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In the following exchange, Rauma analyzes several time series of imprisonment and prison admission rates and conludes that they show no support for Blumstein's stability of punishment hypothesis. Blumstein and his colleagues respond, in part, that Rauma has misinterpreted the empirical implications of their theory. Rauma defends his initial conclusions.

THE EDITORS

CRIME AND PUNISHMENT RECONSIDERED: SOME COMMENTS ON BLUMSTEIN'S STABILITY OF PUNISHMENT HYPOTHESIS*

DAVID RAUMA**

ABSTRACT

In a series of articles, Alfred Blumstein has proposed and tested a homostatic model of punishment in society. Based on ideas found in Durkheim, Blumstein hypothesizes that, over stable historical periods, the level of punishment in a society will be stable as well. After analyzing time series of imprisonment rates for three countries, Blumstein finds support for his hypothesis. In this paper, I re-analyze one of Blumstein's time series and analyze several others, including data for California from 1853 to 1970. These analyses and re-analyses, of both imprisonment and prison admission rates, show no support for the stability of punishment hypothesis. As a consequence, I argue that doubts can be raised about the adequacy of Blumstein's empirical analyses, that the measure of punishment he uses—imprisonment rates—may not be as good a measure of punishment as prison admission rates, and that additional approaches should be explored in order to provide more compelling tests of the stability of punishment hypothesis.

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I. Introduction

Among the many controversies current in criminal justice circles is whether imprisonment is of increasing or decreasing importance for the punishment of convicted offenders. The late 1960s and the early 1970s saw an apparent decline in the use of imprisonment, as measured by both prison admissions and prison populations, and an increase in the use of alternative interventions. This trend was reversed in the middle 1970s, accompanied by an additional stress on imprisonment for violent offenders. California's "use a gun, go to prison" law is one example of this new emphasis. Other states have enacted similar legislation, and more seems to be on the way. One issue is what best indexes the use of punishment in society: the size of prison populations; the number of admissions to prison; or some other measure altogether? Another, larger issue concerns historical trends in the use of punishment, and whether its importance rises and falls in response to policy changes, historical events, or demographic shifts. One popular phrasing of the issue is whether or not society maintains a relatively stable level of punishment over time.

In a series of articles, Alfred Blumstein and several colleagues[1] ("Blumstein") have posed and tested a homeostatic model of punishment in society. Based on ideas proposed by Durkheim, Blumstein hypothesizes that during stable historical periods, societal levels of crime and punishment (as measured by imprisonment rates) will remain stable as well. After analyzing relevant data for California, and re-analyzing some of his, I have found several problems in the statistical procedures Blumstein employs to test the hypothesis. In addition, there are difficulties with Blumstein's interpretation of Durkheim; imprisonment rates may not be the best measure to test Durkheim's ideas concerning stable levels of crime and punishment. In the following pages I will show that the data do not necessarily support Blumstein's contention that the aggregate imprisonment rate in the United States remained stable during the period 1926-70. I will also argue that, relative to imprisonment rates, prison admission rates may be a better measure of punishment.[2]

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1 Blumstein & Cohen, *A Theory of the Stability of Punishment*, 64 J. CRIM. L. & C. 198 (1973); Blumstein, Cohen & Nagin, *The Dynamics of a Homeostatic Punishment Process*, 67 J. CRIM. L. & C. 317 (1977); Blumstein & Moitra, *An Analysis of the Time Series of the Imprisonment Rates in the States of the United States: A Further Test of the Stability of Punishment Hypothesis*, 70 J. CRIM. L. & C. 376 (1979).

2 Although there is a great deal of ambiguity in the term "imprisonment rate," Blumstein defines it as the number of prisoners on hand per 100,000 in the total population. One source of ambiguity is the "correct" population to standardize prison population by: total population; young people, who are most likely to go to prison; or some other population altogether. Such issues will not be addressed here, and all rates in the reported analyses are consistent with Blumstein's usage.

However, United States admissions data show little evidence of stability either. Finally, I will demonstrate that imprisonment and admission rates for California during the period 1853-1970 do not support the hypothesis of a stable level of crime and punishment.

II. Blumstein's Theoretical and Empirical Models

A. The Stability of Punishment Hypothesis

Blumstein's theory begins with a posited underlying behavior distribution in society. Individuals engage in a wide variety of activities, some more common than others, which vary along a unidimensional continuum of conformity to society's norms. At one extreme of the distribution are the most conforming behaviors, while at the other end are the very deviant. It is at this latter extreme that some behaviors, beyond a certain threshold, are defined as criminal and therefore subject to punishment. Citing Durkheim, Blumstein[3] hypothesizes that during stable historical periods, the level of crime will remain relatively constant in society. Crime is defined by societal reaction against it—punishment—and serves to reaffirm the norms characteristic of that society (*i.e.*, the behaviors at the center of the behavior distribution). Thus, crime is only defined when it is punished in some manner, is natural to any society, and helps maintain social solidarity.

From these premises, Blumstein develops a homeostatic model of punishment in society. The distribution of societal behaviors is subject to change over time as some behaviors become more widespread and others become less so. As this occurs, it is possible that the behavior distribution will shift along the continuum of conformity, and forces in society will cause a shift in the threshold of criminality to maintain a stable level of crime. If deviant behaviors become more common and society becomes more deviant, the threshold will be moved to punish fewer types of behaviors. Since more individuals are engaging in them, fewer deviant behaviors need be specified as criminal. If the opposite occurs, and society becomes less deviant, the threshold will be moved to punish more behaviors. Through this homeostatic, over-time adjustment process, society will maintain a relatively stable mean level of punished behaviors (crimes).

Roughly outlined, these are the basic tenets of Blumstein's model. More will be said about the model later; for now the focus is on his empirical tests of the stability hypothesis. Blumstein proposes using imprisonment rates (the number of prisoners per 100,000 individuals in the total population) to test the hypothesis. He reasons that if punishment

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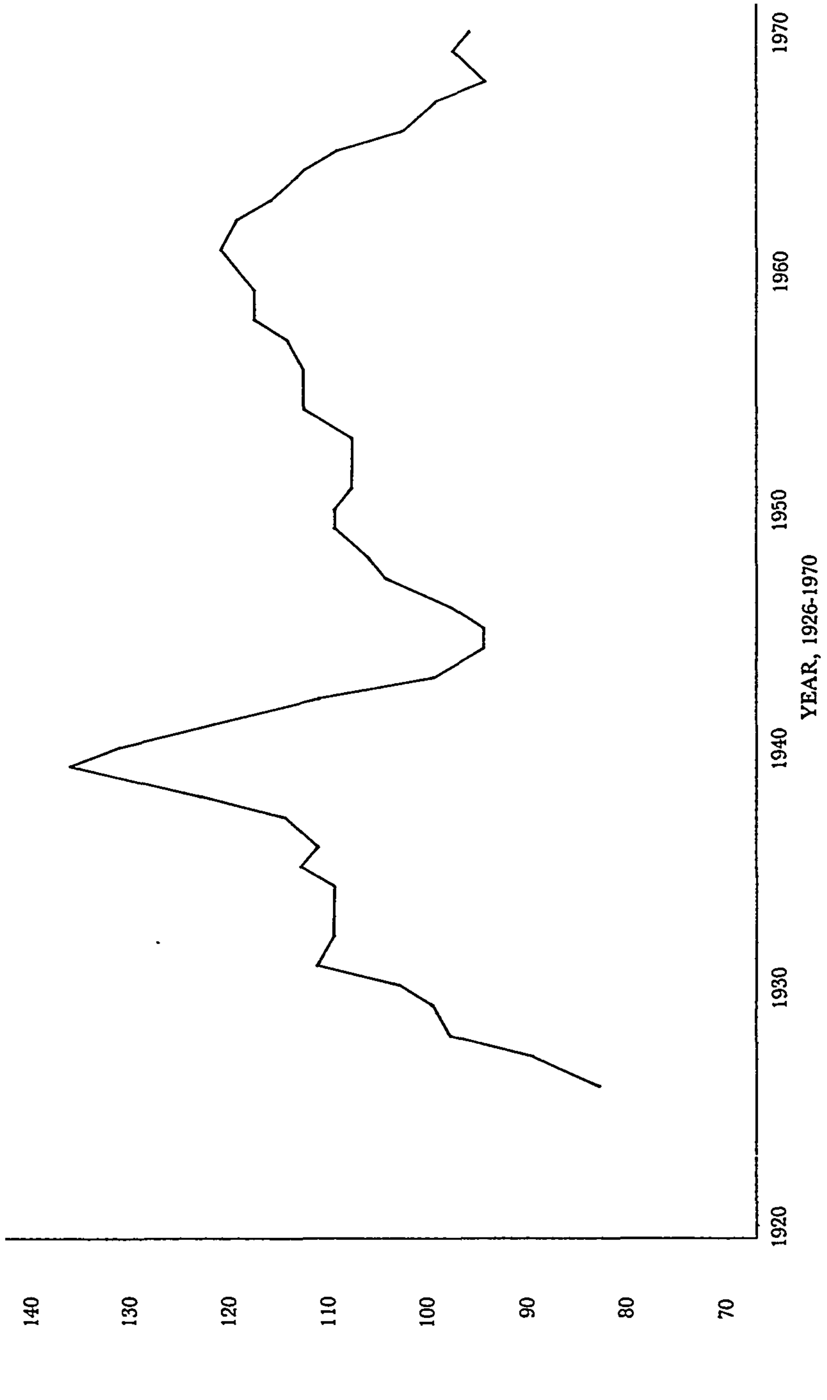
3 Blumstein & Cohen, *supra* note 1, at 200; Blumstein, Cohen & Nagin, *supra* note 1, at 317-20; Blumstein & Moitra, *supra* note 1, at 376-77.

