Post-Prison Success Prediction: A Florida Study

by

Allan R. Sampson

FSU Statistics Report M225

October 1971

Research supported in full by the Florida State University Grant No. 011204-013.
Post-Prison Success Prediction: A Florida Study

by

Allan Sampson

Multivariate statistical methods provide effective tools for the analysis and prediction of post prison success rates. In the past decade some of this methodology has been utilized by researchers interested in this prediction problem, for example Gottfredson (1967), Ballard and Gottfredson (1963), 1967, Gottfredson, Ballard and Lane (1963), Gottfredson and Ballard (1965), and Wilkins and MacNaughton-Smith (1954).

In this paper a random sample of 200 Florida prison system releases is analyzed from several vantage points. Different multivariate techniques are employed, some of which are in common criminological usage and others of which are apparently new in application to this area.

While several incidental aspects are considered, the prime purpose of this preliminary study is to prepare the foundations for obtaining a valid predictive measure of the chance of "success" for a prisoner leaving the Florida penal system without taking into account the effects of parole. Clearly the benefits of such a measure, which could be readily adapted for computer usage, are manifold. One type of predictive measure already implemented in California is the California Base Expectancy Scale (BES), e.g., see Gottfredson (1965). This scale has an apparent criticism in that it applies the same predictive

---

1This research was supported in full by a grant from the Florida State University Committee on Faculty Research Support.
model for a broad spectrum of prisoners. For this reason and the inherent differences between states, our research makes little direct use of the California study.

THE DATA

A random sample of 200 male prisoners released by either parole or sentence expiration between July 1, 1964, and June 30, 1965, was provided by the Florida Division of Corrections. For each of these prisoners the historical data available were an admission card and a release card. Each releasee's record was further searched for recommitment to the Florida state prison system, and such dates were noted accordingly.

Due to the limitations of this study, it was not financially feasible to search out-of-state records or local records for recommitment. For this reason, there is a bias in some of the numerical results -- the qualitative results still holding. A lack of altruism might, in fact, dictate being solely concerned with only Florida recommitments.

The variables obtained from the historic data were ordinalized whenever possible. In contrast with the California BES, where most of the variables were "0-1" variables, e.g., presence or absence of narcotic involvement, it was felt, in the Florida case, ordinal scales could be obtained due to the nature of the raw data, e.g., degree of narcotic involvement. There are, of course, several variables, such as race, which are not amenable to ordering. The ordering imposed was, in most cases, a natural one; but in some circumstances a more
contrived ordering was necessary, e.g., marital status or offense. Heuristically it was believed that the statistical techniques employed were sufficiently robust so that some errors in ordering would minimally affect the results. The potential gain outweighed the potential loss.

In all, there were 33 historical variables, along with date of release, date of recommitment (if any), and whether the releasee was paroled or had his sentence expired. A non-inclusive list of variables includes number of prior commitments, age, number of prior escapes, military service, occupation, socio-economic status at home, education and religious affiliation. Rather than completely list all variables at this time, they will be referred to in an abbreviated fashion as they arise.

PAROLE AND PREDICTIVE ABILITY

We first ask the question, "Do the Florida parole boards discriminate between those who will or won't be successful?" Using the standard success criterion of not returning to prison within a two-year period after release, we obtain Table 1.

TABLE 1
CONTINGENCY TABLE OF SUCCESS -- FAILURE RATES
FOR PAROLEES VERSUS EXPIREES

<table>
<thead>
<tr>
<th></th>
<th>Success</th>
<th>Failure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expiree</td>
<td>108</td>
<td>19</td>
</tr>
<tr>
<td>Parolee</td>
<td>66</td>
<td>7</td>
</tr>
</tbody>
</table>
The $\chi^2$ test for independence of success and parole yields a value of 1.2, on 1 degree of freedom, which is very insignificant, so that we accept the hypothesis of independence. Table 2 gives another representation of this fact.

**TABLE 2**

**SUCCESS RATES FOR PAROLEES AND EXPIREES AT SELECTED TIME PERIODS**

<table>
<thead>
<tr>
<th>Percent successful at</th>
<th>1 year</th>
<th>2 years</th>
<th>3 1/2 years</th>
<th>5 1/2 years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expiree</td>
<td>90</td>
<td>85</td>
<td>80</td>
<td>79</td>
</tr>
<tr>
<td>Parolee</td>
<td>93</td>
<td>90</td>
<td>79</td>
<td>78</td>
</tr>
</tbody>
</table>

Clearly, parole boards are not good predictive instruments.

