Selective Incapacitation Revisited

Why the High-Rate Offenders Are Hard to Predict

. Greenwood, Susan Turner

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Why the High-Rate Offenders Are Hard to Predict

Peter W. Greenwood, Susan Turner

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PREFACE

This is the final report of a project designed to explore the relationship between (1) self-reports of offending and (2) recorded arrests as indicators of individual offense rates. This work was supported by a grant from the National Institute of Justice. It should be useful to researchers and policymakers who are interested in the problem of identifying high-rate offenders for selective handling purposes.

SUMMARY

Studies of incarceration have not produced any conclusive evidence that incarceration results in either reform or rehabilitation of offenders, but it can reduce crime by removing and isolating offenders from the community—at least, it has not been shown that the incarceration of some offenders produces compensating increases in criminality on the part of others (i.e., that nonincarcerated crime partners go out and recruit new partners) or that released offenders have higher crime rates than they had prior to their incarceration. Whether or not such effects may occur, recidivism studies have shown clearly that some offenders will continue to commit crimes if they are not incarcerated.

Discussions of incapacitation effects to date have focused on the magnitude of individual offense rates. If the average individual offense rate is low, incapacitation effects will necessarily be small; but if the average individual offense rate is high, incapacitation effects could be substantial. Recent studies have used self-reported offense-rate data provided by incarcerated offenders and computerized arrest histories provided by several jurisdictions in attempts to categorize offenders by the frequency with which they can be expected to commit crimes. The largest self-reported database created to date is the 1978 RAND Inmate Survey (RIS) of approximately 2,200 men who were serving time in the prisons and jails of California, Michigan, and Texas.[1]

FINDINGS FROM THE RAND INMATE SURVEY

The RIS revealed that offense-rate frequency distributions are extremely skewed toward the high end. Most of the subjects who reported committing a particular offense claimed they did so at fairly low rates, but for every type of crime, a small fraction of the offenders reported much higher rates of activity, raising the average for the sample several orders of magnitude above the median.

This large variation raised the question of whether it was possible to distinguish the high-rate offenders for selective sentencing purposes. If so, the incapacitation effect of a given level of incarceration might be increased by increasing the amount of time served by the small number

[1]The survey sample is described in Jan Chaiken and M. R. Chaiken, *Varieties of Criminal Behavior,* The RAND Corporation, R-2814-NIJ, August 1982.

of high-rate offenders and decreasing time served by the much larger number of low-rate offenders.

An analysis of the RIS subjects who were serving terms for robbery or burglary identified the following seven characteristics that appeared to be associated with individual offense rates for these crimes:[2]

1. Prior conviction for the same type of offense.
2. Incarceration for more than 50 percent of the preceding two years.
3. Conviction prior to age 16.
4. Serving time in a state juvenile facility.
5. Use of hard drugs in the preceding two years.
6. Use of hard drugs as a juvenile.
7. Being employed less than 50 percent of the preceding two years.

These seven items were used to construct a simple additive scale for predicting high-rate offenders. In this scale, each item was counted as 1 if it applied and 0 otherwise. Offenders who scored 0 or 1 were predicted to be low-rate; those who scored 2 or 3 were predicted as moderate-rate; and those who scored 4 or higher were predicted as high-rate. Use of the scale with self-reported data on prior criminal activity correctly predicted the offense rates of 51 percent of the three-state sample of convicted robbers and burglars.

Application of these findings to a variety of selective sentencing policies indicated that a policy that increased the length of time served by predicted high-rate robbers in California while reducing the time served by predicted low- and medium-rate robbers would reduce the robbery rate by about 15 percent and the number of robbers incarcerated by about 5 percent. It was estimated that under a policy of increasing the time served by all convicted robbers equally, it would be necessary to incarcerate 25 percent more robbers to achieve the same 15 percent reduction in robberies.

DESIGN OF THE PRESENT STUDY

The present study was undertaken to determine whether the 7-item scale could be used to predict the individual offense rates of convicted offenders, and to investigate the loss of information that could be

[2]The analysis is reported in Peter W. Greenwood and Allan Abrahamse, *Selective Incapacitation*, The RAND Corporation, R-2815-NIJ, August 1982.

expected to result from using recorded arrest rates rather than self-reported offense rates.

Two samples were examined, both consisting of men released from California correctional institutions. The first sample consisted of approximately 2,700 men who had been committed as juveniles or youthful offenders to two California Youth Authority (CYA) facilities between 1966 and 1971. The official records for this sample revealed that 80 percent of the offenders were arrested for at least one felony during the ten years following their release; they averaged about one arrest per year.

The primary problem encountered in applying the 7-item prediction scale to this sample was the fact that prior records had been coded for only approximately half of the sample. We solved this problem by using the first two years after release from CYA custody to accumulate an arrest history for each subject and extrapolating that information to predict his arrest rate for the next two years.

Another, less serious problem was the fact that two of the items on the original scale—"commitment to a state juvenile facility" and "employed less than 50 percent of the two years preceding commitment"—were not applicable to this sample. We therefore dropped these two items and applied a modified version of the scale.

Our second sample consisted of approximately 200 RIS respondents who had been serving time in California prisons for either robbery or burglary at the time of the survey and who had been released from that commitment at least two years prior to this study. This group included 81 percent (135 out of 167) of the convicted robbers in the RIS sample, but only 47 percent (57 out of 121) of the convicted burglars, because convicted burglars are much more likely to receive jail rather than prison sentences. Approximately 75 percent of this follow-up sample had been arrested during the first two years after their release from prison.

PREDICTION ACCURACY

When we used self-reported offense rates for the RIS sample, the 7-item scale categorized the offenders retrospectively almost as accurately as it had the original RIS population; there was a 1 or 2 percent decrease in the percentage accurately classified caused by sample attrition.

The 7-item scale classified 29 percent of the original RIS sample as high-rate offenders; comparison of this prediction with their self-reports of the two-year period preceding their incarceration showed a relative improvement over chance (RIOC) of 35 percent. When the scale was applied to the 283 offenders incarcerated in California, 44 percent were classified as high-rate and the RIOC improved to 39 percent. Prediction accuracy varied considerably between robbers and burglars in California, with a 44 percent RIOC for the former and only 31 percent for the latter.

Excluding the California prisoners who did not have at least a two-year follow-up history had little effect on prediction accuracy: The RIOC dropped only 2 percent for robbers (to 42 percent) and only 1 percent (to 30 percent) for burglars.

Using the modified 5-item scale for the CYA sample and a score of 3 or higher as the criterion for high-rate offenders (the 29 percent of this sample who were most frequently arrested were each arrested at least 2.2 times per year), we achieved an RIOC of 20 percent—about half the accuracy achieved using self-reported offense rates.

The degree of accuracy for the RIS follow-up subsample was not much better. Fifty-four percent scored 4 or higher on the prediction scale and thus were predicted to be high-rate. (The 50 percent who were arrested most frequently each had more than 0.8 arrests per year.) For this group, the RIOC was 24 percent, slightly better than the 20 percent for the CYA sample but nowhere near the 39 percent obtained with the self-reported data.

DIFFERENCES IN AVERAGE ARREST RATE AMONG PREDICTION GROUPS

Another measure of a scale's validity is its ability to predict the mean offense or arrest rate of offenders in different groups. The average annual rate at which robberies were reported was four times higher among offenders in the original California RIS sample who were predicted to be high-rate offenders than among those who were predicted to be low- or moderate-rate (31 robberies per year vs. 8 robberies per year). This large difference appeared to indicate that selective incapacitation could work. Increasing the terms of those who commit 30 crimes per year while decreasing the terms of those who commit only 8 clearly should result in some crime reduction.

Even after modifying the methodology as suggested by other researchers who reviewed our earlier findings,[3] i.e., using the minimum

[3]See, for example, Christy Visher, "The Rand Second Inmate Survey: A Reanalysis," in Alfred Blumstein, Jacqueline Cohen, Jeffrey A. Roth, and Christy A. Visher (eds.), *Criminal Careers and "Career Criminals,"* Vol. 2, Chap. 5, National Research Council, National Academy of Sciences, Washington, D.C., 1986.

estimated offense rate and including only that subset of California robbers who were included in the follow-up sample, we obtained an annual robbery rate for subjects classified as high-rate that still exceeded the rate of the low- and moderate-rate groups by a factor of 3 (21 versus 7 robberies per year).

The difference among predicted categories of convicted burglars was not nearly as great. The offense rate of predicted high-rate offenders exceeded that of the low- and moderate-rate groups by less than a factor of 2. However, even this modest difference would imply a 10 percent reduction in burglaries for only a 3 percent increase in the number of burglars incarcerated.

The follow-up arrest rate for the 28 percent of the CYA sample categorized as high-rate (2.7 arrests per year), using the 5-item scale, was 2.2 times higher than the rate for those predicted to be low- or medium-rate (1.2 arrests per year).

Average follow-up arrest rates for California RIS offenders who were predicted to be high-rate (1.1 arrests per year) were only 1.4 times as large as the rates of those predicted to be low- and moderate-rate (0.8 arrests per year). This small difference is somewhat disappointing. However, the average arrest rate for the RIS offenders predicted to be high-rate was only 1.3 times as large as the rate for the group predicted to be low- or moderate-rate during the same period for which self-reported offense-rate data were collected. Obviously, if the average self-reported offense rate for one group is 3 times larger than that for another group, but their average arrest rate is only 1.3 times as great, there must be some systematic difference in the frequency with which offenses result in arrests.

PROBABILITY OF ARREST

The self-reported offense rates and counts of official arrests for the RIS prison respondents provide a means of estimating average probabilities of arrest for specific groups of offenders. Depending on whether we count or drop the last arrest and offense for each respondent (the one that placed them in the sample), the estimated probability of arrest for predicted low- or moderate-rate respondents (0.03 to 0.04) is 2 to 3 times higher than that for the predicted high-rate group (0.01 to 0.02).

If the self-reports can be believed, the difference in probability of arrest between predicted high- and low-rate offenders is real. If the difference is not real, the large differences in average self-reported offense rates must be the result of exaggerated or inaccurate self-reporting.

AN INDEPENDENT ASSESSMENT OF OFFENDER COMPETENCE

We examined arrest reports for a subsample of 11 RIS follow-up subjects to investigate whether police descriptions of offender behavior (which are normally included in arrest reports) could provide any independent indication of each individual's probability of arrest. The offense descriptions in the arrest reports indicate a fairly low level of offender competence and skill. Many of the arrests resulted from the offender's failure to take even the most rudimentary steps to avoid identification and apprehension. The reports for a few of the offenders revealed such a consistent pattern of incompetence that these individuals could only be predicted to have a higher-than-average probability of arrest.

On the other hand, explicit evidence of competence was hard to find. The strongest evidence of competent planning and execution we found was in those cases where discovery and arrest appear to have resulted from accidental circumstances, as opposed to sheer bumbling by the offender.

CONCLUSIONS

The findings of this study neither confirm nor refute those of our earlier study of selective incapacitation. They do suggest, however, that high-rate offenders cannot be accurately identified, either prospectively or retrospectively, on the basis of their arrest rates alone. For the kinds of chronic offenders included in the RIS follow-up sample, arrest rates are only weakly correlated with self-reported offense rates.

Validation or refutation of the offense-rate patterns indicated by the RIS will require further self-reporting studies, with greater emphasis on validating the offense rates reported by the respondents. Such studies will have to focus on discrete time periods and specific offenses. If offenders provide approximate locations and times of offenses, such information can be checked against police reports. This procedure should be feasible for any offender who reports more than a few crimes per year.

Alternative methods of validating offenders' self-reports of specific crimes could involve lie-detector tests or random intensive probation surveillance such as is now being imposed on some offenders.

