THREE STRIKES AND YOU'RE OUT: DEMOGRAPHIC ANALYSIS OF MANDATORY PRISON SENTENCING*

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Much of the debate about the costs and benefits of "three-strikes" laws for repeat felony offenders is implicitly demographic, relying on unexamined assumptions about prison population dynamics. However, even state-of-the-art analysis has omitted important demographic details. We construct a multistate life-table model of population flows to and from prisons, incorporating age-specific transition rates estimated from administrative data from Florida. We use the multistate life-table model to investigate patterns of prison population growth and aging under many variants of three-strikes laws. Our analysis allows us to quantify these demographic changes and suggests that the aging of prison populations under three-strikes policies will significantly undermine their long-run effectiveness.

Many U.S. states have recently adopted new prison sentencing rules for repeat felony offenders. Other states are considering such policies. Popularly known as "Three Strikes and You're Out" (3X), these new rules mandate long sentences without parole for those convicted of a third or higher-order felony.

Proponents of 3X argue that its crime-reducing benefits will offset the costs of housing additional prisoners. Critics argue that the potential benefits are small, and that 3X proponents seriously underestimate the policy's costs. Much of this debate is implicitly demographic. Arguments on both sides rely on unexamined assumptions about prison population dynamics and about age-specific patterns of crime and punishment. The costs of implementing 3X rules depend on how they change the size and age structure of state prison populations. Benefits depend largely on the number of crimes prevented through incapacitation, but rates of criminal activity vary greatly by age. Careful demographic analysis can therefore add useful information to current policy debates over the value of 3X laws.

Criminologists have investigated relationships between sentencing policies and prison population growth (Bales and Dees 1992; Blumstein, Cohen, and Miller 1981; Greenwood et al. 1994; Joyce 1992; Langan 1991; Petersilia and Greenwood 1978). Even studies with detailed demographic analysis (e.g., Blumstein et al. 1981), however, have emphasized demographic changes among those at risk of entering prison and their consequences for growth in the total number of prisoners. Many of the relevant questions about 3X policies, in contrast, are about demographic change within the prison population itself. Such questions have received less attention.

In the analysis of 3X policies, even state-of-the-art research has kept the demography extremely simple. For example, Greenwood et al. (1994) analyze California's sentencing policies in an ageless population.[1]

We take a more explicitly demographic approach to investigating 3X laws. We construct a multistate life-table model for prison admissions, releases, and readmissions, with single-year age-specific rates. We derive a different set of transition hazards for each alternative sentencing policy and then analyze policy alternatives by (1) comparing their long-run steady states and (2) comparing the transition paths between current policy and the steady state for the proposed alternative. Baseline transition rates are from recent administrative records from Florida. Because Florida's rates do not differ greatly from those of other states, our simulation results are also applicable to other prison systems.

Our principal goal is to increase the stock of available information on the costs and benefits of mandatory sentencing laws. In doing so, we also hope to illustrate the relevance of demographic methods and models to areas outside of the field's traditional ken.

Our principal finding is that 3X policies are poorly designed from a demographic point of view. Cost-effective policies should selectively incarcerate small numbers of very high-risk criminals. Our simulations show that, given the prevailing age patterns of crime and prison admission, 3X is likely to do the opposite. In the long run, 3X will cause large increases in prison populations, primarily by adding large numbers of inmates who are unlikely to commit future offenses—namely, *old* inmates.

DEMOGRAPHIC MODELING OF PRISON POPULATION DYNAMICS

Demographers bring considerable intuition to the problem of mandatory sentencing and prison population change. From stable-population theory, for example, we know that if there is a constant number B of births year after year, a closed population, and an unchanging age-specific mortality sched-

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1. Greenwood et al. (1994) include desistance behavior in their model, and this serves as a crude approximation of age effects. They assume that each year the hazard of future criminal activity falls to zero for a fixed proportion (typically 10%) of current criminals. In their model, both criminals who are incarcerated and those who are on the street may desist in this manner.

ule, then in the long run the population becomes constant at size Be_0, where e_0 equals life expectancy at birth. An increase in the life expectancy of each individual would therefore (in the long run, with everything else held constant) lead to an exactly proportional rise in the size of the population alive at any one moment.

The same logic applies to prison populations. Incarceration is a kind of birth (i.e., an entry into the population of prisoners), release from prison is a kind of death (an exit from the population), and the average completed sentence is a kind of life expectancy (mean time between entry and exit). Suppose, for example, that prison admissions stayed constant over time, but that a new policy increased the length of all completed sentences by 50%. The analogy with stable population suggests how to translate from the policy to its demographic result: A 50% longer sentence for each individual prisoner should mean that, in the long run, prisons will have to house 50% more inmates on any given day.

Stable-population theory provides some insight into prison population dynamics, but it is incomplete. The incarceration-equals-birth and release-equals-death analogies, although informative, are imprecise. Notably, people cannot be reborn after they die, but they can reenter prison after being released. Such returns are the main reason for 3X rules. Therefore, if we are to understand 3X's demographic implications fully, we need a better analytical model.

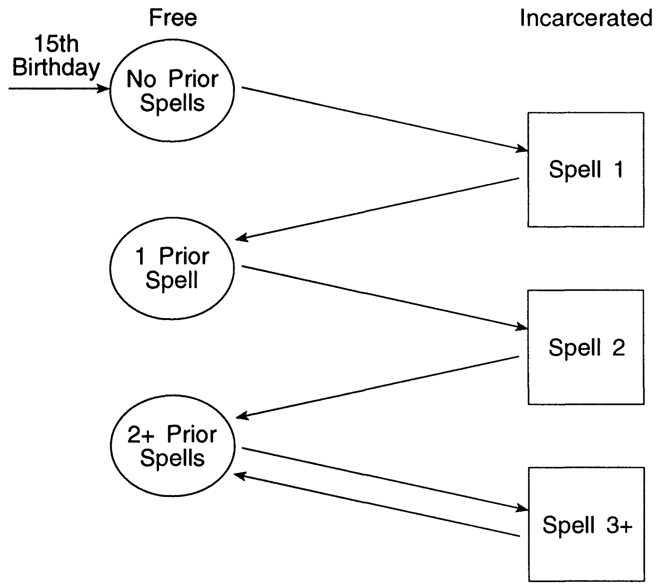
A Multistate Life-Table Model

Migration provides a better analogy to the process of prison admissions, releases, and readmissions. Like the populations of neighboring regions, prison and nonprison populations coexist and exchange members. Over a lifetime, an individual may move back and forth between these populations any number of times, and the intensity of movements at various ages can be summarized in a multistate life table (see Keyfitz 1985: chap. 12; Rogers 1975; or Schoen 1988). The multistate life-table model fits our problem well, and we use it as a general framework for analyzing transitions in and out of prison under different sentencing rules.

Figure 1 presents a highly simplified version of the multistate life-table model we propose. Our main strategy is a three-way disaggregation of both the prison and nonprison populations into (1) those who have never completed a spell in state prison, (2) those with exactly one completed spell, and (3) those with two or more completed spells. This disaggregation is useful because it creates more homogeneous subpopulations (thus making the first-order Markov assumption that is built into the multistate life-table model more plausible), and because it allows us to count the third- and higher-order "strikes" (i.e., entries into prison) that are the focus of 3X laws.

Arrows in Figure 1 indicate the possible transitions between states. We use α, β, and μ to denote hazards of prison entry, prison exit, and death, respectively. The majority of the population never goes to prison, and remains in the upper left circle from age 15 until death. Of those who enter prison (top right square), most are eventually released back

FIGURE 1. A SIMPLIFIED MULTISTATE LIFE-TABLE MODEL



into the nonprison population (middle left circle). Some of those released return for a second spell in prison (middle right square), whereas others do not. By construction, our model is a one-way ladder downward: Once an individual enters prison he cannot return to his initial state. Each strike moves an individual down the ladder by one rung.

Figure 1 omits some important details. In the full model, both prison readmission rates and 3X release rates vary with age *and* with duration in the current state. We effect duration dependence by defining separate states for those entering a given category (e.g., released with one prior spell, or in prison on a third strike conviction) at distinct ages.[2] For example, there are distinct states for "free with one prior spell, age 28, last released at age 28" and "free with one prior spell, age 28, released at age 27." These two states have different hazards for reentry to Spell 2 (0.245 and 0.118, respectively). Similarly, those in prison on 3X convictions are tracked not only by their current age but also by the age at which they entered spell 3+.

The full model effectively has 187 states, not including death. These states are as follows:

1	Free, never been in prison.
2	In prison, Spell 1.
3...63	Free, been in prison once, last reentered free population at age 15...74,75+.

2. For our study (in which we will calculate only the numbers in various states at different ages, rather than the full multistate life table), the version of duration dependence we set out is satisfactory. However, Wolf (1988) provides a elegant alternative for duration dependence that is computationally far more efficient for the full life-table model. We were not aware of his paper until the end of the editorial process, and we thank the editor for calling it to our attention.

64 In prison, Spell 2.
65…125 Free, been in prison twice, last reentered free population at age 15…74,75+.
126 In prison Spell 3+, not subject to 3X rules.
127…187 In prison Spell 3+, subject to 3X rules, entered Spell 3+ at age 15…74,75+.

Most transitions in this model are impossible, as illustrated in the simplified version in Figure 1. For example, the only possible transition (other than death) from State 1 is to State 2. For 15-year-olds, the only possible transition from State 2 is to State 3 (or to State 4 for 16-year-olds, to State 5 for 17-year-olds, etc.). The only possible transitions from States 3…63 are to State 64, and so on.

Data

We obtained data for this study from administrative records of the Florida Department of Corrections, which maintains individual-level computer files of all prison admissions and releases in each fiscal year, and status files that provide mid-year snapshots of the state prison population. Both types of files allow unique identification of individual inmates, a feature that allows us to pool data for several years in order to estimate directly the reentry hazards that are critical to the 3X debate.

Throughout our calculations we disaggregate individuals by a, single year of age; $I = 1$ for those currently incarcerated, and $= 0$ otherwise; $X = 1$ for prisoners sentenced under 3X laws, and $= 0$ otherwise; P, the number of previous prison spells for serious felonies[3] [$P = 0$, 1, or 2+]; and a_e, the age at which an individual entered his or her current state. We use administrative records for the years 1990–1993 and our model of 3X laws, to calculate the following hazard rates:

$\alpha(a,a_e,P)$ = the prison admission rate for a-year-olds who entered their current state (either released or never-incarcerated) at age a_e, and who have P prior spells in prison. If $P = 0$ (no prior spells in prison), then a_e is irrelevant, and is simply the prison admission rate for the general population at age a.

$\beta(a,a_e,P,X)$ = the prison release rate for a-year-olds who entered prison at age a_e, and who have P prior admissions. If $X = 1$, then 3X laws apply, and the prisoner is released if and only if $a - a_e$ exceeds the mandatory minimum sentence; otherwise a_e is irrelevant, and we simply use the observed release rates for a-year-olds.

$\mu(a,I)$ = the mortality rate for a-year-old males in the Florida general population (if $I = 0$) or in Florida prisons (if $I = 1$).

