ABSTRACT

A discrete time model incorporating the courts, corrections and law enforcement components of the criminal justice system is used to determine the effect of various sentencing strategies, optimal sentencing policies which correspond to the greatest possible deterrent effect within a constrained resource situation are determined for the choices of the certainty and severity of punishment. Results from data bases of Georgia, Texas and Missouri are compared. The analysis includes forecasts of long term behavior of the criminal justice system and estimates of separate incapacitation and deterrent effects of the sentencing policies.

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A Comparative Evaluation of Judicial Policy Differences Between Geographic Regions

by

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Introduction

When a sentencing policy is formulated [14,18], there are generally two controllable variables involved [12,14,18]. These are the certainty and severity of punishment by imprisonment [12,18]. A sentencing policy is moderated by the limits of the resource available for imprisonment [4,11,15] and to this extent, a compromise between the probability of an offender being incarcerated and the time he serves must be made [11,13,20]. Ideally, the sentencing policy which has the greatest crime control effect, yet is feasible in terms of available man-years of imprisonment, would be selected [14,18]. A model developed by Deutsch and Malmborg [14], characterizes the relationship between these judicial sanctions and the crime rate. In addition, this model imposes practical data base requirements and is relatively simple to implement.

This paper presents a comparative analysis of judicial practices utilizing data from Texas, Missouri and Georgia. In the first section, a brief summary of the model and its uses is presented. For a comprehensive presentation of the model, the reader should see [14,15]. Uses of the model include the ability to forecast the behavior of the criminal justice system, sensitivity studies involving a changing resource situation, and the separation of the deterrent and incapacitative effects of a sentencing policy based on the model's period by period approach to estimating the average criminal's frequency of offenses [15,21]. The next section provides a careful examination and analysis of the input data from each of the states. The third section summarizes and discusses model results and provides a comparison between the states. In particular, the variation in results for finding optimal sentencing strategies is examined in detail, the differences in potential benefits from doing so is considered, and an evaluation of prevailing policies is offered. Also, the forecasted behavior of each major component in the model over a 25 year horizon is presented for the three states from a comparative perspective. Finally, the incapacitative and deterrent effects of prevailing and optimal policies in the different geographic regions are considered.

The Dynamic Model: An Overview

The model is based upon a description of the crime rate embodied in the equation:

$$Z_t = \lambda_t \left[\frac{C_t}{C_t+P_t}\right] D_t$$

where Z_t = the number of crimes reported in period t.

λ_t = the number of crimes committed by the average offender in period t.

C_t/C_t+P_t = the ratio of the free criminal population to the sum of the prison and free criminal populations in period t (representing the proportion of time an offender is free).

D_t = the proportion of the population engaging in crime during period t.

In the development of the model [4,9,15,20] it is shown how this formulation accounts for the court, corrections and law enforcement bodies of the criminal justice system incorporating appropriate resource and due process constraints within each.

In its original development, the model was intended to capture the relationship between sentencing strategy and the crime rate, where sentencing strategy was defined in terms of the probability of imprisonment, given conviction (Q) and the average sentence lengths (S). Supposedly, the controllable variables Q and S reflect trade-off inherent in sentencing policy. Nagin [18] offered the following definitions of prevailing Q and S in terms of obtainable data:

$$Q_t = \frac{\text{Prison Receptions in Period } t}{\text{Convictions in Period } t}$$

$$S_t = \frac{\text{Prison Population in Period } t}{\text{Prison Receptions in Period } t}.$$

In executing the model, D_t values are determined for each period and equated to the following functional form of deterrence [20]:

$$D_t = \frac{\exp[\gamma_0 + \gamma_{1_t} Q_t + \gamma_{2_t} Q_t S_t]}{1 + \exp[\gamma_{0_t} + \gamma_{1_t} Q_t + \gamma_{2_t} Q_t S_t]}. \qquad \text{[Nagin, 1976]}$$

At that point, numerical values for γ_i values are found (using the values of D_t, Q,) and the solution for the minimization problem:

$$\text{Min:} \quad \gamma_0 + \gamma_1 Q + \gamma_2 QS$$

$$\text{s.t.} \quad 0 < Q \leq 1$$

$$\text{and} \quad Q^*_t S^*_t \leq Q_t S_t$$

is identical as the optimal Q,S solution in period t, since it would correspond to the smallest feasible proportion of the population engaging in illegal activities within the current resource level. Additional results identifying the incapacitative and deterrent effects of a QS sentencing strategy and results forecasted for several years into the future can be output by the model [15].

The Data Base

For executing the model, data from law enforcement, courts and corrections authorities were obtained for Georgia, Texas and Missouri. Specifically, the monthly series of each of the following statistics was collected:

a. Statewide Total Reported Offenses

b. Total State Institution Inmate Population Totals

c. Total State Institution Admissions Totals

In this paper, these statistics, during the period from January 1974 until December 1976, were utilized to execute the model for the three states.

In the following sections, the data are presented. For each statistic, a comparative discussion is provided, followed by a formal statistical analysis of the input series and survey of the statistical identification results. In addition, the prevailing policy variables; average sentence length and probability of imprisonment given conviction, are computed for each state over these 36 periods, and these two series are treated similarly.