FIGURE 1

U.S. Imprisonment Rates, 1926-1970



does remain stable, with only minor fluctuations around the mean (perhaps due to the over-time adjustment), so should the imprisonment rate. Blumstein analyzes various time series of imprisonment rates—for the United States as a whole, 1926-74; for forty-seven states during the same period; for Canada, 1880-1959; and for Norway, 1880-1964—and he finds support for the stability hypothesis.[4]

A fundamental objection can be made to the univariate time series model Blumstein proposes for the aggregate United States data. The United States imprisonment rate series,[5] shown in Figure 1, looks suspiciously like what Box and Jenkins refer to as "uncontrolled series,"[6] which result from nonstationary processes and generally exhibit little or no stability over time. In his analysis, Blumstein models the U. S. series as the realization of a stationary process (*i.e.*, the homeostatic punishment process), and the implications of this model are crucial for his hypothesis. If they are to provide evidence for the stability hypothesis, Blumstein's series must be modeled as realizations of processes with stable means, of which stationary processes are one case. I will argue that Blumstein's model for the U. S. series is perhaps incorrect and is certainly not unique, and therefore provides no compelling evidence for the stability hypothesis. However, some discussion is first necessary of stationary and nonstationary processes, their implications for modeling observed time series, and their implications for Blumstein's hypothesis.

B. STATIONARY AND NONSTATIONARY PROCESSES

Univariate time series, such as the United States imprisonment rate series, can often be characterized as realizations of either stationary or nonstationary stochastic processes. Stochastic only means that the process generating the observed series is not entirely deterministic, but that its values are drawn from a probability distribution. The conditions for a stationary process are rather straightforward in principle, but often difficult to meet in practice. A stationary process is by definition time-invariant, with a stable mean, stable variance, and stable autocovari-

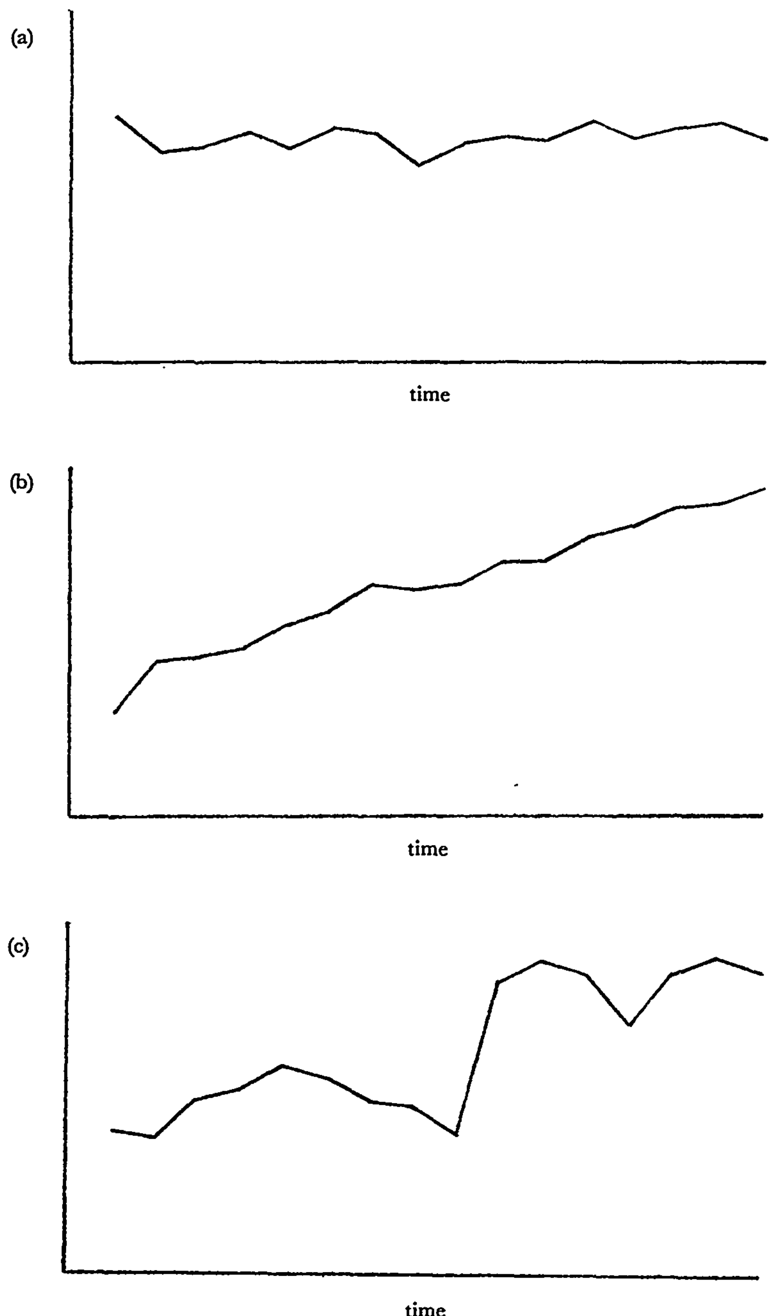
[4] Blumstein, Cohen & Nagin, *supra* note 1, at 330; Blumstein & Moitra, *supra* note 1, at 389.

[5] 1 U. S. DEP'T. OF COMMERCE, HISTORICAL STATISTICS OF THE UNITED STATES: COLONIAL TIMES TO 1970 420 (1975). Prison population data were available for all years from 1926-70, and total United States population was constructed by linear interpolation between census years. From these data imprisonment rates were constructed per 100,000 in the total population. Blumstein's series extends to 1974, but it is doubtful that the four more observations would have any impact on the models estimated here.

[6] G. BOX & G. JENKINS, TIME SERIES ANALYSIS 85-86 (1976).

FIGURE 2

EXAMPLES OF STATIONARY AND NONSTATIONARY TIME SERIES



ances. In fact, all the moments of the probability distribution are fixed.[7] As a consequence, if the same stochastic process were observed in different time intervals, the means, the variances, and the univariate models describing these observed series would, within sampling error, be identical. Figure 2(a), for example, is the realization of a stationary process. With some chance fluctuations, it is stable around a single mean level and it has a constant variance.

On the other hand, there are virtually unlimited ways in which stochastic processes can be nonstationary. In general, two types of nonstationary processes can be distinguished: integrated processes and non-homogeneous processes. The difference between the two depends on which moment of the probability distribution is problematic. Integrated processes have no stable mean;[8] rather, they have changes in mean level which may be deterministic, stochastic, or some combination thereof. Figure 2(b) shows a realization of an integrated process with a constant increment in the mean. Except for that increment over time, the process is stationary. In contrast, Figure 2(c) shows a series with entirely stochastic changes in the mean. The underlying process has random changes in mean level, and, depending on the time interval, the observed time series will show a variety of trends and/or changes in mean level. Except for those random changes, this process is also stationary. Combinations of deterministic and stochastic changes are more difficult to portray, but a common pattern is an over-time trend that is itself subject to randomness.