Transforming the rich set of administrative data into α's, β's, and μ's is a complex process. In the interest of brevity, we omit details here and refer interested readers to Schmertmann, Amankwaa, and Long (1995). The short version of the process is as follows. Estimation of release and mortality hazards β and μ from available data involve only straightforward calculation of events and exposure. For age-specific prison entry and reentry rates, however, we have good information on the number of events, but no exact data on populations at risk. We solve this problem either by estimating the populations at risk (in the case of first entries), or by using the individual-level identifiers in several years of admission and release data to calculate age-specific rates for a small subset of people on whom we have accurate information (in the case of prison reentries).

Release Rates (β). Figure 2 illustrates the calculated hazard rates for release at ages 15 through 75+, represented as points. Each panel also contains a smoothed rate schedule, indicated by a line. We will use these smoothed schedules in the projections below.[4] Several features of these graphs merit attention. First, age-specific release rates are high. For example, consider a rate of 0.5, which is fairly typical of Figure 2. At this rate, approximately 39% of those imprisoned at the start of any given year will have been released by the end of that year. Equivalently, a release hazard of 0.5 implies that the mean length of a spell in prison is two years. High release rates indicate that prison populations have high turnover, especially when compared with the state or national populations with which demographers often work. Like any small, open population, prison populations are demographically very active.

Age-specific release rates tend to decline with the number of prior spells in prison. Those in prison for the first time are, generally speaking, the most likely to be released at any given age, followed by those in for the second time; the least likely to be released are those in prison for the third+ time. Thus, there is some evidence that Florida's sentencing and release policies already penalize multiple offenders, albeit weakly.

Finally, release rates tend to decline with age. This decline may occur for several reasons, the most notable of which is population heterogeneity. Older prisoners have usually been in prison longer than younger prisoners, as most admissions occur at young ages. If longer spells in prison are associated with more serious crimes or with worse behavior while in prison, then one would expect older prisoners to be the least likely to be released. The data in Figure 2 are consistent with this heterogeneity argument.

Entry rates (α). Figure 3 illustrates the calculated hazards for first entry. Points represent calculated rates at single years of age, and the line is a smoothing spline approximation to the rate schedule. All rates are below 1%, indicating that relatively few Floridians ever enter prison.

Another notable feature of Figure 3 is large age differences in first admission rates. Rates rise sharply over ages

3. Serious felonies are murder, manslaughter, sexual offenses, robbery, violent personal offenses, burglary, theft, forgery, fraud, drug offenses, weapons offenses, escape, and several automobile-related offenses, such as DUI and hit-and-run.

4. Schoen (1988:96) advises smoothing when using single-year age-specific rates in multistate life-table applications. We smooth the rate schedules for mortality and release rates with loess and locally linear fits (Cleveland 1979). We smooth the entry and reentry rate schedules with regression splines (Hastie and Tibshirani 1990: chap. 2). Simulation results are insensitive to the choice of smoothing techniques. Using smoothed rates, rather than the single-year rates calculated from the raw data, makes virtually no difference in any of our qualitative or quantitative findings. It does, however, make the projection results less noisy and hence slightly easier to interpret.

FIGURE 2. FLORIDA PRISON RELEASE RATES BY AGE, 1990–1993

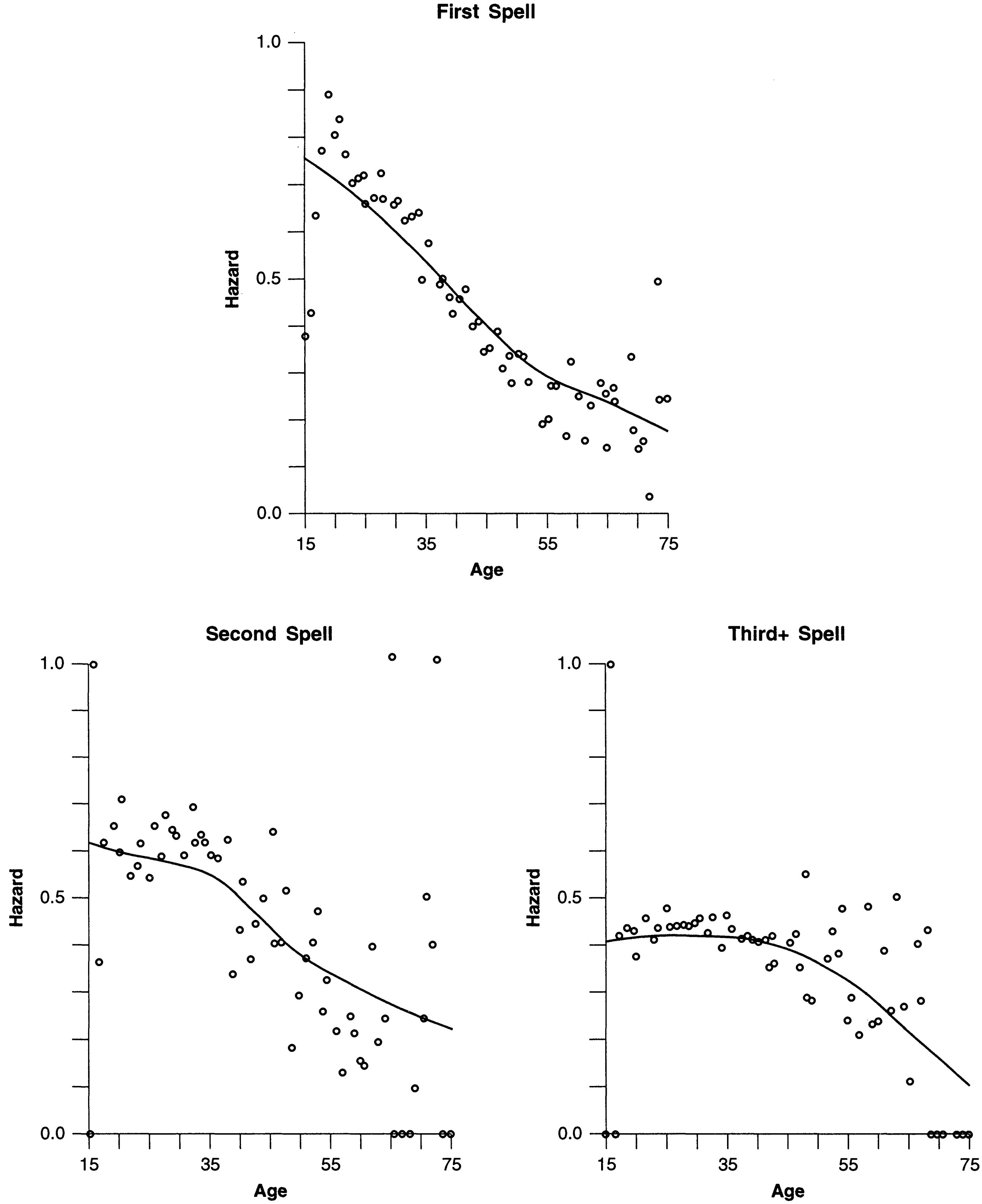
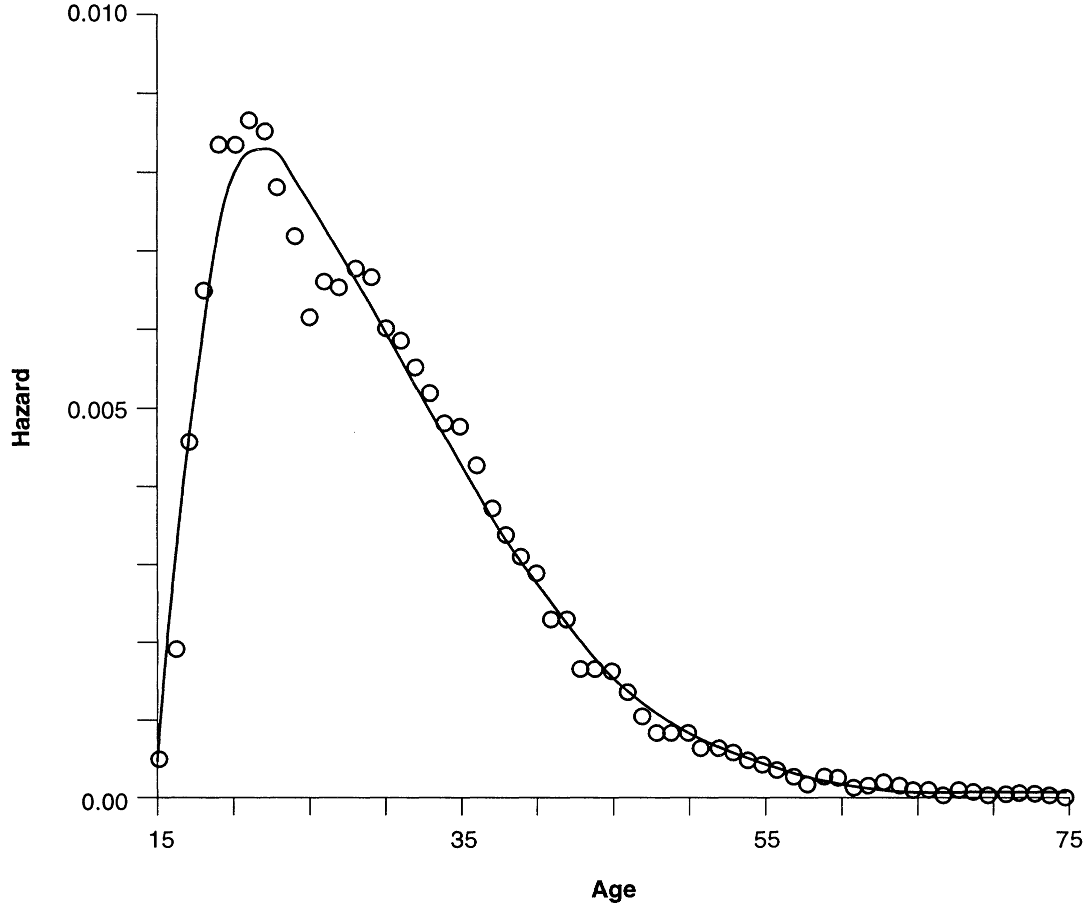


FIGURE 3. AGE-SPECIFIC ENTRY RATES FOR THOSE WITH NO PRIOR SPELLS IN PRISON



15–20 (in the 15–17 range, only a fraction of offenders are tried as adults), peak at ages 20–25, and then fall steadily to near zero at ages 60+. Although the data in Figure 3 are for first admissions only, they also reflect the general age pattern for all admissions. In short, Florida's prison admissions are highly concentrated among the state's youngest adults. There are relatively few admissions at ages 40+, and virtually none at ages 60+.

