Storm Warning

Statistical Models for Predicting Violence

ISBN: 0-478-11303-X

By

Leon Bakker, James O'Malley and David Riley

EXECUTIVE SUMMARY
DEPARTMENTAL NEED FOR PREDICTION OF VIOLENT RECONVICTION
VIOLENCE PREDICTION .4 Problems .4 Useful predictors of Violence .5 Limits of Current Predictors .5 High Risk Offenders Study as an Example of Prediction .6
RESULTS
SUMMARY.7VIOLENT RECONVICTION WITHIN FIVE YEARS.7Important Predictor Variables.8VIOLENT RECONVICTION WITHIN TWO YEARS.9TIME UNTIL VIOLENT RECONVICTION.10HOW ACCURATE ARE THE MODELS.11COMPARISON WITH THE STATISTICAL INFORMATION ON RECIDIVISM (SIR)SCALE.13COMPARISON WITH THE STATISTICAL RISK APPRAISAL GUIDE (SRAG).13OTHER STUDIES THAT HAVE PREDICTED VIOLENCE AND14USED ROC ANALYSIS.14CAN OUR MODELS BE USED?14WHAT MORE NEEDS TO BE DONE.15FINAL COMMENTS.16CONCLUSION.16
BIBLIOGRAPHY17
APPENDIX 1 - METHOD
DATA
APPENDIX 2 - VARIABLES USED IN THE DEVELOPMENT OF THE PREDICTION PROCESS
APPENDIX 3 - COMPUTATION OF THE TIME UNTIL VIOLENT RECONVICTION26

EXECUTIVE SUMMARY

About This Study

- This report develops statistical models for predicting violent reconviction. Statistical models are necessary because:
 - Departmental staff, psychologists and Districts Prison Boards make predictions about an offenders dangerousness when deciding about priority for intervention or release conditions for parole;
 - research shows that human judgements are less accurate than those based on statistical scales; and
 - overseas prediction devices have not been validated on New Zealand offenders.

Key Findings

- The five year violent reconviction model has an overall accuracy of 26% greater than chance;
- The two year model has an overall accuracy of 24% greater than chance;
- The models are as accurate at predicting violence as the best overseas models

Recommendations

- Cut-off levels to classify offenders into risk groups should be established;
- Cost benefit analyses of using the models to screen offenders should be undertaken;
- if the models provide benefit when classifying offenders they should be incorporated into IOMS;
- when additional offender data has been collected through IOMS, development of a hybrid model using dynamic predictors as well as these models should be attempted.

Departmental Need For prediction of violent offending

- Reported violent offences in New Zealand more than doubled between 1986 and 1995. The number of serious assaults rose by over three hundred percent (Statistics New Zealand, 1996). Violent offenders are particularly likely to be sentenced to imprisonment and escalating sentence lengths indicate that these offenders will contribute increasing costs to the Department in future.
- The Departments Integrated Offender Management framework will use the three principles of effective interventions proposed by Andrews, Bonta, Gendreau and others. One of these is that treating the most at risk offenders has a greater impact on crime than treating low risk offenders. To maximise the efficient use of treatment resources we need to be able to accurately identify those most at risk. The high risk offenders study (Bakker, O'Malley and Riley 1994) provided accurate models for reconviction of offenders in general, but they do not indicate whether such reconviction will be for a specific type of offence. In the case of violent offenders determining the risk of further violence would be beneficial.
- The Department of Corrections funds the Montgomery House Violent Offenders programme, and the Rimutaka Prison Special Treatment Unit for Violent offenders. Accurately assessing an offender's violence potential is central to the successful management of these treatment resources. Rather than needing to assess every violent offender an accurate risk prediction device would allow screening so that only high risk offenders would receive more in depth assessment. Risk models for violent reconviction would also be useful in evaluating the violence treatment units' impact on reconviction. Control groups could be tested to ensure that they had the same risk of violent reconviction as the treatment groups.

Violence Prediction

Problems

Violence prediction has generally not been very successful because:

- 1. investigators have focused upon quite different populations (psychiatric inpatients, prison inmates, and community groups);
- 2. there has been no agreed definition of what is to be predicted (arrest, conviction, revocation of parole, readmission, self report etc.);
- 3. the time frames over which people have been followed-up vary enormously from as little as a few days to many years; and
- 4. investigators have employed a variety of predictor variables, or have defined these variables in differing ways.

Despite this some useful predictors have been identified.

Useful Predictors of Violence

•Past Violence:

- The best predictor of future violent behaviour is past acts of violence (Klassen and O'Connor 1994).
- Mulligan (1991) found that New Zealand offenders who had previously committed a violent offence had a 50% chance of committing a violent crime in the future - twice the likelihood of general offenders.
- •Age
- violence peaks in late adolescence and early adulthood (Monahan 1981).
- Mulligan found that 60% of New Zealand violent offenders aged below 20 years were likely to be subsequently convicted of another violent offence as opposed to 44% aged between 20 - 26 and 38% of those above 26 years of age.
- gender (males are more likely than females),
- intelligence (the lower the more violent),
- psychiatric disorder (particularly acute psychotic symptoms), and
- alcohol and drug abuse.

(see Tardiff and Sweillam 1980; Quinsey and Macguire, 1986; Link and Stueve, 1994)

- In addition, certain personality traits especially psychopathy have been found to correlate highly with subsequent violent behaviour (Salekin, Rogers and Sewell, 1996).
- A number of childhood experiences have also been found to relate to subsequent violent behaviour and these include:
 - sadistic or brutal treatment at the hands of a parent,
 - sexual victimisation,
 - behavioural problems and truancy while at school,
 - childhood hyperactivity, and
 - juvenile delinquency.