However, parole boards do discriminate on some basis because the historical characteristics of parolees are highly significantly different from the historical characteristics of expirees. Viewing the historical variables as a multivariate normal vector with unknown mean vector and unknown covariance matrix, we were able to test whether the expiree mean vector and covariance matrix are simultaneously equal to the parolee mean vector and covariance matrix. Such a test is advantageous to the usual multiple univariate $t$-tests because it takes all the variables into account in the same test, whereas the $t$-tests test individually. The statistic's value for this simultaneous test was significant beyond the .001 level.
In Table 3 some interesting comparisons are given for the two populations.

**TABLE 3**
SELECTED VARIABLE COMPARISONS BETWEEN PAROLEES AND EXPIREES

<table>
<thead>
<tr>
<th></th>
<th>Expiree</th>
<th>Parolee</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent white</td>
<td>56</td>
<td>53</td>
</tr>
<tr>
<td>Average age</td>
<td>31.5</td>
<td>26.3</td>
</tr>
<tr>
<td>Average sentence (months)</td>
<td>37.5</td>
<td>55.3</td>
</tr>
<tr>
<td>Average alcohol -- narcotic index (0 = no involvement, 8 = heavy alcohol and heavy narcotic)</td>
<td>1.4</td>
<td>1.0</td>
</tr>
<tr>
<td>Average education index (1 = graduate work, 9 = no schooling)</td>
<td>6.5</td>
<td>6.4</td>
</tr>
<tr>
<td>Average number of months served</td>
<td>25.4</td>
<td>22.2</td>
</tr>
</tbody>
</table>

It appears that parole boards tend to decrease longer original sentences rather than shorter ones (perhaps the mechanics of the parole process necessitate this). Also, parolees tend to be younger. It is interesting to note that in a geographically southern state race itself seems to have little direct influence on parole.
PREDICTIVE MEASURE I

It was demonstrated that parole boards are not effective predictive devices. In this section we consider the standard statistical prognostic measure along with discussing suitable criterions for success.

In most previous studies, where success was predicted only for those who were paroled, the standard measure of success was "the completion of ... two years with no major difficulty," where major difficulty was suitably defined (see Gottfredson (1965, 15)). The particular emphasis in these studies was on a two-year period. In our study we have tried four different "success periods" in which a success constitutes not being returned within the "success period" to a correctional institution under the jurisdiction of the Florida Division of Corrections. (By "success at x years" we mean being successful at least until the end of x years.)

The statistical tool employed was stepwise regression in which the dependent variable was 0 or 1 if the releasee was returned to prison or not, respectively, during the specified success period. While such an analysis is informative, it is important to avoid several pitfalls brought about by the stepwise nature of the regression procedure. Standard statistical levels of significance are not applicable. Also, a decrease in sample size with a fixed number of independent variables will usually observably increase the multiple correlation coefficient (denoted by $R$). And "junk" variables tend to increase $R$ even though they have no real predictive properties. To
avoid this latter predicament, we have arbitrarily limited the number of steps to be at most ten and very frequently five. The first situation is evaded by simply not stating levels of significance.

In Table 4 we present the variables entered at each step and their associated R's for each success period. The entire 200 releasees were used for this Table.

**TABLE 4**

VARIABLES ENTERED BY STEPWISE REGRESSION FOR VARYING SUCCESS PERIODS

<table>
<thead>
<tr>
<th>Success at</th>
<th>1 year</th>
<th>2 years</th>
<th>3 1/2 years</th>
<th>5 1/2 years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>Parole Violator (R = .25)</td>
<td>Parole Violator (R = .24)</td>
<td>Race (R = .23)</td>
<td>Race (R = .25)</td>
</tr>
<tr>
<td>2</td>
<td>Military Service (R = .29)</td>
<td>Race (R = .27)</td>
<td>Age at Crime (R = .31)</td>
<td>Age at Crime (R = .32)</td>
</tr>
<tr>
<td>3</td>
<td>Time Served (R = .32)</td>
<td>Bad Influences in Home (R = .31)</td>
<td>Parole Violator (R = .34)</td>
<td>Prior Felonies (R = .34)</td>
</tr>
<tr>
<td>4</td>
<td>Bad Influences in Home (R = .34)</td>
<td>Crime Index (R = .33)</td>
<td>Prior Probations (R = .36)</td>
<td>Prior Commitments (R = .37)</td>
</tr>
<tr>
<td>5</td>
<td>Educational Level (R = .35)</td>
<td>Parental Status (R = .35)</td>
<td>Bad Influences in Home (R = .37)</td>
<td>Parole Violator (R = .39)</td>
</tr>
</tbody>
</table>