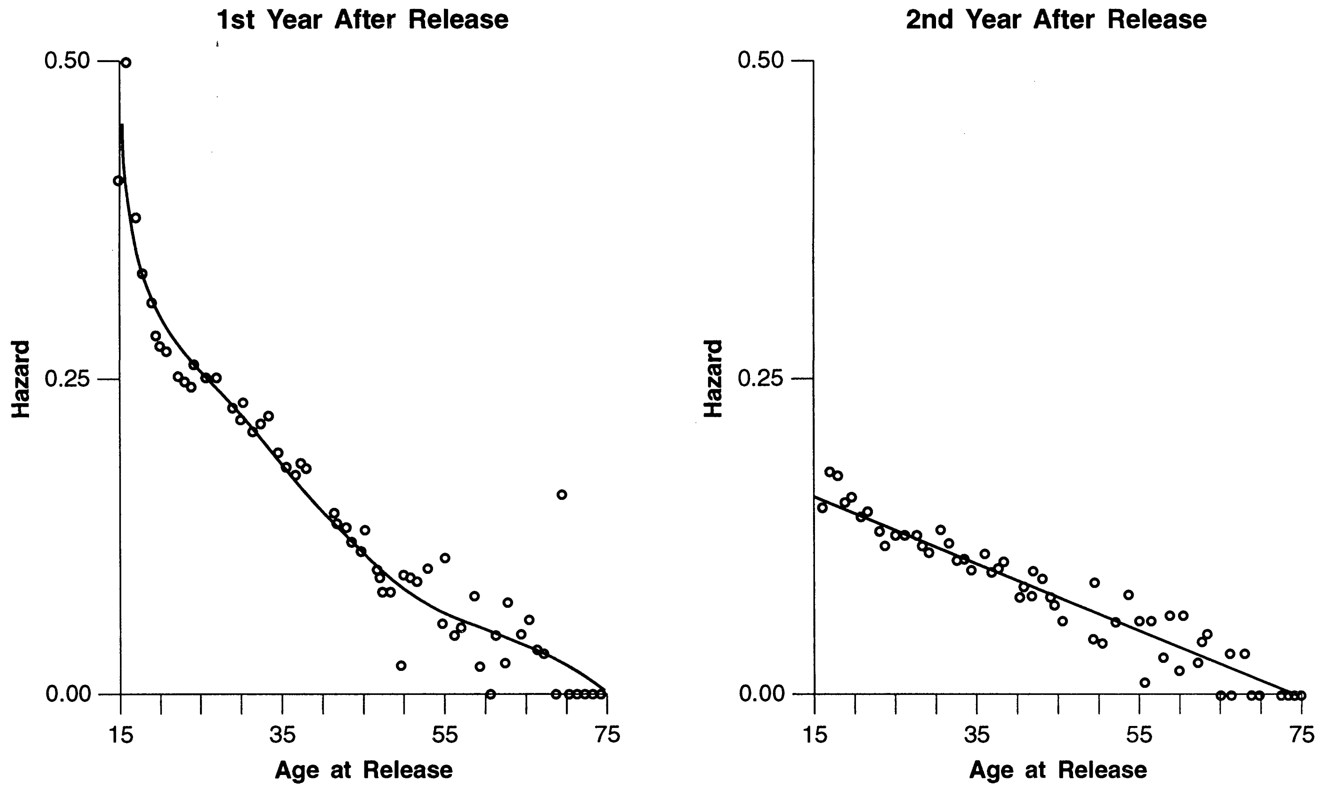
Crimes and first prison admissions are not synonymous, of course, but the age pattern seen for prison admissions in Figure 3 is consistent with the age patterns for offense rates found in virtually all previous research on this topic (e.g., Blumstein et al. 1986: vol. 1; Hirschi and Gottfredson 1983; Nagin and Land 1993). There is debate among criminologists and other social scientists about how the criminal behavior of individuals varies by age and about the analytical relationship between individual behavior and the single-peaked age pattern seen in aggregate crime-rate data (Land, McCall, and Nagin 1996; Nagin and Land 1993). There is little contention, however, about the general shape of the aggregate crimes-by-age schedule, which invariably looks like the schedule for first prison entries in Figure 3.

Figure 4 contains the calculated age-specific prison reentry hazards for the first and second years after release and the corresponding smoothed rate schedules.[5] These rates are constructed from data on prisoners released in the last several years and therefore reflect Florida's current arrest, conviction, and sentencing policies.

Figure 4 illustrates several interesting points, some of which are critical to understanding the consequences of 3X. First, and most important for 3X, reentry hazard rates are very high. This is especially true compared with the rates for first entry illustrated in Figure 4, none of which exceeded 0.01. A typical-looking reentry rate of 0.25 for the first year after release at ages 20–25, for example, indicates that 22% return to prison within 12 months. Second, reentry hazards decline monotonically with age at release. Older prisoners,

5. When interpreting reentry data, remember that returns to prison may be caused either by new crimes and convictions, or by parole violations. This complicates comparison of re-arrest and reentry rates.

FIGURE 4. FLORIDA PRISON REENTRY RATES, BY AGE, FOR THE FIRST AND SECOND YEARS AFTER RELEASE: 1990–1993



when released, are far less likely than their younger counterparts to return to prison at a later time. Third, age-specific reentry rates decline sharply from the first to the second year after release. Apparently there is considerable heterogeneity in propensity to return to prison, with those most prone to return doing so quickly, leaving behind a group that is far more resistant to reentry.

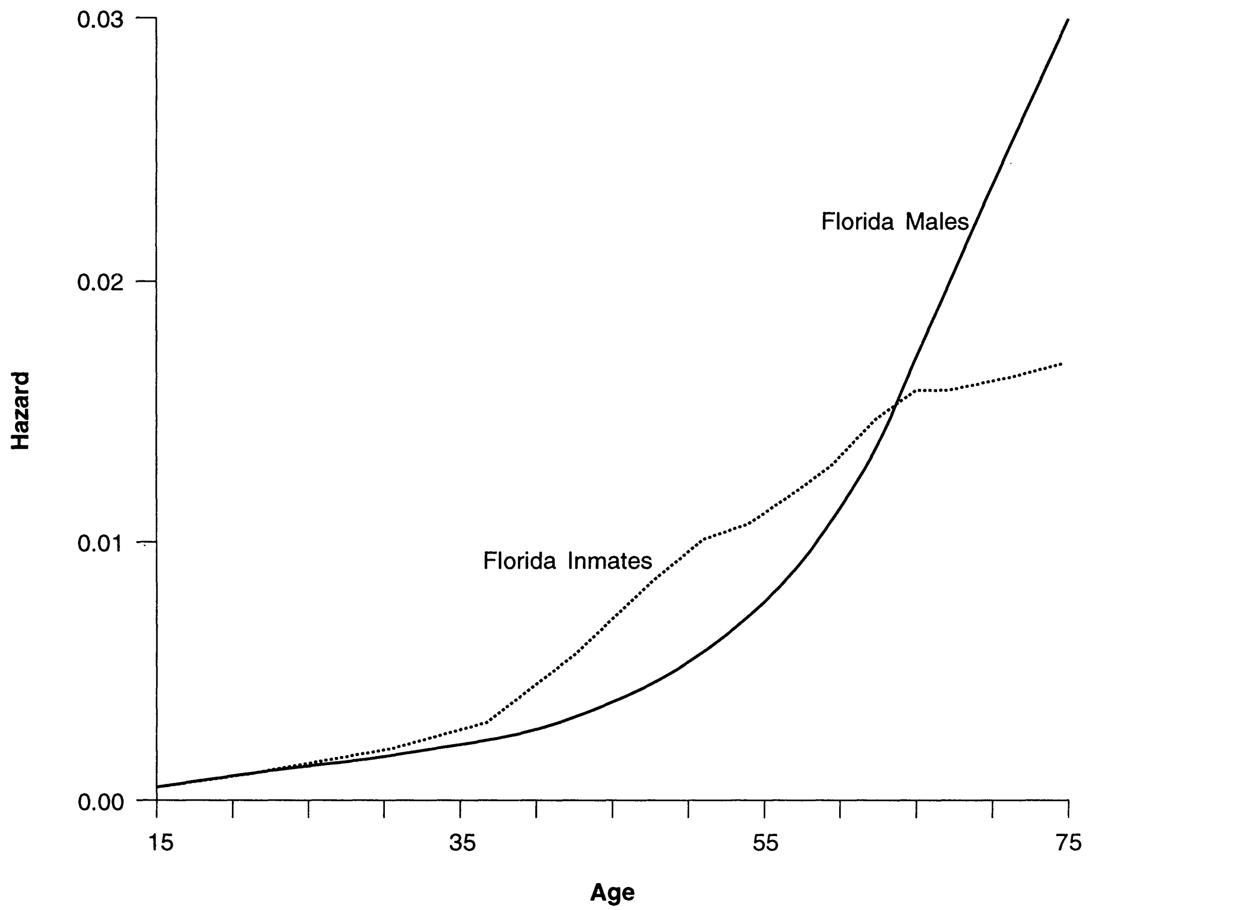
As with the data on first entries, the data on prison reentry for Florida are broadly consistent with existing results in the criminology literature. Many U.S. and Canadian studies have found a negative association between age and recidivism rates (Gendreau, Little, and Coggin 1996). The decline in reentry rates between the first and second year after release also matches known patterns. For example, Greenwood et al. (1994) indicate that 39.3% of prisoners released in California are expected to be re-arrested within one year, and 54.5% within two years. The corresponding hazard rates for re-arrest are 0.50 and 0.29, respectively. Re-arrest rates are not directly comparable with the data in Figure 4, as only a fraction of arrests lead to reincarceration, but they make the Florida data look sensible: A comparison with re-arrest rates in the first year and second year after release makes the sharp drop between first- and second-year reentry rates appear to be a real, and important, feature of the process of prison inflows and outflows.[6]

Mortality Rates (μ). For the nonprison population, we use published life-table data for the U.S. male population (National Center for Health Statistics 1994). For the prison population, we divide age-specific counts of prison deaths by the corresponding midyear prison populations. We then smooth the results into an age-specific mortality schedule for those in jail: $\mu(a,j = 1)$. The results are illustrated in Figure 5.[7]

6. Greenwood et al. (1994) report re-arrest hazards for the first, second, and third years after release of 0.50, 0.29, and 0.19, respectively. We note a similar pattern in Florida reentry rates, with second-year reentry rates close to 50% of first-year rates at all ages. In the absence of detailed data on Florida reentry rates for the third and higher years, we extrapolate reentry rates using this pattern—the estimated third-year rate equals half of the observed second-year rate, fourth-year rate equals half of the third-year rate, etc.—until the estimated reentry rate reached the first-entry rate for the general population, when we assumed that the reentry rate was equal to the first entry rate.

7. For ages 75–120, we estimate mortality using the single-year age-specific $q(x)$ values from the Social Security Administration's period life-table for the year 2000 (Bell, Wade, and Goss 1992). We also assume that prison admission rates are 0 for those 75+ and that release rates for those aged 75+ are identical to release rates for those aged 74. Realistic variations

FIGURE 5. AGE-SPECIFIC MORTALITY RATES FOR FLORIDA MALES AND PRISON INMATES



The primary feature of note in Figure 5 is the crossover of the mortality schedules. Prison death rates are significantly higher than those for the general population at middle adult ages, but lower at ages 65+. We are skeptical about this crossover. Prison mortality rates are estimated from a small number of cases in the highest age groups, so the crossover may simply be the result of noisy data. Alternatively, the low old-age mortality among prisoners may be real, due to selective policies that favor the release of older inmates who are frail or in failing health.[8] Given our uncertainty about prison mortality rates at high ages, we adopt an assumption designed to bias our projection results against finding large effects for 3X: At every age, we assume the prison mortality rate for our projections to be the higher of the two curves, so that prison mortality rates always exceed or equal the rates for the male population of Florida as a whole.