(see Yesavage and Brizer, 1989; Lewis, Princus, Lovely, Spitzer and Moy, 1987)

Generally speaking, predicting violence in the shorter-term is more accurate than in the longer-term. Long term prediction may be particularly important in relation to offenders on parole. The tendency is to over-predict violence in such cases (Riley 1997; c. f. Mossman; 1994); that is, violence occurs less often than we predict.

Limits of Current Predictors

Limits of current prediction research include:

- 1. much of the above information is not always readily available for each offender;
- 2. there are no guidelines for how variables should be combined to give an estimate of risk in other than very general terms. For example, does having two previous violent convictions make a person twice as likely to commit a further violent offence than a person who only has one?

- 3. The problem of assigning appropriate weights to the different predictive variables means that individual judgements of dangerousness will vary considerably between people who make such judgements.
- 4. There is no clear definition of violence
- What is needed is a mechanism which combines the predictor variables and assigns appropriate values of risk¹. For this study violence will be defined as any act against another person which results in a conviction for violent offending. The focus of this study is predicting the likelihood of such offences occurring in the future.

High Risk Offenders Study As an Example of Prediction

- A mechanism for prediction has been developed for general offenders by Bakker, Riley, Deely, O'Malley, Love & Hudson (1994). The High Risk Offenders prediction device predicts reconviction for any offence. The HRO models:
 - are obtained from official conviction information kept on a centralised database;
 - combine and weight a number of variables that predict reconviction with appropriate values to provide a very accurate risk of reconviction;
 - can specify exactly *how much* offenders differ in risk. For example, someone who has a .8 probability is twice as likely to be reconvicted than someone who has a .4 probability. The Department can use the models to develop cost benefit analyses about treating or not treating offenders where programme effectiveness is known. Alternatively, the models provide information about potential future costs through incarceration of offenders, etc.
- Habitual violent offenders tend to have high levels of general offending and tend to have higher reconviction probabilities. It is possible that offenders who have a high risk of violent reconviction could have a comparatively low risk of general reconviction. For example, a person convicted of a violent offence may have a high risk of general reconviction due to committing burglaries but be unlikely to commit further violent offences. Alternatively, a violent offender may be unlikely to commit further offences generally but, if he is reconvicted, it is very likely to be for a violent offence. Therefore, it would be useful to develop a measure of risk specifically for violent reconviction.

¹. A discussion of the issues involved in defining violence can be found in Serin (1995).

RESULTS

Summary

- Our analyses demonstrate that **violent reconviction** can be predicted with a high degree of accuracy.
- The average performance of the model for a violent **reconviction in five years** was 26% better than chance alone.
- The average performance of the model for a violent **reconviction in two years** was 24% better than chance alone.
- **Survival analysis** showed that we can predict the time to reconviction albeit with less accuracy than reconviction.
- We can predict violent reconviction as well as the best overseas studies.

Violent Reconviction within Five years

• Figure 1 provides a visual presentation of the performance of the model. The dashed diagonal trend line represents the ideal relationship. The dots represent the relationship between the predicted proportion of reconvicted offenders and the actual proportion of offenders who were reconvicted.



Figure 1

It is clear from this figure that a strong trend exists and that the proportion of those predicted to be reconvicted is very close to the actual proportion reconvicted. For example, we would expect that 80% of those with a predicted probability of .8 would be reconvicted, in reality 82% were. Most important is the consistent trend that we could use to accurately rank offenders based on their reconviction probabilities. Those with higher probabilities get reconvicted more often than those with lower probabilities. The model's performance deteriorates slightly at the upper end of the probability distribution because of the small number of offenders that have such probabilities.

Important Predictor Variables

- The variables that are most predictive of violent reconviction are similar to those found to be predictive of general reconviction (see O'Malley, 1996). Specifically, important predictors were:
 - Demographic Predictors
 - * gender (males more than females)
 - * ethnicity (Maori more than Pacific Peoples more than Caucasian)
 - * age (young offenders more than older offenders)
 - Conviction History Predictors
 - age at first conviction (the younger the start of a career the greater the probability)
 - * first offence (lower probability if first offender)
 - length of time spent at liberty (greater risk with lower time in the community)
 - * total number of convictions (greater risk with more convictions)
- In addition, having offences for violence, property damage and disorder in their current offences increased offenders' risk. Both the number of previous violent offences and the time spent out of prison between the last two court appearances were found to be predictive of violent reconviction. In total 2037(44%) out of the 4601 offenders were reconvicted of a violent offence in the five years following release.
- Table 1 in Appendix 2 provides the statistical description of the variables, their error and significance levels. The number of previous convictions and whether the offence is in the categories of violence, disorder or property damage have a large impact on the probability. The model suggests that disorderly behaviour and property damage are related to violent offending.

The Two Year Violent Reconviction Model

• Figure 2 illustrates how the model performed against unseen data. Again, the dashed trend line indicates the best possible performance; the closer the black dots are to this trend line the more accurate the model. The model is more inaccurate at the upper levels than the five year model because the number of offenders with predicted probabilities above .6 is very small. This means that individual variation will have a greater impact when only a few offenders are used to establish the proportions than when larger numbers of offenders are available. Because the model works well at the lower and middle probabilities it could be useful in excluding those with low probabilities of further violence from violence treatment programmes.



Figure 2

- The number of offenders who were reconvicted in the two years after release from prison was 1131 (24.6%). Not surprisingly, the variables that are predictive of violence in the two year model are very similar to the five year model. The exception is that a greater emphasis is on the offender's most recent offending rate. This makes sense given that reconviction is more dependent on the speed at which offenders are reconvicted than in the five year model.
- Table 2 of Appendix 2 provides the variables, their error values and significance for the two year violent reconviction model.

