

The Role of Statistical Models in Planning Juvenile Corrections Capacity

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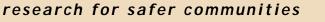


RESEARCH RE

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Report design by David Williams

About the Assessment of Space Needs Project

This report was prepared as part of the Assessment of Space Needs Project, conducted by the Urban Institute of Washington, D.C. The project began with a request from the U.S. Congress. In a November 13, 1997 Conference Report for Public Law 105-119, Congress requested that the U.S. Department of Justice conduct a "national assessment of the supply and demand for juvenile detention space," including an assessment of detention and corrections space needs in 10 States. In particular, Congress expressed this concern:

The conferees are concerned that little data exists on the capacity of juvenile detention and corrections facilities to handle both existing and future needs and direct the Office of Justice Programs to conduct a national assessment of the supply of and demand for juvenile detention space with particular emphasis on capacity requirements in New Hampshire, Mississippi, Alaska, Wisconsin, California, Montana, West Virginia, Kentucky, Louisiana, and South Carolina, and to provide a report to the Committees on Appropriations of the House and the Senate by July 15, 1998 (U.S. House of Representatives 1997).

The U.S. Department of Justice's Office of Justice Programs (OJJDP) responded to this request by taking two actions. The first action was to submit the required report to Congress in July 1998 (see DOJ 1998). The report was prepared by OJJDP with assistance from the Urban Institute, the National Center for Juvenile Justice, the National Council on Crime and Delinquency, and the American University in Washington, D.C.

The second action taken by OJJDP was to fund a more extensive investigation of the issues raised by the report as part of the Juvenile Accountability Incentive Block Grants program. The investigation, known as the Assessment of Space Needs in Juvenile Detention and Corrections, was conducted by the Program on Youth Justice within the Urban Institute's Justice Policy Center. The project analyzed the factors that contribute to the demand for detention and corrections space in the states and the methods used by states to anticipate future demand. Products of the work included an Internet-based decisionmaking tool that state and local juvenile justice agencies may employ to forecast detention future and corrections populations (http://jf.urban.org). The Assessment of Space Needs Project was completed in March 2002.

The Urban Institute's approach to conducting the Assessment of Space Needs Project was guided by the comments and criticisms received from the project's advisors and consultants:

Advisory Committee

- Dr. Arnold Irvin Barnett, Massachusetts Institute of Technology
- Dr. Donna M. Bishop, Northeastern University
- Mr. Edward J. Loughran, Council of Juvenile Correctional Administrators
- Dr. James P. Lynch, American University
- Dr. Samuel L. Myers Jr., University of Minnesota
- Ms. Patricia Puritz, American Bar Association

Consultants

- Mr. Paul DeMuro, Independent Consultant, Montclair, New Jersey
- Dr. William J. Sabol, Case Western Reserve University
- Dr. Howard N. Snyder, National Center for Juvenile Justice
- Mr. David J. Steinhart, Independent Consultant, Mill Valley, California

For more information about the Assessment of Space Needs Project, see the web site of the Urban Institute's Program on Youth Justice at http://youth.urban.org or telephone the Urban Institute at 202-833-7200 or OJJDP at 202-307-5929.

About the Author

Dr. Daniel P. Mears is a research associate in the Justice Policy Center at the Urban Institute in Washington, D.C. Before joining the Urban Institute in 2001, he was a postdoctoral research fellow with the Center for Criminology and Criminal Justice Research at the University of Texas-Austin. Dr. Mears has published research on a range of juvenile and criminal justice issues, including screening and assessment, sentencing, juvenile justice reforms, drug treatment, mental health treatment, immigration and crime, gender and delinquency, domestic violence, and prison programming. He is a graduate of Haverford College and holds a Master's degree and Ph.D. in sociology from the University of Texas-Austin.

About the Urban Institute

The Urban Institute is a nonprofit nonpartisan policy research and educational organization established in 1968 to examine the social, economic, and gover nance problems facing the nation. It provides information and analysis to public and private decisionmakers to help them address these challenges and strives to raise citizen understanding of these issues and trade-offs in policymaking.

About the Justice Policy Center

One of nine policy centers within the Urban Institute, the Justice Policy Center carries out nonpartisan research to inform the national dialogue on crime, justice, and community safety. Researchers in the Justice Policy Center collaborate with practitioners, public officials, and community groups to make the Center's research useful to not only dec isionmakers and agencies in the justice system, but also to the neighborhoods and communities harmed by crime and disorder.

About the Program on Youth Justice

This report was developed by the Urban Institute's Program on Youth Justice, which identifies and evaluates programs and strategies for reducing youth crime, enhancing youth development, and strengthening communities. The Program on Youth Justice was established by the Urban Institute in 2002 to help policymakers and community leaders develop and test more effective, research-based strategies for combating youth crime and encouraging positive youth development.

Researchers associated with the Program on Youth Justice work to transcend traditional approaches to youth justice research by

- studying all youth, not just those legally defined as juveniles;
- considering outcomes for families, organizations, and communities as well as individuals;
- sharing insights across t he justice system, including prevention programs, police, courts, corrections, and community organizations; and
- drawing upon the expertise of multiple disciplines, including the social and behavioral sciences as well as professional fields such as medicine, public health, policy studies, and the law.

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This report was prepared for the Assessment of Space Needs Project, which was funded by the Office of Juvenile Justice and Delinquency Prevention (OJJDP) and is housed within the Urban Institute's Justice Policy Center and the Center's Program on Youth Justice. Development of the report benefited from significant contributions by Dr. Jeffrey Butts, director of the Assessment of Space Needs Project and director of the Program on Youth Justice. The original conceptualization of this and other reports from the Assessment of Space Needs Project was informed by discussions with members of the project's Advisory Committee and consultants, especially William Sabol, formerly of the Urban Institute, and Howard Snyder of the National Center for Juvenile Justice.

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Several current and former employees of the Urban Institute played critical roles in the project, notably Dr. Adele Harrell, director of the Justice Policy Center at the Urban Institute. Emily Busse and Alexa Hirst helped to organize the information gathered during the project's visits to juvenile justice agencies throughout the country, and they contrbuted to the initial drafts of several project reports. Ojmarrh Mitchell provided important criticisms of the research design as it was being developed, and Nicole Brewer, Dionne Davis, and Erika Jackson played other key roles in ensuring the success of the project. David Williams was responsible for the graphic design of the project's various reports. Finally, the Urban Institute gratefully acknowledges the patience and efforts of the many state and local officials who hosted the project's site visits and assisted in the collection of data and other information. In particular, the study could not have been conducted without the support of the following agencies:

- California Youth Authority
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- Kentucky Department of Juvenile Justice
- New Hampshire Department of Youth Development Services
- Oregon Office of Economic Analysis
- Oregon Youth Authority
- Texas Juvenile Probation Commission
- Texas Youth Commission
- Texas Criminal Justice Policy Council
- West Virginia Division of Juvenile Services
- Wisconsin Department of Corrections, Division of Juvenile Corrections
- Wisconsin Office of Justice Assistance
- Wisconsin—Dane County Juvenile Court Program
- Wisconsin—Milwaukee County Department of Human Services, Delinquency & Court Services Division

The Role of Statistical Models in Planning Juvenile Corrections Capacity

SUMMARY

Because incarcerating young offenders is expensive, forecasting the future need for secure bed space is critical for correctional planning. The goal of this report is to examine, through analysis of variation among states in their use of juvenile incarceration, the utility of relying on explanatory statistical models to inform correctional bed-space planning. The primary conclusion is that these models provide relatively little information that policymakers can use. However, they can identify potential factors that may influence juvenile correctional capacity needs. Ultimately, an effective forecasting process should include, but not be limited to, statistical analyses and other types of empirical modeling.

INTRODUCTION

Because building and operating juvenile correctional bed space is costly, policymakers desire forecasts that can help them anticipate future capacity needs. One forecasting approach consists of statistically modeling factors that may account for differential rates of juvenile incarceration. If these factors account for variation in juvenile incarceration rates, it may be possible to predict future bed-space capacity needs.

