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AN ANALYSIS OF THE TIME SERIES OF THE IMPRISONMENT RATE IN THE STATES OF THE UNITED STATES: A FURTHER TEST OF THE STABILITY OF PUNISHMENT HYPOTHESIS*

ALFRED BLUMSTEIN** AND SOUMYO MOITRA***

I. INTRODUCTION

Building on Durkheim's notion[1] that a society maintains a constant level of crime through a continual readjustment of the boundaries of behavior that might be characterized as "deviant," Blumstein and Cohen[2] have hypothesized that it is not crime that is stable, but rather the level of *punishment*, and imprisonment rate per capita in particular, that the society maintains around a constant level. While the homeostatic level will vary from one society to another, it is plausible that such a steady level could exist. On the one hand, there will always be individuals engaging in unacceptable behavior, and if there should happen to be too few of them, then definitions of unacceptability can be revised.[3] Thus, if the amount of criminal activity drops off, what were formerly considered annoying but non-criminal activities could then begin to be considered criminal. On the other hand, if the level of activity that was categorized as criminal were to increase substantially, a society could find itself unable or unwilling either economically or politically to cope with that volume. It could adapt to this situation by taking a more lenient view of activity that was previously considered criminal but only marginally so, perhaps by decriminalizing that behavior, or at least by reducing the penalty.

Blumstein, Cohen, and Nagin[4] examined the dynamics of the process by which this stability is maintained, concluding that the oscillatory nature of the time series of imprisonment rate per capita cannot be adequately explained by a simple balancing of prison receptions and releases. Rather, a more elaborate model which incorporates a homeostatic shifting in the demarcation between punishable and non-punishable behavior is required to explain these oscillatory patterns. As imprisonment rates increase[5] the threshold of punishable behavior can be expected to rise. When the imprisonment rates decline[6] those thresholds can be expected to drop.

This subtle and implicit process of societal adaptation is not instantaneous. It requires several years for the adaptation mechanisms to detect the shifts and to accommodate them, thus giving rise to an oscillatory process. This process was studied in the United States, Norway, and Canada. Although the process was at different levels in each nation, it was stable in each. All three time series were describable by a second-order autoregressive process, with time periods of 11.2 years for the United States, 25.4 years for Norway, and 15.7 years for Canada.

The existence of such a stable imprisonment rate suggests that, as a nation's prison population begins to fluctuate, pressure is generated to restore the prison population to that stable rate. The process of restoration would typically be through some form of "adaptation" by the various agencies within the nation's criminal justice system. One form of adaptation could result in changes in the manner in which discretion is exercised by the various functionaries within the criminal justice

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[1] *See* E. DURKHEIM, THE RULES OF SOCIOLOGICAL METHOD (1964).

[2] *See* Blumstein & Cohen, *A Theory of the Stability of Punishment*, 64 J. CRIM. L. & C. 198 (1973).

[3] *See* K. ERIKSON, THE WAYWARD PURITANS (1966).

[4] Blumstein, Cohen & Nagin, *The Dynamics of a Homeostatic Punishment Process*, 67 J. CRIM. L. & C. 317 (1977).

[5] For example, this increase could be caused by demographic shifts such as the aging into the imprisonment-prone years of the cohorts of a "baby boom."

[6] For example, this decline could occur as the "baby boom" cohorts age out of the imprisonment-prone years.

system. If prison populations get too large, police can choose not to arrest, prosecutors can choose not to press charges, judges can choose not to imprison, or parole boards can choose to deny requests. This exercise of discretion presumably would be focused on those crimes or offenders that are the most marginally criminal.

Similarly, if the populations drop too far below the stable rate, then pressure would develop to sanction certain kinds of behavior that previously had been tolerated as more annoying than harmful. Alternatively, the level of punishment for a given type of offense could be increased, either by increasing the "branching ratios" or probabilities of penetration through the criminal justice system, especially from conviction to imprisonment, or by increasing the time served in prison for a particular offense.

To the extent that the imprisonment rate may indeed be stable, then knowledge of that fact should influence the debate over imprisonment policy. Most positions in the imprisonment policy debate focus on the amount of punishment that should be delivered. The policy, however, is much more appropriately viewed as a question of allocating a limited capacity, defined by the stable imprisonment rate, among alternative kinds of offenses and offenders. For example, this would require those who call for greater punishment for certain offenses to identify other offenses that should be treated less severely in order to provide the needed prison space.

The empirical analyses of the homeostatic hypothesis in the Blumstein and Cohen study[7] and in the Blumstein, Cohen, and Nagin study[8] were based on aggregate rates for only three nations. To explore the applicability of this theory to a larger number of jurisdictions, we examined the imprisonment rates of the individual states in the United States. These jurisdictions are reasonably comparable in that they share similar but distinct criminal codes and procedures, are linked together by a common Constitution, and have similar but distinct cultural environments. The decisions made in the individual states' criminal justice systems, however, are reasonably independent. Together, they offer the additional opportunity to explore the degree to which neighboring states, or states that are similar in other ways, display similar punishment patterns.

[7] *See* Blumstein & Cohen, note 2 *supra.*

[8] *See* Blumstein, Cohen & Nagin, note 4 *supra.*

II. Data and Methodology

The basic data for this analysis were the average daily prison population and the total population for each state for each year from 1926 to 1974. The data on state populations were developed by linear interpolation between the decennial census years. The data on prison populations were collected from the reports of the departments of corrections of individual states.[9] These data report the number of prisoners maintained in state institutions. They do not include prisoners in federal institutions. The data also exclude prisoners in local jails,[10] mental institutions, and other forms of incarceration. Variations in these other populations may be related to the prison population, and may indeed account for some of the fluctuations, but the presumption here is that the state prison represents the most severe form of punishment, short of capital punishment, in which the state engages.

Of the fifty states, the imprisonment data from Hawaii and Alaska could not be analyzed because it covered an insufficient number of years. Also, the data from Delaware had major gaps in the reports and displayed extreme shifts which probably reflected major changes in reporting practice. For this reason, Delaware was also excluded from the analysis.

The remaining forty-seven states provided the data base that was analyzed. The basic data on prison population and total population for each state were available for those forty-seven states. In some cases, observations on prison population were missing for some short intervals. In these cases, the missing values were estimated by linear interpolation between the available data points.

The analysis was conducted in two parts. First, the hypothesis of trendlessness in the individual states' imprisonment rates was explored, and second, the fine structure of the imprisonment-rate time series in the states was analyzed.

III. Examination of Time Trends Through Regression Analysis

We approach the issue of testing for trendlessness by estimating the simple regression model:

$$P_{it} = a_i + b_i t$$

[9] These data are available from the authors. Daniel Nagin arranged for the collection of these data, and his assistance in that regard is very much appreciated.