SIMULATION RESULTS

Stationary Population Under Current Rates

Our model disaggregates the population by age and state (e.g., never in prison, in first prison spell). As in any multistate life table model, populations are vectors. We use a column vector,

$$N(a,t) = [N_1(a,t)...N_S(a,t)]',$$

to denote the population at age a and time t, disaggregated into subpopulations in states $1,2,\ldots,S$.[9]

in assumed rates for 75- to 120-year-olds have only trivial effects on simulation outcomes.

8. We thank an anonymous reviewer for pointing out this possibility.

9. In our model, $S = 187$, as described earlier. In our simulations, we calculate only the numbers of people alive in each state at each age in the stationary population. This is equivalent to calculating only the l_x column of a standard life table. Full multistate life tables, like their single-state counterparts, include many other interesting indices of state-specific survivorship (e.g., L_x, e_x) and also include gross flows between states at various ages. See Rogers (1975) or Schoen (1988) for thorough descriptions of multistate life tables.

Our first simulation exercise finds the long-run steady state—that is, the stationary population vectors $\mathbf{N}^*(a)$—associated with the current admission, release, and mortality rates.[10] This population would arise in the long run if all transition hazards and the size of 15th-birthday cohorts remained constant into the indefinite future.[11]

Figure 6 compares the steady-state prison population with the actual prison population observed in Florida on June 30, 1993.[12] Both populations are disaggregated by age and spell number. The steady-state population matches the overall age structure of the 1993 cross section well. Over five-year age groups, the index of dissimilarity[13] between the two total population curves is 0.15. The steady state does a credible, but less convincing, job of matching the disaggregated pattern of spell number by age. Over the three spell types, the index of dissimilarity is 0.24; over the 48 (age × spell) combinations, it is 0.33. The numbers of prisoners in second and especially third+ spells in the 25–40 age range is notably lower in the steady state than in the current population.

Figure 7 compares age-specific counts of annual admissions and releases in the steady-state model and in the fiscal year 1992–1993 data. The steady-state simulation matches the actual data very well for these inflows and outflows, which are important for simulating policy changes. Over five-year age groups, the index of dissimilarity between steady state and actual admissions is 0.04; for releases, the index is 0.12.

There is no reason to expect that an actual population will exactly match the long-run patterns that arise when its demographic rates are continued forever. Thus, it is no surprise that the actual prison population differs somewhat from its long-run, stationary equivalent. In fact, it is remarkable that the two populations in Figures 6 and 7 look so similar.

The steady state approximates the cross-sectional data well because prison populations have high turnover, and because they are concentrated in a narrow band of ages. A prison population is virtually reconstructed within a short period, so that there is a short "population memory." In this case, recent rate levels should explain most of the cross-sectional pattern, and they do. The exception to this short-memory rule lies in the distribution of the population by number of previous spells. Previous spells are more affected by past transition rates and past fluctuations in population size, and it is precisely in this area that the disparity between synthetic and actual cross sections is greatest.

Although the current and steady-state populations differ in some important ways, they are sufficiently similar to make the steady state a useful baseline for analysis. Each policy experiment that we report has a similar logic:

1. We use the steady-state population as the initial population.[14]
2. Starting from this initial population, we project the population forward *at new rates that reflect the particular 3X policy being analyzed.* We analyze short-term prison population dynamics during a transition to the 3X policy in question and, by looking at the new steady state, estimate the long-term results of the policy.

Three-Strikes Policy Simulations

In this section we report our findings from a variety of 3X simulation exercises. Each policy experiment has three parameters: (1) minimum sentence (M), the minimum sentence that an inmate convicted under 3X laws must serve without chance of parole; (2) coverage (C), the proportion of those entering a third+ spell in prison who are subject to 3X laws (0–100%, with lower numbers representing more selective targeting of 3X to certain types of offenders); and (3) deterrence (D), the percent reduction in criminal activity *among ex-prisoners who are no longer incarcerated* that is caused by the existence of the 3X law (0–100%, with lower numbers representing little change in criminal behavior due to 3X; in most of our experiments, deterrence is 0). Given these parameters, we implement 3X by setting release rates equal to 0 for prisoners who are in a third or higher spell and are subject to 3X rules. Specifically, we use the baseline rates, except that we change

$$\beta[a, a_e, P = 2+, X = 1] = 0 \text{ when } a - a_e \le M,$$

and we alter β to ensure immediate release for (P = 2+, X = 1) prisoners when the minimum sentence has been com-

10. Formally, the stationary population in our model is a solution to the vector differential equation

$$d\mathbf{N}(a) = [\mathbf{M}(a)]\, \mathbf{N}(a)da,$$

where $\mathbf{N}(15)$ is known and $\mathbf{M}(a)$ is the matrix of hazards at exact age a, arranged as indicated in Rogers (1975: chap. 3). In practice, we approximate numerically with

$$\mathbf{N}(a + \Delta) = [\, \mathbf{I} + \mathbf{M}(a) \cdot \Delta]\, \mathbf{N}(a),$$

where we use a value of $\Delta = 0.1$ years. This allows up to 10 transitions per year per individual, which is sufficient for high accuracy even with high transition rates. Changing the value of Δ to, say, 0.2 or 0.05 years alters our simulation results only trivially. Schoen (1988: section 4.3) discusses several calculation methods for multistate life tables; our approach is essentially a numerical version of his "constant forces" method.

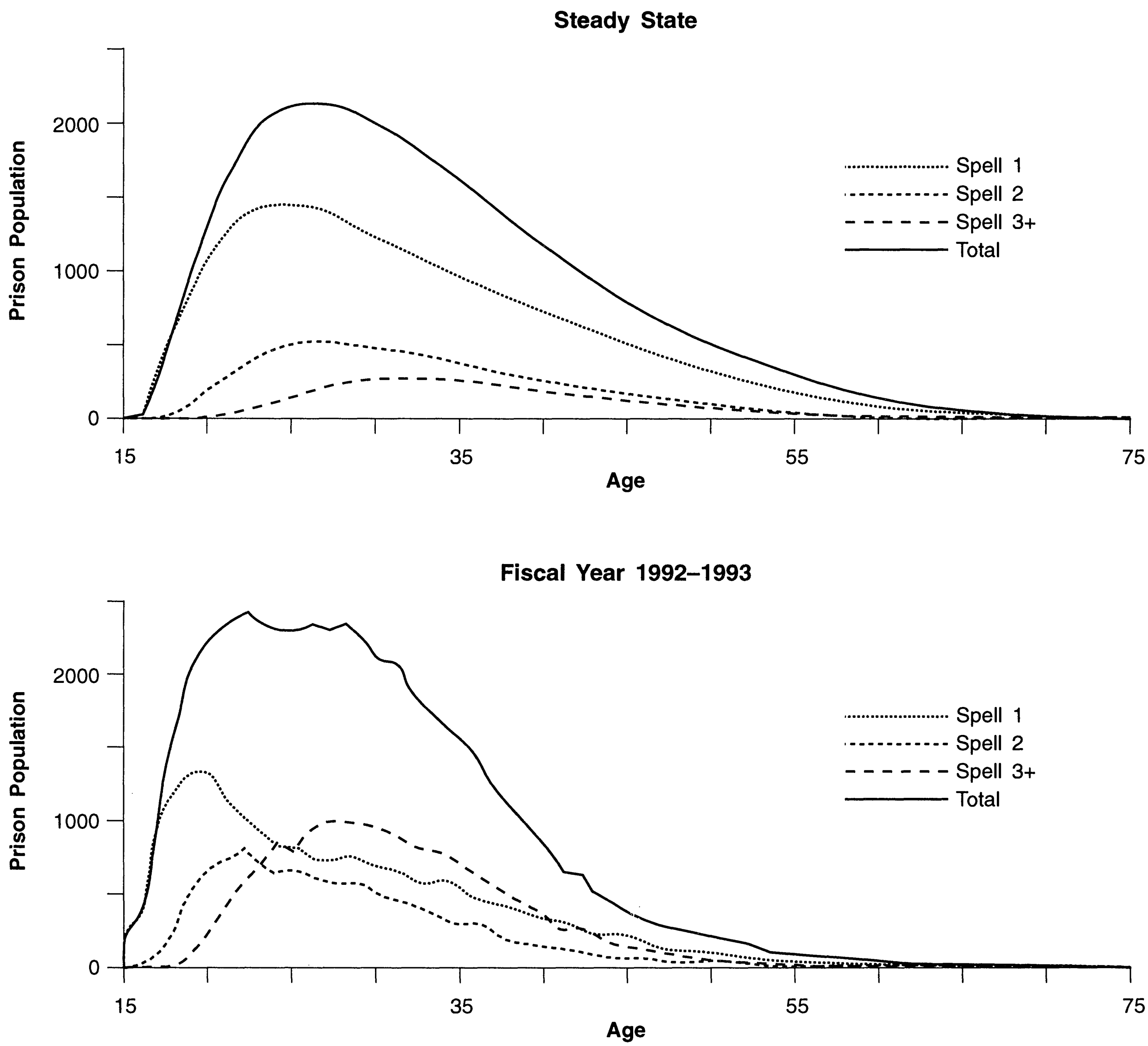
11. We scale the radix (i.e., the constant annual number of 15th birthdays) so that the model's stationary prison population equaled the actual 1992–1993 Florida prison population. The radix necessary to match 1992–1993 is 130,572. For comparison, the number of 15-year-olds enumerated in Florida in the 1990 census was 152,172. We do not expect an exact match, of course, as the prison population in 1992–1993 includes effects of past fluctuations in cohort sizes and in admission and release rates. We conclude only that our radix seems roughly consistent with the available data.

12. Florida's fiscal year 1992–1993 ran from July 1, 1992 to June 30, 1993.

13. For any vectors x and y of distributions over a set of discrete categories, the index of dissimilarity is $D(x,y) = 1/2 \times (\Sigma_c\, |x_c - y_c|)$, where c indexes categories. In our calculations x and y are the steady-state and actual prison populations, and categories are 16 age groups (15–19,20–24,...,70–74,75+), 3 spell categories (1,2,3+), and 48 age × spell combinations.

14. There is analytical advantage in using the steady-state population, rather than the observed current population, as the experimental baseline. Specifically, the steady-state data include disaggregated population counts (such as the age-specific distribution of prior spells in prison for the non-incarcerated population), which are unavailable in the administrative data. Greenwood et al. (1994) use the same strategy in their analysis of 3X in California.