Conventional views suggest that juvenile crime drives bed-space capacity. That is, if juvenile crime rates increase, so, too, should juvenile correctional bed space. Yet, there may be a range of social conditions that can affect bedspace use and demand and, in turn, pressure to create more capacity. For example, corrections officials may be influenced by prosecutorial sentencing practices that increase rates of admissions. When admission rates increase, there may be pressure to shorten sentences to avoid exceeding capacity. In addition, policymakers may be influenced by economic, social, or political considerations that are independent of changes in crime.

The goal of this report is to illustrate the limited utility of relying on statistical models to explain juvenile correctional bed-space capacity. Data on juvenile incarceration rates are used to answer the question, "what characteristics of states are associated with higher juvenile incarceration rates?" The analysis relies on crosssectional, state-level data and represents but one approach among many to statistically modeling the factors that drive juvenile correctional bedspace needs and policy. The report concludes by discussing some of the benefits and limitations of using statistical models to forecast juvenile correctional bed-space needs and capacity.

MODELING STATE VARIATIONS IN THE USE OF JUVENILE INCARCERATION

Explanation of incarceration rates, whether juvenile or adult, or across space or over time, remains an ongoing challenge for researchers (Greenberg and West 2001). At first glance, the answer seems self-evident: States with higher juvenile crime rates presumably have higher juvenile incarceration rates. But this view assumes that juvenile crime rates are the sole measure of need that policymakers use to determine bed space capacity. In reality, other factors may be linked to incarceration rates.

A study of variation among states in the use of juvenile incarceration is different than one aimed at predicting juvenile incarceration levels within one state over time. The latter activity is frequently the approach adopted by states when they try to antic ipate how many new beds or facilities they should add or eliminate. However, the underlying goal is similar: In both instances, researchers attempt to identify factors associated with the use of incarceration that therefore might be used to predict juvenile correctional capacity needs.

Relatively few studies have systematically examined variation in state-level juvenile incarceration rates. Most research, conducted primarily by state planning agencies, has relied on atheoretical empirical strategies for estimating bedspace needs. These strategies typically involve analysis of juvenile incarceration trends in a particular state. However, recent studies provide a foundation for attempting a state-level study, especially Greenberg and West's (2001) and Jacobs and Carmichael's (2001) respective analyses of state-level variation in adult incarceration rates and McGarrell's (1991) study of juvenile incarceration rates in public facilities between 1975 and 1987. Review of these and other studies, as well as consideration of unique aspects of juvenile justice, suggest several hypotheses about the potential role of certain factors in driving state juvenile correctional capacity.

Upper Age of Jurisdiction

States use different upper age boundaries for defining who is or is not a "juvenile." In some states, this boundary may be age 15, while in others it may be age 16 or 17 (Snyder and Sickmund 1999). In states with lower age boundaries, there may be lower incarceration rates. Why? Younger age groups typically have lower crime rates. In essence, therefore, the age boundary may serve as a proxy measure of le vels of juvenile crime. For example, 17-year-olds on average commit more crime than youths who are 16 and under, which may generate higher aggregate confinement rates.

In addition, some research (e.g., Mears 2001a) suggests that there is a tendency among states to incarcerate younger offenders less often than older offenders. Thus, if a state defines its juvenile population to be younger than in another state (e.g., ages 10 to 15 rather than ages 10 to 16 or 17), it might possibly have a lower incarceration rate.

Another possibility is that states with lower age thresholds for defining juveniles may have a "get tough" orientation, as reflected in their policy of legally placing all youths 16 and older into the adult system. These states may be more inclined to be lenient with their juvenile offenders, given that many of the older, more serious offenders have been excluded from the juvenile justice system.

Economic Factors

Economic conditions vary considerably across states. At any given time, some states may suffer severe economic hardships, including downturns in local economies, relatively low per capita or family incomes, and high unemployment and poverty rates, while others may enjoy economic prosperity.

Such variation may be linked to juvenile incarceration rates. For example, economically disadvantaged states may be less likely to take an accommodating view of juvenile offending. The sentiment thus may be that a "get tough" response to juvenile crime is warranted. Conversely, well-to-do states may be more inclined to view youths as "just kids" and therefore rely less heavily on incarcerative sanctions. In these states, there may also be more resources (e.g., higher per capita incomes and, correspondingly, tax revenues) available to support such efforts.

An additional influence of economic conditions may be through social class dynamics. States with greater income differences between the least and most wealthy may be more likely to support punitive sanctioning. When the differences between the poor and wealthy increase, high levels of real or perceived disorder can arise, resulting in more restrictive and punitive social control efforts. Although relatively little attention has been given to this issue as it applies to juvenile incarceration, researchers have posited and tested similar hypotheses about adult incarceration rates. This research indicates mixed support for a significant relationship between adult incarceration rates and poverty, unemployment, and economic inequality (Greenberg and West 2001; Jacobs and Carmichael 2001).

Education

Investments in education, or levels of educational achievement, may reflect the extent to which a state is youth-oriented. States with greater levels of student or school funding and lower rates of high school dropouts may, for example, view incarceration as an ineffective use of funds. When faced with a decision about using state revenues, such states may be more inclined to give priority to education rather than incarceration. This priority may be independent of concerns about crime, or it may stem from a belief that education represents an effective strategy for preventing juvenile crime. A related hypothesis is that states with higher percentages of high school dropouts may be more likely to rely on incarceration as a means of social control (McGarrell 1991).

Political Factors

Since state juvenile correctional policies flow directly from legislative funding decisions, it seems likely that political factors affect juvenile incarceration rates. Political factors can vary enormously, including changes in the balance of power among the state leadership and unantic ipated traumatic events (e.g., violent and highly publicized crimes that occur during elections). Indeed, studies of the origins and developments of the U.S. juvenile justice system highlight the interplay of numerous political events (Feld 1999). Few of these studies, however, provide concrete guidance about exactly how political factors affect state-level juvenile incarceration policies.

One possibility is that states with a greater percentage of voters participating in elections are more likely to be comprised of individuals who feel enfranchised, in control of social conditions, and responsible for the social welfare of the less well-to-do (McGarrell 1991). In these states, the public may adopt a more accommodating view of juvenile crime and thus be less likely to endorse punitive sanctions.

A more direct link may be between the percent of a state's electorate voting Democratic and juvenile incarceration rates. Conventional wisdom suggests Democrats typically are more supportive of rehabilitative interventions, while Republicans are less so (Jacobs and Carmichael 2001). On the other hand, empirical research does not support this simplified view as applied to support for juvenile sanctioning, suggesting that there may be no such link (Mears 2001b).

Finally, in states where the child welfare system is state-run rather than county-run (i.e., centralized rather than decentralized), juvenile incarceration rates may be higher, especially during periods of welfare reform. Historically, there are times during which offenders are more likely to be handled by the welfare or mental health system rather than the justice system, and vice versa (Liska et al. 1999; McGarrell 1991). During periods of welfare reform, especially those periods where decreasing emphasis is given to welfare benefits, one might anticipate that states increasingly would rely on their justice systems to manage offenders who otherwise might typically be managed through the welfare or mental health systems. In such periods, this impact might be even greater in states where welfare policy is state-run because a centralized mechanism exists for ensuring a reduction in welfare benefits and a corresponding emphasis on incarceration.

Other political factors (e.g., the structure and dynamics of networks of leadership) might be relevant and, indeed, critical to understanding and predicting juvenile incarceration rates. Unfortunately, these factors rarely lend themselves readily to empirical analysis (see, however, Greenberg and West 2001; Jacobs and Carmichael 2001). Yet, as will be discussed below, there are ways in which these factors can be æsessed indirectly and then used to help inform the generation and interpretation of forecasts.