Time Until Violent Reconviction Model

- The third and final model is of the survival time of those reconvicted of a violent offence (2037 offenders).²
- The performance of this model is illustrated in Figure 3. It is clear that the model is substantially less effective than the previous models. This is not surprising when one thinks of what is being predicted. The earlier models predicted whether or not something would happen but here the model attempts to predict how long until this occurs. There are likely to be many factors that we do not have information on that affect the timing of reconviction; more so than whether or not it will occur at all.



Figure 3

• A further problem with the survival analysis is that it does not take into account that offenders may have been reimprisoned for non-violent offending; unlike the reconviction models presented earlier. This time was not included in the calculation of time to reconviction for a violent offence. Consequently, such reimprisoned offenders would have had less time to commit further violent offences. This introduces additional error into the data and makes the model less effective.

² Survival analysis can be used to test the relationship between predictor variables and the time to a particular event (in this case reconviction for a violent event).

- A detailed description of the process used to establish the survival models is provided in Appendix 3. Table 3 of Appendix 2 provides the error and significance values for the predictor variables used to model survival.
- It is possible to use the survival model to give a probability of a person being reconvicted of a violent offence at any given time following release (the proof of this is provided in Appendix 3 with a worked example). Treatment providers for violent offenders need to evaluate their programmes, often with only a short period of time since the programme was completed; finding a control group that is similar for risk of reconviction is difficult. This model will allow better matching of the treatment group with a control group after any length of time up to five years.

How Accurate Are the Models?

- The graphs indicate the relative performance of the models but not in a way that allows comparison with other research. All prediction scales use cut-off scores to categorise offenders into levels of risk. That is, depending upon an individual's score, he or she may be categorised as a high risk for reoffending or a lower risk. Where the cut-offs are set will also effect the relative numbers of offenders the scale targets. If the cut -offs are set high then fewer people will be classified as at risk. The disadvantage of this is that more people who will re-offend get classified as not being at risk. Consequently, the cut-offs used will be determined by policy and operational concerns such as resources available etc. Different scales and prediction devices therefore have different cut-offs. This makes comparison between scales difficult.
- A method which allows comparison of the different means of predicting violence, regardless of the different cut-offs used, the baserates of violence and techniques used is the Receiver Operator Characteristic (ROC) curve³.
- The actual measure of overall accuracy is provided by calculating the area under the ROC curve (AUC); the larger the area the more accurate, overall, the device. A perfect prediction device would have an AUC value of 1; the chance situation would

³ ROC analysis was first used in signal detection theory. Subjects were required to detect the presence or absence of a signal. A "hit" was when the signal was correctly detected and a "false positive" when a subject detected a signal that was not present. The same situation exists in prediction research. An ROC analysis takes into account both the hits and false positives and provides an estimate of the sensitivity of the prediction device. Usually the results are graphed. The hits are indicated on the Y-axis and the X-axis indicates the false positives. The totals of hits and false positives for each cut-off score are plotted producing a curve. If a prediction device was never wrong then the curve would appear as a triangle. If the device was only right 50% of the time then it would be plotted as a straight diagonal line and would be equivalent to the chance situation. That is, If one were to select by using chance only, one would be correct 50% of time (just as if one were to toss a coin to make the decision). The ROC curve provides a measure of how much more accurately a prediction device will choose than chance. Bonta et al (1996) and Mossman (1994) have used ROC analysis to assess the accuracy of predictions of reoffending. Substantial descriptions of the history and development of ROC analysis are provided by both studies.

have a value of .5. A value of .75 for the AUC would indicate an overall accuracy of 75%. $^{\rm 4}$



Figure 4

• Figures 4 and 5 provide the ROC for the five year, and two year, violent reconviction model. The .76% and .74% indicate that the models are very accurate overall.



Figure 5

⁴ This does not give the accuracy of the model at a particular cut-off but averages the performance of the model across all possible cut -off points. In practice the accuracy of the model will be determined by the specific cut-offs are set.

Comparison with The Statistical Information on Recidivism (SIR) Scale

- Bonta et al (1996) re-validated their Statistical Information on Recidivism (SIR) scale. They found that SIR scores showed modest association with future violent behaviour; the univariate correlation for broadly defined violence was .2. They summarised the performance of the SIR in predicting violence - "the results do indicate that violent behaviour can be predicted beyond chance levels and suggest some optimism in making advances in the statistical prediction of violence."
- Bonta et al. report that the overall accuracy of the SIR scale at predicting general recidivism produced an area under the ROC curve (AUC) of .74. The SIR provided an AUC of .65 when predicting narrowly defined violence (including homicide, sexual assault and aggravated assault). Broadly defined violence (including the above offences and weapons offences, robbery and less serious sexual offences) resulted in an AUC of .64. The .76 AUC for the five year model in this study therefore indicates superior prediction.
- The Bonta et al. article used a more restrictive measure of recidivism than our study incarceration within three years. As a consequence the offences committed by their offenders would have been more serious than those used in this study. This would also explain the lower reconviction rate found in their study. As mentioned earlier, one advantage of the ROC analysis is that it is independent of base-rate. Even though the reconviction rates for the Bonta study and ours differ, we can compare the performance of the two prediction devices using ROC analysis. As all the offenders in our sample were also released from prison, the offenders are comparable to those in the Bonta et al paper. In addition, seriousness of offence was not found to be a significant predictive variable in our models, suggesting that the more conservative definition of violence used by Bonta et al. is unlikely to explain the difference in performance between their model and ours.
- Another reason for the improvement in accuracy will be that our models were not limited to a specific set of items selected for prediction of general recidivism such as the SIR uses. Instead we used the most predictive variables obtained from criminal history information specifically to predict subsequent violence.⁵