More effort must be devoted to checking on the reliability of and resolving inconsistencies in the information provided by individual respondents, including:

- Corroborating their self-reports of specific offenses through independent sources.
- Verifying the probability of arrest implied in self-reported offense rates by analyzing police descriptions of the offenses for which respondents were caught.
- Estimating the magnitude and source of the income obtained by suspected high-rate offenders who claim to be abstaining from crime.

Unless we can identify some specific characteristics of high-rate offenders or their recorded offenses that can distinguish their expected probability of arrest from the average experienced by all offenders, individual arrest rates will remain a poor predictor of individual offense rates within a chronic-offender population.

ACKNOWLEDGMENTS

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I. INTRODUCTION

For many years, imprisonment was looked upon as a way to reform and rehabilitate offenders. However, extensive reviews of the treatment evaluation literature during the early 1970s concluded that imprisonment does not result in lower rates of recidivism than other forms of treatment or no treatment at all. Attention, therefore, shifted to the other utilitarian purposes of imprisonment, including incapacitation and general deterrence.

The incapacitation effect of imprisonment refers to the prevention of crimes by removing offenders from the community. The higher the rate at which an offender would commit crimes if he were free, the greater the expected incapacitation effect of any given sentence.

The increasing interest in incapacitation has led to a number of attempts by researchers to estimate individual offense rates, using self-reported data provided by incarcerated offenders and computerized arrest histories provided by several jurisdictions.

The largest body of self-reported data was collected in the 1978 RAND Inmate Survey (RIS) of approximately 2,200 male inmates serving time in the prisons and jails of California, Michigan, and Texas (Chaiken and Chaiken, 1982).

FINDINGS FROM THE RAND INMATE SURVEY

The RIS found that offense-rate frequency distributions were extremely skewed toward the high end of the range. For every type or combination of offenses examined, most of the subjects who reported committing the offense reported doing so at fairly low rates. For example, the median annual offense rate among those who committed burglary was less than six crimes per year. However, for every type of crime, a small fraction of the offenders reported crimes at much higher rates, *raising the average for the sample to several orders of magnitude higher than the median.* The most active 10 percent of the burglars surveyed reported committing more than 200 burglaries per year while they were free (Chaiken and Chaiken, 1982).

This large variation in individual offense rates raises the question of whether high-rate offenders could be distinguished for selective sentencing purposes. If this were possible, the amount of crime prevented through incapacitation might be increased by increasing the amount of time served by the small number of high-rate offenders, while alleviating prison overcrowding by decreasing the time served by the much larger number of low-rate offenders.

An analysis of those subjects who were serving terms for robbery or burglary at the time of the RIS survey (Greenwood and Abrahamse, 1982; Greenwood, 1983) identified seven items that appeared to be associated with individual rates of burglary and robbery:

1. Prior conviction for the same type of offense.
2. Incarceration for more than 50 percent of the preceding two years.
3. Conviction prior to age 16.
4. Having served time in a state juvenile facility.
5. Use of hard drugs in the preceding two years.
6. Use of hard drugs as a juvenile.
7. Being employed less than 50 percent of the preceding two years.

In subsequent analyses, Greenwood and Abrahamse used these seven items to construct a simple additive scale in which each item was given a value of 1 if it was true and 0 if it was not. Offenders who scored 0 or 1 on this scale were predicted to be low-rate; those who scored 2 to 3 were predicted as moderate-rate; and those who scored 4 or higher were predicted as high-rate.

Greenwood and Abrahamse also attempted to estimate the effects of different sentencing policies on California's crime rates and prison population. They concluded that a sentencing policy that increased the length of time served by predicted high-rate offenders while reducing the time served by predicted low- and medium-rate offenders would reduce the robbery rate in California by about 15 percent and would reduce the number of incarcerated robbers by about 5 percent. Under a policy of increasing the time served by all convicted robbers equally, it would be necessary to incarcerate 25 percent more robbers to produce the same 15 percent reduction in robberies.

In the past four years, there has been considerable discussion of the methodological and policy issues raised in the Greenwood and Abrahamse study (Blumstein et al., 1986; Cohen, 1983; Moore et al., 1984; von Hirsch, 1985; von Hirsch and Gottfredson, 1984). A central concern of all the discussants has been the accuracy with which future offense rates can be predicted. The Greenwood and Abrahamse prediction scale was tested only in a retrospective analysis of the same database on which it was developed. Furthermore, the equations that were used to estimate future incapacitation effects assumed that residual career lengths (the length of time remaining until the offender dropped out of criminal activity) were relatively long compared with the sentences he would serve. However, Cohen (1983) has pointed out that this is not the case: Some of the selective policies analyzed by Cohen involved terms of up to 8 years for predicted high-rate offenders, while average residual career lengths have been estimated at somewhere between 5 and 15 years. Cohen shows that ignoring the fact that a certain percentage of offenders will spontaneously end their criminal careers while they are incarcerated leads to an inflated estimate of incapacitation effects and an underestimate of the required prison population.

This issue is of concern only when one attempts to project rates measured at a previous time out to some future time. The problem can be avoided entirely if one is able to *measure* the rates for the time period of interest. That is the approach taken in the present study.

An optimum validation study for the Greenwood and Abrahamse model would involve (1) identifying an appropriate sample of offenders, say, at the time of arrest; (2) allowing a period of time to elapse in which the offenders would be free to engage in crime (i.e., not incarcerated); and (3) obtaining self-reports of how much crime they did. Unfortunately, it would probably be prohibitively expensive and time-consuming to track down and interview individual offenders several years after they were released from custody. Therefore, we have used a considerably more modest form of validation, relying on official arrest records rather than self-reports to measure individual criminal activity.

OBJECTIVES AND DESIGN OF THE STUDY

The analyses described in this report were performed to determine:

1. The accuracy with which the Greenwood and Abrahamse 7-item scale, or others like it, could predict subsequent recidivism and arrest rates for samples of chronic offenders.
2. Whether predicted differences in mean arrest rates reflect the magnitude of differences among individual offense rates shown in the RIS self-reported data.

Although individual arrest rates appear to be only weakly correlated with self-reported rates of offending (around 0.2 on the RIS), we have used such arrest rates because (1) prospective self-reported offense rates for serious offender populations are not available, (2) individual arrest rates are the best available proxy for individual offense rates, and (3) their use as measures of criminal activity is standard practice in criminological research. Since individual arrest and offense rates are positively correlated, and individual offense rates are on the average several times larger than arrest rates, the differences in average individual offense rates among groups will usually be larger than those in arrest rates. Therefore, our estimates of differences in offense rates should be conservative.

We analyze follow-up arrest histories for two samples of male offenders after their release from California correctional facilities. The first group consists of approximately 2,700 young men who were committed to two California Youth Authority (CYA) facilities between 1966 and 1971. Variables coded from their official records are used to construct a 5-item scale which approximates five of the items on the Greenwood and Abrahamse scale. An analysis of this sample and the accuracy with which the 5-item scale predicted recidivism and arrest rates during the two years following the CYA offenders' release from custody is presented in Sec. II.

The second group consists of approximately 200 RIS respondents who were serving time in California prisons for burglary or robbery at the time of their interviews and who had been released from prison at least two years prior to the time we coded their rap sheets. (These are some of the individuals for whom the original 7-item scale was developed.) In Sec. III we compare the predictive accuracy of the 7-item scale for the first two years after release with its predictive accuracy for the two years preceding incarceration.

The predictive accuracy for both the CYA and California prison samples was considerably poorer than that achieved by applying the scale retroactively to offenders who provided self-reports of their offense rates. Section III shows that part of this difference in predictive accuracy may be due to systematic differences in the arrest probabilities of low- and high-rate offenders.

Section IV describes a small pilot study undertaken to determine whether the police reports that describe the crimes for which offenders were arrested can be used to provide an independent assessment of arrest probabilities.

Finally, Sec. V presents our conclusions about the appropriateness and effectiveness of selective sentencing policies, given the current state of knowledge, and suggests the direction future research should take.

II. THE CALIFORNIA YOUTH AUTHORITY CHRONIC OFFENDERS

The ideal sample with which to explore the predictability of future offenses, from an incapacitation perspective, would consist of convicted offenders for whom complete follow-up arrest histories were available for an extended period of time. Such a sample would exactly reflect the offender population for whom judges must make sentencing decisions. The next best sample would consist of offenders committed to a particular type of correctional facility and released at about the same time. Selective incapacitation decisions for such offenders would be limited to the amount of time they should serve. Excluded from the study would be offenders who do not serve any time at all and those committed to less severe or more severe sentences.

If sentencing judges are able to discriminate between low- and high-risk offenders to any degree (as the Greenwood and Abrahamse study suggested they can), the incarceration sample would necessarily under-represent offenders from both tails of the risk (or offense-rate) distribution.[1] This is the type of sample assembled by CYA researchers Rudy Haapanen and Carl Jesness for their 1982 study of chronic offenders.[2] That study used data on approximately 2,700 male subjects who had been committed to one of two CYA facilities, the Preston School of Industry and the Northern California Youth Center (YCRP), during the late 1960s and early 1970s.[3] The records include each offender's characteristics at the time of his CYA commitment (age, race, education, etc.); characteristics of the commitment offense; and the date and offense type for all the offender's known arrests and commitments at the time of the CYA commitment and for a period of from 8 to 14 years thereafter. We used this database for our early explorations of arrest-rate prediction because it contained complete follow-up criminal-history records for a large sample of relatively serious offenders. Although it did not contain information on the full range of personal characteristics and prior record variables covered by the RIS,

[1]The sample for the RIS included both jail and prison inmates to minimize this type of sample censoring.

[2]The Haapanen and Jesness analysis focused primarily on whether or not the subjects had recidivated at all, not on the rate of subsequent arrests.

[3]The file also includes data on youths who were committed to a third facility, Fricot Ranch, but these subjects were not included in our analyses because they were considerably younger and more likely to have been committed for status offenses.

we believed that this analysis would complement our analysis of follow-up arrest histories for the RIS subjects in that it would cover a wider range of offender types and a longer follow-up period.

CHARACTERISTICS OF THE SAMPLE

The CYA sample consisted of all the youths committed to the Preston School of Industry between February 1966 and March 1967 and all those committed to the YCRP between August 1969 and March 1971. Placements to specific institutions are made by a classification board following commitment by juvenile or criminal courts. At the time these youths were committed, California's criminal courts were placing most of the young men under 21 years of age who required state commitment in the CYA rather than state prison. The CYA population was about equally divided between juvenile and criminal court commitments, and it could retain jurisdiction over a ward until his twenty-third birthday.

Table 2.1 shows the median ages for the two samples and the distribution of subjects between the two institutions. Preston was used to hold the older and more difficult cases, including a fair number of transfers who had "flunked out" of other CYA facilities.

We collapsed the approximately 100 different offense codes included in the file[4] into two aggregate levels. The first distinguishes among seven types of offenses. (Table 2.2 shows the sample breakdown by commitment offense.) The second, more aggregate level groups the first three categories (violent, robbery, burglary) under "safety offenses" and the latter four under "nonsafety offenses."

The follow-up arrest records for our samples cover an average of about ten years, during which the 2,783 offenders were arrested a total of 26,000 times—about 9.5 arrests apiece. Fifty-two percent were

Table 2.1

CHARACTERISTICS OF THE PRESTON AND YCRP SAMPLES

Facility	Commitment Period	Sample Size	Median Age
Preston	2/66–3/67	1,715	17.6
YCRP	8/69–3/71	982	16.6

[4]The file contains the most serious charge for each arrest incident.

