National Corrections Reporting Program (NCRP) White Paper Series

White Paper #2: NCRP Reporting

November 22, 2011

Prepared by:
William Rhodes, Principal Investigator
Gerald Gaes, Principal Investigator
Tom Rich, Project Director
Yuli Almozlino
Mica Astion
Christina Dyous
Ryan Kling
Jeremy Luallen
Kevin Neary
Michael Shively

Abt Associates Inc.
55 Wheeler Street
Cambridge, MA 02138

This project was supported by Grant No. 2010-BJ-CX-K067 awarded by the Bureau of Justice Statistics, Office of Justice Programs, U.S. Department of Justice. Points of view in this document are those of the author and do not necessarily represent the official position of the U.S. Department of Justice. This copy is not to be disseminated or cited.

This white paper is one in a series of white papers produced by Abt Associates Inc for the NCRP project. The first white paper, titled *Observations on the NCRP,* focused on Abt Associates' recommendations for improving the quality of National Corrections Reporting Program (NCRP) data. In particular, the *Observations on the NCRP* white paper introduced the concept of term and history records; described how we construct term records from the NCRP A (admission), B (release), and D (custody) records; and explained how we address inconsistencies in the A, B, and D records.

This second white paper illustrates how the term and history records can be used to help answer some questions of interest to policymakers, practitioners, and researchers. The illustrations are not comprehensive. Rather, our goal is to stimulate discussion with BJS that will lead to other applications of term and history records. As others make suggestions, those suggestions will be integrated into computing routines and into this white paper.

We begin the discussion below by reviewing basic concepts and definitions. A second section presents some basic tabulations on admissions and releases that are derived from the term records. We then discuss some more advanced analyses on time served and recidivism using the history records.

Basic Concepts and Definitions

During the last several months, the Abt team has been working with A, B and D records to build an analysis file comprising *term records* and *history records*. Defining these records requires defining an *observation period*:

An observation period spans the time between December 31 of the first year when we observe D records and December 31 of the last year when we observe D records. This definition assumes that we observed A and B records between these bracketing dates.[1]

We define a term record:

> A term record is an augmented B record that pertains to each term that an offender spends in prison during the observation period.[2] Some offenders enter prison during the observation period and are in prison as of the end of the observation period. In this case the term record has a mock release date that is later than the end of the observation period. Some other offenders serve terms that began before the observation period and ended after the observation period. In this case the term record has an actual admission date and a mock release date. For all other offenders, the term ended during the observation period so we observe both the admission and release dates.[3]

We define a history record:

> A history comprises all the term records during the observation period for a single offender within a state. The file wherein each case represents a term captures exactly the same information as the file wherein each case represents a history. The term file is merely reorganized into the history file to facilitate tabulation.[4]

As discussed in the earlier white paper, the term record replaces A, B and D records. We think of the A, B and D records as raw data. The term record reflects considerable diagnostic testing, corrections, and imputations based on these raw data. The process of assembling the term records is discussed in a companion white paper and in technical documentation. We anticipate that few users would want to

---

1 We specify December 31 because this is the date for which most states provide census (D) records. The date is not crucial, however. In some states we have B records that end before the first census records and we have some A records that start after the last census records. We discard those specific A and B records because (1) we lack diagnostic tests prior to and after the observation period, and (2) we lack the ability to impute A and B records for offenders who were always incarcerated between the first and last census records. One solution is to acquire census records for missing years.

2 For making prison projections, one would want to predict the release date. This white paper will discuss predictions, but predictions are unnecessary for most tables and figures appearing in this white paper.

3 This abstracts from the fact that the dates are sometimes missing. In some states missing admission and release dates occur with enough frequency to affect statistics. When tabulations are affected, the programs used for file assembly use imputations based on the D records.

4 A simple program converts the term file into a history file. Without loss of generality, one could think of the analysis file as being the term file.

work with the raw A, B and D records. [5] When put into the form of a history file, the term records supports a study of recidivism, and therefore, the history file becomes a substitute for C records that may be otherwise unavailable.

We need to develop table shells and figures to report results. This white paper suggests some tables/figures and demonstrates these analyses with data from Iowa. The illustrations are not publication quality. Tables and figures are available for other states, but are not part of this white paper with one exception: a few inter-state comparisons for time served are discussed.

Basic Tabulations[6]

The term records allow us to construct basic tabulations that would otherwise have been based on A, B and D records.

- We can construct a smoothed history of admissions. For now, assume that we would plot admissions on a daily basis and then use a smoothing device to show trends. This can be supplemented with actual numbers.
- Similarly, we can construct a smoothed history of releases.
- We can combine a smoothed history of admissions minus releases.
- Finally, we can provide a smoothed history of prison populations.

The four figures described above can also be produced for subsets of the population. For example, BJS may want to see breakdowns by offense type, sex, and race/ethnicity.[7] Graphs are simple to construct, although it may be more informative to show statistical trends.

We can tabulate cumulative admissions as a function of time (days in Figure 1). The horizontal axis shows days starting on 1/1/2002 and ending on 12/31/2010. The vertical lines overlaid on the figure demark the date December 31 for each year. The vertical axis reports cumulative admissions. The

---

5 No information is lost by collapsing A, B, and D records into terms. Analysts who are willing to accept our diagnostic tests, corrections and imputations would have no need for A, B and D records. But it is important to note that for analysts who are unwilling to accept our diagnostic tests, corrections and imputations would have to be performed on their own prior to using the raw data. We assume that few analysts would want to go to that trouble.

6 All analysis was done with Stata. The program tab1.do will perform the analysis reported immediately below. The analyst may want to make minor changes, such as selecting subgroups for analysis.

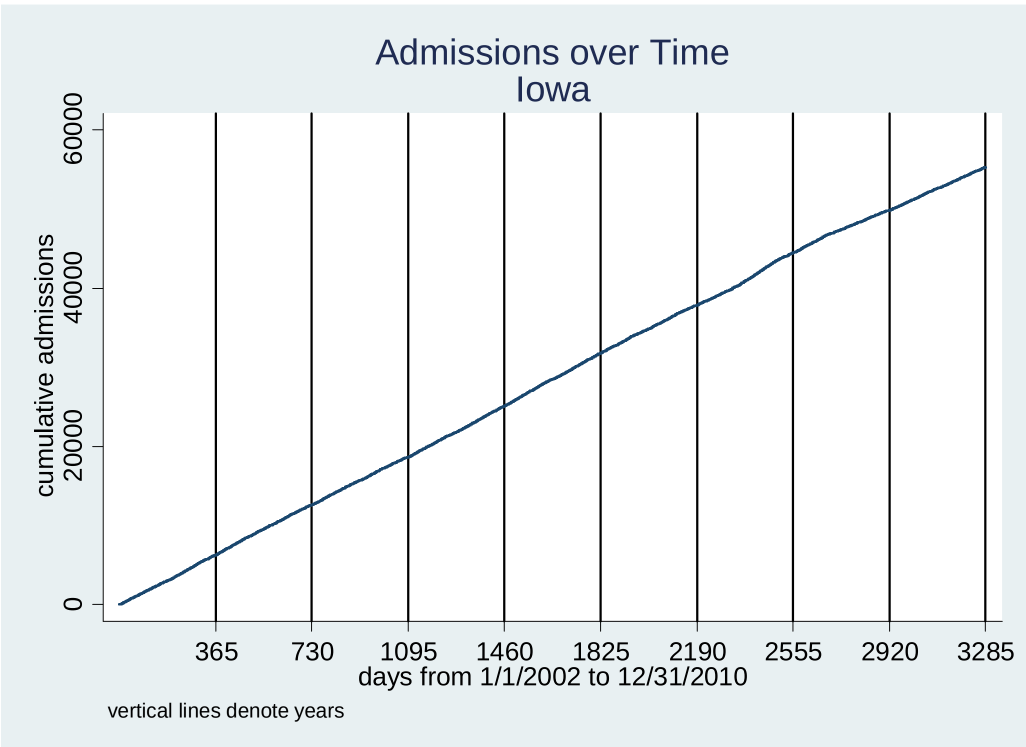
7 We discourage stratification by type of admissions and type of release. These details may be accurate in some states, but they appear unreliable in most. There are two problems. It seems likely that prison authorities (or, at least, those who enter data into data systems) are unaware of admission type. Or, if admission type is recorded accurately, the type may have little meaning. As an illustration, some offenders may be revoked for a technical violation of the conditions of supervision, while other offenders may be resentenced following a technical violation of the conditions of supervision. Both administrative actions have the same consequences, but the former implies relatively high revocation rates compared with the latter.