Comparison with the Statistical Risk Appraisal Guide (SRAG)

 Rice and Harris (1993, cited in Bonta et al 1996) reported a .73 AUC for the Statistical Risk Appraisal Guide (SRAG) in the prediction of violent re-offending among a group of mentally disordered offenders. The difficulties with their study revolve around the problem of generalising from such a specific sample to a more general group of offenders. In addition a factor found in other studies to be predictive

⁵ The use of sophisticated statistical procedures such as logistic regression, also increase the accuracy of the models. There are some problems with regression analyses when applied to the prediction task. For example, non linear relationships and multi-collinearity, (see Brennan 1993 for a fuller discussion). We adopted a conservative approach in developing our models and removed variables that did not add significantly to the models' predictive accuracy, and have reduced the effect of such factors.

of violence (schizophrenia, Swanson Holzer, Ganja and Jono, 1990) was found to be negatively correlated with violent recidivism. Further, no validation studies using this scale on subjects outside of the development sample have been published. The models reported in this study have been developed on one sample and validated on unseen data. The .76 area therefore represents the five year model's performance on a typical sample of serious offenders.

Other Studies That Have Predicted Violence and Used ROC Analysis

 Mossman (1994) applied ROC analysis to a sample of violence prediction studies reported in the literature. Those comparable to this study (retrospectively fitted and validated on different samples than they were developed on) produced an average AUC of .7130 ± .0085. Two studies conducted post 1986 obtained an average AUC of .7956 using discriminant function analysis to obtain violence predictions and validating them on a separate sample.

Other Studies that have not Used ROC Analysis

- The literature on risk prediction supports the view that using actuarial data such as criminal history data is valuable (See Gendreau, Little and Goggin 1996). However, Gendreau et al. found that dynamic predictors (predictors that can be changed such as education) were slightly more effective than static predictors (predictors that cannot be changed such as previous criminal history). Among the actuarial measures the LSI-R (Level of Services Inventory- Revised, Andrews and Bonta; 1994b) produced the highest correlation with recidivism at r =.35. Unfortunately, prediction of violence has not produced such high correlations.
- The PCL-R has been used to predict violence and was found to have a correlation of .29 (Gendreau, Little and Goggin;1996). Other studies have combined actuarial measures with scores from the PCL-R to get a better outcome than either on their own (for example Harris, Rice and Quinsey 1993). Serin (1995) considers the Harris et al. findings to represent the current standard in actuarial models using weighted historical and clinical (PCL-R) information. He also cites concerns with their study in that it was based on a criminal psychiatric population and requires replication with a uniquely criminal population.

Can Our Models Be Used?

 The development of violence models is a continuation of a process to develop risk measures for New Zealand offenders. We have built on the information obtained when developing a general reconviction risk model which obtained an area under the ROC curve of .80. (See O'Malley, Bakker, and Riley, 1994). This latter model is to be implemented as part of the Integrated Offender Management System (IOMS); extension of this to enable prediction of violence will be relatively simple. The result of this computerisation will be that for all convicted offenders, up-to-date probabilities will be available to any authorised user. It is unlikely that the specific probability will be provided but that cut-offs will be established with ranges of risk being provided, for example high, medium and low.

- The IOMS will make criminal history information available for providing the probabilities obtained from these models. The computerisation of all criminal conviction history information has been used in New Zealand for almost twenty years and the data will be transferred to the new system.
- Staff will have to trained to use the predictions from the violence models but given that they will already have received training for the HRO models this should require minimal modification of the training modules.
- The violence models have the added benefit of being developed and validated on a New Zealand sample. Overseas prediction devices such as the SRAG have not been validated in New Zealand.
- It is not envisaged that these risk models will be utilised on their own⁶. Rather they should be used as a screening device preceding more in depth assessment. These models can provide accurate probabilities for those who do not have a previous violent conviction. It can therefore be used to exclude those with lower risks from treatment resources or, to target those who, though having a lack of previous violent convictions, might nevertheless be at risk. The Department of Corrections is currently developing a needs assessment strategy which will enable those with higher risks to be given priority for treatment resources which focus on their criminogenic needs (Gendreau, Little and Goggin; 1996). There may be some utilisation of the models in parole decisions but only for those with shorter sentences; those with longer sentences are already catered for by a decision making device specifically developed for them.

What more needs to be done?

- The cut off levels to establish the high, medium and low risk categories are yet to be developed. The costs and benefits involved in treating offenders who do not need treatment versus missing offenders who do treatment combined with the resources available for interventions all need to be included in establishing these cut-offs.
- If the cost benefit analysis demonstrates value in using the violence models, the IOMS can readily be modified to include the necessary calculations.
- Given that the IOMS will collect substantial amounts of information about offenders, a hybrid model should be developed similar to the SRAG of Harris et al, as the combination of static and dynamic predictors, as well as psychometric data such as

⁶ Indeed a disadvantage of the models is that they are developed from mostly static data (not all the variables are static as some are related to rate measures which can change over time, but, all are actuarially based). These models do not utilise dynamic predictors found in the literature as being predictive of reoffending generally, or specifically related to violence.

the PCL-R appears to hold the greatest promise for further increasing predictive accuracy.

