AN ANALYSIS OF THE TIME SERIES OF THE IMPRISONMENT RATE IN THE U.S. STATES

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October, 1977

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I. INTRODUCTION

In examining trends over time in the use of incarceration as an instrument of the criminal justice system, it has been noted that the imprisonment rate tends to be stable over time for three countries: the U.S., Norway and Canada. Blumstein, Cohen and Nagin [1][2], have shown that the time series of the imprisonment rates (i.e., prisoners per 100,000 population) over the years are trendless, albeit with different characteristic rates for each nation. In addition, the fluctuations around the stable rate for each nation were found to be similar in the sense that all three time series followed a second-order autoregressive process.

The existence of such a stable imprisonment rate suggests that, as a nation's prison population fluctuates around that stable rate, 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 criminal justice system when the prison population deviates too far from the stable rate. The adaptation could take place through revision in the exercise of discretion by any of the various functionaries within the criminal justice system. If prison populations get too high, police can choose not to arrest, prosecutors not to press charges, judges not to imprison, or parole boards to release early. This discretion would presumably 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 crack down more harshly on certain kinds of behavior that may previously have been viewed as more annoying than harmful, and which were formerly tolerated. 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 is indeed stable, then knowledge of that fact should influence the form of the debate over imprisonment policy. Most positions in the debate about imprisonment 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. This requires, for example, that those who call for more punishment for some offenses should accompany their demands with proposals of other offenses that should be treated less severely in exchange in order to provide the needed capacity.

The observations thus far have been based only on aggregate rates for three nations, and the generality of the phenomenon is thus not yet established. To explore its applicability to a larger number of jurisdictions, we examine here the imprisonment rates of the individual states in the United States. These jurisdictions are reasonably comparable in sharing similar but distinct criminal codes and procedures, linked together through a common Constitution. They have similar but distinct cultural environments and their criminal justice systems are reasonably independent. Together, they offer the opportunity to explore patterns that may prevail among groups of states.

II. DATA AND METHODOLOGY

The basic data for this analysis are 1) the average daily prison population and 2) 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*. These data report the number of prisoners maintained in the state-level institutions. Therefore, they do not include prisoners in Federal institutions, and so each state's prison population refers only to action taken by that state. The data also exclude prisoners in local jails**, 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 an ultimate form of punishment short of execution.

Of the fifty states, Hawaii and Alaska did not have imprisonment data over a sufficient number of years for analysis. Also, the data from Delaware had major gaps in the reports and displayed extreme shifts, which probably reflected major changes in reporting practice; thus Delaware was also excluded from the analysis.

The remaining 47 states provided the data base that was analyzed. The basic data on prison population and total population for each state are

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

**Since different states may apply different criteria (typically length of sentence) in assigning sentenced offenders to state or local institutions, comparison across states of the absolute level of the imprisonment rate may thus not be fully valid.

available for those 47 states. Some states had observations on prison population missing for some years, typically very short intervals, and in these cases the missing values were estimated by linear interpolation between the available data points.

The analysis was conducted in two parts; first, an exploration of the hypothesis of trendlessness in the individual states' imprisonment rates, and second, an analysis of the fine structure of the imprisonment-rate time series in the states.

III. EXAMINATION OF TIME TRENDS THROUGH REGRESSION ANALYSIS

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

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

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

*We refer to this as percentage slope. This is the annual change in imprisonment rate as a percent of the mean imprisonment rate.

**Of course the P_{it}'s are autocorrelated. But they are autocorrelated only through the index parameter to which is also the independent variable in the regression equation. Since t is used as an independent variable, the successive observations P_{it}, (t=1,...,49) are otherwise independent and in the full regression equation, $P_{it} = a_i + b_i\ t + e_{it}$, the e_{it}'s can be taken to be independently distributed random variables with normal distribution around zero. A test of the residuals, e's confirmed this.

Table 1

STATE	INTERCEPT	SLOPE	ST DEV	T VAL	MEAN	COEF.VAR	SL/MEAN
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

Regression Data

Fi 1

Imprisonment Rate the U.S.