Social Factors

Numerous social factors might contribute to juvenile incarceration rates. One underlying mechanism through which these factors may operate is by affecting perceived or real threats to social order. From this perspective, certain social conditions may elicit a political response aimed at enhancing state control over certain populations, including juvenile offenders. Consider, for example, states with higher percentages of families with children headed by single parents. In such states, policymakers may come to believe that families are insufficiently capable of controlling children and thus may seek **e**course in incarcerative sanctions as a means of social control. Similar patterns can be hypothesized for states with higher teen birth or death rates, higher concentrations of minority populations, or greater population density (see, generally, Greenberg and West 2001). In each instance, social dynamics may contribute to a political context that views more restrictive, punitive approaches to juvenile crime as an effective or necessary strategy for maintaining or stabilizing the broader social order (McGarrell 1991).

Crime

As discussed earlier, conventional wisdom suggests that higher juvenile crime rates will be associated with higher incarceration rates (Jacobs and Carmichael 2001). The greater use of incarceration simply represents a logical and proportional response to increased offending (McGarrell 1991). However, this view neglects the fact that increased juvenile crime need not mean increases in the types of crime that society typically would view as warranting incarceration. Moreover, it ignores the fact that juvenile sentencing policy may be more responsive to concerns about crime generally, not just juvenile crime.

Based on such considerations, one might hypothesize that juvenile incarceration rates should be driven primarily by violent juvenile crime rates and possibly by overall violent crime rates. Although they may also be responsive to juvenile and overall property crime rates, one would anticipate a much more muted relationship since incarceration generally is viewed as a sanction appropriate for serious and violent dfending. Because incarceration policies may be driven by many factors other than crime, the effect of crime rates on incarceration rates may not be especially strong. As Greenberg and West (2001) have noted, "We expect a state's [incarceration] responses to be conditioned by its ability to finance their cost, and by its political culture. The anxieties and fears that lead residents and politicians to support the expanded use of imprisonment can be heightened or moderated by factors other than crime" (618).

Crime Control Approaches

Finally, juvenile incarceration rates may be higher in states with higher adult incarceration rates and in states relying more heavily on the death penalty and police to control crime. In each instance, measures can be taken to represent the general orientation of a state toward controlling crime (Greenberg and West 2001; Jacobs and Carmichael 2001; McGarrell 1991). The assumption is that juvenile incarceration policies reflect, at least in part, the overriding philosophies of social control embedded in state criminal justice policies.

DATA

To examine these hypotheses, data on state juvenile incarceration rates and measures of the different independent variables were collected. These data came from a wide range of sources. Many of the measures have been compiled by organizations such as the United Way of America, the Census Bureau, and the Office of Juvenile Justice and Delinquency Prevention for readily available access.

Table 1 describes the specific variables and data used for the subsequent analyses. As shown in this table, the analyses relied on cross-sectional, state-level data. Dependent variables included juvenile incarceration rates in 1997—that is, the number of juveniles, as age-defined by each state, in custody per 100,000 resident youths. Incarceration consists of placement in either public or private facilities, including placement of accused and adjudicated youths in detention centers, shelters and group homes, intake centers, and state-run training/correctional facilities.

The analyses focused on the total incarceration rate as well as the juvenile incarceration rates in public and private facilities. Where possible, data for 1996 were used to predict 1997 incarceration rates on the assumption that factors from the year or two preceding the year of interest would be most relevant to predicting incarceration rates. However, on occasion, data for 1996 were unavailable. In such cases, data from years immediately preceding or following 1996 were used. However, since data at this unit of analysis typically do not change dramatically from one year to the next, this approach should not significantly alter the results.

As table 1 shows, the age of juvenile jurisdiction varied across states. As of 1997, only 3 states used age 15 as the upper age of jurisdiction, 10 states used age 16, and the remaining 37 states used 17 as the upper age. (Although the definition of a "juvenile" may vary, many states provide for incarceration of youths in juvenile correctional facilities for indeterminate sentences that exceed the age of juvenile court jurisdiction. In the analyses below, the upper age of jurisdiction is coded dichotomously, with "1" indicating states with age 17 as the upper age of jurisdiction and "0" indicating states with age 15 or 16 as the upper age of jurisdiction.

Several economic variables were used in the analyses. These included median family income, measured in thousands of dollars, and the percent of the resident population living below the poverty level. In addition, a measure of economic inequality was used, operationalized by computing a ratio of the average family income for the top fifth of each state's population **d**vided by the average family income for the bottom fifth. Finally, the unemployment rate, measured as the number of unemployed citizens per 1,000 civilians in the labor force, was included.

Education variables included per-student expenditures, student-teacher ratios, and percent of high school dropouts. The student-teacher ratios measure the number of students per teacher in public elementary and secondary schools. The high school dropout rate reflects the percentage of youths ages 16 to 19 who dropped out of high school.

Three political variables were employed. The first was the percent of the voting age population who voted in the 1996 national elections. The second was the percent of the total popular vote, including minority party vote, voting as Democrats in the 1996 presidential election. The

TABLE 1. Description of Variables

Dependent Variables	
Incarceration rate	Number of delinquent offenders in public or private detention or correctional facilities per 100,000 youths age 10 to upper age of jurisdiction, 1997 (Sickmund 2000).
Incarceration rate (public)	Number of delinquent offenders in public detention or correctional facilities per 100,000 youths age 10 to upp age of jurisdiction, 1997 (Sickmund 2000).
Incarceration rate (private)	Number of delinquent offenders in private detention or correctional facilities per 100,000 youths age 10 to upper age of jurisdiction, 1997 (Sickmund 2000).
Independent Variables	
Upper Age of Jurisdiction	Upper age of juvenile court jurisdiction, where 1 = 17, 0 = 15-16 (Stahl, McGlynn, and Wan 2000).
Economic	
Median family income	Median family income, 1996 (Census Bureau 2001a).
Percent in poverty	Percentage of the population below federal poverty level, 1996 (Census Bureau 2001b).
Income inequality	Ratio of average family income for top fifth of the population divided by average family income for bottom fift 1996 (Economic Policy Institute and Center on Budget and Policy Priorities 2000a, b).
Unemployment rate	Number unemployed per 100 civilians in labor force, 1996 (Bureau of Labor Statistics 2001).
Education	
Per-student expenditures	Public school expenditures (1997-98 dollars) per student, 1996 (National Center for Education Statistics 2000a, b).
Student-teacher ratios	Pupil-to-teacher ratios in public elementary/secondary schools, 1996 (National Center for Education Statistics 2000a, b).
Percent high school dropouts	Percentage of youths ages 16-19 who are high school dropouts, 1996 (Casey Foundation 2001).
Political	
Percent voting	Percentage of voting age population that voted in national election, 1996 (Federal Election Commission, 2000)
Percent voting Democratic	Percentage of total popular vote, including minority party vote, voting Democratic for presidential 1996 electi (Census Bureau 1998, 56).
State child welfare system	Child welfare (protection and prevention) system, 1996 (Watson and Gold 1997), where 1 = state-administered and 0 = county-administered.
Social	
Percent single-parent families	Percentage of families with children headed by a single parent, 1996 (Casey Foundation 2001).
Teen birth rate	Number of births per 1,000 females ages 15-17, 1996 (Casey Foundation 2001).
Teen death rate	Accidents, homicides, and suicides per 100,000 youth ages 15-19, 1996 (Casey Foundation 2001).
Percent black	Percentage of total population reporting race as black, 1996 (Census Bureau 1998, 6).
Population density	Resident population per square mile of land area, 1997 (Census Bureau 1998, 2).
Violent crime rate	Reported murders, forcible rapes, robberies, aggravated assaults per 100,000 resident population, 1996
Property crime rate	[violent]; burglaries, larcenies, auto thefts per 100,000 resident population, 1996 [property] (Bureau of Justic Statistics 2000).
Juvenile violent arrest rate	Juvenile (under age 18) arrests for murder, forcible rape, robbery, and aggravated assault per 100,000 youth
Juvenile property arrest rate	(ages 10-17), 1996 [violent]; and burglary, larceny, auto theft arrests per 100,000, 1996 [property] (Snyder 1997b). When 1996 data were unavailable, data are for 1995 (D.C., Florida, Vermont) or 1997 (Illinois, Kentucl Mississippi, Montana, Tennessee) (Snyder 1997a, 1998).
Crime Control Approach	
Adult incarceration rate	Number of state/federal adult inmates per 100,000 resident population, 1996 (Gilliard and Beck 1997).
Death penalty	Number of times death penalty administered, 1977-1996 (Snell 1997).
. ,	Number of police officers per 100,000 residents, 1996 (Census Bureau 1998, 18).