[10] Since different states may apply different criteria in assigning a sentenced offender to a state or local institution, it is difficult to compare the absolute levels of the state imprisonment rates across states.

where P_{it} is the prison population (R_{it}) divided by the total population (N_{it}, in units of 100,000) of state $i(i = 1, 2, \cdots, 47)$ in year $t(t = 1, \cdots, 49$ for the years 1926, $\cdots$, 1974). Any trends in imprisonment rate are represented by the estimated slopes of the regression lines, $\hat{b}_i$. The states' mean imprisonment rates ($M_i = \sum_{t=1}^{49} P_{it}/49$), the standard deviation (σ_i) of the imprisonment rates, the coefficients of variation (σ_i/M_i), the percentage time trend ($100\ \hat{b}_i/M_i$),[11] and the t-statistics for the $\hat{b}_i$ provide a basis for interpreting the observed distributions of the trend lines.[12] The estimates of these statistics are shown in Table 1. The same statistics were also calculated for the total United States as the aggregation of the prison population and the total population of the forty-seven states included in the analysis, *i.e.*, $P_{US,t} = \sum_{i=1}^{47} R_{it}/\sum_{i=1}^{47} N_{it}$.

Figure 1 displays the time series of the imprisonment rate in the United States. This series has an average rate of 96.51 prisoners per 100,000 population, a standard deviation of 10.56, and a coefficient of variation of 0.11. The time series is fairly steady, starting with its minimum value of 76.4 in 1926, increasing in the 1930's to a maximum of 120 in 1940, declining during World War II, and then reestablishing a fairly stable rate of about 100, with a period of decline during the mid-1960's. This time series is trendless, with a slope of −.12 change in prisoners per 100,000 population per year, or a −.12% change per year; this trend is not significantly different from zero statistically. This result is consistent with the observation of trendlessness for total United States prison populations, including the federal system, which was reported in Blumstein and Cohen.[13]

Figure 2 is a scattergram of slopes of the regression lines ($\hat{b}_i$) plotted against the state means (M_i). The distribution of means is seen to be fairly symmetrical about the aggregate United States mean of 96.51 per 100,000 inhabitants. The coefficients of variation for the individual states' time series lie mostly in the range of 15 to 25%, as revealed in Table 1. The states with the highest means are Nevada at 169.75, followed by Maryland, Alabama, Georgia, and Florida, generally southern states. The ones with the lowest means are New Hampshire at 37.69, followed by North Dakota, Rhode Island, and Massachusetts, generally New England states. The rest appear to be more or less clustered in the middle. The considerable range in the means reflects the many cultural, legal, social, and historical differences across the states. There may also be an effect due to different policies among the states in assigning individuals to state prisons or to local jails, which are not included in our data.

The distribution of the slopes is seen to be quite asymmetric, with twenty-eight states having negative slopes that are significantly different from zero statistically. Only six states have positive slopes, and only three of those, South Carolina, North Carolina, and Texas, have slopes greater than 1.0 per 100,000 per year. Even the highest positive slope is less than 1.5, or a ratio of slope to mean of about 2%, which is still quite small.

The distribution of the relative percentage slopes ($100\ \hat{b}_i/M_i$) is very similar to that of the slopes displayed in Figure 2. The principal differences occur at the extreme values of the means and the slopes, with the percentage slope exceeding the slope for small values of the mean and being smaller for the larger means. Thus, the slope of 1.45 for South Carolina becomes 2.02% of the mean, the largest percentage slope, and the percentage slopes become somewhat more negative for the states with low means. On the other hand, the absolute slope of −2.7 for Nevada becomes −1.59% of its mean. The values of these percentage slopes are displayed in Table 1.

Among the states with negative slopes, all have slopes less than 1.5 in absolute magnitude except Nevada at 2.7, which, probably because of its large transient population, is an outlier in many things. The largest group of states, twenty-four, have slopes in the range −.5 to +.5. All states except Nevada fall in the range −1.5 to +1.5, which is a reasonably small trend. In particular, some of the most populous states have slopes that are either zero, *e.g.*, New York, California, and Pennsylvania, or very close to zero, *e.g.*, Ohio and Connecticut. This influence of the large states, along with the positive slope of Texas, generates the trendless national mean.

In relating the trends for the individual states to the national trendlessness, one might anticipate that there would have been a convergence toward

[11] This is referred to as a percentage slope. This is the annual change in imprisonment rate as a percent of the mean imprisonment rate.

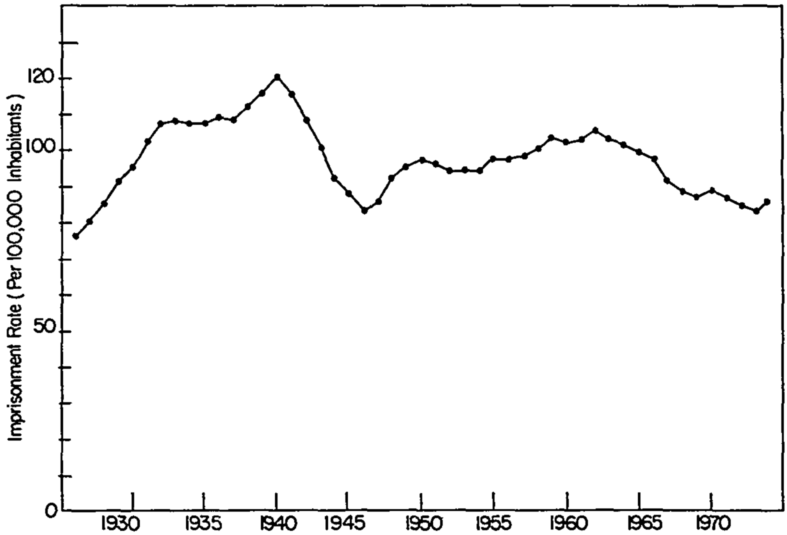
[12] Of course, the P_{it}'s are autocorrelated. But they are autocorrelated because of the index parameter t. Since t is used as the independent variable in the regression equation, the successive observations, P_{it} ($t = 1, \cdots, 49$), are otherwise independent, and in the full regression equation, $P_{it} = a_i + b_i t + e_{it}$, the residuals, e_{it}, can be assumed to be independently normally distributed random variables with zero mean. A normality plot test of the residuals confirmed the validity of this assumption.

[13] Blumstein & Cohen, note 2 *supra*.