Table 2.2

BREAKDOWN OF THE SAMPLE BY COMMITMENT OFFENSE

Offense Category	Offenses	Percent of Sample Committed to CYA for These Offenses
Violent	Homicide, rape, assault	15.9
Robbery	Armed, unarmed, attempts	17.2
Burglary	Burglary, receiving stolen property	18.9
Theft	Larceny, forgery, petty theft, fraud	25.4
Drugs	Use, possession, sale, manufacturer, etc.	6.4
Status offense	601 WIC (runaway, truant, curfew, etc.)	5.7
Other	Drunk driving, disturbing the peace, carrying concealed weapons, etc.	10.5

eventually arrested for at least one violent-aggressive offense, 80 percent were arrested for at least one felony, and only 7 percent experienced no arrests. In attempting to distinguish offenders who continued experiencing arrests from those who did not, Haapanen and Jesness (1982) found associations among prior record and social-background variables (verbal aptitude, social maladjustment, social anxiety, obtrusiveness, parental acceptance, prior offenses), but these associations explained only about 8 percent of the variance.

RECORDED ARREST HISTORIES

No prior arrests were recorded for about half the sample. Most California counties maintain an extensive array of local treatment programs for juvenile offenders, so it is very unlikely that any youthful offender would be sent to the CYA for a first offense unless the offense was extremely serious. Prior-record variables were coded by the CYA researchers only if they were available in the ward's folder at the time the records were computerized. The absence of these data prevented us from constructing two key prediction variables: (1) previous conviction for the same type of offense and (2) incarceration for more than 50 percent of the preceding two years.

The follow-up arrest records were considerably more complete. They included dispositions for most arrests and covered at least eight years for 95 percent of the sample. Table 2.3 shows a rough breakdown of the sample by number of arrests. Five percent of the sample

Table 2.3

NUMBER OF ARRESTS OF SAMPLED OFFENDERS IN FOLLOW-UP PERIOD

Number of Arrests	Percentage of Sample
0	7
1–5	26
6–10	28
11–20	30
More than 20	9

died during the follow-up period; accidents and homicide were the leading causes of death.

The Preston "graduates" had a somewhat higher frequency of arrest than the YCRP "graduates": 43 percent of the former had more than 10 arrests, compared with only 31 percent of the latter. First arrests occurred most frequently in the three to nine months following release, after which the rate of first arrests dropped off sharply. Thirty-six percent of the sample were arrested within the first six months; 63 percent, within the first year; 81 percent, within the first two years; and 89 percent, within the first four years.

To deal with the problem of missing prior records, we divided the follow-up period for each subject into six-month intervals, beginning with date of release from the CYA. For each six-month interval, we counted the number of recorded arrests (broken down into the seven categories) and calculated the fraction of the interval that the subject was not incarcerated and was therefore able to commit crimes on the street. The first two years of the follow-up period were used to construct the prior-record variables (prior convictions for the offense being predicted and percent of time incarcerated) for use in the prediction scale. We created our dependent arrest-rate variables starting with arrests occurring in the third year following release from the CYA.

CONSTRUCTING THE PREDICTION SCALE

The 7-item prediction scale developed by Greenwood and Abrahamse contains two items that could not be used for the CYA sample: commitment to a state juvenile facility, and being employed less than 50 percent of the preceding two years. Everyone in this sample had been committed to a juvenile facility at the time data collection began, and no information was available on employment histories, either before or after commitment.

Table 2.4 shows how the remaining five variables were defined in the CYA database; the wording used in the RIS analysis is also given, for comparison.

The 5-item scale did not divide the sample into fractions that would enable us to construct comparable risk groups. Table 2.5 shows how the 2,268 subjects for whom we had all the necessary data to calculate arrest rates for follow-up year 3 were distributed on the 5-item scale, compared with the distribution on the 7-item scale. The CYA respondents are more concentrated at the low end, with 37 percent in the 0 or 1 category and only 7 percent scoring 4 or more. With this distribution, it is not possible to match the marginal frequencies obtained with the 7-item scale on the original RIS data. However, if we include those who scored 3 or higher in the predicted high-rate category, the proportion of the CYA sample falling into the three predicted categories will be somewhat comparable to that of the RIS sample.

Table 2.4

DEFINITIONS IN THE 7-ITEM SCALE AND THE 5-ITEM SCALE

Item	7-Item Scale	5-Item Scale
1.	Prior conviction for the type of offense being predicted	Arrest for safety crime in follow-up years 1 or 2
2.	Incarcerated more than 50 percent of the preceding 2 years	Incarcerated more than 50 percent of follow-up years 1 and 2
3.	Conviction before age 16	Less than 16 years of age at time of first incarceration
4.	Drug use in preceding 2 years	Arrested for drug-related crime during follow-up years 1 and 2
5.	Drug use as a juvenile	Self-reported drug use as a juvenile
6.	Served time in a state juvenile facility	N.A.
7.	Employed less than 50 percent of the preceding 2 years	N.A.

Table 2.5

DISTRIBUTION OF CYA AND RIS SAMPLES ON THE 5-ITEM SCALE

Prediction Scale Rate	Percent of CYA Sample	Percent of RIS Sample
0	11	27
1	26	
2	34	44
3	23	
4+	7	29

THE ARREST-RATE PREDICTION ACCURACY OF THE 7-ITEM SCALE

The accuracy achieved with the 7-item scale on the RIS data is shown in Table 2.6, which compares the predicted scores with self-reported offense rates for robbery and burglary. Overall, 51 percent of the respondents were placed in the correct category by the prediction scale.[5]

If a prediction scale is used to divide a sample into two groups rather than three, it becomes much easier to construct summary statistics describing the accuracy of the scale. Table 2.7 shows the accuracy with which the 7-item scale classified the RIS respondents when the low and medium categories were collapsed into a single (low) category.

The measure of prediction accuracy we use throughout this section is the relative improvement over chance[6] (RIOC) measure developed by Loeber and Dishion (1983), which takes into account the limitations on prediction accuracy imposed by differences in the row and column marginals. Thc RIOC for the three-state sample shown in Table 2.7 is 35 percent.

The relationship between predicted and actual arrest rates in follow-up years 3 and 4 for the CYA sample is shown in Table 2.8. Overall, 44 percent of the sample were assigned to the correct

[5]Thirty-five percent would be placed correctly purely by chance, if there was no association between the scale and the data.

[6]

$$RIOC = \frac{PC - RC}{MC - RC} = \frac{\textit{Percent correct} - \textit{Random correct}}{\textit{Maximum percentage correct} - \textit{Random correct}}$$

Table 2.6

PREDICTED VERSUS SELF-REPORTED OFFENSE RATES FOR RIS ROBBERY AND BURGLARY OFFENDERS, USING THE 7-ITEM SCALE

(In percent; N = 781)

Score on Prediction Scale	Self-Reported Offense Rate			
	Low	Medium	High	Total
Low (0–1)	14	10	3	27
Medium (2–3)	12	22	10	44
High (4–7)	4	10	15	29
Total	30	42	28	100

NOTE: PC = 51 percent; RC = 35 percent.

Table 2.7

PREDICTED VERSUS SELF-REPORTED OFFENSE RATES FOR THE THREE-STATE SAMPLE OF ROBBERY AND BURGLARY OFFENDERS

(In percent; N = 781)

Collapsed Prediction Scale	Collapsed Self-Reported Offense Rates		
	Low	High	Total
Low (0–3)	58	13	71
High (4–7)	14	15	29
Total	72	28	100

categories, 7 percent less than the correct assignments made with the 7-item scale on the RIS data. Also, the fraction of extreme false positives and negatives is considerably higher: 7 percent of the CYA sample were predicted low but turned out high, and 6 percent were predicted high but turned out low, compared with the 3 and 4 percent figures achieved for the RIS respondents. The 7-item scale accurately identified about half of the self-reported high-rate offenders in the RIS, whereas the 5-item scale accurately identified only 41 percent of the high-rate offenders in the CYA sample.

When the low- and medium-rate categories are combined, the RIOC for the CYA group is only 0.20, compared with an RIOC of 0.35 for the RIS respondents.

Table 2.8

PREDICTED VERSUS ACTUAL ANNUAL ARREST RATES FOR THE CYA SAMPLE IN FOLLOW-UP YEARS 3 AND 4: ALL ARRESTS

(In percent; N = 2,355)

Predicted Arrest Rate	Scale Score	Actual Arrest Rates: Low (rate ≤ .5)	Medium (.5 < rate < 2.2)	High (rate ≥ 2.2)	Total
Low	0 to 1	20	11	7	38
Medium	2	12	12	10	34
High	3+	6	10	12	28
Total		38	33	29	100

NOTE: PC = 44 percent; RC = 34 percent.

The 7-item scale was developed to identify offenders who reported having high robbery and burglary rates, but it did not consider other types of offenses. We might expect the 5-item scale to perform better in identifying offenders with high rates of safety arrests, which include burglary, robbery, and other serious crimes against the person (murder, rape, kidnap, assault). Table 2.9 shows how well it performs this task.

The marginals for the predicted and actual arrest-rate categories cannot be made to match as closely as in the previous tables, because of the large fraction of the sample (57 percent) who did not experience

Table 2.9

PREDICTED VERSUS ACTUAL ANNUAL ARREST RATES FOR THE CYA SAMPLE IN FOLLOW-UP YEARS 3 AND 4: SAFETY ARRESTS ONLY

(In percent; N = 2,355)

Predicted Arrest Rate	Scale Score	Actual Safety Arrest Rates: Low (rate = 0)	Medium (0 < rate < .62)	High (rate > .62)	Total
Low	0 to 1	26	6	7	38
Medium	2	19	6	9	34
High	3+	12	4	12	28
Total		57	15	28	100

NOTE: PC = 44 percent; RC = 35 percent.

any safety arrests during years 3 and 4. Nevertheless, the scale achieves the same degree of accuracy (44 percent) in predicting safety-arrest rates as it achieved in predicting arrest rates for all offenses, while RIOC improves slightly, to 0.22.

ALTERNATIVES TO THE 5-ITEM SCALE

Up to this point, we have derived scale scores simply by assigning a value of 1 to each characteristic possessed by the offender. Thus, the same score would have been assigned to a person who was under 16 years old at first incarceration as to one who had a drug arrest during the past two years. We next attempted to determine whether particular combinations of items could be used to more accurately assign persons to predicted arrest-rate groups. For this analysis, we computed the average arrest rate for every combination of the five scale items and tried to visually identify patterns associated with low, medium, and high rates. Several alternatives to the 5-item scale were also tested. The most accurate one used the following criteria:

- *Low-rate*: Offender had none of the characteristics on the 5-item scale, or had only drug use as a juvenile and no other characteristic.
- *Medium-rate*: Offender was predicted to be neither high- nor low-rate, i.e., assignment was by default.
- *High-rate*: Offender had a drug arrest within the previous two years, with or without any other characteristics, or was less than 16 years of age at the time of first incarceration and spent more than 50 percent of the previous two years in prison, with or without other characteristics.

The results of applying this alternative rating scheme to the CYA sample are shown in Table 2.10. Although this technique accurately classified a higher percentage of the sample (46 percent vs. 44 percent), the percentage who would be correctly classified by random assignment also increased by 2 percent (to 36 percent) because of the large increase in the medium-rate category. This increase also decreased the percentage of extreme false positives and negatives to 4 percent and 3 percent, values similar to those achieved in classifying the self-reported offense rates of the RIS sample. However, the combination of variables used in this alternative technique does not seem to substantially improve the underlying prediction accuracy of the basic scale. None of the other combinations we tested did even this well.

Table 2.10

ALTERNATIVE SCALE—PREDICTED VERSUS ACTUAL ARREST RATES FOR THE CYA SAMPLE IN FOLLOW-UP YEARS 3 AND 4: ALL ARRESTS

Predicted Arrest Rate	Scale Score	Actual Arrest Rates: Low (rate = 0)	Medium ($0 < \text{rate} < 2.5$)	High ($\text{rate} \geq 2.5$)	Total
Low	0 to 1	11	10	3	24
Medium	2	12	24	14	50
High	3+	4	12	11	26
Total		27	46	27	100

NOTE: PC = 46 percent; RC = 36 percent.

