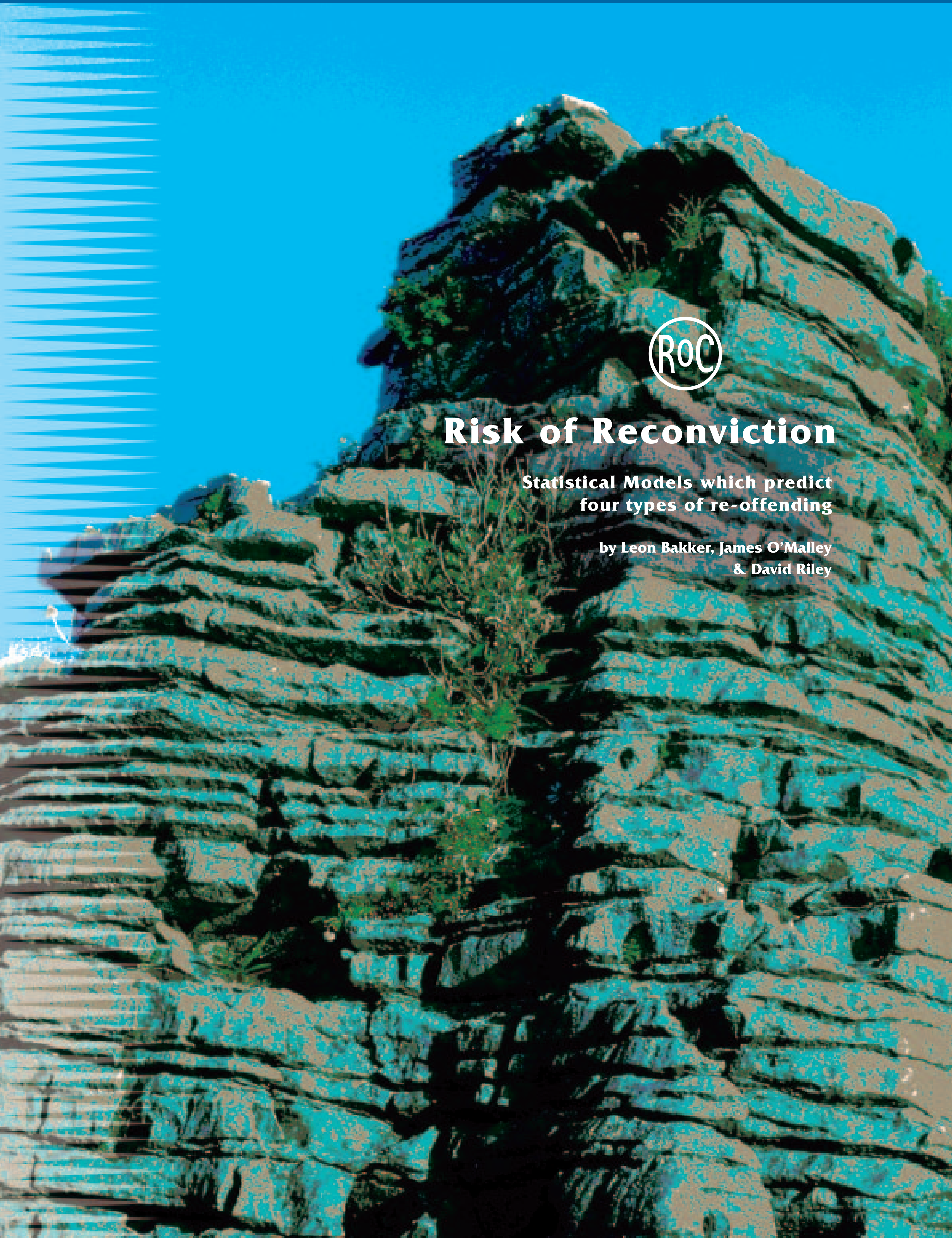
DEPARTMENT OF CORRECTIONS



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Risk of Reconviction

Statistical Models which predict four types of re-offending

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PSYCHOLOGICAL SERVICE

RISK OF RECONVICTION

STATISTICAL MODELS PREDICTING FOUR TYPES OF RE-OFFENDING

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Executive Summary

The ability to predict that an individual will be re-convicted is crucial to criminal justice management decisions, and has been intensively investigated since the 1920's. This paper reviews the field of risk prediction and highlights problems that have plagued research in this area. One main difficulty, particularly for North American studies, is following-up large numbers of individuals who travel beyond their original jurisdiction and whose subsequent re-convictions remain unknown.

The current investigation was a collaboration between the Psychological Service of the Department of Corrections and the Department of Mathematics and Statistics at the University of Canterbury. It was based on the considerable offender information stored on the Government computing facility at Wanganui. Sophisticated statistical procedures determined the relationships between various social and demographic variables and criminal histories and subsequent re-offending. The study, in contrast to many overseas, was vast: the entire criminal histories of 133,000 individuals were analysed to develop and test prediction models.

Models were developed that predicted a number of possible outcomes:

- whether a further conviction would occur during a five-year follow-up
- if a conviction did occur, whether the offence would be at a low, medium or high level of seriousness
- whether an individual would be imprisoned
- if the individual was imprisoned, whether they would be sentenced to a short, medium or long prison term

Predictions were couched in terms of probabilities: a model calculating the likelihood of an event was deemed to be more useful than one yielding a categorical prediction that the event would or would not occur.

The models proved to be accurate. They were developed on one body of information and then tested on datasets not used in their construction. Validating the models on new data drawn from another period showed the relationship between re-conviction and criminal history variables to be stable over time, and justifies a high level of confidence in them as decision-making tools for use in the New Zealand corrections system. They provide a basis for the targeting of rehabilitative programmes so that the most effective use is made of departmental resources.

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Table of Contents

Introduction

The ability to predict criminal behaviour accurately is crucial to operating any effective correctional system. Discriminating between individuals' risk of re-conviction is important for making management decisions: in particular, in deciding what restrictions are appropriate to individual sentences, how limited rehabilitative efforts should be allocated, and what judgements should be made about release on parole.

Since risk appraisal is central to almost every decision made about every offender within the criminal justice system, it has been intensively investigated over the last 70 years.

The first systematic investigation was carried out by Ernest Burgess in 1928. He published the results of a study of more than 3,000 men paroled from an Illinois penitentiary. Using their criminal records, he coded 21 "facts" – type of offence, length of sentence, age etc. – then evaluated whether any of these were associated with any particular parole outcome. Not surprisingly, some variables showed a positive relationship to re-offending, and so formed the basis of the first objective prediction device.

Research on the prediction of criminal behaviour has substantially increased over the last 25 years and become progressively more sophisticated. This reflects developments in statistical methodology as well as the ability of computers to store and manipulate more and more data.

Scales developed to predict recidivism are still imperfect. Nevertheless, the most significant conclusion to be drawn from research is that statistical or actuarial scales consistently outperform the judgements of experts in almost every investigation comparing these two approaches to risk assessment. This is the case irrespective of the experience and professional training of those making judgements: risk scales consistently predict more accurately than social workers, correctional officers, parole boards, psychologists and psychiatrists (Gottfredson and Gottfredson,1988).

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Prediction Scales

The literature on risk assessment is vast and not reviewed here in detail. Instead, this report outlines the general approach, and comments on methodological inadequacies.

Because they are easy to use, additive point scales have been the most popular form of risk assessment in criminal justice. They consist of a number of items found to correlate with later criminal behaviour. The absence or presence of each item is checked to find a final score indicating level of risk.

Individual items on additive point scales may be assigned differing values to reflect their perceived relative importance to later criminal offending. Sometimes these weightings are established statistically, but also according to the subjective judgements of those developing the scale.

Prediction devices like this have been heavily criticised for their poor psychometric properties and the inadequacy of the information they yield (Brennan,1993). They have also been criticised on the grounds that a single score fails to provide enough detailed information to facilitate all the decisions which must be made in a criminal justice setting – if offending occurs, for example, is it likely to be violent; if a negative parole outcome is predicted, does this imply re-imprisonment?