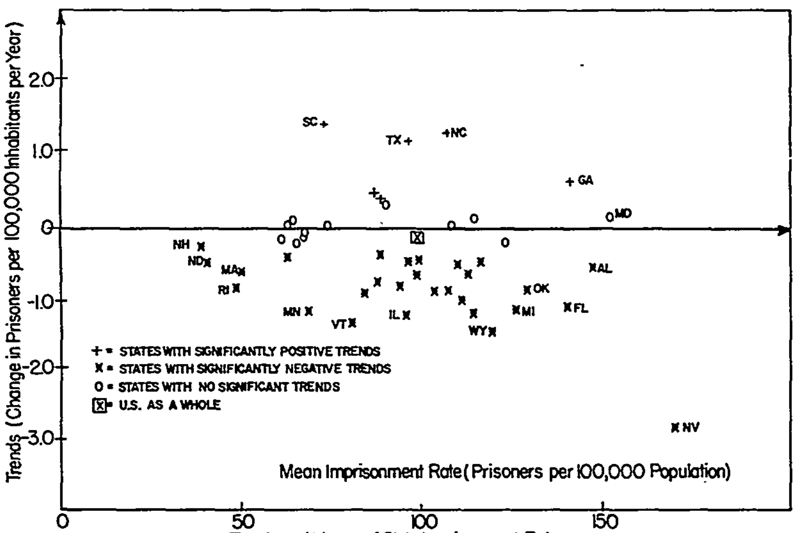
TABLE 1

TIME-TREND PARAMETERS OF STATE IMPRISONMENT RATES

State (i)	Intercept (a_i)	Slope ($\hat{b}_i$)	Standard Deviation (σ_i)	t-statistic for $\hat{b}_i$	Mean (M_i)	Coefficient of Variation (σ_i/M_i)	Percentage Slope ($100\hat{b}_i/M_i$)
MAINE	62.58	0.06	9.61	0.59	64.01	0.15	0.09
NH	44.72	−0.28	9.63	−3.14	37.69	0.26	−0.73
VT	112.45	−1.29	21.93	−11.04	79.62	0.28	−1.62
MASS	63.91	−0.59	12.66	−6.32	48.83	0.26	−1.21
RI	68.06	−0.82	15.92	−7.77	47.06	0.34	−1.75
CONN	72.00	−0.41	9.22	−5.71	61.62	0.15	−0.66
NY	80.79	0.31	18.55	1.70	88.58	0.21	0.34
NJ	74.47	−0.04	7.25	−0.49	73.57	0.10	−0.05
PENN	62.62	−0.00	9.01	−0.05	62.51	0.14	−0.01
OHIO	122.64	−0.49	16.59	−3.28	110.10	0.15	−0.45
IND	130.79	−0.92	19.84	−6.24	107.32	0.18	−0.86
ILL	125.94	−1.20	27.19	−5.75	95.24	0.29	−1.26
MICH	154.47	−1.12	24.40	−6.17	125.80	0.19	−0.89
WIS	71.76	−0.25	12.84	−2.05	65.32	0.20	−0.39
MINN	97.03	−1.16	19.07	−12.53	67.53	0.28	−1.71
IOWA	107.47	−0.91	18.27	−7.11	84.35	0.22	−1.07
MO	113.67	−0.83	18.75	−5.73	92.55	0.20	−0.89
NDAK	52.51	−0.48	9.05	−8.34	40.21	0.22	−1.20
SDAK	68.58	−0.07	12.59	−0.57	66.76	0.19	−0.11
NEBR	82.73	−0.16	12.29	−1.35	78.57	0.16	−0.21
KAN	137.16	−1.03	26.11	−4.78	110.95	0.24	−0.93
MD	145.97	0.18	17.91	1.02	150.59	0.12	0.12
VA	126.46	−0.18	21.21	−0.85	121.89	0.17	−0.15
WVA	143.92	−1.15	27.40	−5.27	114.62	0.24	−1.00
NCAR	71.32	1.36	25.67	8.28	106.11	0.24	1.29
SCAR	34.81	1.45	22.75	16.21	71.77	0.32	2.02
GA	123.32	0.69	23.53	3.26	141.04	0.17	0.49
FLA	166.47	−1.03	29.74	−3.98	140.29	0.21	−0.73
KY	127.55	−0.63	23.71	−2.88	111.47	0.21	−0.57
TENN	97.66	−0.40	12.07	−3.77	87.47	0.14	−0.46
ALAB	159.55	−0.49	22.75	−2.29	146.94	0.15	−0.34
MISS	108.54	−0.50	13.54	−4.31	95.91	0.14	−0.52
ARK	73.98	0.48	14.52	3.73	86.14	0.17	0.55
LA	106.13	0.02	16.27	0.15	106.76	0.15	0.02
OKLA	149.13	−0.78	27.36	−3.11	129.33	0.21	−0.60
TEX	64.82	1.17	23.43	7.21	94.66	0.25	1.24
MONT	106.60	−0.76	21.12	−4.18	87.31	0.24	−0.87
IDAHO	71.26	−0.16	15.93	−1.02	67.15	0.24	−0.24
WYO	155.17	−1.42	25.19	−9.72	118.92	0.21	−1.20
COLO	128.13	−0.48	15.83	−3.38	115.87	0.14	−0.42
NMEX	111.00	−0.46	19.49	−2.48	99.37	0.20	−0.46
ARIZ	134.89	−0.86	19.90	−5.55	112.90	0.18	−0.76
UTAH	54.87	0.19	10.95	1.82	59.79	0.18	0.32
NEV	238.60	−2.70	46.12	−10.94	169.75	0.27	−1.59
WASH	114.64	−0.67	16.25	−5.16	97.48	0.17	−0.69
OREG	76.77	0.38	12.77	3.34	86.58	0.15	0.44
CALIF	110.79	0.14	23.46	0.59	114.28	0.21	0.12
U.S. (47 states)	99.48	−0.12	10.56	−1.12	96.51	0.11	−0.12



Imprisonment Rate for the U.S., 1926–1974
FIGURE 1



Trends and Means of State Imprisonment Rate
FIGURE 2

a national mean imprisonment rate by the individual states. This would have been brought about over the period of observation by growing communication among the states, by general influence of national mass media, and by greater federal involvement in state criminal justice policies, especially in the period of the 1960's and 1970's. This convergence would have been observed if the states with high imprisonment rates displayed negative trends and the states with low imprisonment rates displayed positive trends, *i.e.*, if a negative association were displayed on Figure 2. The relationship has not been observed, as is evident from Figure 2. This has been confirmed by a correlation analysis (r = .000), where the slopes and means were found to be clearly independent.

From this analysis, four groups emerge. First, the largest group consists of twenty-eight states with negative slopes that are generally small but significantly less than zero statistically (with the exception of Nevada) covering the range from −.34 to −1.20. The second group is composed of thirteen states without trends, *i.e.*, with slopes not significantly different from zero. Three states, North Carolina, South Carolina, and Texas, that have comparatively high positive slopes, but still less than 1.5 per year make up the third group. Georgia, Arkansas, and Oregon with smaller but significantly positive slopes are in the fourth group. Clearly, a sizeable number of states do display a discernible trend in imprisonment rates, but that the trend is relatively small.