Note: State-level data are available from many different sources. Some organizations, such as the United Way (2001), the Census Bureau (1998), and the Office of Juvenile Justice and Delinquency Prevention, compile these data in a readily accessible format.

final political variable was a measure of whether the child welfare system, including prevention and protection systems, was administered by the state (coded as "1") or county (coded as "0").

The measures of social conditions covered several distinct dimensions of social life. These included the percentage of families with children headed by a single parent; the teen birth rate (number of births per 1,000 females ages 15 to 17); the teen death rate (number of accidents, homicides, and suicides per 100,000 youths ages 15 to 19); the percent of the total state population consisting of black residents; and population density (population per square mile of land area).

Crime rates were categorized into four groups. These included the violent crime rate, measured as the reported number of murders and non-negligent homicides, forcible rapes, robberies, and aggravated assaults per 100,000 residents. The property rate was measured as the number of burglaries, larcenies, and auto thefts per 100,000 residents. These rates, using the same sets of offenses, were computed separately for youthful offenders (ages 10 to 17), using 100,000 youths ages 10 to 17 as the denominator.

Finally, three different crime control variables were computed. The first was the adult incarceration rate (number of state and federal adult inmates per 100,000 residents). The second was the number of times the death penalty was administered. And the last was the police protection rate, measured as the number of police officers per 100,000 residents.

Table 2 provides descriptive statistics for these different variables. Across the 51 states (including the District of Columbia), the average juvenile incarceration rate, used as the dependent variable in the subsequent analyses, was 308. The average public and private incarceration rates were 229 and 79, respectively. Inspection of the independent/predictor variables shows that, as with the dependent variables, the standard deviations typically are quite large relative to the mean values for each variable. This indicates considerable variability across states along these different dimensions.

METHOD

Ordinary least squares (OLS) regression was used to examine the relationship between state-level juvenile incarceration rates (total and public vs. private facilities) and a set of predictors. Both univariate and multivariate analyses were used to identify whether specific factors were associated with juvenile incarceration rates. They also were used to demonstrate the extent to which various factors can account for variation in incarceration rates.

It should be reiterated that an analysis of between-state variation in incarceration rates is similar, but not identical, to an analysis of within-state/over-time variation in incarceration rates. The between-state approach helps to identify the characteristics of states with higher incarceration rates. The within-state/over-time approach helps to identify factors associated with increases in incarceration rates. These factors may overlap. For example, states with higher rates of single-parent households may have higher incarceration rates and, within a state, increases in rates of single-parent households may be associated with increased incarceration rates. But these factors need not necessarily overlap or operate in the same manner. Thus, the cross-sectional (between-state) analysis provided below primarily serves to illustrate the types of factors that may drive juvenile incarceration rates in particular states.

For some of the regression analyses, factor analysis was used to distill down the large number of independent/predictor variables. This statistical approach enables researchers to identify constructs or "factors" that may underlie a set of variables and thus simplify the interpretation of regression analyses (Stevens 1992).

TABLE 2. Descriptive Statistics

	Mean	Standard Deviation	N
Dependent variables			
Juvenile incarceration rate	308.00	120.51	51
Juvenile incarceration rate (public)	228.59	109.97	51
Juvenile incarceration rate (private)	79.41	56.29	51
Predictor variables			
Upper age of jurisdiction of 17	.75	.44	51
Economic			
Median family income, \$	36,556.70	5,756.87	50
% population below poverty level	12.85	3.96	50
Inequality	9.51	1.47	50
Unemployment rate	5.15	1.16	50
Education			
Public school expenditures per pupil, \$	5,919.94	1,259.75	50
Pupil-teacher ratio	16.70	2.19	50
% teens high school dropouts	9.32	2.96	50
Political			
% voters voting in 1996 national election	51.56	6.76	50
% voters voting Democratic in 1996 presidential election	47.95	8.56	51
Child welfare system state-run	.71	.46	51
Social			
% families with single parent	26.12	3.92	50
Teen birth rate	30.98	9.86	50
Teen death rate	68.22	37.65	51
% population black	11.05	11.95	51
Population per square mile	182.29	244.28	51
Crime			
Violent crime rate	505.86	251.92	50
Property crime rate	4,313.30	1,041.04	50
Juvenile violent crime rate	417.00	274.86	50
Juvenile property crime rate	2,670.50	908.51	50
Crime control approaches			
Adult incarceration rate	350.35	206.22	51
Death penalty count	7.02	16.82	51
Police protection rate	286.39	88.05	51

RESULTS

Single Variable Analyses

Vigure 1 depicts a conceptual model for ex- Γ plaining and predicting state-level juvenile incarceration rates. The model suggests that each of a range of types of factors—such as the upper age of juvenile court jurisdiction; economic, social, and political conditions; crime and different crime-control approaches-contribute to lower or higher juvenile incarceration rates. It bears emphasizing, however, that the effects of many of these factors may be indirect (e.g., one predictor may influence another, which in turn may contribute to incarceration rates). The effects also may be interactive (e.g., the effect of one predictor on incarceration rates may vary depending on the level of another predictor). Although such effects may exist, at present there is little theoretical or empirical research providing guidance about how models should be specified to capture them.

To assess the relationships suggested by the conceptual model, table 3 presents the results of an OLS regression analysis of state juvenile incarceration rates on the different predictors shown in table 1 and depicted in figure 1. Two columns are most relevant for the purposes at hand: the column of unstandardized coefficients and the column of adjusted R²s.

The unstandardized coefficients indicate how much the incarceration rate increases for a unit increase in the predictor. For example, every one-unit increase in the percent of high school dropouts results in an increase by 12 in the juvenile incarceration rate. These coefficients should not be compared with one another to determine the relative predictiveness of one variable against another because each variable is measured using a different metric. Standardized coefficients (betas) can be used for such comparisons. However, they can be more difficult to interpret because the standardized metric has no intuitive meaning. Rather, the comparisons across variables are between the influence of one standard deviation change in a particular variable versus a standard deviation change in another.

The adjusted R^2s show the amount of variation in the incarceration rate for which each variable can account. For example, the adult incarceration rate accounts for close to 30 percent of the variation. By contrast, the juvenile violent crime rate accounts for only 14 percent of the variation in the incarceration rate.

As shown in table 3, only some of the independent variables were statistically associated with the dependent variable (i.e., the incarceration rate). These included the percent of teen high school dropouts, percent of families with single parents, the teen birth rate and death rate, the percent of the population that is black, the violent crime rate and property crime rate, the juvenile violent crime rate, the adult incarceration rate, and the police protection rate. Notably, the upper age of jurisdiction, economic variables, and political variables showed no statistically significant relationship with the juvenile incarceration rate. For those variables that were significant, the relationship was consistently positive, that is, increases in each variable were associated with increased incarceration rates.