Much research on risk prediction has suffered from methodological weaknesses. The following have been identified:

1. Prediction models are often trialed on the same dataset used for their construction. This artificially enhances the accuracy of the resulting scale by capitalising on the unique features of that one set of data. The scale's performance is likely to deteriorate when it is applied to another population.
2. Statistical techniques often used to develop prediction scales have been unable to account for complex interactions between predictor variables (multi-collinearity). In this case, a linear relationship between the score on any given scale and the outcome (ie. re-offending) cannot be assumed.
3. The reliability, completeness and accuracy of information used in scale construction are sometimes questionable, particularly in North America, where most of this research has been done. Prediction research there has been hampered by difficulties following-up and determining outcomes for individuals who travel out of state and out of reach of the study.
4. Many prediction studies have been comparatively small-scale and based on few subjects. The size of the dataset has restricted use of sophisticated statistical techniques.
5. Some commonly used prediction scales have been introduced without fundamental measurement procedures, such as item-analysis, scale reliability assessment and validation.

6. The effectiveness of some instruments has been marred by lack of training in those administering them, who fail to understand underlying principles. This often makes applying the scale results in the real world questionable.
7. Many instruments use arbitrary cut-off points yielding categorical yes/no answers on re-offending potential. While this is of some value, an instrument yielding a probabilistic statement about future events is often more useful in a criminal justice context.
8. Finally, most available scales address only one potential outcome (eg. recidivism, or revocation of parole). Other outcomes may be as important, depending on the context in which the prediction device is used (eg. to only predict re-offending; to facilitate a decision based on the probability of serious re-offending or re-imprisonment; to predict the type of re-offending, such as violence).

Gottfredson and Gottfredson (1994) recently reviewed 30 years of their own and others' work in the field of prediction, and struck a pessimistic note. They conclude that:

(1) the best available predictors are still quite poor;

(2) the most sophisticated statistical measures may produce predictions that are no better than simple ones, and in some respects may be worse; and

(3) even with these limitations, however, predictions made with the use of statistical devices outperform those made without such help.

Static vs Dynamic Predictors

Over the last few years, statistical risk prediction instruments have been criticised for comprising a list of factors unchangeable by individual effort. Age of first conviction, number of prison sentences and escape history always feature in an individual's risk assessment, whatever that person may have done to rehabilitate themselves (Bonta,1997).

To avoid over-reliance on these "tombstone" predictors, investigators, particularly in Canada, have introduced the concept of "risk/needs" scales. These combine historical criminal history and other static variables, with dynamic variables – termed "criminogenic needs" (Andrews and Bonta,1994).

Falling into this second class are variables like education, employment, criminal attitudes and associates, and alcohol and drug use. These, like static predictors, also correlate with subsequent offending. Including them in scales, it is argued, allows for an individual's risk rating to change as a result of their own efforts and/or any treatment they receive.

We believe that attempting to combine need and risk measures in a single scale in New Zealand would be premature. The relationship between so-called "criminogenic needs" and subsequent offending is still somewhat unclear, and scales incorporating these measures tend not to weight them in a way that reflects their relationship to later criminal offending. Also significant is the finding that studies examining the effect on subsequent offending of targeting various criminogenic needs have yielded equivocal results (Palmer,1994).

A major practical disadvantage to developing a prediction device based on social variables is that any investigation in this area has to be both prospective and longer-term. Variables included in various risk/needs inventories are not routinely or consistently recorded on file. Collecting such data from large samples of offenders would involve enormous resource investment, and data would have to be evaluated over a long time to account for later criminal behaviour.

We consider that, for the foreseeable future at least, dimensions of risk and need should be considered separately by the Department of Corrections. Risk should be a guide as to who should have priority for rehabilitation; need should provide objective information about which aspects of individual functioning should be a priority for intervention.

Developing a New Zealand Measure

In deciding to develop a risk measure appropriate to the New Zealand offender population, several preliminary decisions were made to determine the shape of the investigation.

- **We needed a large sample on which to develop our measures of risk** so data could be subjected to highly sophisticated analysis, and we could derive a measure which would be stable across many offender groups and over time. North American investigations have typically focused on modest numbers (3,000 subjects is a large study in North American terms). Consequently, the level of statistical sophistication and applicability of results to various offender sub-groups have been limited. Restricted sample size has often meant that, once a prediction device has been derived, it is "tested" or "validated" on the same sample and gives rise to the problems noted earlier.
- **We wished to develop an instrument for use in the near future.** It was, therefore, important to access historical information already collected. Attempting to obtain detailed information from large numbers of offenders currently serving sentences would have been an unmanageable and prohibitively expensive task. Even had it not, calculating relationships between personal information and outcome would have required protracted follow-up time (counted in years).
- **The most useful prediction would be an expression of probability of an event occurring within a specified time.** This, as opposed to a categorical device yielding predictions about whether a person would or would not be reconvicted or imprisoned. Some scales sort offenders into categories representing levels of risk. We considered that if it were possible to discriminate more finely, this would be highly desirable. As well as aiding decisions about offender management, probabilistic statements could also, then, form the basis of sophisticated evaluations of various interventions. In other words, if we successfully developed probabilistic statements about the likelihood of reconviction or certain types of offending, the Department would, for the first time –

and uniquely in terms of jurisdictions – be able to match those receiving certain interventions with others not receiving them. This would allow a much more methodologically rigorous form of programme evaluation than has been possible before.

- **We wished to develop a means of predicting whether someone would be reconvicted within a given time, but also to find ways of measuring the likelihood of other outcomes** (eg. whether someone might offend seriously; the probability of their being imprisoned in a specified time; the probability of their receiving a prison sentence of a particular length). The Department of Corrections is committed to *Reducing Re-offending,* but this phrase can be interpreted in several ways. Any prediction instrument ought to be able to predict a range of possible outcomes because, depending on the circumstances of an individual case, decisions must be based on judgements about such a range.
- **We wanted to be able to capture existing information electronically** because of the complexity of the process, and to avoid the less than successful implementation of many risk assessment devices (Schneider, Ervin and Snyder-Joy,1996). It would also allow us to call up individual information easily in future, and avoid the necessity of field staff undertaking complicated tasks requiring a high degree of accuracy.

Methodology

With these considerations in mind, we decided to use the vast amount of criminal justice data stored on the government computer facility at Wanganui. The entire criminal histories of all those convicted of an imprisonable offence in 1983, 1988 and 1989 were electronically downloaded to form the datasets on which the investigation was based. Data were extracted in September 1993 (and towards the end of 1994 for the 1989 data) and represented the entire offending histories of 133,000 individuals.

Eight fields of data were retained for each criminal conviction. They included data on conviction, Police offence code (detailed information on type of offence), number of charges, details of types and length of sentence for each conviction, and a measure of each conviction's seriousness. Data also included basic demographic information on each individual: date of birth, race, and sex.

Data held at Wanganui is used in the judicial process, and is highly accurate. The major potential difficulty was with offenders using aliases. To minimise the impact of any error resulting from aliases a master identification number was assigned to offenders entered under more than one name.

Available information on offenders included a complete record of any offending prior to 1983, 1988 and 1989, and for five years after the offences committed in those years. The statistical task was to model mathematically the precise relationships between offenders' demographic and criminal history *before* their court appearance/s in 1983, 1988 or 1989, and any further convictions.

For clarity's sake, 1983, 1988 and 1989 are here referred to as the criterion period for offenders, and time before and after these years as the pre- and post-criterion period.

With the data segregated into pre- and post-criterion periods, we created variables containing or summarising individual information. Variables developed at this stage were used for subsequent analysis. (A full list and description is provided in **Appendix A;** pre-criterion variables are summarised under **Raw Predictor Variables**, post-criterion variables under **Response Variables**.)

We used logistic regression to determine relationships between raw predictor variables and significant future events. The overall size of the dataset made it possible to randomly divide the 1988 dataset into two equal portions, This allowed us to model the relationships between predictor variables and outcome on one half of the dataset, in order to develop the prediction models, and then test or validate them on the remaining half.

This procedure avoided the difficulties identified earlier, arising when a prediction device is validated on the same dataset used in its development, resulting in "shrinkage" when applied to other data to make predictions.