Final Comments

- The attempt to predict the length of time to reconviction was not particularly effective. The difficulty of predicting a continuous variable rather than a dichotomous variable such as reconviction is not surprising. There may be many more factors that influence the timing of reconviction than affect whether or not one will be reconvicted. This model may find use in determining reconviction probabilities for evaluation purposes when comparing groups with different lengths of time in which to reoffend.
- Also of note are the variables that have been found to be predictive. In addition to variables already found in the literature to be predictive such as the length of time at large and the number of previous violent offences, offences such as disorderly behaviour and property damage have been found to be linked with violence. This supports the view that violent offenders express violence in other ways than just toward people.

Conclusion

- The results show that we can use criminal conviction histories to predict subsequent violent behaviour. The process of modelling developed for the High Risk Offenders project has again proven successful. While not as accurate as the earlier general reconviction models, it is still possible to produce models that significantly improve over chance.
- This study has demonstrated that violent reconviction can be predicted with some accuracy for New Zealand offenders released from prison using readily available actuarial information. While violent reconviction has been defined broadly (any subsequent violent conviction regardless of its seriousness) the performance of the models is still similar to that obtained in overseas studies. The application of this model to helping select offenders for treatment and for assessing comparability of groups for evaluation purposes, should mean better management of resources for treating violent offenders and may aid in parole decisions for less serious imprisoned offenders.

Bibliography

- Bakker, L.W., Riley, D.R., Deely, J., O'Malley, A.J., Love, H., & Hudson, S. (1994) High Risk Offenders: A Step towards more accurate prediction. <u>Paper</u> <u>presented at New Zealand - Australia Corrections Health Conference</u>
- Bonta J., Harman, W.G., Hann, R.G. & Cormier R.B. The prediction of recidivism among federally sentenced offenders: re-validation of the SIR scale. <u>Canadian Journal of Criminology January 1996 61 -79</u>
- Brizer D.A. (1989). Introduction: Overview of current approaches to the prediction of violence. In D.A. Brizer & M. Crowner (Eds.), <u>Current</u> <u>approaches to the prediction of violence</u>. (pp 1-3), Washington: American Psychiatric Press Inc.
- Gendreau P., Little T., and Goggin C. (1996) A Meta-Analysis of the Predictors of Adult Offender Recidivism: What Works! <u>Criminology, 34, 575 -</u> <u>607</u>
- Grisso T., and Appelbaum P.S. (1992). Is it unethical to offer predictions of future violence? Law and Human Behavior, 16, 621 633.
- Harris G.T., Rice M.E., & Cormier C.A. (1993). Psychopathy and violent recidivism. Law & Human Behavior, 15, 625-637.
- Harris G.T., Rice M.E., & Quinsey V.L. (1993). Violent recidivism of mentally disordered offenders: The development of a statistical prediction instrument. <u>Criminal Justice & Behavior</u>, 20, 315-335.
- Hart S.D., & Hare R.D. (1989). Discriminant validity of the psychopathy checklist in a forensic psychiatric population. <u>Psychological</u> <u>Assessment: A Journal of Consulting & Clinical Psychology</u>, <u>1</u>, 211-218.
- Hart S.D., Kropp P.R., & Hare R.D. (1988). Performance of male psychopaths following conditional release from prison. <u>Journal of Consulting and</u> <u>Clinical Psychology</u>, <u>56</u>, 227-232.
- Klassen D., & OE Connor W.A. (1994). Demographic and case history variables in risk assessment. In J. Monahan & H.J. Steadman(Eds.), <u>Violence and mental disorder: Developments in</u> <u>risk assessment</u>. (pp229-259), Chicago: The University of Chicago Press.
- Lidz C.W., Mulvey E.P., & Gardner W., (1993). The accuracy of predictions of violence to others. <u>Journal of the American Medical Association</u>,

<u>269</u> , 1007-1011.

- Monahan J. (1981). <u>The clinical prediction of violent behaviour</u>. Washington:Government Printing Office.
- Monahan J. (1993). Limiting therapist exposure to <u>Tarasoff</u> liability: Guidelines for risk containment. <u>American Psychologist</u>, <u>48</u>, 242 250.
- Mossman D. (1994). Assessing predictions of violence: being accurate about accuracy. Journal of Consulting and Clinical Psychology, 62, 783 792.
- Mullen P.E. (1996). The dangerousness of the mentally ill and the clinical assessment of risk. In W. Brooklands (Ed.), Psychiatry and the law: <u>Clinical and legal issues</u>, (pp 93-116). Wellington: Brooker
- Mulligan A. (1991) Base rates and reconviction rates for New Zealand violent offenders. Unpublished Masters Thesis
- O'Malley, A.J. (1996) Statistical Models for Recidivism. Unpublished Report. Department of Mathematics and Statistics, University of Canterbury, New Zealand.
- Otto R.K. (1992). Prediction of dangerous behavior: A review and analysis of #second generation" research. <u>Forensic Reports</u>, <u>5</u>, 103-133.
- Rice M.E. & Harris G.T.(1993) Violent Recidivism: Assessing Predictive Validity. <u>Penetanguishene mental Health Centre Research Report 10(6)</u>. Penetanguishene Ontario: Mental Health Centre cited in Bonta J., Harman, W.G., Hann, R.G. & Cormier R.B. The prediction of recidivism among federally sentenced offenders: re-validation of the SIR scale. Canadian Journal of Criminology January 1996 61 -79
- Riley, D. (1997) Issues in the Assessment of Violence and Aggression. In Love, H. & Whittaker, W. (Eds), <u>Practice Issues for Clinical and Applied</u> <u>Psychologists in New Zealand</u>, New Zealand Psychological Society (in press)
- Serin R.C. Assessment and Prediction of Violent Behaviour in <u>Offender</u> <u>Populations in Forensic Psychology Policy and Practice in</u> <u>Corrections</u>
- Spier P., <u>Conviction and Sentencing of Offenders in New Zealand: 1987 to 1996</u> Ministry of Justice Published Report 1997

Statistics New Zealand (1996). <u>New Zealand now: Crime</u>. Wellington:

Statistics New Zealand.

