No. 530 December 2016

Abstract | This study examined recidivism in an Australian correctional population. Three different groups of offenders were identified from their recidivism profiles: low-risk or slow recidivists, moderate-risk or delayed recidivists, and high-risk or rapid recidivists. Slow recidivists were more likely to be younger Indigenous men, with a history of both drug use and parole suspension or cancellation. Delayed recidivists were more likely to be younger non-Indigenous women serving shorter sentences. Rapid recidivists were differentiated only by being more likely to serve shorter sentences.

Data were drawn from the Queensland Corrective Services Integrated Offender Management System.

The findings will be useful to policymakers and practitioners working in corrections and related fields.

Recidivism among prisoners: Who comes back?

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Understanding whether, when and why offenders might reoffend following release from prison is a fundamental concern for corrections management and for crime control more broadly. Recidivism among prisoners is traditionally studied by looking at short-term changes in the chances of failure—that is, of returning to prison for a new offence—over a follow-up period. This survival time analysis strategy focuses on the time to failure or recidivism, which is really the probability at each point over a follow-up period that an offender, who has not yet reoffended, will do so (Maltz 1984).

While this strategy offers the advantage of looking at variations in the chances of recidivism occurring over the follow-up period, it suffers from two interrelated limitations. Traditional survival analysis takes a one-size-fits-all approach and assumes that the chances of recidivism apply equally to all offenders in the relevant correctional population. In addition, since the probability of reoffending increases with each additional unit of time—for example a day—the traditional survival analysis also presumes that, eventually, all offenders in the sample will reoffend if they can be tracked for long enough (Bushway et al. 2004).

However, both correctional practice experience and the growing body of research on desistance from offending (Laub & Sampson 2001) suggest that assuming a single survival distribution for a

correctional population is likely to be an oversimplification. This is because some offenders will not fail, never returning to corrections for a new offence. Among those who do, time to failure will vary; some may reoffend quickly following release and others more slowly.

To the extent that these distinct recidivism types can be identified, it is also possible that predictors of recidivism might explain the chances of recidivism within each group differently. Put simply, the usual factors that explain reoffending might apply for some recidivism types but not others. Improving how possible variation—or unobserved heterogeneity—in the likelihood of recidivism among prisoners re-entering the community is accounted for could allow correctional resources to be better targeted.

This study examined whether it is possible to observe any unique recidivism groups in an Australian correctional population. To do this, we use a strategy recently employed by Morris et al. (2013) called survival mixture modelling. The results of their research on a US sample showed there were unique types of recidivists who were influenced differently by factors that normally predict recidivism for all offenders in traditional survival analyses. The study tested the extent to which this was also true in a sample of offenders released from adult prisons on a parole order in Queensland from 1 July 2007 to 30 June 2009. Any recidivism occurring within three years of release is accounted for.

The following research questions were addressed.

- Can a sample of parolees be divided into distinct classes of offenders according to their recidivism profiles?
- If so, which offender characteristics explain recidivism within each of identified recidivism classes?
- Finally, which offender characteristics explain membership in one class versus another?

Method

The study estimated continuous-time survival (Cox) mixture models (Asparouhov, Masyn & Muthén 2006; Singer & Willett 2003). This approach offers the advantage over traditional survival analysis of accounting for different pathways of recidivism risk and empirically assessing whether certain factors influence some recidivism groups and not others (Morris et al. 2013).

This method blends traditional survival analysis—which makes it possible to assess the risk or hazard of reoffending on any given day for an offender who has not yet done so—with the advantages of more recent latent variable approaches that allow heterogeneity in outcomes for sub-populations to be accounted for.

Data source

The study used data from the Queensland Corrective Services (QCS) Integrated Offender Management System (IOMS) operational database. The IOMS database holds data on a range of variables relating to the timing of offenders' movements through various orders while under QCS supervision in custody or the community. For example, these movements could include the start and end dates of custodial episodes, parole orders, other community supervision orders or the suspension or cancellation of these orders. IOMS also contains data on a range of offender-specific demographic, offence type and institutional variables. All offenders released from a QCS prison on

parole at any point during the two-year period from 1 July 2007 to 30 June 2009 were assessed during the three-year follow-up period.

