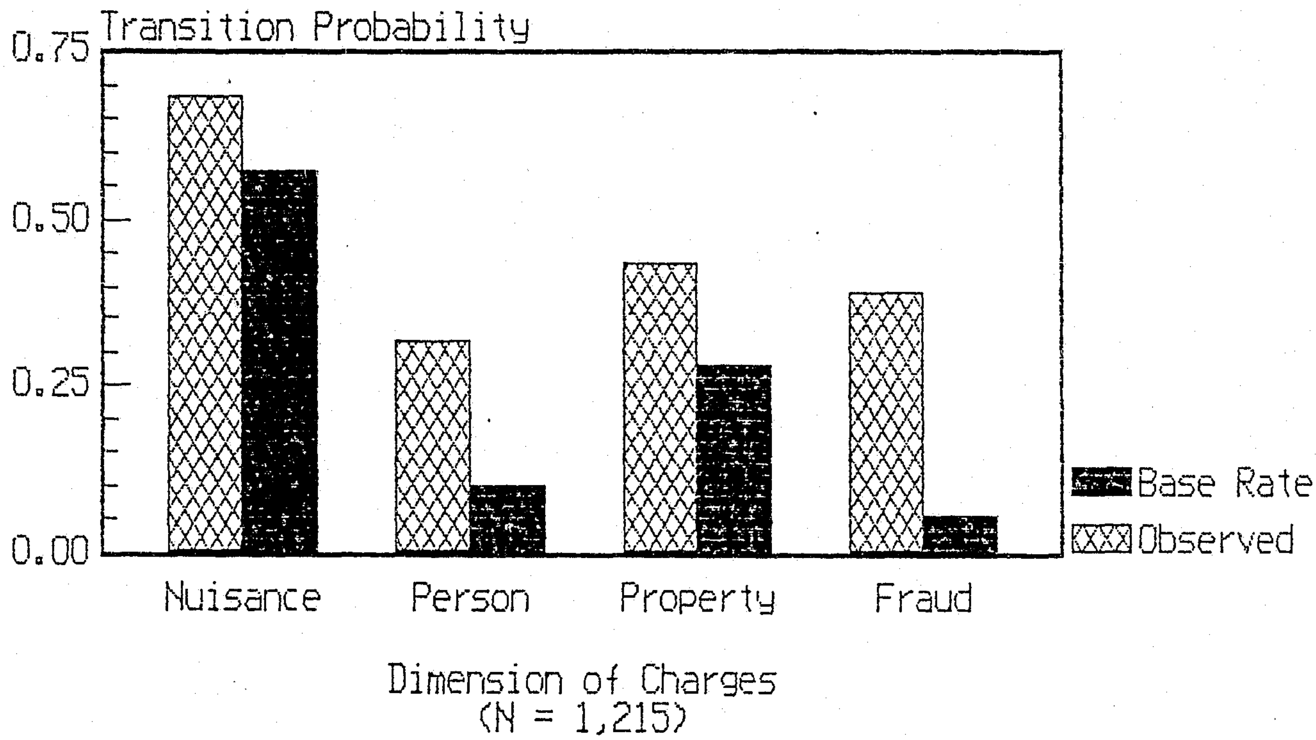


Figure 22: Transition Probabilities
Charges Six and Seven
Diagonal Cells Only
(Charge Seven Base Rates For Comparison)

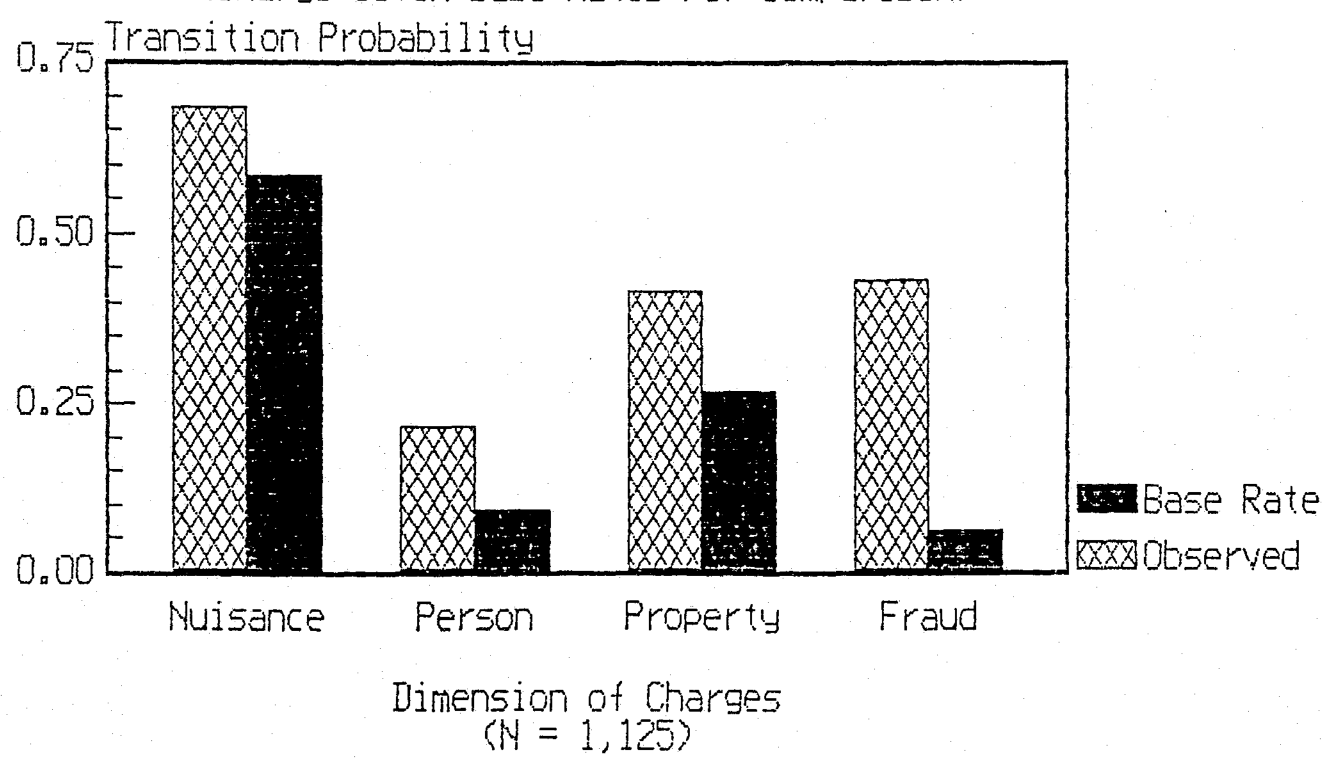
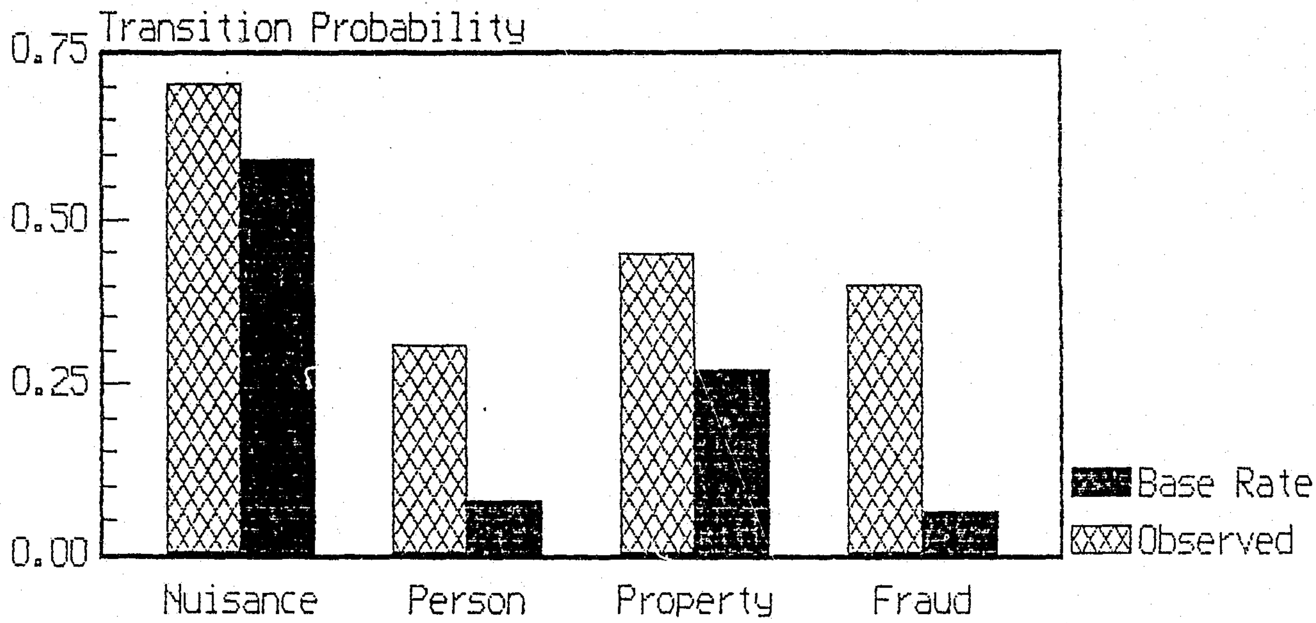
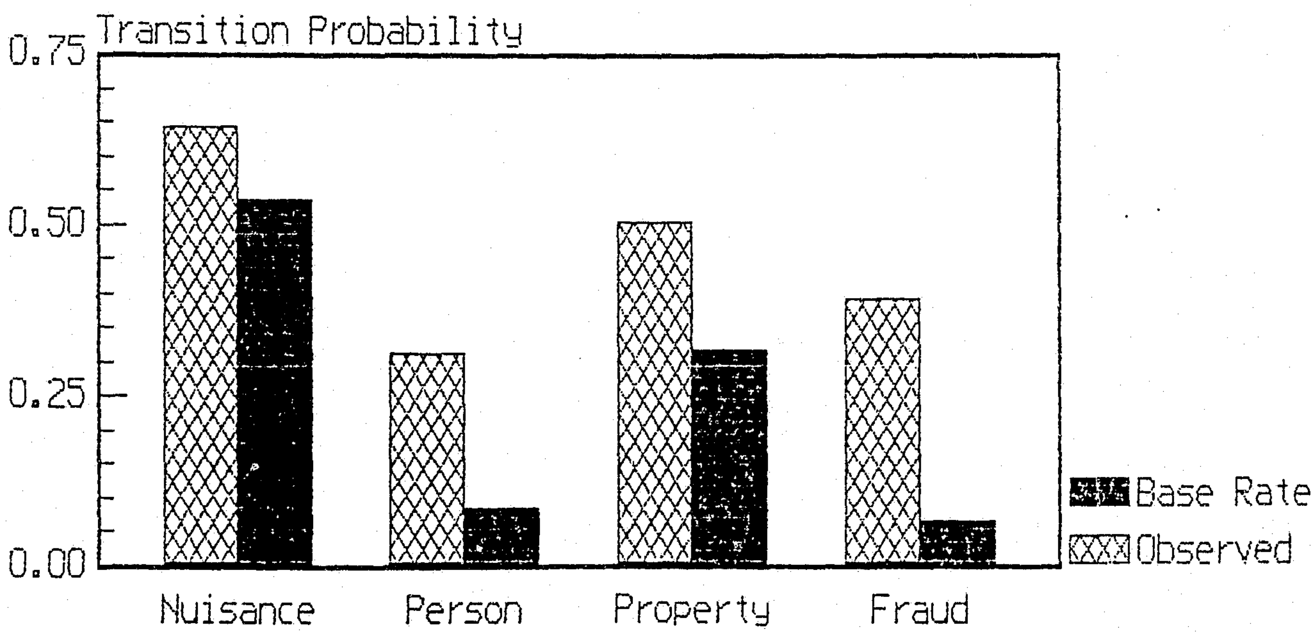


Figure 23: Transition Probabilities
Charges Seven and Eight
Diagonal Cells Only
(Charge Eight Base Rates For Comparison)



Dimension of Charges
(N = 1,020)

Figure 24: Transition Probabilities
Charges Eight and Nine
Diagonal Cells Only
(Charge Nine Base Rates For Comparison)