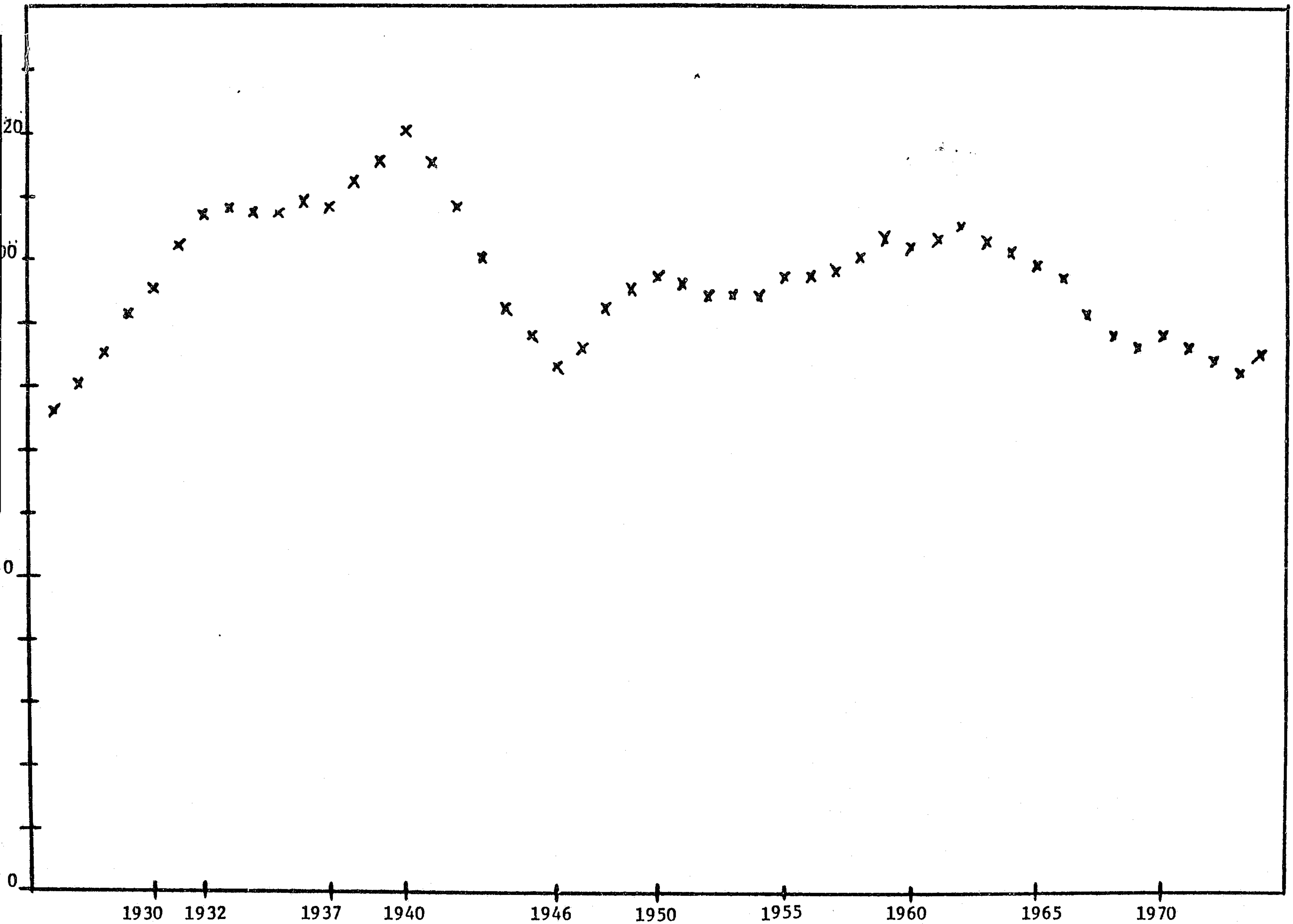

Figure 2: Trends and Means of State Imprisonment Rates (1926-1974)

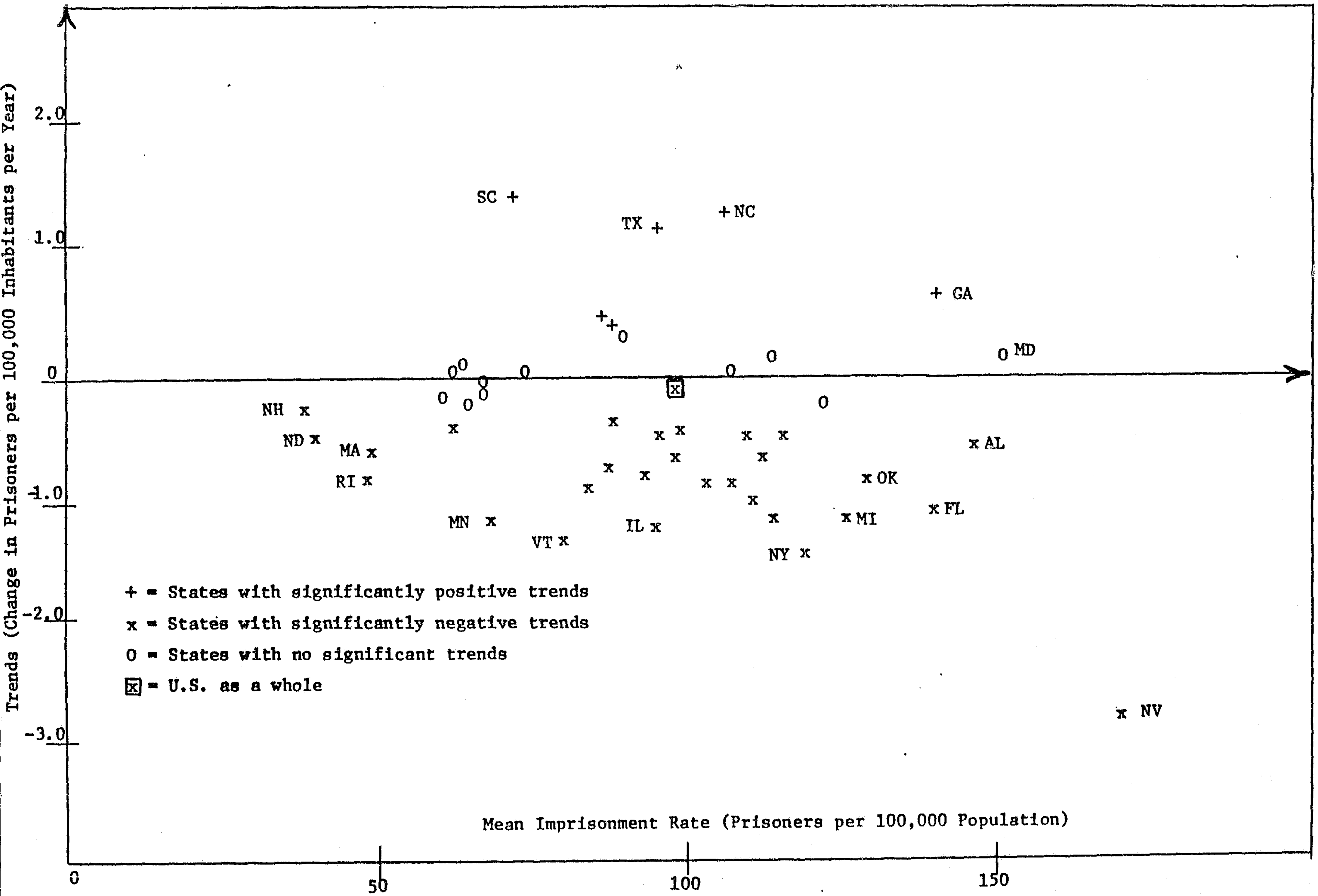

Figure 1 displays the time series of the U.S. imprisonment rate. This series has an average rate of 95.6 prisoners per 100,000 population, a standard deviation of 10.56, and a coefficient of variation of 0.11. The time series is fairly steady, starting with its minimum value of 76.4 in 1926, increasing in the 1930's and reaching a maximum of 120 in 1940, declining during World War II, and then re-establishing a fairly stable rate of about 100, with a period of decline during the mid-Sixties. This time series is trendless, with a slope of -.12 change in prisoners per 100,000 population per year, or a -.12 percent change per year; this trend is not statistically significantly different from zero. This result is consistent with the observation of trendlessness for total U.S. prison populations, including the Federal system, which was reported in Blumstein and Cohen [1].