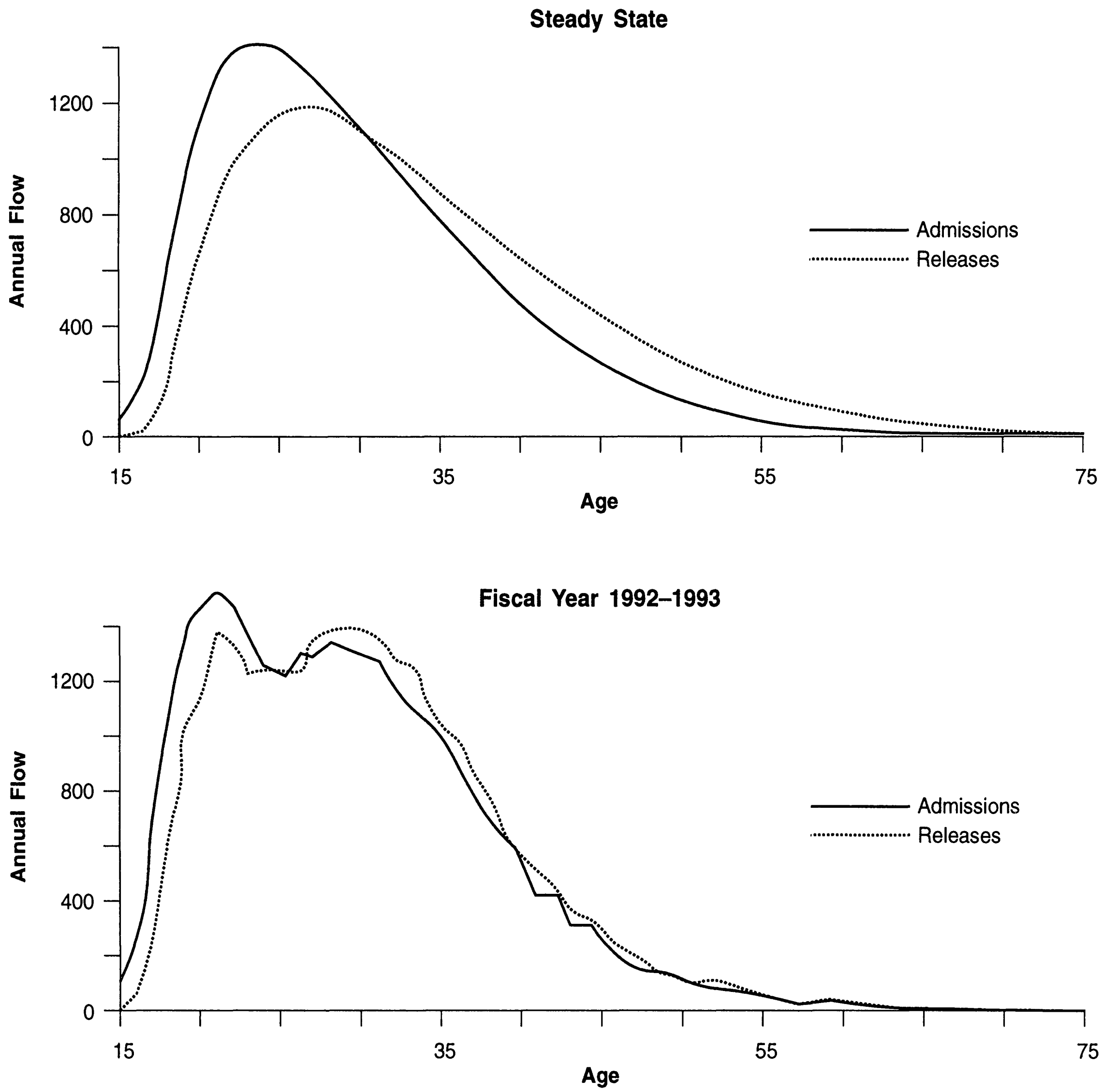
FIGURE 6. STEADY-STATE AND ACTUAL PRISON POPULATIONS, BY AGE AND SPELL NUMBER



pleted. The assumption that all 3X prisoners are released immediately after completing the minimum sentence generally biases our simulations toward finding smaller population changes under 3X, because we assume the lowest possible value for prisoner-years per 3X conviction.

Appendix Tables A1 and A2 contain summary results for policy experiments over various (*M*,*C*,*D*) combinations. Before proceeding, it is important to highlight what we are doing, and what we are not doing, in these experiments. We are *not* in any sense making forecasts for Florida's prison system. We have *not* attempted to make accurate and precise models of real-world sentencing policies. Our approach is analytical rather than predictive. By adopting generic models of 3X policies, we trade real-world specificity for analytical insight. The objective of our simulation exercises is to learn about the basic demographic consequences of various sentencing policies, keeping other factors constant. We also hope to learn about the sensitiv-

FIGURE 7. STEADY-STATE AND ACTUAL PRISON POPULATION FLOWS, BY AGE

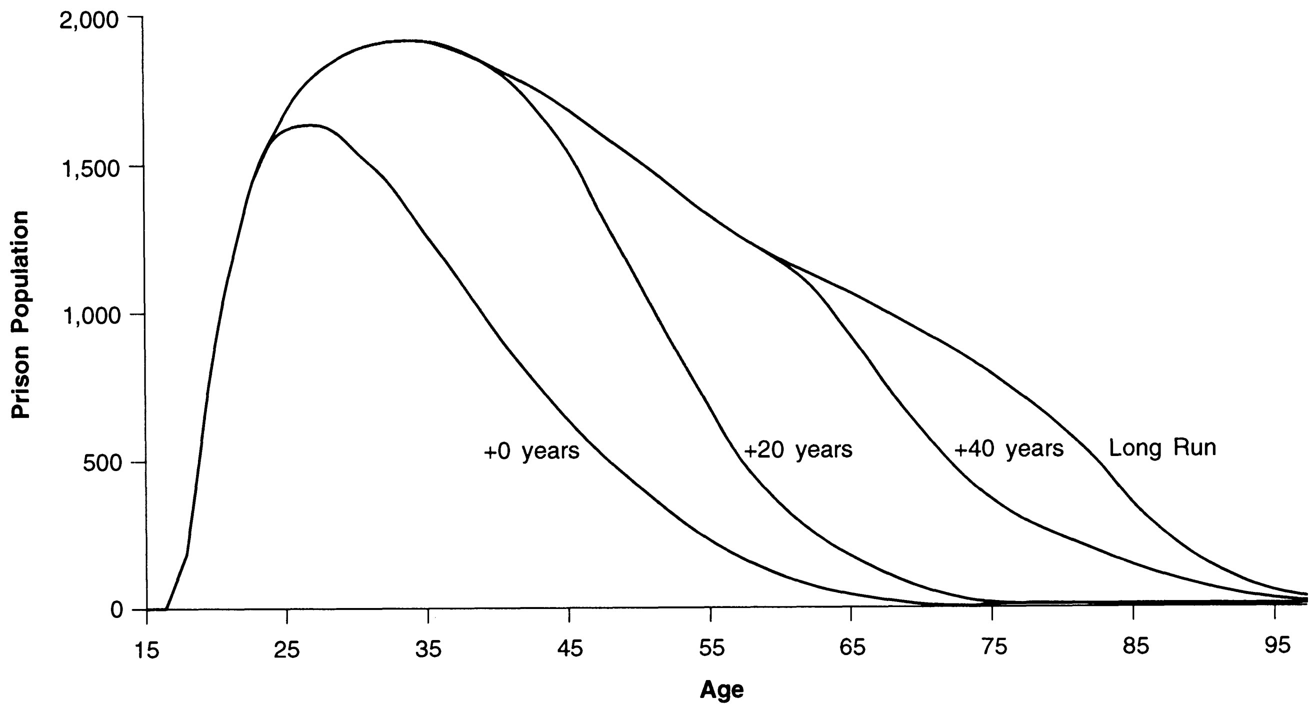


ity of demographic changes to policy parameters and possible behavioral changes.

Full 3X policy. We begin with a policy that we call *full 3X*—mandatory life sentences for all third strikes, with no deterrence. In our notation this corresponds to M = 200+ years, C = 100%, D = 0%. The full 3X policy leads to the greatest demographic changes in prison populations, and as such it will illustrate most clearly the patterns of change that occur. In subsequent experiments, we relax the extreme assumptions about coverage, sentence length, and deterrence.

We wish to analyze the direction, magnitude, and speed of prison population change under the full 3X policy. To do this, we simulate a transition from the steady-state population to the new long-run state that arises if release rates are 0 for those in prison for the third+ time. Because this is an analytical exercise rather than a forecast, we maintain the simplifying assumption that the size of 15th-birthday cohorts remains constant into the indefinite future. This everything-else-equal approach is appropriate, as our focus is on the impact of changes in release policies, and we do not want to

FIGURE 8. EVOLUTION OF THE PRISON POPULATION, BY AGE, UNDER A FULL 3X POLICY



confound policy effects with external effects caused by fluctuations in fertility, mortality, and migration rates. Any realistic forecast of prison population changes, however, must incorporate the effects of past and expected future changes in basic demographic rates on the sizes of future 15th-birthday cohorts.

Figure 8 illustrates the projected changes in prison populations under a full 3X policy, showing age-specific counts of prisoners 0, 20, and 40 years after implementation, as well as the new long-run equilibrium. Population increase would be gradual, with the number of prisoners growing steadily for approximately 50 years and then leveling off at a new long-run size.

The manner in which the prison population grows is interesting: There is virtually no growth in the number of prisoners under age 25 because few people reach a third spell in prison at such a young age. After 3X starts, growth spreads like a wave from younger to older ages over a period of about 80 years. The population of prisoners in their 30s and 40s grows rapidly during the first 20 years of the policy and then levels off. Similarly, the population of prisoners in their 50s and 60s grows over the second 20 years, and the population of prisoners in their 70s and 80s grows (less rapidly, because of mortality) in the third 20-year period.