The final analytical sample for this cohort included 6,253 adult offenders. Their mean age at first release was 30 years; 89 percent were men and 32 percent were Indigenous. Offenders could be released on one of two possible parole order types depending on the length of the custodial sentence they served before their index parole release. The index parole release included one of two possible parole order types in Queensland: board-ordered parole for offenders serving sentences of more than three years (13%), and court-ordered parole for offenders sentenced to three years or less (87%). The median sentence length for the custodial sentence before the index release was 12 months.

Outcome variable

For the purposes of the study the outcome variable was time to first new offence or, more specifically, the number of days from the date of the index parole release to either the date of return to prison for a new offence or the end of the three-year follow-up period, whichever came first. The measure of time free was adjusted by excluding any time the offender was removed from the community because their parole order was suspended or cancelled; both would mean the offender was returned to custody without having committed a new offence. Overall, over a quarter (27%) of the sample reoffended before the end of the follow-up. On average, offenders were free for 961 days (or 2.6 years).

Explanatory variables

Available explanatory variables traditionally used in analyses of correctional data to predict the likelihood of recidivism were included in the study.

Demographic variables included gender (female=0, male=1); reported Indigenous status (non-Indigenous=0, Indigenous=1); relationship status (in a relationship, married or other=0; not in a relationship=1); country of birth (foreign-born=0, Australian-born=1); dichotomised age at time of release (aged 35 years and older=0; aged under 35 years [sample mean]=1); dichotomised level of education (completed year 11 or higher=0; completed year 10 or less=1).

Offence-related variables included the dichotomous variable violent onset offence, coded 1 if the most serious offence connected to the episode before the index parole release was a violent offence, and coded 0 if not. Violent offences included a number of offences against the person as classified by the Australian and New Zealand Standard Offence Classifications (ANZSOC; Australian Bureau of Statistics 2011). These included homicide and related offences (111–131), serious assault resulting in injury, serious assault not resulting in injury and common assault (211–213), aggravated and non-aggravated sexual assault (311–312), abduction, kidnapping and the deprivation of liberty (511–521), aggravated robbery, non-aggravated robbery and blackmail and extortion (611–621). Nearly half (49.6%) the offenders in this sample had committed a violent onset offence. The index sentence length, in months, was also included, as was the type of parole order (court-ordered parole=0, board-ordered parole=1) and a dichotomised measure of a record of parole suspensions or cancellations on the index order (no=0, yes=1).

Institutional variables included three variables capturing additional criminal justice information about the offender. These are cumulative variables that could pertain to the index period of QCS supervision or to previous periods. Drug use history is an institutional flag variable indicating any report of an offender's previous drug use history; it was coded 0 for no reported history and 1 for any reported drug history. Prison escape history was coded 0 for no recorded history of escape and 1 for any history of escape. Finally, prison incident history reflected any record of disciplinary incidents while in prison, and was coded 0 for no recorded incidents and 1 for any recorded incidents.

Analysis

The study estimated a survival (Cox) mixture model which made it possible to detect unique latent classes of offenders based on their recidivism profiles (eg quicker or slower recidivists), while simultaneously estimating the differential influence of the explanatory variables on the distinct latent classes of offenders (Asparouhov, Masyn, & Muthén 2014). This model groups offenders based on their recidivism profiles, estimates the influence of the explanatory variables on the risk of recidivism within each class and estimates whether the explanatory variables predict class membership (ie a between-class effect). The within- and between-class estimates are presented separately in Tables 1 and 2 below.