The standard deviation for the United States as a whole is 10.56, or about one half the mean of the individual states' standard deviations ($\bar{\sigma} = 1/47 \sum_{i=1}^{47} \sigma_i = 18.7$). If the states had been completely independent in their behavior and all the states equally populated, then the national standard deviation would have been $18.7/\sqrt{47} = 2.7$. Of course, this independence did not prevail in view of such common factors affecting state prison populations as national economic conditions, military conscription, national changes in demography, culture, law, and public opinion. This interaction among the states is most clearly reflected in high pairwise correlations observed among the midwestern states, with r about .80 to .90, as well as among other groups of states. Most of the interstate correlations are positive, but the southern states, which had high correlations with each other, had generally weak and negative correlations with the nonsouthern states.

IV. Examination of Patterns Through Time-series Analysis

In addition to observing the simple time trends resulting from the regression analyses, it is desirable to inquire further into the detailed patterns of the time series in the individual states so as to provide further confirmation of trends in those cases where they do exist. It would be interesting to identify periodicities in a state's patterns, and to examine whether the pattern of periodicity is consistent across similar states, and especially in neighboring states. Such information also permits future prison populations to be forecast with greater precision than is possible by simple extrapolation of the time trend.

This analysis can be performed with the Box-Jenkins[14] method of time-series analysis. Such analyses make use of the autocorrelation function, which is defined for a time-series $\{z_t;\ t = 1, 2, \cdots, N\}$ and a lag interval k as:

$$\rho_k = \frac{E[(z_t - \mu)(z_{t+k} - \mu)]}{E[(z_t - \mu)^2]E[(z_{t+k} - \mu)^2]}$$

where $\mu = \sum_{t=1}^{N} z_t/N$. This function is estimated from the time series data by:

$$\hat{\rho}_k = \left\{\frac{1}{N}\sum_{t=1}^{N-k}(z_t - \mu)(z_{t+k} - \mu)\right\} \Bigg/ \left\{\frac{1}{N}\sum_{t=1}^{N}(z_t - \mu)^2\right\}.$$

The autocorrelation function ρ_k thus reflects the linkage between the value of the time series at any time point t and the point k years later. In general, for some k large enough, this linkage should become small enough to ignore.

With the autocorrelation function, by computational procedures described by Box and Jenkins,[15] we can determine *stationarity*,[16] *i.e.*, whether the process is changing over time and the nature of such changes, and *periodicity*,[17] *i.e.*, whether there are characteristic cyclical or other periodic patterns in the process. We can also develop forecasting equations for estimating future values of the process as a function of the recent past values, which are useful for generating forecasts and also for inferring general features of the process from the form of those equations.

A forecasting equation is derived by first defining the following quantities:

z_t is the observed value of the time series at time t ($t = 1, 2, \cdots, N$).

B is the "backward shift operator" defined as $Bz_t = z_{t-1}$.

∇ is the "backward difference operator" defined as $\nabla z_t = z_t - z_{t-1} = (1 - B)z_t$.

Box and Jenkins characterize a stationary, *i.e.*, steady, time series as one in which successive values are generated by imposing a series of independent shocks, a_t, on the previous values. These shocks are assumed to be identically normally distributed with mean zero and variance σ_a^2. This process is supposed to generate the process $\{z_t\}$ by a "linear filter," which simply takes a weighted sum of previous shocks, so that

[14] *See* G. Box & G. Jenkins, Time Series Analysis (1970).

[15] *Id.*

[16] Stationarity is detected by observing the successive values of the autocorrelation function. If they die out after a few lags, about five, then the series is considered stationary.

[17] Periodicity is detected by observing whether the autocorrelation, ρ_k, is particularly high at values of k that are multiples of some basic period.

$$\begin{aligned} z_t &= \mu + a_t + \psi_1 a_{t-1} + \psi_2 a_{t-2} \cdots \\ &= \mu + B^0 a_t + \psi_1 B a_t + \psi_2 B^2 a_t + \cdots \\ &= \mu + (B^0 + \psi_1 B + \psi_2 B^2 + \cdots) a_t \\ &= \mu + \psi(B) a_t \end{aligned}$$

where μ is the mean value of the process, and $\psi(B)$ is the system of weights called the "transfer function."

A special case of this process is the "autoregressive model," in which the current value of the process (z_t) is expressed as a weighted linear sum of a limited number of previous values of the process and a shock for the current time period; the number of such previous values necessary is the "order" of the process. Thus, we define $\bar{z}_t = z_t - \mu$, the deviation from the mean value. Then, an autoregressive process (AR) of order p is expressed as follows:

$$\bar{z}_t = \phi_1 \bar{z}_{t-1} + \phi_2 \bar{z}_{t-2} + \cdots + \phi_p \bar{z}_{t-p} + a_t \quad \text{or} \quad \phi(B)\bar{z}_t = a_t.$$

Another kind of process is the moving average process. In this case, $\bar{z}_t$ is expressed in terms of a finite number of previous values of a_t. Thus

$$\bar{z}_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q} = \theta(B) a_t.$$

If q such terms are required, then the process is described as "moving average of order q."

A time series can have features of both of these processes, and it would be represented by an equation of the following form:

$$\bar{z}_t = \phi_1 \bar{z}_{t-1} + \cdots + \phi_p \bar{z}_{t-p} + a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q}$$

or

$$\phi(B)\bar{z}_t = \theta(B) a_t.$$

In the autoregressive process, the current value is clearly influenced by prior realizations of the process. A larger deviation at an earlier time would tend to persist, and so the process may be viewed as having considerable "inertia." The moving-average process, on the other hand, is more responsive to more recent fluctuations or shocks.

In general, a series may behave in a non-stationary manner with no fixed mean. This would occur, for example, if there was a time trend in the mean. Non-stationary behavior can be represented by a generalized autoregressive operator $\Phi(B)$ through the relationship.

$$\begin{aligned} \Phi(B) &= \phi(B)(1 - B)^d \\ &= \phi(B)\nabla^d \end{aligned}$$

where $\phi(B)$ is the stationary autoregressive operator. In a relationship of this form, there are no restoring effects tending to bring z_t to a mean value. The value, d, represents the number of repetitions of the backward difference operations required to transform the general non-stationary series to a stationary one. Thus, a linear time trend would be reflected in a value of $d = 1$, quadratic time trend in a value of $d = 2$, etc. Consequently, the general model can be written as

$$\phi(B)\nabla^d z_t = \theta(B) a_k.$$

This general model is called the "autoregressive integrated moving average model," or "ARIMA." If ϕ and θ are of orders p and q respectively, it is called an "ARIMA model of order (p, d, q)." In the special cases, where $p = 0$, the series is an "integrated moving average (IMA)"; where $q = 0$, the series is "integrated autoregressive (IAR)"; and if $p = q = 0$, then it is simply denoted as "integrated (I)."