The other type of nonstationary process, a non-homogeneous process, has no constant variance.[9] It may also have no stable mean, but, for time series modeling purposes, the variance problem is usually the first concern. For example, an observed time series with a constant mean but an increasing or decreasing variance over time (*i.e.*, increasing or decreasing oscillations around the mean) is a realization of a non-homogeneous process. Series with exponential growth patterns, and therefore no constant mean, are also realizations of non-homogeneous processes.

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[7] Box and Jenkins describe a strictly stationary stochastic process as one in which the joint probability distribution for T observations is unaffected by a change in time origin. The mean, variance, autocovariances, and *all* higher order moments must be unaffected by time origin—they are time invariant. Normally, time series analysis proceeds under the assumption of weak stationarity, where all moments up to some order are assumed to be unaffected and the probability distribution is assumed to be multivariate normal. Second-order stationarity, in which the mean and the variance are assumed constant, and the assumption of normality are enough to produce strict stationarity. *Id.* at 26-30.

[8] *Id.* at 84-114; C. GRANGER & P. NEWBOLD, FORECASTING ECONOMIC TIME SERIES 40-41 (1977).

[9] C. GRANGER & P. NEWBOLD, *supra* note 8, at 304.

As a consequence, the first issue in time series modeling is whether or not an observed series is the result of a stationary process. Plots of the series and its autocorrelation function can be used to determine if the observed series results from a stationary process or an integrated process. Non-homogeneous processes are sometimes more difficult to identify, and the autocorrelation function is of limited use as a diagnostic device. Although certain types of nonstationarity can be tested for (*e.g.*, linear trends), a formal statistical test for stationarity has not been developed: a single test cannot be applied to determine if a series results from a stationary or nonstationary process.[10] However, through various diagnostic devices the nature of the underlying process can usually be ascertained. Since there are a wide variety of ways in which nonstationarity can occur, it is not always readily apparent, nor is it always clear-cut. Some series can be modeled equally well as realizations of stationary or nonstationary processes. Consequently, a wide variety of diagnostic checks are sometimes necessary.

Fortunately, realizations of integrated and non-homogeneous processes can often be transformed and modeled as though the underlying processes were stationary. Observed time series can be differenced to remove changes in mean level.[11] Differencing involves subtracting past values of the time series from current values in order to remove those changes, resulting in a new series with a zero mean. However, a series without a constant variance cannot be differenced to solve the problem; other transformations are necessary, the most common being the logarithmic.[12] And if the log transformed series has changes in mean level, it must also be differenced to produce a new series with a constant mean and a constant variance. Here again, the usual diagnostic devices can be used to judge if the transformations were necessary and resulted in a stationary series. (The underlying process and the observed time series

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[10] In general, the existing tests for stationarity all require some specification of the form that the possible nonstationarity takes. For example, Dickey and Fuller propose a test based on the null hypothesis that the observed series is generated by a particular type of integrated process called a "random walk." Dickey & Fuller, *Distribution of the Estimators for Autoregressive Time Series with a Unit Root*, 74 J. AM. STATISTICAL A. 427 (1979). Box and Pierce and Box and Jenkins propose a test (the Q-statistic) for the autocorrelation function to test the adequacy of *estimated* univariate models. Box & Pierce, *Distribution of Residual Autocorrelations in Auto-Regressive Integrated Moving Average Time Series Models*, 65 J. AM. STATISTICAL A. 1509 (1970); G. BOX & G. JENKINS, *supra* note 6, at 290-93. Other tests are possible, including Blumstein's test for a deteministic trend, but they involve specific assumptions about the nature of the non-stationarity. Consequently, diagnosing nonstationarity can be a trial and error process: different transformations are tried, and different time series models are estimated, and at each stage the relevant diagnostics are checked and compared to other possible representations of the underlying process. The general aim is to find the most parsimonious model possible to *adequately* represent the underlying stochastic process.

[11] *See generally* G. BOX & G. JENKINS, *supra* note 6, at 85-114.

[12] C. GRANGER & P. NEWBOLD, *supra* note 8, at 304.

will hereafter be referred to interchangeably. This is a convention in time series modeling which, for the purposes of exposition, is often more convenient than distinguishing between the two.)

Whether or not the observed series is transformed, standard time series modeling procedures can be employed after stationarity has been determined. Various orders of autoregressive and/or moving average models can be estimated to represent the stochastic process generating the observed series. Alternative models are occasionally possible, and a choice must then be made as to which is the "best" model. The most often used criterion for choosing a model is parsimony (*i.e.*, the fewest transformations and the fewest estimated parameters), but the selection among equally credible models can be difficult. Univariate models in general have little substantive meaning; it is instructive to distinguish stationary from nonstationary series, and autoregressive from moving average processes, but little additional insight is gained from distinguishing, for example, various orders of autoregressive processes. Consequently, parsimony is primarily a statistical criterion, not a theoretical criterion for model choice.

The implications of stationarity for Blumstein's hypothesis should be apparent. The homoestatic punishment process, as Blumstein describes it, is a stationary process (or, at worst, a non-homogeneous process with a constant mean), and observed time series of imprisonment rates should have constant means. Furthermore, in the absence of a definitive test for stationarity, Blumstein must make a compelling case that series he models as stationary are not nonstationary. Blumstein imposes a theoretical constraint on these series, and he must show that the constraint is statistically valid. In other words, Blumstein must demonstrate that any alternative time series models, perhaps equally parsimonious but resting on the assumption of nonstationarity, are less plausible than the models he presents. Since evidence for the stability hypothesis requires that observed time series have stable means, nonstationarity should be ruled out as a competing explanation for the behavior of such series.

C. TIME SERIES MODELS FOR UNITED STATES IMPRISONMENT RATES

Blumstein models the United States imprisonment rate series (and other series as well) as a stationary series, but *only* because it does not have a deterministic linear trend over time.[13] However, at first glance

[13] Blumstein tests for a deterministic linear trend by regressing each of the imprisonment rate series, for the United States and the individual states, on linear counters. Blumstein & Moitra, *supra* note 1, at 377-81. This is a test for a purely deterministic linear trend, and Blumstein never discusses other types of nonstationarity, not due to linear trends. There is no indication that he considered other types when modeling the various series.

(see Figure 1), the series seems to have different trends in two parts of the series: a positive trend in the period 1926-39; and another positive trend, with a different slope, in the period 1946-61. The other sections of the series appear to have negative trends, but they are short and therefore difficult to judge. As Blumstein notes, the series tends to remain within a particular range, but he only rules out the possibility of a deterministic trend, and changes in mean level are apparent regardless. If the series were longer, changes in mean and slope could become more pronounced. For example, although her data are incomplete, Cahalan[14] provides evidence that United States imprisonment rates were, on the average, lower during the 1800s.[15] If the United States series does not

TABLE 1

REPLICATION OF BLUMSTEIN'S UNIVARIATE MODEL FOR U.S. IMPRISONMENT RATES 1926-70

$$y_t = \mu + \frac{a_t}{(1 - \phi_1 B^1 - \phi_2 B^2)}$$

Parameter	Coefficient	t-Value
μ (Mean)*	107.66	29.77
ϕ_1 (1st AR parameter)**	1.54	15.11
ϕ_2 (2nd AR parameter)***	− .70	− 6.86

N = 45 Residual Mean Square Error = 16.04
Q-Statistic = 14.3 (for 10 lags, p > .05)

*Blumstein reports the parameter δ, rather than the mean, μ. The mean is a more useful parameter, but one can be converted to the other:

$$\mu = \frac{\delta}{1 - \phi_1 - \ldots - \phi_p}$$

**A first-order Autoregressive parameter
***A second-order Autoregressive parameter

[14] Cahalan, *Trends in Incarceration in the United States Since 1880*, 25 CRIME & DELINQUENCY 9 (1979).

[15] Cahalan makes some interesting historical points, but her lack of data tends to invalidate her argument that imprisonment rates have been increasing since the 1880s. With data for only nine years over an eighty year span, it is difficult to determine whether a trend exists or whether the data are for atypical years in the series. Her use of ordinary least squares to estimate a trend for *only nine observations* is misleading—the standard errors will probably be enormous and any trend would be indistinguishable from chance. It should be noted that, in his rebuttal, Blumstein's estimation of a dummy variable regression model for those nine data points is equally misleading. Blumstein & Moitra, *Growing or Stable Incarceration Rates: A Comment on Cahalan's "Trends in Incarceration in the United States Since 1880"*, 26 CRIME & DELINQUENCY 91 (1980).

have a constant mean, as Figure 1 suggests, Blumstein's evidence for a homeostatic punishment process is weakened.