Total Reported Offenses

For generating monthly figures of total reported offenses in each state, the seasonality of monthly data from a major metropolitan area in that state was imparted to the annual state total offenses figures. For the cases of Georgia, Missouri and Texas, the major metropolitan areas used were Atlanta, St. Louis and Dallas, respectively. Figure 1 shows a plot of the Total Reported Offenses Time Series obtained for each state from January 1974 until December 1976.

The mean value of the Georgia total offenses monthly series was 16,449 inmates, while the mean value of the offenses series in Missouri was considerably higher, with a value of 19,658. The population totals of Georgia and Missouri are approximately 4.95 and 4.70 million, respectively, suggesting the monthly per capita rate of crime to be greater in Missouri than Georgia. The mean of the Texas series (48,132 inmates) was in order of magnitude larger, reflecting the fact that the population of that state is considerably larger (about 12.7 million). This put the per capita crime rate in Texas at an intermediate level with respect to Georgia and Missouri.

Statistical analysis of the total offenses series for the three states suggested total offenses to be modeled by a seasonal nonstationary process. Table 1 summarizes the results of the statistical identification and parameter estimation. In each case, total reported offenses were forecasted for each state using the corresponding model presented in Table 1.

Prison Populations

The second component of the data base necessary for executing the model is the monthly record of state institution inmate population totals. Figure 2 shows the series from January 1974 until December 1976, for the states of Georgia, Missouri and Texas.

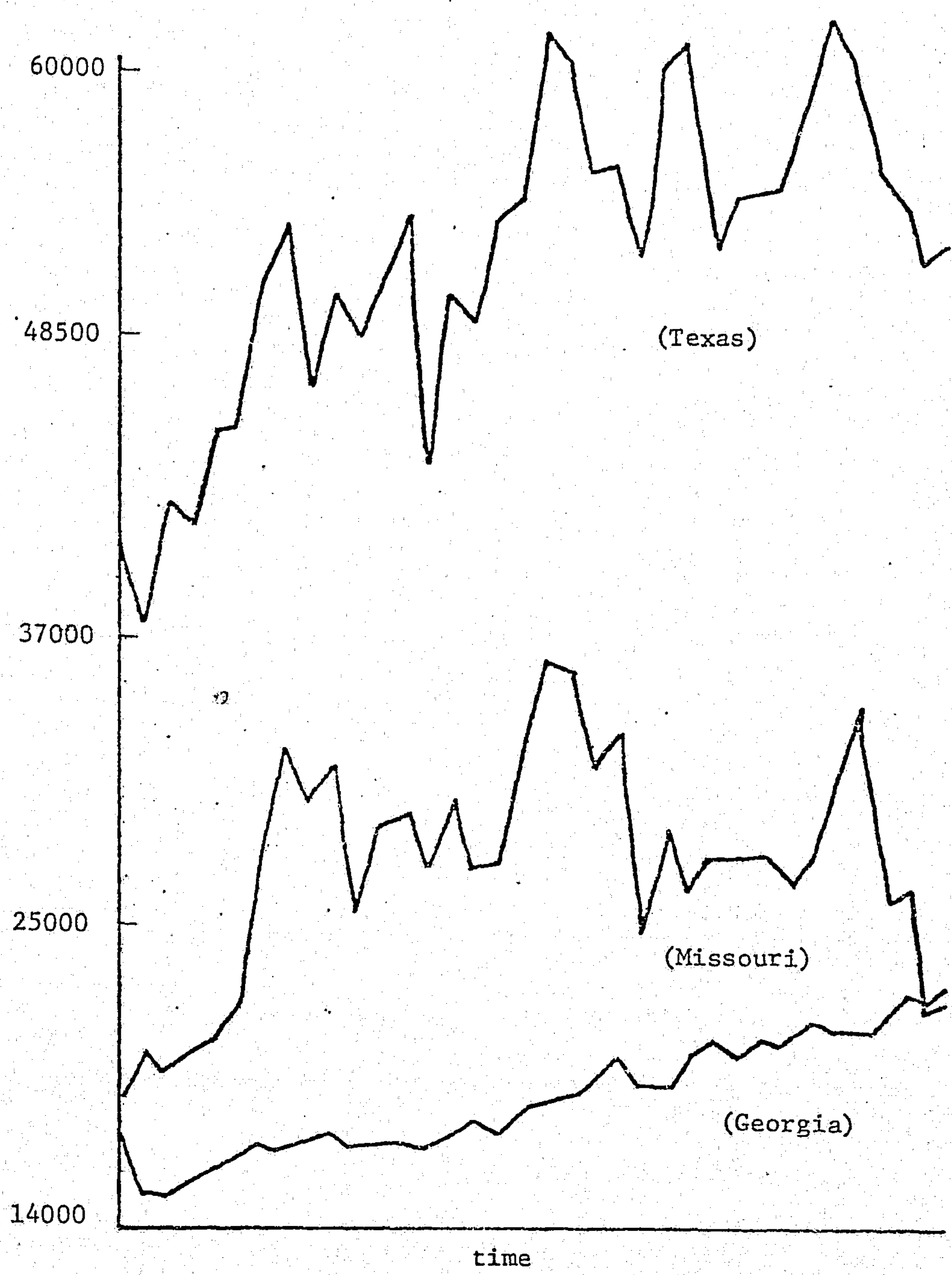

Figure 1. Total Reported Offenses Time Series (1974-1976)