DIFFERENCES IN ARREST RATES ACROSS PREDICTION CATEGORIES

For policy purposes, the percentage of offenders who are accurately classified is less important than the difference in average arrest rates experienced by offenders in the different categories. The mean offense rates reported by RIS respondents differed by more than a factor of 10 between the predicted low- and high-rate categories, even though only 51 percent were accurately classified.

Individual arrest rates, like self-reported offense rates, are skewed toward the high end, although not by as much. The median arrest rate for the CYA sample during follow-up years 3 and 4 was 1 arrest per year, while the average was 1.5. Ten percent of the sample had more than 4 arrests per year. But the arrest-rate distribution does not have the long right tail that was characteristic of the self-reported offense-rate distributions.

Table 2.11 shows the variation of average annual arrest rates (for any crime and safety crimes only) among the three rate categories defined in Table 2.8. On the average, offenders who were predicted to have high rates were arrested 2.7 times as frequently as those predicted to have low rates. Also, the average fraction of time members of each group are incarcerated appears to be directly proportional to arrest rates, as predicted by the Shinnar and Shinnar (1975) formulas for calculating incapacitation effects.

In our analysis, the 5-item scale proved to be a rather poor predictor of follow-up arrest rates. About 44 percent of the CYA offenders were correctly assigned to the three predicted arrest-rate categories (high,

Table 2.11

AVERAGE ANNUAL ARREST[a] RATES BY PREDICTION SCALE CATEGORY FOR FOLLOW-UP YEARS 3 AND 4

(Arrests per year)

Prediction Scale Categories	Arrest Rate (Any Arrest)	Safety Arrest Rate	Fraction of Time at Risk	Fraction of Time Incarcerated
Low	1.0	0.27	0.91	0.09
Medium	1.5	0.42	0.85	0.15
High	2.7	0.68	0.73	0.27

[a]Defined as the total number of arrests divided by the total time at risk for all respondents in the category.

medium, low), 7 percent less than the percentage of correct assignments achieved with the self-reported data of the RIS group. Seven percent of the assignments were extreme false positives (predicted high-rate who were actually low-rate), and 6 percent were false negatives (predicted low-rate who were actually high-rate), compared with 4 and 3 percent on the original RIS data. The RIOC for the arrest predictions was only 0.20, while that achieved with self-reported offense rates was 0.35.

Attempts to improve the predictive accuracy of the scale by modifying cutpoints, including additional variables, or using different combinations of variables were to no avail.

To determine how much of the decrease in prediction accuracy might be caused by the use of the 5-item scale rather than the 7-item, we classified the 283 California RIS respondents (convicted robbers and burglars only) with both scales. The RIOC achieved with the 5-item scale was 0.35; the 7-item scale produced an RIOC of 0.39 (see Table 3.1)—about a 10 percent difference in prediction accuracy. We thus conclude that about one-third of the loss in accuracy in our predicted arrest rates is due to the use of the 5-item scale rather than the 7-item.

Despite this rather poor predictive accuracy, the average annual rate of safety arrests for the 28 percent of the CYA sample predicted to be high-rate was 2.5 times larger than that for the 38 percent predicted to be low-rate. It remains to be seen whether this difference in arrest rates is sufficient to justify selective sentencing.

III. RAND INMATE SURVEY RESPONDENTS

This analysis focuses on those RIS respondents who were serving time in California prisons for either robbery or burglary, a subset of the sample for whom the 7-item prediction scale was developed. It does not include jail inmates because we lacked the appropriate identifiers for locating their follow-up criminal records.

The follow-up RIS database consists of 65 inmates who were serving time for burglary and 139 who were serving time for robbery, a total of 204 individuals.[1] Rap sheets were obtained from the California Department of Justice in early 1984. At that time, nine of the robbers had not been released, so they are not included in our follow-up arrest-rate calculations. However, they represent the full range of prediction scores and self-reported offense rates, so their omission should not bias the sample in any particular direction.[2] The median follow-up period for the sample was four years, and at least two years of data were available for 188 subjects. During the follow-up period, 79 percent of the sample were arrested and more than 50 percent were imprisoned for a subsequent offense.

SAMPLE DECAY

One of the primary objectives of the analyses reported here was to determine how well the 7-item scale would predict high rates of arrest of individuals in a given period following release from prison. Since many of the respondents in the RIS sample were not available for the follow-up study, we first had to determine how changes in the composition of the sample affected the accuracy of the 7-item scale for its original purpose, i.e., identifying self-reported high-rate offenders.

We first examined the original three-state subsample of 781 convicted robbers and burglars on which the scale was developed; we then looked at the California sample, and then at the California follow-up sample, which consisted of prison inmates only. Finally, we considered the effects of alternative techniques for calculating offense rates

[1]The original RIS sample comprised 207 convicted robbers and burglars, but we were unable to obtain rap sheets for three subjects (two had died and the records of the other had been purged).

[2]Our earlier analysis (Greenwood and Abrahamse, 1982) had also shown that there was no relationship between sentence length and self-reported offense rates.

developed by Christy Visher (1986) for the National Academy of Sciences Panel on Criminal Careers.

The predictive accuracy of the 7-item scale for distinguishing among California robbery and burglary defendants is shown in Table 3.1. Forty-four percent of the respondents were classified as high-rate, as compared with 29 percent in the three-state sample. Fifty-three percent of the California respondents were accurately classified by the 7-item scale, and the RIOC when the low and medium categories were combined was 0.39—both values slightly higher than those for the three-state sample. This result had been anticipated by Greenwood and Abrahamse (1982), who showed that the prediction scale made fewer errors in classifying California respondents than in classifying offenders from other states.

Table 3.1 also shows the multiple-regression results for predicting high offense rates using the items on the 7-item scale. Nearly 30 percent of the overall variance is explained by these items. Five of the seven items are significantly related to high offense rates. Conviction before the age of 16 and having served time in a juvenile facility are not significantly related to high offense rates.

The scale does differentiate somewhat better among the California robbers than among the burglars, as shown in Tables 3.2 and 3.3 (the RIOC for robbery is 0.44, while that for burglary is 0.31).

There was ample opportunity for ambiguities to arise in the calculation of each respondent's individual offense rate. Each respondent was asked in several different ways about the number of crimes he committed, in an attempt to check on the reliability of the answers. If the answers were inconsistent, or if there was some uncertainty about the amount of time the offender was actually at risk, the uncertainty was reflected in a range of possible offense rates, calculated by dividing the number of crimes committed by time at risk.

In the original analysis, Greenwood and Abrahamse (1982) used the highest reported value of individual offense rate whenever this ambiguity occurred. In reanalyzing those data, the National Academy of Sciences Panel (Visher, 1986) used a figure close to the lowest reported value.[3] To make the two studies consistent, we also used the minimum estimate whenever a range was possible. Tables 3.4 and 3.5 show that the use of this alternative convention for computing offense rates does not appreciably change the predictive ability of the scale, as compared

[3]Visher followed a rigorous procedure in reestimating street months, months of time served, and number of crimes committed (the variables used in the calculation of the offense rate). The procedures differed in important ways from the original RAND estimates, but the revised estimates were practically identical to the earlier minimum estimates.

Table 3.1

PREDICTED VERSUS SELF-REPORTED OFFENSE RATES FOR ROBBERY AND BURGLARY FOR CALIFORNIA ONLY

(In percent; N = 283)

Score on Prediction Scale	Self-Reported Offense Rates: Low	Medium	High	Total
Low (0–1)	8	8	3	19
Medium (2–3)	9	16	12	37
High (4–7)	4	11	29	44
Total	21	35	44	100

NOTE: RC = 51 percent; PC = 70 percent; IOC = 19 percent; MC = 100 percent; RIOC = 39 percent.

Regression Analysis Using Log (Max Lambda +0.5) as a Dependent Variable

Model $R^2 = 0.283$, $p < 0.0001$
Adjusted $R^2 = 0.265$
N = 283

Variable	Parameter Estimate	Probability > |T|
Prior adult conviction for same type of offense	0.60	0.01
Incarcerated > 50% previous 2 yrs	0.93	0.00
1st conviction < age 16	0.02	0.94
Juvenile commitment	0.35	0.19
Drug use in previous 2 yrs	1.17	0.00
Juvenile use of hard drugs	0.80	0.00
Employed < 50% previous 2 years	0.64	0.00

Table 3.2

ORIGINAL CALIFORNIA JAIL AND PRISON SAMPLE OF BURGLARS: MAXIMUM OFFENSE RATE

(In percent; N = 120)

Predicted Rate (7-item scale)	Actual Rate		
	Low + Medium (<36)	High (≥36)	Total
Low + medium (0–3)	45	16	61
High (4+)	16	23	39
Total	61	39	100

NOTE: RC = 52 percent; MC = 100 percent; PC = 68 percent; IOC = 16 percent; RIOC = 31 percent.

Table 3.3

ORIGINAL CALIFORNIA JAIL AND PRISON SAMPLE OF ROBBERS: MAXIMUM OFFENSE RATE

(In percent; N = 163)

Predicted Rate (7-item scale)	Actual Rate		
	Low + Medium (<4.8)	High (≥4.8)	Total
Low + medium (0–3)	39	14	53
High (4+)	14	33	47
Total	53	47	100

NOTE: RC = 50 percent; MC = 100 percent; PC = 72 percent; IOC = 22 percent; RIOC = 44 percent.

Table 3.4

ORIGINAL CALIFORNIA JAIL AND PRISON SAMPLE OF BURGLARS: MINIMUM OFFENSE RATE

(In percent; N = 121)

Predicted Rate (7-item scale)	Actual Rate: Low + Medium (≤20)	Actual Rate: High (>20)	Total
Low + medium (0–3)	45	17	61
High (4+)	17	22	39
Total	62	38	100

NOTE: RC = 53 percent; MC = 99 percent; PC = 67 percent; IOC = 14 percent; RIOC = 30 percent. Numbers do not add to totals because of rounding.

Table 3.5

ORIGINAL CALIFORNIA JAIL AND PRISON SAMPLE OF ROBBERS: MINIMUM OFFENSE RATE

(In percent; N = 167)

Predicted Rate (7-item scale)	Actual Rate: Low + Medium (≤2.4)	Actual Rate: High (>2.4)	Total
Low + medium (0–3)	38	13	51
High (4+)	15	34	49
Total	53	47	100

NOTE: RC = 50 percent; MC = 98 percent; PC = 72 percent; IOC = 22 percent; RIOC = 46 percent.

with Tables 3.2 and 3.3. None of the entries in the prediction table changed by more than 2 percent, and the RIOC remained virtually unchanged.

Tables 3.6 and 3.7 show how well the prediction scale worked with the follow-up California sample. These results differ from those in the previous tables in that they do not include respondents who were in jail at the time of our survey or who were never released. The jail inmates were, on the average, less active than the prisoners, and those serving the longest prison terms were most likely to have injured a victim.

A much higher fraction of the follow-up sample of burglars (Table 3.6) are classified as high-rate by the prediction scale (54 percent, compared with 39 percent of the original sample). However, the RIOC remains unchanged at 0.30. There was far less attrition in the follow-up sample of robbers (Table 3.7) than in the sample of burglars: 135 of the original 167 robbers were available for follow-up, whereas only 57 of the original 121 burglars were available. The follow-up robbery sample is also more representative of the original robbery sample than is the follow-up burglary sample, because prison commitment for robbery tends to be based on the seriousness of the crime (weapon used, injury, vulnerability of the target), whereas prison commitments for burglary are strongly influenced by prior record (Greenwood, Abrahamse, and Zimring, 1984). Some evidence for this difference in sentencing patterns (and ultimately sample censoring) is indicated by the very slight increase in the fraction of the robbery sample identified as high-rate by the prediction scale (53 percent, up from 49 percent). The RIOC declines slightly in the follow-up sample, from 0.46 to 0.42.