Dimension of Charges
(N = 937)

Figure 25: Transition Probabilities
Charges Nine and Ten
Diagonal Cells Only
(Charge Ten Base Rates For Comparison)

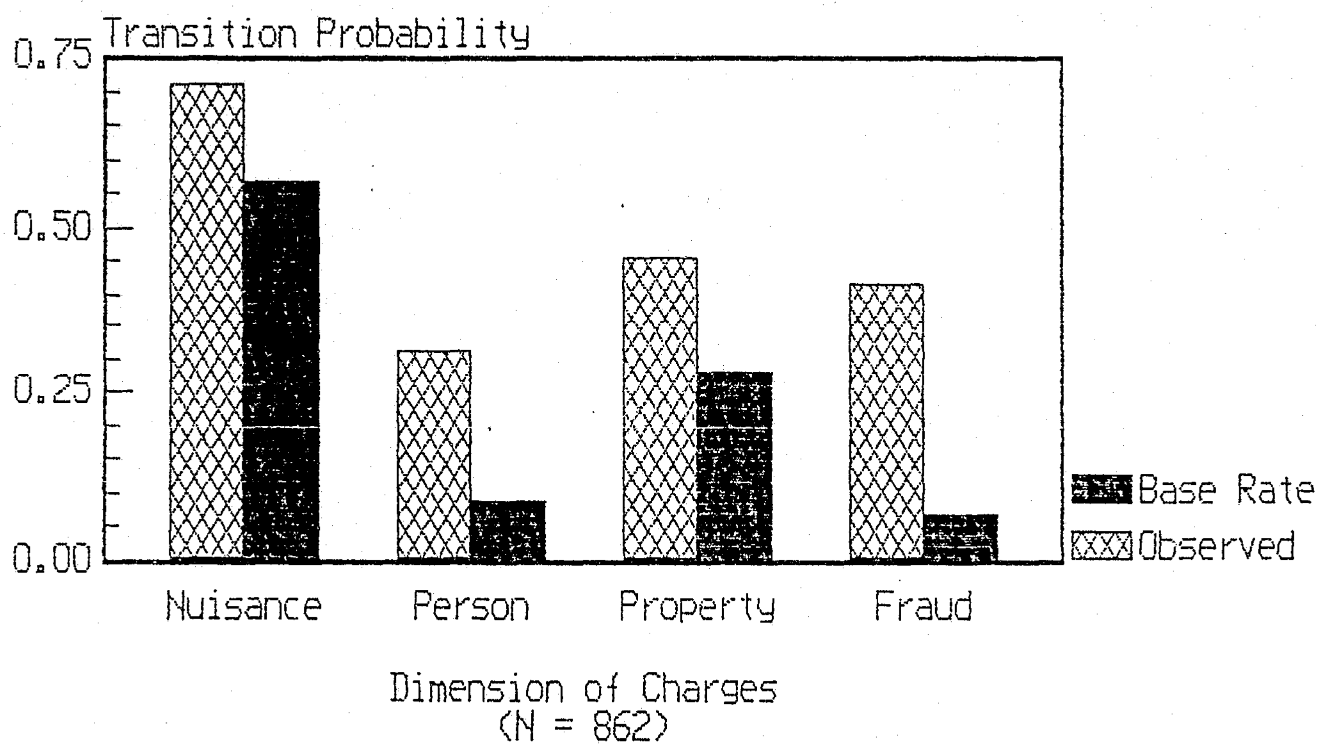


Figure 26
Changes in Farrington's
"Coefficient of Specialization"
As a Function of Transitions

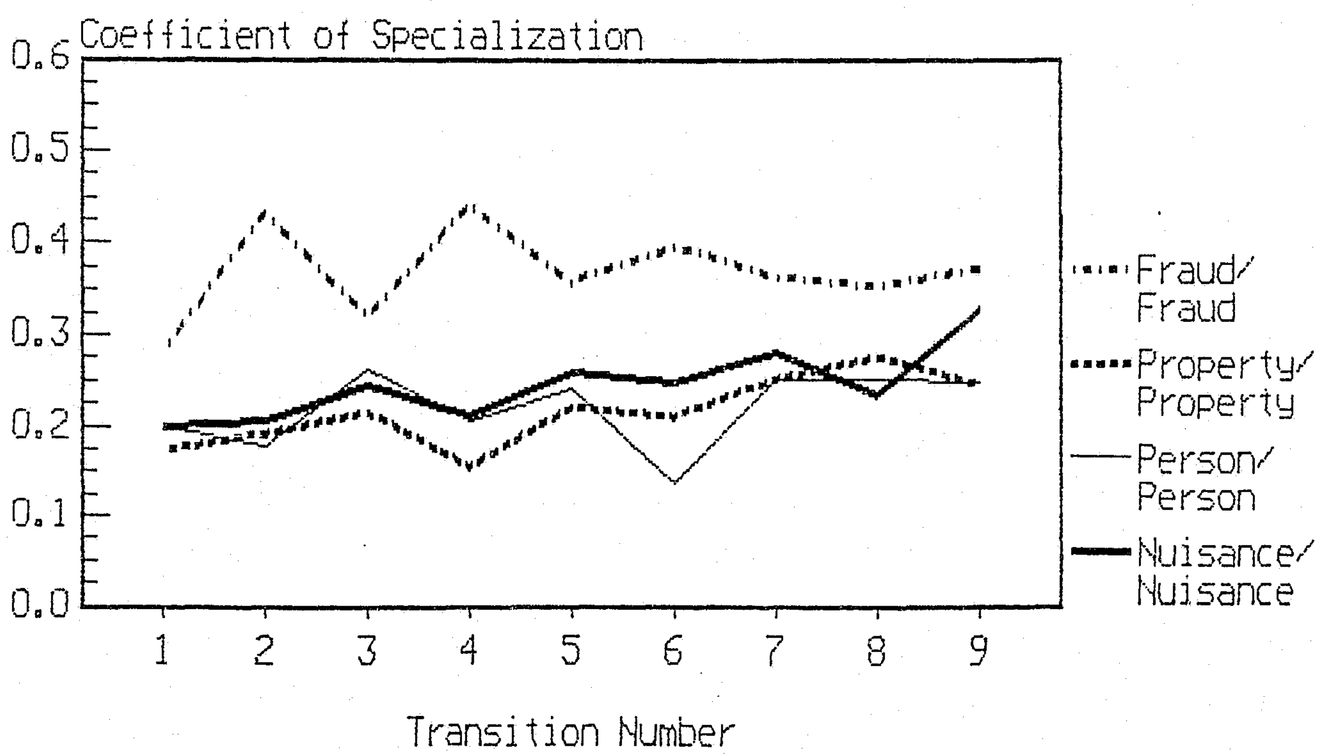


Figure 27: Trend in Farrington's
"Coefficient of Specialization"
As a Function of Transitions:
Property Offenses

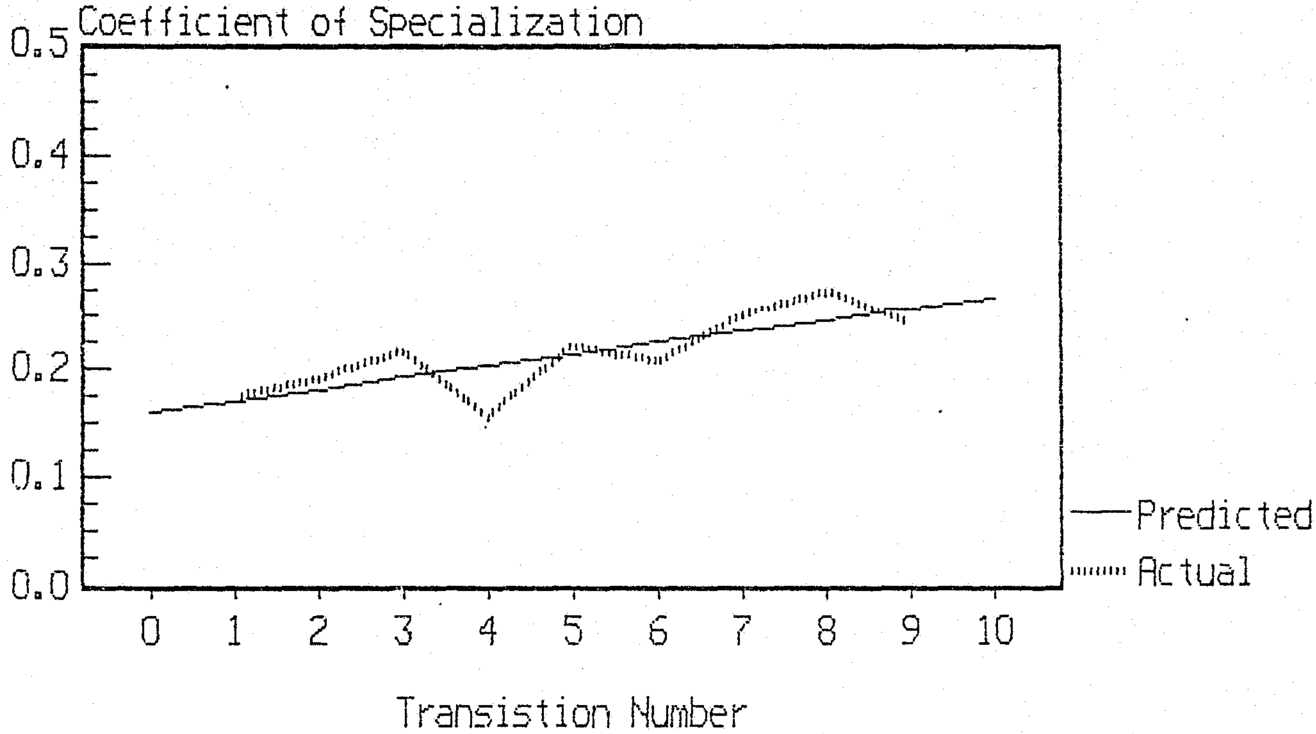


Figure 28: Trend in Farrington's
"Coefficient of Specialization"
As a Function of Transitions:
Nuisance Offenses

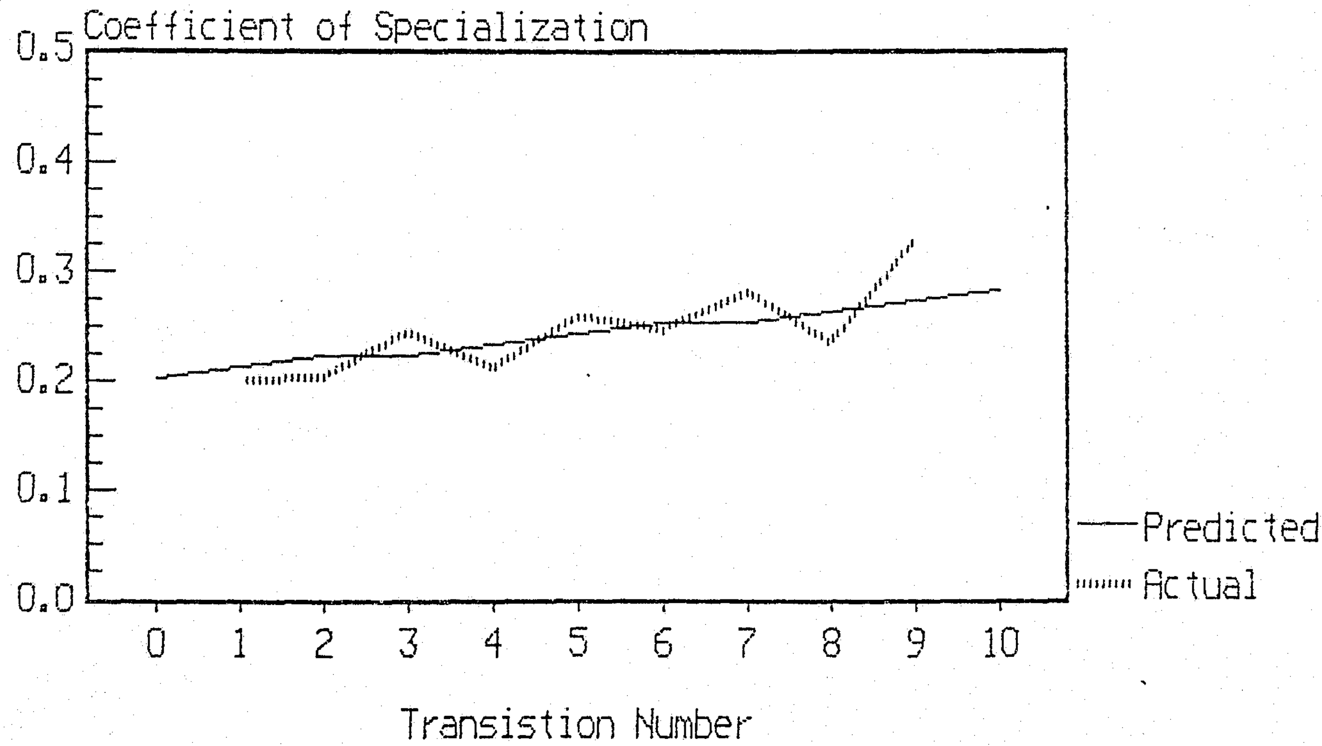


Figure 29
Changes in Farrington's
"Coefficient of Specialization"
As a Function of Transitions