We will now use these concepts of time-series analysis to discover if a series is periodic and to estimate its period, to assess the presence of stationarity, or, for non-stationary series, to discover the amount of differencing (the value of d, usually 1 or 2) required to produce stationarity, and to develop an initial estimate of the order of the autoregressive operator and of the moving average operator.

The basic time-series analysis permits categorizing the forty-seven states into four groups based on the presence or absence of periodicity and stationarity in their time series. Within this general structure, the states can then be grouped according to the presence of autoregressive or moving average operators or both.

The classification of the states according to this structure is shown in Table 2. The states with stationary time series are also expected to be those with zero slopes in the regression analysis, reflecting fluctuation, either periodic or aperiodic, around a fixed mean.

A typical stationary aperiodic time series is represented by that of Pennsylvania in Figure 3. Three of the four states in the stationary aperiodic group, the northeastern states of Maine, New York, and Pennsylvania, also have zero slope. West Virginia

TABLE 2

CLASSIFICATION OF STATES BY STATIONARITY AND PERIODICITY

Stationary						Non-Stationary						
Non-Periodic		Periodic				Non-Periodic			Periodic			
State	Slope	State	Slope	Period (years)		State	Slope	d	State	Slope	Period (years)	d
ME	0	NJ	0	9		NH	−	1	VT	−	3	2
NY	0	MD	0	19		MA	−	2	GA	+	14	1
PA	0	VA	0	21		RI	−	1	FL	−	21	1
WV	−	SD	0	≥25		CT	−	1	KY	−	20	1
		NB	0	≥25		MI	−	1	TN	−	≥25	1
		ID	0	≥25		MN	−	1	AL	−	20	1
		UT	0	9		ND	−	1	MS	−	21	1
		CA	0	≥25		NC	+	1	LA	0	25	1
		OH	−	24		SC	+	1	MT	−	24	2
		IN	−	21		TX	+	1	NM	−	20	2
		IL	−	≥25		OK	−	1	CO	−	≥25	2
		WI	0	24		AZ	−	1	OR	+	18	1
		IA	−	23		WY	−	2				
		MO	−	22		NV	−	2				
		KS	−	≥25		WA	−	2				
		AR	+	21								