The changes in predictive accuracy, as measured by RIOC, caused by using minimum estimates of offense rate and using only California prison inmates are summarized in Table 3.8.

The difference between the mean offense rates for low- or moderate-rate offenders and that for high-rate offenders, shown in Table 3.9, has also been reduced. The mean offense rate for predicted high-rate burglars was 2.4 times that for predicted low-rate burglars in the original sample, but only 1.7 times as great in the follow-up sample. In the original sample, the mean offense rate for high-rate robbers was 4 times that for predicted low-rate robbers, but only 3 times as great in the follow-up, using the minimum estimated offense rate.

In summary, the use of the minimum estimates of offense rate rather than the maximum, and the reduction in the follow-up sample due to the loss of the jail inmates both introduce modest reductions in the accuracy of the 7-item scale in categorizing offenders and in the differences between mean offense rates for the predicted low- and high-rate groups. However, this modest decline in prediction accuracy

Table 3.6

FOLLOW-UP CALIFORNIA PRISON SAMPLE OF BURGLARS: MINIMUM OFFENSE RATE

(In percent; N = 57)

Predicted Rate (7-item scale)	Actual Rate		
	Low + Medium (≤12)	High (>12)	Total
Low + medium (0–3)	28	18	46
High (4+)	18	37	54
Total	46	54	100

NOTE: RC = 50 percent; MC = 100 percent; PC = 65 percent; IOC = 15 percent; RIOC = 30 percent. Numbers do not add to totals because of rounding.

Table 3.7

FOLLOW-UP CALIFORNIA PRISON SAMPLE OF ROBBERS: MINIMUM OFFENSE RATE

(In percent; N = 135)

Predicted Rate (7-item scale)	Actual Rate		
	Low + Medium (≤2.4)	High (>2.4)	Total
Low + medium (0–3)	33	14	47
High (4+)	16	37	53
Total	49	51	100

NOTE: RC = 50 percent; MC = 98 percent; PC = 70 percent; IOC = 20 percent; RIOC = 42 percent.

Table 3.8

EFFECTS OF CHANGES IN SAMPLE AND OFFENSE-RATE DEFINITION ON PREDICTION ACCURACY FOR SELF-REPORTED OFFENSES (RIOC)

	Subgroups	
Sample and Offense Rate Definition	Convicted Burglars	Convicted Robbers
Original RIS California sample: maximum offense rate	0.31	0.44
Original RIS California sample: minimum offense rate	0.30	0.46
Follow-up California sample: minimum offense rate	0.30	0.42

Table 3.9

EFFECTS OF SAMPLE DECAY ON MEAN OFFENSE RATES FOR PREDICTED CATEGORIES

(Offenses per year)[a]

	Predicted Offense Rate Category	
Sample and Estimate	Low and Medium	High
Convicted Burglars		
Original California sample: maximum offense rate estimate	65.0	156.3
Original California sample: minimum offense rate estimate	49.5	127.8
Follow-up sample: minimum offense rate estimate	69.4	117.3
Convicted Robbers		
Original California sample: maximum offense rate estimate	7.7	30.9
Original California sample: minimum offense rate estimate	5.4	20.6
Follow-up sample: minimum offense rate estimate	7.1	20.8

[a]For convicted burglars this is the rate of self-reported burglaries per year, for convicted robbers it is the rate of self-reported robberies.

should not impair the usefulness of the RIS follow-up sample for testing the accuracy of the 7-item scale in predicting follow-up arrest rates.

FOLLOW-UP ARREST HISTORIES

Rap sheets for the RIS respondents were obtained from the California Department of Justice in February 1984. The median follow-up period for the sample was about four years. During this time, almost 80 percent of the sample were arrested at least once, 64 percent had been incarcerated in prison or in jail, and 54 percent were imprisoned at least once. Our analyses focus primarily on the first two years following release from the RIS term and include only those 176 subjects with at least two years of follow-up data and for whom we have a minimum offense rate for the two-year period preceding the RIS incarceration. We omitted 10 subjects who had not been released from their RIS incarceration, 6 for whom we did not have two full years of follow-up data, 3 for whom rap sheets could not be located by the California Department of Justice, and 12 (8 burglars and 4 robbers) who had missing minimum offense-rate values for the two-year period preceding the RIS incarceration.

RECIDIVISM RATES

The 7-item scale was developed to identify self-reported high-rate offenders, not to predict which ones would continue to commit crimes in the future. Nevertheless, those who commit crimes at high rates should be more vulnerable to arrest in any finite period than those who are less active.

Predicted and reported values for several simple recidivism measures are shown for the sample in Table 3.10. Predicted low- and moderate-rate offenders are those who scored less than 4 on the scale; predicted high-rate offenders are those who scored 4 or more. The self-reported low- and moderate-rate burglars committed 12 or fewer burglaries per year, and the low- and moderate-rate robbers committed 2.4 or fewer robberies per year.[4]

The most obvious point made by Table 3.10 is that the 7-item prediction scale predicts recidivism rates better than do self-reported offense rates. This observation suggests that self-reported offense rates for the two-year period preceding imprisonment are only weakly associated with the arrest rates the offenders experience after their release from prison. Klein and Caggiano (1986) found a low correlation between predictor scale scores and recidivism rates across all three states included in the RIS.

[4]Because seven robbers had self-reported offense rates of 2.4 crimes per year, we were unable to divide the sample to exactly match the division on predicted rate.

Table 3.10

FOLLOW-UP PERFORMANCE MEASURES BY PREDICTED AND SELF-REPORTED OFFENSE RATES

	Predicted Rate		Self-Reported Rate	
Performance Measure	Low + Moderate (N = 81)	High (N = 95)	Low + Moderate (N = 84)	High (N = 92)
Percent arrested during 1st 2 years	70.4	80.0	73.8	77.2
Percent with a safety arrest during 1st 2 years	46.9	54.7	47.6	54.4
Percent "failed" during entire follow-up[a]	75.3	86.3	78.6	83.7

[a]A failure is any one of the following: (1) an arrest, (2) a jail term, or (3) a prison term. Note that a person could be returned to prison without a corresponding arrest. Measures calculated for the 176 offenders with (1) at least 2 years of postrelease follow-up and (2) non-missing minimum lambda values.

ARREST RATES

In the absence of self-reported offense data, individual arrest rates have traditionally been used as a measure of individual criminal activity. Those who are arrested most frequently are assumed to be the most active offenders (Wolfgang, Figlio, and Sellin, 1972; Blumstein and Cohen, 1979). Table 3.11 shows how well the 7-item scale and self-reported offenses distinguish among the sample according to rate of arrest. Subjects who were predicted to be low- or moderate-rate (i.e., who scored 3 or less on the prediction scale) were arrested an average of 0.78 times per year, while those predicted to be high-rate were arrested 1.1 times per year—one-third more often.

Table 3.11 shows clearly that self-reported offense rates for the two-year period preceding imprisonment are only weakly associated with arrest rates for the two-year period following release. The difference in mean arrest rates between the predicted low- and high-rate groups is considerably greater than the difference between groups categorized by self-reported offense rates.

Table 3.11

MEAN ARREST RATE DURING FOLLOW-UP YEARS 1 AND 2, BY PREDICTED AND SELF-REPORTED OFFENSE RATES

		Mean Annual Arrest Rate	
Offense Rate Category	(N)	Any Arrest	Safety Arrest
Predicted rate (7-item scale)			
Low and moderate	(81)	0.78	0.41
High	(95)	1.11	0.52
Self-reported rate			
Low and moderate	(84)	0.92	0.43
High	(92)	0.98	0.51

In the Greenwood and Abrahamse (1982) analysis of selective incapacitation, the mean self-reported offense rates of predicted high-rate offenders were at least twice those of the predicted low- and moderate-rate offenders (see Table 3.9). If, in fact, we cannot categorize offenders into groups that differ in their mean offense rates by more than 30 percent, the potential gains in incapacitation effect from selective sentencing are considerably smaller than was estimated in the 1982 study.

WHY ARE THE DIFFERENCES IN MEAN ARREST RATES BETWEEN PREDICTED HIGH- AND LOW-RATE CATEGORIES SMALL?

At least three factors help explain the small differences between the mean arrest rates of the predicted low- and high-offense-rate groups:

1. The 7-item scale is less accurate for predicting differences in arrest rates than it is for predicting differences in self-reported offense rates.
2. The frequency distribution of individual arrest rates does not have the long right-hand tail of high-rate subjects that occurs in the frequency distribution of self-reported offense rates.
3. There seems to be little correlation between individual arrest rates and self-reported offense rates within this sample.

Prediction Accuracy

Table 3.12 shows that the 7-item scale is much less accurate for predicting arrest rates than it is for distinguishing among prisoners on the basis of self-reported offense rates. The RIOC for predicted rates is only 0.22, compared with 0.39 for the same subjects according to their self-reported offense rates.

When we regress self-reported offense rates (actually, the log of self-reported offense rates) on the items on the prediction scale, we are able to explain about 25 percent of the variance (adjusted R^2), as shown in Table 3.13, and five of the seven items are statistically significant. When we regress individual follow-up arrest rates (again, the log of the arrest rates) on the items, we are able to explain only about 2 percent of the variance (adjusted R^2), and only one item is statistically significant (see Table 3.14). Thus, our ability to predict arrest rates within this sample is extremely low.

Differences Between Offense-Rate and Arrest-Rate Frequency Distributions

One of the most significant findings in the earlier RIS analyses was the extreme skewness of individual offense-rate frequency distributions. For every type of crime examined, a small number of individuals reported annual commission rates that were many times greater than the median (Chaiken and Chaiken, 1982; Greenwood and Abrahamse, 1982). For example, the median rate of self-reported robberies in the follow-up sample of robbers was 2.6 per year. However, 10 percent of

Table 3.12

PREDICTED VERSUS ACTUAL ARREST RATES DURING FOLLOW-UP YEARS 1 AND 2, USING 7-ITEM PREDICTION SCALE

Predicted Rate (7-item) scale)	Actual Arrest Rate: Low + Medium (<.78)	High (≥.78)	Total
Low + medium (0–3)	28	18	46
High (4+)	23	31	54
Total	51	49	100

NOTE: RIOC = 0.22.

Table 3.13

REGRESSION ANALYSIS USING LOG (MIN LAMBDA +0.5) AS A DEPENDENT VARIABLE[a]

Variable	Parameter Estimate	Prob. > |T|
Prior adult conviction for current offense	0.65	0.02
Incarcerated > 50% of preceding 2 yrs	1.08	0.00
First conviction < age 16	−0.26	0.41
Juvenile commitment	0.37	0.25
Heroin/barbiturate use in preceding 2 yrs	0.71	0.02
Juvenile use of heroin/ barbiturates	0.74	0.02
Employed < 50% of previous 2 yrs	0.81	0.01

[a]Model R^2 = 0.261, $p < 0.0001$; adjusted $R^2 = 0.23$.