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 U.S. mean of 96.5 per 100,000 inhabitants. There is considerable variability across the states; New Hampshire has the lowest rate with 37.6, and Nevada the highest with 169.8. The coefficients of variation for the individual states' time series lie mostly in the range of 15 to 25 percent, as revealed in Table 3.

The states with the highest means after Nevada are Maryland, Alabama, Georgia, and Florida, generally southern states. The ones with the lowest means are New Hampshire, 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 across the states in assigning individuals to local jails or to state prisons.

The distribution of the slopes is seen to be quite asymmetric, with 28 states having negative slopes that are statistically significantly different from zero. Only six states have positive slopes, and only three of them (South Carolina, North Carolina, 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 per cent, which is still quite small.

The distribution of the relative percentage slopes (100 $\hat{b}_1/M_1$) is very similar to that of the slopes displayed in Figure 2. The principal differences occur at the extreme values of the means and 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 1.4 for South Carolina becomes 2.0 per cent 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 -1.7 per cent of its mean. The values of these percentage slopes are displayed in Table 3.

Among the states with negative slopes, all have slopes less than 1.5 in absolute magnitude except Nevada (2.7) (which, probably because of its large transient population, is an outlier in many things). The largest group of states (24) 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 a national mean imprisonment rate by the individual states. This might have been brought about over the period of observation by growing communication among the states, general influence of national mass media, and by greater Federal involvement in criminal justice policies across the states, 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. This relationship has not been observed, as is evident from Figure 2, and has been confirmed by a correlation analysis, where the slopes and means are clearly independent ($r = .24$).

From this analysis, four groups of states emerge. First, the largest group comprises 28 states with negative slopes that are generally small but statistically significantly less than zero (aside from Nevada, covering the range from -.34 to -1.20); second, 13 states without trends, i.e., with slopes not significantly different from zero; third, three states (North Carolina, South Carolina, and Texas) that have comparatively high positive slopes, but still less than 1.5 per year; finally, Georgia, Arkansas, and Oregon with smaller but significantly positive slopes. Thus, it is seen that a sizeable group of states do display a discernible trend in imprisonment rates, but that the trend is relatively slow.

The standard deviation for the U.S. as a whole is 10.6, or about half of the mean standard deviation of the individual states $(\overline{\sigma} = \sum_{i=1}^{m} \sigma_i = 18.7)$

If the states had been completely independent in their behavior and all states were equally populated, then the national standard deviation would have been 2.7. Of course, this independence does not prevail in view of such common factors as national economic conditions, military conscription, national changes in demography, culture, law and public opinion, and the consistent effects of all of these on the state prison populations. This interaction among the states is most clearly reflected in high pairwise correlations observed among the mid-western states (with r about .80 - .90), as well as among other groups of states. Most of the inter-state correlations are positive, but the southern states had generally weak and negative correlations with the other states.

IV. EXAMINATION OF PATTERNS THROUGH TIME-SERIES ANALYSIS

In addition to observing the simple time trends, which result from the regression analyses, it is desirable to inquire further into the patterns of the time series in the individual states and have further confirmation of trends in cases where they 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 neighboring states. In addition, such information 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 [3] method of time-series analysis. Such analyses make use of the autocorrelation function, which is defined for a time-series $\{z_t;\ t=1,2,\ldots,N\}$ 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:

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

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 [3], we can determine stationarity* (i.e., whether the process is changing over time and the nature of such changes) and periodicity** (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:

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* Stationarity is detected by observing the successive values of the autocorrelation function. If they die out after a few lags (about 5), then the series is considered stationary.

** Periodicity is detected by observing whether the autocorrelation (ρ_k) is particularly high at values of k that are multiples of some basic period.

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

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

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

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 $\bar{\bar{z}}_t = z_t - \mu$, the deviation from the mean value. Then, an autoregressive process (AR) of order p is expressed as follows:

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

Another kind of process is the moving average (MA) 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 $\phi(B)\bar{z}_t = \theta(A)a_t$.

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 "intertia." The moving-average process, on the other hand, is more responsive to the 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.

$$\Phi(B) = \phi(B)(1-B)^{d}$$

$$= \phi(B)\nabla^{d}$$

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. Thus, 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 would now like to use these concepts of time series analysis to discover 1) if a series is periodic and its period; 2) the presence of stationarity, or, for non-stationary series, the value of d (usually 1 or 2) required to produce stationarity, and 3) an initial estimate of the order of the autoregressive operator and of the moving average operator.

The basic time-series analysis permits categorizing the 47 states into 4 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 (the Northeastern states of Maine, New York, and Pennsylvania) also have zero slope; West Virginia is also in that group, but its slope is statistically significantly negative, probably because of a recent change in its pattern*.

For the largest group of states, the 16 states with periodic stationary time series (as illustrated by Illinois in Figure 4), the period is generally long, in the neighborhood of 19 to 25 or more years** for all states other than New Jersey and Utah, which have a short period of 9 years. In 9 of these 16 cases, the slopes of the regression lines are also

*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 WV 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.