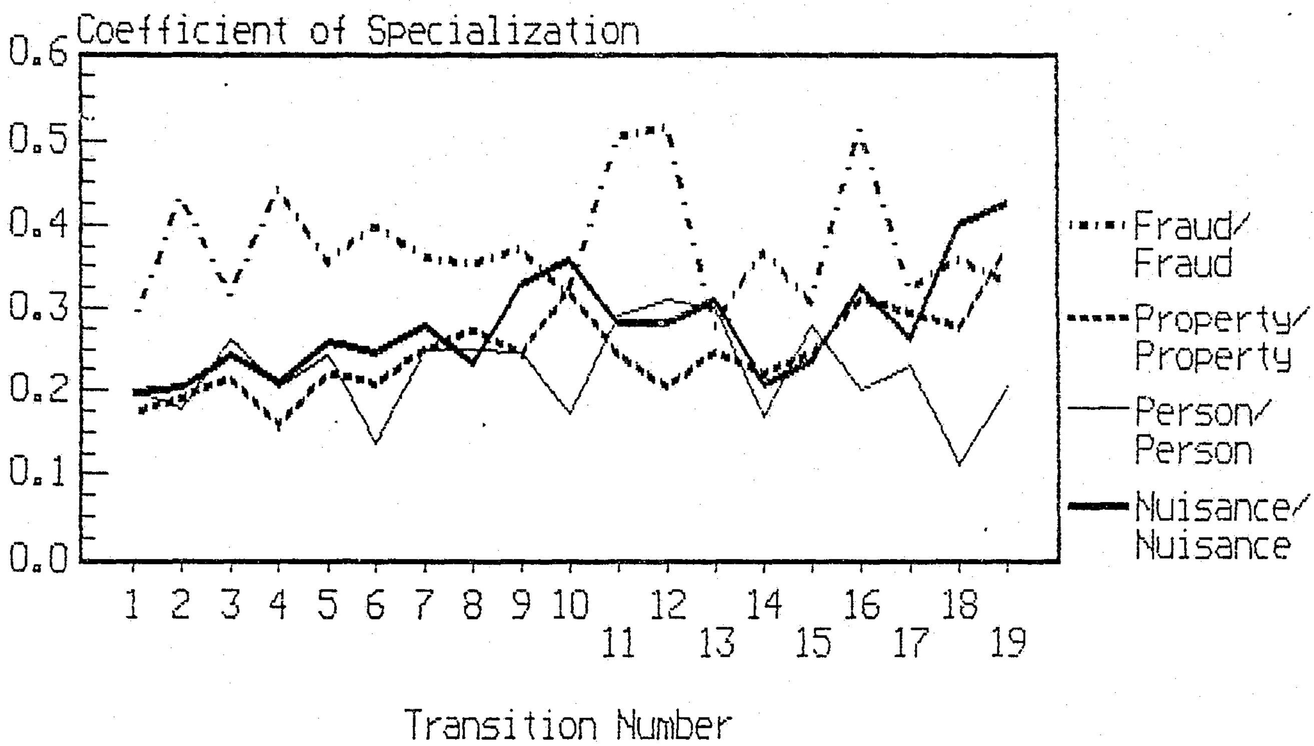


Figure 30: Trend in Farrington's
"Coefficient of Specialization"
As a Function of Transitions:
Nuisance Offenses

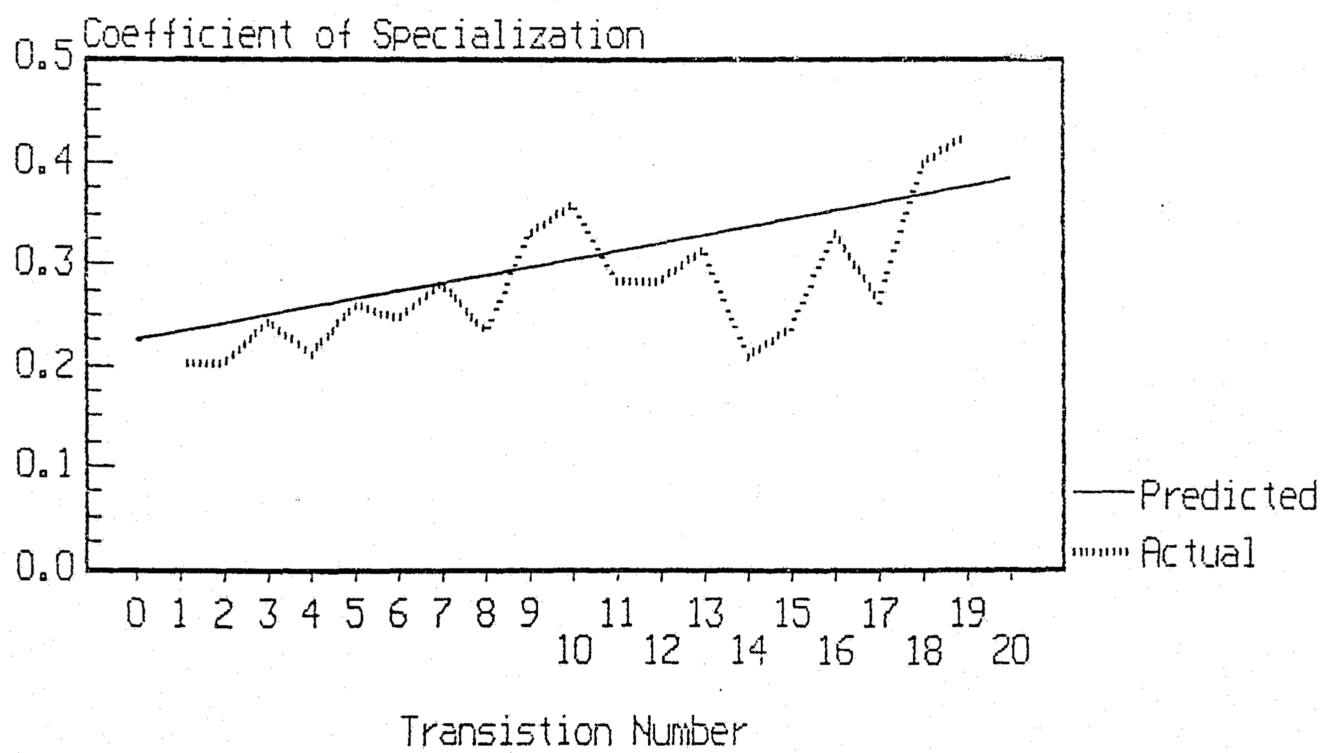


Figure 31: Changes in Farrington's "Coefficient of Specialization" As a Function of Transitions (Most Serious Charge Per Arrest Episode)

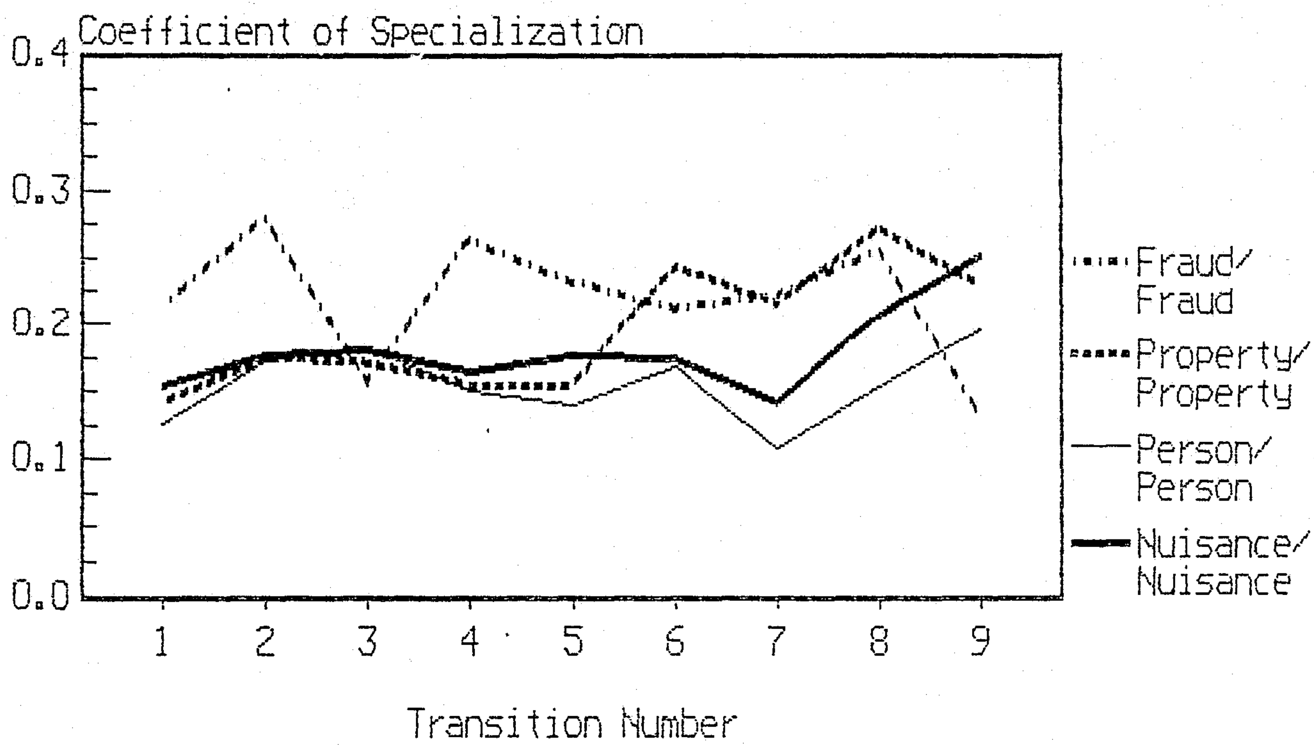
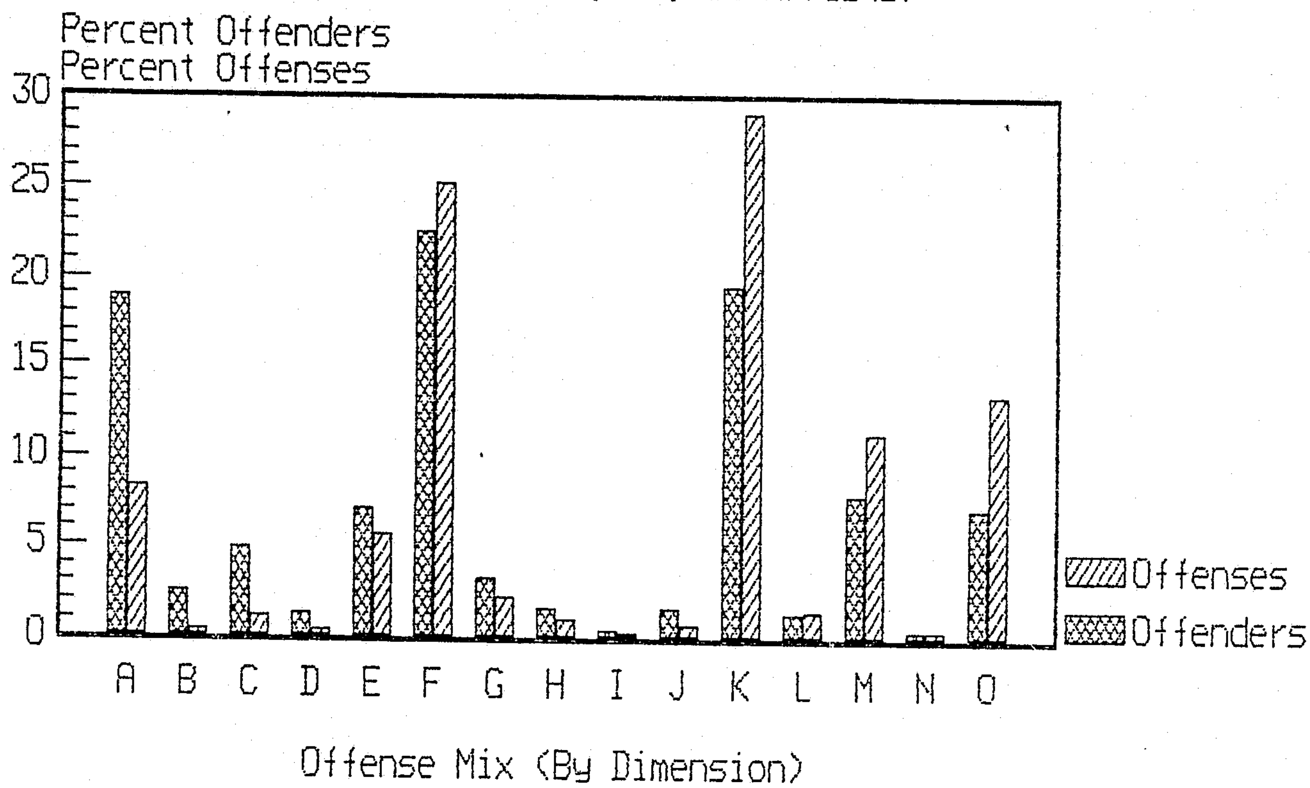