- Steadman H.J., and Cocozza J.J. (1974). <u>Careers of the criminally insane:</u> <u>Excessive social control of deviance</u>. Lexington: Lexington Books.
- Swanson J.W., Holzer C.E., Ganja V.K., and Jono R.T. (1990). Violence and psychiatric disorder in the community. Evidence from the epidemiologic catchment area surveys. <u>Hospital and community psychiatry</u>, <u>41</u>, 761 780.
- Tardiff K., and Sweillam A. (1980). Assault, suicide, and mental illness. Archives of General Psychiatry, <u>37</u>, 164 - 169.
- Thornberry T.P., and Jacoby J.E. (1979). <u>The criminally insane: A community</u> <u>follow-up of mentally ill offenders</u>. Chicago: University of Chicago Press.

Appendix 1

METHOD

Data

The prediction models were developed from the criminal histories of all inmates released from prison in 1990. These 4601 offenders were selected because:

- the same length of time post release (on average about five years) was available for them to re-offend; and
- serious violent offenders almost without exception receive sentences of imprisonment.

The conviction information contained on the database provided information about the:

- date of conviction;
- specific offence;
- number of charges or counts;
- sentence given;
- sentence length;
- sentence start date; and
- date of release from prison.

We created variables that contained or summarised information on individuals. Subsequent analyses used these variables. A full list and description of these variables is provided in Appendix 1. In addition, information on ethnicity, date of birth and gender was available.

Modelling Process

- In total two logistic regression models and one survival model were developed. Three properties are generally associated with well performing models. The model should:
 - fit the data there should be enough variables to provide an accurate fit to the data, but not too many so that the model would be over-complicated and incapable of accurate prediction of unseen data.
 - have a high degree of predictive power. It should give good predictions of the outcomes sought. Of prime importance is how well the model performs on unseen data as this reflects the actual conditions under which it will be used in practice.
 - *make sense*. It should not contain spurious variables or have excessive multi-collinearity.
- The prime purpose in developing the model was to maximise predictive power. Because earlier modelling work had identified the most predictive variables it was

possible to utilise these in the development of the violent reconviction model. Stepwise logistic regression was used to introduce the variables into the model. Nonsignificant variables were then excluded and the analysis re-run. This process was continued until only significant variables remained. The final model was then repeated with changes in the order of the predictive variables to which the Swhwarz Criterion⁷ could be applied. The SchwarzCriterion compares the performance of a model with the best possible model that could be developed. The lower the SchwarzCriterion the better the model. The model with the lowest Swhwarz Criterion value was then selected.

Validation of the Model

• The model was then tested on unseen data (another data set other than the one on which the model was developed) to validate its performance. For this study the data set was randomly divided in two using one half to develop the model and the other half to test it. By comparing the predicted number of offenders with a given probability who would be reconvicted with the actual number of offenders who were reconvicted it was possible to evaluate the model's accuracy.

Models Developed

- There were three models that were developed. A model that :
 - provided five years for a person to be reconvicted of a violent offence;
 - allowed two years for reconviction; and
 - sought to predict the length of time until reconviction for a violent offence.

⁷ The Swharz Criterion is a statistic that assesses the parsimony of a model based upon the number of variables, data set size etc.

Appendix 2

Variables Used in The Development of the Prediction Models

The variables listed here are defined in such a way as to give weight to values which increases risk; for example as males are more at risk than females gender will equal one if the subject is a male and 0 if a female. When this variable is used in the calculation of the probability gender will contribute to the result only if the offender is a male (this is because if the offender is a female the parameter for gender in the model will be multiplied by 0 and will therefore not contribute).

- Gender Male
- Ethnicity X Equal to 1 if the offender has unknown ethnicity
- Log of the offender's age at the estimated date of release from the criterion prison sentence less 13 years. (This variable estimates the possible length of the adult offence history)
- Log of time at large (Time out of prison) since the offenders thirteenth birthday.
- Status -X Equals 1 if the offender has only one episode of offending 0 otherwise
- The log of time at large between the criterion court appearance and the previous episode of offending. (This is only defined if the offender has more than one court appearance in their criminal history.)
- The Log of the total number of convictions in the offenders past (including the criterion court appearance.
- Violence Equal to one if the offender has a conviction for a violent offence in the past and zero otherwise
- Log of the total number of past convictions for violent offences. This variable is set to zero if the offender has no such convictions
- Disorderly Behaviour Equals 1 if the offender has been convicted for disorderly behaviour in the past and 0 otherwise
- Log of the total number of past convictions for disorderly behaviour. This variable is set to zero if the offender has no such convictions.
- Log of the total number of past convictions for property damage. This variable is set to zero if the offender has no such convictions.