figure implies a fairly constant growth in admissions, but this is deceptive. Reports from a regression appear just below the figure.

The regression models cumulative admissions as a function of the start of the term. The independent variables are the start of the term, the square of the start of the term, and the cube of the start of the term. The regression results suggest that admissions were increasing at an increasing rate for 3.6 years. Afterward they were increasing, but at a decreasing rate. A second observation is that the root mean-squared error (Root MSE) is 163. This implies that on any day, the cumulative number of admissions may be ±319 inmates about this polynomial.

Granted, the figure is not especially enlightening for Iowa because the rate of admissions is essentially constant over time, but this may not be true in other states. Therefore, showing the ability to graph admissions as a function of time is important for demonstrating the utility of the NCRP. Furthermore, graphing admissions is an important diagnostic tool. Observing a break in the series would trigger an investigation to determine if the break is real or is an artifact due to data quality issues.

Figure 1



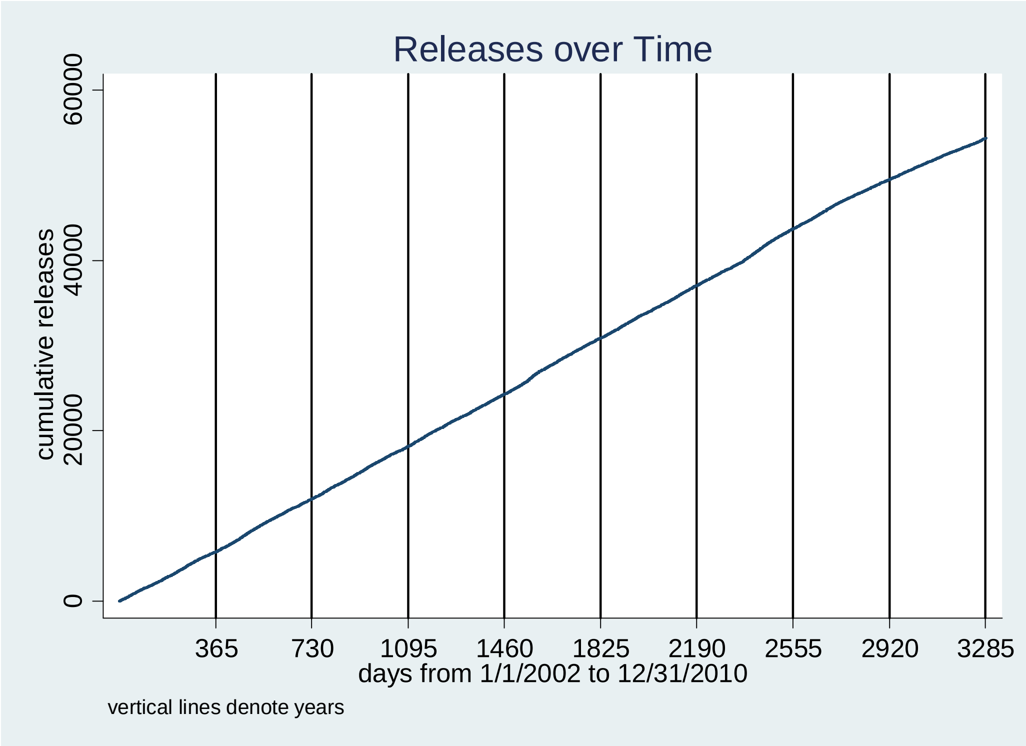
Source	SS	df	MS
Model	9.3182e+12	3	3.1061e+12
Residual	1.2852e+09	48175	26677.2826
Total	9.3195e+12	48178	193438685

Number of obs =	48179
F(3, 48175) =	.
Prob > F =	0.0000
R-squared =	0.9999
Adj R-squared =	0.9999
Root MSE =	163.33

admission	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
start_term	14.11626	.0078487	1798.56	0.000	14.10088	14.13165
start_term~q	.0009127	5.58e-06	163.48	0.000	.0009017	.0009236
start_term~u	-2.30e-07	1.12e-09	-204.89	0.000	-2.32e-07	-2.28e-07
_cons	206.7729	2.951317	70.06	0.000	200.9883	212.5576

We can perform the same exercise with releases. For the same reason as was indicated above, releases appear to occur at a fairly constant rate over time, but a polynomial regression provides more insight. Consistent with the pattern seen for admissions, releases increase at an increasing rate for about 4.1 years, and they increase at a decreasing rate thereafter.

Figure 2



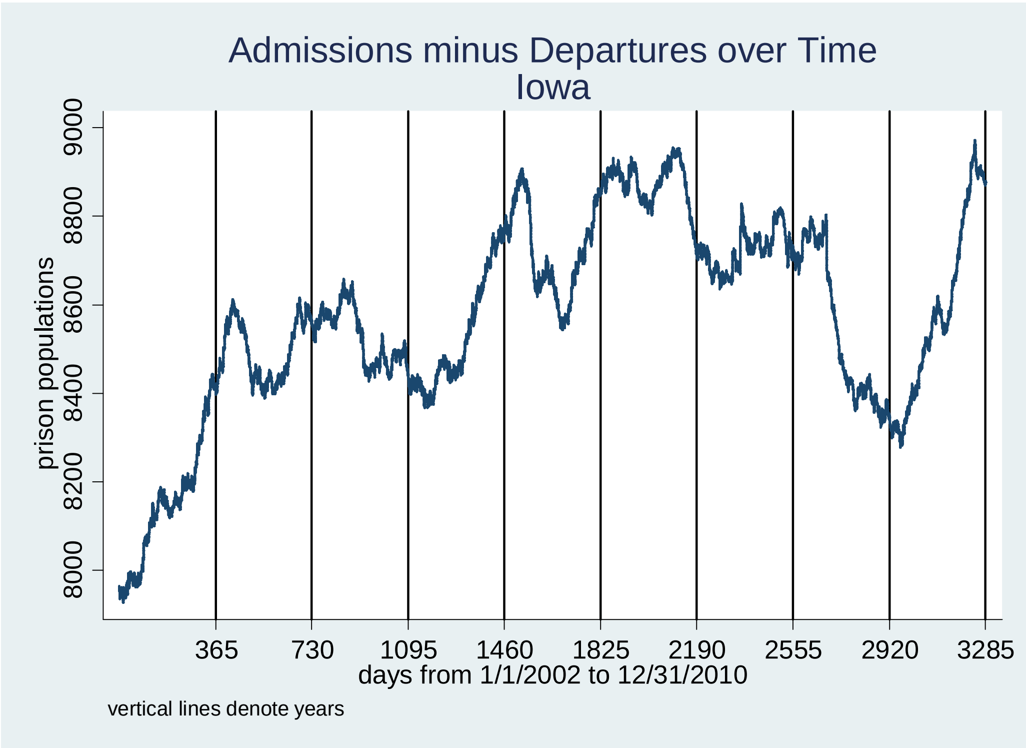
Source	SS	df	MS
Model	8.4087e+12	3	2.8029e+12
Residual	1.3996e+09	46554	30064.3074
Total	8.4101e+12	46557	180641160