Table 1. Results of Statistical Identification and Parameter Estimation

TOTAL REPORTED OFFENSES

State	Model	Parameter Values	
Georgia	$(0,1,1)(0,1,1)_{12}$	$\theta_1 = 0.270$	$\theta_{12} = 0.153$
Missouri	$(0,1,1)(0,1,1)_{12}$	$\theta_1 = 0.399$	$\theta_{12} = 0.694$
Texas	$(0,1,1)(0,1,1)_{12}$	$\theta_1 = 0.320$	$\theta_{12} = 0.288$

STATE INSTITUTION INMATE POPULATION TOTALS

State	Model	Parameter Values	
Georgia	$(0,1,1)(0,1,1)_{12}$	$\theta_1 = 0.6279$	$\theta_{12} = 0.2028$
Missouri	$(0,1,0)(0,0,0)$	$\theta = 0.6413$	
Texas	$(0,2,1)(0,0,0)$	$\theta = 0.7039$	

STATE PRISON ADMISSION TOTALS

State	Model	Parameter Values
Georgia	$(0,0,0)(0,0,0)$	—
Missouri	$(0,1,0)(0,0,0)$	$\theta_1 = 0.7489$
Texas	$(0,1,0)(0,0,0)$	$\theta_1 = 0.6889$

AVERAGE SENTENCE LENGTH

State	Model	Parameter Values
Georgia	$(0,0,0)(0,0,0)$	—
Missouri	$(0,0,0)(0,0,0)$	—
Texas	$(0,0,0)(0,0,0)$	—

PROBABILITY OF IMPRISONMENT GIVEN CONVICTION

State	Model	Parameter Values
Georgia	$(0,1,1)(0,0,0)$	$\theta_1 = 0.7706$
Missouri	$(0,0,0)(0,0,0)$	—
Texas	$(0,0,0)(0,0,0)$	—