To more formally test for changing levels in the U. S. series, I re-estimated Blumstein's[16] univariate model and then developed an alternative. Table 1 contains the replication of Blumstein's model. The model is estimated with four more observations than Blumstein's, but the difference is trivial: the coefficients are approximately the same, and the model does seem to fit. However, there are two qualifications to Blumstein's model, the latter of which applies to any model estimated for this data set. First, within sampling error, the model and therefore the underlying process is nonstationary. The estimated coefficients do not sum to greater than 1.0, which is an easy check for stationarity in a second-order autoregressive process;[17] however, if a confidence interval of only plus or minus one standard error were placed around the coefficients, they could sum to over 1.0. Also, the coefficients are correlated at .87, which suggests that they are unstable and that their exact values are almost inseparable from one another. These are reasons for uneasiness about the model, although, without a test for stationarity, Blumstein's model cannot be rejected outright.

The second qualification is the sample size. With forty-five observations, the estimated coefficients may differ greatly from the parameters for the underlying process and the standard errors may be biased. The Box-Jenkins time series techniques used here are maximum likelihood techniques, which are only fully appropriate for larger samples than the U. S. series. Box and Jenkins[18] recommend that no fewer than

TABLE 2

ALTERNATIVE UNIVARIATE MODEL FOR U.S. IMPRISONMENT RATES 1926-70

$$(1 - B^1)y_t = \frac{a_t}{(1 - \phi_1 B^1)}$$

Parameter	Coefficient	t-Value
ϕ_1 (AR parameter)*	.57	4.60

N = 45 Residual Mean Square Error = 18.27
Q-Statistic = 13.0 (for 10 lags, $p > .05$)

*A first-order Autoregressive parameter

16 Blumstein, Cohen & Nagin, *supra* note 1, at 321.

17 G. BOX & G. JENKINS, *supra* note 6, at 58.

18 *Id.* at 18. The class of maximum likelihood estimators is not unbiased and efficient for small samples. Rather, they are only asymptotically consistent and efficient. See J. KMENTA,

fifty observations be used; therefore, the United States series is a borderline case and estimated models may differ greatly from the underlying process. Any results for the United States series should be treated with caution.

Table 2 contains the results for the alternative model. After examining the autocorrelation functions for the imprisonment rate series and its first difference (of order one), I decided that the first difference was needed to produce a stationary series. I also examined the autocorrelation function for the second-differenced series (each of order one) because second-differencing is often required when the original series has changes in slope,[19] but the additional transformation did not seem necessary. I then estimated a first-order autoregressive model with a first difference, a specification consistent with the autocorrelation function for the first-differenced series. The model passes all diagnostics, indicating a reasonable fit to the data. To test for a deterministic linear trend in the data (neither the plot nor the autocorrelation functions showed signs of nonlinear trends), I added a trend parameter to the model.[20] The parameter was not significant and was dropped. The result is a different univariate model than Blumstein's, with different substantive conclusions for his hypothesis. The two models are equally simple, but the alternative model contains a first difference, implying that the series was not stationary for the forty-five year period. Again, it must be emphasized that the sample size is small and the estimated model may be erroneous: if a different time interval was observed, the result could be a series with a visibly stable mean. If these results have not refuted Blumstein's contention that United States imprisonment rates were stable, they at least provide a viable alternative model, consistent with the data and inconsistent with the stability hypothesis. The residual mean square error for the alternative model is slightly higher than for Blumstein's, but the transformed series is stationary and the Q-statistic for the autocorrelation function is slightly better. In short, the two models are *at least* equally plausible.[21]

ELEMENTS OF ECONOMETRICS 174-82 (1971) for a discussion of maximum likelihood estimators and their properties.

19 G. BOX & G. JENKINS, *supra* note 6, at 91.

20 A trend parameter, estimated for a first-differenced series, is the constant increment in the series over time—it is a slope parameter.

21 One characteristic of a stationary series is that differencing it will not produce a nonstationary series. G. BOX & G. JENKINS, *supra* note 6, at 29-30. It could therefore be argued that the first-differenced United States series has to be stationary if the original series is stationary. There are two responses to this argument. First, the autocorrelation function for the original series shows the common pattern for an integrated process—large positive autocorrelations that do not decrease quickly to zero at longer lags. The first-differenced series shows the common pattern for a stationary, first-order autoregressive process—a large correlation at a

Thus far, a different model has been posed for only one of the fifty series Blumstein's conclusions are based on. The weight of evidence is still with Blumstein; however, there are enough questions about the replicated analysis to raise similar questions about the results of his other analyses.[22] To summarize, Blumstein fails to consider the possibility of nonstationarity that is not due to a linear trend. In fact, *all* of the series he presents graphically show signs of nonstationarity in various forms, often not due to a linear trend. Furthermore, the time series for the total United States and the individual states are short and models for them should be treated cautiously. Finally, it is hard to believe that, if the United States series is not stationary around a single mean level, particular states will necessarily be stationary. Blumstein's evidence for the stability hypothesis is less compelling than it appears because at least one alternative model for the United States series, containing a first difference, cannot be ruled out.

III. Admission Rates: An Alternative Measure of Stability?

Although the evidence for the stability hypothesis is questionable, it remains an intriguing idea. Imprisonment rates, however, may not be an adequate index of punishment in the United States as a whole or in individual states. For one thing, imprisonment rates confound the length of prison sentences, a measure of severity, with the actual number of individuals being punished. Also mixed in are policy variables such as parole, probation, indeterminate sentencing, and other alternative interventions. On these grounds, it seems that actual prison admissions might be a better measure of punishment. Also, a careful reading of Durkheim supports this conclusion.

For Durkheim,[23] crime is a normal feature of all societies. The collective sentiments that, according to Durkheim, make a society are distributed in varying degrees throughout it. Some individuals will hold these sentiments less strongly than others and be more likely to deviate from them (this is similar to Blumstein's underlying behavior distribution). When these individual deviations offend sentiments strongly held by other members, there is likely to be strong reaction against them, resulting in punishment of some type. The qualification is that crimes

lag of one, and quickly decreasing autocorrelations at longer lags. Second, even if the original U. S. series is stationary, or almost stationary, no restrictions are necessarily implied on alternative models. An equally parsimonious and adequate model might be estimated for the differenced series as for the original series.

22 *See also* notes 13 & 15 *supra*.

23 E. Durkheim, The Rules of Sociological Method 66 (S. Solovay & J. Mueller trans. 1930).

can only be defined when there is reaction against them.[24] The reaction is the one universal characteristic of crime.

As such, crime is "useful" to society for the response it evokes.[25] Punishment of offenders serves to clarify and reinforce the collective sentiments of society in non-offenders. The aim is not merely to punish the offender, but to instruct others in the meaning of society. This is a form of general deterrence, where non-criminals are warned from becoming criminals. Durkheim[26] notes that in advanced societies, the organization of penal law, with predetermined sentences for specific crimes, does not by itself constitute punishment. The only organization that constitutes "punishment proper" is the tribunal, acting as an intermediary between society and the offender. "Punishment consists, then, essentially in a passionate reaction of graduated intensity that society exercises through the medium of a body acting upon those of its members who have violated certain rules of conduct."[27] It is the act of punishment, such as the jury trial *or the sentencing to prison*, that is important for society, and not just the existence of criminal law, criminal justice systems, or prison populations.

With these things in mind, I examined the United States prison admission rates (the number of individuals admitted to federal and state institutions per 100,000 in the total population) for the period 1926-70.[28] The data include both new admissions and individuals returned by the courts for new violations (*e.g.*, parole violators). Re-commitment is an act of punishment (often involving a court hearing); consequently, individuals returned to prison have been included in the admissions data.[29] Figure 3 is the graph of this time series. Although it is more ambiguous, the series also shows signs of changes in mean level. There seems to be no trend in the early years, unlike the imprisonment rate series, but there is a slight trend in the period 1946-61. The autocorrelation function for the undifferenced series is striking because it is nearly identical to that for the undifferenced imprisonment rate series. In other words, the patterns of autocorrelations at various lags for the two observed series are about the same in terms of signs and magnitudes. Since the imprisonment rate series is apparently nonstationary, it is likely that the admission rate series is nonstationary as well. The first-differenced series (of order one), however, is stationary. In fact, after differencing,

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24 E. DURKHEIM, THE DIVISION OF LABOR IN SOCIETY 70 (G. Simpson trans. 1933).