Number of obs	= 46558
F(3, 46554)	= .
Prob > F	= 0.0000
R-squared	= 0.9998
Adj R-squared	= 0.9998
Root MSE	= 173.39

releases	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
end_term	12.92383	.0085234	1516.28	0.000	12.90712	12.94053
end_term_sq	.0015025	6.06e-06	248.11	0.000	.0014906	.0015143
end_term_cu	-3.36e-07	1.22e-09	-274.63	0.000	-3.38e-07	-3.33e-07
_cons	191.5703	3.23771	59.17	0.000	185.2243	197.9163

We can see these results in a different way by plotting the cumulative number of admissions minus departures. After adding the prison stock to the beginning of this figure (rather than starting the figure at zero) we have a day-by-day tabulation of the stock. Among other things, we note that the stock of prisoners fluctuates over time. Consequently, year-by-year comparisons based only on a December 31 date tell only part of the story and may be misleading.

Figure 3



There is no problem with producing the same figures by groups of the offender population. The next figure shows admissions minus departures for women. There is some potential story telling here. There is a sharp drop in the prison population for women toward the middle of the time series, which does not occur for men. Perhaps there was an issue with overcrowding for women that causes early release for many women. There appears to be a sharp decrease for men and women toward the end of the time series. Again, we would not necessarily see these patterns if we used prevalence estimates from December 31 of each year.

Figure 4

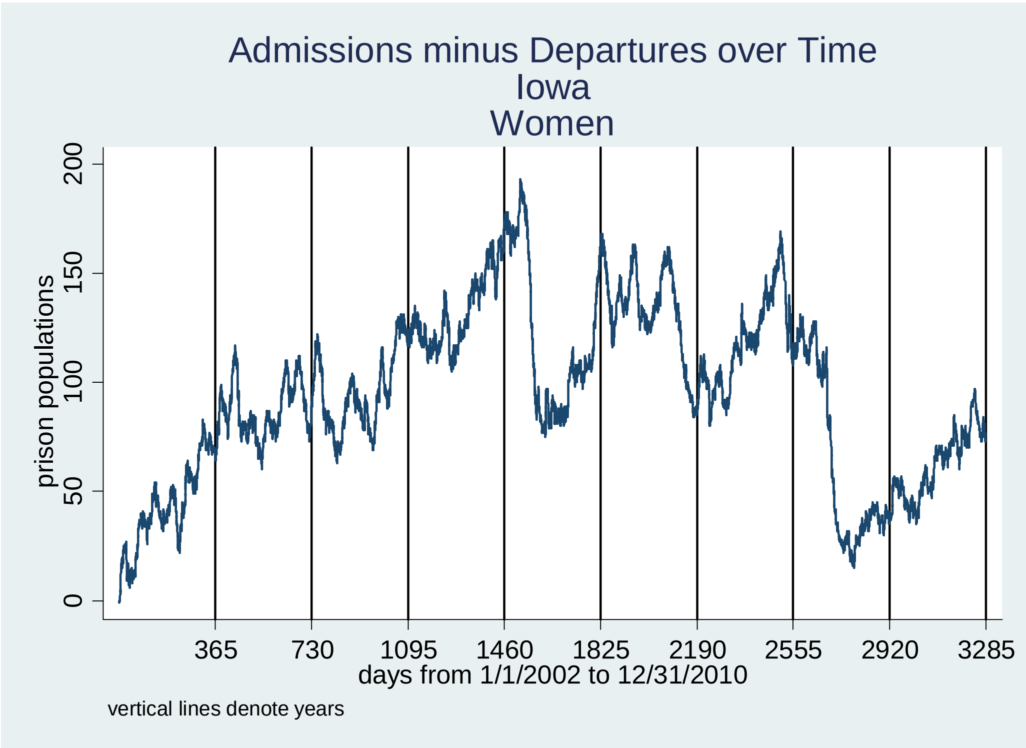
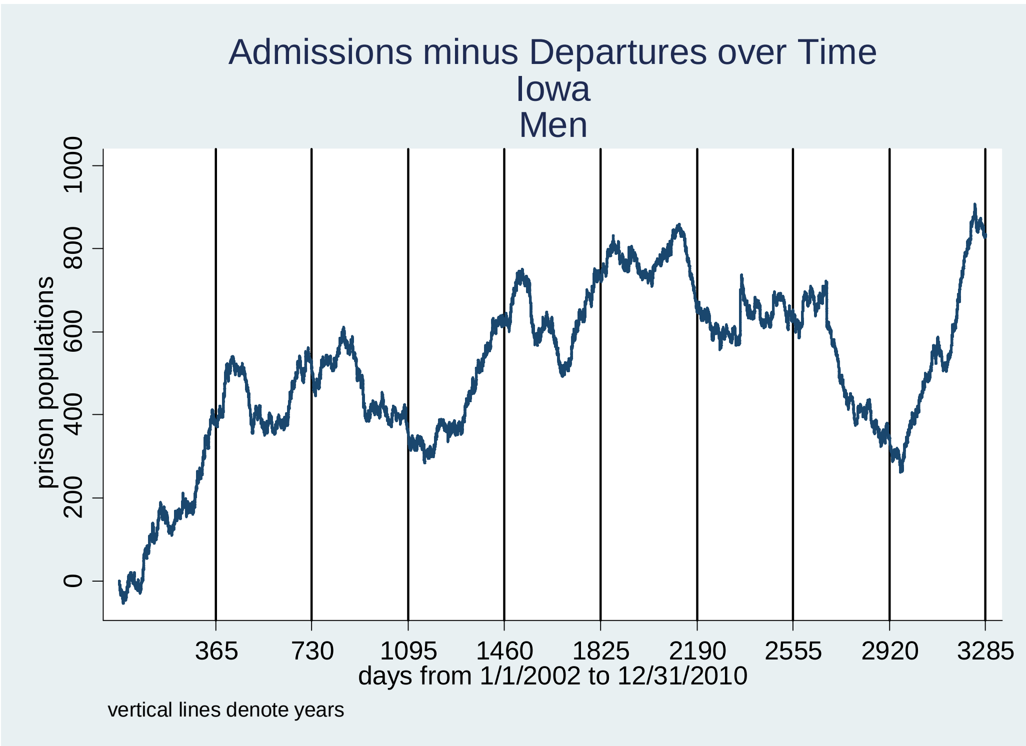


Figure 5



Tabulations based on History Records[8]

We derive history records by combining term records for the same offender. The history records provide the means to construct some unusual, informative tables and statistics. These tables/statistics are most informative when we have a lengthy observation period.