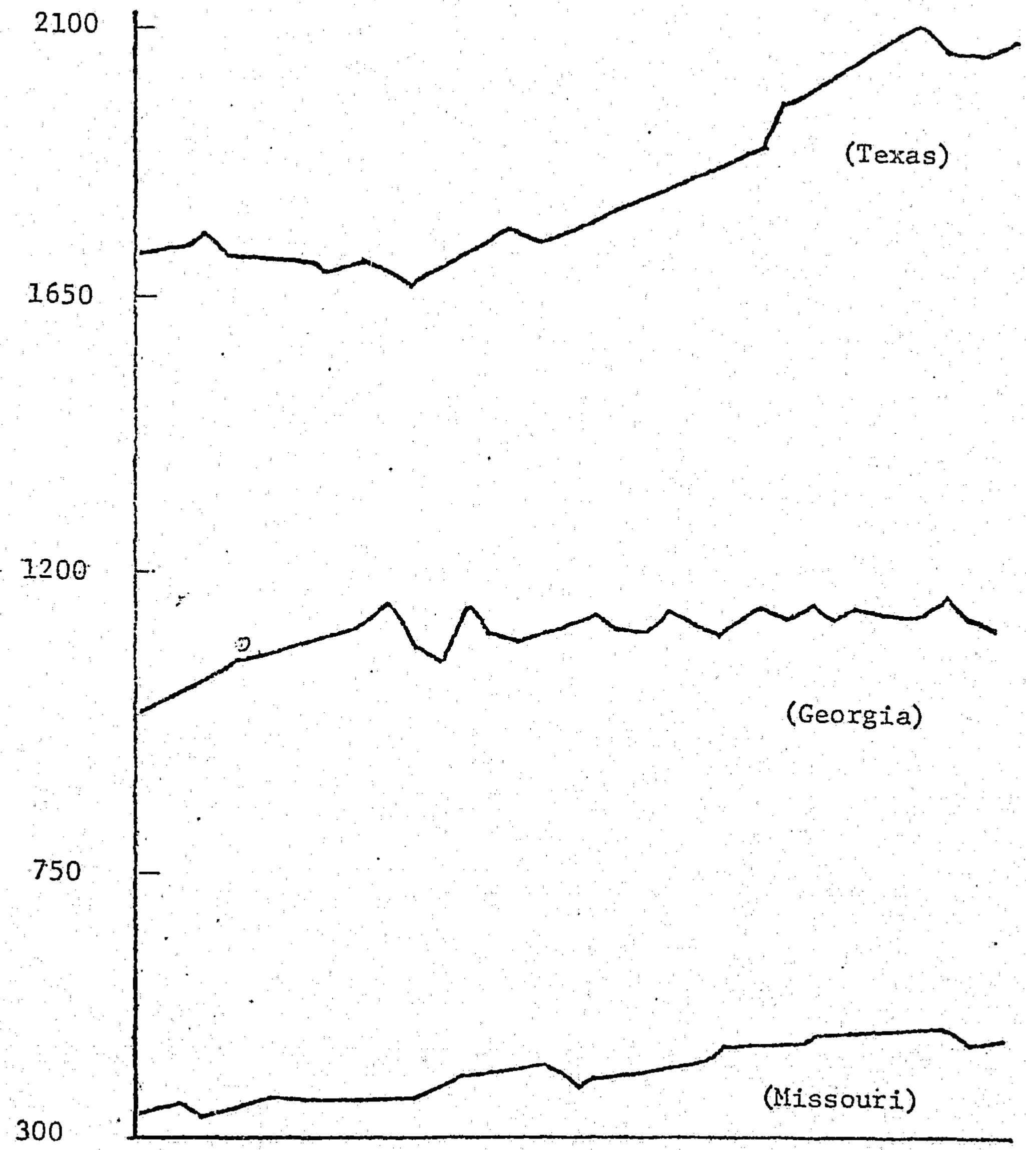

Figure 2. Prison Population Time Series (1974-1976)

Interestingly, the mean of the Missouri prison population series is slightly over one-third of the analogous value in the Georgia data, despite the fact that the populations of the two states differ only slightly. This result provides considerable insight into judicial practices of state courts, as discussed in a subsequent section. The ratio of the mean of the Texas prison population time series to the state population was found to be intermediate with respect to the analogous ratios for Georgia and Missouri. That is, the per capita prison population was found to be highest in Georgia, followed by Texas and Missouri, respectively.

Table 1 shows the results obtained from statistical identification and parameter estimation to determine the correct form of the empirical stochastic multiplicative forecasting models. Among the models used to forecast prison populations in each of the states, all are nonstationary and nonseasonal, with the exception of Georgia, where the prison populations were found to behave in a seasonal fashion as well as being nonstationary.

Prison Admissions

The 36 monthly totals of admissions to adult state penal institutions, during the period from January 1974 until December 1976 for the states of Texas, Missouri and Georgia, are plotted in Figure 3. The series for Georgia demonstrated the highest per capita prison reception rate of the three states for which analysis was performed. The mean value of the Georgia prison admission series was 643 inmates.

Monthly observations of prison admissions in Missouri state prisons were consistent with their corresponding prison population observations. Consistent in the sense that Missouri has the lowest per capita rate of