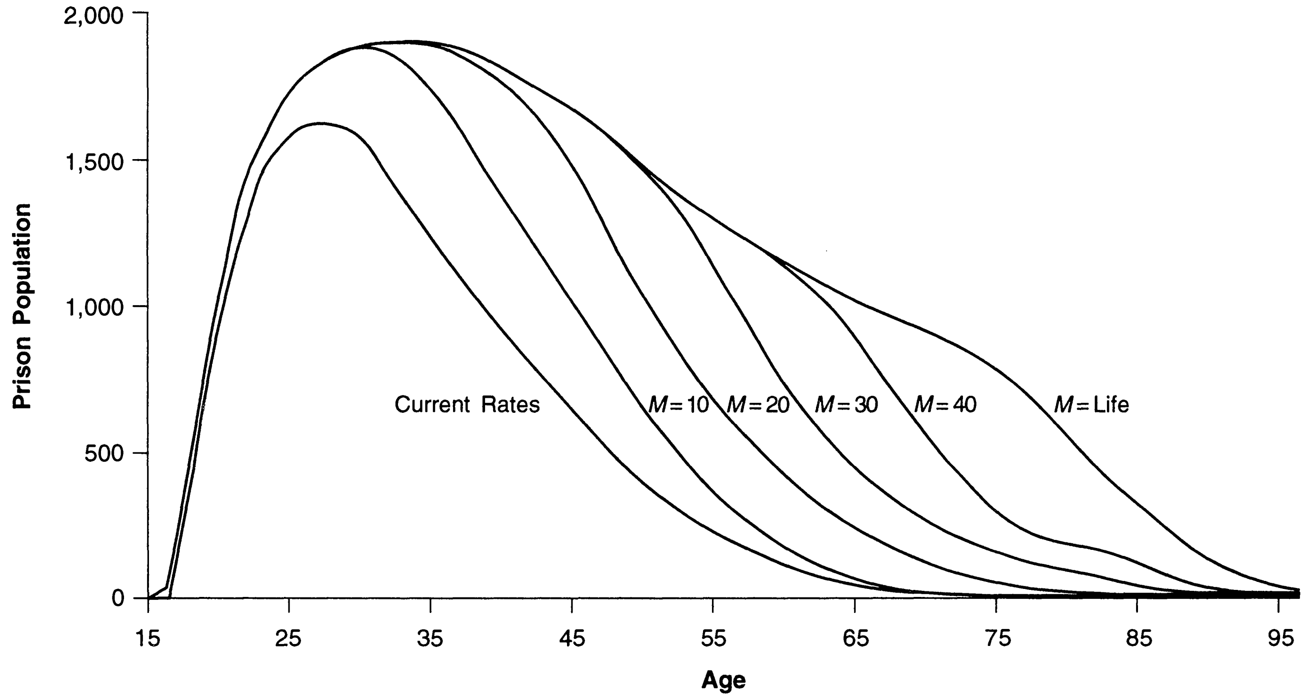
This wave of growth begins passing through the prison population as the first cohorts who have spent their high-risk years subject to 3X start accumulating third strikes. This results in a build-up of prisoners with 3X sentences, most of whom are initially young. As time passes, the first cohorts at the leading edge of the 3X wave get older, replacing in the age distribution previous cohorts that were not as affected by the new laws. Consequently, the number of middle-aged prisoners rises. The number of younger prisoners remains constant, however, as the positions in the age distribution formerly occupied by the leading-edge cohorts are taken up by other, more recent cohorts with similar accumulations of 3X prisoners. This process continues until the last of the leading-edge cohort dies, when the prison population has become stationary in its new form.

This simulated transition leads to several immediate conclusions about the likely effects of a full 3X policy. Growth of the prison population would be substantial. Holding all other demographic factors constant and changing to full 3X would more than double the total prison population in the long run: In our simulation the increase was 129%. For Florida, this would mean more than 60,000 additional prisoners in the state system on any given day, even if fertility, mortality, and in-migration remained constant at current levels.

On a more positive note, prison population growth is not all loaded at the front end of the process. Under a full 3X policy, the prison population would double gradually over about 60 years rather than overnight.

Prison population aging under full 3X is also dramatic, as illustrated in Figure 8. Although the overall prison population

FIGURE 9. STEADY-STATE POPULATIONS, BY AGE, WITH VARYING MINIMUM SENTENCES



more than doubles in the long run, the population at ages 60+ grows by a factor of nearly 20 (2% of the current steady-state population is 60+; 19% of a larger steady-state population would be 60+ under full 3X), and at ages 80+ the growth factor is over 200. As with total population growth, these aging effects occur steadily over about 60 years from the beginning of a 3X policy. The most alarming part of the story—multifold growth in the numbers of very old prisoners—happens last in the process. For example, in our simulations the population of prisoners 60+ rises sharply, but this increase starts to happen only about 30 years after initiating a full 3X policy.

Variations in minimum sentence. Three-strikes laws would have less dramatic effects on prison populations if mandatory sentences were, say, 20 or 30 years without parole rather than life without parole. Demographic modeling allows us to estimate how sensitive prison population changes are to the length of 3X sentences. In this section, we briefly report on policy experiments that keep coverage at 100% and deterrence at 0%, but differ from the full 3X policy by varying the minimum sentence for a third strike.

Figure 9 illustrates the age-specific steady-state populations for M = 10, 20, 30, 40, and life. In these simulations coverage is fixed at 100%, and deterrence is fixed at 0%. The figure also includes the steady-state population under current policy (the lowest curve) for reference.

Several points are worth noting in Figure 9. First, although the effects on the long-run state prison population are smaller when 3X sentences are shorter, they are still substantial. For example, minimum 3X sentences of 10, 20, and 30 years would cause long-run prison population increases of 31%, 61%, and 84%, respectively. For prison systems that are already overcrowded, these increases may be significant: In Florida, for example, 20-year minimum sentences for 100% of 3X offenders would eventually lead to more than 30,000 additional prisoners in the state system on any given day, holding all other factors constant.

Figure 9 also illustrates the effects of sentence length on prison age structure. Obviously, shorter sentences mean younger prisoners. Because of the possible high expenses associated with older prisoners, an interesting metric for age structure is the fraction of prisoners who are 60+ years old. One can see from Figure 9 that the bulk of prison population growth with 10- to 30-year minimum sentences occurs among prisoners younger than 60. In the steady state at current rates, 2% of prisoners are 60+. With 10-, 20-, and 30-year minimums, the proportions 60+ would be 2%, 5%, and 9%, respectively. As noted earlier, this proportion rises to 19% with life sentences. Because of the distinct age pattern in prison entries, sentence length has a strong effect on the aging of the prison population under 3X, with shorter sentences associated with much less aging.

Finally, there are obvious similarities between Figure 9, which represents the long-run populations under various minimum sentences, and Figure 8, which represents the short-run evolution of the prison population at various times after implementation of a full 3X policy with mandatory life sentences. This similarity is not a coincidence. The prison population evolves similarly in all of the policy experiments: It grows and ages as a leading-edge cohort (the first cohort subject to 3X during the peak ages for criminal activity), accumulates third strikes and mandatory sentences, and then settles into a steady state as the leading-edge cohort eventually exits the prison population and later cohorts follow the same pattern of prison entry and exit. With shorter minimum sentences the leading-edge cohort exits prison faster and at younger ages (more often by release and less often by death). This decreases the time to the steady state and makes the steady-state population younger.

Variations in 3X coverage. The demographic impact the full 3X policy is large, suggesting that the costs of casting a broad net to catch hard-core offenders may also be large. Many 3X proposals, however, define more restrictive conditions under which a convicted felon receives a 3X sentence: For example, he or she may have to commit a certain type of crime, or commit multiple crimes within a specified number of years. Partial 3X proposals come in a variety of forms (see Greenwood et al. 1994). This variety, together with a general lack of data that is disaggregated in the right form for evaluating a particular law, makes it difficult to analyze a broad spectrum of 3X proposals within a single, unified modeling framework.

We can gain some demographic insight about such policies, however, by treating the problem generically. We will suppose there are some policy variants under which 10% of all third admissions to prison are out, others under which 20% are out, and so forth. These are the coverage rates (C) defined earlier.

Figures 10a and 10b summarize a variety of policy experiments in which we allow coverage to differ from 100%. Each experiment is represented by a star in the figures, with linearly interpolated values for intermediate levels of C. Figure 10a reports on the growth of the steady-state population under various policies; Figure 10b reports on population aging. Deterrence (D) is assumed to be 0 in all of these experiments, but minimum sentences (M) vary, with each line in the figures corresponding to a distinct level of M. In both figures, 3X coverage is represented on the horizontal axis, with more easterly values corresponding to higher coverage and a broader 3X net.

The simple story that arises from these experiments is that coverage matters. The demographic impact of 3X on the prison population is quite sensitive to the value of C. The degree of coverage is particularly important when 3X sentences are long. Conversely, length of sentence matters relatively little for prison population growth or aging when coverage ranges from 10% to 20%.

These results suggest that careful targeting of 3X may be important in increasing its cost effectiveness. Deciding which 10–20% of third-time felons should be subject to long mandatory sentences remains a difficult problem, but our analysis indicates that narrowing the coverage and selecting 3X prisoners more carefully could substantially reduce the costs associated with prison growth and aging.

Variations in deterrence. There is general consensus in the empirical literature on crime that the deterrence effects of mandatory sentencing policies are small (U.S. Sentencing Commission 1991). Nevertheless, it is useful to know what levels of deterrence would be necessary to offset the population growth caused by 3X policies.

Note that by *deterrence* we mean a reduction in criminal activity among those who are *not* incarcerated. It is important to distinguish deterrence from *incapacitation*, which is a reduction in criminal activity that occurs when a criminal is incarcerated and his or her criminal career is interrupted. In this section, we are investigating the potential effects of behavioral changes that would reduce the number of 3X prison entries. In the multistate life-table model, we simulate deterrence effects by altering the hazard rates for transitions from the "not in prison, 2+ strikes" population to the 3X prison population. Specifically, we multiply all of the entry hazards $\alpha(a,a_e,P=2+)$ by a deterrence factor $(1-D/100)$, where D is the deterrence rate.

Figure 11a reports results for prison population growth; Figure 11b reports results for aging. Coverage is fixed at 100% in these experiments, whereas deterrence (measured on the horizontal axis) varies from 0% (its value in all previous experiments) to 50%. Results from the empirical literature in criminology suggest that the true value of D is close to 0; even the middle values of D (20–30%) in our experiments are probably excessively optimistic.

Several points are important in these figures. First, our experiments show that deterrence could cancel or even reverse the population growth effects of 3X. However, this would happen only if 3X sentences were very short and deterrence levels were unrealistically high.