Distribution of Time Spent In Prison

One table of interest is the distribution of time spent in prison conditional on spending some time in prison. This seems like an interesting policy concern, and many researchers have used NCRP data to investigate the burden that prison places on subgroups of the general population. The burden would seem to be very different if many people spent a short time while few spent a long time than it would be if a few people spent a short time while many spent a long time.

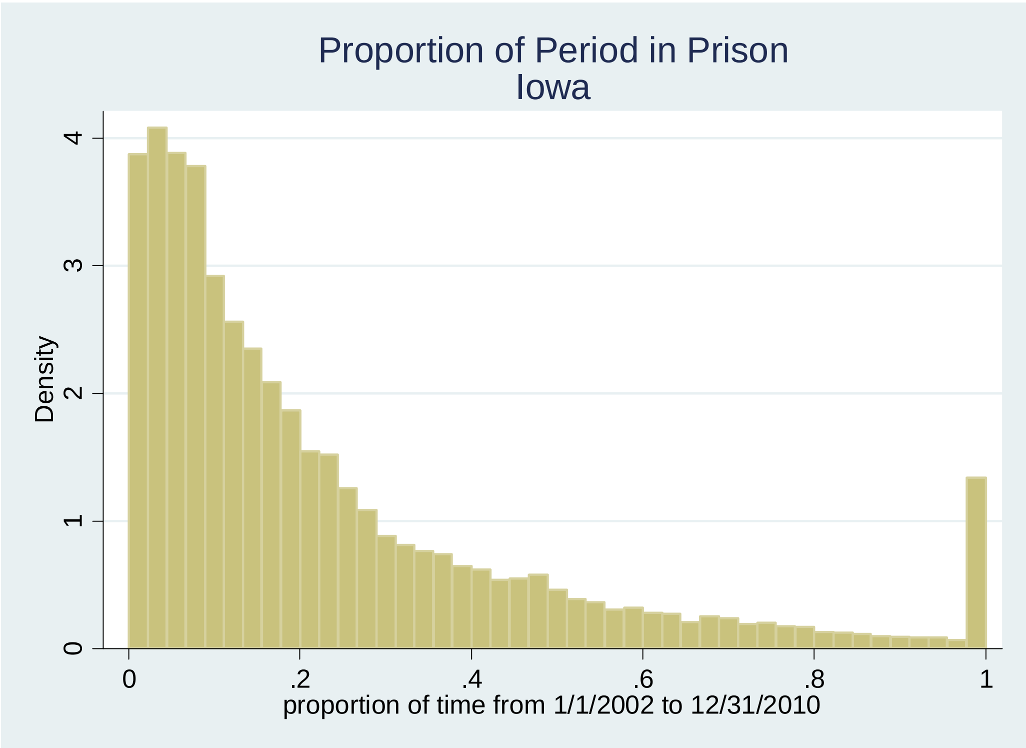
Although there are exceptions, most offenders will not enter prison before they are eighteen. Therefore, we limit the tabulation to offenders who were eighteen or older at the beginning of the observation period.

The first graph shows the distribution of time spent in Iowa prisons by all offenders who spent some time in Iowa prisons during the observation period. The figure shows that most offenders spend a small proportion of the period in prison while a few offenders spend a large proportion of the period in prison. A relatively small number spent the entire period in prison. The table below the figure makes the same point. According to the table, the average offender who spent any time in prison spent about one-quarter of the period in prison.

The previous version of the NCRP could not *readily* answer these questions because the previous version of the NCRP did not link term records over time for the same individual. In theory a researcher could have performed this linking, but that researcher would have confronted difficult reliability and validity issue. The new-NCRP solves those reliability and validity issues allowing researcher to do what they do best: answer research questions. Undoubtedly, researchers will find other ways to pose and answer the burden question.

8 The program tab2.do will perform this analysis.

Figure 6

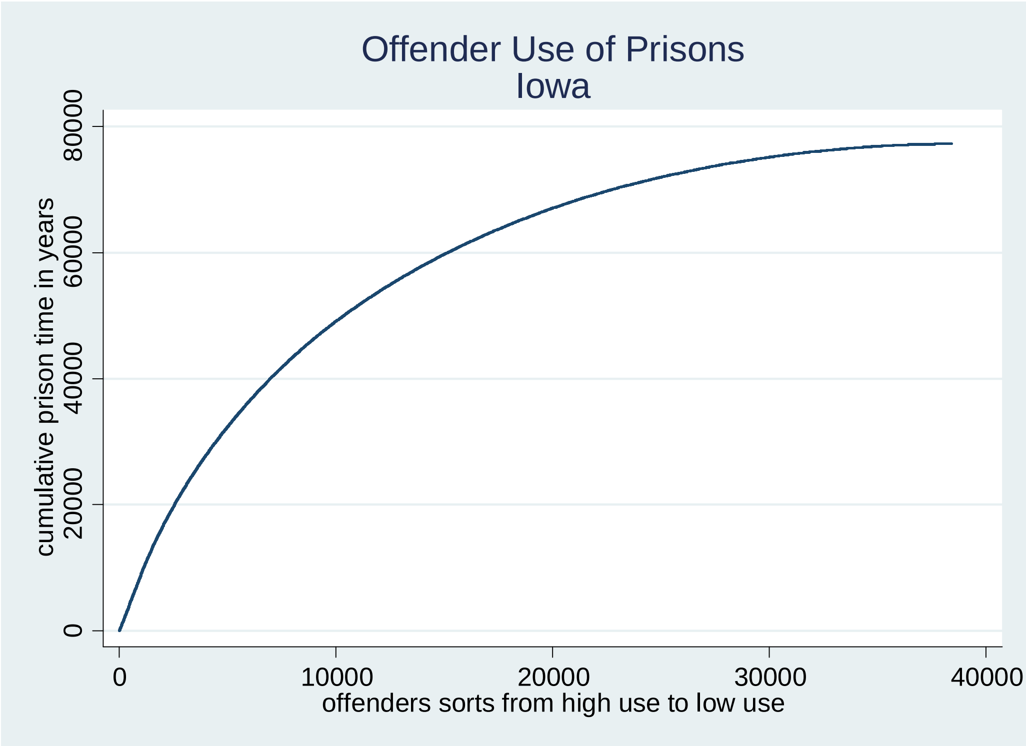


total_time

	Percentiles	Smallest		
1%	.0027389	.0003043		
5%	.0127815	.0003043		
10%	.026476	.0003043	Obs	33916
25%	.0629945	.0003043	Sum of Wgt.	33916
50%	.1466829		Mean	.2318666
		Largest	Std. Dev.	.2393428
75%	.3128863	1		
90%	.5781143	1	Variance	.057285
95%	.7884967	1	Skewness	1.62506
99%	1	1	Kurtosis	5.151247

A second figure and table tell a similar story. The figure represents the total demands on Iowa prisons, measured in prisoner-years. The data are sorted so that the high-use offenders appear first on the horizontal axis and the low-use offenders appear last. The table shows the proportional use attributable to offenders. Looking at high-use offenders, five percent of the offenders account for nearly twenty-one percent of prison time. Twenty five percent account for sixty-two percent of prison time. Looking at low-use offenders, fifty percent use somewhat more than fifteen percent of the prison space; twenty-five percent use less than four percent of the prison space.