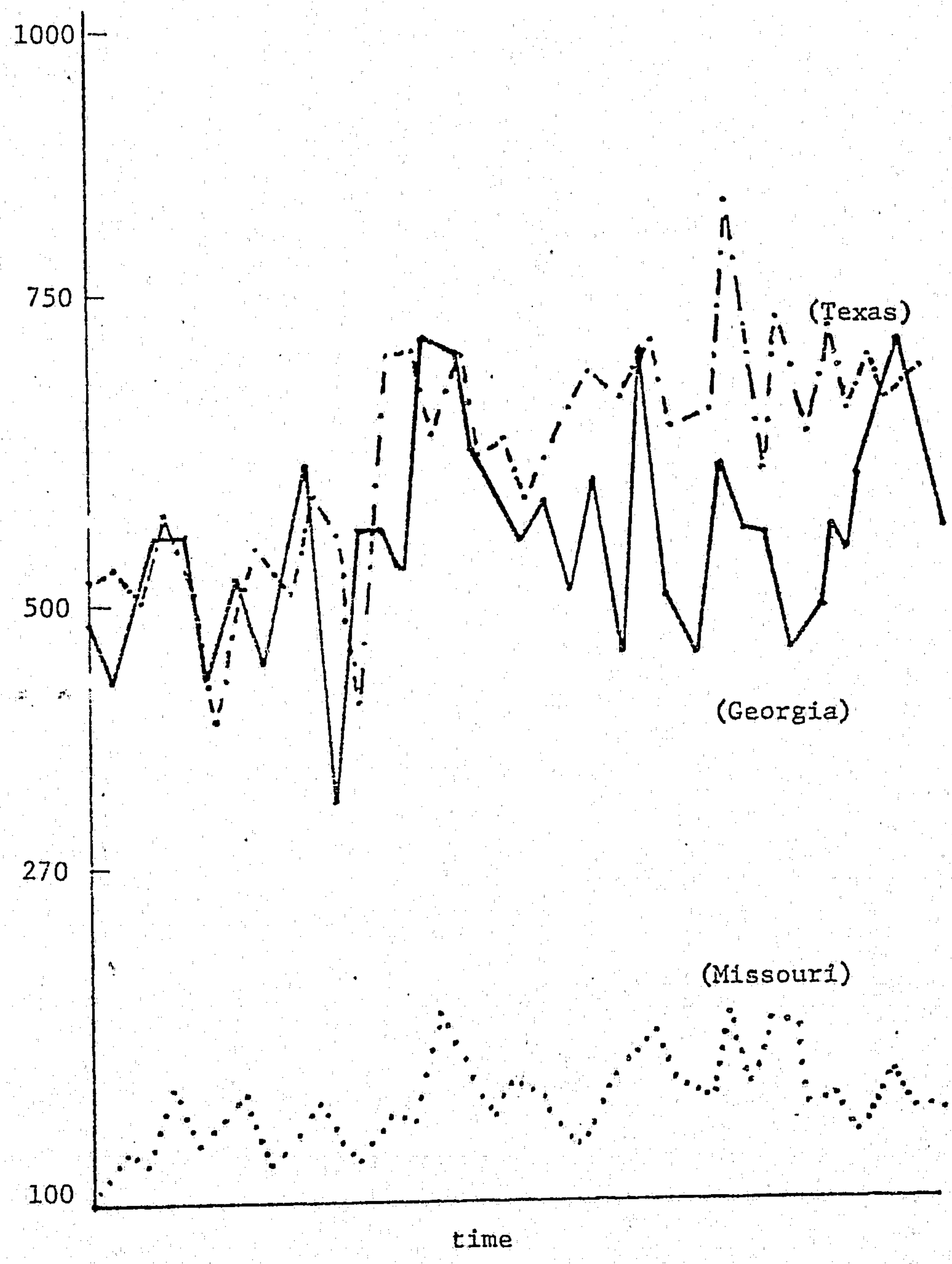

Figure 3. Prison Receptions Time Series (1974-1976)

prison receptions and releases of the three states analyzed, and the lowest per capita prison population.

The prison admissions series for the state of Texas demonstrated the lowest per capita prison reception rate of the three states for which analysis was performed. The monthly per capita state prison admission rate in Texas was considerably closer to the same figure for the state of Missouri than for Georgia. This means that monthly prison turnover is much higher in Georgia than either Missouri or Texas, indicating that Georgia prisons process more individuals (per capita) in a given time period than the other two states. The implication of this for judicial policy becomes evident in the next section.

From the statistical analysis presented in Table 1, it can be observed that nonstationarity is present in prison receptions for Missouri and Texas, while in Georgia, the series resembles a white noise process. This result further distinguishes the corrections system in Georgia from the other two states, and is a major contributer to differences in judicial policy discussed in the next section.

Average Sentence Length

To obtain observations of prevailing average sentence lengths for each state, the procedure is to divide the prison population time series by the prison admissions time series. Figure 4 is a plot of the monthly average sentence length time series obtained for the states of Texas, Missouri and Georgia, from January 1974 until December 1976. For the state of Georgia, the mean value of the average sentence length of 1.67 years was considerably below the analogous values for Texas or Missouri. In Missouri, the mean average sentence length of 23.51 years was an