As noted before, we wished to produce an instrument yielding probabilistic estimates not only of recidivism but other significant events. We decided to produce models for four different events for any offender, which were:

1. the probability an offender would be re-convicted over a five year period;
2. the probability, if an offender were re-convicted, of the offending being at a low, medium or high level of seriousness;
3. the probability, if reconviction did occur, of imprisonment; and
4. the probability, if an offender were re-convicted and imprisoned, of their receiving a short, medium or long prison sentence.

This model is represented in the figure below.

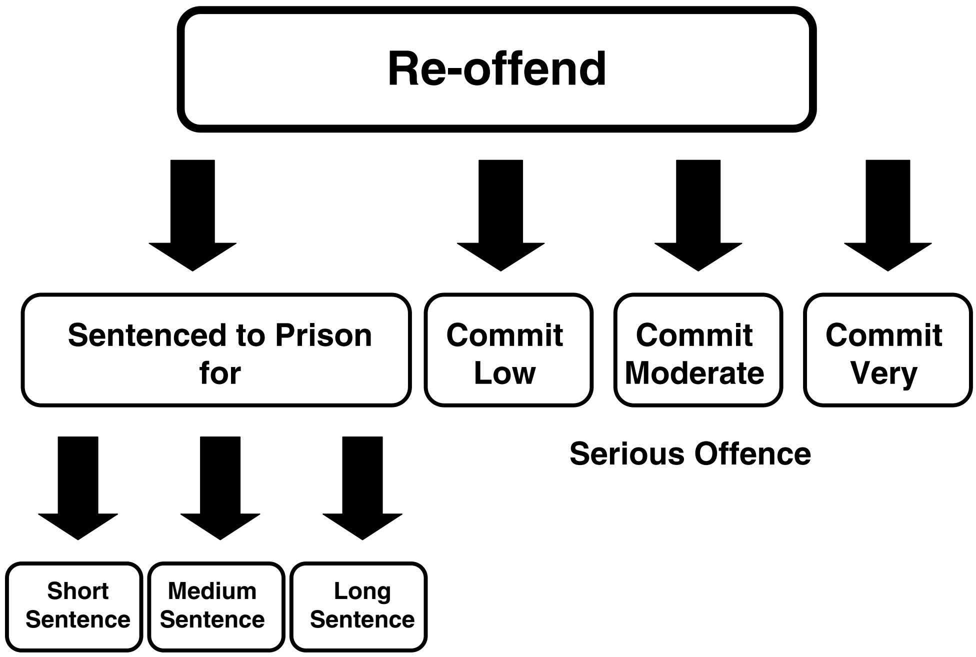

Figure 1: Models of Reoffending

Figure 1 shows the four models are, in fact, hierarchical. First, there is a model for whether an individual is reconvicted. Conditional on re-conviction, separate models are developed for whether re-offending will be of low, medium or high seriousness. Also conditional on re-conviction, a further model relates to the probability of a person receiving a prison sentence. Finally, if a prison sentence is imposed, the fourth model estimates the probability of a short, medium or long prison sentence.

There are advantages to this way of conceptualising event prediction. It makes it possible to calculate separately the variance associated with each model in the diagram: an estimate of the likelihood of someone being imprisoned has been separated from the likelihood of their re-conviction during a specified period; and the variance associated with each of those events has been separately calculated. This allows a more fine-grained evaluation for any given offender.

Even though the probability of an ultimate event (eg. receiving a prison sentence) may be the same for any two individuals, they may differ with respect to specific probabilities assigned to events that must occur before each can receive a prison sentence. So, someone may have a high probability of reconviction, but a modest or low probability of being imprisoned. Or, an individual may have a low probability of reconviction but, conditional on their reconviction, a high probability of being sentenced to imprisonment.

The probability of an eventual outcome – receiving a prison sentence – for each individual may be the same, but result from different probabilities relating to reconviction and imprisonment.

Put in a pragmatic context, developing models this way allows judgement in situations where, for instance, the probability of reconviction may be low, but, if it occurs, brings a high probability of being serious. This would prompt different decisions from a situation in which someone had a high probability of re-offending but, were that to occur, a low probability of re-offending seriously.

The way in which these models have been calculated – by apportioning the variance in the data to each of the outcomes, and generating probabilistic statements about the likelihood of outcomes – allows a simple calculation of, for instance, the probability of a long prison sentence. This is done by multiplying the probability of re-conviction, the probability of being imprisoned, and the probability of receiving a long prison sentence. The product indicates the likelihood of someone receiving a long prison sentence during the follow-up period.

We wanted three properties to be reflected in the models we developed. These were:

1. **The models should fit the data**; that is, as much as possible of the variance in information relating to the predicted event should be accounted for. Enough variables would be used as were needed to accurately predict the event.
2. **The models should have a high degree of predictive power**; they should allow good prediction of the event under consideration, but not employ too many variables. This would risk over-complication of the models, and inaccuracy when applied to data other than those on which they were developed. Ideally, a model should predict future events as effectively from new data as from data on which it was developed. This is essential if a predictive model is to be any use. How well a model performs on novel cases is vital to its user.
3. **The model should make sense**; this alerts the investigator to spurious variables and excessive multi-collinearity. It can also signal possible cause and effect relationships by favoring inclusion of variables that intuitively make sense or are consistent with existing research evidence.

We used logistic regression in developing these models, aimed at finding the optimum set of explanatory variables. We then employed the Schwarz Criterion (1978) to measure how well the models fitted the data.

Models were developed on the dataset of individuals offending in 1988. We divided this dataset randomly in half, so we could use one half to develop the models, the other to test them.

Given the exploratory nature of this investigation, a large number of variables were created, summarising aspects of the criminal history data. Many differed only slightly, and some were, in fact, novel combinations of information not previously used in predictive research. The model development process involved seeking and defining the relationship of these variables, individually or in combination, with the event we wished to predict.

This was, in fact, a laborious trial and error process, involving stepwise regression techniques to determine which variables, and which combinations of variables, most completely and exhaustively contributed to the predictive accuracy of each model.

Once the best-performing model was developed, we used the Schwarz Criterion to ensure the best compromise between predictive accuracy and number of variables. This mathematical exercise produces the "best" model in terms of number of predictor variables and model accuracy.

To avoid the dangers noted earlier, models developed on one half of the 1988 dataset were then tested against the other half, and variables failing to contribute significantly to the models' predictive power were removed.

Developed models were then tested on datasets drawn from the histories of those convicted of imprisonable offences in 1983 and 1989. They performed as accurately as they had with the 1988 dataset, which was encouraging, since this was unseen and temporally remote data, indicating the models' stability over time.

The Prediction Models and Their Interpretation

The main issue here is whether or not a correlation exists between what an offender has done in the past and what they will do in the future. Does, for example, the likelihood of someones reconviction, their number of later offences and their seriousness, increase with the number or seriousness of previous convictions?

The models we developed do reflect these relationships. We have depicted the models' performance, when applied to a dataset comprised of all persons convicted of an imprisonable offence in 1989, in a series of graphs. For each predicted event, sample subjects are assigned to a probability category representing the probability of their re-offending in a particular way. In the *phase one* model, for example, which predicts whether an individual will be re-convicted in the follow-up time period, everyone with a probability of reconviction of say 0.85 (ie. an 85% chance of reconviction) is placed in the "0.85" category.

The proportion of individuals in that category actually re-convicted during the follow-up is calculated. Predicted probability of re-offending (the horizontal axis of the graph) is plotted against the outcome: whether offending occurred or not (the vertical axis of the graph). The point on the graph (the black dot) relating to individuals in the 0.85 (85% chance of re-conviction) category represents the accuracy of the model's prediction.

Each point on the graph indicates the extent to which individuals in any given predicted category of reconviction were actually reconvicted. If the model were 100% accurate, all dots would fall on the 45-degree trend line.

The graphs depicting models' performance relate to 1989. Thus, all material on the accuracy of predictions made by these models relates to novel data; that is, data not used in the development of the prediction models.

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The Models

The Reconviction Model or Phase One Model

The first prediction equation models the one event which must occur before any subsequent events shown in **Figure 1** can take place: the offender is reconvicted in the post-criterion period. Number, severity and frequency of convictions are irrelevant to this model.