Predictor Variable	Coefficient	Std. Error	Chi-Square	P-Value
Intercept	-0.2181	0.4057	0.2891	0.5908
Gender				
- Male	0.6859	0.1429	23.0370	0.0001
Ethnicity				
- Caucasian	-0.1243	0.3430	0.1314	0.7170
- Maori	0.2822	0.3425	0.6788	0.4100
- Pacific Peoples	0.0640	0.3695	0.0300	0.8625
Log Age at Release Date	-1.1279	0.0679	275.84	0.0001
Log Number of Convictions	0.2969	0.0444	44.6948	0.0001
Violent Criterion Offence	0.5240	0.0920	32.4271	0.0001
Log Total Prev. Violent Offences	0.2764	0.0562	24.1560	0.0001

Table 1: Violent Reconviction Model Fit

Disorder Criterion Offence	0.3881	0.0949	16.7391	0.0001
Log Total Prev. Disorder Offences	0.2031	0.0552	13.5503	0.0002
Log Total Prev. Prop. Dam. Offences	0.3847	0.0849	20.5138	0.0001

Table 2 : Violent Reconviction in Two Years Model Fit

Predictor Variable	Coefficient	Std. Error	Chi-Square	P-Value
Intercept	-0.2181	0.4057	0.2891	0.5908
Gender				
- Male	0.6859	0.1429	23.0370	0.0001
Ethnicity				
- Caucasian	-0.1243	0.3430	0.1314	0.7170
- Maori	0.2822	0.3425	0.6788	0.4100
- Pacific Peoples	0.0640	0.3695	0.0300	0.8625
Log Age at Release Date	-1.1279	0.0679	275.84	0.0001
Log Number of Convictions	0.2969	0.0444	44.6948	0.0001
Violent Criterion Offence	0.5240	0.0920	32.4271	0.0001
Log Total Prev. Violent Offences	0.2764	0.0562	24.1560	0.0001
Disorder Criterion Offence	0.3881	0.0949	16.7391	0.0001
Log Total Prev. Disorder Offences	0.2031	0.0552	13.5503	0.0002
Log Total Prev. Prop. Dam. Offences	0.3847	0.0849	20.5138	0.0001

Table 3: Time Until Violent Reconviction Model

Predictor Variable	Coefficient	Std. Error	Chi-Square	P-Value
Intercept	.61881	0.0832	55.385	0.0001
Log Total Time At Large	.11340	0.0336	11.405	0.0007
First Offence	.37000	0.2699	1.8790	0.1704
Log Time at Large Between Criterion and				
previous offence	.04409	0.0175	6.2827	0.0122
Log Total Number of Violent Convictions	-0.09706	0.0272	12.7505	0.0004

Prediction Summary Table For Violent Reconviction Within 5 Years

Gp	Pr No	Pr Yes	H Rt	M Rt	FA Rt	D Rt	R Rt	Pr Cor
none	0.0000	1.0000	1.0000	0.0000	1.0000	0.4427	0.4427	
0.05	0.0326	0.9674	0.9980	0.0020	0.9431	0.4568	0.9733	0.4736
0.10	0.0800	0.9200	0.9897	0.0103	0.8647	0.4763	0.9429	0.5136
0.15	0.1341	0.8659	0.9720	0.0280	0.7816	0.4970	0.9076	0.5521
0.20	0.1854	0.8146	0.9524	0.0476	0.7051	0.5176	0.8863	0.5860
0.25	0.2402	0.7598	0.9249	0.0751	0.6287	0.5389	0.8615	0.6164
0.30	0.3004	0.6996	0.8910	0.1090	0.5476	0.5638	0.8394	0.6466
0.35	0.3664	0.6336	0.8409	0.1591	0.4688	0.5877	0.8078	0.6683
0.40	0.4310	0.5690	0.7855	0.2145	0.3970	0.6112	0.7796	0.6838
0.45	0.5001	0.4999	0.7153	0.2847	0.3288	0.6335	0.7479	0.6907
0.50	0.5651	0.4349	0.6475	0.3525	0.2660	0.6592	0.7238	0.6957
0.55	0.6355	0.3645	0.5626	0.4374	0.2071	0.6834	0.6953	0.6909
0.60	0.7096	0.2904	0.4674	0.5326	0.1498	0.7126	0.6677	0.6807
0.65	0.7800	0.2200	0.3643	0.6357	0.1053	0.7332	0.6392	0.6599
0.70	0.8496	0.1504	0.2592	0.7408	0.0640	0.7630	0.6140	0.6364
0.75	0.9096	0.0904	0.1664	0.8336	0.0300	0.8149	0.5943	0.6142
0.80	0.9552	0.0448	0.0898	0.9102	0.0090	0.8883	0.5782	0.5920
0.85	0.9817	0.0183	0.0373	0.9627	0.0031	0.9048	0.5659	0.5720
0.90	0.9963	0.0037	0.0079	0.9921	0.0004	0.9412	0.5591	0.5605
0.95	1.0000	0.0000	0.0000	1.0000	0.0000	0.5573	0.5573	0.5573
0.96	1.0000	1.0000	0.0000	0.0000	1.0000	0.0000	0.5573	0.5573
all	1.0000	0.0000	0.0000	1.0000	0.0000	0.5573	0.5573	0.5573