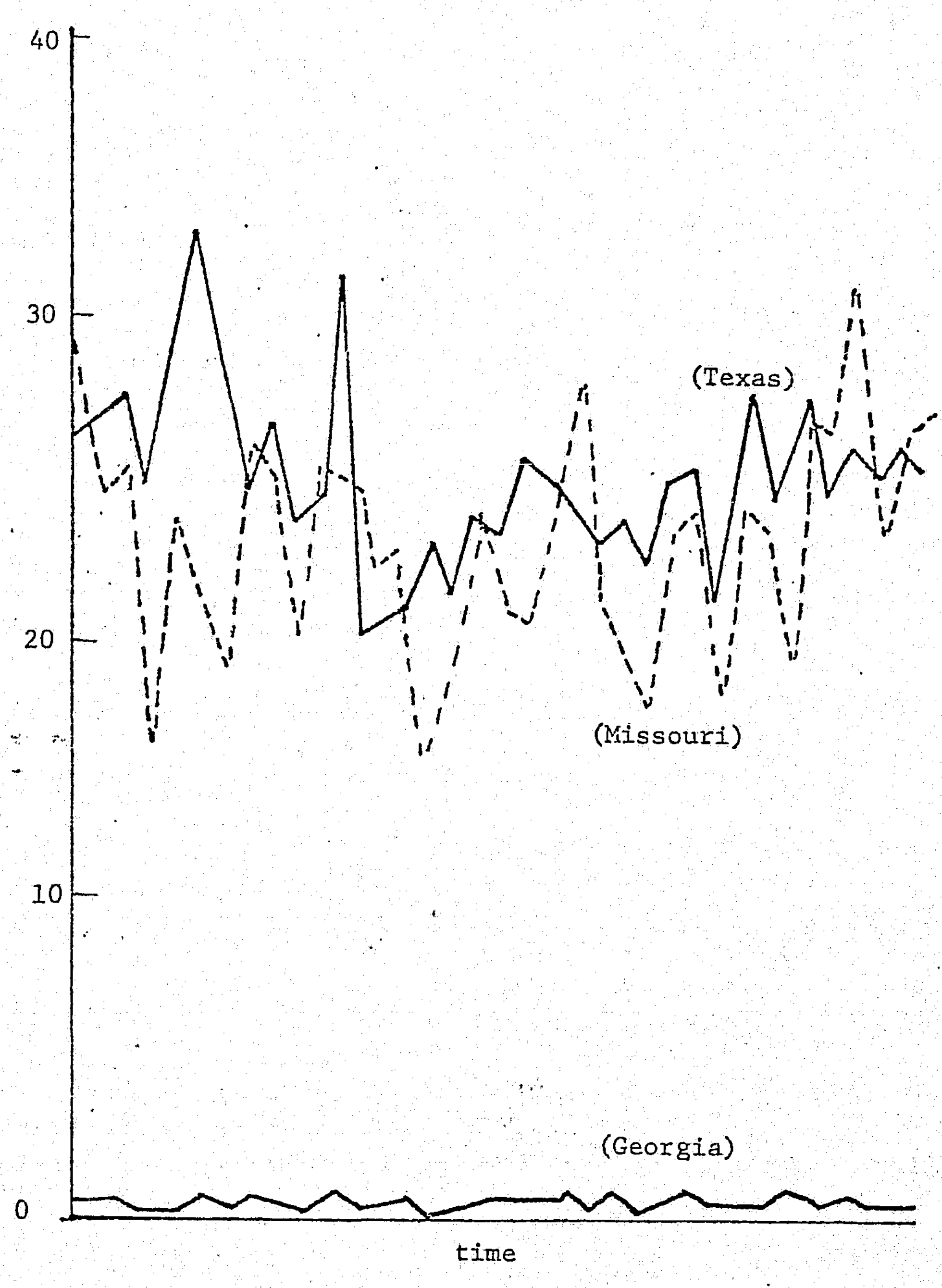

Figure 4. Average Sentence Length Time Series (1974-1976)

order of magnitude larger than the mean for the Georgia series.

This result implies that judicial policy in the state of Missouri is oriented largely toward the severity of punishment. As a result, we would expect that individuals admitted would remain incarcerated for many periods, thus contributing to the extremely low turnover which was observed. In fact, later analysis of imprisonment probabilities for the state of Missouri will show that judicial behavior in that state imposes prison sentences only infrequently, yet tends to delegate severe sentences when the imprisonment option is exercised. In our analysis for the state of Georgia, on the other hand, it was found that more frequent prison disposition of criminal cases was practiced, yet sentences tended to be of shorter duration.

Like Missouri, the time series of average sentence lengths for the state of Texas was an order of magnitude larger than the Georgia series. The mean of the Texas series, equalling 25.62 years, was the largest among the three states considered in the analysis. Clearly, judicial policy in the state of Texas is also oriented strongly toward the severity of punishment, as opposed to its certainty. Indeed we find this to be the case when imprisonment probabilities in the state of Texas are considered.

Table 1 gives the results from statistical identification of the average sentence length time series. In all three cases, the series resembled white noise processes.

Probability of Imprisonment Given Conviction

For the 36 month period from January 1974 until December 1976, the monthly probability of imprisonment given conviction was calculated for the states of Texas, Missouri and Georgia, and is plotted in Figure 5.

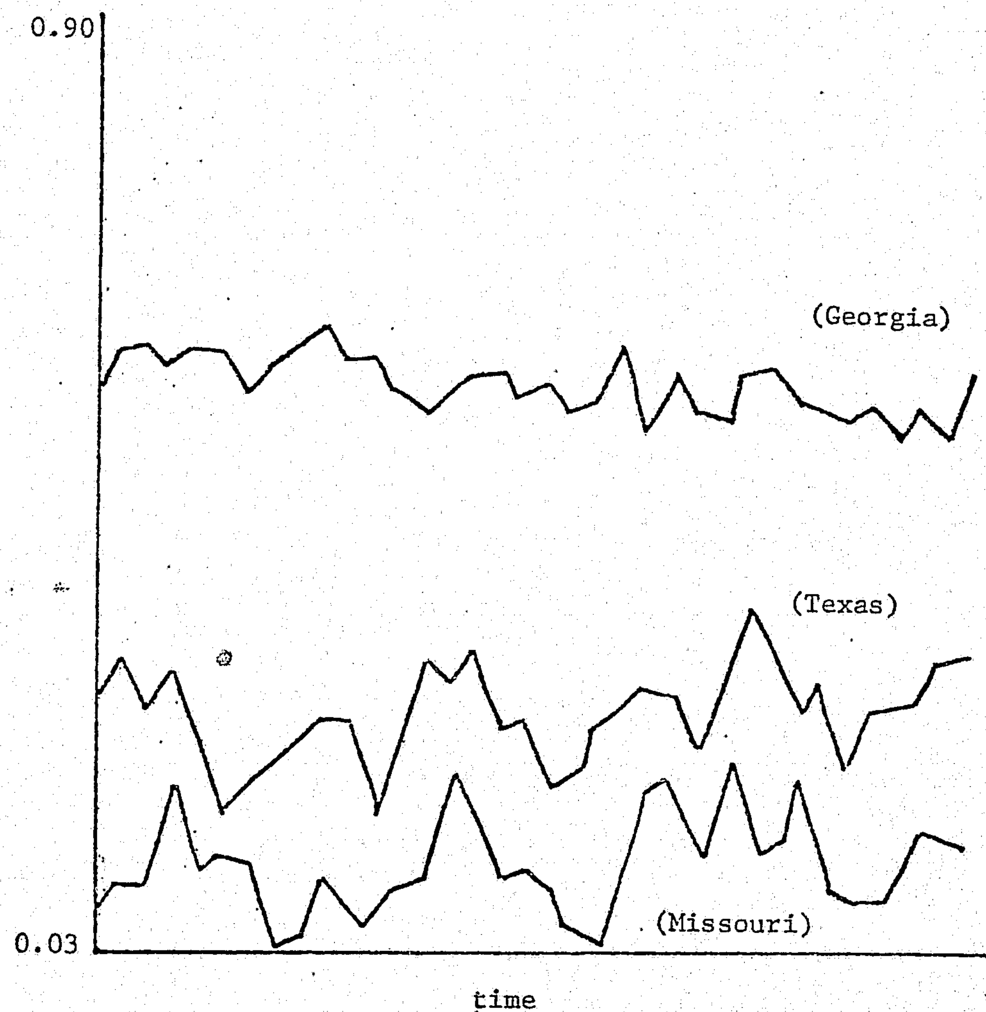

Figure 5. Imprisonment Time Series

In calculating imprisonment probabilities for the state of Georgia, it was found that their values were an order of magnitude larger than analogous values for Texas or Missouri. The mean value of the series was 0.306.