In order to arrive at the best-fitting model (ie the one with the number of recidivism classes or subgroups that best fit the data), the authors estimated a baseline survival mixture model and compared this to a series of models, each with one additional class. To select the optimal solution, each model was compared to a model with one fewer class using a combination of empirical fit indices, and considerations such as the meaning and distinctiveness of the classes and consistency with previous research findings (Nylund, Asparouhov & Muthén 2007).
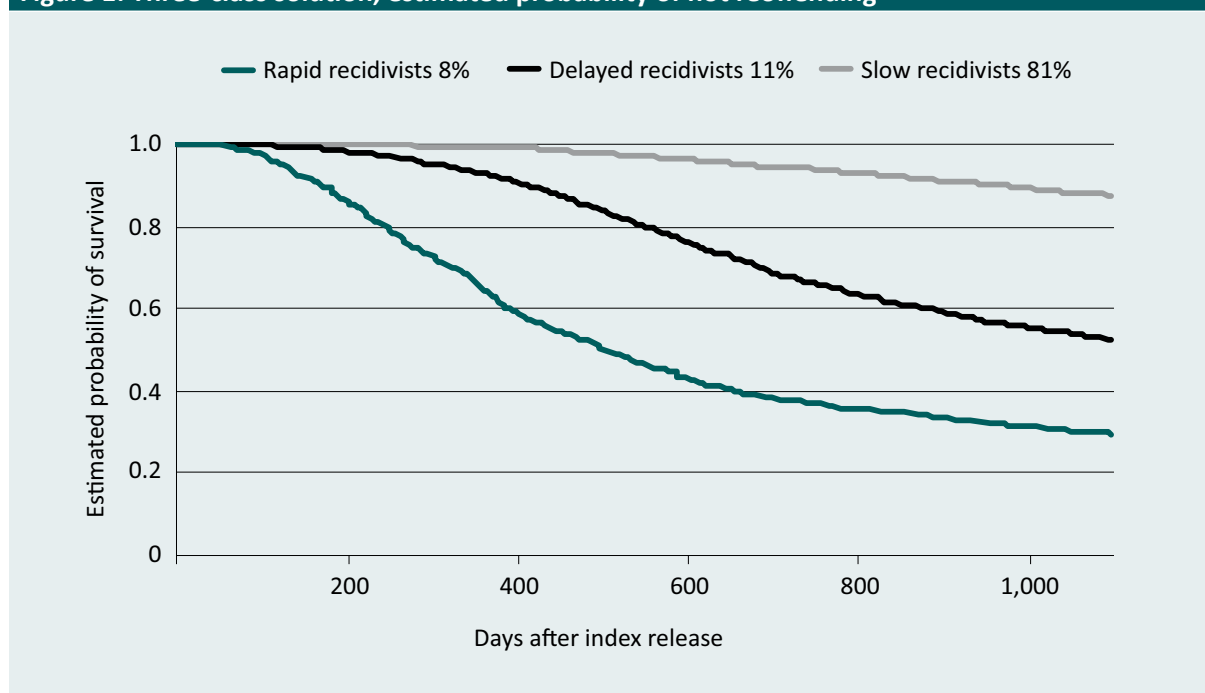
Results

Model selection: How many classes of recidivists?

Initial testing revealed the Queensland data best fit a three-class model (Figure 1). These classes represented groups of offenders who were clearly differentiated based on their recidivism profiles, including:

- a low-risk (slow recidivist) group comprising 81 percent of the total sample based on most likely class membership, with a median time to recidivism of 734 days (or 24.1 months). An estimated 12 percent of this subgroup had been reimprisoned by the end of the three-year follow up;

- a moderate-risk (delayed recidivist) subgroup comprising 11 percent of the total sample, with a median time to reimprisonment of 611 days (or 20 months). An estimated 48 percent of this group were reimprisoned by the three-year mark; and

- a high-risk (rapid recidivist) subgroup who were reimprisoned most often and most quickly, comprising eight percent of the total sample, with a median time to reimprisonment of 382 days (or 12.6 months). Approximately 71 percent had been reimprisoned by the three-year mark.

Figure 1: Three-class solution, estimated probability of not reoffending

Which explanatory variables predict recidivism within the classes?

The survival (Cox) mixture model results for the within-class part of the model are presented in Table 1. These show how the predictive value of the explanatory variables for the estimated risk of recidivism within each of the three identified classes in the selected model varies. The significant coefficients from the Cox regression analyses are presented in Table 1 as both the log hazard and hazard ratios (HR), or as a measure of how likely recidivism is in one group as compared with another over time.

Low-risk (slow) recidivists

Net of the other variables in the model, offenders in the low-risk subgroup with a higher risk of recidivism at any point over the three-year follow-up period were younger (under 35 years; 1.18; 3.24 HR, $p<0.05$) Indigenous (1.67; 5.32 HR, $p<0.05$) men (1.23; 3.42 HR, $p<0.05$), with reported parole suspensions or cancellations (0.54; 1.72 HR, $p<0.05$) and a history of drug use (1.81; 6.08 HR, $p<0.001$).