Among the statistically significant predictors, the adult incarceration rate was the most predictive, explaining close to 30 percent of the

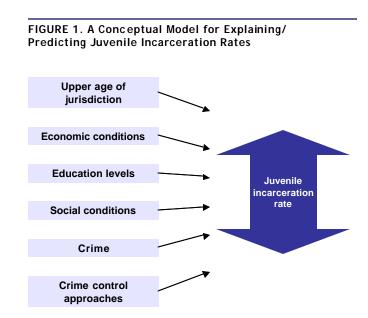


TABLE 3. Ordinary Least Squares Univariate Regression Models of State Juvenile Incarceration Rates (1997) on Select Predictors^a

	Intercept ^b	Coefficient ^C	Standard error d	Adjusted R ²	N
Upper age of jurisdiction of 17	321.62***	-18.27	39.03	016	51
Economic					
Median family income	213.75*	.00	.00	005	50
% population below poverty level	277.36***	1.86	4.06	016	50
Inequality	128.57	18.16	10.62	.038	50
Unemployment rate	211.45**	17.46	13.67	.013	50
Education					
Public school expenditures per pupil	282.42***	.00	.01	020	50
Pupil-teacher ratio	139.27	9.70	7.23	.016	50
% teens high school dropouts	185.31	12.44*	5.14	.090	50
Political					
% voters voting in 1996 national election	385.10**	-1.63	2.37	011	50
% voters voting Democratic in 1996 presidential election	177.91	2.71	1.98	.017	51
Child welfare system state-run	318.93***	-15.49	37.35	017	51
Social					
% families with single parent	58.58	9.29*	3.89	.088	50
Teen birth rate	194.67***	3.44*	1.56	.073	50
Teen death rate	215.22***	1.36**	.41	.164	51
% population black	261.39***	4.22**	1.31	.158	51
Population per square mile	292.48***	.09	.07	.010	51
Crime					
Violent crime rate	202.63***	.20***	.06	.177	50
Property crime rate	161.03*	.03*	.02	.073	50
Juvenile violent crime rate	235.65***	.17**	.06	.135	50
Juvenile property σ ime rate	233.37***	.03	.02	.023	50
Crime control approaches					
Adult incarceration rate	194.01***	.33***	.07	.296	51
Death penalty count	301.44***	.94	1.02	003	51
Police protection rate	132.14*	.61***	.18	.185	51

a. The incarceration rate includes public and private facilities. Analysis of disaggregated rates (i.e., public vs. private facilities) produced similar results.

b. The intercept represents the value of the dependent variable when the predictor equals zero. Often, the intercept is not easily interpretable because zero is not a realistic or possible value. A significant intercept indicates that after controlling for the predictor(s), the mean of the dependent variable is different from zero. Typically, one does not examine the significance of intercepts. For this reason, and to simplify presentation of the results, the intercept standard errors are not presented.

c. Coefficients represent the amount by which the dependent variable will increase for a one-unit increase in a given predictor. For example, for every 1 percent increase in the percentage of teen high school dropouts, the state delinquency incarceration rate rises by 12.44 per 100,000.

d. The standard error measures how much variation there is about the estimated coefficient. The larger the standard error relative to a given coefficient, the less confident we can be in the accuracy of the coefficient.

e. The adjusted R^2 measures how much of the variation in a dependent variable is explained by one or more predictors. For example, the teen high school dropout variable explains 9 percent of the variation in the incarceration rate.

* p < .05, ** p < .01, *** p < .001

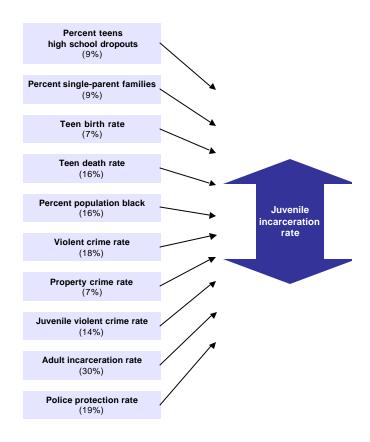
variation in state-level juvenile incarceration rates (see figure 2). The police protection rate was the next most predictive (19 percent), followed by the violent crime rate (18 percent), the teen death rate (16 percent), the percent of the population that is black (16 percent), and the juvenile violent crime rate (14 percent).

Of course, prediction does not recessarily imply an ability to change an outcome. Consequently, we should not assume that a variable accounting for more of the variation in incarceration rates necessarily is more important. For example, the teen birth rate, which æcounts for 7 percent of the variation in juvenile incarceration rates, presumably is more susceptible to policy influence than the percent of the population that is black. Thus, even though the latter variable explains more of the variation in juvenile incarceration rates (16 percent), it may be less important than the teen birth rate if policy relevance is the guiding criterion of evaluation.

Even if a variable explains relatively little of the variation in incarceration rates, the magnitude of effect might suggest potential policy relevance. For example, for each 1 percent increase in families with single parents, the juvenile incarceration rate increases by 9. The relatively small amount of variation (9 percent) explained by this variable suggests, however, that an increase of this size cannot be reliably anticipated because many other factors affect the remaining variation (91 percent) in the incarceration rate.

In short, the different variables are *e*lated to and account for variation in juvenile incarceration rates to different extents. Closer inspection of the results suggests a further observation—namely, the ability of these different variables to predict juvenile incarceration rates is quite low. As figure 3 shows, among those variables significantly related to incarceration rates, some only explain 2 percent of the variation in the rates. Even the best predictor, the adult incarceration rate, accounts for only 30 percent of the variation. Such prediction might be considered reasonable under many circumstances. In the context of developing incarceration policies, however, many policymakers might prefer a much greater ability to identify more precisely the determinants of juvenile incarceration rates.

FIGURE 2. Differences in the Extent to Which Different Factors Account for Variation in State Juvenile Incarceration Rates (Based on Univariate Regression Analyses)



Notes: A convenient way of comparing the relative influence of different factors in predicting a particular outcome, such as juvenile incarceration rates, is to examine the extent to which each can account for variation in that outcome. Factors that explain a greater percentage of the variation in the outcome may be thought of as more predictive than others. Greater prediction is not necessarily the best measure of importance, however, since some highly predictive factors cannot be changed by policy.

Multivariate Analyses with Many and Few Predictors

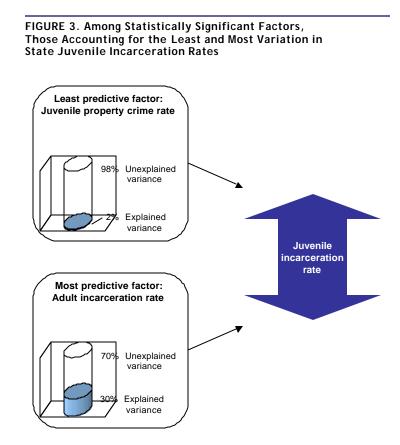
One problem with the previous analysis is that many of the different predictor variables may be related not only to the dependent variable (i.e., the incarceration rate) but to each other. In such instances, it can be difficult to discern the net effect of each variable. Multivariate modeling allows researchers to remedy this problem by controlling for the effects of each of the different predictors.

A key challenge with multivariate analyses lies in knowing what variables to include. This issue can be particularly challenging when the

number of observations is small, as is the case here, where there are only 49 observations (two of the states were not included in the analyses because of missing data). When one is interested primarily in prediction, procedures are available that allow statistical programs to select the model that explains the most amount of variation in the dependent variable. Researchers typically differentiate between explanatory models, which may not be the most predictive models but can be used to provide meaningful descriptions of variation in an outcome, and non-explanatory, predictive models that aim only to account for as much of the variation in an outcome as possible (Sabol 1999, 45).

Table 4 presents the results of a non-explanatory, predictive model (column 1) using all the variables listed in table 1. As is evident from a comparison of tables 3 and 4, the coefficients and statistical significance of many of the variables changed. More important, from the standpoint of prediction, our ability to predict juvenile incarceration rates inproved marginally, from 30 percent (if only the adult incarceration rate were used) to 32 percent (if all the variables in column 1 were used).

This improvement is quite small, especially given the large number of variables added to the model. An alternative approach to model specification is to identify the most predictive models that use the fewest numbers of variables—that is, the most parsimonious and predictive models. Columns 2 and 3 present two different but equally parsimonious (two predictors) and predictive (23 percent) models. In one, the juvenile property crime rate and the adult incarceration rate contribute to an explanation of the juvenile



Notes: A convenient way of comparing the relative influence of different factors in predicting a particular outcome, such as juvenile incarceration rates, is to examine the extent to which each can account for variation in that outcome. Factors that explain a greater percentage of the variation in the outcome may be thought of as more predictive than others. Greater prediction is not necessarily the best measure of importance, however, since some highly predictive factors cannot be changed by policy.