Technical information on the error and significance level of variables in this model is given in **Appendix B**. The Schwarz Criterion was close to that of the optimally fitting model for these data. It contained several variables found to be unique when it was tested on the unseen half of the 1988 dataset.

This model's performance is shown in **Figure 2**. Its accuracy is best understood from the perspective of how well its probabilities relate to the numbers of offenders showing that probability who were actually reconvicted. If, for example, this model gives an individual 0.85 probability of reoffending, then 85% of those assigned it should re-offend.

The plot of predicted probabilities represented by the points on the **Figure 2** graph (black dots) are very close to the perfectly performing model (represented by the dashed diagonal

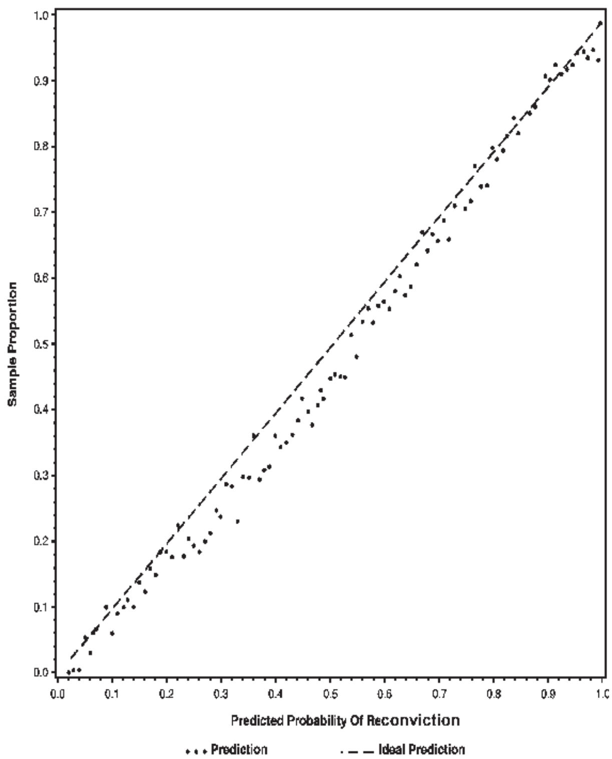

Figure 2: The Reconviction Model

line). In other words, when the prediction equations were applied to individuals convicted in 1989, the probabilities of reconviction assigned to any given individual were close to the actual rate of reconviction observed over a five-year follow-up period.

A check of subsequent offending history of those assigned a low probability of reconviction (eg. 0.2) showed that close to 20% of this group were actually reconvicted. Similarly, close to 80% of those assigned high probability of reconviction (eg. 0.8) were subsequently reconvicted.

Figure 2 also reveals that predicted probabilities fall close to the trend line indicative of a "perfect" model across the range of probabilities. So the model is not only accurate, but also capable of discriminating between individuals across the range of probabilities of reconviction.

That the actual number reconvicted almost exclusively increases over successive probability categories, implies that, even if the probabilities over a small range of the scale become less precise over time, they will still accurately rank offenders as to likelihood of future reconviction.

The Seriousness Models

This defined the seriousness of an offence by the average length of prison sentence it attracts. This scale, developed by Spier *et al* (1993), assigns a value in days to each offence, representing the number of days in prison for that offence averaged over one year's sentencing.

Maximum seriousness of later offending was defined as low, medium or high, depending on whether it was assigned a value under 14 days, 14 to 55 days, or 56 days or more. These cut-off points were based on percentages of offenders in the dataset falling within these seriousness categories, and are approximately equal in size. So someone whose subsequent offences resulted in a maximum seriousness value of 28 days imprisonment would be classified as an offender of medium seriousness.

Only two models were needed to define the three categories of seriousness we wished to predict. The probability of an individual offending at a low, medium and high level of seriousness must logically add up to 1.0, and calculating the probability of reconviction at two levels of seriousness automatically defines the probability of any individual's reconviction at the third level.

We developed models to predict high and low seriousness of reconviction. These were based on information about reconvicted offenders from the 1988 dataset, so that the variance associated with non-reconviction was not included. Distribution of seriousness values is, not surprisingly, skewed to the left, due to many offenders who committed offences not carrying a prison sentence, and therefore having a seriousness value of zero.

The Low Seriousness Model

Output from this model yields the probability that, given a person's reconviction, the maximum seriousness of any offence over the follow-up period will be less than 14 days. The model's performance is graphically represented in **Figure 3**, with technical data relating to the model provided in **Appendix B**.

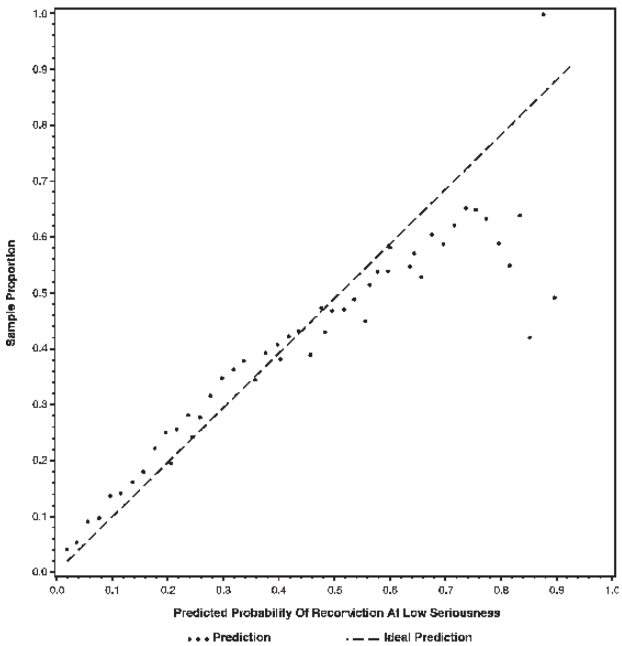

Figure 3: The Low Seriousness Model

Figure 3 plots the performance of the low seriousness model of re-offending on unseen 1989 data. It shows that the model accurately predicts low seriousness offending across most of the spectrum, since the dots fall close to the "ideal" model performance represented by the 45 degree dashed line.

There is variability at the upper end of the graph, but the prediction equation appears to accurately map the proportion of individuals who subsequently re-offend at a level of low seriousness. Part of the reason for this dispersion at the upper probability levels (above a probability of 0.8) is the very few individuals with a prediction of re-offending at a low level of seriousness in that range. Under these circumstances the model's accuracy must be expected to fluctuate.

The High Seriousness Model

This model predicts whether an offender will re-offend at least once, with a conviction exceeding a seriousness value of 56 days during follow-up. Its performance is presented in **Figure 4**, with technical information appearing in **Appendix B**.

The performance of this model on unseen 1989 data is encouraging. All predictions fall relatively close to the 45-degree “ideal” trend line, and once again, the model’s slight instability at the upper end of the graph is due to small numbers in these categories.

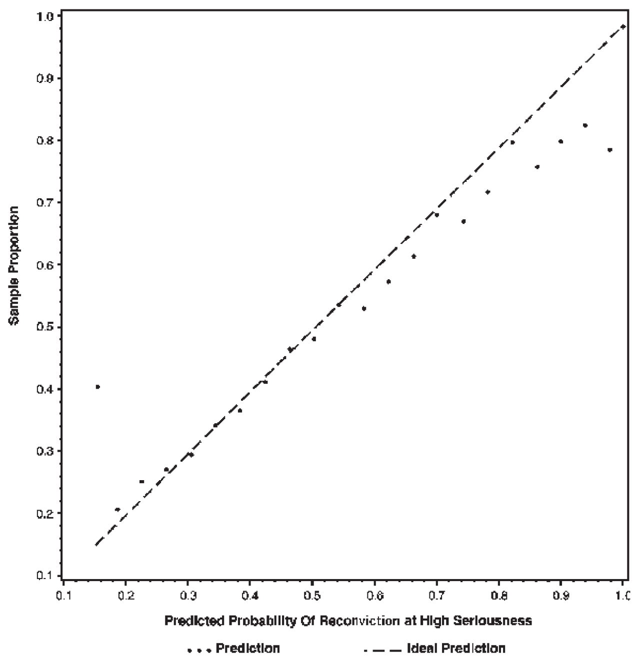

Figure 4: The High Seriousness Model

The Imprisonment Model

This model was developed in the same way as the model for predicting seriousness of reoffending, in that only those who are subsequently reconvicted can attract a prison sentence. Its primary purpose is to separate those who do and do not receive a custodial sentence on reconviction.