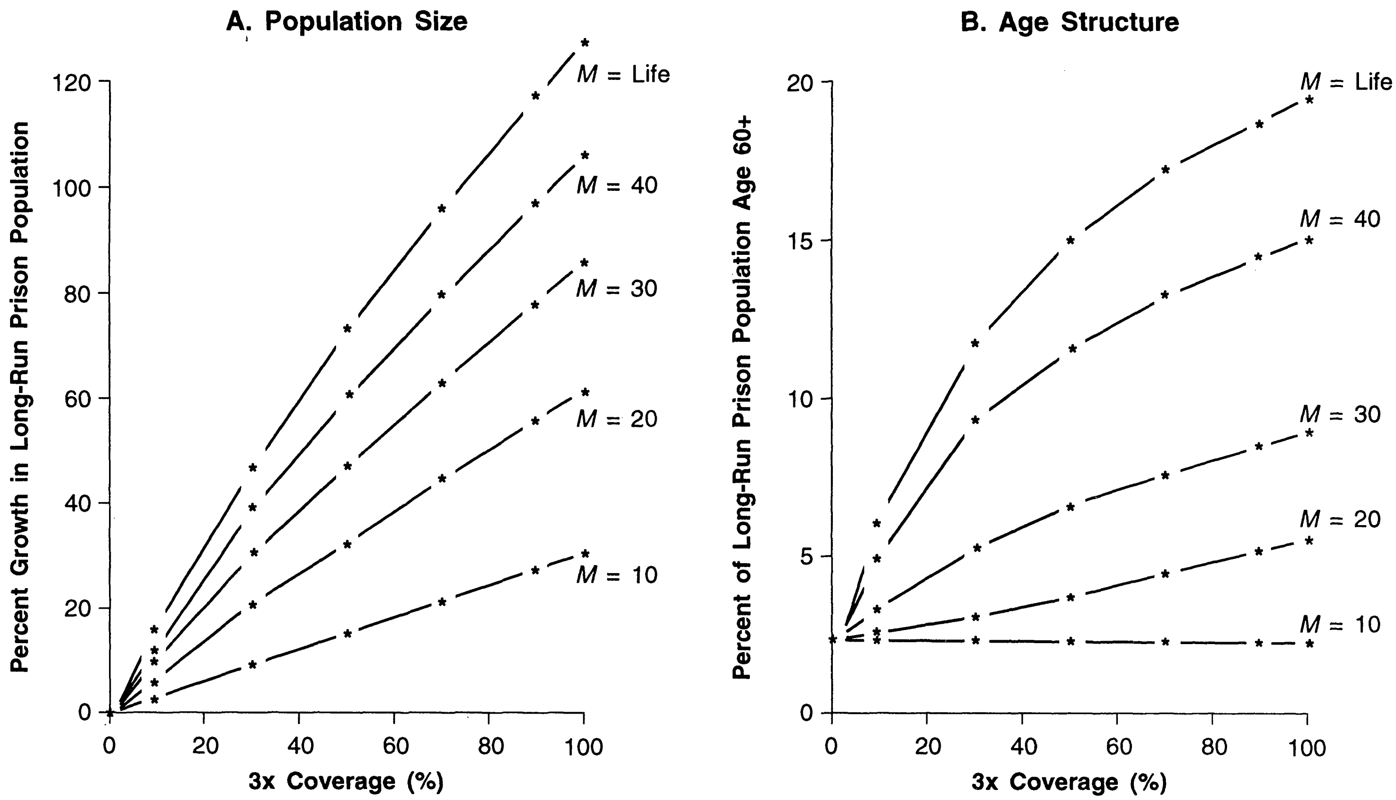
Second, prison population growth is somewhat sensitive to deterrence levels, even at low levels of D. For example, long-run prison population growth under a full 3X policy would fall from the 129% reported earlier to 105% if $D=10$, or to 81% if $D=20$. In Florida, for example, a 10% or 20% deterrence level could reduce the long-run number of state inmates under 3X by perhaps 10,000–20,000, which is obviously significant, even though overall growth in the prison system would still be extremely large in any of these scenarios. As the figure illustrates, the effects of deterrence on prison growth are slightly weaker when 3X sentences are shorter.

Finally, our experiments illustrate that deterrence effects will *not* matter much for prison aging under 3X. The level of aging under 3X (measured as the steady-state fraction of prisoners who are age 60+) is not sensitive to the level of deterrence. In short, the length of 3X sentences has far more impact on prison population aging than the level of deterrence. Realistic variation in deterrence levels has only small effects on aging, even when 3X sentences are long.

DISCUSSION

Our simulation model allows detailed examination of the mechanics of prison population change. The demographic

FIGURE 10. EFFECTS OF COVERAGE AND MINIMUM SENTENCE ON LONG-RUN PRISON POPULATION, WHERE DETERRENCE = 0



dynamics of incarceration are interesting in themselves, but what do they imply for the effectiveness of alternative policies?

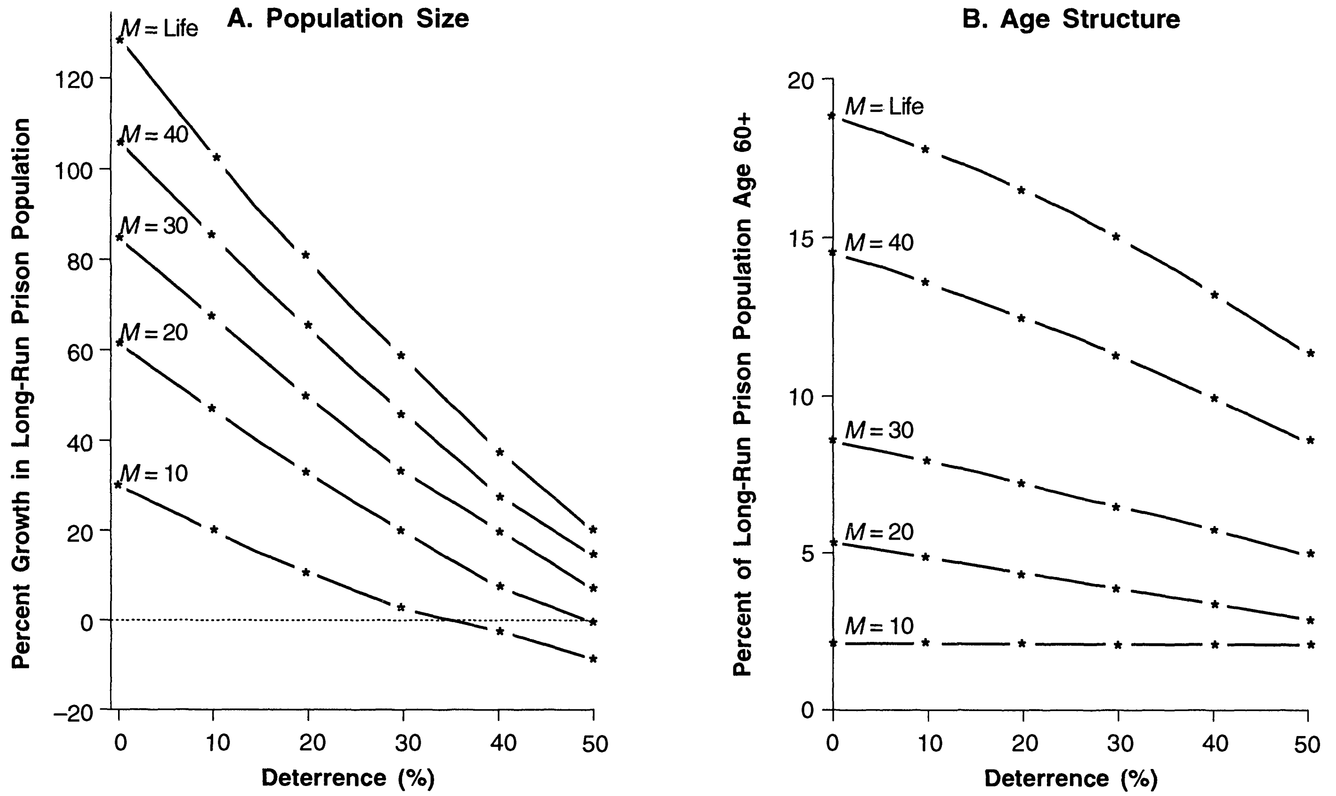
One of the main motivations for 3X and other mandatory sentencing laws is to prevent crimes by forcibly separating high-risk offenders from the rest of the population. Our demographic analysis, which focuses on the age structure of crime and punishment, clarifies some important issues about the effectiveness of 3X in preventing crime through incapacitation.

Stated in demographic terms, the costs and benefits of any new sentencing policy depend not on the characteristics of the *people* that they move from streets to prisons, but rather on the characteristics of the *person-years* that they move. The riskiest person-years, during which more crimes are likely to be committed if the individual is on the street, are those lived by younger and higher-rate criminals. Transferring these risky person-years from streets to prisons would have a high benefit-to-cost ratio. Similarly, person-years lived by older and lower-rate criminals are less risky, and a policy that transferred those person-years into prisons would have a lower benefit-to-cost ratio. Thus, there are two important questions to consider when evaluating the marginal effect of a new sentencing policy that switches a person-year from streets to prisons: (1) What kind of person is being incarcerated, and (2) how old are they during the year in question?

Previous studies of sentencing policies have generally focused on the first question. There is evidence of extreme skewness in the distribution of crime rates across individuals (Visher 1986), raising the possibility that increased prison sentences for a selected group of criminals might move relatively risky person-years off streets and into prisons at relatively low cost. Laws such as 3X attempt to use an individual's criminal history as a means of identifying and selectively incarcerating high-rate offenders. Criminologists (Canela-Cacho, Blumstein, and Cohen 1997; Greenwood et al. 1994) have made important contributions by analyzing how effectively 3X and similar laws will perform this filtering.

In contrast, our demographic analysis focuses on the second question, that of the *ages* at which the additional prisoner-years generated by 3X will be lived. We thus highlight an important kind of criminal heterogeneity that has been underemphasized in earlier studies of sentencing policy—heterogeneity by age. There is considerable evi-

FIGURE 11. EFFECTS OF DETERRENCE AND MINIMUM SENTENCE ON LONG-RUN PRISON POPULATION, WHERE COVERAGE = 100%



dence, both in our Florida data and in earlier criminology studies (Blumstein et al. 1986; Hirschi and Gottfredson 1983; Land et al. 1996; Nagin and Land 1993) that criminal activity tends to decrease significantly as an individual ages. Because of the age pattern of crime, the public safety benefits of keeping any particular criminal incarcerated generally decline each year.

Our analysis shows that as a 3X system evolves, a prison population will grow primarily through the addition of aging and (eventually) aged individuals. Thus, the benefits of a 3X policy will generally decrease over time, while the costs (such as medical care for aged inmates) will likely rise.