TABLE 4. Ordinary Least Squares Regression of State Juvenile Incarceration Rates (1997):
The Most Predictive vs. the Most Parsimonious Multivariate Models

	Most predictive model	Most parsimonious model 1	Most parsimonious model 2
Intercept	-365.78	89.51	118.25*
	(239.38)	(56.05)	(51.97)
Public school expenditures per pupil	.02		
	(.02)		
Pupil-teacher ratio	12.39		
	(8.87)		
Child welfare system state-run	-54.32		
	(33.14)		
% families with single parent	10.37		
	(5.65)		
% population black	-3.27		
	(2.67)		
Pop per square mile	.11		
	(.09)		
Violent crime rate	.26*		.19***
	(.11)		(.06)
Property crime rate	04*		
	(.02)		
Juvenile violent crime rate	26*		
	(.11)		
Juvenile property crime rate	.07***	.04*	.03*
	(.02)	(.02)	(.02)
Adult incarceration rate	.33*	.36***	
	.33 (.16)	(.10)	
Adjusted D ²			.229
Adjusted R ² N		.231 49	. 229 49
/ V	47	47	47

Notes: Standard errors are in parentheses. The most parsimonious models are those that use the fewest significant predictors while still achieving a relatively high degree of prediction. The first such model was identified by allowing all variables to be entered and then eliminating, one by one, those that did not retain a level of significance of p < .10. The second model allowed variables to be entered one by one, retaining those that were significant and eliminating those that were not.

* p < .05, ** p < .01, *** p < .001

incarceration rate, while in the other, the violent crime rate and juvenile property crime rate are the primary predictors.

Once again, the concern arises that both the most predictive model and the most parsimonious and predictive models account for no more than 23 to 32 percent of the variation in juvenile incarceration rates (see figure 4). Put differently, even with these models, between 68 and 77 percent of the variation in juvenile incarceration rates remains unexplained.

An additional problem lies in the fact that the effects of key variables vary considerably, depending on which variables are included. In general, researchers feel confident in the relationship between one variable (e.g., crime rates) and another (e.g., incarceration rates) when this rela-

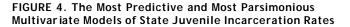
tionship remains largely unchanged by inclusion of other variables in predictive models (Stevens 1992). This stability is conspicuously absent in the models of state-level juvenile incarceration rates. Many variables emerge as statistically significant in some models, but not in others. In still others, their significance levels may not change, but the direction or size of their effects (as measured by the unstandardized coefficients) do.

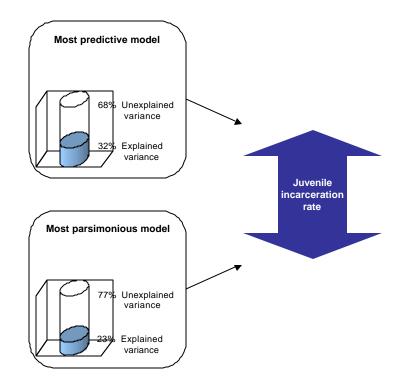
This issue applies not only to cross-sectional analyses but to within-state/over-time analyses as well. Indeed, the issue is even more problematic. With time series analyses of this type, frequently there are few data points (e.g., there may be annual data going back only 10 or so years). In addition, certain statistical issues must be addressed, further decreasing the leverage that can be obtained from the few available data points. For example, almost all trend data manifest naturally occurring seasonalities (i.e., variations that occur systematically and repeatedly. whether daily, weekly, monthly, yearly, or otherwise) that must be

taken into account before estimating the effect of certain variables (Yaffee 2000).

Statistical Regression Analyses with One Underlying Factor

In situations where one is confronted with many possible factors that may be related to an outcome, controlling for these different factors can be a useful way to identify net effects of each factor. However, this approach can be problematic when one or more of the predictors is correlated with another, a situation commonly referred to as "multicollinearity" (Stevens 1992). It also can be problematic simply from the standpoint of interpretation.





Notes: A convenient way of comparing the relative influence of different factors in predicting a particular outcome, such as juvenile incarceration rates, is to examine the extent to which each can account for variation in that outcome. Factors that explain a greater percentage of the variation in the outcome may be thought of as more predictive than others. Greater prediction is not necessarily the best measure of importance, however, since some highly predictive factors cannot be changed by policy.

One solution lies in the removal of variables that seem similar to one another. Another approach is to employ a statistical methodology, such as factor analysis, for identifying any underlying constructs, or "factors." With factor analysis, the correlations and intercorrelations among a set of variables are examined to determine if underlying factors can be discerned based on certain statistical criteria. To examine the possibility that one or more factors might be present in the data used in the predictive analyses, a factor analysis was conducted using all of the variables in table 1.

The resulting analysis identified several underlying factors, but only one emerged for which any meaningful interpretation could be provided (see table 5). This factor, "social disadvantage," had an eigenvalue of 6.97. Eigenvalues measure the amount of variation in the total sample accounted for by a given factor. When a factor explains little of the variance in the total sample, its eigenvalue is low. Typically, 1.0 is used as a cut-off point, but this decision is relatively arbitrary, and other cut-offs can be used (Stevens 1992). The eigenvalue of 6.97 for the factor presented here suggests a clear underlying construct. In addition, it is the only factor for which, as noted above, an obviously meaningful interpretation could be provided based on review of the specific variables that were correlated with it.

As table 5 shows, about half of the predictors were highly correlated with, or "loaded highly on," social disadvantage. The term seems appropriate because the contributing factors all appear to reflect characteristics of places where social problems are pervasive and resources are lower, relative to more advantaged and well-todo places.

To determine if this factor could predict juvenile incarceration rates, a regression analysis was run using only this one variable (see table 6). The results indicated a strong and statistically significant relationship between social disadvantage and the dependent variable. Specifically, for each unit increase in social disadvantage, the juvenile incarceration rate increased by 42.

TABLE 5. Factor Analysis: Identifying "SocialDisadvantage" as an Underlying Measure^a

Predictor variables	Correlation: Social disadvantage ^b
Upper age of jurisdiction 17 years	227
Economic	
Median family income	271
% population below poverty level	.648*
Inequality	.704*
Unemployment Rate	.514*
Education	
Public school expenditures per pupil	312
Pupil-teacher ratio	.228
% teens high school dropouts	.742*
Political	
% voters voting in 1996 national election	703*
% voters voting Democratic in 1996 presidential election	.085
Child welfare system state-run	012
Social	
% families with single parent	.774*
Teen birth rate	.918*
Teen death rate	.501*
% population black	.690*
Pop per square mile	029
Crime	
Violent crime rate	.797*
Property crime rate	.619*
Juvenile violent crime rate	.416
Juvenile property crime rate	008
Crime control approaches	
Adult incarceration rate	.830*
Death penalty count	.463
Police protection rate	.452

a. One use of factor analysis is to identify a small subset of dimensions from among a much larger set of variables. The results here are from an unrotated factor analysis that produced five factors with eigenvalues above 1.0. The eigenvalue for the largest factor, presented here, was 6.974. The loadings for the other factors were 4.270, 2.387, 1.763, and 1.151, respectively. Eigenvalues measure the amount of variation in the total sample accounted for by a given factor. When a factor ex plains little of the variance in the total sample, its eigenvalue is low. Typically, 1.0 is used as a cut-off point, but this decision is relatively arbitrary, and other cut-offs can be used (Stevens 1992). The eigenvalue of 6.974, coupled with the specific pattern of factor loadings for the other factors do not; hence, only this factor is presented in this table.

b. The presented values are "factor loadings," which are analogous to correlations. The squared factor loading for a given variable is equal to the percent of variance in that variable that is explained by the factor. The loadings with asterisks indicate variables most strongly associated with the factor. Inspection of these variables suggests a common underlying construct, termed here as "social disadvantage." The term seems appropriate because the contributing factors all appear to reflect characteristics of places where social problems are pervasive and resources are lower, rela-

tive to more advantaged and well-to-do areas.