**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.

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 Rates for Pennsylvania

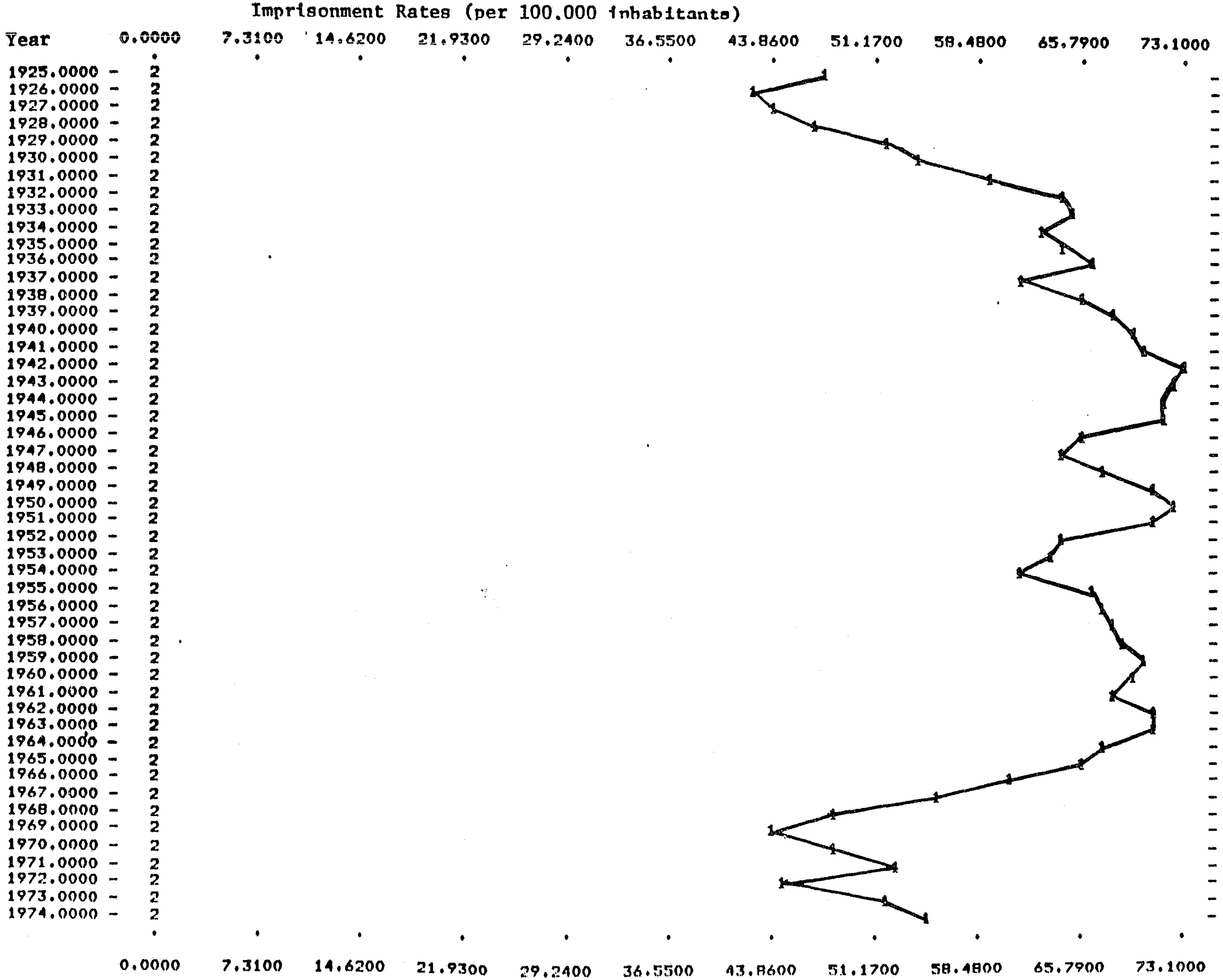
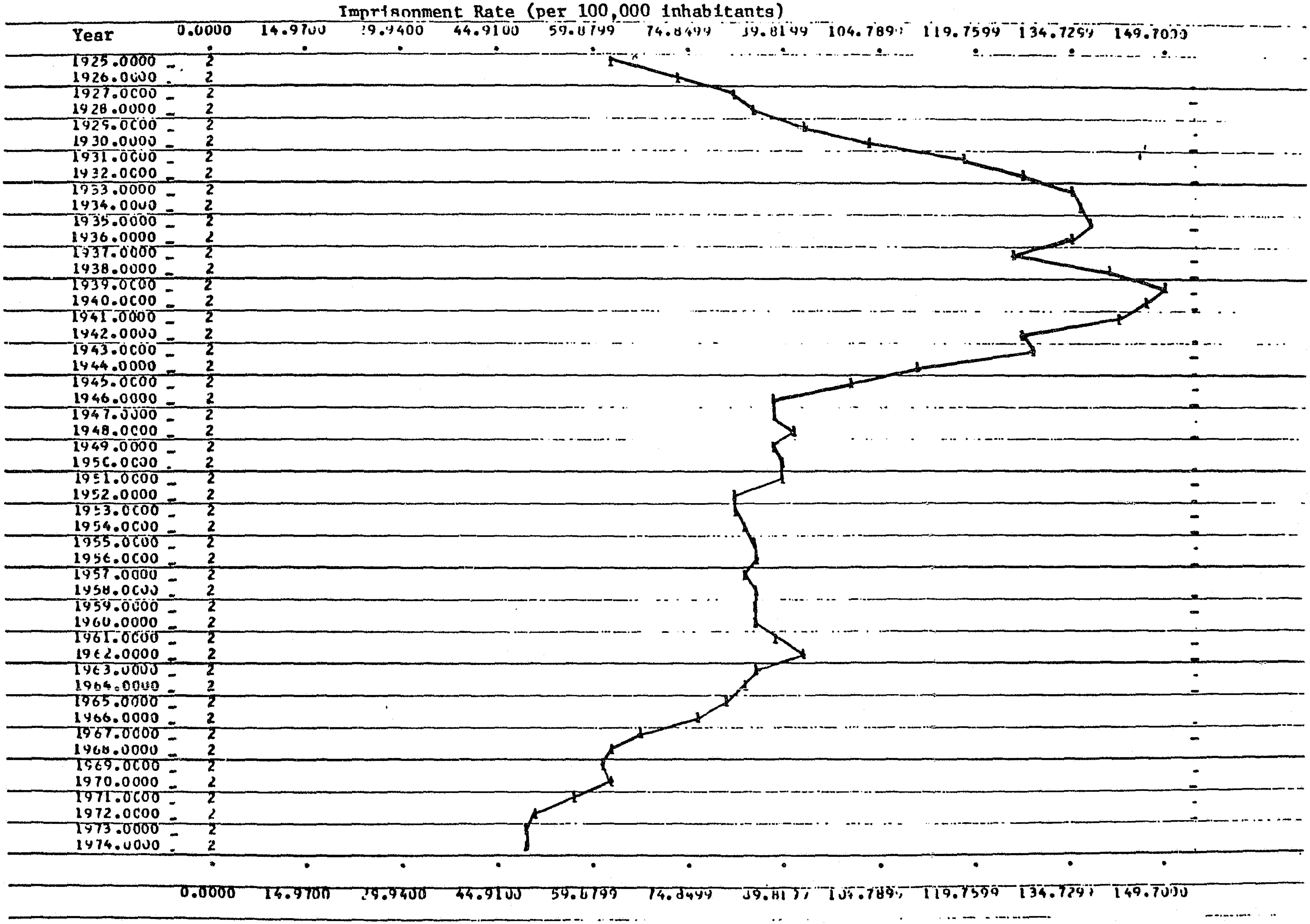