The variable "Parole Violator" is one if the current term is a result of parole violation and zero otherwise. "Bad Influences In Home" is a variable that is scaled from 0 to 4, with 0 indicating no such
influences, 3 indicating alcoholism or narcotics usage, and 4 marking a combination of bad influences.

From this table we can immediately make two observations yielding notable conclusions:

1. Predictive ability as measured by $R$ remains constant for different success periods. Thus, success at two years is not necessarily the best criterion from a point of view of predictability.

2. The intrinsic nature of the best prognostic variables changes over time. To predict success at an early time point the best variables are among those which can be changed by the releasee over time, e.g., education or military service. On the other hand, to predict success at a later period, the most useful variables are among those which cannot be changed with time, e.g., race or number of prior commitments. What is notable is that this change in variable type obtained from the statistical analysis is what one would intuitively expect from a sociological point of view.

Of interest is the predictive equation itself for the measure $P$ of success at 2 years, with high $P$ being desirable. (Again, due to the bias in the data, this equation is not numerically exact; but it is, nonetheless, qualitatively informative.) We have

$$P = 1.08 - .51PV - .15R - .02C + .03FFS + .04BIH,$$

where
PV = 1 if current term is due to parole violation and 0 otherwise,
R = 1 if releasee is black and 0 otherwise,
C = ordinal coding of offense where apriori high repeat crimes
are given a high coding, e.g., auto theft (7.8), burglary
(7.4), and low repeat crimes given low coding, e.g.,
homicide (2.0), sex offenses (2.0) ²,
PSF = scale of parental family status ranging from both parents
together (1) to runaway as child or removal from unfit
parents (7),
BIH = scale of bad influences in home ranging from no such
influence (0) to combination of bad influences (4).

This equation is represented in a manner where success is assumed
(that is, the constant is 1.08) and then P is decreased accordingly.

For post-prison prediction purposes there appears to be a more
informative measure of "goodness of fit" than R. The releasees are
first ranked on the basis of the predicted dependent variable. Decile
groupings are formed from this ranking with Group 10 being that
10% of the population with the highest predicted success rates. Within
each of these ten groups the actual mean success rate is computed.
If we had an ideal predictive instrument, then we would expect
Groups 10, 9, ..., I + 1 to have 100% actual success rates, Group I to
have an intermediate percentage actual success rate and Group I - 1,

²The coding for most offenses was obtained by essentially using the per-
centage of repeaters from a given crime as given by the Uniform Crime
Reports (1967). For those crimes not available in the FBI report, values
were assigned according to the percentages given in Glaser (1964).
I - 2, ..., 1 to have a zero percentage actual success rate. Realizing that this ideal is virtually unachievable, we at least have a standard by which to measure experimental results.

As an independent validation sample was not available, the 200 releasees were used as the test population. For this case, we used success at 2 years and at 5 1/2 years as the criterion and employed the regression coefficients based on the ten variables entered by the stepwise regression program for each success criterion. These results are displayed in Table 5.

\[
\begin{array}{cccccccccc}
\text{Success at} & 10 & 9 & 8 & 7 & 6 & 5 & 4 & 3 & 2 & 1 \\
\text{2 years} & & & & & & & & & & \\
\text{Actual success} & 100 & 95 & 100 & 100 & 100 & 85 & 90 & 75 & 60 & 65 \\
\text{percentages} & & & & & & & & & & \\
\text{Success at} & 100 & 95 & 90 & 90 & 95 & 80 & 60 & 50 & 40 \\
\text{5 1/2 years} & & & & & & & & & & \\
\text{Actual success} & & & & & & & & & & \\
\text{percentages} & & & & & & & & & &
\end{array}
\]

From this table it can be seen that if only those persons who would have fallen into Groups 5 through 10 had been released their percentage success rate at 5 1/2 years would have been 94% versus 78% success rate for parolees.
And at the same time, a larger proportion of people could have been paroled than were actually paroled. (This assumes the effect of parole does not decrease success chances.) But to reiterate, for complete validation of the simple regression model as measured by this decile grouping device, an independent sample is needed.