Table 3.14

REGRESSION ANALYSIS USING LOG (ARREST RATE +0.5) AS A DEPENDENT VARIABLE[a]

Variable	Parameter Estimate	Prob. > |T|
Prior adult conviction for current offense	0.21	0.04
Incarcerated > 50% of preceding 2 yrs	0.03	0.77
First conviction < age 16	0.01	0.93
Juvenile commitment	0.12	0.29
Heroin/barbiturate use in preceding 2 yrs	0.06	0.61
Juvenile use of heroin/barbiturates	−0.06	0.58
Employed < 50% of previous 2 yrs	0.18	0.10

[a]Model R^2 = 0.058, $p < 0.1818$; adjusted $R^2 = 0.018$.

this group reported committing more than 66 robberies per year. Among the full follow-up sample of convicted robbers and burglars, the median rate of self-reported robberies, burglaries, thefts, and assaults was 34 per year. However, the most active 15 percent reported more than 380 crimes per year. Clearly, the differences in mean offense rates between the predicted low- and high-rate categories depend on the ability of the scale to identify this small number of self-reported high-rate offenders. Their offense rates dominate the average of any group of which they are a part.

Frequency distributions for individual arrest rates are not nearly as skewed. The median arrest rate of our sample during the first two years after release from custody was 0.76 arrests per year. The highest arrest rate experienced by any one subject was 6.6 arrests per year. The 90th percentile of the distribution for individual arrest rates is less than four times the median, whereas for self-reported offense rates the 90th percentile is more than fifteen times the median.

Low Correlations Between Arrest Rates and Self-Reported Offense Rates

The primary factor limiting the predictive accuracy of the 7-item scale for follow-up arrest rates is the lack of correlation between arrest rates and the self-reported offense rates on which the scale was developed. Individual arrest rates during the first two years after release from prison show absolutely no correlation with self-reported offense rates for the two-year period preceding incarceration, nor are they correlated with arrest rates during that period.

There is a significant, but low, correlation between individual arrest rates for robbery, assault, grand theft auto, forgery, fraud, and burglary and self-reported offense rates for the same offenses for the same two-year preincarceration period. Therefore, even within the same time period, there is only a weak association between self-reported offense rates and arrest rates for this chronic-offender population.

Further evidence regarding this somewhat surprising finding is provided by Table 3.15, which shows the mean arrest rates experienced by subgroups of the follow-up sample during the same two-year period. While their average self-reported offense rates differed by more than a factor of 2 (see Table 3.9), the arrest rates of the predicted high-rate group exceeded those of the predicted low- and moderate-rate group by less than 50 percent, slightly more than the difference between the mean arrest rates for these same two groups during the two years following their release.

Table 3.15

AVERAGE ARREST RATES DURING TWO-YEAR PERIOD PRECEDING RIS INCARCERATION

(Arrests per year of street time)

Predicted Offense Rate	Arrest Rate
Low and moderate (n = 71)	2.6
High (n = 91)	3.5

NOTE: 14 of 176 offenders dropped from analysis due to missing data for arrests during the two-year period preceding RIS incarceration.

PROBABILITY OF ARREST

The disparity between mean self-reported offense rates and mean arrest rates clearly suggests some systematic differences in the probability of arrest of the high- and low-rate groups. In the remainder of this section, we develop and present several estimates of the average probability of arrest of offenders in different predicted offense-rate categories. Our findings consistently suggest that the high-rate offenders in the sample have lower probabilities of arrest, on the average, than the low-rate offenders.[5]

An unbiased estimate of the probability of arrest (q) for any group of offenders during a specified time period is provided by

$$q = \frac{A}{C}$$

where A is the total number of arrests experienced by the group and C is the total number of crimes committed. However, because the reporting time period for each offender in the sample ends with exactly one arrest and one offense (the crime that led to incarceration), it can be argued that it would be more appropriate to subtract one arrest and one crime from each offender. The resulting estimate, which we will call q^1, is then obtained by

$$q^1 = \frac{A - n}{C - n}$$

where n is the number of subjects.

[5]For these analyses, we included all 204 of the robbers and burglars in the RIS sample because we are interested in the two-year period prior to incarceration and not the follow-up period.

Our best estimate of the number of crimes committed by any one offender during the two-year period preceding incarceration is the self-reported "minimum crimes committed" variable used to calculate minimum offense rates. To be consistent with our follow-up arrest measures, which include all offense types, we use an aggregate measure of crimes committed which simply sums up all assaults, robberies, burglaries, thefts, grand thefts, forgeries, and frauds. We do not include drug sales, because their high volume and low probability of arrest would tend to dominate and distort estimates for other offense types.

The RIS data provide both self-reported and official rap sheet counts of the number of arrests occurring during the two-year period preceding incarceration. For this analysis we use only the official record count, since all of our other arrest-rate analyses are based on official record data. Again, we constructed an aggregate arrest measure by summing the arrests for all types of crime except drug use or sale.

Tables 3.16 and 3.17 display estimates of the probability of arrest for the follow-up sample, classified as low- and moderate-rate or high-rate on the basis of both the 7-item scale and self-reported offenses. In Table 3.16, the estimated probability of arrest (q) for each group is simply the total number of arrests experienced by each subject in the group divided by their total number of self-reported offenses (excluding drug crimes and arrests). In Table 3.17 the estimate of probability arrest (q^1) for each group was obtained by subtracting one arrest and one offense from each offender count and dividing the sum of the remaining arrests by the sum of the remaining offenses.

Table 3.16 shows that the predicted low- and moderate-rate offenders had twice the probability of arrest (0.04) of the predicted high-rate offenders (0.02). The self-reported low- and moderate-rate offenders were three times as likely to be arrested (0.06) as the self-reported high-rate offenders (0.02). The adjusted figures in Table 3.17 show even more difference in probability of arrest between the low- and high-rate offenders.

If we believe that self-reported offense rates are a reasonably accurate measure of the differences in offense rates between groups, the RIS data inform us that the average low- and moderate-rate offenders in prison are two to four times more likely to be arrested for any one offense than is the average high-rate offender. If, on the other hand, we believe that arrest rates are a reasonably accurate measure of differences in offense rates between groups, and that there are no systematic differences in probability of arrest, we must disregard the high offense rates reported by some of the RIS subjects as boasting or wishful thinking.

Table 3.16

ESTIMATED PROBABILITY OF ARREST, q, BY PREDICTED AND ACTUAL SELF-REPORTED OFFENSE-RATE CATEGORY

	Method of Classification	
Predicted Rate	7-Item Scale	Minimum Self-Reported Offense Rate
Low and moderate	0.04	0.06
High	0.02	0.02

Table 3.17

ESTIMATED PROBABILITY OF ARREST, q^1, BY PREDICTED AND ACTUAL SELF-REPORTED OFFENSE-RATE CATEGORY

	Method of Classification	
Predicted Rate	7-Item Scale	Minimum Self-Reported Offense Rate
Low and moderate	0.03	0.04
High	0.01	0.01

If we believe that the systematic differences in probability of arrest revealed by the RIS data are in fact real and stable over time, the difference in follow-up offense rates between the low- and high-rate groups would not be the modest 49 percent reflected by their arrest rates (the "any arrest" column in Table 3.11), but the 170 percent difference that we obtain when we divide each group's arrest rate by its respective probability of arrest (see Table 3.18).

The RIS data cannot help us determine which of these competing hypotheses is true. If we want to know whether there are substantial, stable, and persistent differences in the probability of arrest faced by different types of offenders, we will have to collect information or individual offense and arrest rates that can be validated better than the RIS data.

Table 3.18

ESTIMATED AVERAGE INDIVIDUAL OFFENSE RATES IN FOLLOW-UP PERIOD, ASSUMING DIFFERENT PROBABILITIES OF ARREST

Predicted Rate	Arrest Rate (u)	Probability of Arrest (q)	Offense Rate ($\lambda = u/q$)
Low or moderate	0.79	0.04	19.8
High	1.10	0.02	55.0

IV. A CLOSER LOOK AT INDIVIDUAL PROBABILITIES OF ARREST

In the analyses described above, we attempted to use the frequency of individual arrests as a measure of criminal activity rate and to compare estimated rates with self-reported offense rates. While offenders with higher self-reported offense rates do have somewhat higher arrest rates, the differences between high- and low-rate groups estimated from arrest reports are not nearly as large as those estimated from self-reports. This disparity may be due in part to systematic differences in individuals' probability of arrest.

THE CONVENTIONAL ASSUMPTIONS

In using individual arrest rates (u) as a surrogate measure for offense rates (λ), we assume that $u = \lambda q$, where q is the probability of arrest for any one crime. But if q is in fact correlated with λ or any of the variables used to predict it, the relationship between u and λ will not be linear.

The probability of arrest for a given crime has traditionally been assumed to be equal across all offenders, primarily for analytic simplicity, but also because no one has presented data to show that this assumption is unrealistic. The q_i for crime type i that has been assumed to apply equally to all offenders has been calculated by dividing the estimated number of offenses[1] occurring during a given period into the number of arrests recorded during that same period, multiplied by an adjustment factor that accounts for the average number of offenders who participate in any given crime (Blumstein and Cohen, 1979; Greenwood and Abrahamse, 1982; Blumstein et al., 1986). No one, to our knowledge, has questioned this assumption or speculated about what factors might cause q to vary, if it does.

[1]Officially reported offenses multiplied by an underreporting ratio (j) were

$$j = \frac{\textit{Number of offenses reported in victimization survey}}{\textit{Number of those offenses reported to the police}}$$

THEORETICAL REASONS FOR THE VARIANCE IN PROBABILITY OF ARREST

There are at least three basic phenomena that might affect the distribution of q among offenders: (1) natural ability and predisposition, (2) learning, and (3) differential attrition. Natural abilities and predisposition are the specific skills required to successfully commit crimes and avoid apprehension and also the mental attitude and personal characteristics required to maintain a successful criminal lifestyle. Locating targets and planning crimes represent only part of the effort required. Crime partners must be recruited and managed, and some of them may try to cheat or turn their partners in to the police in return for favors. There are run-ins with the law, inevitable periods of incarceration, unexpected emergencies to handle, and opportunities to take advantage of. The demands of the criminal lifestyle are in many ways similar to those on an individual in a legitimate small business. Thus, some offenders will be more successful than others, regardless of their experience.

Learning refers to experience in different types of crime situations, either personal or as related by someone else. As in any trade, there are tricks in the criminal repertoire that only experience can teach: methods of gaining entry to buildings; how to carry and conceal a weapon; how different types of victims will react; the amount of money victims will have; how to dispose of different types of property; how to respond to the police when stopped; when particular types of targets are risky; how long a stolen car or credit card can be used before it becomes too hot; and so forth. The amount of knowledge an offender obtains is a function of his experience and his ability to learn. The ability to learn from experience is a function of both intellect and the desire to improve.

Differences in attrition, i.e., in leaving crime for other occupations, reflect the effects of differences in natural ability and learning on access to legitimate employment opportunities and the deterrent effects of sanction policies.

In general, we would expect few chronic offenders to demonstrate great natural ability for crime or much ability to learn from their experiences. Most of these individuals do not enter into a criminal lifestyle because they have made cost/benefit calculations of the relative economic return from alternative occupations. Most chronic offenders have failed at everything else—school, the military, regular employment, personal relationships, etc. Most are not very good at delaying gratification or thinking through the consequences of their acts (Petersilia, Greenwood, and Lavin, 1977; Wilson and Herrnstein, 1985). We might expect those offenders with the most natural ability to also be those most likely to find satisfactory legitimate employment.

Offenders with high natural ability and a resulting low probability of apprehension would be expected to commit more crimes, while those with low ability and high probability of arrest are more likely to be deterred and to commit crimes only sporadically. In other words, only a small proportion of adult career criminals have a high level of natural talent, find crime relatively rewarding, and therefore do a lot of it; a much larger proportion are not particularly successful at crime, but they periodically return to it because they are not good at anything else.

These characteristics are very much like those of the "intensives" and "intermittents" described in Petersilia, Greenwood, and Lavin (1977). They are also consistent with the patterns of offense rates and arrest probabilities found in the RIS. Most of the self-reported high-rate offenders had a lower-than-average proportion of crimes resulting in arrest, while most low-rate offenders had a relatively high proportion of crimes resulting in arrest.