Figure 7



temp3

	Percentiles	Smallest		
1%	.0448743	.0001166		
5%	.2077215	.0002331		
10%	.3510392	.0003497	Obs	38409
25%	.6223983	.0004662	Sum of Wgt.	38409
50%	.8552544		Mean	.7592452
		Largest	Std. Dev.	.2539065
75%	.9649356	.9999999		
90%	.9941513	1	Variance	.0644685
95%	.9985633	1	Skewness	-1.152889
99%	.9999368	1	Kurtosis	3.383115

We can also produce similar tabulations after stratifying by factors of interest. As an illustration, the following table is based on African-Americans. The patterns for African-Americans appear to be the same as the pattern for all Iowa prisoners. One might conclude that *conditional on ever serving prison time*, the burden of prisons is no greater for African-Americans than it is for whites. Of course this is not to argue that the burden of prison is not greater on African-Americans in general.

	Percentiles	Smallest		
1%	.0394822	.0004935		
5%	.1891025	.0009871		
10%	.3301724	.0014806	Obs	7997
25%	.606958	.0019741	Sum of Wgt.	7997
50%	.8501847		Mean	.7520151
		Largest	Std. Dev.	.2602225
75%	.9647852	.9999996		
90%	.9943734	.9999997	Variance	.0677158
95%	.9987492	.9999999	Skewness	-1.108828
99%	.9999515	1	Kurtosis	3.230171

Repeated Exits and Admissions into Prison

What is the pattern of repeated exits and admissions into prison?[9] This question is answerable using the history file. If the NCRP provided reliable admission and release codes, and if the NCRP provided more reliable C records, we could answer questions about recidivism while offenders were under community supervision. Unfortunately, the NCRP does not provide reliable admission codes, release codes, or C records. Nevertheless, in states where offenders are routinely released to community supervision, an analysis of recidivism is informative about outcomes while under supervision for short periods of time, so a study of recidivism is a proxy study for failure on community supervision.

This is similar to a traditional survival time problem. One problem is that that when we dealt with the A→B→B problem we sometimes imputed a pattern of A→B […] A→B where […] implies a period at liberty. We may eventually want to treat these imputations as special cases and exclude them from the analysis, but the current analysis makes no special provisions. The likely bias is that we would see more prison returns, and they would happen sooner, than happens in reality. However, deleting these imputed cases would introduce a bias in the opposite direction. This is a problem for future consideration.

There are limitations. The outcome measure is returning to prison, and in the NCRP prison use is reported differently across the states. For example, some states have integrated correctional systems, so returning to prison means jail or prison. In contrast, in other states NCRP excludes jails, so recidivism is defined literally as a return to prison. Furthermore, the time from when an offense occurred (marked by an arrest) and incarceration often has delays. Some delays are attributable to the pace of criminal justice administration, and some others are attributable to waits in jail for prison space to become available. Finally, in this analysis recidivism means returning to prison in the same state. Some offenders commit new crimes outside the state, but even when this happens, the revocation process often returns them to the state in the NCRP data.

Putting these limitations aside, the first figure shows the probability of returning to prison stratified by sex (male = 1 and female = 2). As Figure 8 shows, men are somewhat more likely to recidivate. The probability of eventual recidivism is near 0.5, but this probability slightly overstates the probability of recidivism.

Figure 9 shows the hazard function for returning to prison. The hazard declines over most of the follow-up period. This is a typical shape for a hazard representing recidivism, because the worse risks are identified early and returned to prison.

9 Tab3.do produces the figures.

Figure 8

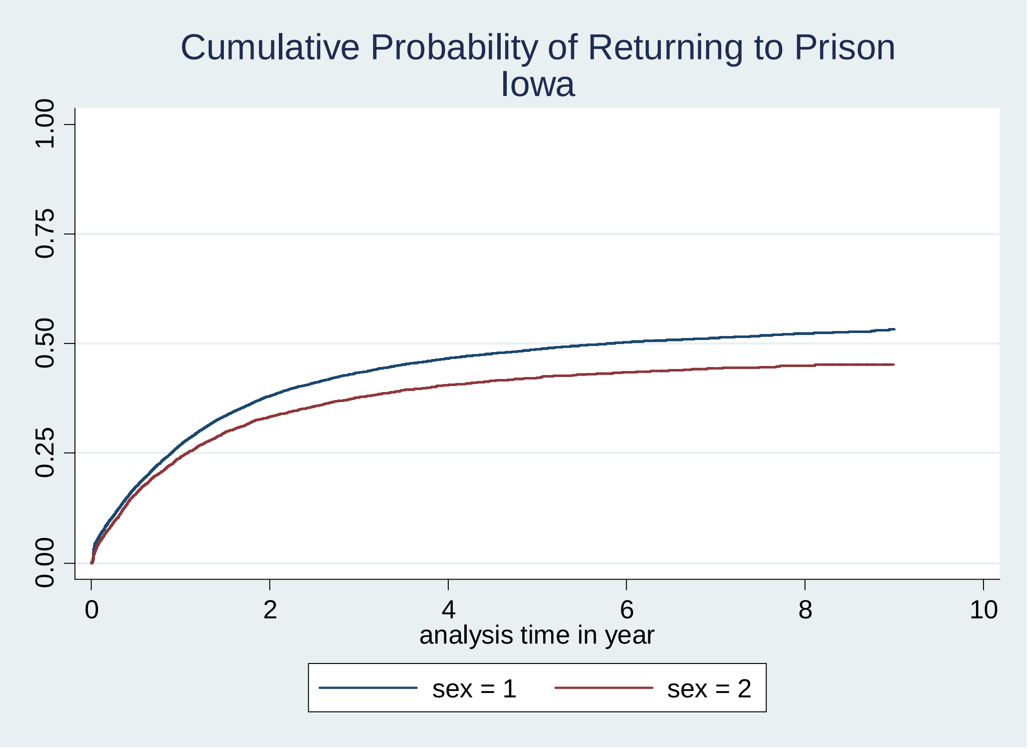


Figure 9

There appears to be an inconsistency among findings. A few offenders account for a large proportion of prison time, yet recidivism is high. Given that recidivism is likely, why do we not find that a large proportion of offenders spend a large proportion of time in prison?

There are several explanations, but one is that a small number of offenders enter the recidivism analysis multiple times. They inflate the recidivism statistics because they necessarily fail quickly. An alternative approach to the recidivism analysis would be to assign sampling weights so that an offender who appears three times in the recidivism analysis would receive a weight of 1/3 and an offender who appears once in the recidivism analysis would receive a weight of 1. We leave this to future development.

Changes in Recidivism

An interesting question is whether recidivism has increased or decreased over time. Given the introduction of evidence-based practices into community corrections, we would hope that recidivism has fallen, but this is an empirical question. To answer this question for Iowa, we estimated a Cox proportional hazard model. The explanatory variables are:

end_term	Basically this is the date when the offender ended his prison term and hence the date when he was first at risk of recidivism. However, to facilitate interpretation, we scaled this variable so that it was 0 at the earliest observed date (January 1, 2002) and 1 at the latest observed date (December 31, 2010). Hence this variable ranged from 0 to 1.
end_term_sq	This is the square of end_term. Adding the square to the model allows us to test for non-linear trends.
use_age	This is the offender's age in years. Age was recorded at the time that the offender exited from prison.
use_age_sq	This is the square of the offender's age.
black	This indicates that the offender was an African-American.
other_race	This indicates that the offender was a member of another minority group.
male	This indicates that the offender was male.

Results appear in the table. The relative hazard ratio is reported as Haz. Ratio. When the relative hazard is greater than 1, we infer that a variable is associated with increased recidivism. When the relative hazard is less than 1, we infer that a variable is associated with reduced recidivism.