Recall that we have established a significant differentiation on the basis of historical variables by parole boards. It seems appropriate, therefore, to explore the possibility that one might have better predictive ability within the population of parolees or, similarly, expirées. Using the same type of model as before, we were able to show that among expirées predictive ability as measured by $R$ increased with longer success periods, while the converse was true for parolees. However, there was not the same type of stability of the independent variables entered by the stepwise regression program as there was for all 200 releasees. For instance, race was not one of the five most important variables for predicting among the parolees. Also, there was a great deal of shifting of variables for the different success periods. This phenomenon is due in part to the smaller sample size of parolees and of expirées.

**PREDICTIVE MEASURE II**

There is an obvious deficiency about the approach in the previous section and, similarly, about the approach taken by the California BES. A HOMOGENEOUS RELEASEE POPULATION IS ASSUMED. In the nomenclature of multivariate normal statistics, the releasees are assumed to comprise
an independent sample from multivariate normal populations with common mean vectors and covariance matrices. Such an assumption is highly unwarranted. It is in this direction that improvement in predictive ability can be obtained. The task, a difficult one, is to identify homogeneous releasee subpopulations; that is, we must cluster the releasees. (For a review and comparison of clustering procedures, see Fortier and Solomon (1966) or Gower (1967).)

In approaching the clustering of releasees there seem to be two major considerations: forming a meaningful distance measure between releasees and identifying clusters based on this measure. This latter aspect is one that is currently being widely investigated, while the former consideration is one for which results are available (e.g., Gower (1966)).

Three measures of distance were considered for this study, one of which was immediately discarded. This was Euclidean distance between the vectors of historical variables. The criticism of this distance is that it treats all variables equally. For instance, in this case age would be more important than race because the age variable is numerically much larger than the race variable. One way of counteracting this is to standardize all variables across releasees and then form the geometric distance. This, of course, tends at least to weigh all variables equally. We denote this measure as the S-distance.

In his 1966 paper, Kendall proposed a metric which he believed could adeptly handle simultaneously ordinal data and "0-1" data. For each
historical variable he substituted the appropriate rank of that variable. To form the distance between two releasees he computed the weighted Euclidian distance between the ranks of the historical variables with the weight for each variable being the inverse of its variance. This distance we denote the $K$-distance.

To search for actual clusters, a straightforward approach was taken along the lines discussed by Gower (1966). Basically, the procedure provides the most contrasting, two-dimensional view of the data based on the specific distance measure employed. Then the clusters are obtained visually.

Using this procedure with both the $K$-distance and $S$-distance, remarkably similar results were attainable. About $3/4$ of the releasees seemed randomly dispersed on the graph while a fairly distinct cluster of 48 releasees appeared. For these 48 individuals a predictive model was built. Even taking into account the effects of reduced sample size, the value of $R$ was quite high --indicating a good fit.

While the cluster was obtained statistically, this group is readily characterized as primarily the young, first-time offenders. We give in Table 6 a comparison of the mean values of some selected historical variables for both the cluster of 48 and the entire 200 releasees.
TABLE 6  
SELECTED VARIABLE COMPARISONS  
BETWEEN CLUSTERED POPULATION AND TOTAL POPULATION

<table>
<thead>
<tr>
<th></th>
<th>Cluster (48)</th>
<th>All Releasees (200)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prior Commitments</td>
<td>.02</td>
<td>.40</td>
</tr>
<tr>
<td>Age</td>
<td>18.80</td>
<td>29.60</td>
</tr>
<tr>
<td>Sentence (months)</td>
<td>30.10</td>
<td>44.00</td>
</tr>
<tr>
<td>Time Served (months)</td>
<td>16.40</td>
<td>24.30</td>
</tr>
<tr>
<td>Number of dependents</td>
<td>.13</td>
<td>.76</td>
</tr>
<tr>
<td>Success Rate at 2 Years</td>
<td>.81</td>
<td>.87</td>
</tr>
</tbody>
</table>

The surprising difference in success rates (at 2 years) may be explained by presuming that the first offender is less likely to leave the state (and, thus, avoid detection by this study). However, this success rate difference does deserve further study.