Figure 32: Offense Mixing
Most Serious Offense Per Arrest Episode
(N = 2,002 Offenders, 14,480 Arrests)



Note: A = Nuisance Offenses Only
B = Person Offenses Only
C = Property Offenses Only
D = Fraud Offenses Only
E = Nuisance + Person Offenses
F = Nuisance + Property Offenses
G = Nuisance + Fraud Offenses
H = Person + Property Offenses
I = Person + Fraud Offenses
J = Property + Fraud Offenses
K = Nuisance + Person + Property Offenses
L = Nuisance + Person + Fraud Offenses
M = Nuisance + Property + Fraud Offenses
N = Person + Property + Fraud Offenses
O = Nuisance + Person + Property + Fraud Offenses

Figure 33: "Specialists," By Dimension of Specialization (Most Serious Charge Per Arrest Episode) (N = 552)

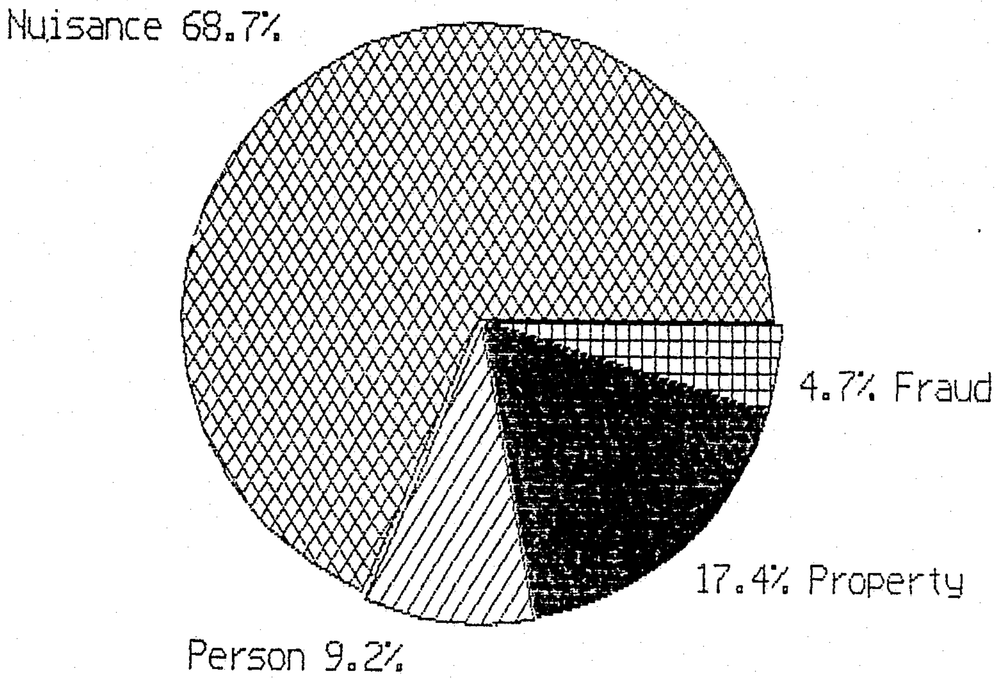


Figure 34: Arrest Offenses of "Specialists" By Dimension of Offense (Most Serious Charge Per Arrest Episode) (N = 552 Offenders, N = 1,470 Arrests)

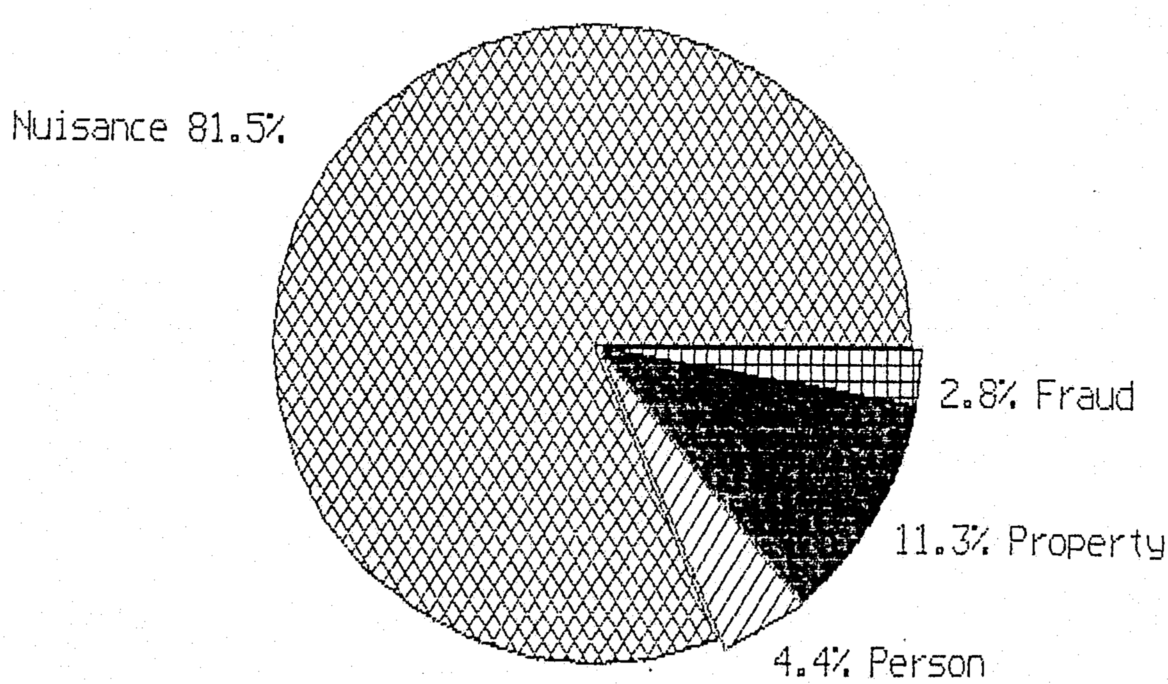


Figure 35: Percent of Offenses
Committed by Specialists By Dimension
(N = 14,480 Arrests)

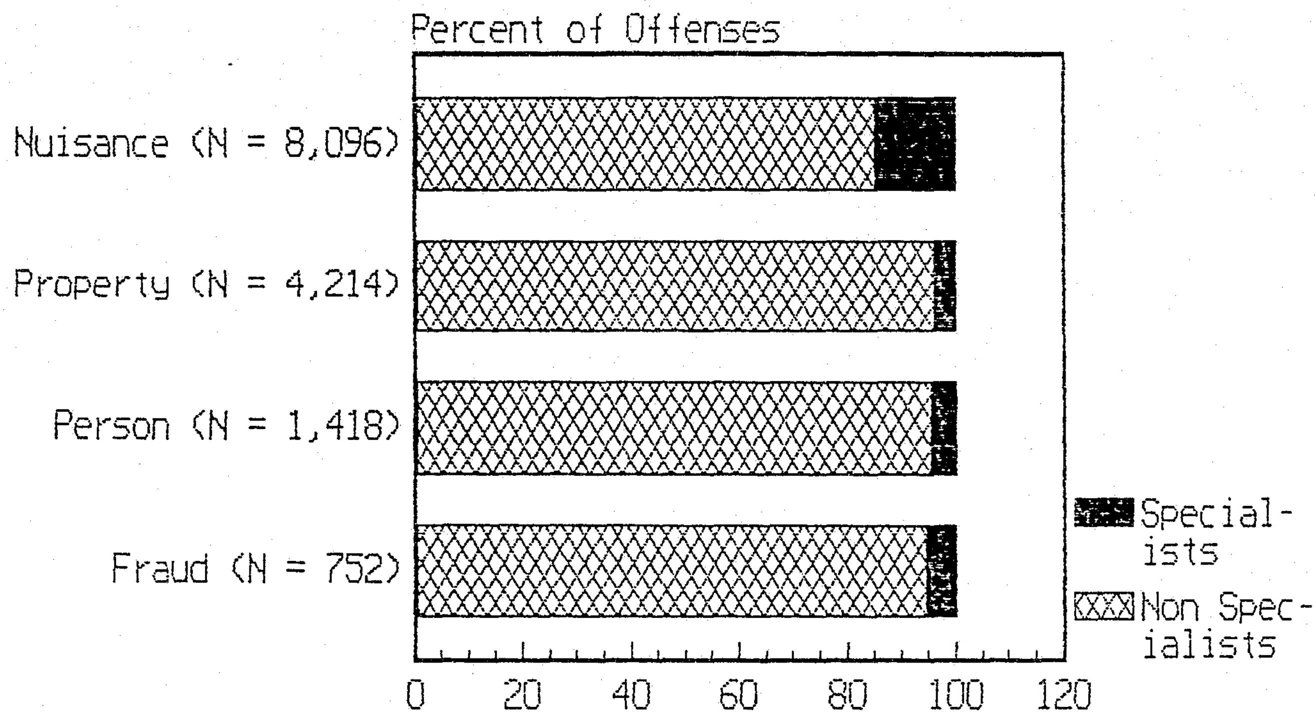
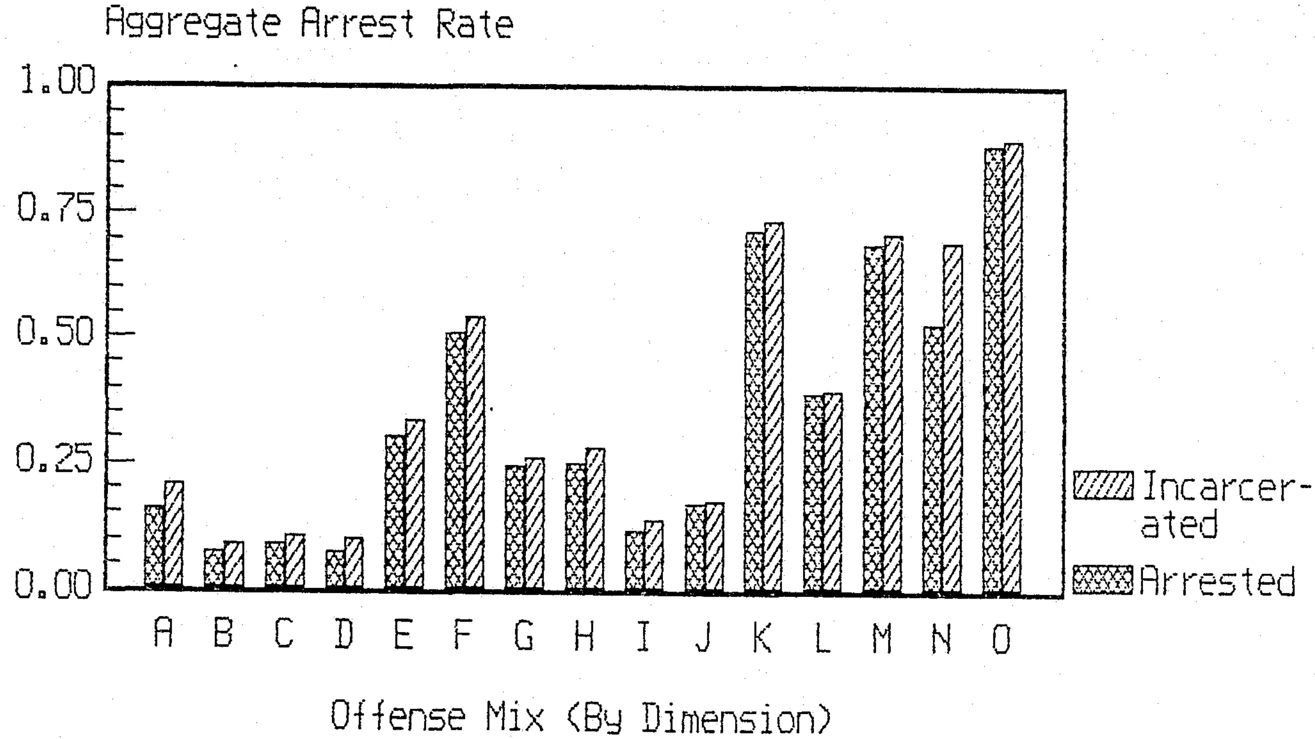