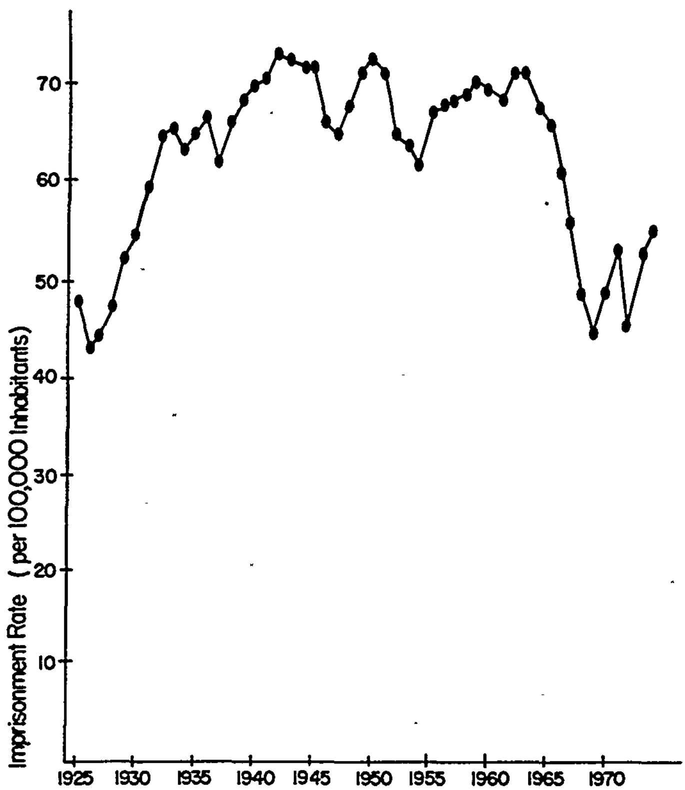


FIGURE 3
Imprisonment Rate for Pennsylvania

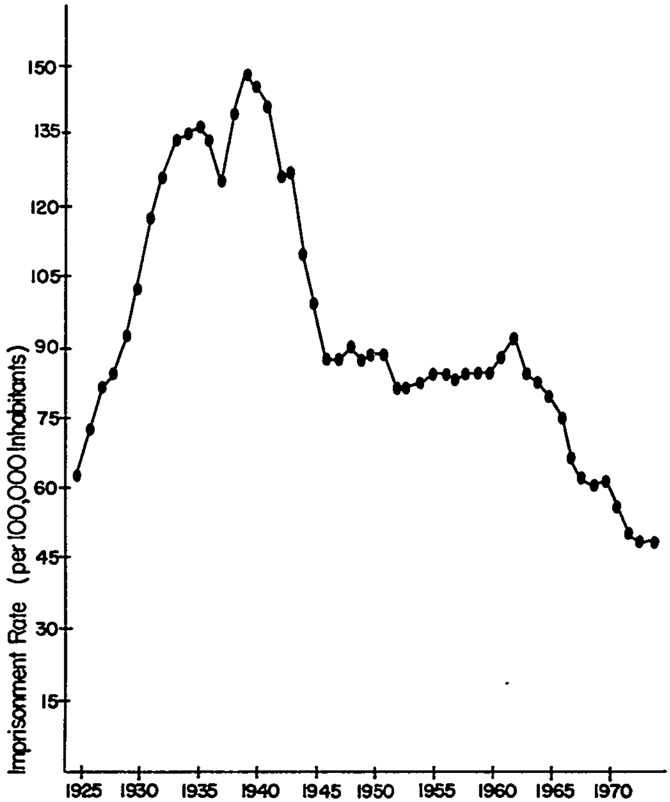


FIGURE 4
Imprisonment Rate for Illinois

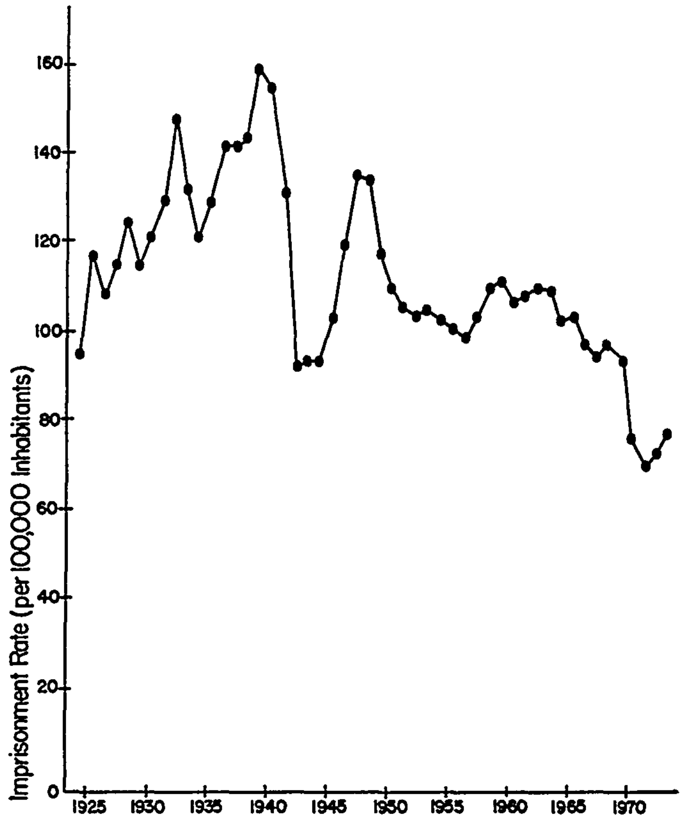
is also in that group, but its slope is significantly negative statistically, probably because of a recent change in its pattern.[18]

The largest single group of states is composed of the sixteen states with periodic stationary time series, as illustrated by Illinois in Figure 4. The period is generally long, around nineteen to twenty-five or more years[19] for all states other than New Jersey and Utah, which have a short period of nine years. In nine of these sixteen cases, the slopes of the regression lines are also zero. In the other seven cases, however, the slopes in the regression analysis are different from zero, and the period is long in all these cases. The stationarity found in the time-series analysis indicates that this apparent slope is an artifact resulting from the fact that the second cycle of the nineteen to twenty-five year process was only partially completed since the trend line through that partial cycle generates a slope that would presumably become zero when the cycle is completed. The six states with negative slope were all increasing their imprisonment rates in 1974, that is, returning to the stable level, thus confirming the general effect. Arkansas, the one state with a positive slope, appears to be on the other part of its cycle, and thus can be expected to decrease its imprisonment rate. These projections are just the opposite of what would be reached by the regression analysis alone, which would predict continuation of the aggregate trend. Taking these periodic projections into account, the time-series analysis suggests stationarity in twenty of the forty-seven states.

The twenty-seven states with non-stationary

[18] The regression analysis indicates that West Virginia has a significant downward trend, whereas the time series analysis shows it to be stationary. The imprisonment level in West Virginia fluctuated around a steady value for most of the time, and then decreased steadily after 1964. The time-series model puts less weight on that recent trend and so indicates stationarity, whereas the regression analysis fits a line with negative slope to the data to minimize the squared error.

[19] Because the data covered only 49 years, periods longer than 25 years could not be discerned. This periodicity, approximating one generation, could be reflecting generational cycles in birth rates.



Imprisonment Rate for Arizona
FIGURE 5

time series all have non-zero slopes, again confirming the consistency between the time series and the regression classifications.[20] Arizona, as demonstrated in Figure 5, represents a typical non-periodic non-stationary time series, and Tennessee, as demonstrated in Figure 6, is a typical periodic one. In nineteen of the twenty-seven states, a single differencing (d = 1) is required to establish stationarity, suggesting a predominantly linear trend in those states. This trend is negative in thirteen of the states, positive in five, and is zero in Louisiana.

The other eight states require two differencings (d = 2). These are the western states of Washington, Nevada, Montana, Wyoming, Colorado, and New Mexico, and the New England states of Maine and Vermont. These series are characterized by occasional steep trends in the time series.

The non-periodic non-stationary group of fifteen states includes the three states with the comparatively highest positive slopes, *i.e.*, North Carolina, South Carolina, and Texas. All the other states in this group have decreasing imprisonment rates, and comprise three regional groupings: the New England states of Massachusetts, New Hampshire, Rhode Island, and Connecticut; the midwestern states of Michigan, Minnesota, and North Dakota; and the western states of Oklahoma, Arizona, Wyoming, Nevada, and Washington.

The periodic non-stationary group includes a large group of southern states: Kentucky, Tennessee, Alabama, Mississippi, Louisiana, Florida, and Georgia. It also includes the western group of Montana, New Mexico, Colorado, and Oregon, as well as Vermont. Thus, nine of the eleven western states, all save Utah and California, are non-stationary, and six of the eight states with d = 2, *i.e.*, those with their imprisonment rates decreasing

[20] The singular exception is Louisiana, which does have a zero trend, but its time-series displays sharp and short fluctuations, and so requires a single differencing to produce stationarity. In this case, the single differencing is required for smoothing rather than for removing a time trend, a distinction noted by Fuller. W. FULLER, INTRODUCTION TO STATISTICAL TIME SERIES (1976). Thus, Louisiana could reasonably be considered one of the stationary states.

faster than linearly, are western states. This may reflect the fact that their population has grown faster than their prison capacity. This growth accelerated after World War II, the later part of the 1926–1974 period studied. This change in trend could account for the quadratic effect implied by d = 2.

The classification of time-series patterns reveals some striking regional consistency, as shown in the map of Figure 7. The strongest pattern is reflected in the ten midwestern states, Ohio, Illinois, Indiana, Wisconsin, Iowa, Missouri, Kansas, Arkansas, South Dakota, and Nebraska, which are stationary periodic with long time periods. The nature of the pattern is reflected in the time series of Ohio, Indiana, and Illinois, depicted together in Figure 8. The only other stationary periodic states are the neighboring states of New Jersey, Maryland, and Virginia and the western neighbors, Utah and Idaho.

The second largest single group consists of six southern states, Kentucky, Tennessee, Louisiana, Alabama, Mississippi, and Florida. All six of these states have non-stationary periodic time series with decreasing trends. The time series for Kentucky, Tennessee, and Louisiana are shown in Figure 9. Georgia also falls in the same category; however, it has increasing imprisonment rates, a characteristic it shares with its neighbors South Carolina and North Carolina, as well as with Texas and Oregon. Thus, Georgia's shading reflects its membership in both groups.

The stationary non-periodic states include only the four northeastern states of Maine, New York, Pennsylvania, and West Virginia. The New England neighbors of New Hampshire, Maine, Rhode Island, and Connecticut are all non-stationary non-periodic, as are the three neighboring north-midwestern states of Michigan, Minnesota, and North Dakota.