Interpretation is straightforward for binary variables: African-Americans and members of other minority groups have higher recidivism rates. Men have recidivism rates that are higher than the recidivism rates for women. Interpretation is less straightforward for variables measured on a continuous scale and especially for variables that enter as powers (age-squared and end_term-squared).[10] Age does not seem to matter much according to a casual examination of the statistics, but in fact it is highly significant when we apply a joint test, and we conclude that recidivism always decreases with age.

For present purposes, the most important variables are end_term and end_term-squared because these indicate whether recidivism is increasing or decreasing over time. Some calculus shows that recidivism rates increase for the first 3.5 years and then decrease thereafter. On January 1, 2002 the relative hazard is fixed at 1. (This follows because end_term is 0 at the earliest date.) Near June 30, 2005 the hazard is estimated as 1.17. On December 31, 2010 it is estimated as 0.79. Recidivism rates are lower at the end of 2010 than they were at the beginning of 2002. Changes in recidivism rates are coincident with changes in admissions, which were identified earlier.

```
Cox regression -- Breslow method for ties

No. of subjects =        51206                    Number of obs   =     51206
No. of failures =        22253
Time at risk    =   147385.303
                                                  LR chi2(7)      =   1030.16
Log likelihood  =   -231305.03                    Prob > chi2     =    0.0000
```

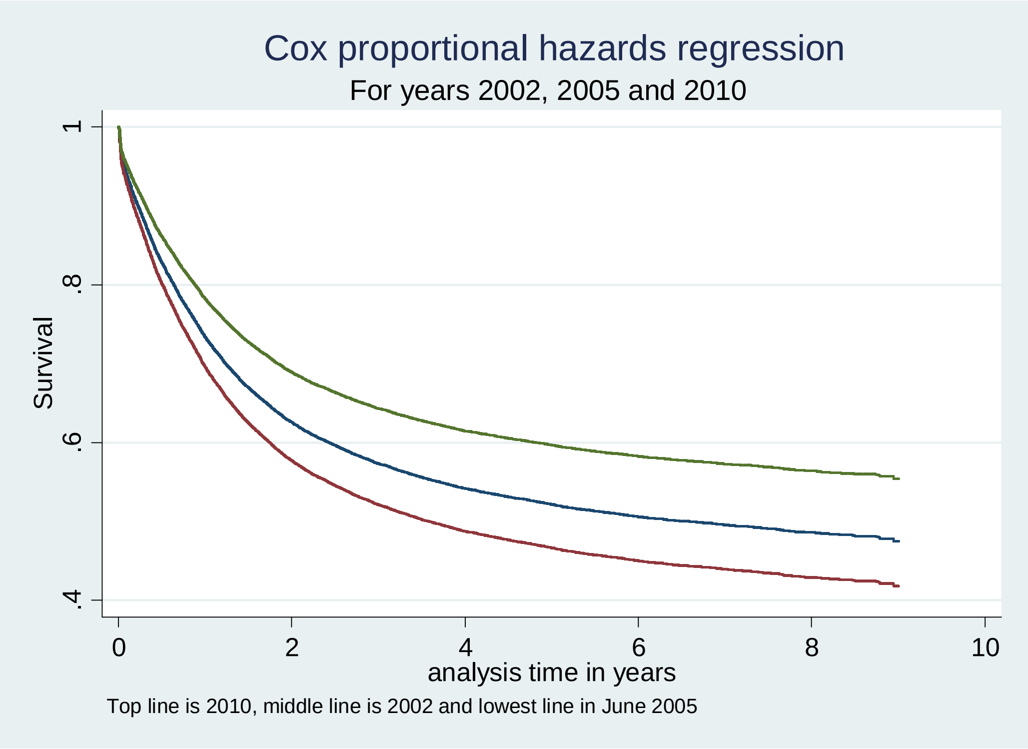
_t	Haz. Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
end_term	2.255544	.2273486	8.07	0.000	1.851203	2.748202
end_term_sq	.3516674	.0383207	-9.59	0.000	.2840389	.4353979
male	1.193361	.0255409	8.26	0.000	1.144338	1.244485
black	1.390883	.0212748	21.57	0.000	1.349804	1.433213
other_race	1.167705	.0519964	3.48	0.000	1.070115	1.274196
use_age	.998541	.0052891	-0.28	0.783	.9882281	1.008961
use_age_sq	.9998252	.000074	-2.36	0.018	.9996802	.9999701

We could perform a more refined analysis of recidivism, but the intention is demonstration of concept. The history file supports an analysis of criminal recidivism and, especially, provides a basis for inferring how recidivism rates have varied over time. The figure shows the estimated survival functions for offenders who began supervision in 2002 (the middle curve), June 2005 (the lowest curve) and 2010 (the highest curve). Survival is the cumulative probability of not returning to prison. The curve pertains to white men who are thirty-years-old. The figure has the advantage of graphically depicting the improvement in recidivism rates over time.[11]

[10] First, the Z-scores are not very useful. Statistical significance should be based on a joint test such as a likelihood ratio test or a Wald test. Second, when the parameters have different signs, one cannot tell how recidivism behaves over time without mathematical manipulation. The approach is to solve the derivative of the quadratic. If the solution falls outside the range of acceptable values, the changes are monotonic. Otherwise, the solution reflects a high point or low point.

[11] It is poor statistical practice to depict a survival curve for offenders entering supervision at the end of 2010. The entire curve is inferred because none of this follow-up period is observed. The figure is not well-labeled. We use it only to illustrate possibilities.

Figure 10



Projections

BJS has expressed interest is projecting future prison populations. Projections have three components. One component is to project the remaining time to be served by offenders who are in prison on December 1, 2010. This is doable, but not demonstrated here. A second component is to anticipate new arrivals. This is doable by inspecting a recent year or years to identify prisoners who have never before served prison terms.[12] The third part is to account for offenders who recidivate. That is where the survival analysis enters the picture.

Therefore it is possible to simulate future prison populations using the NCRP data. As is true of all simulations, one must assume that the near future is similar to the recent past.

Time Served

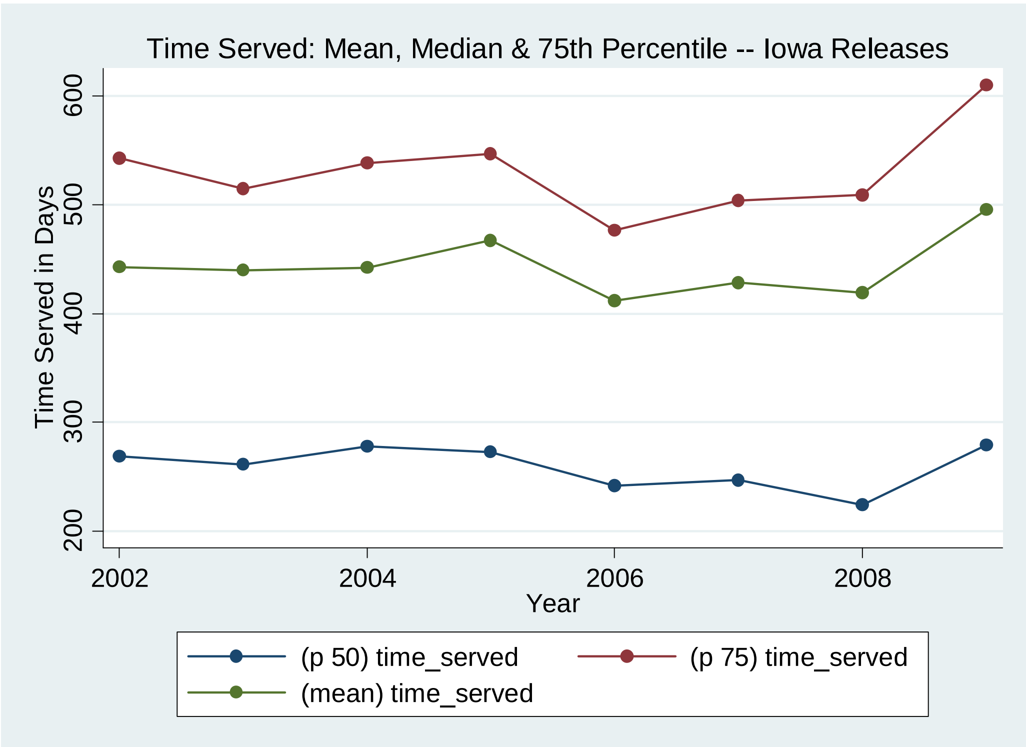
The term records can also be used to construct a picture of the amount of time an inmate serves in prison over the period of the time series. We depict this in two ways. We show time served in days for admission cohorts as well as release cohorts. For someone who has been released, we clearly know their length of stay as long as there is not an error in the admission and release dates. For