The model's performance is presented in **Figure 5**, with technical data appearing in **Appendix B**. The plot of the model's performance shows predictions to be reasonably accurate over the entire range of probabilities. Moreover, the plotted points, almost without exception, show increases from one category to the next, enabling offenders to be ranked accurately as to their likelihood of being imprisoned later.

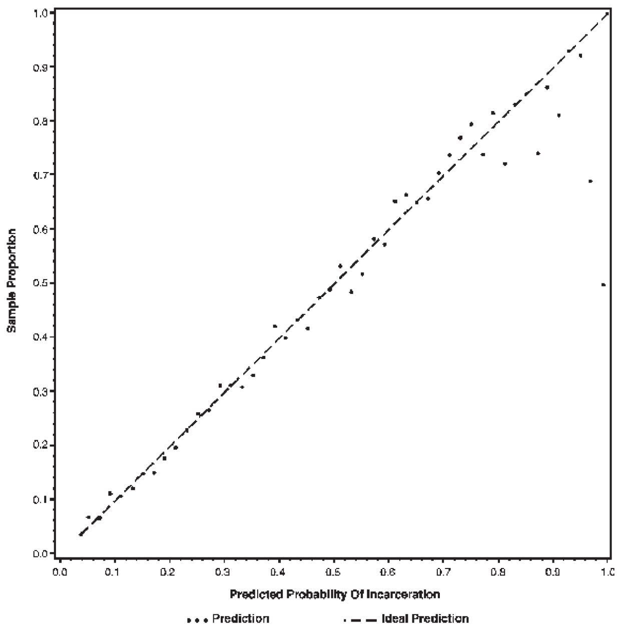

Figure 5: The Imprisonment Model

The Short Prison Sentence Model

This third phase model predicts the likelihood of an offender receiving a prison sentence of less than four months during the follow-up period, given their having been sentenced to at least one prison term. This model was developed on 8,150 offenders in the 1988 dataset who were given prison sentences in the post-criterion period. The model's performance is graphed in **Figure 6**, technical data presented in **Appendix B**.

The plot in **Figure 6** shows this model operates with good predictive accuracy on unseen data from the 1989 dataset. Fluctuations at the extremes are again caused by small numbers of offenders in those categories (in this case, fewer than 10). Predicting on the basis of such small numbers will be always subject to these fluctuations.

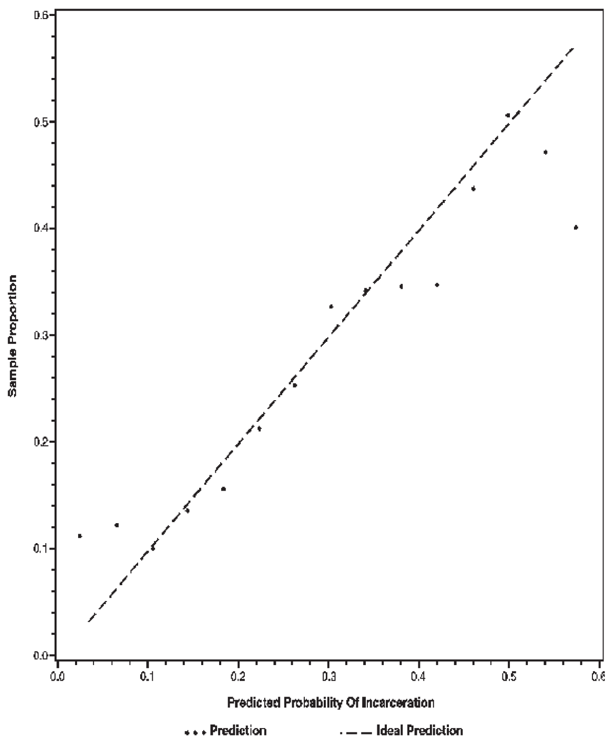

Figure 6: The Short Prison Sentence Model

The Long Prison Sentence Model

This model estimates the likelihood of an offender being imprisoned for more than one year within the follow-up period, given that they receive a prison term in this time. The model's performance on the 1989 dataset is presented in **Figure 7**, technical details in **Appendix B**.

As with the previous models, the performance of this model is close to the "ideal", with fluctuations at the graph's upper end caused by low numbers of offenders in these categories (fewer than five).

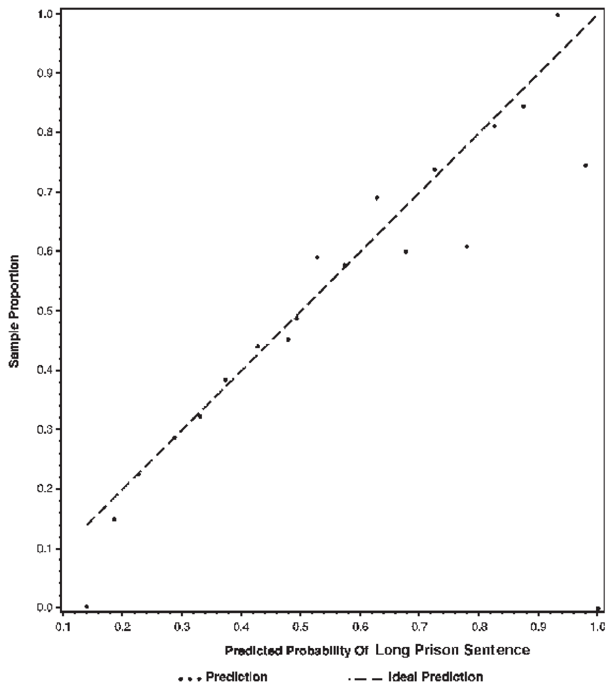

Figure 7: The Long Prison Sentence Model

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Discussion

The results reported here demonstrate the accuracy of using criminal history and basic demographic data to assign probabilities of reconviction to individual offenders. It has also proved possible to develop probabilistic models which will predict conviction within a given seriousness category, probabilities of incarceration, and probabilities of the offender receiving a short, medium or lengthy prison term.

We have confidence in the use of these models, given their accuracy and their ability to remain robust over time and on data other than that on which they were developed.

These models are an improvement over previous work described in the literature, which raises the question of how such precision was achieved. Several factors seem to account for it:

- Many overseas investigations have been comparatively small-scale, based on a few thousand subjects. As well, they have been affected by substantial shrinkage in datasets due to the follow-up difficulties noted before. The power of the dataset in this study is enormous compared to that of overseas work: 48,500 1988 subjects, from which only 400 were removed due to incomplete data. This left more than 24,000 subjects on which to develop initial models, and a further 24,000 on which models could be tested. Even when other, more specific events, such as imprisonment, were modeled, it was possible to use more than 8,000 subjects in developing our models.
- Data available to us were relatively accurate and complete compared to overseas jurisdictions. We obtained complete criminal histories, and these included convictions only, rather than less representative and possibly less reliable information on arrests.
- Many variables developed in this investigation to summarise criminal history are unique in the literature. Exponential seriousness and rate measures, for instance, have been important in our models. Other investigations have possibly summarised and coded data for computer analysis in a way that has resulted in the loss of vital criminal history information.
- The statistical procedures used to interrogate the data in this investigation, and the thoroughness with which we developed models, are not widely evidenced in the literature. Interaction effects between predictor variables, for instance, have been located and incorporated into models. We followed a process of testing and selecting from a very large number of possible variables only those that improved predictive accuracy. Logistic regression enabled non-linear trends in the data to be accurately incorporated. In addition, dividing response variables into those applying to different models allowed separation of predicted events into discrete components, and eliminated from subsequent analyses interference from variables not associated with that particular event. This has had the added advantage of enabling the probabilities associated with each step in the model to be viewed and compared, resulting in a

better understanding of the relative probabilities associated with each stage of the model. Two individuals with the same probability of returning to prison for a long period may, for instance, have markedly different probabilities of being reconvicted and sentenced to prison.