In determining imprisonment probabilities in Missouri, it was found that the series represented a departure from the Georgia results in two respects. First, the magnitude of monthly imprisonment probabilities for Georgia was nearly ten times the magnitude of those for Missouri. This result provides convincing evidence that judicial behavior can differ greatly from state to state, especially in terms of sentencing practices. In fact, these results suggest that the disposition of judicial policy in Missouri has an almost opposite emphasis from judicial policy in Georgia. The mean of the imprisonment probability series in Missouri was 0.04504.

The mean value of the Texas imprisonment probability series was found to be 0.0686, of the same order of magnitude as the Missouri series. This suggests that judicial practices in these states are quite similar and in sharp contrast to the situation existing in Georgia.

One possible interpretation of the stationary imprisonment probabilities for the state of Missouri and Texas is that judicial policy has remained relatively stagnant over the past several years. That is, the current policy has remained unchanged from past years, while in Georgia a more dynamic judicial process prevails. Alternatively, the prisons capacity in that state may be crippled by its obligation to fulfill numerous sentences of long duration imposed in past years. In any case, our analysis could be helpful in evaluating the Missouri policies as possibly suggesting ways for improving the situation.

Results from Executing the Model

Now that the data bases for Texas, Missouri and Georgia have been presented and discussed, we are prepared to present the results from the model in each state and provide a comparison. The results from executing the model for the three states are first discussed, followed by a presentation of results for extensions to the model. Specifically, the results from the model involving the average criminal's level of deviance (λ_t), deterrent effects, and the effect of optimization are discussed for each state. In addition, the savings in crimes due to optimization, and the separation of deterrent and incapacitative effects are presented for each state with a comparison offered.

Results for λ_t

In this analysis, it was found that the behavior of λ_t in Missouri was expected to behave in a manner similar to λ_t for Georgia. On the other hand, λ_t for Texas was found to grow only slightly. This result can be explained by the slow growth behavior of the prison population forecasting model for Missouri, and the near stationary behavior of the prison populations in Georgia. This behavior of the prison populations is in contrast to the behavior of crime rates which were predicted to rise sharply in both Georgia and Missouri. During this same period, Texas prison populations are expected to grow considerably along with the crime rate, thereby moderating the growth of λ_t. In all three cases, the proportion of the criminal population which remains at large, C_t/C_t+P_t, is expected to remain nearly stable. Tables 2 and 3 present sample results for λ_t and C_t/C_t+P_t, respectively, for each of the three states.

Table 2. λ_t for Five Sample Periods

Period	Georgia	Missouri	Texas
March 1975	.2938	.2568	.2813
January 1983	.4361	.3283	.3063
May 1987	.5330	.3238	.3117
July 1990	.5954	.4231	.3340
November 1994	.6724	.5643	.4062

Table 3. $\frac{C_t}{C_t+P_t}$ for Five Sample Periods

Period	Georgia	Missouri	Texas
March 1975	.8330	.8231	.8403
January 1983	.8340	.8307	.8486
May 1987	.8340	.8258	.8605
July 1990	.8380	.8283	.8585
November 1994	.8350	.8285	.8486

Deterrent Effects in Georgia, Missouri and Texas

In order to illustrate the impact on the prevailing judicial policy in Georgia, Missouri and Texas, clear of any factors relating to the size and population of the individual states, it is appropriate to examine their deterrent effects. This is because the deterrent effect represents a proportion of the population in each state and as such, is dimensionless. The deterrent effects for five periods of interest during the 24 year simulation are presented in Table 4 for each of the three states.

The results in Table 4 suggest that expenditures for corrections in Texas, ultimately produces the smallest deterrent effect of the three states.

Table 4. Deterrent Effects for Five Sample Periods

Period	Georgia	Missouri	Texas
March 1975	1.32%	1.12%	1.09%
January 1983	1.42%	1.11%	1.07%
May 1987	1.43%	1.31%	1.16%
July 1990	1.39%	1.13%	1.19%
November 1994	1.42%	1.20%	1.13%

The most apparent reason behind this result is that Texas also allocates the largest resource in terms of its corrections capacity constraint and therefore, would expect to recieve a higher return. This reasoning also extends to Missouri, which bankrolls the second largest corrections system, followed by Georgia, which allocates the smallest resource to obtain the smallest deterrent impact. This analysis, of course, says nothing about the per dollar efficiency of the corrections allocation within each state, which is addressed in a subsequent section.