There are two basic methods for attempting to assess an active offender's probability of arrest. The first is to divide the number of times he was arrested by a self-reported count of all his crimes during that period. The basic problem with this approach is that both λ and q are dependent on a count provided by the respondent. An inflated value of self-reported offenses will automatically lead to a low estimate of q.

The second method is to make an independent determination, for each of the crimes that resulted in an arrest, of the likelihood that an offense executed in the manner described in the police reports might lead to arrest. The remainder of this section explores this second approach.

METHODOLOGY FOR QUALITATIVELY ESTIMATING INDIVIDUAL PROBABILITIES OF ARREST

To determine whether data in police incident and arrest reports can be used to predict an individual offender's probability of arrest, we first examined a set of police reports to find out if they were sufficiently descriptive to permit an assessment. The set of reports, recent burglary and robbery arrest reports made by the Oxnard California Police Department, satisfied this criterion.

We next selected a subsample of RIS cases representing the following types of offenders:

- *High-low*: Respondents who were both predicted and self-reported high-rate offenders before the survey, but who had a *low arrest rate* in the follow-up period.
- *High-high*: Respondents who were both predicted and self-reported high-rate offenders before the survey, and who had a *high arrest rate* in the follow-up period.
- *Low-high*: Respondents who were both predicted and self-reported low-rate offenders before the survey, but who had a *high arrest rate* in the follow-up period.

We excluded the category of respondents who were both predicted and actual low-rate offenders before the survey, and who had a *low arrest rate* in the follow-up period, because this was the group of least interest and the one for whom data were most difficult to obtain. Finally, we required that a record of arrests for serious crimes be available in California Department of Corrections (CDC) cumulative case folders for members of the subsample who had been imprisoned at least once after their RIS term.

The criteria we used to define the low and high categories were:

- Predicted and self-reported high-rate offenders before the survey were those who scored 4 or higher on the 7-item scale and who had committed more than 12 burglaries per year[2] (if their RIS sentence was for burglary) or more than 2.4 robberies per year (if their RIS sentence was for robbery).
- Predicted and self-reported low-rate offenders before the survey were those who scored 3 or less on the 7-item scale and who had committed 12 or fewer burglaries per year (if their RIS sentence was for burglary) or 2.4 or fewer robberies per year (if their RIS sentence was for robbery).
- High arrest rate in the follow-up period was defined as 0.5 or more arrests per year of street time during the first two years after release.

We restricted the subsample to only those respondents who were in the robbery/burglary follow-up sample and who had been committed to the CDC at least once. The resulting subsample of thirty respondents was distributed as shown in Table 4.1.

We next asked the CDC where each offender was in the system, so that we could locate the records. (Those still in prison would have their records at the institution in which they were housed; records for

[2]All offense rates in these criteria are based on minimum offense rates estimated from RIS self-reported data as described in Sec. III.

Table 4.1

CHARACTERISTICS OF FOLLOW-UP SUBSAMPLE

Subsample Category	RIS Conviction Crime		Total
	Burglary	Robbery	
High-low	2	3	5
High-high	7	9	16
Low-high	4	6	9

those on parole would be at the appropriate regional parole office; and records for those who had completed parole would be in the CDC archives at Vacaville.) The largest number of case records were at Vacaville (eight) and the second largest number were at the San Francisco Regional Parole Office (three). These eleven cases comprised our subsample.

None of the records contained descriptions of more than three or four crime incidents, even though each respondent had been arrested at least ten times—some as many as twenty times. The CDC apparently periodically purges case folders of old records to make them easier to handle. Under the old indeterminate-sentencing law, an offender who was sent to prison was assigned a CDC number for life. But since the 1978 determinate-sentencing law was enacted, an offender who is recommitted to prison after successfully completing his one-year period of parole is assigned a new number, and a new case record is started.

For this study, we took verbatim descriptions of all the crime incidents in presentence reports or other case records for our subsample of offenders, along with extracts from any other descriptive material, such as social histories or diagnostic reports.

FACTORS INDICATIVE OF HIGHER- OR LOWER-THAN-AVERAGE PROBABILITY OF ARREST

We read through the descriptions to identify specific elements that common sense suggested might be associated with either a higher- or lower-than-average likelihood of arrest. Table 4.2 shows the 20 elements we identified and the frequency with which they occurred in the records we reviewed.

Many of these elements were obvious and required little interpretation or judgment—for example, the use of an identifiable vehicle that

Table 4.2

ELEMENTS INDICATING HIGHER- OR LOWER-THAN-AVERAGE PROBABILITY OF ARREST

Element	Description	Frequency of Occurrence in Records of Respondents
	Planning	
11	Indication that crime was planned beforehand	5
12	Evidence of possible crime in progress was visible to neighbor or passerby	7
13	Victim or offender made noises that could be heard by neighbor	1
	Victim or Witnesses	
22	Intended victim thwarted the crime	0
23	Unrewarding target	1
24	Unintended confrontation with witness	2
25	Victim knew offender	1
	Transportation	
31	Use of disguised or stolen vehicle	0
32	Use of identifiable and traceable vehicle	3
33	Erratic driving leading to traffic stop	1
	Handling of Stolen Goods	
42	Identifiable stolen goods still in possession of offender	1
43	Suspicious looking stolen goods being transported in plain sight	2
	Unforeseen Events	
51	Arrest due to unforeseen/unexpected event	2
	Offender Behavior	
62	Offender intoxicated or high on drugs during the crime	1
63	Failure to anticipate reasonable security measures at target	2
64	Failure to abort crime after encountering potential witness	1
65	Failure to control victim as intended	1
66	Committing numerous crimes, of a similar nature, close together in time	4
67	Unnecessary violence	1
	Other	
88	Special code used to indicate offender whose record indicates he engages in erratic behavior because of mental illness or heavy use of alcohol or drugs	1

could be traced to the offender or one of his crime partners, or indications that the offender and victim were acquainted or that the offender continued with the crime after encountering a potential witness. Such factors indicate a lack of caution and a higher-than-average probability of arrest. We even found one robber who drove away in his own vehicle after an unsuccessful attempt at armed robbery of a woman shopper in a market parking lot, and another offender who assaulted his landlord in a dispute over the rent.

Elements in Table 4.2 with codes ending in 1 are those that we believe should lead to a lower-than-average probability of arrest. The most frequently encountered element of this type was evidence of planning the crime beforehand, e.g., a confession by someone who planned a robbery, the presence of multiple weapons and face masks, or surreptitious entry into a business location leading to the burglary of large amounts of merchandise. Preplanning (Element 11) was indicated in 5 of the 34 incidents that were coded. The only other element encountered that indicated a lower-than-average likelihood of arrest was arrest due to an unexpected event (Element 51): One offender robbed a gas station that happened to be next door to a premise that was under surveillance by a police stakeout team, and a handgun was found under the front seat of another offender's car when he was stopped for a traffic violation.

The most frequently encountered element indicative of a higher-than-average probability of arrest was the commission of a crime that was potentially visible to neighbors or passersby (Element 12). In one incident, the offender broke into a locked fire-department vehicle which was parked in front of the Captain's house, and sat there for several minutes before exiting with a radio transceiver.

PATTERNS OF COMPETENCY AMONG INDIVIDUAL OFFENDERS

Table 4.3 summarizes the data coded for each respondent in the subsample. The "type of offender" codes show whether the offender was categorized as high-low, high-high, or low-high. The primary crime (e.g., burglary or robbery) is the type of crime the offender appeared to do most often, according to self-reports (or recent arrests). The "average score per incident" was computed by simply summing the elements indicative of lower-than-average probability of arrest and those indicative of higher-than-average probability of arrest for each incident, dividing by the number of incidents coded, and multiplying by 100.

Table 4.3

SUMMARY OF CODABLE ELEMENTS AFFECTING PROBABILITY OF ARREST

Offender Number	Type of Offender	Primary Crime[a]	Average Score per Incident	Number of Incidents Coded	Number of + Factors	Number of − Factors	Comments
2	HL	R	100	1	1	0	Bright; thin folder; heavy juvenile record; probably a skillful offender
1	HH	B	−50	4	1	3	House burglar; no employment
3	HH	B	0	3	2	2	Somewhat crazy; glue sniffer; arson
4	HH	R,A	−25	4	1	2	
7	HH	R	−67	3	0	2	Junkie; hustler; polite; high lambda; hard to believe
9	HH	R	NA	0	0	0	88 – crazy; alcoholic
10	HH	R	−175	5	0	7	Erratic; desperate robberies
11	HH	B	−120	5	0	6	Heavy drug use
5	LH	B,L,A	−100	4	0	4	Booster; junkie; assaultive; dumb
6	LH	R	0	3	2	2	Caught only for self-reported crimes; arrests appear due to bad luck
8	LH	B	−67	3	0	2	Dumb; car burglaries
Total				35	7	30	

[a]R = robbery; B = burglary; A = assault; L = larceny.

The comments reflect summary impressions from the presentence reports and diagnostic materials in the case folders.

We were not able to code any offenses for Respondent 9, even though his rap sheet lists 28 arrests dating back to 1956 and his case folder contains reports on several of his most recent arrests, because all of his recent arrests involved weapons or disorderly conduct charges rather than clearly purposeful or predatory crimes. For instance, he was arrested in 1980 for drinking whiskey in public. He was also charged with possession of a knife and a toy pistol, which were found in a jacket beside him. In 1981, he walked up to two police officers and spit two balloons of heroin out of his mouth, right at their feet. When the police tried to search him he put up a fight and was charged with "assaulting a police officer," in addition to "possession of drugs" and "possessing a dangerous weapon" (a knife was found in his pocket). In 1982, police responded to a call from a restaurant complaining that a patron was being bothersome and was carrying a knife. Once again, Respondent 9 was arrested for possession of a concealed weapon.

Respondent 2 had the highest average score. He was our only self-reported and predicted high-rate robber who had a low arrest rate during the follow-up period (0.49 arrests per year). His minimum self-reported offense rate was 137 robberies per year. The subject, now in his late 20s, was arrested for armed robbery when he was 16 and was placed in a local juvenile facility, from which he ran away. He was subsequently placed in the CYA. During the follow-up period of this study, he was arrested for murder, attempted murder, and robbery, but was convicted and returned to prison only for the robbery. All the charges grew out of a single incident, in which the respondent and two partners attempted to hold up a business establishment. The respondent was driving the car and waiting outside. Apparently, when one victim tried to wrestle the gun away from one of the partners, one victim was shot and killed and another was wounded. The partners made their escape, and the crime was not solved immediately. In fact, there is no indication in the record of how it was eventually solved. The two partners were both sentenced for murder, but the subject was given only three years for robbery. His sentence may reflect the fact that he cooperated in the cases against his partners.

The records show that this subject is very bright, having an I.Q. above 120. He completed his general equivalency diploma (GED) while in the CYA and works occasionally for a West Coast shipping line. He seems to get along well in prison, but there are police allegations that he is gang-involved. He has never been married. This respondent looks like a classic professional criminal: He is bright, violent, and has a good cover occupation. It is not surprising that he is not arrested often.

The most incompetent offenders were Respondents 10 and 11. Both were classified as high-high. Respondent 10 is in his late 20s. A social evaluation made in 1976 described him as introverted but candid in his responses to the interviewer. At that time, he was said to be married and to have a good relationship with his family. According to his RIS data, he committed many burglaries (his minimum self-reported offense rate was 378 per year) and seldom got caught. We found records for five offenses: two burglaries and three robberies. In one burglary, he was observed sitting with another man in a parked vehicle outside a house, and checking the screens and doors. Sounds were later heard coming from the house, and the respondent and his partner were seen carrying articles out of the house and driving away. The crime was reported. Shortly thereafter, the police responded to another call reporting a burglary in progress and apprehended the respondent and his partner trying to jump-start their car, which contained stolen goods.