Figure 4

Imprisonment Rates for Illinois



zero. In the other 7 cases, however, the slopes in the regression analysis are different from zero (6 are negative, 1 is positive), even though the stationarity of the time-series analysis indicates that this apparent slope is a result of only partial completion of the second cycle of the 19-25 year process, and the trend line through that partial cycle generates a slope that would presumably be driven to zero when the cycle is completed. The six states with negative slope are now all increasing their imprisonment rate, confirming this general effect, that is, returning to the stable level. Arkansas, the one state with a positive slope, appears to be on the other part of its cycle, and 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. Thus, taking these periodic projections into account, the time-series analysis suggests stationarity in 20 of the 47 states.

The 27 states with non-stationary time series are all seen to have non-zero slopes, again confirming the consistency between the time series and the regression classifications*. Arizona (Figure 5) represents a typical non-periodic non-stationary time series, and Tennessee (Figure 6) is a typical periodic one. In 19 of the 27 states, a single differencing (d=1) is required to establish stationarity, suggesting a predominantly linear trend in those states. This trend is negative in 13 of the states, positive in 5, and is zero in Louisiana.

The other 8 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

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* The singular exception is Louisiana, which displays a zero trend, but requires a single differencing to produce stationarity in the presence of sharp and short fluctuations, [4].

Figure 5

Imprisonment Rates for Arizona

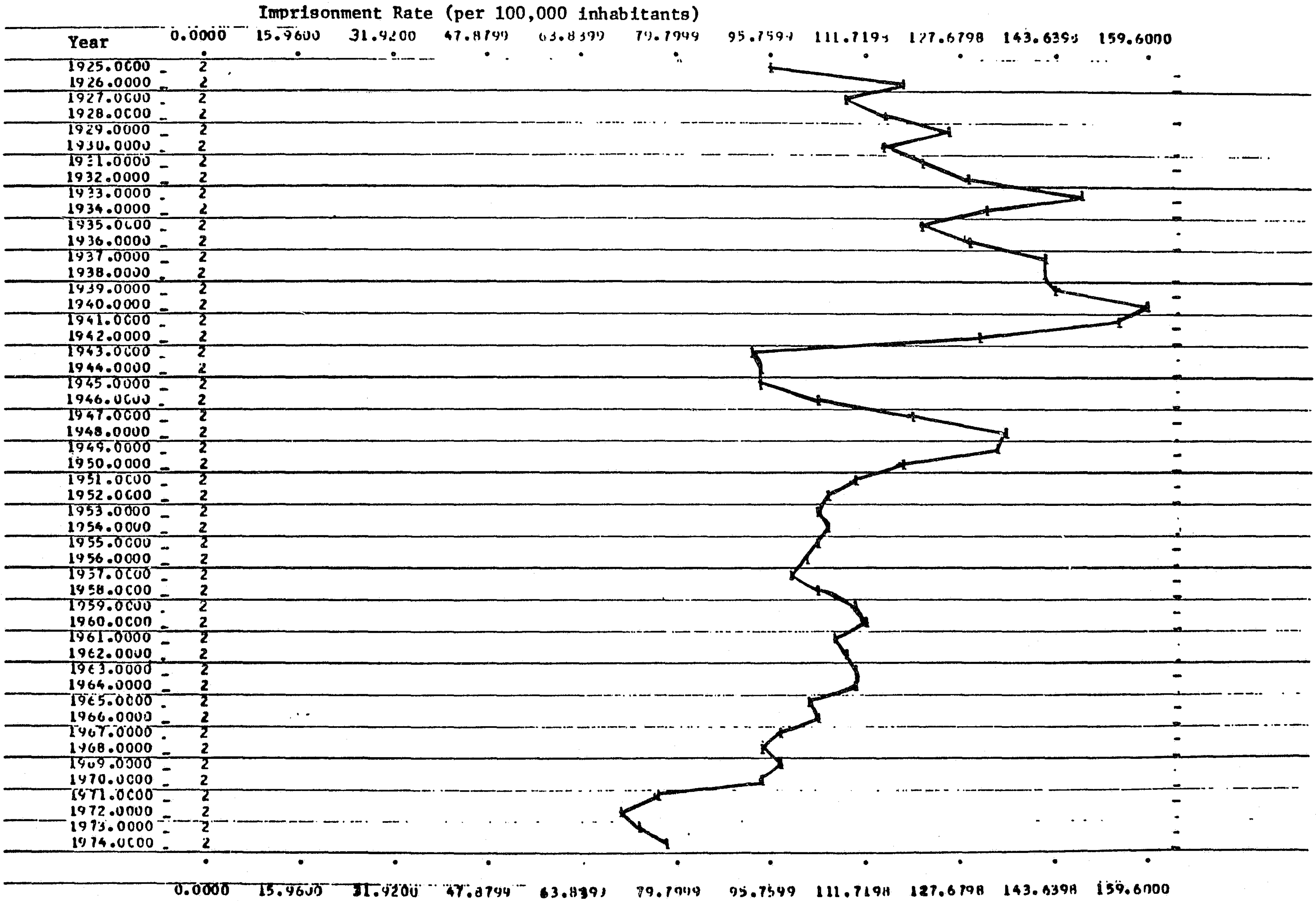
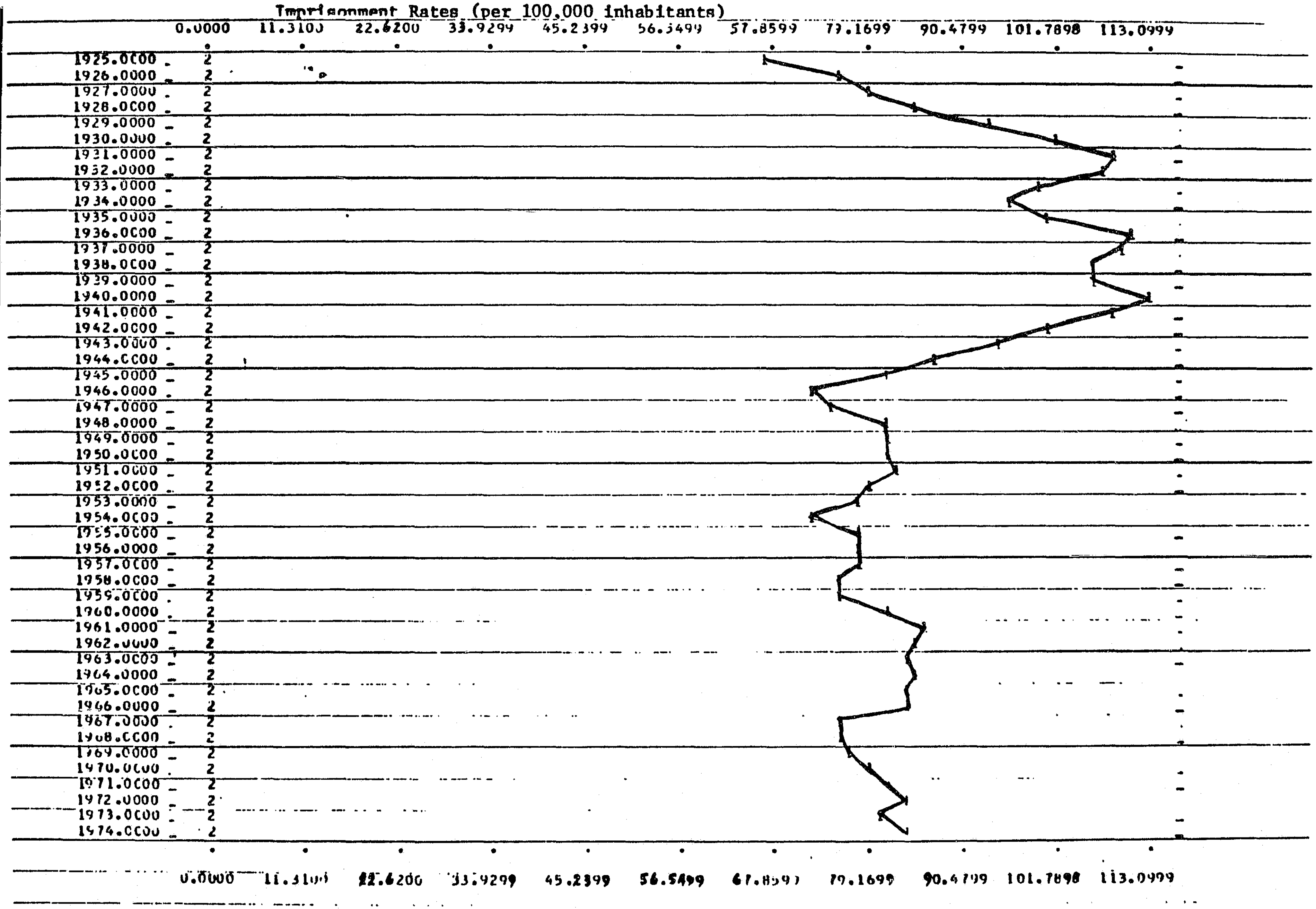