The actual five variables entered by the stepwise regression program along with R and a decile plot based on these five variables (analogous to Table 5) are given in Table 7. The criterion employed was success at 2 years, and the population was the 48 releasees who formed the cluster.
TABLE 7
REGRESSION AND DECILE ANALYSIS FOR THE CLUSTERED POPULATION

<table>
<thead>
<tr>
<th>(A) Variable</th>
<th>Step 1</th>
<th>Step 2</th>
<th>Step 3</th>
<th>Step 4</th>
<th>Step 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>I.Q.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(R = .50)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sentence</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(R = .63)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prior Commitments</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(R = .70)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(R = .74)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(R = .78)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| (B) Group           | 10     | 9      | 8      | 7      | 6      |
| Actual success      | 100    | 100    | 100    | 100    | 100    |
| percentages         |        |        |        |        | 100    |
|                     |        |        |        |        | 60     |
|                     |        |        |        |        | 0      |
|                     |        |        |        |        | 33\(^3\) |

For this cluster the actual equation used to predict P, the measure of success at 2 years is

\[ P = -.60 -1.11NPC -.19R + .09A + .025 -.12Q \]

where

NPC = number of prior commitments to Florida prison system,
R = 1 if releasee is black and 0 otherwise,
A = age (in years) at time of admission,
S = sentence (in months) or average of minimum and maximum sentence if the sentence were indeterminate,
Q = 1 if releasee's I.Q. is 140 or above, 2 if I.Q. is between 130 and 139, and so on so that Q = 9 if the I.Q. is under 70.

Again, while the actual coefficients utilized to obtain P may be slightly biased, this equation is highly instructional. Note that among

\(^3\)Group 1 contains only 3 individuals, one of whom was successful at 2 years, while all other groups each contain 5 individuals.
these young, primarily first time, offenders any prior commitments al-
most surely predicate failure. Also, a high Q score (indicating a low
I.Q.) weighs heavily against success. Race appears itself to have little
effect. On the other hand, the older the individual among this group,
the more chances of success. For example, if NPC = 0 and A is relatively
quite high, other things being equal, such a releasee would have a
moderately good chance of success. He would be among those whose
first offense occurs comparatively late in life. Strangely, a longer
original sentence seems to increase slightly the chances of success.
This might be a purely statistical phenomenon. However, this occurrence
may reflect a possibility that first-time offenders who have committed
a crime, which falls into the high repeat bracket, may receive a short
sentence due to the lack of the seriousness of the crime and the fact
that this is their first offense.

CONCLUSIONS

It has been verified that the traditional prognostic instrument, the
parole board, has no predictive ability. By using stepwise regression
on mainly ordinal data, we were able to obtain a moderately effective
predictive measure. This approach is deficient because the resultant
model was required to be applicable for all releasees. Cluster analysis
appears to be an instrument that will aid in radically improving pre-
dictive ability. Within homogeneous clusters it is reasonable to ex-
ppect a regression model to work. Even with the small sample available
for this preliminary study, one such cluster is tentatively identified and predictive ability as measured by $R$ and by decile groupings is dramatically increased for this group of releasees. It is reasonable to expect further identification of such clusters when a larger sample is studied.

Once the main releasee clusters are identified, multiple discriminate analysis could be employed to classify a new releasee into his appropriate cluster. Then the model developed for that group would be applicable. It is possible to envision a dynamic system that would first classify a new releasee and then readjust the clusters (and the multiple discriminant function) taking into account this new releasee. Even the releasee's post prison performance could be taken into account to readjust the regression coefficients within his cluster. With a system like this we would have a continually updated predictive measure.

ACKNOWLEDGEMENTS

The data for this research was supplied by the Florida Division of Corrections. Mr. Anthony Quinzi did a capable job of searching each releasee's file for recommitment to the Florida prison system. Special thanks go to Mr. Charles Eichman for supplying numerous references and suggestions. I am also indebted to Professor C. R. Jeffery for several helpful conversations.
REFERENCES