In an earlier burglary, the respondent and a partner had been arrested after being questioned by the victim's neighbor, who heard them prowling around. The respondent had told the neighbor that they thought the house was for sale. They were driving the respondent's own car.

The three robberies in our subsample all involved women. One respondent robbed a pedestrian on the street with an automatic pistol. In the second robbery, a woman parked her car in front of a dry-cleaning establishment and was approached by the robber as she opened the trunk of her car. There was no money in her purse, so the robber took her car keys and made her sit in the car while he made his escape. In the third attempted robbery, the robber approached two women who had just parked their car at a shopping center. He pulled out his gun and told them to get back in the car and drive. One of the women ducked behind another car and began to scream. The robber began to chase them, shouting that he had a real gun. Finally, frustrated by his inability to catch them, the robber returned to his own car and drove off. A witness wrote down his license number.

The social evaluation for this third respondent indicated that he began heavy drug use while he was in the eleventh grade. He has been in several drug treatment programs, but has had no permanent success. At the time of his most recent robbery arrest, he had been kicked out of his wife's house and was living with his parents. He was again using narcotics.

Respondent 11 is almost 40 years of age. His minimum self-reported offense rate for burglary was 18 per year. We coded five incidents for him. In one incident, a woman reported that she had stopped her car at a stop sign behind the subject's vehicle. He got out of his car, came back, reached through the passenger window of her car, and took her purse. He returned to his car and drove off. The entire incident was observed by a witness, who noted the offender's license number. He was driving his own car.

In another incident, the same respondent was observed standing at the rear of a parked car while his partner was inside the car removing the radio. The respondent had pliers and screwdrivers in his pocket. In another incident, he and a partner were observed by the police loading a bundle of clothing through the passenger window of a car late at night. A nearby clothing store had a broken window. Another time, he was caught hiding inside a service station from which he had been attempting to steal tools. The police had observed a broken window and a partially open door at 2:00 a.m. and had stopped to investigate. The respondent was intoxicated.

A social evaluation of this offender describes him as "appearing depressed and evidencing no enthusiasm, interest, or hope in his future . . . the impression was left of an irresponsible, inadequate man lacking in motivation to alter his lifestyle." His mother was neurotic and overprotective. He had left school in the eleventh grade, where he was doing below-average work. At that age, he was using heroin, Seconal, and LSD. He had participated in a number of drug treatment programs, without success. All his evaluations conclude that he is not motivated to change.

Respondent 5, a middle-aged man, was characterized as having a high probability of arrest. He apparently commits relatively few crimes (his self-reported minimum burglary rate was 0.9) but is frequently arrested. His rap sheet shows 23 arrests, primarily for theft, receiving stolen property, burglary, and disorderly conduct (see Table 4.4). One petty theft charge involved the theft of two pairs of pants from a department store. After trying them on, he stuffed them under his coat and tried to leave without paying. He was observed and arrested by a security guard. In another incident, the respondent stuffed a whole suit into a day bag. Again he was caught by a security guard.

He was charged with battery after assaulting his landlord in a dispute over the rent. His escape in the same month was actually a failure to return to the court after being out on a three-hour pass. A later arrest for petty theft resulted from being observed by two police officers while he and a friend were hurrying along the street carrying nine leather jackets that had their price tags still on. The subject was held (according to him, because of his record of prior arrests), and his friend was released. The respondent claimed that the coats were his friend's and he was only helping him move them.

Table 4.4

SUMMARY CRIMINAL HISTORY FOR SUBJECT #5

Date	Charge	Disposition
11/71	Possession of hypodermic needle	Dismissed
12/71	Receiving stolen property	Released
2/72	Transporting and sale of narcotics	3 yrs in SS, 77 days in county jail
7/75	Resisting arrest	?
12/75	Petty theft	2 days in jail
7/76	Under the influence of controlled substance	90 days in jail, SS
7/77	Grand theft	?
11/77	Petty theft	15 days in jail (bench warrant—failure to appear)
12/77	Petty theft	?
3/78	Disorderly conduct	?
3/78	Grand theft	?
4/78	Receiving stolen property	?
5/78	Receiving stolen property	1 year and 4 months in CDC
4/79	Grand theft	?
6/79	Receiving stolen property	?
7/79	Receiving stolen property	Dismissed
8/79	Petty theft	6 months in jail
12/79	Disorderly conduct	Prosecutor reject
12/79	Attempted burglary	180 days in jail
3/80	Battery	Failure to appear
4/80	Escape	16 months in prison
3/82	Grand theft	1 year in jail
12/82	Petty theft	?

This case illustrates the large discrepancies that can occur between offense rates estimated on the basis of self-reports and those estimated from arrests. In late 1978, this offender was serving a 16-month sentence for receiving stolen property and second-degree burglary. In the RIS, he reported that he had committed one burglary during the two-year period preceding his term; his rap sheet also shows one arrest. Can we believe his implicit claim that he gets arrested for most of his crimes? The ones we read about were so poorly planned and executed that his claim sounds quite credible indeed.

According to his social history, the respondent was born in the South and came to California when he was 14 years old. He claims that for most of his adult life, he has moved back and forth between California and his home state. His rap sheet lists 16 aliases and 8 dates of birth. The only way we could verify his claim of low activity (at least on the crimes we asked about) and high vulnerability to arrest would be to ask him some detailed questions about his sources of income and daily activities and try to check them out. This would require an interview following an arrest, conviction, or start of incarceration, focusing on a fairly short period of recent time.

CONCLUSIONS

The small pilot study described in this section was designed to determine (1) whether the offense descriptions contained in police arrest reports provide adequate information to permit a rough assessment of an offender's probability of arrest for a particular crime, and (2) whether examining several such reports might enable us to discern some consistent pattern of skill or competence for each offender. Most of the crimes described in the 34 arrest reports we examined and coded showed little sophistication or planning. In many, the offenders appeared to have taken foolish risks for very modest potential gains.

Even within this small sample, some offenders appeared to consistently engage in less well-thought-out and therefore riskier and less remunerative offenses than others. These systematic differences between offenders—i.e., in the relative skill and care with which they select targets and carry out crimes—would seem to provide a rough basis for categorizing offenders according to the likelihood of arrest for their offenses.

This type of analysis might be useful for resolving apparent inconsistencies between arrest rates and self-reported offense rates. Since there is generally little opportunity or means to validate self-reported offense information, this approach may be useful in studies designed to identify and distinguish high-rate offenders from less-active offenders. An independent assessment of probability of arrest could be made, using the procedures described here, for those offenders who report an extremely high or low number of offenses relative to the number of times they were arrested. The consistency between the probability of arrest suggested by an individual's arrest reports and that implied by his self-reports could be used to identify unreliable responses.

V. CONCLUSIONS

This study has investigated how accurately a 7-item scale designed to predict self-reported offense rates could predict individual post-release arrest rates. The study examined two groups of California offenders: approximately 2,700 young men who were released from two CYA institutions during the early 1970s, and approximately 200 former prison inmates who had responded to the 1978 RIS.

We found that for both samples, the 7-item scale was only about half as accurate in predicting follow-up arrest rates as it was in predicting retrospective self-reported offense rates. The highest RIOC achieved with the scale was 24 percent; alternative versions of the scale proved to be no more accurate.

Even with this poor predictive accuracy, the average arrest rates experienced by the predicted high- and low-rate groups in the CYA sample differed by more than a factor of 2. However, the difference in average arrest rates between the predicted high- and low-rate RIS groups was only about 30 percent.

The poor predictive accuracy and modest differences in average arrest rates of the groups categorized by the scale do not appear to justify the large differences in sentence length for offenders in different categories that would be necessary to achieve significant selective incapacitation effects, at least for the types of chronic offenders studied here.

Moreover, there is little or no apparent correlation between individual offense rates and individual arrest rates. The correlation between self-reported offenses and recorded arrests during the two-year period preceding the incarceration was less than 0.2 for the RIS respondents. There was no correlation between the number of self-reported offenses preceding the survey and the number of arrests in the follow-up period.

There is apparently an inverse relationship between self-reported offense rates and probability of arrest. Self-reported low- and moderate-rate offenders appear, on the average, to be two or three times more likely than high-rate offenders to be arrested for each offense they commit.

The offense descriptions contained in police arrest reports for a small subsample of the RIS respondents showed that most offenders demonstrated a low level of competence in avoiding arrest; greater incompetence and lack of precautions were found among those who reported lower offense rates but had higher arrest rates in the follow-up period.

POLICY IMPLICATIONS

The objective of any selective incapacitation policy is to identify and target high-rate offenders for longer periods of incarceration. The effectiveness and fairness of any such policy depend critically on the accuracy with which high- and low-rate offenders can be distinguished, and the magnitude of the differences in their average offense rates.

The Greenwood and Abrahamse (1982) analysis of self-reported offense data concluded that significant reductions in crime rates could be achieved by increasing the terms of predicted high-rate offenders and reducing those of predicted low-rate offenders. It was estimated that robbery rates in California and the number of robbers incarcerated could be reduced by 15 percent and 5 percent, respectively, by doubling the terms of predicted high-rate robbers and cutting the terms of all other robbers to one year.

Several subsequent reanalyses of these data suggest that these initial estimates were overly optimistic. Adjustments to the self-reported offense data and the Greenwood and Abrahamse incapacitation model suggested by the subsequent analyses include:

1. Reducing the estimated values of individual offense rates derived from the survey by adopting conservative rules for resolving ambiguities within the data (Visher, 1986) and truncating extreme values (Spelman, 1986).
2. Adjusting the model for estimating incapacitation effects to explicitly account for expected residual career length (Cohen, 1983; Spelman, 1986), the participation of multiple offenders in many offenses, and the fact that most offenders engage in many different crime types (Spelman, 1986).

Spelman (1986) has argued that these adjustments produce estimated incapacitation effects that are only about 5 percent as large as those originally estimated by Greenwood and Abrahamse (1982).

It is clear that substantial differences in sentence lengths for the types of chronic offenders studied here cannot currently be justified on selective incapacitation grounds alone, because there are no reliable methods for either measuring or predicting future offense rates. Furthermore, the development of reliable offense-rate prediction models is hindered by (1) the methodological problems encountered in attempting to obtain accurate information about individual offense rates directly, through interviews or observations, and (2) the apparent weak correlation between individual offense rates and the most frequently used substitute measure for them, individual rates of arrest.

IMPLICATIONS FOR FURTHER RESEARCH

These findings suggest that further attempts to justify, develop, or evaluate selective incapacitation policies will require reliable self-reported offense data from an appropriate prospective sample. Individual arrest rates are much easier to obtain, but they do not provide adequate estimates of individual offense rates to serve as a basis for selective sentencing policies.

The accuracy and reliability of self-reported offense rates may be improved by additional efforts to probe the reasonableness of extreme answers or to provide corroborative evidence. High individual offense rates might be corroborated by obtaining specific dates and locations for a sample of reported offenses, so that the incidents could be verified against police records of reported crimes. Of course this process would be subject to the 50 percent or higher rate of nonreporting that victimization surveys have found.

It is highly unlikely that self-report surveys will ever be conducted for more than a handful of samples, so it is extremely important to attempt to learn more about the relationship between individual offense rates and probability of arrest. Future studies of individual offense rates should include data on self-reported offense rates as well as official arrests. Furthermore, it would be useful to code and analyze a number of characteristics of the offenses for which a subsample of subjects were arrested that appear to be related to their probability of arrest. These data could be used to corroborate the individual probabilities of arrest implied by each subject's self-reported offense rate and recorded arrests.

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