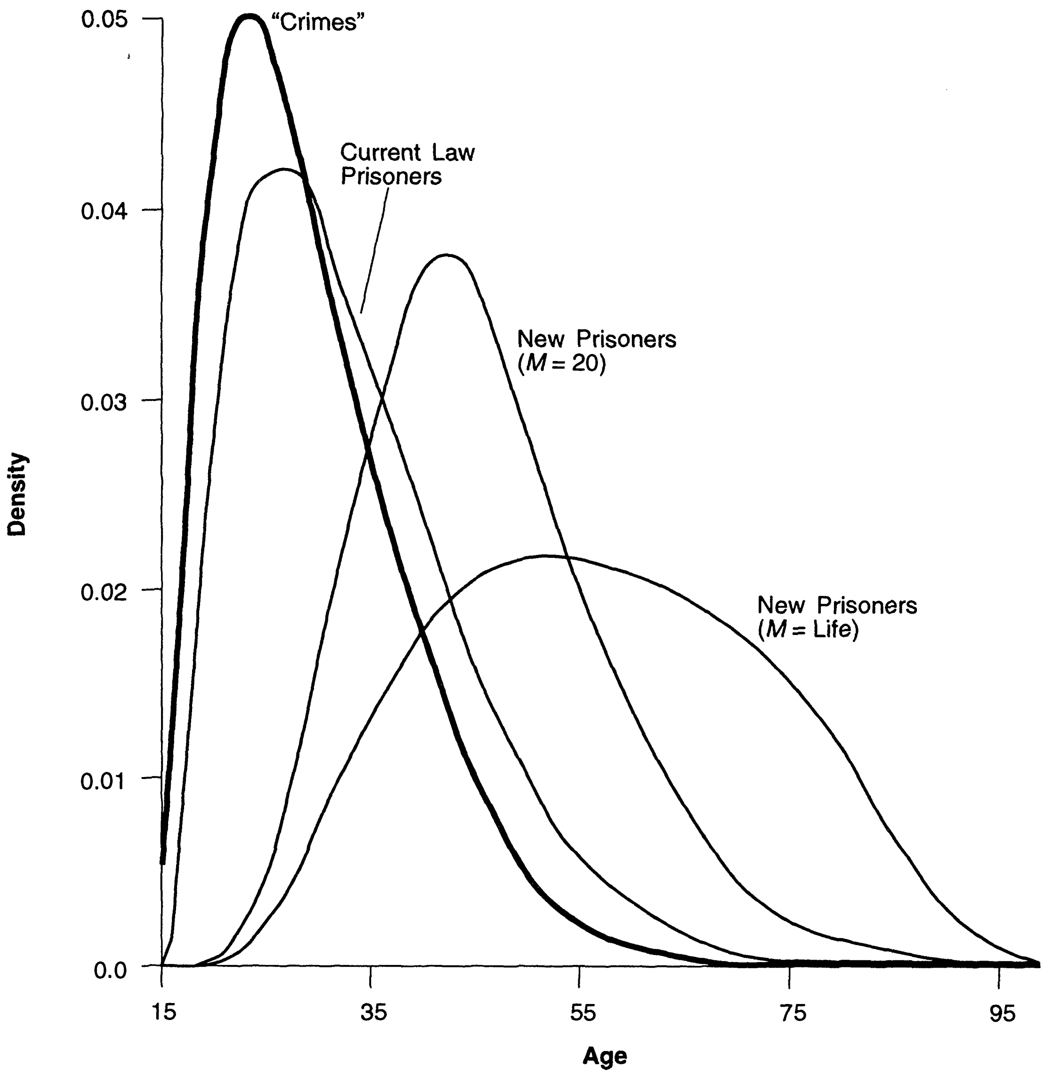
Taking an explicitly demographic point of view clarifies the importance of age heterogeneity. Figure 12 contains four relevant age distributions. The leftmost (and therefore youngest) distribution, labeled "Crimes," is that of steady-state prison entries at current rates. It shows, by age of offender, the relative volume of crimes serious enough to warrant a state prison sentence under current policies. Although it is imprecise, one can think of the height of the leftmost curve as a crude index of the number of serious crimes that might be prevented by incapacitating a person of a given age for one year.

The second age distribution in Figure 12, labeled "Current Law Prisoners," is that of the steady-state prison population at current rates. The similarity of this distribution to the "Crimes" distribution illustrates an important (and probably overlooked) virtue of current policies that have short average sentences and high prison turnover: These policies allocate the bulk of scarce prison space to those in the highest-risk age categories.

The third and fourth curves in Figure 12, labeled "New Prisoners (M = 20)" and "New Prisoners (M = Life)," illustrate the age distribution of the *extra* prisoners added in the long run by a 3X policy with a mandatory minimum of 20 years and life, respectively. For both curves, coverage is 100%, and deterrence is 0%. Clearly, the long-run effect of these policies is to add large numbers of individuals (or equivalently, person-years) to very low-risk age categories. Longer minimum sentences lead to more serious misallocations of prison space.

Both the public debate and policy analysis of 3X have generally ignored age effects like those we illustrate. Doing so yields an incomplete analysis that underestimates costs and overestimates benefits. Age effects on crime rates are strong, and longer sentences will lead to much larger and much older

FIGURE 12. LONG-RUN AGE DISTRIBUTIONS OF CRIME AND PUNISHMENT



prison populations. Taken together, these facts imply that the aging of prison populations under 3X policies will significantly undermine the long-run effectiveness of the policies.

APPENDIX: 3X SIMULATION RESULTS

The appendix tables contain summary results for our 3X policy experiments with the multistate life-table model. Some of these results are also presented graphically in the body of the paper (Figures 10 and 11). Appendix Table A1 reports results for a set of experiments in which minimum sentence (*M*) and coverage (*C*) vary, but there are no deterrence effects of the 3X policy ($D = 0$). Appendix Table A2 reports results for experiments in which *M* and *D* vary, with coverage fixed at 100%. We do not investigate interactions between coverage and deterrence, primarily because we believe (as do most criminologists) that actual deterrence effects are likely to be close to 0.

Appendix Table A3 illustrates the joint consequences of the changes in population size and age structure displayed in Figures 10 and 11. It reports the ratio (number of prisoners 60+) / (number 60+ in steady-state baseline) for various experiments. For example, with 50% coverage and 20-year mandatory minimum sentences, the number of prisoners aged 60+ will be 2.51 times as high as under the current-rate baseline.

APPENDIX TABLE A1. POLICY EXPERIMENTS WITH VARYING MINIMUM SENTENCE AND COVERAGE, BUT WITHOUT DETERRENCE

	Experimental Parameters			Steady-State Populations by Age				Percent Aged 60+	Size of 60+ Population Relative to Baseline
Miminum Sentence	*M*	*C*	*D*	Total	Aged 50+	Aged 60+	Aged 70+		
Baseline: Current Rates	0	0	0	50,573	4,107	1,004	175	2.0	1.00
10-Year Mandatory Sentences	10	10	0	52,268	4,333	1,043	179	2.0	1.04
	10	30	0	55,556	4,818	1,132	186	2.0	1.13
	10	50	0	58,717	5,343	1,236	195	2.1	1.23
	10	70	0	61,759	5,898	1,352	204	2.2	1.35
	10	90	0	64,692	6,480	1,481	216	2.3	1.48
	10	100	0	66,120	6,780	1,551	222	2.3	1.54
20-Year Mandatory Sentences	20	10	0	54,238	5,131	1,271	211	2.3	1.27
	20	30	0	61,116	7,139	1,867	301	3.1	1.86
	20	50	0	67,459	9,102	2,525	411	3.7	2.51
	20	70	0	73,337	11,020	3,228	535	4.4	3.21
	20	90	0	78,801	12,895	3,961	668	5.0	3.94
	20	100	0	81,394	13,816	4,335	736	5.3	4.32
30-Year Mandatory Sentences	30	10	0	55,929	6,527	1,863	320	3.3	1.86
	30	30	0	65,743	10,922	3,444	603	5.2	3.43
	30	50	0	74,516	14,813	4,873	883	6.5	4.85
	30	70	0	82,405	18,290	6,186	1,160	7.5	6.16
	30	90	0	89,539	21,423	7,403	1,437	8.3	7.37
	30	100	0	92,857	22,879	7,983	1,574	8.6	7.95
40-Year Mandatory Sentences	40	10	0	57,193	7,789	2,853	598	5.0	2.84
	40	30	0	69,257	14,432	6,168	1,348	8.9	6.14
	40	50	0	79,954	20,244	9,046	1,993	11.3	9.01
	40	70	0	89,485	25,359	11,560	2,552	12.9	11.51
	40	90	0	98,020	29,890	13,773	3,044	14.1	13.71
	40	100	0	101,957	31,962	14,781	3,268	14.5	14.72
Mandatory Life Sentences	Life	10	0	57,865	8,463	3,524	1,028	6.1	3.51
	Life	30	0	71,186	16,359	8,091	2,572	11.4	8.06
	Life	50	0	83,027	23,317	12,111	3,931	14.6	12.06
	Life	70	0	93,604	29,478	15,669	5,132	16.7	15.60
	Life	90	0	103,093	34,963	18,834	6,202	18.3	18.76
	Life	100	0	107,479	37,484	20,287	6,692	18.9	20.20

APPENDIX TABLE A2. POLICY EXPERIMENTS WITH VARYING MINIMUM SENTENCE AND DETERRENCE, AND COVERAGE FIXED AT 100%

	Experimental Parameters			Steady-State Populations by Age				Percent Aged 60+	Size of 60+ Population Relative to Baseline
Miminum Sentence	*M*	*C*	*D*	Total	Aged 50+	Aged 60+	Aged 70+		
Baseline: Current Rates	0	0	0	50,573	4,107	1,004	175	2.0	1.00
10-Year Mandatory Sentences	10	100	0	66,120	6,780	1,551	222	2.3	1.54
	10	100	10	61,464	6,054	1,386	204	2.3	1.38
	10	100	20	57,073	5,407	1,244	190	2.2	1.24
	10	100	30	52,965	4,839	1,122	177	2.1	1.12
	10	100	40	49,158	4,345	1,019	166	2.1	1.01
	10	100	50	45,675	3,924	932	157	2.0	0.93
20-Year Mandatory Sentences	20	100	0	81,394	13,816	4,335	736	5.3	4.32
	20	100	10	74,328	11,853	3,619	609	4.9	3.60
	20	100	20	67,641	10,064	2,985	498	4.4	2.97
	20	100	30	61,377	8,457	2,432	403	4.0	2.42
	20	100	40	55,585	7,039	1,960	324	3.5	1.95
	20	100	50	50,314	5,816	1,568	260	3.1	1.56
30-Year Mandatory Sentences	30	100	0	92,857	22,879	7,983	1,574	8.6	7.95
	30	100	10	84,119	19,603	6,727	1,304	8.0	6.70
	30	100	20	75,801	16,532	5,569	1,060	7.3	5.55
	30	100	30	67,970	13,688	4,514	845	6.6	4.49
	30	100	40	60,698	11,100	3,571	656	5.9	3.56
	30	100	50	54,063	8,797	2,747	496	5.1	2.74
40-Year Mandatory Sentences	40	100	0	101,957	31,962	14,781	3,268	14.5	14.72
	40	100	10	91,860	27,330	12,523	2,755	13.6	12.47
	40	100	20	82,225	22,944	10,387	2,273	12.6	10.34
	40	100	30	73,136	18,846	8,399	1,827	11.5	8.36
	40	100	40	64,686	15,083	6,576	1,420	10.2	6.55
	40	100	50	56,975	11,704	4,944	1,058	8.7	4.92
Mandatory Life Sentences	Life	100	0	107,479	37,484	20,287	6,692	18.9	20.20
	Life	100	10	96,511	31,981	17,161	5,642	17.8	17.09
	Life	100	20	86,047	26,767	14,200	4,648	16.5	14.14
	Life	100	30	76,182	21,891	11,436	3,720	15.0	11.39
	Life	100	40	67,014	17,412	8,898	2,869	13.3	8.86
	Life	100	50	58,658	13,388	6,623	2,107	11.3	6.60

APPENDIX TABLE A3. SIZE OF PRISON POPULATION AGED 60+, RELATIVE TO BASELINE POPULATION AGED 60+

	Minimum Sentence				
Coverage	10 Years	20 Years	30 Years	40 Years	Life
0%	1.0	1.0	1.0	1.0	1.0
10%	1.0	1.3	1.9	2.8	3.5
30%	1.1	1.9	3.4	6.1	8.1
50%	1.2	2.5	4.9	9.0	12.1
70%	1.4	3.2	6.2	11.5	15.6
90%	1.5	3.9	7.4	13.7	18.8
100%	1.5	4.3	8.0	14.7	20.2

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