Figure 36
Aggregate Individual Arrest Rates
By Offense Mix and Type of
"Active" Offender



Note: A = Nuisance Offenses Only
B = Person Offenses Only
C = Property Offenses Only
D = Fraud Offenses Only
E = Nuisance + Person Offenses
F = Nuisance + Property Offenses
G = Nuisance + Fraud Offenses
H = Person + Property Offenses
I = Person + Fraud Offenses
J = Property + Fraud Offenses
K = Nuisance + Person + Property Offenses
L = Nuisance + Person + Fraud Offenses
M = Nuisance + Property + Fraud Offenses
N = Person + Property + Fraud Offenses
O = Nuisance + Person + Property + Fraud Offenses

Figure 37
Aggregate Individual Arrest Rates
By Age and Type of "Active Offender"

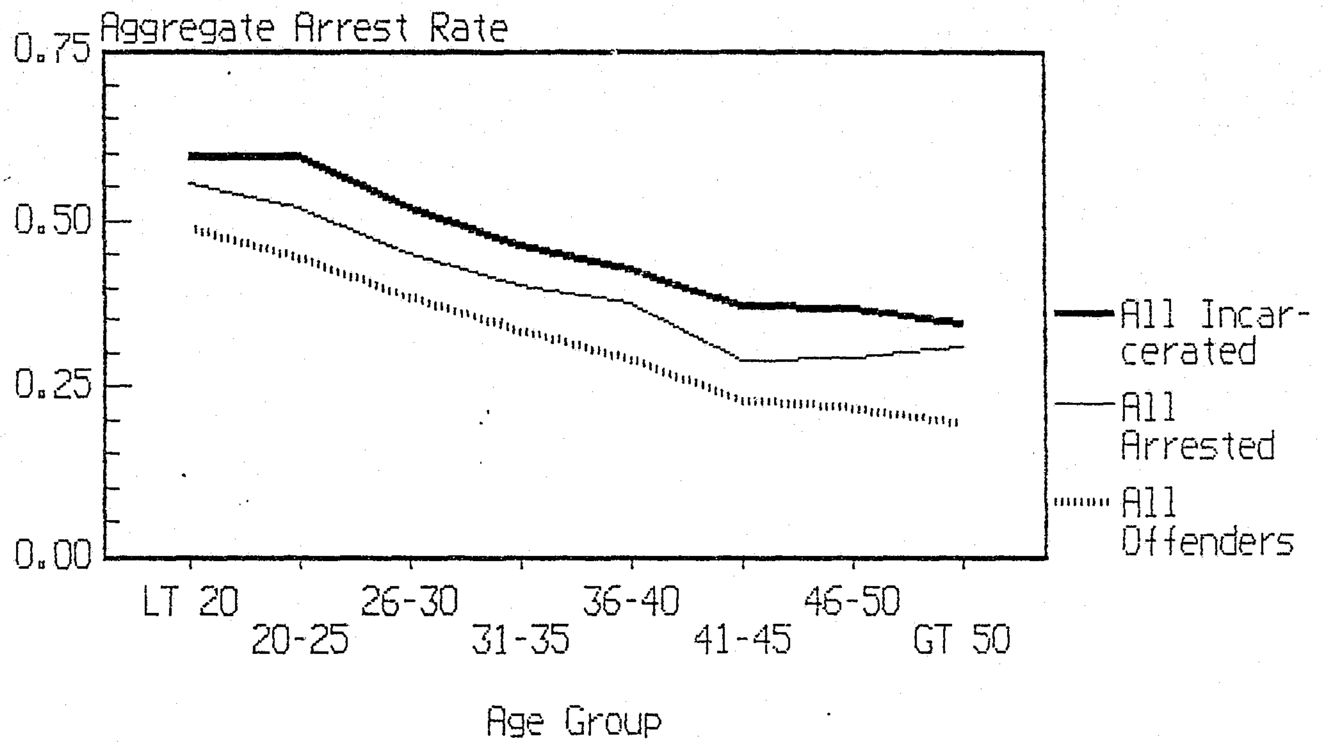


Figure 38
Probabilities of Arrest/Incarceration
Risk By Stakes (Person Offending)
(N = 2,454)

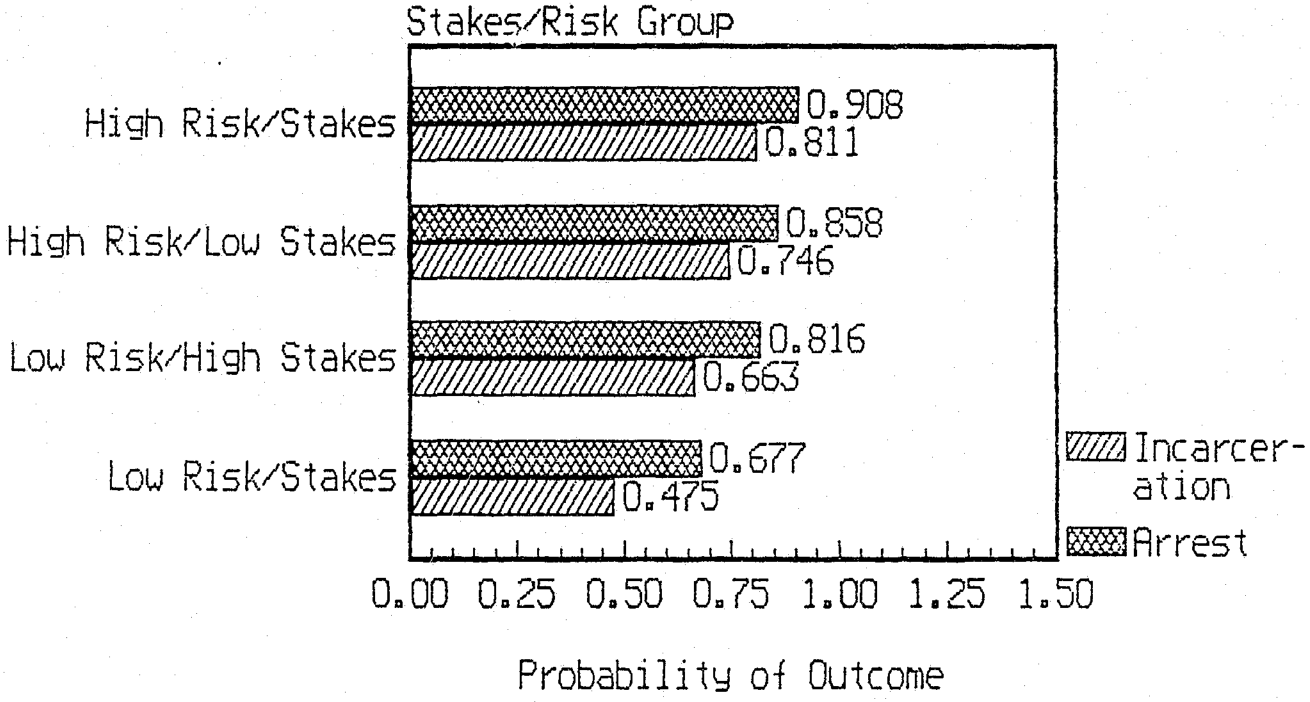


Figure 39
Rates of Offending (Total and Person)
Risk By Stakes (Person Offending)
(N = 2,454)

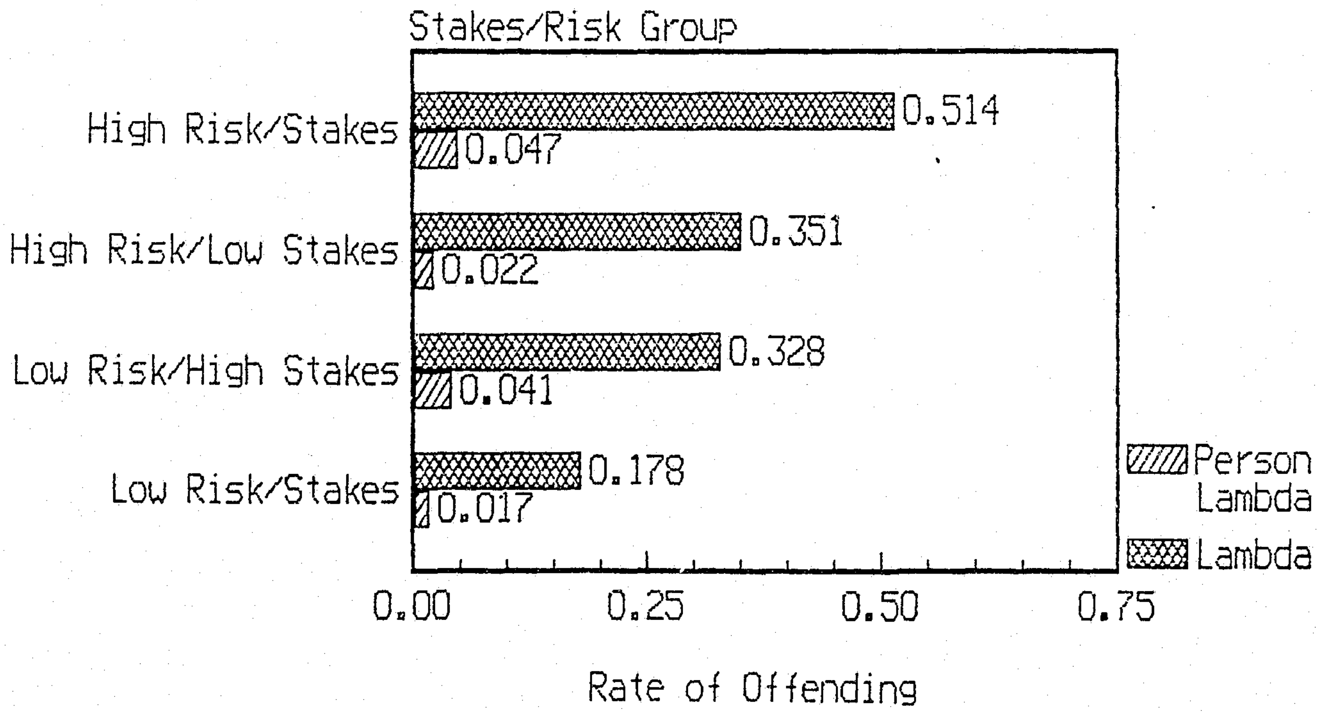


Figure 40
Rates of Offending (Property/Nuisance)
Risk By Stakes (Person Offending)
(N = 2,454)