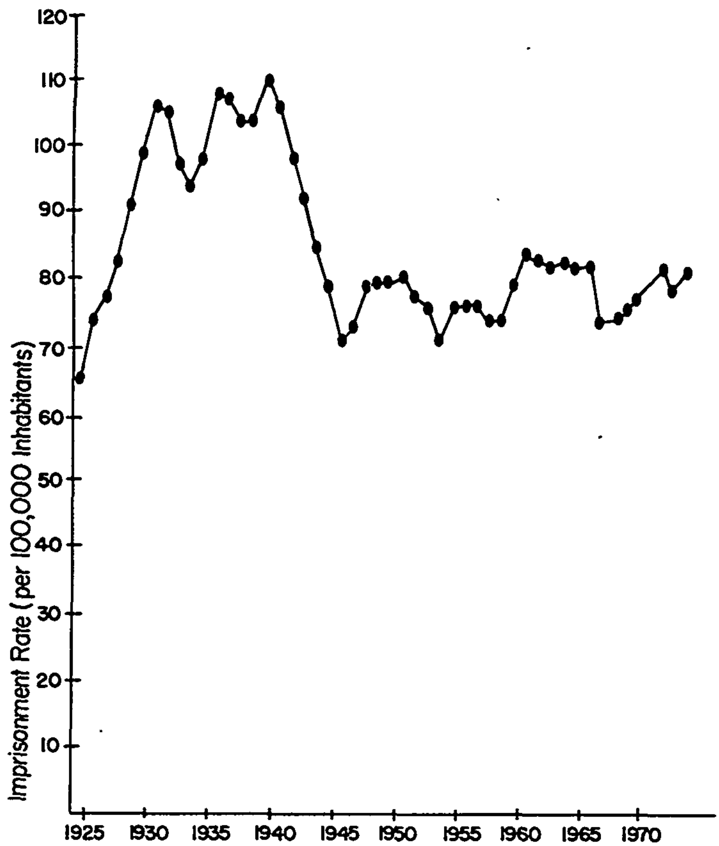


FIGURE 6
Imprisonment Rate for Tennessee

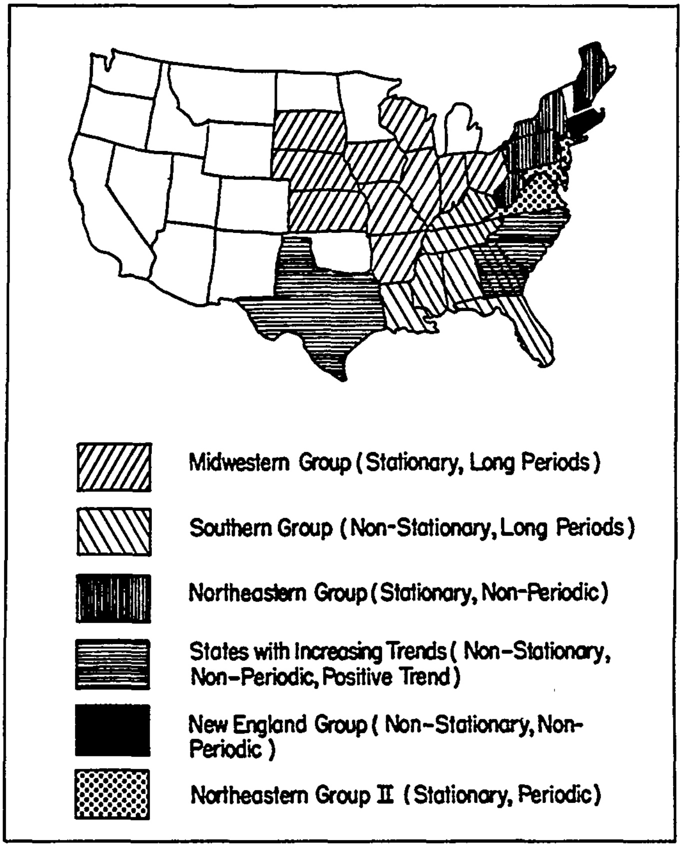


FIGURE 7
Regional Grouping

Table 3 classifies the states on the basis of the ARIMA classification. Here, the states are first partitioned, as before, on the basis of stationarity and periodicity, and then according to an autoregressive component [AR or IAR, depending on stationarity], to a moving-average component [MA or IMA], to both autoregressive and moving-average components [ARMA or ARIMA], or to neither [simply I].

The regional patterns are largely preserved in this finer classification. The group of northeastern states, Maine, New York, Pennsylvania, and West Virginia, all have AR time series. The New England states of New Hampshire, Massachusetts, and Rhode Island are all non-periodic ARIMA, while Connecticut and Vermont are somewhat different. Connecticut is simply an integrated series (I), and Vermont is ARIMA but periodic.

The states in the largest group of ten midwestern states divide into two groups of five. Ohio, Indiana, Illinois, Iowa, and Arkansas have AR time series, while Wisconsin, Missouri, South Dakota, Nebraska, and Kansas have ARMA time series.

Among the seven southern states, Florida, Kentucky, and Tennessee fall into the same ARIMA group, while Georgia, Alabama, and Louisiana have integrated series. Mississippi has an annual pattern of an IAR time series. The sense of regional homogeneity is enhanced by noting first that when regional groups are split into this finer classification scheme, neighboring states continue to stay together, even in these finer subdivisions. Furthermore, when a state is distinguished from those states whose patterns it shared in the prior analysis, it tends to be classified like its neighbors. Thus, Mississippi has an integrated time series like Georgia, Alabama, and Louisiana, but also has an AR component like Arkansas, another neighbor. Similarly, North Carolina is separated from South Carolina and Texas, because it has an AR component, while they are IMA. But in this classification it is similar to Virginia and Maryland, which have AR