Moderate risk (delayed) recidivists

In contrast, for offenders classified as delayed recidivists, the log hazard for recidivism increased when offenders were non-Indigenous (Indigenous= -2.01; 0.14 HR, $p<0.001$) women (men= -0.63; 0.53 HR, $p<0.05$) in a relationship (that is, not single, separated, divorced or widowed; not in a relationship= -0.78; 0.46 HR, $p<0.05$); they were younger (0.78; 2.18 HR, $p<.05$) and their sentences were shorter (sentence length= -0.15; 0.87 HR, $p<0.001$).

High-risk (rapid) recidivists

While the relationships between the predictors and the risk of recidivism in the high-risk subgroup were more like those of the delayed subgroup than the low-risk subgroup, most of these variables were not statistically significant. For example, male and female offenders were equally likely to reoffend after controlling for the other variables, as were Indigenous and non-Indigenous. The exception in this subgroup was sentence length; being released from a shorter sentence, rather than longer one (sentence length= -0.15; 0.86 HR, $p<0.001$) increased the recidivism log hazard.

Table 1: Three-class Cox mixture model parameter estimates within each class			
	Low risk (Slow recidivists)	Moderate risk (Delayed recidivists)	High risk (Rapid recidivists)
	Estimate	Estimate	Estimate
Violent onset offence	0.43	0.07	0.33
Male	1.23*	-0.63*	-0.43
Indigenous	1.67*	-2.01***	-0.25
Not in a relationship	0.66	-0.78*	-0.48
Australian born	0.42	0.84	0.03
Younger age (<36 years)	1.18*	0.78*	0.24
Lower education level (<grade 11)	0.09	0.43	0.50†
Length of sentence before release (months)	-0.01	-0.15***	-0.15***
Parole order suspended or cancelled	0.54*	0.12	-0.33
Released on board-ordered parole	0.09	0.43	0.96
Reported drug history	1.81***	-0.49	0.24
Reported escape history	-0.61	0.11	0.24
Reported prison incident(s) (1 or more)	0.82†	-0.81	-0.21

† $p<0.1$; * $p<0.05$; ** $p<0.01$; *** $p<0.001$
Source: QCS 3-year follow-up, n=6,253

Do the explanatory variables predict low risk, moderate risk and high risk of recidivism?

Table 2 presents the results of the 'between' part of the model—the multinomial logistic regressions based on three comparisons. The first two compare the moderate- and high-risk subgroups to the low-risk subgroup (the reference category), and the third compares the moderate-risk subgroup to the high-risk subgroup (the reference category). A positive estimate indicates that, after accounting for the other variables, individuals with that characteristic are likely to belong to the subgroup of interest, while a negative parameter estimate would suggest membership of the reference subgroup.

Violent-onset offending did not predict membership in one group over another for any of the comparisons. Beyond this finding the table shows that, compared with the low-risk subgroup, moderate-risk recidivists were more likely to be Indigenous, to have been released on board-ordered parole and to have a recorded history of drug use and escape. A similar set of characteristics predicted membership of the high-risk subgroup rather than the low-risk group.

The final comparison shows that, relative to the high-risk subgroup, offenders in the moderate-risk subgroup were more likely to be women, to have no record of prison incidents and to be serving board-ordered parole.

Table 2: Three-class Cox mixture model (continued) parameter estimates between each class			
	Planned comparisons (multinomial regression results)		
	Moderate-risk vs Low-risk (reference)	High-risk vs Low-risk (reference)	Moderate-risk vs High-risk (reference)
	Estimate	Estimate	Estimate
Violent onset offence	-0.01	-0.36	0.35
Male	0.21	1.38***	-1.17**
Indigenous	1.68***	2.03***	-0.35
Not in a relationship	0.01	0.87†	-0.86
Australian born	-0.02	-0.13	0.11
Younger age (<36 years)	0.15	-0.03	0.18
Lower education level (<grade 11)	0.28	0.17	0.12
Parole order suspended or cancelled	0.21	0.16	0.05
Released on board-ordered parole	0.89*	-0.40	1.29*
Reported drug history	0.96***	0.91***	0.05
Reported escape history	0.85**	0.81*	0.04
Reported prison incident(s) (1 or more)	0.16	0.81*	-0.65**

† $p<0.1$; * $p<0.05$; ** $p<0.01$; *** $p<0.001$
Source: QCS 3-year follow-up, n=6,253

Discussion

The study aimed to extend current Australian research on recidivism. Many previous studies have applied traditional Cox survival models that assume homogeneity within correctional samples (for a review see Payne 2007). More recently, that method has been teamed with propensity score matching to allow survival analysis of empirically matched samples of offenders (eg Wai-Yin, Poynton, van Doorn & Weatherburn 2014). In either case, the population under consideration is assumed to be homogeneous in relation to recidivism. However, since evidence suggests that, within any given offender population, not all offenders will fail (Kurlychek, Bushway & Brame 2012) and those who do will fail at different times, it is reasonable to expect heterogeneity of survival.