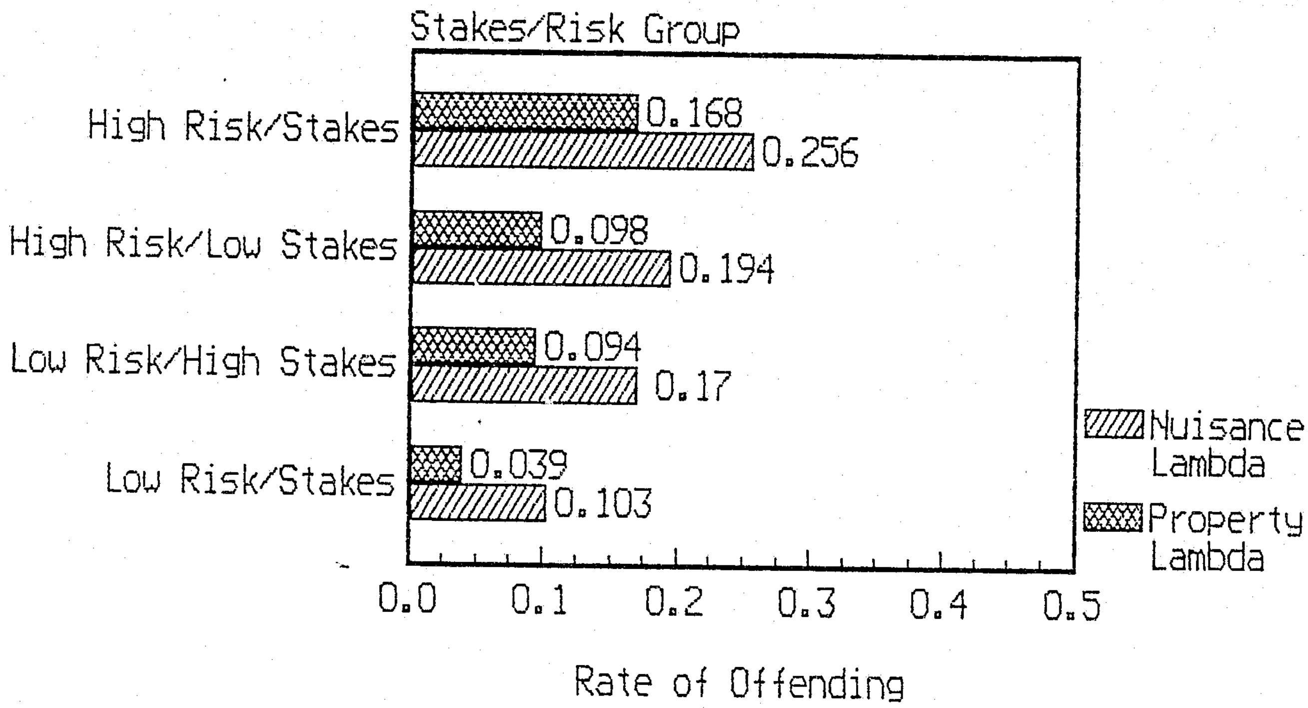


Figure 41
Relative Sizes of Outcome Groups
Stakes By Risk (Person Offending)
(N = 2,454)

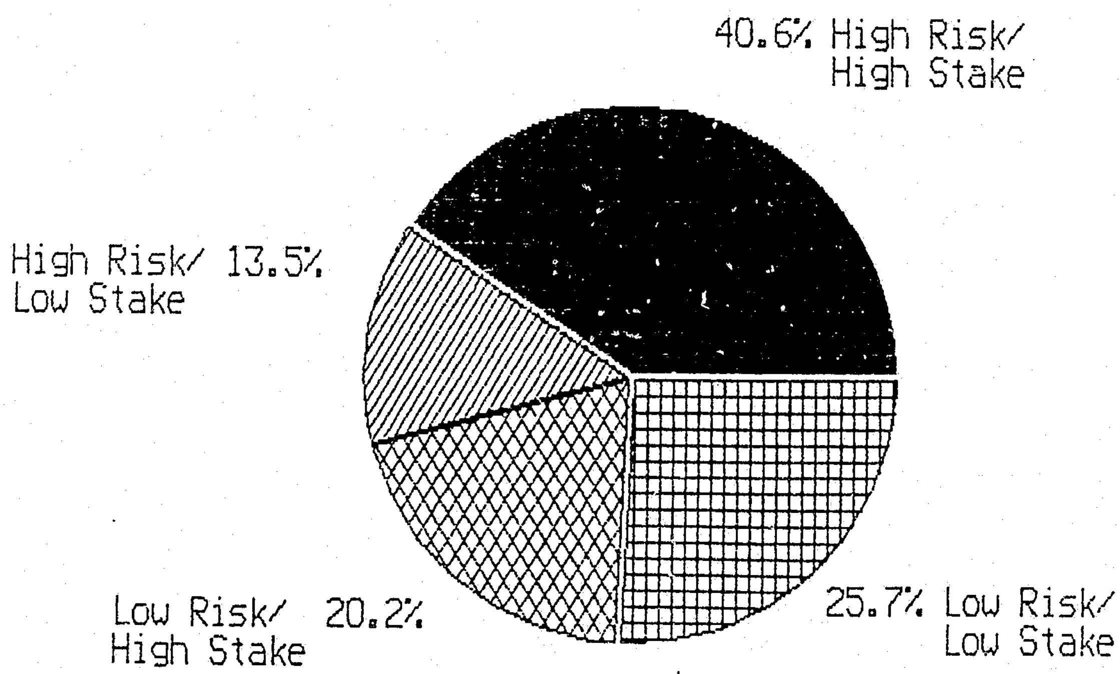


Figure 42
Probabilities of Arrest/Incarceration
Risk By Stakes (Nuisance Offending)
(N = 2,454)

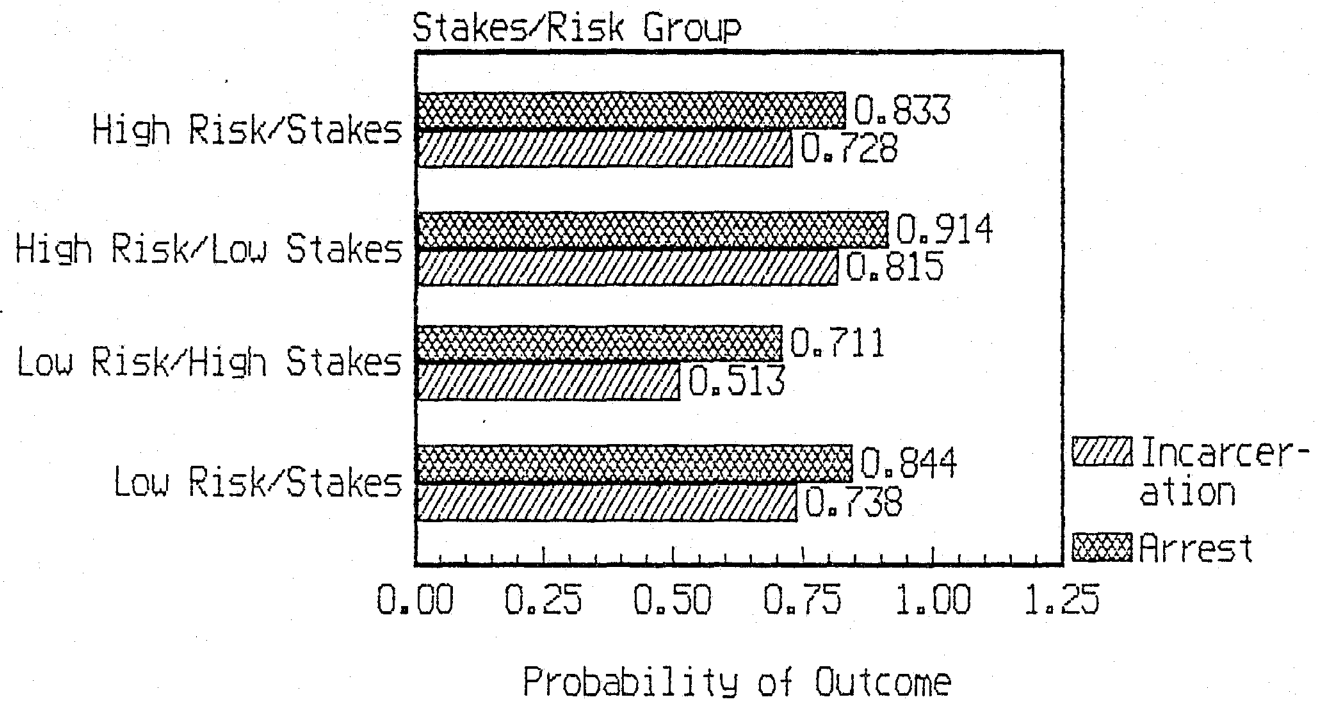


Figure 43
Rates of Offending (Total and Person)
Risk By Stakes (Nuisance Offending)
(N = 2,454)

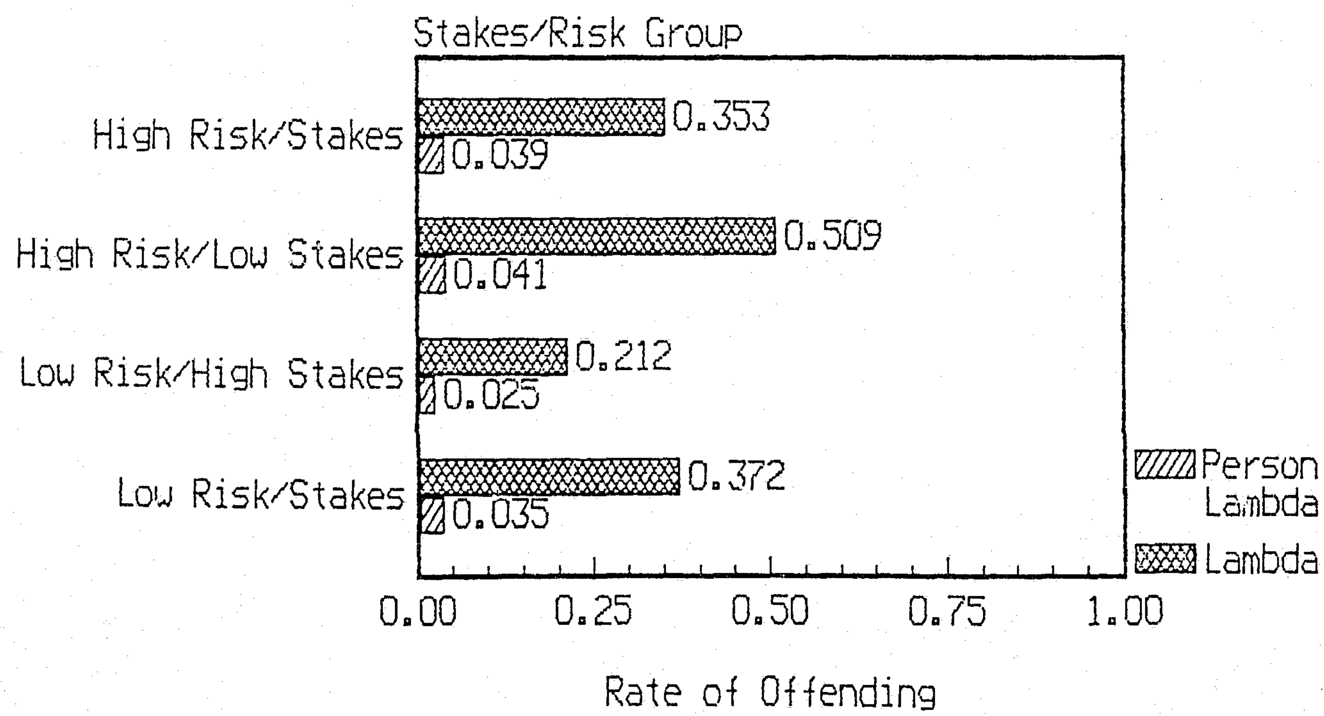


Figure 44
Rates of Offending (Property/Nuisance)
Risk By Stakes (Nuisance Offending)
(N = 2,454)