Figure 6

Imprisonment Rates for Tennessee



characterized by occasional steep trends in the time series.

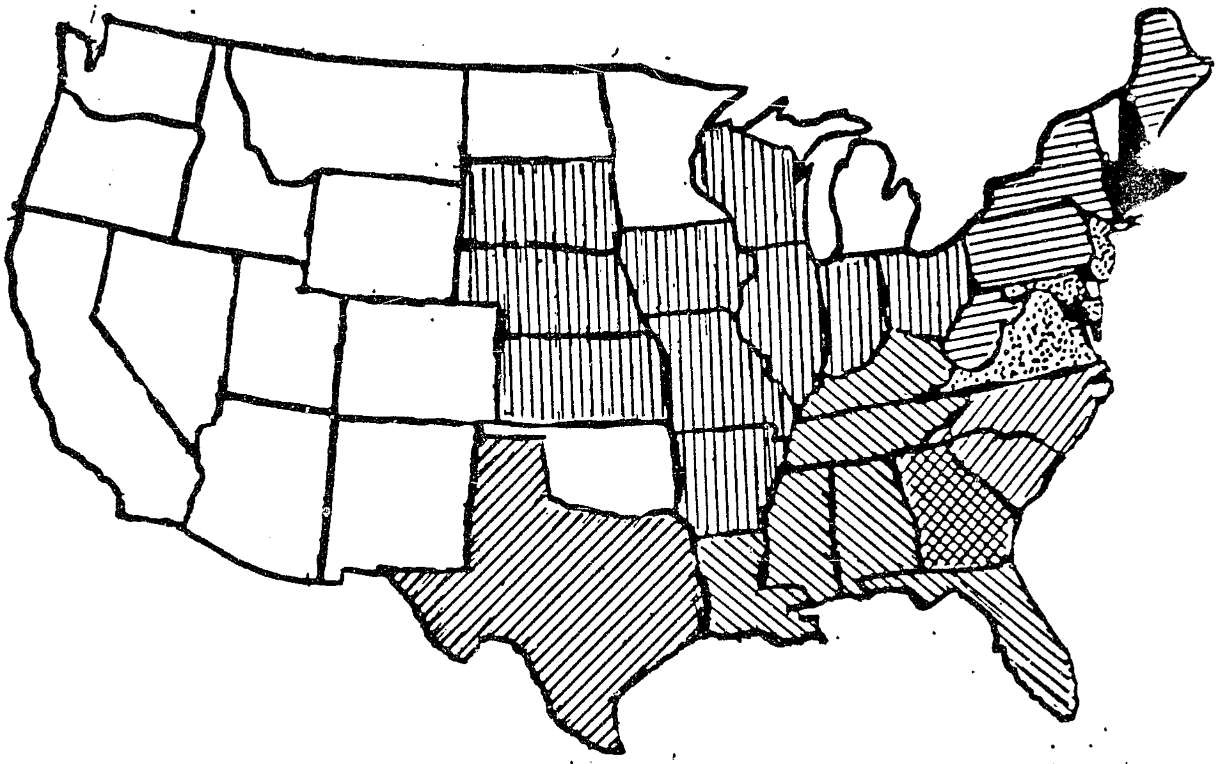
The non-periodic non-stationary group of 15 states includes the three states with the comparatively high positive slopes, North Carolina, South Carolina and Texas. It also includes a large group comprising most of the southern states: Kentucky, Tennessee, Alabama, Mississippi, Louisiana, Florida and Georgia. Only Georgia and Oregon have an increasing trend in their imprisonment rates. 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 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 10 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 the six southern states, Kentucky, Tennessee, Louisiana, Alabama, Mississippi, and Florida; the first three of these are shown in Figure 9. All six of these states have non-stationary periodic time series with decreasing trends. Georgia also falls in the same category; however, it has increasing imprisonment levels,