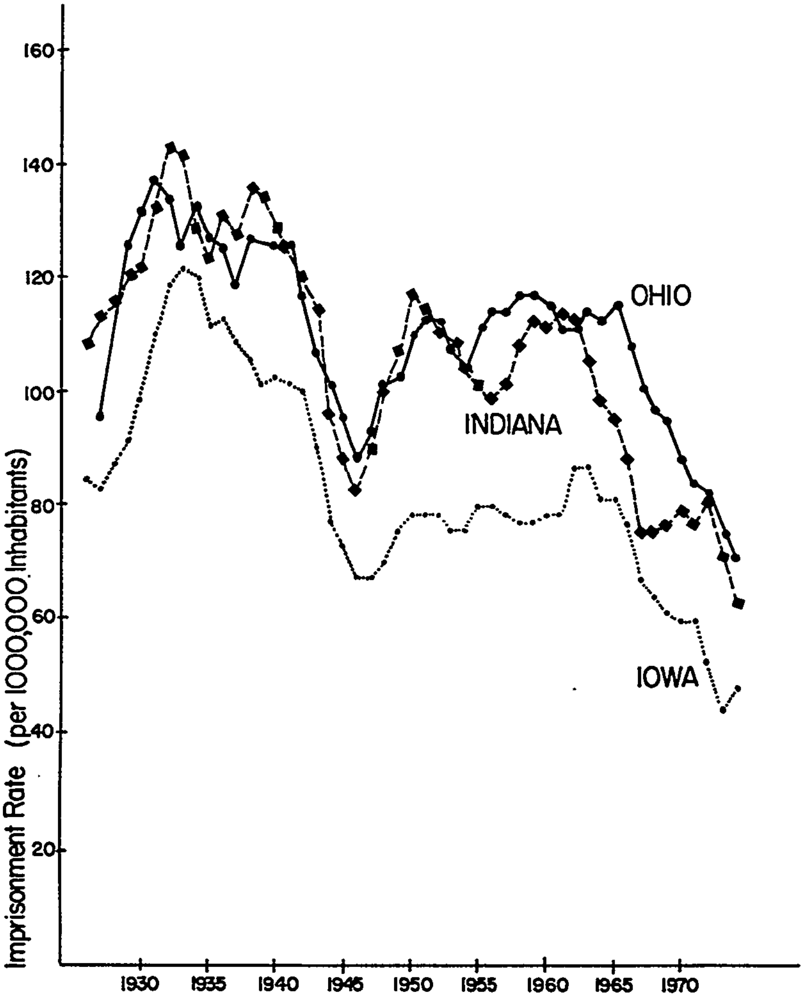


FIGURE 8
Imprisonment Rates for 3 Midwestern States

TABLE 3
ARIMA CLASSIFICATION OF STATES

Stationary			Non-Stationary						
Non-Periodic	Periodic		Non-Periodic			Periodic			
AR	*AR*	*ARMA*	*I*	*IMA*	*ARIMA*	*I*	*IAR*	*IMA*	*ARIMA*
ME	OH	NJ	CT	MI	NH	GA	MS	MT	FL
NY	IN	WI		MN	MA	AL			KY
PA	IL	MO		OK	RI	LA			TN
WV	IO	SD		SC	ND				CO
	MD	NB		TX	NC				NM
	VA	KS			WY				OR
	AR	ID			NV				VT
	UT	CA			WA				
					AZ				

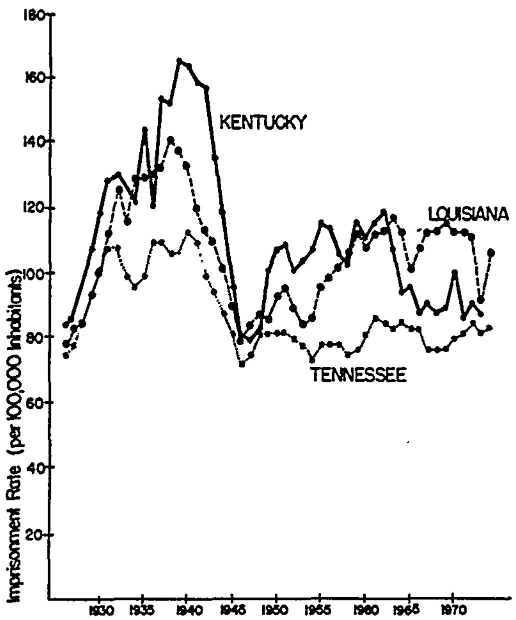


FIGURE 9
Imprisonment Rates for 3 Southern States

time series and also similar to Kentucky and Tennessee, which are ARIMA. On the other hand, we note that Oklahoma has an IMA series, like Texas and South Carolina.

North Dakota is also separated from the others in its regional group, Michigan and Minnesota, which are IMA, but Montana also has an IMA series, which again suggests regional influences. The scattered nature of the western states is again confirmed, with no clear regional grouping arising from this classification.

V. Summary

In examining the trends in the per capita imprisonment rates in the forty-seven states, it has been noted that almost half, twenty, are trendless, *i.e.*, stationary, and that the trends in the remainder are small, *i.e.*, less than 2% of the mean per year in all cases. These findings are thus consistent with the general homeostatic process previously observed in the United States as a whole and in other countries.[21] Thus, a phenomenon previously observed in three nations now appears to hold reasonably well across a wide variety of independent, albeit related, jurisdictions.

In examining the time series of per capita imprisonment rates within the individual states, it has been noted that all have experienced fluctuations in the imprisonment rates to varying degrees, with the coefficients of variation generally in the range of 15 to 25%. In particular, these fluctuations have been identifiably periodic in twenty-eight states, suggesting the existence of forces drawing short-term fluctuations in the imprisonment rate back to the long-term stable level. Thus, deviations around that level are much more appropriately viewed as transient fluctuations than as a continuing divergence. Where a trend does exist, it is much smaller than the amplitude of the fluctuations, another result that is consistent with the hypothesis of stable imprisonment rates.

The existence of regional similarities in the patterns of imprisonment-rate time series also suggests that the fluctuations are not simply random. Groups of neighboring states are subjected to related socioeconomic and political forces, and these could well exert a common regional influence on the imprisonment decisions made in each state within the region. The common influences could include similar historical and social development, cultural homogeneity, and related economic activity. The related patterns are most apparent and widespread in the midwest and the south, the two regions with perhaps more internal similarities than any other. The consistency of these patterns within the regions and the differences across the regions suggest the need for further analysis to identify the factors that influence the imprisonment-rate patterns.

The analysis of the oscillatory patterns of the imprisonment rates suggests that short-term projection into the future of a state's imprisonment rate is much more likely to be reliably performed by time-series analysis rather than by extrapolation of a time trend, at least for the states with periodic time series. In addition, it is important to incorporate into any such forecasts other factors such as demographic or migration patterns. The time-series implicitly incorporates past influences of such factors, but cannot be sensitive to future changes that depart from the patterns that prevailed in the past. If those future changes can be estimated independently, then their effects can be incorporated explicitly.

One of the important areas for future investigation is the identification of the causes of the observed variation in the mean imprisonment rate across the states. Some of the variation may be a result of differences among states in assigning pris-

[21] *See* Blumstein & Cohen, note 2 *supra*; Blumstein, Cohen & Nagin, note 4 *supra*.

oners to state institutions,[22] or in reporting the imprisonment data.[23] These artifactual differences have to be accounted for before one can reasonably identify the cultural or socioeconomic factors that determine a state's imprisonment rate.

Further analysis would be required to identify the adaptive mechanisms by which the homeostatic level is maintained. During periods of declining imprisonment rate, as the threshold of seriousness warranting imprisonment is increased, one would expect the average seriousness of the offenses of committed offenders to be increasing. During periods of increasing imprisonment rate, the opposite effects would be expected. During the periods of increasing imprisonment rate, controlling for offense and offender seriousness, one would also expect to see increases in the branching ratios reflecting deeper penetration into the criminal justice system or in time served in prison. The particular decision stage or stages where that occurs, however, will differ in different jurisdictions, depending on the particular officials who exercise the primary discretion.

Pursuit of these issues is desirable in order to provide the theoretical and operational insights necessary to understand the criminal justice system, as well as to improve it.

[22] For example, some restrict state prisons to persons with sentences of at least two years, while others may have different rules.

[23] For example, some states may include the population of some local jails in their reported state prison populations.