The accuracy of these models and the information they yield is valuable to the Department of Corrections. They allow treatment to be prioritised on an empirical rather than an intuitive basis. Offenders with a probability of serious re-offending can be given priority in treatment or rehabilitative programmes.

When treatment resources are limited and decisions must be made about who should receive them, this is best done on the basis of objective information about which offenders are most likely to commit serious crimes. The models will also, given an offender with a known probability of returning to prison for a specified time, allow Corrections management to assign likely costs to future services.

These models will set criteria for evaluating rehabilitative programmes by enabling probabilities of reconviction to be assigned to offenders participating in them. Using these models, a comparison group could be matched exactly with a treatment group for probability of reconviction or conviction for a serious offence – a much more methodologically sound form of evaluation.

In practise, the equations giving rise to these models require access to the criminal history of every offender. This information must be processed to obtain the necessary predictor variables before prediction formulae can be applied. Given the introduction of a new Corrections information system, incorporation of risk models would reduce the need for user friendliness and computational ease which, overseas writers have suggested, limit the applicability of sophisticated statistical applications in a correctional setting. Probabilities are unlikely to be comprehensible to frontline staff, and would need to be categorised to make them accessible to potential users.

These models are all somewhat conservative, due to the requirement they be equally accurate when applied to criminal histories other than those on which they were developed. Any variables threatening to decrease accuracy were removed during the developmental phases. The resulting models may be under-developed in preference to being over-complicated and potentially less robust.

By referring to a validation sample chosen from a much earlier period (1983), we have been able to demonstrate the models' robustness over time. Given significant changes in sentencing practices as a consequence of 1985 and 1987 legislation, this is encouraging. Validating the models on 1989 data has demonstrated their accuracy to predict with new data. They can be used with confidence on offenders entering the criminal justice system in the coming years.

References

Andrews D.A., and Bonta J. (1994). *The Psychology of Criminal Conduct.* Cincinnati O.H., Anderson.

Bonta J. (1996), Risk-need assessment and treatment in A.T. Harland (ed), *Choosing correction options that work: Defining the demand and evaluating the supply*. Thousand Oaks, California, Sage.

Bonta J. (1997). Do we need theory for offender risk assessment? *Forum on Corrections Research*, *9*, (1).

Brennan T. (1993). Risk assessment: an evaluation of statistical classification methods in *Classification: a tool for managing today's offending*. American Correctional Association.

Burgess E. (1928). Factors determining success or failure on parole in A. Bruce, A. Harno, E. Burgess, and J. Landesco (eds). *The workings of the indeterminate-sentence law and parole system in Illinios.* Springfield Illinios, State Board of Parole.

Gottfredson M.R., and Gottfredson D.M. (1988). *Decision making in criminal justice*. New York, Plenum Press.

Gottfredson S.D., and Gottfredson D.M. (1994). Behavioural prediction and the problem of incapacitation. *Criminology*, *32*, 441-474.

Palmer T. (1996). Programmatic and non-programmatic aspects of successful intervention. In A T Harland (ed), *Choosing correctional options that work: Defining the demand and evaluating the supply.* Thousand Oaks, California, Sage, PD 131-182

Schwarz G. (1978). Estimating the Dimension of a Model *Annals of Statistics* 6, 461-464.

Schneider A.L., Ervin L., and Snyder Joy Z. (1996). Further exploration of the flight from discretion: The role of risk/need instruments in probation decision. *Journal of Criminal Justice*, *24*, 109-121.

Spier P., Luketina F., and Kettles (1993). *Changes in the seriousness of offending and the pattern of sentencing: 1979 to 1988*. Wellington, New Zealand Department of Justice.

Appendix A

A: The Raw Predictor Variables

The following lists contain the variables actually used to summarise the mass of data in the Wanganui database. The entire analysis is based on either these variables or transformations of them. The first list contains the variables used to summarise the past time period and the second list contains the variables which summarise the post time period.

The Raw Predictor Variables

- Personal Characteristic Variables
  - *Race:* For this study there are four categories of race: Caucasian, Maori, Polynesian and Others.[1]
  - *Gender:* A nominal variable that identifies a subject's sex. Since it only has two levels it can simply be treated as a covariate and entered automatically into regression equations.
  - *Agepri*: A continuous variable containing an offender's age at the end of the past time period.
  - *Agefirst:*[2] The age of the offender at the time of their first conviction.
- Frequency Variables
  - *Nopric$_r$:* The number of court appearances (when $t = r$) and convictions (when $t = 0$) in the past time period. Subjects in the dataset with zero counts for either measure are excluded from all subsequent analysis involving these variables. This ensured that both variables were strictly positive.
- Jail and Time at Large Variables
  - *Prijail*: The total estimated amount of time in years that an offender spent in prison during the past time period. This is only an estimate since, due to the parole and early release etc, the exact length of time an offender spends in prison is not always known. "It is estimated by multiplying the given sentence length by .7, a historical estimate of the average proportion of the sentence that an offender actually serves."
  - *Noprison:* The number of occasions that an offender was sentenced to jail during the past time period.

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[1] Originally there were separate categories for Asians, Indians and Negros. However, due to the low numbers of observations in each of these categories it was decided that they should be merged with the "Others" category.

[2] Since this variable contains information about an offender's criminal history, it is more of a characteristic that an offender adopts and keeps throughout their life, than a personal characteristic.

- *Punishmr.* An indicator variable which classifys offenders according to whether or not the form of punishment for their most recent crime in the past time period involved prison.

- *Maxjpri:* The maximum sentence length (in years) handed down to the offender during the past time period.

- $Timatl_i$: The offender's *i*th most recent past time at large. The time at large between two court appearances is the time that has elapsed between them minus any time spent in prison following the earlier court appearance. Of course the actual time spent in prison has to be estimated (refer to the above description for *Prijail*).

  These variables are not defined over the entire population of offenders. In fact $Timatlg_i$ is only defined for those offenders who have had at least $i + 1$ court appearances during the past time period. $Timatlg_i$ was calculated for $i = 3$, 2 and 1.

- Seriousness Variables

- *Totprsr:* The sum of the seriousness ratings of all the crimes committed by the offender in the past time period. As previously stated the seriousness of a crime is defined to be the average prison sentence length (in days) a person receives if convicted for that crime.

- $Exsrprc_{t100a}$ The past total seriousness measure calculated with respect to t using a scale factor of a $t = r$ stands for court appearances whilst $t = o$ stands for convictions. This class of variables is called "Exponential" (or Discounted) Seriousness measures. They are just weighted forms of total seriousness. The total (when $t = r$) or maximum (when $t = o$) seriousness of the crimes convicted of at the *n*th most recent court appearance is multiplied by a^{n-1} prior to summation. Hence, the most recent total or maximum seriousness is multiplied by 1, the second most recent by a and so on. The values of a used were { 0. 9, 0.8, 0.7, 0.6, 0.5, 0.4 }. Note that when $t = r$ and $a = 1$ this is *Totprsr.*

- $Mxsrprc_t$: The maximum seriousness measures for the past time period. When based on court appearances (indicated by $t = r$) the seriousness ratings of crimes convicted of at the same court appearance are summed together before the maximum is taken. The measure based on convictions (indicated by $t = o$) is just the maximum seriousness rating associated with a single conviction in the past time period.

- $Mnsrprc_t$: The mean seriousness measures for the past time period. The respective calculation methods are as for $Mxsrpr_t$ except that the mean, instead of the maximum, is taken.

- $Srlastc_{ti}$: The total (when $t = r$) or maximum (when $t = o$) of the seriousness ratings of the crimes the offender was convicted of at their *i*th (i =3,2,I) most recent court appearance in the past time period. $Srlastc_{t1}$ would be equivalent to $Exsrprc_{to}$, if the later had been calculated. Like their most recent time at large counterparts, $Srlastc_{t3}$

and $Srlastc_{t2}$ are not defined for offenders who did not have at least 3 and 2 court appearances, respectively, in the past time period.