25 Durkheim seems to stop short of describing crime as "functional" for society.

26 E. DURKHEIM, *supra* note 24, at 94.

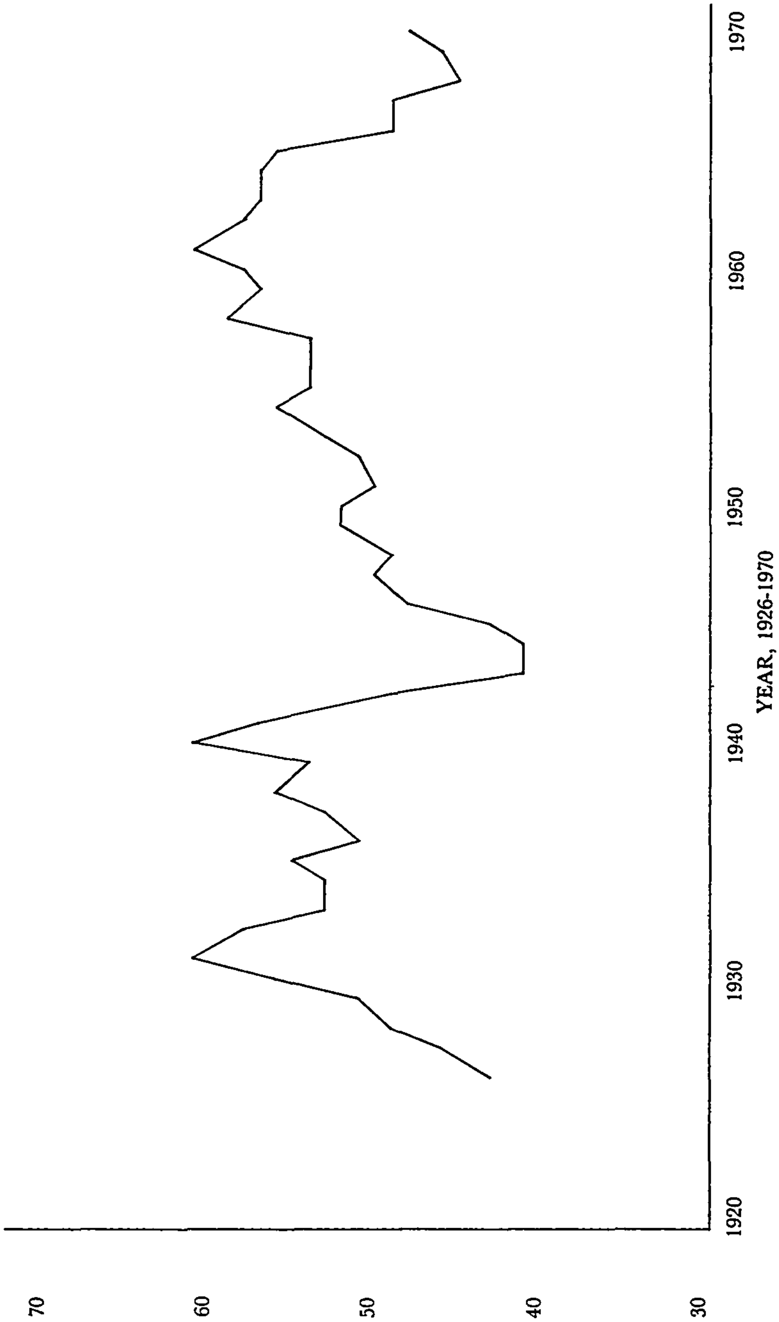
27 *Id.* at 96.

28 1 U.S. DEP'T OF COMMERCE, *supra* note 5, at 420.

29 The same analysis was done using only new United States admissions, and the results were the same. The series is a random process after first differencing.

FIGURE 3

U.S. Prison Admission Rates, 1926-1970



the admission rate series is a normal random process, meaning that there are no systematic patterns of statistically significant autocorrelations to model. A simple model with a first difference and a trend parameter was estimated, but the trend parameter was not significant. The univariate model for the United States admission rate series is a first difference of order one. Again, there is no apparent support for the stability of punishment hypothesis—there was no stable level of prison admissions in the United States for the period 1926-70.

IV. Imprisonment and Admissions in California

Thus far, the models presented have been for very short series (forty-five observations) that are risky for Box-Jenkins techniques. They are not conclusive evidence for or against the stability hypothesis. As an additional test of Blumstein's model, apart from the tests with Blumstein's data, I analyzed California's imprisonment and admission rates for the period 1853-1970.[30] The California data actually provide an opportunity to do several things. First, there are 118 observations in each series and Box-Jenkins techniques can be used with greater confidence to test the stability hypothesis. Second, there is the chance to test Blumstein's[31] contention that a fundamental change in United States society after World War I altered the level of punishment. In response to Cahalan,[32] Blumstein asserts that the positive trends she reports for United States imprisonment rates over a longer time period are really due to an upward shift in the 1920s from one stable level to another.[33]

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30 The California data come from a larger study of California prison admissions for the period 1851-1970, funded by the National Institute of Justice (Grant No. 78-NI-AX-0093). Sheldon L. Messinger and Richard A. Berk are principal investigators of that project. The first two years of the data set, 1851-52, are dropped here because they precede the construction of San Quentin prison and are outliers relative to the following years. Imprisonment rates are for prisoners on hand, on one day of the year: on December 31 until 1867, and on June 30 thereafter (the end of the California fiscal year). Admission rates include new felony admissions, court commitments (*e.g.*, parole violators, or civilly committed drug addicts), and a number of lesser categories (*e.g.*, escapees returned). The admissions data therefore represent the widest possible punishment "net," when punishment is defined in terms of prison admissions. An analysis was done using only new felony admissions, and the conclusions remained the same—there was no evidence for the stability hypothesis, nor for a shift during the 1920s. Also, an analysis was done using total prison and parole population. The results were predictable—there was again no evidence for the stability hypothesis, nor for a shift during the 1920s. From these various analyses, of both the U. S. and California series, it is clear that the results are robust with respect to the definition of punishment. In each case, no evidence for the stability hypothesis emerges.