However, only 12 percent of the variation in juvenile incarceration rates could be accounted for in this model, leaving 88 percent unexplained (see figure 5). An additional problem lies in the fact that policymakers might find it difficult to know how to address the general problem of social disadvantage. They might find that a more specific problem, such as the teen birth rate, would more readily lend itself to effective intervention. In theory, however, it would be possible to focus on the range of factors contributing to the construct of social disadvantage.

Multivariate Analyses: Public vs. Private Facilities

To determine whether the results obtained in the analyses of total juvenile incarceration rates differed for public versus private facility rates, the above analyses were rerun using the disaggregated rates—that is, the juvenile incarceration rate in public facilities and the juvenile incarceration rate in private facilities. The results are presented in table 7 (public facilities) and table 8 (private facilities).

Several differences emerge when these disaggregated rates are compared with one another and with the total juvenile incarceration rate. First, there is a greater ability to predict the public facility incarceration rate (37 percent), compared with the private facility incarceration rate (21 percent) or the overall incarceration rate (32 percent). Second, the particular variables included in the most predictive models vary somewhat, with the public facility and total incarceration rates showing greater similarities. For example, in both cases the juvenile violent crime rate and juvenile property crime rate were statistically significant predictors. However, there were striking differences as well. For example, in the public facility model, the violent and property crime rates were not significant, but they were significant in the total incarceration rate model. Third, similar variability was

TABLE 6. Ordinary Least Squares Regressionof State Delinquency Incarceration Rates (1997)on Social Disadvantage^a

Intercept	301.00*** (15.11)
Social disadvantage	42.03** (15.27)
Adjusted R ²	.121
Ν	49

a. Standard errors are in parentheses. The model indicates that for every standard deviation increase in social disadvantage, the juvenile incarceration rate increases by 42 per 100,000. The social disadvantage scale is a function of many different variables. Those most strongly contributing to the scale include percent of the population below the federal poverty level, extent of inequality, unemployment rate, percent of teenagers who are high school dropouts, percent of voters who voted in the 1996 national elections, percent of single-parent families with children, teen birth rate, teen death rate, percent of the population that is black, violent crime rate, property crime rate, and adult incarcer ation rate.

* p < .05, ** p < .01, *** p < .001

FIGURE 5. Social Disadvantage and Its Ability to Account for Variation in State Juvenile Incarceration Rates

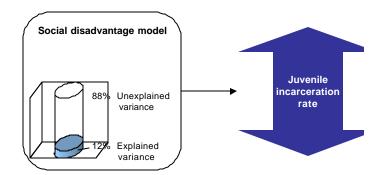


 TABLE 7. Ordinary Least Squares Multivariate Regression of State Juvenile Incarceration Rates

 (Public Facilities) (1997)

	Most predictive model	Most parsimonious model 1	Most parsimonious model 2	Social disadvantage model
Intercept	180.59	-203.50	10.028	224.29***
	(112.68)	(111.17)	(53.97)	(14.18)
% population below poverty	-9.25	-11.49*		
	(5.93)	(5.44)		
Inequality	26.21	38.19*		
	(17.70)	(15.66)		
Unemployment rate	22.19	21.60		
	(14.05)	(13.88)		
% teens high school dropouts	7.92			
	(6.50)			
Child welfare system state run	-52.59	-43.85		
	(29.34)	(28.39)		
Population per square mile	.08			
	(.08)			
Violent crime rate	.17	.19		
	(.11)	(.10)		
Property crime rate	03	03		
	(.02)	(.02)		
Juvenile violent crime rate	23*	22*		
	(.10)	(.09)		
Juvenile property crime rate	.07***	.07***	.04*	
	(.02)	(.02)	(.02)	
Adult incarceration rate	.22	.25	.36***	
	(.14)	(.13)	(.10)	
Social disadvantage				47.10**
				(14.32)
Adjusted R ²	.374	.372	.256	.170
Ν	49	49	49	49

Notes: Standard errors are in parentheses. The most parsimonious models are those that use the fewest significant predictors while still achieving a relatively high degree of prediction. The first such model was identified by allowing all variables to be entered and then eliminating, one by one, those that did not retain a level of significance of p < .10. The second model allowed variables to be entered one by one, retaining those that were significant and eliminating those that were not.

* p < .05, ** p < .01, *** p < .001

TABLE 8. Ordinary Least Squares Multivariate Regression of State Juvenile Incarceration Rates
(Private Facilities), 1997

	Most predictive model	Most parsimonious model 1	Most parsimonious model 2	Social disadvantage model
Intercept	-121.60	-134.92	-65.21	76.71***
	(129.71)	(106.40)	(83.58)	(7.60)
Median family income	04*	04		
	(.00)	(.00)		
Unemployment rate	-19.13*	-18.09*	-12.72	
	(7.44)	(6.98)	(6.61)	
Public school expenditures per pupil	.02	02*		
	(.01)	(.01)		
Pupil-teacher ratio	8.16	7.26		
	(4.27)	(4.20)		
% teens high school dropouts	-4.47			
	(3.33)			
% voters voting in 1996 national election	2.52	2.98*	3.12*	
	(1.29)	(1.27)	(1.25)	
Teen death rate	.58			
	(.52)			
Violent crime rate	. 10**	.09**	.09**	
	(.04)	(.03)	(.03)	
Social disadvantage				-5.07
				(7.68)
Adjusted R ²	.208	.194	.162	012
Ν	49	49	49	49

Notes: Standard errors are in parentheses. The most parsimonious models are those that use the fewest significant predictors while still achieving a relatively high degree of prediction. The first such model was identified by allowing all variables to be entered and then eliminating, one by one, those that did not retain a level of significance of p < .10. The second model allowed variables to be entered one by one, retaining those that were significant and eliminating those that were not.

* p < .05, ** p < .01, *** p < .001

present for the most parsimonious models as well. Fourth, taken as a whole, the public facility and total juvenile incarceration rate models were most similar, likely reflecting the fact that the vast majority of juveniles are placed in public facilities, creating a significant correlation between the two incarceration rates and the factors that are associated with them.

Predicting Incarceration Rates: Explained vs. Unexplained Variance

From the perspective of developing juvenile correctional policies, one ideally has recourse to a model that can explain much of the variation in juvenile incarceration rates. As the above analyses suggest, many models simply account for far too little of this variation to be useful in developing public policy. These models may be quite useful for testing different theories about juvenile incarceration policies. But tests of theories, even those that support partic ular theories, do not necessarily translate into useful or effective policy implications.

To compound this problem, there is an additional consideration: Even with a set of factors that can explain an outcome, many of them may not be susceptible to influence. For example, teen birth rates might be susceptible to policy influence, but the demographic factors, such as the age, sex, and race/ethnic composition of a juvenile population, generally are not.

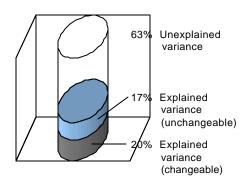
In the above analyses, the best predictive model was for public facility juvenile incarceration rates, for which 37 percent of the state-level variation could be explained. However, 63 percent of the variation is unexplained. Of the 37 percent of explained variance, it probably is the case that only some fraction involves variables that policymakers can influence. Figure 6 depicts this situation. Using an arbitrary cut-off of 20 percent, it illustrates the idea that in any predictive model, there always is unexplained variance, explained variance involving variables that cannot be changed, and explained variance involving variables that might be susceptible to a policy intervention.

THE BENEFITS AND LIMITATIONS OF STATISTICAL MODELS FOR JUVENILE CORRECTIONAL PLANNING

S tatistical approaches to understanding, explaining, and predicting juvenile incarceration rates can vary tremendously. They may vary with respect to the precise focus of analysis. For example, is the focus on explaining why some states have different incarceration rates than others? Is it on explaining why, within one state, some counties have higher incarceration rates than others? Or is it on predicting what future incarceration rates will be within a local jurisdiction or a state?