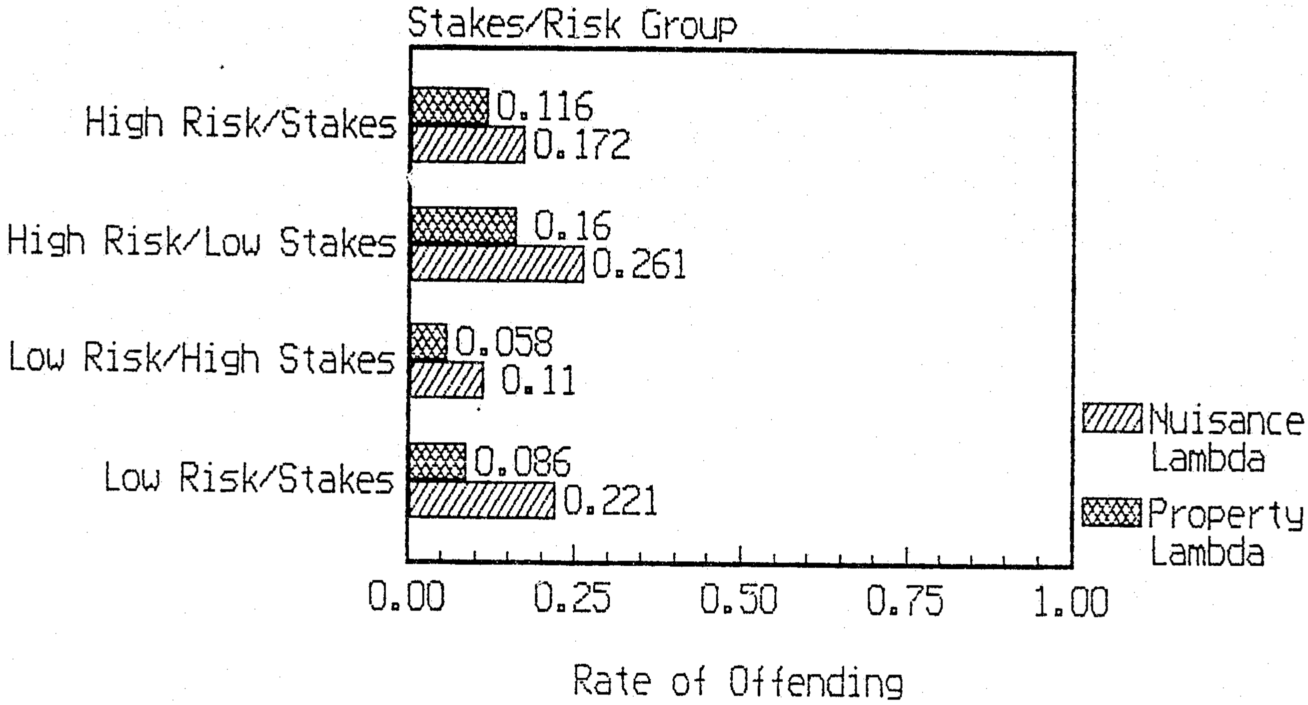


Figure 45
Relative Sizes of Outcome Groups
Stakes By Risk (Nuisance Offending)
(N = 2,454)

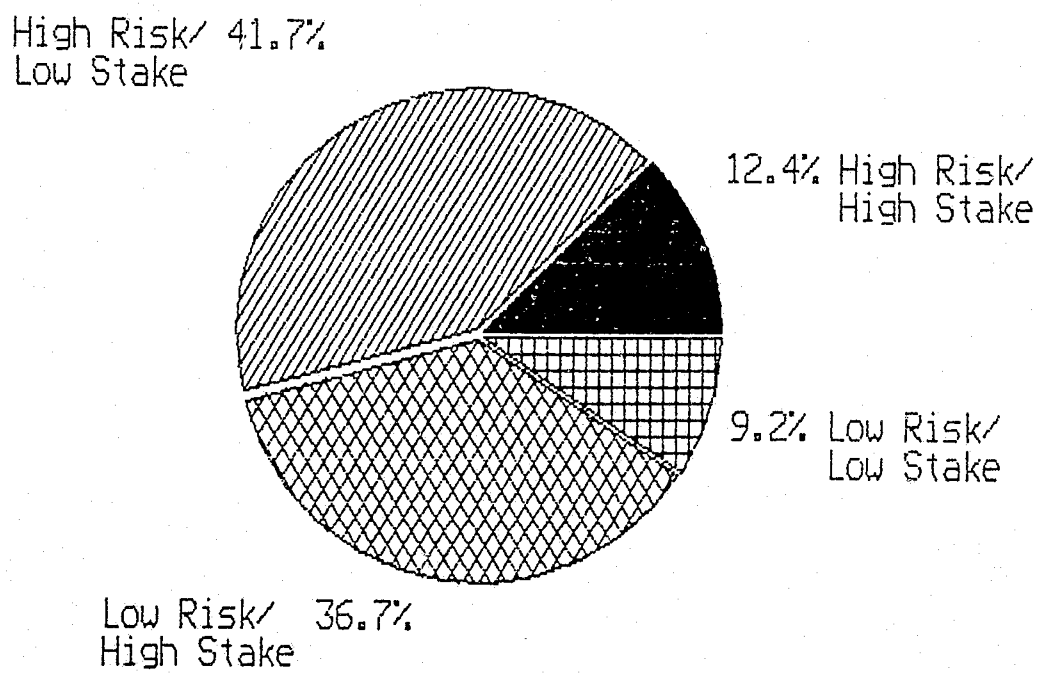


Figure 46
Probability of Arrest
Risk X Stakes X Rate(Person Offending)
(N = 2,454)

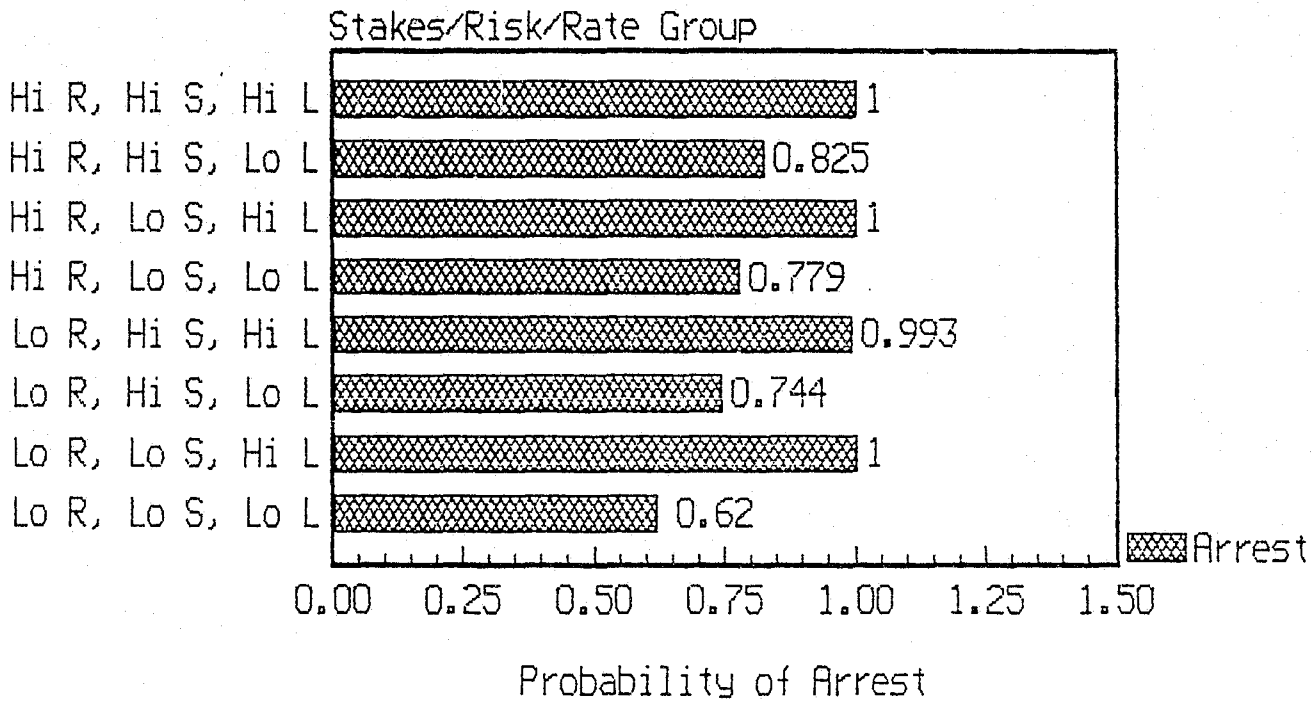


Figure 47
Probability of Incarceration
Risk X Stakes X Rate(Person Offending)
(N = 2,454)

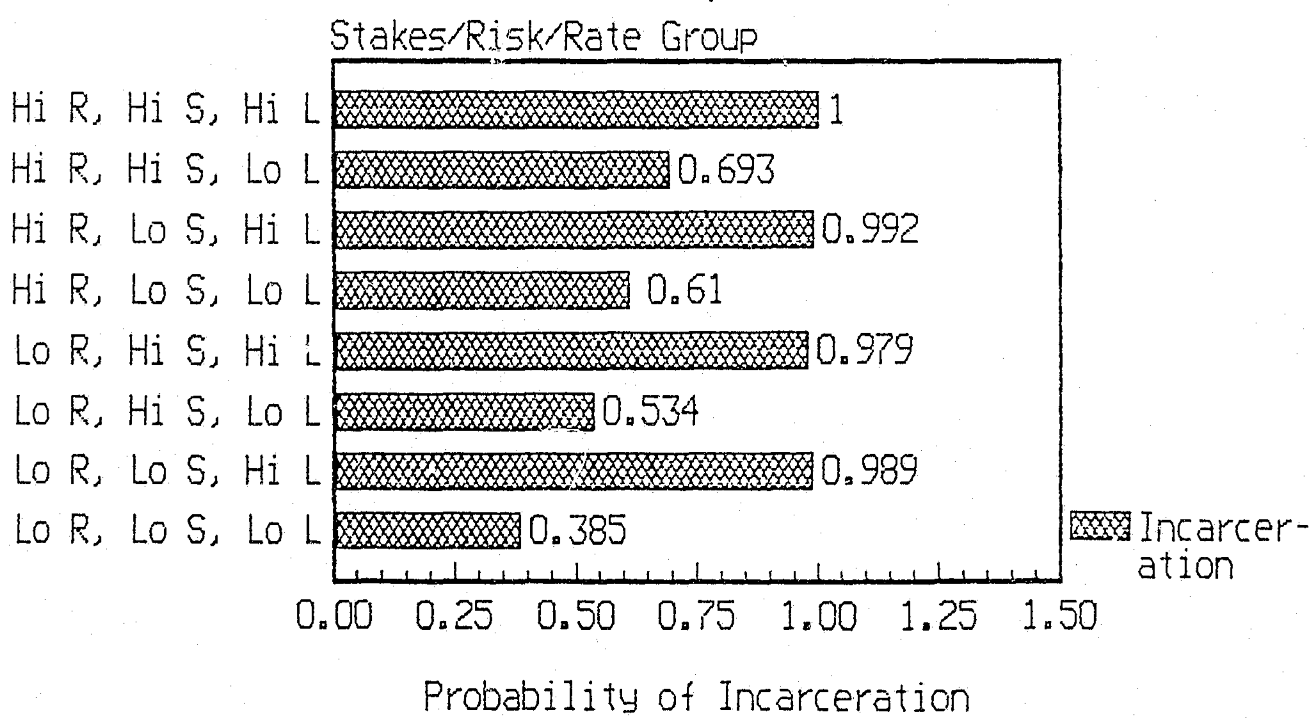


Figure 48
Rate of Offending
Risk X Stakes X Rate(Person Offending)
(N = 2,454)