Figure 7

Regional Groupings



Midwestern group

Southern group

Northeastern group I (Maine, New York, Pennsylvania, West Virginia)

States with increasing trends

New England group (New Hampshire, Connecticut, Rhode Island, Massachusetts)

Northeastern group II (New Jersey, Maryland, Virginia)

Figu

Imprisonment Rates fo : Midwestern States

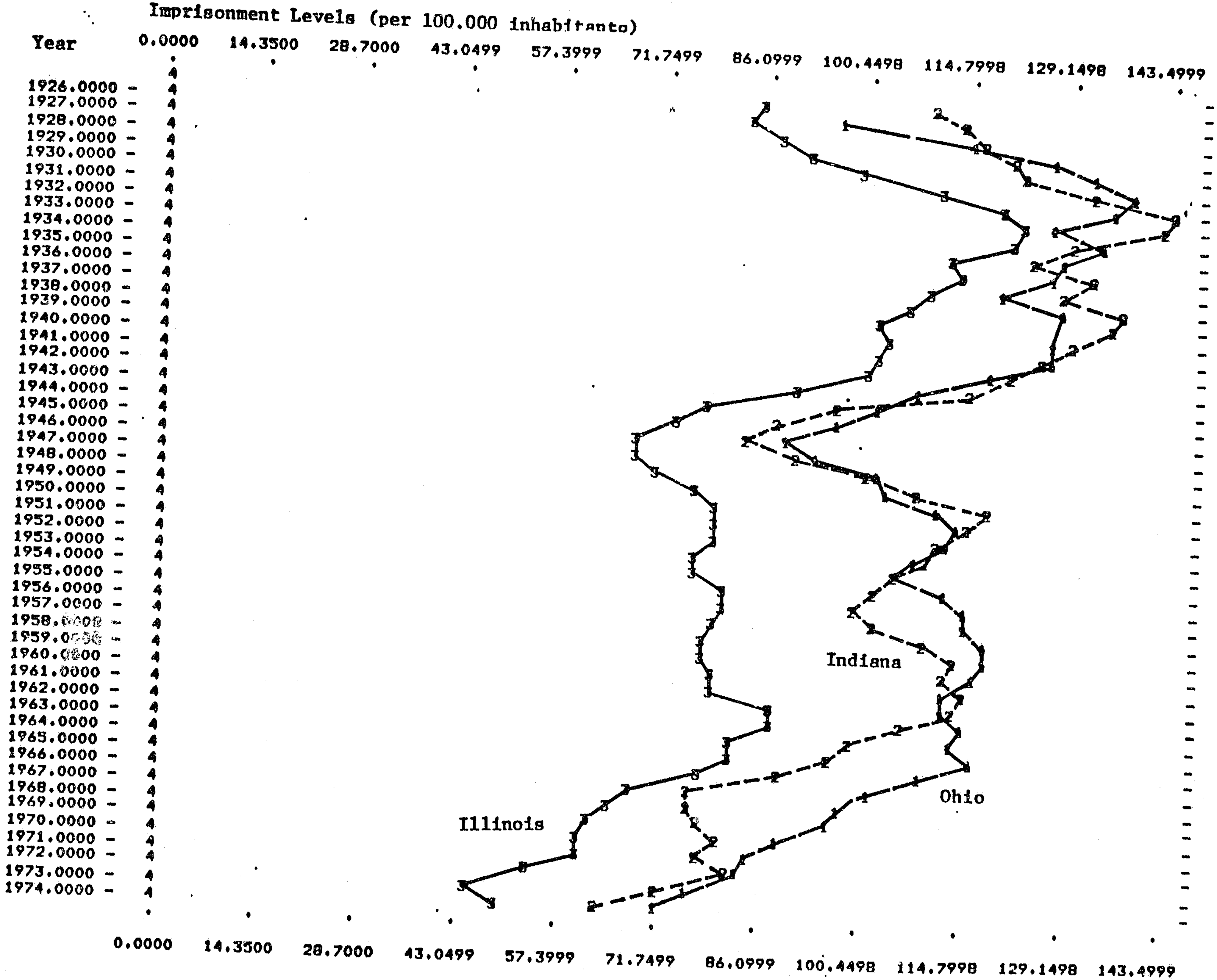
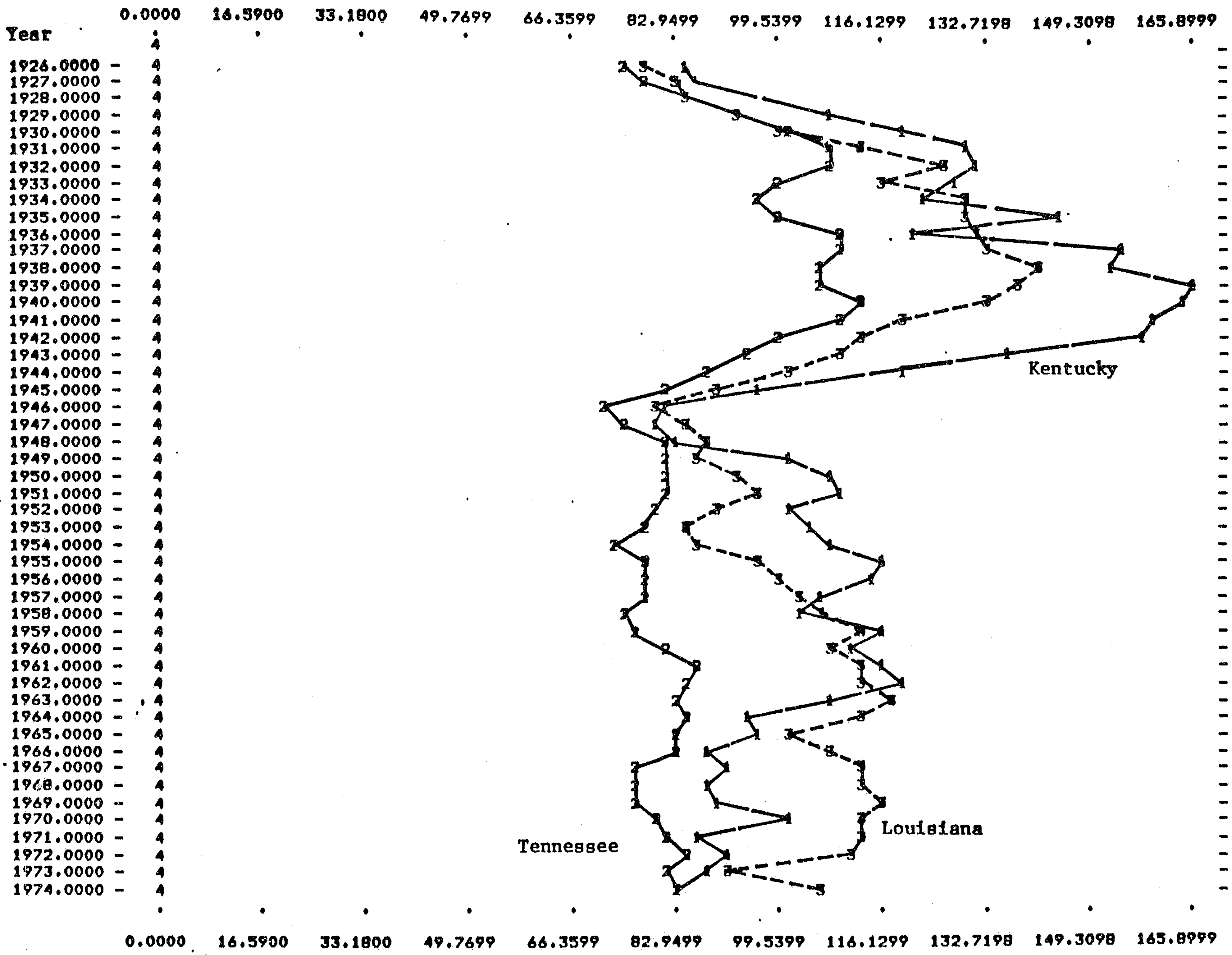