If possible heterogeneity is overlooked, the usefulness of the usual explanatory variables linked to reoffending could be incorrectly assessed. That is, if offenders can be distinguished based on whether they are likely to offend and how quickly, they may also have unique risk factors. To test this, this study applied a latent variable approach like that of Morris et al. (2013), allowing the underlying structures in the data to be seen.

The results support the conclusion that parolees fall into distinct recidivism groups. About eight in 10 offenders released on parole in Queensland were likely to fall into the low-risk recidivism class. Most (88%) of these offenders had not reoffended at the three-year mark; the remaining offenders were much more likely to return to prison, but did so more or less quickly. At the far end of the spectrum, the smallest proportion of offenders fell into a very high-risk recidivism class. Most of these offenders were likely to fail by the end of the follow-up period and, further, failure was likely to occur rapidly. Those at moderate risk of reoffending were relatively likely to reoffend by the end of the study (about a half were reimprisoned), but to do so more slowly than their high-risk counterparts.

The research also identified unique sets of offender characteristics associated with the hazard of recidivism within the three groups. For most offenders classified as low-risk (slow) recidivists, being young, male and Indigenous with a history of drug use and previous parole violations—all factors commonly associated with reoffending in other Australian research (Payne 2007)—increased the chances of recidivism.

In contrast, these factors did not predict recidivism within the more serious moderate- and high-risk groups. For members of both these groups, a shorter sentence was associated with a higher risk of recidivism. In fact, this was the only variable to reach statistical significance for the high-risk group. This finding is consistent with earlier research that showed sentence length is inversely related to the risk of recidivism (Holland, Pointon & Ross 2007), and might also reflect that offenders with shorter sentences receive less assistance both while imprisoned and upon release (Borzycki & Baldry 2003).

Apart from shorter sentences, a seemingly contradictory set of characteristics was associated with a greater risk of recidivism within the moderate-risk group—that is, being female, non-Indigenous and in a relationship rather than single, divorced or widowed. These characteristics could reflect how offenders in this group fail; specifically, they may reoffend due to a gradual accumulation of social pressures when they re-enter the community (Maruna 2001; Morris et al. 2013). Previous research has demonstrated that women can be especially likely to face social and economic marginalisation when they re-enter the community, a cumulative situation that may lead to eventual reoffending (Reisic, Holtfreter & Morash 2007).

The survival mixture model also allowed membership of one group rather than another to be examined. These between-group results suggested that offenders likely to belong to a particular recidivism group were not necessarily those in the group most likely to reoffend. Notably, compared to the low-risk group, the moderate- and high-risk recidivists were more likely to be Indigenous, to have been released on board-ordered parole, and to have a recorded history of drug use and escape. Nonetheless, these characteristics did not increase offenders' risk of recidivism within these higher-risk groups.

The analyses presented here are limited in a number of ways. As with all studies drawing on administrative data sources, this study was necessarily limited by the nature of the available data. Future work of this kind could be improved through access to some additional key criminal career variables related to offence history and, in particular, juvenile offending history. Variables that better capture the dynamic processes that influence behaviour at the point of reoffending would also help to better differentiate the recidivism groups.

The estimated class proportions and shapes of the recidivism profiles the study observed were consistent with the findings of Morris et al's (2013) two-year follow-up of prisoners released from Florida prisons between 1999 and 2001, suggesting a degree of external validity in the classes observed. However, further research will be necessary to determine the extent to which these findings are generalisable beyond these contexts and to longer follow-up periods.

In summary, these results may have implications for correctional policy and practice. The research presents a strategy to account for unobserved heterogeneity in recidivism within offender samples that could improve correctional policy and practice by allowing increasingly scarce resources to be more effectively targeted.

Acknowledgements

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URLS correct at August 2016

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