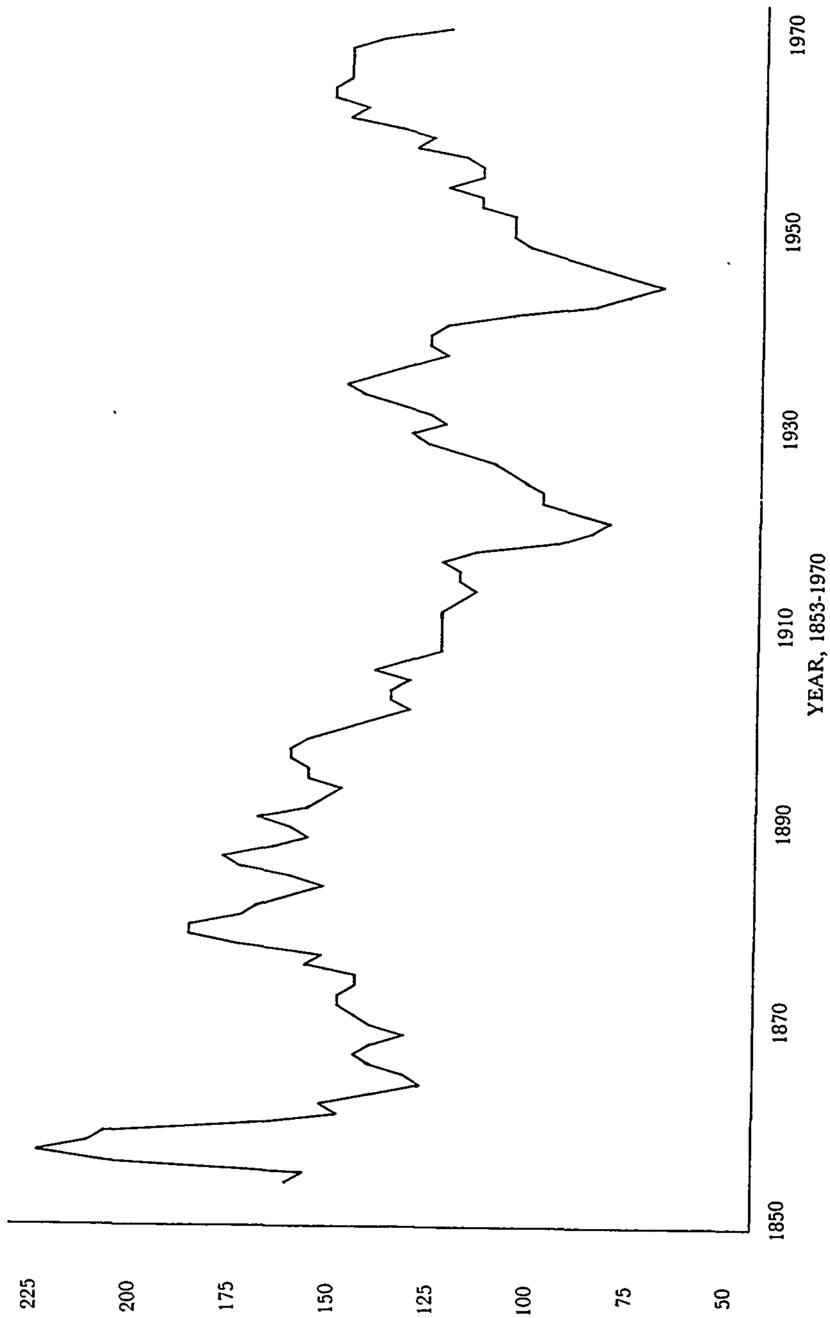
31 Blumstein & Moitra, *supra* note 15.

32 Cahalan, *supra* note 14.

33 *See* note 15 *supra* for comments on the Cahalan-Blumstein exchange.

FIGURE 4

CALIFORNIA IMPRISONMENT RATES, 1853-1970



According to Blumstein, increased mobility and urbanization in the 1920s led to a loosening of community controls on deviance and increased reliance on formal controls represented by the criminal justice system. The change was apparently not a movement in the underlying behavior distribution, but a change in the underlying homeostatic process and perhaps a change to another societal type. Imprisonment rates therefore increased during that period, but became stable at a new, higher level. Using an intervention model (directly analogous to the dummy variable regression model Blumstein estimates for Cahalan's data), a test for such a shift can be made.[34] Blumstein's data for the United States and the individual states begin in 1926 and he is unable to test for that shift.

Figure 4 shows California's imprisonment rates from 1853 to 1970. Recalling the U. S. series, this series also exhibits signs of stochastic changes in level, with perhaps several levels and a downward trend in the middle. The autocorrelation functions for the original and first-differenced series (of order one) showed that a first difference was necessary for a stationary series. Table 3 contains the results for the final univariate model, which is a first difference and a first-order moving average process. A model with a trend parameter was also estimated, but the parameter was not significant and was dropped. Consistent with the United States data, the first difference is evidence that California imprisonment rates were not constant over the 118 year period.

To test for a shift in level during the 1920s, I set up an intervention

TABLE 3

UNIVARIATE MODEL FOR CALIFORNIA IMPRISONMENT RATES 1853-1970

$$(1 - B^1)y_t = (1 - \theta_1 B^1)a_t$$

Parameter	Coefficient	t-Value
θ_1 (MA parameter)*	–.42	–5.20

N = 118 Residual Mean Square Error = 67.93
Q-Statistic = 19.5 (for 36 lags, $p > .05$)

*A first-order Moving Average parameter

34 Intervention models, in their simplest form with shifts from one level to another, are nothing more than regression models with parameters for serial correlation in the residuals. Intervention models are superior to generalized least squares because both autoregressive and moving average processes can be estimated with maximum likelihood techniques. GLS is in practice a weighted least squares procedure that is usually limited to simple autoregressive models. For an excellent discussion of intervention models, see Box & Tiao, *Intervention Analysis with Applications to Economic and Environmental Problems*, 70 J. AM. STATISTICAL A. 70 (1975).

model with a dummy variable for the change in level. Intervention models are simply regression models with autoregressive and/or moving average parameters to model serial correlation in the residuals. However, using a dummy variable to model a shift in level poses an important theoretical issue: a dummy variable tests for a *deterministic* change in level from one mean to another. In terms of the regression model, the residuals are the realization of a normal random process, the dummy variable is a shift in mean for that process at some point in time, and the observed series (the dependent variable) is an integrated process resulting from the stationary residual series and the shift in mean level. Figure 2(c) is an example of a series that could perhaps be modeled as an integrated series with a single shift in mean level (provided there were theoretical reasons for believing the change was deterministic). Previously, I have been modeling the various univariate time series as though changes in level were stochastic, but Blumstein's argument is that a shift was caused by a second variable (*i.e.*, a change in United States society). In that case, there should be no need to difference the observed series because the dummy variable will model that change. However, if there were only stochastic changes in mean level, or if additional shifts occurred earlier or later, the observed series will still have to be differenced and a simple change in level is no longer being modeled. If differencing is not required, yet another test is whether the dummy variable has a positive and significant effect. To summarize, if a change in level occurred during the 1920s, there should be no need to difference the California series, and the coefficient for the dummy variable should be positive and statistically significant.

TABLE 4

INTERVENTION MODEL FOR CALIFORNIA IMPRISONMENT RATES 1853-1970

$$(1 - B^1)y_t = \omega_o(1 - B^1)X_t + (1 - \theta_1 B^1)a_t$$

Parameter	Coefficient	t-Value
ω_o (shift parameter)	.05	.01
θ_1 (MA parameter)*	−.42	−5.15

N = 118 Residual Mean Square Error = 68.52
Q-Statistic = 19.5 (for 36 lags, p > .05)

*A first-order Moving Average parameter

I initially set up the intervention model with no differences and no parameters for possible serial correlation in the residuals, only the dummy variable and the mean. The autocorrelation function for that model showed the residuals to be nonstationary despite the dummy variable for a shift, and I differenced both the independent and dependent variables.[35] Table 4 contains the results for the final model. The coefficient for the dummy variable is not significant; otherwise, the model is identical to the model estimated for the univariate series. The dummy variable adds *nothing* to the model, either in terms of explained variance or reparameterization. In case the year in which the shift had occurred was misspecified, I examined the cross correlations between the residuals of the model and the dummy variable, before and after the dependent variable was differenced. Blumstein is not clear on the specific year of the change (he guesses at 1925). In place of exact theory, I looked for large positive cross correlations between the dummy variable and the residuals at other lags, and settled in 1925 as the most likely year for the change. I also looked for patterns in the cross correlations showing dynamic changes from level to level, but saw none.[36] The conclusion is that there was no stable level for California's imprisonment rates, nor was there an increase in level during the 1920s.

I performed the same analyses on California's admission rate series for the 118 year time period. Figure 5 shows the series. These analyses were more complicated than the previous because the admission rate series is nonhomogeneous. Looking at Figure 5, one can see that fluctuations in the series are greater earlier than later. I took the natural logarithm of the series, which resulted in a new series with a constant variance.[37] The logged series is in terms of percent changes from year to year, but the change in units has no effect on Blumstein's stability hypothesis, nor on his assertion of a shift during the 1920s. As discussed earlier, the mean is at issue in Blumstein's model. The log transformation will change the units of the observed series, but the notion of a stable mean, or several means still applies whether the data are in original units or in terms of percent changes.

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35 A dummy variable representing a shift from one level to another, when differenced, becomes a single value of one in a series of zeros. If the dependent variable is differenced, the dummy variable may or may not be differenced depending on the type of shift in the original series that is being modeled. I examined cross-correlations between the residuals of the intervention model and the differenced and undifferenced dummy variable, but in neither case was there a hint of Blumstein's shift.

36 Intervention models have the added advantage over dummy variable regression models (OLS and GLS) of conveniently modeling dynamic effects in the transition from one level to another. A parameter can be included in the model to represent a gradual shift to a new level (with increments over several time periods). If the parameter is positive, there was a gradual shift; but if the parameter is negative, there was an oscillation with both increases and decreases until the new level was reached. *See* Box & Tiao, *supra* note 32.