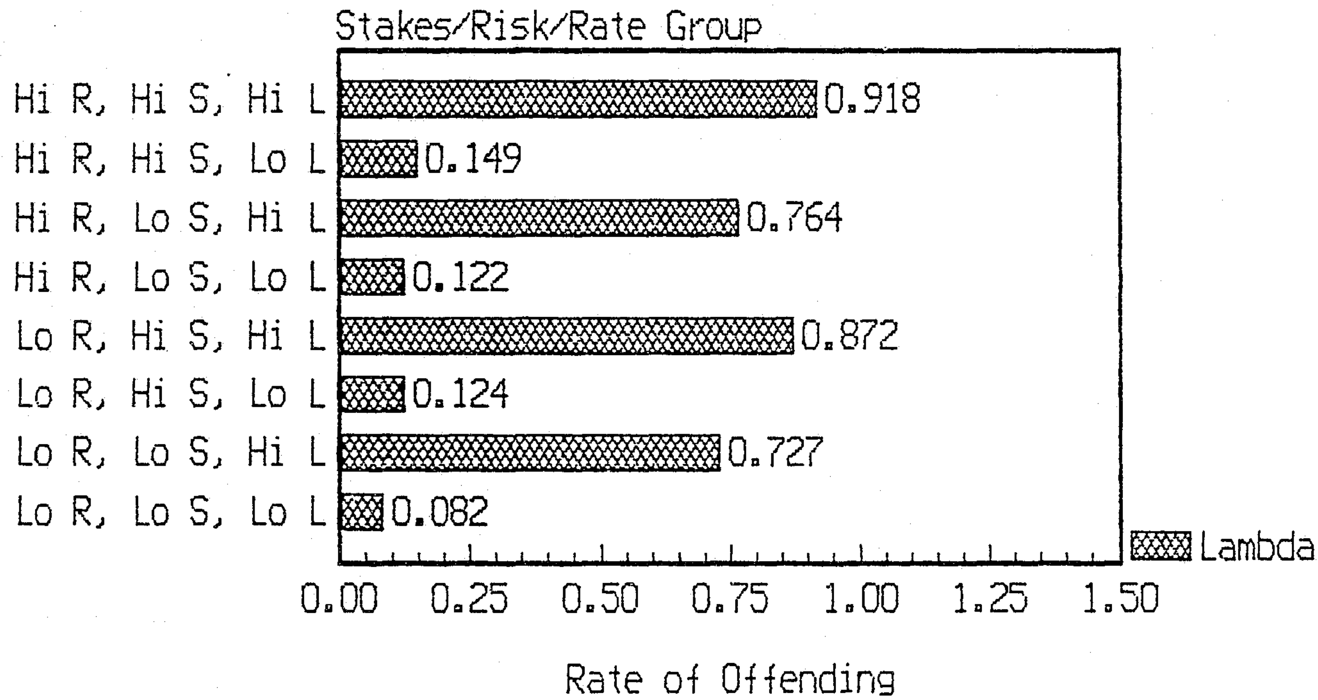


Figure 49
Rate of Offending, Person Offenses
Risk X Stakes X Rate (Person Offending)
(N = 2,454)

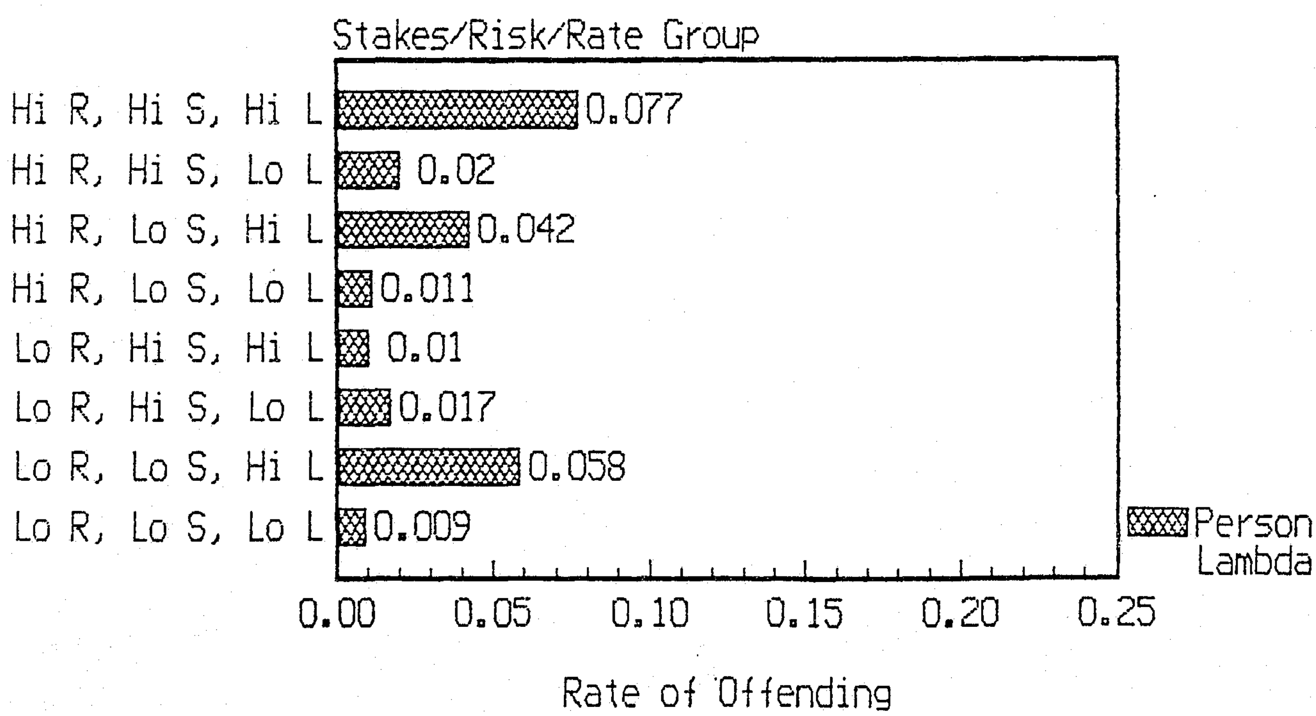


Figure 50
Rate of Offending (Property Offenses)
Risk X Stakes X Rate (Person Offending)
(N = 2,454)

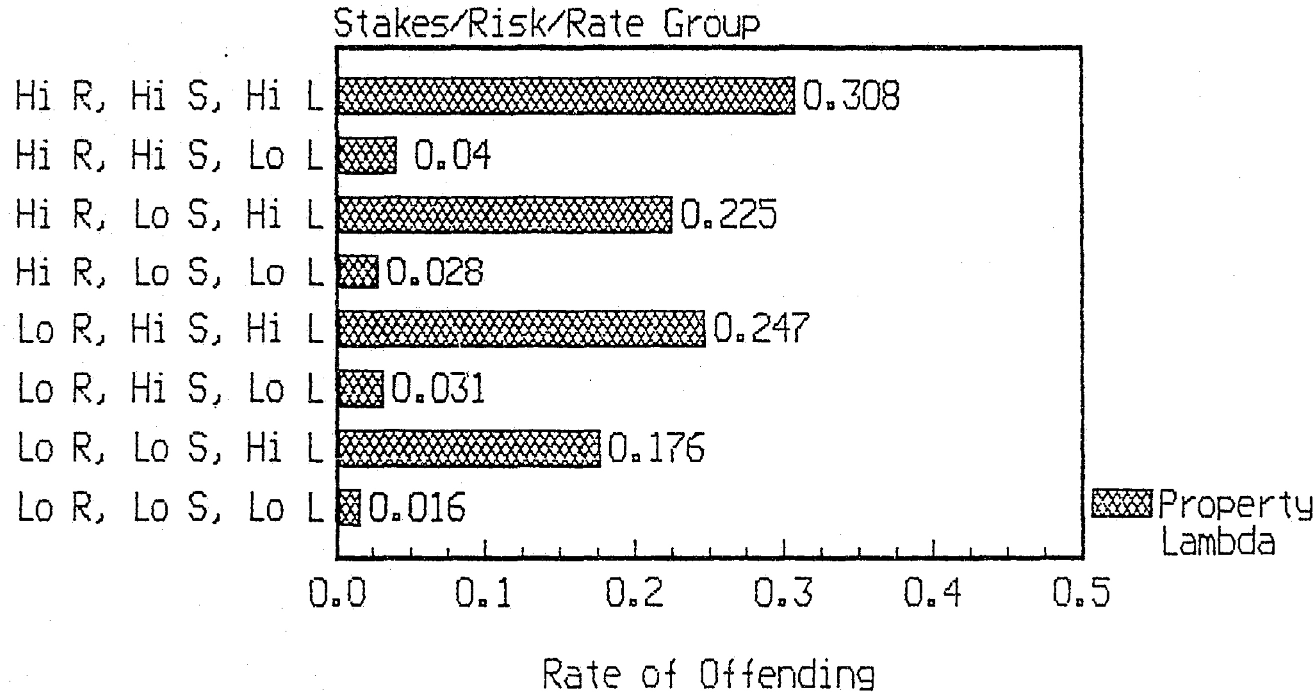


Figure 51
Rate of Offending (Nuisance Offenses)
Risk X Stakes X Rate (Person Offending)
(N = 2,454)

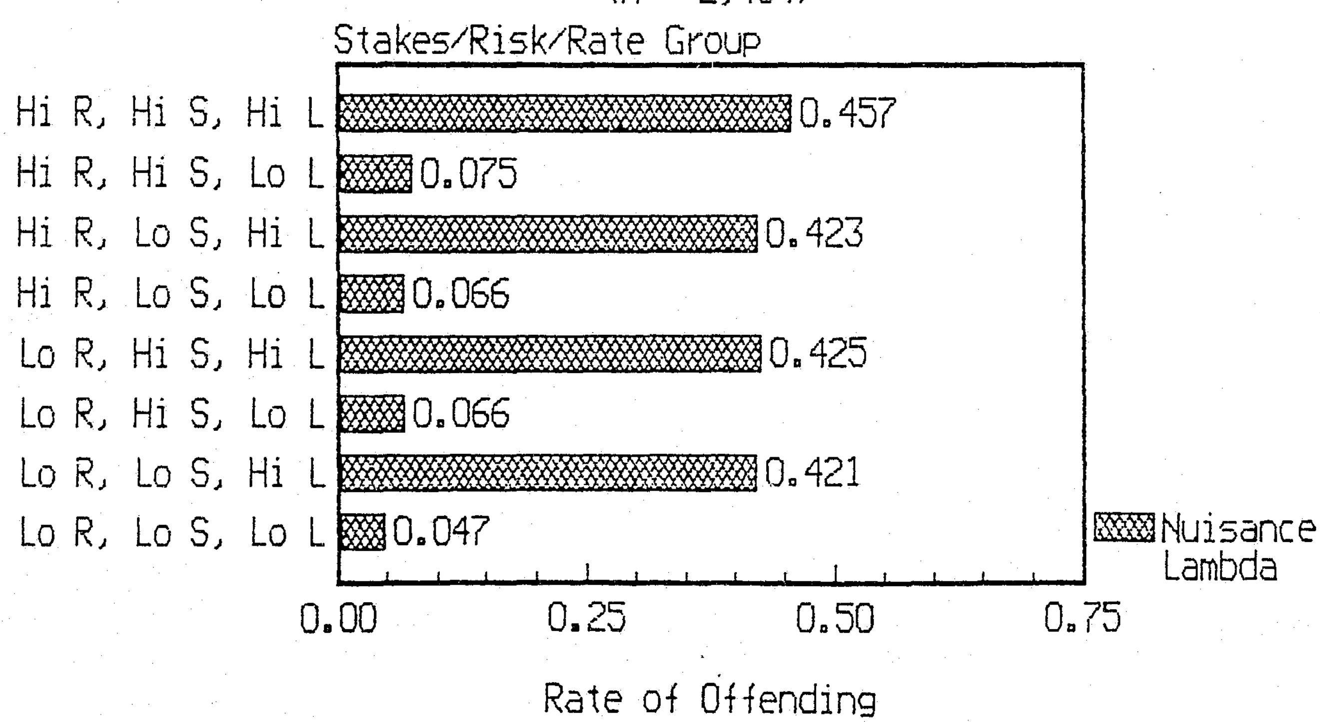


Figure 52
Relative Sizes of Outcome Groups
Risk X Stakes X Rate (Person Offending)
(N = 2,454)