[12] According to the survival analysis, if an offender enters prison for the first time in 2009 or 2010, then that is likely to be his first prison term. We infer this from the survival curve. We can adjust this inference slightly to account for recidivism that occurs after a long period of quiescence.

admission cohorts, there will be a subsample of inmates in any given year who were not released at any time during the time series history. Of course, the longer the time series period and the earlier the admission in the time series, the less likely there will be an admission without a release. For this analysis, we have adopted a simplified imputation method for someone who has an admission and no release. This is explained in greater detail in the previous white paper, "Observations on the NCRP." The algorithm looks for an admission without a release. It checks to see if there are D records. If there is at least one, it takes the most recent D record date, December 31, XXXX (XXXX corresponds to the year the last D record was found) and adds a uniform random proportion of 365 days to that date. If there is no D record, it takes the admission date and adds a uniform random proportion of 30 days to the admission date. We will develop a more sophisticated method for this imputation, but for now we demonstrate how the imputed release dates can be used to construct time served over time.

In the first graph, we show the mean, median, and 75th percentile for inmates released from prisons in Iowa each year from 2002 until 2009.

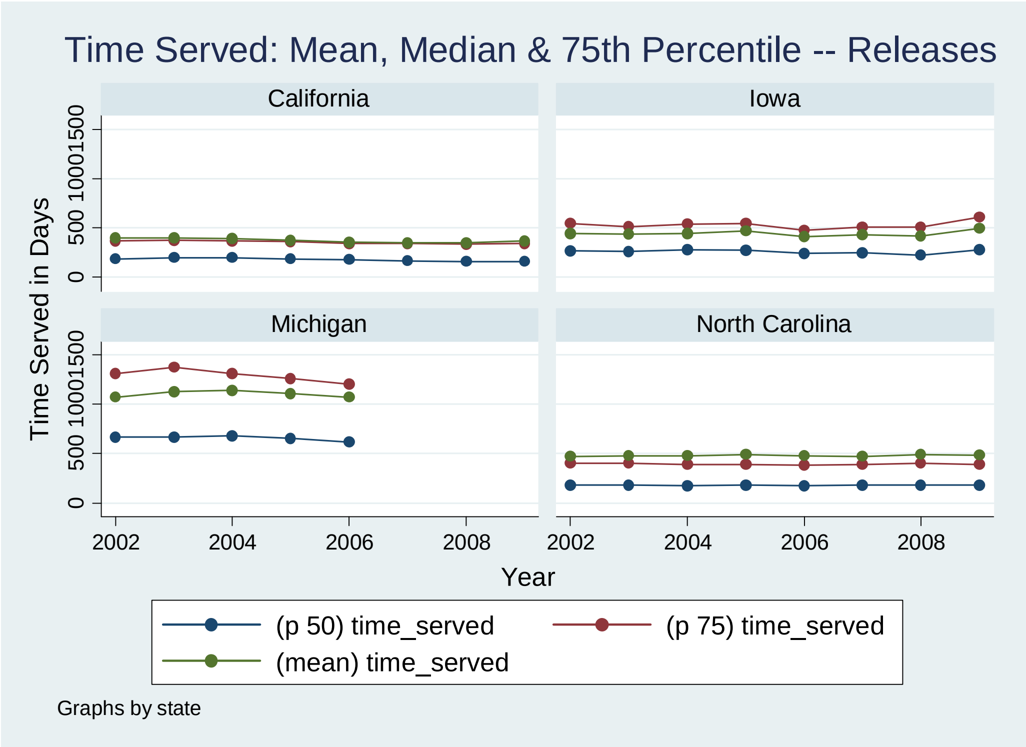
Figure 11



The mean time served over time tracks more closely to the 75th percentile than the 50th percentile which is what we would expect for a distribution of time served with right tail skewness. For inmates released from Iowa prisons, even those in the 75th percentile never exceed two years in prison. Release cohorts are notoriously unreliable for observing trends in time served, since they are composed of offenders who are admitted at many different points in time. In the next two sets of slides we show trends in time served contrasting admission and release cohorts as well as comparing

Iowa to several other states. The first graph compares time served over time for inmates released from California, Iowa, Michigan, and North Carolina.

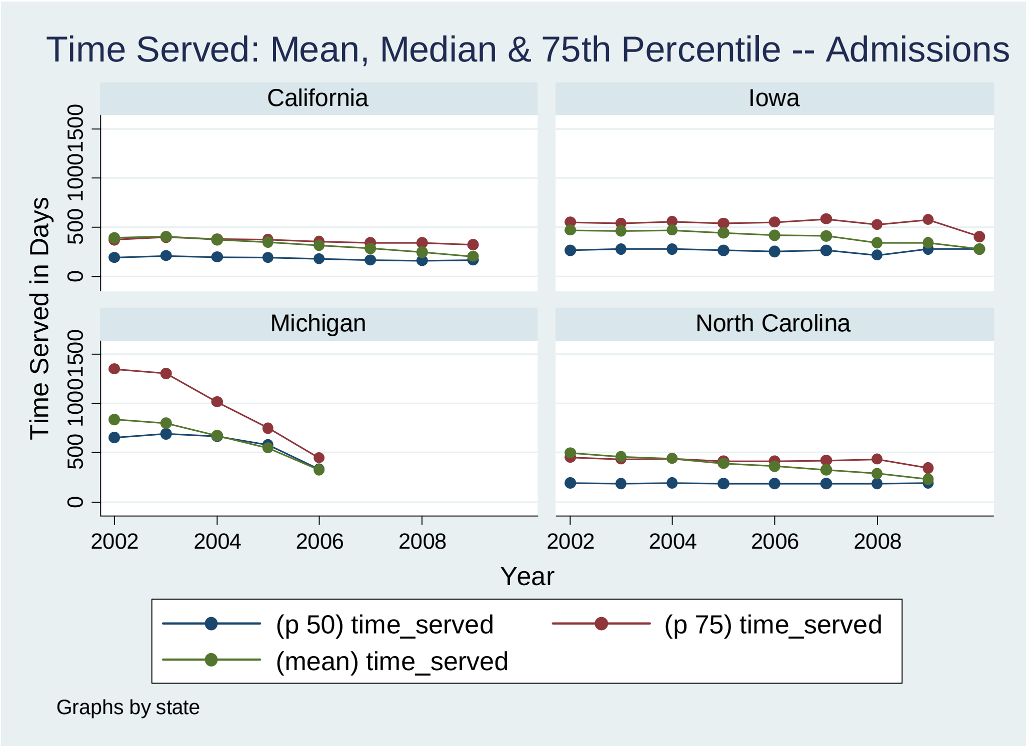
Figure 12



For the release cohorts, time served shows a considerable amount of stability except for Michigan.