37 C. GRANGER & P. NEWBOLD, *supra* note 8, at 304.

FIGURE 5

CALIFORNIA PRISON ADMISSION RATES, 1853-1970

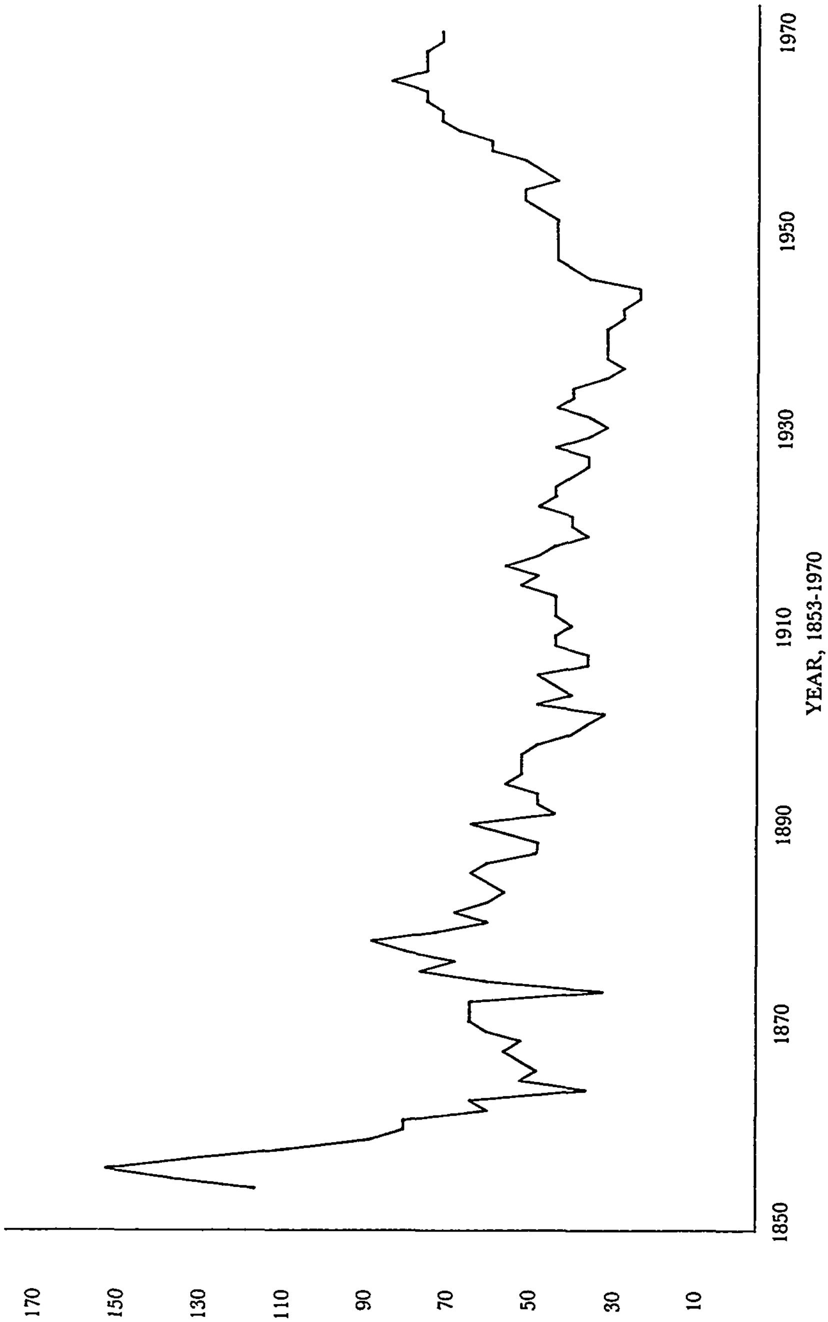

TABLE 5

UNIVARIATE MODEL FOR CALIFORNIA PRISON ADMISSION RATES 1853-1970

$$(1 - B^1)\ln y_t = (1 - \theta_1 B^1)\ln a_t$$

Parameter	Coefficient	Value
θ_1 (MA parameter)*	.18	2.03

N = 118 Residual Mean Square Error = .024
Q-Statistic = 28.8 (for 36 lags, p > .05)

*A first-order Moving Average parameter

The autocorrelation function for the logged series showed that a first difference (of order one) was necessary in order to produce a stationary series. Table 5 contains the results for the final model, which is a first difference and a first-order moving average process. I tried adding a trend paramater because there is a slight downward trend in the series, but it was not significant for a one-tailed test at the .05 level. The univariate model for the logged California admission rate series contains a first difference, which, again, is evidence against the stability of punishment hypothesis.

Although the slight downward trend in the series implies that there was no upward shift in the 1920s from one level to another, I constructed an intervention model as a formal test. The results for the final model are in Table 6. The story is the same as for the California imprisonment rate series: Blumstein's model did not work—the residuals were nonstationary and the dependent variable had to be differenced. The dummy variable is not significant and the rest of the model is identical to the univariate model. I examined the cross correlations and put the

TABLE 6

INTERVENTION MODEL FOR CALIFORNIA PRISON ADMISSION RATES 1853-1970

$$(1 - B^1)\ln y_t = \omega_o(1 - B^1)\chi_t + (1 - \theta_1 B^1)\ln a_t$$

Parameter	Coefficient	t-Value
ω_o (shift parameter)	.18	1.19
θ_1 (MA parameter)*	.19	2.04

N = 118 Residual Mean Square Error = .024
Q-Statistic = 27.7 (for 36 lags, p > .05)

*A first-order Moving Average parameter

shift at 1922. There were no hints of dynamic changes. Again, there is no evidence in California for Blumstein's hypothesis.

For the purpose of comparison, it should be noted that Blumstein modeled the California imprisonment rate series from 1926 to 1974 as a stationary series. I replicated that analysis for the period 1926 to 1970 and found the series to be non stationary. In fact, the model for that series is identical to the model for the 118 year series: a first difference and a first-order moving average process. After extensive analysis of the California data, I can find no evidence that imprisonment rates, nor admission rates, have remained stable over long periods of time, but that is not the model Blumstein proposes. That argument also raises the issue of what stability means and how it can be measured. These issues will be considered later.

V. BLUMSTEIN'S HOMEOSTATIC MODEL

In addition to the objections concerning his empirical work, several objections can be made to Blumstein's homeostatic model of punishment. Perhaps the most serious error he makes is in formulating the policy implications of the model. I will briefly present these objections in turn.

A significant problem with Blumstein's model, and his whole approach, is the role of aggregation. The process described—the stability of punishment—takes place on a system-wide level, and Blumstein makes little attempt to understand its behavioral implications for lower levels in the system. How the various levels of organization work together to produce a homeostatic system is never clearly explained. At one point, Blumstein states that "[i]f 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 [*sic*] requests."[38] This is the extent to which he describes the lower levels of the system. Police, prosecutors, judges, and parole boards certainly do have the discretionary power attributed to them, but the questions remain as to why any of them should care if the prisons are too full, how they would find out, what pressures might be exerted on them to reduce prison populations, and why officials in one state would care what happens in another state. That it all somehow "works out" is not a satisfactory answer to a problem that has long plagued macro sociologists and macro economists. Other, similar questions could be raised, but Blumstein never addresses these important social science issues. In-

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38 Blumstein & Moitra, *supra* note 1, at 377. I assume that this is a typographical error in the sentence; otherwise, it is inconsistent with the point Blumstein is making.

stead of providing a behavioral explanation of the mechanism maintaining the stability of punishment, he only provides a description of the outcome: stable imprisonment rates.

Another objection, discussed earlier in another context, is to Blumstein's use of imprisonment rates to test the stability hypothesis. In one article, Blumstein[39] poses a three-population model as a description of how the homeostatic punishment process works on a societal level. However, his division of society into prison, criminal, and law-abiding populations does not imply the stability hypothesis at all. Rather, length of prison sentences is again confounded with the actual number of punishments meted out at any given moment. As such, Blumstein's model is a control model, not a punishment model. If imprisonment rates did remain stable over time, the implication would be that a certain percentage of the population always remained under control in prison, not that a certain percentage was punished. This is a very different result than intended, and may be an inconsistency in Blumstein's argument.