Each type of focus entails a different set of policy implications. If, for example, we want to develop a policy to reduce rates of juvenile incarceration in large, urban counties, then we need to understand what it is about these counties that gives rise to greater rates of incarceration. By contrast, if we want to develop a policy to reduce incarceration at the state level, then we need to understand what factors have driven incarceration trends in the past, identify whether these factors will continue to be relevant (and, if so, what their levels will be in future years), and determine how exactly a policy could be developed to intervene effectively in changing one or more of these factors.

FIGURE 6. The Best Statistical Models Typically Account for Very Little of the Variation in Juvenile Incarceration Rates



Statistical approaches also can vary with respect to the type of statistical analysis employed. For example, different states may employ quite different statistical methodologies to predict their future incarceration trends. Two of the more common statistical approaches include regression and time series analysis, the latter of which includes a large subset of different statistical approaches (Yaffee 2000).

Regardless of the focus of analysis or the specific type of statistical approach employed, statistical analyses in general can provide certain benefits. They also have significant limitations that can offset these benefits. At the very least, these limitations require careful consideration of the exact meaning and usefulness of statistical analyses.

Benefits

UNDERSTANDING FACTORS THAT AFFECT INCAR-CERATION RATES. Statistical models can provide researchers and policymakers with a better understanding of a range of factors—social, legal, economic, educational, political, and others that affect juvenile incarceration rates. Analysis of these factors can provide a basis for anticipating the general direction in which future incarceration rates are likely to go. They also can provide a rough sense of the potential magnitude of change that is anticipated.

IDENTIFYING FACTORS THAT CAN INFLUENCE IN-CARCERATION RATES AND THAT CAN BE CHANGED. Sophisticated statistical models may also enable researchers to identify predictive factors that are especially amenable to policy influence. In these instances, policymakers might focus less on the overall predictive ability of a model and instead on those factors that can be changed and that contribute to incarceration trends. Less sophisticated models may not provide this type of information, but rather may identify only the direction and approximate magnitude of growth that can be anticipated in future years. RELATIVELY FEW DATA REQUIREMENTS. Statistical models generally require few data elements, and many of these may be readily available through a variety of data sources (see, e.g., table 1). The more data elements that are available and that go back for a greater number of time periods, the greater the likelihood that researchers can develop more accurate explanations about past trends and possible future trends.

Limitations

LIMITED ABILITY TO REDICT THE FUTURE. The potential benefits of statistical forecasting approaches generally are offset by a range of critical limitations. Perhaps the most important limitation is that even the best predictive models explain little of the variation in past trends. Thus, their ability to forecast the future accurately is nominal Moreover, the further the timeline for the forecast (say, 4 to 5 years), the less accurate the forecast is likely to be, which is true for correctional forecasting and other types of forecasting as well (Penner 2001).

In the context of juvenile incarceration forecasts, a large part of the problem lies in the fact that several key factors influence incarceration trends: (1) the supply of youthful offenders, (2) prosecutorial and judicial practices, (3) correctional practices (e.g., how long youthful offenders are held in custody), and (4) policymakers' decisionmaking priorities and practices. Each of these factors bears directly on juvenile incarceration trends, yet none of them can be predicted with a great deal of accuracy. *Indeed*, *it is likely because of our limited ability to predict these factors that the best statistical models account for relatively little of the variation in juvenile incarceration trends*.

Another reason that statistical models rarely explain much of the variation in juvenile incarceration trends lies in the fact that few jurisdictions or states have sufficient data or analytic resources to conduct predictive analyses. Even when such resources are available, significant methodological problems, such as multicollinearity among key predictors, undermine the reliability of forecasts.

Finally, even the best predictive models generally must be updated frequently to maintain their predictive utility (Butts and Adams 2001; Penner 2001; Sabol 1999). Few states have the capacity to develop and improve statistical models on an ongoing basis. As a result, the annual forecasts undertaken or contracted for by various jurisdictions generally become increasingly less predictive over time.

RELIANCE ON FORECASTS ABOUT KEY PREDICTORS.

The best statistical models for projecting future incarceration trends must rely on projections about other future events. For example, many states examine how incarceration trends follow arrest rates. To anticipate future arrest rates, which they need to apply their statistical models of incarceration trends, they examine predictors of arrest rates, such as changes in the demographic composition of the state over the next five to ten years. In essence, then, juvenile incarceration projections entail forecasts built on forecasts, which are built on even more forecasts. In each instance, any given forecast is subject to considerable error. As a result, the ultimate forecast-future juvenile incarceration rates or bed-space needs (as defined by, e.g., arrests for violent felony offenses)-itself is premised on a series of errors that compound one another.

INABILITY TO ANTICIPATE IMPORTANT SOCIAL AND POLICY CHANGES. Perhaps the most difficult-toanticipate factor affecting juvenile incarceration rates—and possibly the most important (i.e., predictive)—is what policymakers will do in the future. Policymakers decide whether to fund additional bed-space construction. They also determine what types of policies will be pursued, and many of these policies may affect both the supply of youthful offenders and the prior ities and actions of prosecutors, judges, and corrections officials. For example, consider a newly developed policy—implemented several months after a highly sophisticated forecast was conducted requiring that all incarcerated youths be retained in custody until they achieve an age-appropriate education level. The result likely would be a dramatic increase in juvenile incarceration rates due to much longer periods of incarceration. (Most youths sent to correctional facilities operate at an educational level several years below what their age would indicate.)

A recent example of this type of issue comes from the 77th Texas legislative session. House Bill 53 was submitted in early 2001 mandating that all youths released from the Texas Youth Commission (TYC) must reach an educational skill level equivalent to his/her age level. The Texas Criminal Justice Policy Council (TCJPC), the agency charged with assessing such policies, was able to use pre- and posteducational scores for youths, broken down by TYC classification categories, to calculate the time needed for these category-specific youths to reach an age-appropriate educational level. (Offenders with high school or general equivalency diplomas were removed from each classific ation.) TCJPC calculated the time that would have to be served by youths within each classification category to attain an age-appropriate level of education. They then were able to show that under the proposed legislation, TYC would need approximately 2,000 more beds over the next four years (TCJPC 2001).

In this particular example, TCJPC relied on a nonstatistical approach to forecasting, in large part because no statistical approach adequately allows for incorporating information about unusual and unanticipated types of policy. A statistical approach might be appropriate if many such policies had been enacted in the past, and if statistical models were able to account for any subsequent fluctuations in juvenile incarceration trends. But to date there are few if any sources providing such information. LIMITED ABILITY TO AFFECT THE FUTURE. Not only are the best statistical models limited in their ability to predict the future, but many of the factors helpful to predicting future incarceration rates may not be susceptible to policy influence. For example, the occurrence of local, state, or political elections may help account for juvenile incarceration rates. However, that fact does not imply any obvious policy implication since elections are a staple of American democracy. There may be some factors, such as teen birth rates. which are both linked to juvenile incarceration rates and susceptible to policy intervention. Even in these instances, relatively little research exists to support strongly the notion that targeting a particular factor can significantly reduce incarceration rates.

CONCLUSION

Local and state jurisdictions need effective detention and correctional bed-space planning strategies. Although many juvenile justice agencies believe statistical approaches to forecasting can provide the best guidance, these approaches suffer from many problems. Statistical analyses rarely explain much of the variance in past incarceration trends. They rely on assumptions or projections about predictors of future incarceration trends—assumptions and projections that may be in error. And they cannot adequately incorporate information about changing social and political conditions.

Statistical models may be most useful when they provide general guidance about how some factors are potentially linked to juvenile correctional bed-space needs and capacity. Ultimately, however, if forecasts are to be more accurate, credible, and useful, statistical analyses must be part of a more general and ongoing adaptive forecasting process (Butts and Adams 2001; Sabol 1999). A forecasting process should include statistical modeling, but it also should incorporate information not readily quantified or susceptible to statistical analysis (e.g., prosecutorial practices), and it should address the fact that many assumptions on which statistical and empirical models are built require constant revision. In short, statistical models are not a solution, merely one of several tools that can help inform juvenile correctional bed-space policy.

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