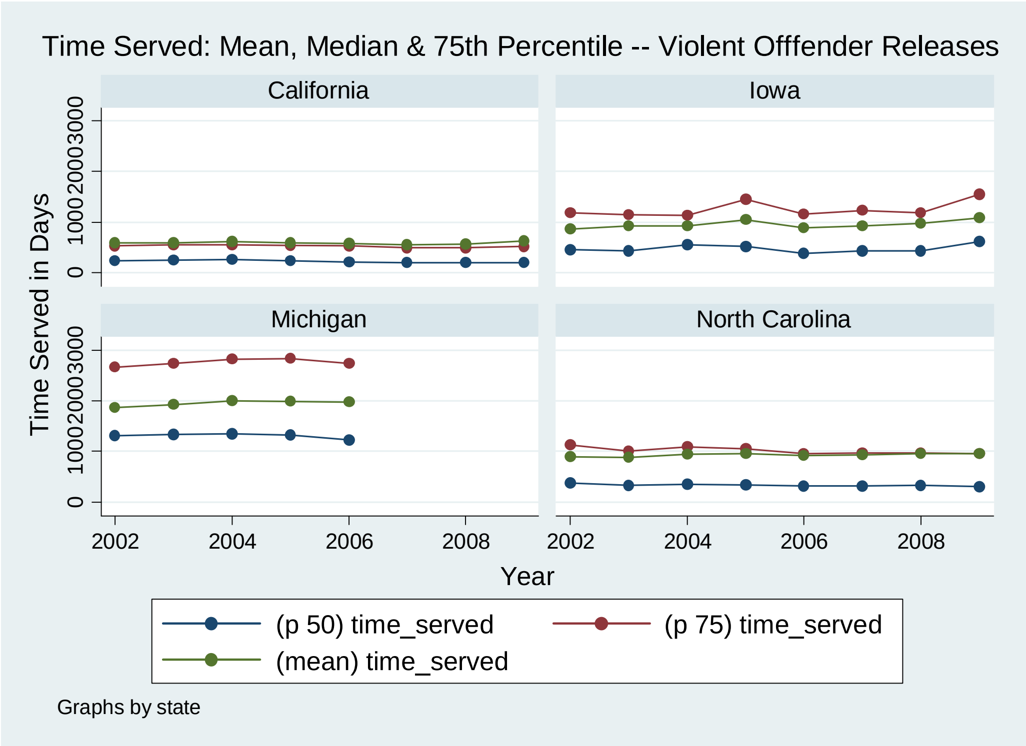
The next set of graphs for admissions cohorts shows a somewhat different picture. Mean time served declines for Michigan and less so for California, Iowa, and North Carolina, but this could be an artifact of our imputation for release dates. While the admission cohorts will be more accurate in depicting changes in time served over time, they will necessarily be sensitive to imputations for time served for prisoners who have not yet been released.

Figure 13



Since all of the graphs use the same Y-axis scale, it is clear that, on average, at least at the beginning of the period, Michigan had higher mean, median, and 75th percentile levels. However, we have to be cautious in comparing average time served across states. States have different policies on where they assign sentenced inmates with short sentences. A few states have a combined prison-jail system and report admission and release dates for everyone when they make their NCRP submission. Other states send inmates with a sentence of one year or less to local jails, and the submitting jurisdictions only provide data on prison inmates. However, this threshold varies from 3 months to 2½ years. Some time served comparisons may be less sensitive to these threshold issues such as those for offenders sentenced for a violent crime and less likely to serve that sentence in a local jail. In Figure 14, we show time served comparisons for inmates whose sentencing offense is violent (e.g. homicide, robbery, assault, kidnapping).

Figure 14



Among these four states, Michigan has higher median and average time served over time than the other three states. The average for Michigan is about 2,000 days (5.5 years) while for Iowa and North Carolina, it is about 1,000 days (2.75 years) and for California the average is about 500 days. But even these differences could be due to the composition of offense, criminal history, and types of admissions in each state. For example, in California, a high proportion of admissions are for parole revocations and these prison terms are typically shorter than those for new court admissions. We have argued (footnote 7) that the admission codes are unreliable, and even if they were accurate, they are ambiguous. Regardless of the type of admission, jurisdictions which house offenders for longer periods of incarceration will confront different issues than those who house offenders with shorter terms.

Comments

When put into the form of term and history files, the NCRP is able to answer many questions about corrections across the United States. This white paper identifies only a few of these questions and illustrates how the NCRP answers them using data from Iowa. There is nothing special about Iowa except that it has consistently reported A, B, and D records since 2001.

Not all states have submitted NCRP records with a sufficiently long time-series to support useful trend analysis. We are asking states to report retrospectively over a long period, so an increasing number of states will be providing useful data. Some states have failed to report for one or more years during an observation period, but we are hopeful of recovering those missing data. Otherwise, we will develop imputation routines for missing years so that the NCRP can support justifiable trend statistics.

Many of the tables presented here would be more informative if the statistics were stratified. As an example, anyone concerned with correctional health care would want to understand trends in the age composition of prisons. Making such adjustments is straightforward.

The tables presented in the white paper also suffer from cosmetic deficiencies. The intent is to revamp computing programs to provide publication quality tables and figures that adhere to BJS standards for titles, subtitles, and other formatting.

The tables and figures appearing in this white paper are illustrations of what the new NCRP can provide. Some illustrations are novel. The novelty is dictated sometimes by the limitations to BJS data (e.g., NCRP does not reliably distinguish between new admissions and revocations) and sometimes by the strengths of the BJS data (e.g., NCRP links admissions and releases for individual offenders over the observation period). For example, for the first time, NCRP is able to routinely report on offenders' cycling into and out of prison, providing a crude but reliable ongoing analysis of recidivism. As another example, the concept of the "burden of prison" is another novel but useful way to view correctional statistics.

Other tables and figures are more traditional. For example, we have reported flows (admission and exits) and stocks (prison population), which are minimal statistics expected of the NCRP. Even when the subject is traditional, however, the presentation has not been conventional. For example, we know of no other running tabulations of prison stocks, despite the fact that the running tabulations provide a very different view of stocks than do tabulations on prison populations on a standard date (December 31).

Building tables and figures is an act of imagination, and the illustrations in this white paper only begin to use that imagination. We anticipate that this white paper will stimulate conversation about other ways of looking at NCRP data that exploit the term file structure. We consider this white paper to be a dynamic draft in the sense that as Abt Associates and BJS refine their ideas about reporting shells, those refinements will be built into updated versions of this white paper.

Finally, this white paper has not addressed a subject that interests BJS: developing a national roll-up of correctional statistics. The view at Abt Associates is that the national roll-up requires reliable state-level statistics augmented with imputations to account for states that do not report. Consequently, we have placed our priority on first getting the state-level statistics correct, but we have not lost sight of the goal of deriving a national roll-up.