Comparison of the Effect of Optimization

The most astounding contrast between the three states existed within the optimization process. Table 5 is a summary of the resulting optimal judicial policy for each period for each state. Bear in mind that these results are strictly for constant input values of decision variables Q and S, and as such, the results apply for every monthly period within the 25 year horizon.

Earlier results from the model [15] have shown the results for Texas and Missouri to be totally consistent with senstivity studies performed for the Georgia data base. That is, for relaxation of the Georgia capacity

Table 5. Summary of the Optimization Process for Decision Variables Q and S

	Georgia	Texas	Missouri
prevailing Q	0.30606	0.0686	0.0450
prevailing S	1.11 yrs.	25.62 yrs.	23.51 yrs.
Q*	.4605	.6753	.6024
S*	1.67 yrs.	2.60 yrs.	1.76 yrs.
ΔQ	+.15	+.61	+.56
ΔS	-.56 yrs.	-23.02 yrs.	-21.75 yrs.

constraint corresponding roughly to the existing Missouri and Texas capacity constraints, the optimal policy is found to be very close to the same form. This would lead us to conclude that despite differences in the nature of corrections resource allocation between states, the social mechanisms underlying the deterrent effect are essentially the same. Consequently, the prescription for judicial policy should also be roughly consistent. Given the present magnitude of this allocation, a more efficient strategy for controlling crime within existing corrections capacity is to insure a higher level of imprisonment probability with shorther sentences, i.e., increase the flow rate of individuals within the prison system without increasing capacity.

Comparison of Crimes Prevented Through Optimization

To further illustrate the significance of potential improvment through policy adjustment, Table 6 illustrates the number of crimes saved in each of the states for five sample periods during the simulation, and

Table 6. Crime Saving Percentages

Period		Georgia crimes saved%	Missouri crimes saved%	Texas crimes saved%
March	1975	360...2.28%	4372...43%	11875...33%
January	1983	590...2.28%	5606...43%	13056...33%
May	1987	744...2.28%	6152...43%	15123...33%
July	1990	825...2.28%	7720...43%	16617...33%
November	1994	939...2.28%	9561...43%	18121...33%

the corresponding percentage savings. Clearly, the potential improvement in crime control for the state of Georgia is the lowest, due to the fact that Georgia maintains the lowest corrections capacity of the three states. Also, Georgia's prevailing judicial policy is closest to the theoretically correct policy, further narrowing the margin for improvement.

The most important result from Table 6 is that the states of Missouri and Texas stand to realize a substantial improvement in the efficiency of their corrections system without allocating additional funds. The model suggests that these two states can upgrade their crime control effectiveness by redustributing the dollars they are now using for long term incarceration and maintenance of high security institutions. Texas and Missouri represent prime examples of the predominance of the certainty of punishment as opposed to its severity within the feasible region of spending.

Separating Incapacitation from Deterrence Effects

One additional result obtained from the model relates to the separation of deterrence and incapacitation. Table 7 is a summary of the average distribution of the crime control effect stemming from general deterrence and incapacitation under current and optimal policies for each of the three

Table 7. Distribution of Crime Control Effect

	Georgia		Missouri		Texas	
	optimal policy	prevailing policy	opt. pol.	prev. pol.	opt. pol.	prev. pol.
Incapacitation:	13%	24%	8%	93%	6%	98%
Gen. Deterrence:	87%	76%	92%	7%	94%	2%

states involved in the analysis. From the table, it can be seen that the redistribution of these measures is far more pronounced in Texas and Missouri than in Georgia. This stems from the nature of the shift in policy brought about by the optimization process. It is also evidence of the relatively small impact of incapacitation as compared with deterrence under optimal conditions, once again emphasizing that it is effectively the threat of punishment, as opposed to the actual punishment, which is most correlated with controlling crime. As a final note, it should be mentioned that the averages appearing in Table 7 represent a much smaller sample under current policy for Missouri. This is because the recursive accumulation procedure for calculating the incapacitative effect in that state required a much larger start up period than for Georgia, due to high average sentence lengths under prevailing policy. Consequently, this quantity could be determined for only a small number of periods.

The incapacitative effect in the state of Texas, under prevailing policy, could not be obtained, due to the fact that the average sentence length under prevailing policy (26.52 years) exceeded the duration of the the simulation. As a result, the value in Table 7, estimated by assuming the unit percentage relation between incapacitative effect and sentence length in Texas, was the same for Missouri.

Conclusion

A discrete time model has been presented, incorporating the court, corrections and law enforcement components of the criminal justice system. This model is used to determine the effect of various sentencing strategies. Although the results from this analysis should not be regarded as a final comparison, results have provided preliminary insight into the question of judicial policy differences between geographic regions.

Our results would indicate that extreme variation in judicial practices exist between states. Specifically, judicial policies in Missouri and Texas were in order of magnitude different from judicial policy in Georgia. In addition, it was determined that the state of Georgia spends less money per capita than either Texas or Missouri, whose sentencing practices have comparable per capita crime control potential.

A similarity in results, which was common to each data base, was that it was the certainty of punishment, as opposed to its severity, which exhibited the greatest crime control potential relative to the prevailing policy. In addition, in states where prevailing judicial policy was found to be highly suboptimal, the potential returns for optimization of the current policy are greatest in terms of crime control effectiveness.

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