A third objection is to his estimation of flow rates for the three-population model, simulation of changes in the model, and formulation of policy implications.[40] The system Blumstein proposes, with population flows between the prison, criminal, and law-abiding groups, is underidentified. The intent is to show how changes in these populations, particularly the exchanges between the criminal and law-abiding, work to maintain a relatively stable prison population. The system is characterized by seven values, only three of which are known for the data set he uses as an example (Canadian imprisonment rates from 1925 to 1960). Of the seven parameters in the model, only one is known for that data set. The other six are estimated using "guesstimates" of the four unknown system values. For example, one guess is that, over this period, 33 percent of released prisoners returned immediately to the criminal population. Another unknown value is the actual size of the criminal population. Blumstein calculates the other model parameters using several estimates of that value, simulates changes in the system based on changes in the individual parameters, all others held constant, and draws conclusions from this simulation analysis. To assert that the conclusions have policy implications is inappropriate. Blumstein estimates

39 Blumstein, Cohen & Nagin, *supra* note 1. Blumstein poses two models, but concentrates on this one. Therefore, I have chosen it to discuss rather than the other.

40 Although Blumstein's estimation of flow rates is based on the second-order autoregressive model he consistently finds for imprisonment rates in various countries, the following criticisms apply regardless of the time series model estimated. The aim in this section is to discuss Blumstein's general approach; his particular time series analyses have already been argued.

model parameters only for the Canadian series, yet he broadly asserts that the activities of the criminal justice system "alone have very little impact on the size of the criminal population."[41] In contrast, economists have also used aggregate data and many more explanatory variables (and often equally fuzzy assumptions) to estimate the deterrent effects of punishment in the United States. In a review of these studies, Brier and Fienberg[42] "find no reliable empirical support in the existing econometrics literature either for or against the deterrence hypothesis." Using weak data and a tenuous model, Blumstein makes statements that are thinly supported by any of the empirical or simulation analyses he provides.

VI. CONCLUSIONS

After re-analyzing one of Blumstein's time series, analyzing several others, and trying alternative measures of punishment, I find no support for the stability of punishment hypothesis. In the case of California, when tests are made for possible shifts in level, no support for the hypothesis emerges. Blumstein has other time series that he analyzes, and the sheer mass of evidence may be on his side. However, competing explanations cannot be ruled out. Blumstein tests only for linear trends in the data, and ignores other sources of instability such as changes in mean level.

On the other hand, univariate models of imprisonment and admission rate time series are not adequate tests for the presence of homestatic tendencies. For example, there may be tremendous oscillation in these series over time only because of shifts in the underlying behavior distribution and complementary shifts in the use of punishment. The rates are an end result of the adjustment process, and are not necessarily stable over time. Despite apparent instability in the observed rates, the underlying punishment process may tend toward stability and observed rates may not explicitly show it. Furthermore, representing a time series with a univariate model assumes that the current values of the series are determined solely by its past values and both current and past *random* shocks. In other words, the univariate series is primarily self-driven, and only random events are allowed to affect it otherwise.

Blumstein's homeostatic model suggests that more is going on than can be represented by a univariate model. If there are frequent or dramatic shifts in the underlying behavior distribution resulting in a nonstationary imprisonment rate series, there may still be evidence for a

41 Blumstein, Cohen & Nagin, *supra* note 1, at 329.

42 Brier & Fienberg, *Recent Econometric Modeling of Crime and Punishment: Support for the Deterrence Hypothesis*?, 4 EVALUATION REV. 147, 188 (1980).

tendency toward stable levels of punishment. The supposed shift in United States society during the 1920s is an example, which was tested for as a possible source of nonstationarity in the California data. In addition, Blumstein's hypothesis assumes stable historical periods, but it is unclear how stable periods are defined. Figure 1 shows adjacent peaks and valleys in the United States imprisonment rate series corresponding to such destablizing periods as the Great Depression and World War II. The longer California series span the entire history of the state to 1970, from the Gold Rush years through the close of the frontier in the 1890s, the great dust bowl migrations of the 1930s, and the tremendous post-World War II population growth. Can this be considered a stable historical period? If the underlying behavior distribution in society is frequently or constantly changing, can society ever be considered stable? If the idea of a homeostatic process is to be empirically useful, additional thought must be given to the concept of stability, how it can be measured, and how it can be tested. Of particular importance are general questions such as the following. Does a homeostatic process necessarily imply an observed stability (such as a stationary series), or only a tendency toward stability which may seldom be realized? Under what conditions do tendencies toward stability emerge, and how can these tendencies be measured? Finally, what other factors affect the use of punishment besides shifts in individual behavior, and do these factors imply stability or instability?

The questions of what constitutes stability and how it can be measured are involved and of interest if one wants to explicitly test for a homeostatic punishment process. Of more general interest, whether or not one posits homeostatic processes, are what other factors may affect the use of punishment over time. There are a number of other possible explanations which do not depend on the presence or absence of homeostatic processes. Several of these explanations will be mentioned here, in passing, to give a sense of the alternatives and to demonstrate the limitations of univariate time series models for understanding complex social phenomena.[43]

One promising perspective, which is hardly new, is represented by the work of Rusche and Kirchheimer.[44] Their theory of punishment contains two key variables: labor supply and economic conditions. When labor is in short supply, there will be less tendency to use punish-

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43 For a fuller treatment, as well as direct tests for homeostatic tendencies, see Berk, Rauma, Messinger & Cooley, *A Test of the Stability of Punishment Hypothesis: The Case of California, 1851-1970*, 46 AM. SOC. REV. (forthcoming).

44 G. RUSCHE & O. KIRCHHEIMER, PUNISHMENT AND SOCIAL STRUCTURE (1939); Rusche, *Labor Market and Penal Sanction: Thoughts on the Sociology of Criminal Justice*, 10 CRIME & SOC. JUSTICE 2 (1978).

ments that are wasteful of labor (*e.g.*, mutilation in earlier historical periods, or the death penalty). Unless imprisonment can be economically profitable, fines will be more common so as not to deprive the economic system of workers. When economic conditions are hard, such as periods of depression, harsher penalties will be more common. In support of their theory, Rusche and Kirchheimer present a history of punishment since the Middle Ages. Related historical accounts, generally supporting their position, can be found in Foucault,[45] Perry,[46] and Ruggiero.[47]

It is also possible that changes in penal philosophy and/or changes in legal systems will affect the use of punishment. Ignatieff[48] details the history of punishment during England's Industrial Revolution and how changes in penal policies affected the construction, use, and operation of prisons. Currie,[49] for example, contrasts the punishment of witches in England and in continental Europe during the Renaissance, and finds tremendous differences in the use of punishment resulting from fundamental differences in their respective legal systems. For even more grounded accounts, actual prison records can be read and a great deal learned about penal philosophy, the daily operations of prisons, and how prison officials view their roles as society's "punishers."[50]

Whether or not a homeostatic process is posited, multivariate models for the use of punishment should be considered and tested. The univariate and intervention models tested here are often termed "models of ignorance." When theory is simple or nonexistent, such models frequently suffice, but the homeostatic process Blumstein proposes is more complex than the empirical tests he makes. Blumstein only tests for a *visibly* stable outcome of the process, and, for example, ignores shocks to the system such as wars, depressions, or other social upheavals. Such shocks may be compensated for in a homeostatic manner, but the homeostatic punishment process cannot be explicitly represented by univariate models and therefore no direct tests for it can be made. Even though no evidence has been found here for Blumstein's stability hypothesis, much more work remains to be done before a good case, for or against, can be made.

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45 M. FOUCAULT, DISCIPLINE AND PUNISH: THE BIRTH OF THE PRISON (1980).

46 M. PERRY, CRIME AND SOCIETY IN EARLY MODERN SEVILLE (1980).

47 G. RUGGIERO, VIOLENCE IN EARLY RENAISSANCE VENICE (1980).

48 M. IGNATIEFF, A JUST MEASURE OF PAIN (1979).

49 Currie, *Crimes Without Criminals: Witchcraft and Its Control in Renaissance Europe*, 3 LAW & SOC. REV. 7 (1968).

50 Annual reports of the California State Board of Prison Directors, dating back to the 1850s, are fascinating reading. Not only are details provided about the actual operations of prisons, but some idea of evolving penal philosophies and actual policies is evident over a long time span. Occasionally, there are even attempts by the directors and the wardens to theorize about punishment, social control, and their own role in society.