- Offence Type Variables

  $Offcat_i$*:* These ten nominal variables categorize the crime with the highest seriousness rating at an offender's i'th (i = 3,2,1) most recent court appearance. Due to the dependance on court appearances $Offcat_i$ is only defined for offenders with at least i distinct court appearances. The 10 categories are based on a Justice Department study which condensed the original 26 categories.

The categories are:

1. Violent
2. Disorderly conduct
3. Sex
4. Drugs related
5. Theft
6. Property damage
7 Weapons
8. Breaches
9. Driving
10. Other

Like the race and sex characteristics these variables have no natural ordering.

- $Crmfpri_i$*:* The number of convictions in crime category i during the past time period.

The Raw Response Variables

- Frequency Variables
- $Noposc_t$*:* The number of court appearances (when t = r) and convictions (when t = o) in the post time period.
- Jail and Time at Large Variables
- *Postjail:* The total time, in years, the offender spends in jail during the post time period.
- *Nopossen:* The number of jail sentences received during the post time period.
- $Timatlg_p$*:* The time, in years, from the start of the post time period until the first subsequent conviction. To allow for survival analysis type studies, $Timatlg_p$ is censored on the right if the offender has not reoffended by the end of the post time period.

- Seriousness Variables

- *Totposer*- The sum of the seriousness ratings of all the crimes committed in the posterior time period.
- *Mxsrptc*$_t$*:* As for *,Mxsrprc*$_t$ but for the post time period.
- *Mnsrptc*$_t$*:* As for *,Mnsrprc*$_t$ but for the post time period.

· Crime Type Variables

- *Crmfpos*$_i$*:* The number of convictions received for offences in crime category *i* . during the post time period.

B: Variables Appearing in the Sub-Models

This list contains the predictor variables which appear in the sub-models.

The Finalised Predictor Variables

- *Gender* - This indicator variable allows a model to distinguish between males and females. A male is coded as a 1 and a female is indicated as a 0.
- *Race* - This variable is represented by the three dummy variables in the models. These indicate whether or not the offender is Caucasian, Maori or Polynesian. Offenders in the "Other races" category are given zero values for all three of these indicator variables.
- *Gender Race* - The interaction effect between Gender and Race.

  Since Gender has two levels and *Race* has four, three dummy variables are required to include this effect in a model. The dummy variables used in this analysis estimate the interaction effect between *Gender* and the Caucasian, Maori and Polynesian levels of *Race*. To avoid saturating the model the effect for the "Others" category of *Race* is not explicitly represented in the model.

  These interaction effects are calculated at the expense of the alternative "means approach" estimates. Here the variation in the data is proportioned out to the individual populations as opposed to main factor and interaction effects.
- *Status* - This is a two dimensional variable which separates the offenders into two categories, "Offenders" and "Reoffenders". The former have only one past court appearance and so are yet to reoffend, whilst the latter have more than one past court appearance. *Status* is represented in a model by the "offender" and "reoffender" indicator variables. These eliminate the need for the constant term.
- *Offcat*$_i$ - An indicator variable of the event that an offender's most recent conviction is for an offence in crime category *i*. As a group these variables form the *Offcat* factor. In some cases the full factor is a component of the model whilst in other cases only the indicator variables of a few categories are.

- *Lgtimlgm* - This variable is a transformation of *tottimlg*, the "total time at large" It is the natural logarithm of *tottimlg* - 13. To ensure that this variable is properly defined, it is assumed that a person cannot receive a conviction until he/she has reached the age of 13. Any observations violating this assumption are considered corrupt and subsequently excluded from all subsequent analysis.
- $Lgtimlg_l$ - This is the natural logarithm of $timatlg_l$, the time spent in the community between the offenders most recent two court appearances. However, since $timatlg_l$ is undefined for the sub-population of offenders who only have one past court appearance, $Lgtimlg_l$ cannot automatically appear in a model. All of the offenders with only one past court appearance must be given an arbitrary value[3] $Lgtimlg_1$ and an indicator variable of this sub-population must accompany $Lgtimlg_1$ in the model. The latter is simply achieved by forcing the *Status* variable to replace the intercept term in any model containing $Lgtimlg_1$.
- $Nopric_t$ - The number of court appearances (when $t = r$) or convictions (when $t = o$) attained during, the past time period.
- $Logprc_t$ - The natural logarithm of $Nopric_t$. To satisfy the sampling criterion each offender must have appeared in court on at least one occasion and received at least one conviction during the past time period. Thus, these variables are well defined.
- $Rateprc_t$ - The rate (per year) of the occurrence of court appearances (when $t = r$) or convictions (when $t = o$) over the past time period. The denominator in both cases is *Tottimlg* -13 and not *Agepri*. Dividing by the time during which convictions can be received makes the measure more meaningful and increases its range.
- *Jail* - The indicator variable of a prison sentence during the past time period.
- *Logprjl* - The natural logarithm of *Prijail*, the estimated number of years an offender spent in prison during the past time period. This increment has the intuitive appeal of representing the holding time associated with a court appearance.
- *Rtjlprm* - The rate (per year) at which prison sentences were received during the past time period. The denominator used is the same as the denominator used to calculate *Rateprc*t.
- *Punishmr* - An indicater variable of whether or not the form of punishment associated with an offender's most recent conviction involves a prison sentence. The assigned levels are: 1=Yes, O=No.
- *Ljail* - An indicator variable of the event (*Maxjlpri*< 1/3 years). This is past time period counterpart of the response event used in the Short Prison Sentence Model.
- *Hjail* - The indicator variable analogous to *Ljail* but for the event (*Maxjlpri*> year)and the Long Prison Sentence Model.

- $Lgexsc_{r100a}$, - The natural logarithm of $Exsrprc_{r100a}$, : the total prior seriousness measure based on court appearances with a scaling factor of *a*. Since many crimes have 0 seriousness ratings these measures are incremented by the smallest nonzero seriousness rating (0.025) before being transformed.
- $Mnsrprc_{o}$, - The mean seriousness of the crimes an offender received convictions for during the past time period.
- *Lser* - An indicator variable of the event ($Mxsrprc_{o}$, < 14). This is classified as a seriousness variable since the maximum seriousness of any crime committed in the past time period, $Mxsrprc_{o}$, is in the seriousness class of variables. Furthermore, *Lser* is the past time period counterpart of the response variable for the low seriousness model.
- *Hser* - An indicator variable analogous to *Lser* but for the event ($Mxsrprc_{o} \geq 56$) and for the High Seriousness Model.

Appendix B

Table 1: Model For Reconviction

Predictor Variable	Category	**Parameter Estimate**	Std Error	Chi-Square	P-Value
Status	Constant				
-Offenders		-1.2657	0.2316	29.8685	0.0001
-Reoffenders		-0.8483	0.3106	7.4573	0.0063
Gender	Characteristic				
-Males^{o}		2.0273	0.1893	114.7339	0.0001
-Males^{r}		1.5782	0.2781	32.1940	0.0001
Race	Characteristic				
-Caucasian^{o}		1.1287	0.1425	62.7305	0.0001
-Maori^{o}		1.5413	0.1449	113.1781	0.0001
-Pacific Peo.^{o}		0.7863	0.1592	24.4027	0.0001
-Caucasian^{r}		0.5169	0.1598	10.4713	0.0012
-Maori^{r}		0.7792	0.1603	23.6163	0.0001
-Pacific Peo.^{r}		0.2471	0.1743	2.0087	0.1564
Gender/Race	Interaction				
-Caucasian		-0.0256	0.1221	0.0439	0.8340
-Maori		-0.0150	0.1227	0.0150	0.9026
-Pacific Peo.		0.2494	0.1352	3.3994	0.0652
Lgtimlgm^{mo}	Time at Large	-1.0981	0.0342	1030.675	0.0001
Lgtimlgm^{mr}	Time at Large	-0.8589	0.0477	324.1781	0.0001
Lgtimlgm^{fo}	Time at Large	-0.5386	0.0534	101.5978	0.0001
Lgtimlgm^{fr}	Time at Large	-0.4614	0.1031	20.0171	0.0001
Lgtimlg1^{m}	Time at Large	-1.1539	0.0116	176.5135	0.0001
Lgtimlg1^{f}	Time at Large	-0.1411	0.0256	30.4660	0.0001
Logprcra^{m}	Frequency	0.5119	0.0509	101.5978	0.0001
Logprcra^{f}	Frequency	0.8510	0.1198	50.4641	0.0001
Rtcrprm^{m}	Rate	0.6651	0.0842	62.3555	0.0001
Rtcrprm^{f}	Rate	0.1398	0.2267	0.3801	0.5376
Logexc$_{90}^{mo}$	Seriousness	0.0730	0.00721	102.6800	0.0001
Logexc$_{90}^{mr}$	Seriousness	0.0920	0.00788	136.1790	0.0001
Logexc$_{90}^{fo}$	Seriousness	0.0913	0.0131	4802260	0.0001
Logexc$_{90}^{fr}$	Seriousness	0.0818	0.0176	21.5538	0.0001
Offcat$_{9}^{mo}$	Crime Type	-0.4369	0.0602	52.6075	0.0001
Offcat$_{9}^{mr}$	Crime Type	-0.1221	0.0372	10.8061	0.0001
Offcat$_{9}^{fo}$	Crime Type	-0.8894	0.1883	22.3207	0.0001
Offcat$_{9}^{fr}$	Crime Type	-0.0397	0.1200	0.1907	0.7405