Gp	Pr No	Pr Yes	H Rt	M R,t	FA Rt	D Rt	R Rt	Pr Cor
none	0.0000	1.0000	1.0000	0.0000	1.0000	0.2458	0.2458	
0.05	0.0952	0.9048	0.9947	0.0053	0.8755	0.2702	0.9863	0.3384
0.10	0.2030	0.7970	0.9646	0.0354	0.7424	0.2975	0.9572	0.4314
0.15	0.3208	0.6792	0.9089	0.0911	0.6043	0.3290	0.9302	0.5218
0.20	0.4425	0.5575	0.8117	0.1883	0.4746	0.3579	0.8954	0.5957
0.25	0.5529	0.4471	0.7091	0.2909	0.3617	0.3899	0.8707	0.6557
0.30	0.6607	0.3393	0.5871	0.4129	0.2585	0.4254	0.8464	0.7035
0.35	0.7503	0.2497	0.4668	0.5332	0.1790	0.4595	0.8253	0.7340
0.40	0.8233	0.1767	0.3492	0.6508	0.1205	0.4859	0.8057	0.7492
0.45	0.8802	0.1198	0.2520	0.7480	0.0767	0.5172	0.7911	0.7583
0.50	0.9276	0.0724	0.1698	0.8302	0.0406	0.5766	0.7800	0.7653
0.55	0.9583	0.0417	0.1043	0.8957	0.0213	0.6146	0.7702	0.7637
0.60	0.9757	0.0243	0.0654	0.9346	0.0110	0.6607	0.7645	0.7620
0.65	0.9887	0.0113	0.0309	0.9691	0.0049	0.6731	0.7591	0.7581
0.70	0.9948	0.0052	0.0115	0.9885	0.0032	0.5417	0.7557	0.7546
0.75	0.9987	0.0013	0.0018	0.9982	0.0012	0.3333	0.7543	0.7537
0.80	1.0000	0.0000	0.0000	1.0000	0.0000	0.7542	0.7542	
0.85	1.0000	0.0000	0.0000	1.0000	0.0000	0.7542	0.7542	
0.90	1.0000	0.0000	0.0000	1.0000	0.0000	0.7542	0.7542	
0.95	1.0000	0.0000	0.0000	1.0000	0.0000	0.7542	0.7542	
1.00	1.0000	0.0000	0.0000	1.0000	0.0000	0.7542	0.7542	
all	1.0000	0.0000	0.0000	1.0000	0.0000	0.7542	0.7542	

Prediction Summary Table For Violent Reconviction Within 2 Years

Appendix 3

Computation of the Time until Violent Reconviction.

Although there is some evidence that the more complicated gamma or Weibull models may fit the data slightly better, the data were fit to an exponential model. The primary justification for this is that the less complex nature of the exponential model enables a more straight forward and interpretable representation when it is applied. The more commonly used log-normal and log-logistic models are out performed by the exponential model on these data.

The time to reconviction was converted into years and then log transformed before fitting the model. This resulted in a substantial improvement in the model fit. The resultant model is rather simplistic and the coefficients of the variable terms are all consistent with expert opinion. Note that the coefficients of the above model are aligned towards survival. The negatives of these coefficients indicate the relationship between the predictor variables and the risk of reconviction over increasing time.

The output from this model can be transformed into a cumulative probability that is a function of time. The transformation of the fitted model to the conditional cumulative probability that the offender is reconvicted of a violent offence within *t* years is:

 $p(recon < t | viol) = \frac{1 - exp(-exp(-\chi'\beta)t)}{1 - exp(-exp(-\chi'\beta))t_{post}}$

where $\boldsymbol{\chi}$ represents the vector containing the values of the variables in the above table,

 β is the associated vector of parameter values and t_{post} is the length (in years) of the posterior time period. For any time this function yields the probability that the offender has been reconvicted of a violent offence, given that the offender is reconvicted of a violent offence during the posterior time period.

Example

Suppose an offender has spent 20 years of their lifetime free, has 5 past convictions including 2 convictions for violent offences, and spent half a year free between their two most recent convictions. That is:

- Log Time at large = log(20 13) = 1.9459,
- Status = 0,
- Log Time at Large between the criterion and previous episodes of offending = log(O.5) = -0.6931; and
- Log Total Number of past Violent convictions = log(2) = 0.6931.

Hence, the linear component evaluates to:

 $X'\beta = 0.6189 + 0.1134 * 1.9459 + 0.3700 * 0 + 0.0441 * (-0.6931) - 0.0971 * 0.6931 = 0.6189 + 0.2207 + 0 - 0.0306 - 0.0673 = 0.4663$

Taking the length of the posterior time period to be 5 years, tpost 5, and so:

p(recon < <i>t</i> l viol)	=	<u>1 - exp(- exp(-0.4663)t)</u> 1- exp(- exp(-0.4663)5)
	=	<u>1 - exp(-0.6273t)</u> 1 - exp(-0.6273 * 5)
	=	<u>1 - exp(-0.6273t)</u> 1 - exp(-3.1365)
	=	<u>1- exp(-0.6273t)</u> 1 - 0.0434
	=	<u>1 - exp(-0.6273t)</u> 0.9566
	=	1.0454 * (1 - exp(-0.6273t))

The multiplication by the term 1.0454 has the effect of making the probability of reconviction within 5 years equal to 1. Substituting t = 2 into the above formula then yields the probability of a violent reconviction within 2 years given a violent reconviction in 5 years. This is easily observed to be:

p(recon < 2 1 viol)	=	1.0454 * (1 - exp(-0.6273 * 2))
	=	1.0454 * (I - exp(-1.2546))
	=	1.0454 * (l - 0.2852)
	=	1.0454 * 0.7148
	=	0.7473

To obtain the unconditional probability that the offender is reconvicted of a violent offense in this time, this probability must be multiplied by the probability of the offender incurring a violent reconviction during the posterior time period. Let p(viol) denote the probability that a certain offender is reconvicted during the posterior time period (i.e. within 5 years). Then:

p(recon < t) = p(recon < t | viol)p(viol)

is the unconditional probability. If p(viol) = 0.6 for the above offender we then have:

One problem with the response event modeled here is that a prison sentence associated with some other type of crime may precede reconviction for a violent crime. Such offenders will take much longer to commit a violent offense, if at all, during a posterior time period. This increases the noise in the data and so reduces efficacy of modeling the event. For this reason survival models dealing with general reconviction or re-imprisonment would appear to be more purposeful.