Figure 9

Imprisonment Rates for 3 Southern States



a characteristic it shares with its neighbors, South Carolina and North Carolina, as well as Texas and Oregon.

The stationary non-periodic states include only the four northeastern states of Maine, New York, Pennsylvania, 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 northmidwestern states of Michigan, Minnesota and North Dakota.

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, within each group, according to which states have an autoregressive component (AR or IAR, depending on stationarity), a moving-average component (MA, or IMA), both autoregressive and moving-average components, (ARMA, or ARIMA), or 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, Maine and Rhode Island are all ARIMA, while Connecticut and Vermont are somewhat different. Connecticut is simply an integrated series (I), and Vermont is also ARIMA but is periodic, while the others are not.

The states in the biggest group of 10 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 unusual pattern of an IAR time series. The sense of regional homogeneity is enhanced by noting first that when regional groups are split in this finer classification scheme that neighboring states tend to stay together even in the finer subdivisions, and that the exceptions to the previous patterns tend to shift into a classification like one of its other 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, it is similar to Virginia and Maryland, which have AR time series and also 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, again suggesting 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 47 states, it has been noted that almost half (20) 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 stability-of-punishment previously observed in the U.S. as a whole and in other countries [1] and [2].

In examining the time series of per capita imprisonment rate 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 per cent. In particular, these fluctuations have been identifiably periodic in 28 states, suggesting the existence of forces drawing short-term fluctuations in the imprisonment rate back to the long-term stable level. Thus, fluctuations around that level are much more appropriately virwed as transient deviations than as implying a diverging trend. In all cases, the overall trend 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 some consistency, at least within regions, of the factors influencing imprisonment decisions. These patterns are most apparent in the midwest and south, and also in the northeast with smaller groups. These common influences could include similar historical or social development, cultural homogeneity, regional economic activity (e.g., agriculture or industry) within a geographical region. The consistency of these patterns within the regions - and their differences across the regions - suggests the possibility of identifying the factors that influence the imprisonment-rate patterns.

The study also suggested that, at least for the states with periodic time series, projection of the diverging time series is a more reliable means of making the predictions than extrapolation of a time trend, since it uses more of the information in the data and yields more insights in the processes.

In addition, it is important to incorporate into the forecasting ..er factors like demographic or migration patterns, since the time-series analysis by itself may not be sensitive to the estimable effect of projections of these factors, especially if they can be expected to change their patterns in the future.

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 priosners to state institutions (e.g., some restrict state prisons to persons with sentences of at least two years) or in reporting the imprisonment data (e.g., some states may include the population of some jails in their reported prison populations). These artifactual differences have to be accounted for before one can reasonably identify the determinants of a state's imprisonment rate.

ACKNOWLEDGMENT

This study was supported by PHS Research Grant No. 1 R01 MH 28437-01 from the National Institute of Mental Health, Center for Studies of Crime and Delinquency.

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