Table 2: Conditional Model For a Low Seriousness Offence

Predictor Variable	Category	**Parameter Estimate**	Std Error	Chi-Square	P-Value
Status	Constant				
-Offenders		-1.6530	0.4429	13.9276	0.0002
-Reoffenders		-1.5052	0.4482	11.2784	0.0008
Gender	Characteristic	-0.3208	0.3178		
-Males				1.0184	0.3129
Race	Characteristic				
-Caucasian		-0.4080	0.2701	2.2824	0.1309
-Maori		-0.6403	0.2701	5.604	0.0178
-Pacific People		0.5012	0.2885	3.0188	0.0823
Gender/Race	Interaction				
-Caucasian		0.8392	0.2699	9.6706	0.0019
-Maori		0.7196	0.2697	7.1164	0.0076
-Pacific People		0.5939	0.2883	5.7681	0.0001
Lgtimlgm^{m}	Time at Large	0.5339	0.0372	254.7996	0.0001
Lgtimlgm^{f}	Time at Large	0.3559	0.0597	35.4982	0.0001
Lftimlg1	Time at Large	0.1045	0.0129	65.6247	0.0001
Rtcrpm	Rate	-0.4680	0.0599	60.9361	0.0001
Logproff	Frequency	-0.1811	0.0323	31.4059	0.0001
Logprjl	Prison	-0.0492	0.00827	35.3165	0.0001
Punishmr	Prison	-0.3541	0.0772	21.0608	0.0001
Lser	Seriousness	0.3285	0.0496	43.8901	0.0001
Logexc$_{40}$	Seriousness	-0.0544	0.00986	30.3962	0.0001
Offcat	Crime Type				
Violent		-0.5234	-0.1864	7.8821	0.0050
Disorder		0.3737	0.1892	3.9003	0.0483
Sex		-1.3090	0.2601	25.331	0.0001
Drugs		0.4160	0.1841	5.1052	0.0239
Theft		-0.4845	0.1832	6.9948	0.0082
PropDam		0.3305	0.1911	2.9930	0.0836
Weapons		0.2190	0.1948	1.2639	0.2609
Breaches		-1.1053	0.1985	31.0182	0.0001
Driving		-0.0596	0.1848	0.1041	0.7470

Table 3: Conditional Model For a High Seriousness Offence

Predictor Variable	Category	**Parameter Estimate**	Std Error	Chi-Square	P-Value
Intercept	Constant	-0.0978	0.6513	0.0226	0.8806
Gender	Characteristic				
-Males		0.6526	0.5560	1.3773	0.2406
Race	Characteristic				
-Caucasian		0.6071	0.5224	1.3508	0.2471
-Maori		0.6724	0.5221	1.6586	0.1978
-Pacific People		0.5698	0.5364	0.1285	0.2881
Gender/Race	Interaction				
-Caucasian		-0.6849	0.5222	1.7201	0.1897
-Maori		-0.6615	0.5219	1.6064	0.2050
-Pacific People		-0.5785	0.53663	1.1636	0.2807
$Lgtimlgm^{m}$	Time at large	-0.8307	0.0352	556.2826	0.0001
$Lgtimlgm^{f}$	Time at Large	-0.4905	0.0701	48.9968	0.0001
Rtcrprm	Rate	0.2597	0.0402	41.7237	0.0001
Logproff	Frequency	0.1545	0.0308	25.0703	0.0001
Logprjl	Prison	0.0550	0.00707	60.6516	0.0001
Punishmr	Prison	0.2979	0.0527	31.9214	0.0001
Hser	Seriousness	0.4129	0.0373	122.2672	0.0001
$Logexc_{70}$	Seriousness	0.0493	0.00859	32.9610	0.0001
Offcat	Crime Type				
-Violent		0.0739	0.1965	0.1414	0.7069
-Disorder		-0.2498	0.2013	1.5399	0.2146
-Sex		1.2806	0.2385	28.8220	0.0001
-Drugs		-0.0842	0.1956	0.1855	0.6667
-Theft		0.1464	0.1938	0.5704	0.4501
-PropDam		-0.1191	0.2029	0.3449	0.5570
-Weapons		0.00561	0.2059	0.0007	0.9783
-Breaches		-0.1004	0.2002	0.2214	0.6161
-Driving		-0.4640	0.1966	5.5715	0.0183

Table 4: Conditional Model for Incarceration

Predictor Variable	Category	**Parameter Estimate**	Std Error	Chi-Square	P-Value
Status	Constant				
-Offenders		-3.0713	0.2094	215.0338	0.0001
-Reoffenders		-2.9912	0.2095	203.8707	0.0001
Gender	Characteristic				
-Males		1.4962	0.0996	225.4447	0.0001
Race	Characteristic				
-Caucasian		-0.2410	0.2006	1.4437	0.2295
-Maori		-0.0285	0.2008	0.0201	0.8872
-Pacific People		-0.0948	0.2101	0.2037	0.6517
Lgtimlgm^{m}	Time at Large	-0.3606	0.0377	91.6054	0.0001
Lgtimlg1	Time at Large	-0.1254	0.0125	101.0727	0.0001
Rtcrprm	Rate	0.3309	0.0410	65.2889	0.0001
Logproff	Frequency	0.4005	0.0311	165.6311	0.0001
Jail	Prison	0.3284	0.0472	48.3819	0.0001
Punishmr	Prison	0.3199	0.0527	36.8430	0.0001
Logexc$_{40}$	Seriousness	0.0592	0.0105	31.5800	0.0001
Mnsrcopr	Seriousness	0.00267	0.000422	40.0092	0.0001
Offcat	Crime Type				
-Drugs		-0.2835	0.0440	41.5786	0.0001

Table 5: Conditional Model For a Short Prison Sentence

Predictor Variable	Category	**Parameter Estimate**	Std Error	Chi-Square	P-Value
Intercept	Constant	0.0385	0.1286	0.0898	0.7644
Gender	Characteristic				
-Males		-1.8092	0.1395	168.1805	0.0001
Lgtimlgm^{m}	Time at Large	0.4539	0.0478	90.2814	0.0001
Totproff	Frequency	-0.0133	0.00166	64.2279	0.0001
Ljail	Seriousness	0.3657	0.0703	27.0498	0.0001
Logexc$_{50}$	Seriousness	-0.0512	0.00166	64.2279	0.0001

Table 6: Conditional Model for a Long Prison Sentence

Predictor Variable	Category	**Parameter Estimate**	Std Error	Chi-Square	P-Value
Intercept	Constant	-2.4637	0.1476	278.6710	0.0001
Gender	Characteristic				
-Males		1.4169	0.1409	42.4478	0.0001
Lgtimlgm^{m}	Time at larage	-0.2142	0.0470	22.7990	0.0001
Hjail	Prison	0.2680	0.0923	8.4322	0.0037
Prjlwcrm	Prison	1.6877	0.2188	59.4682	0.0001
logexc$_{40}$	Seriousness	0.0839	0.0144	33.8461	0.0001

Notes

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