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Converging Science and Policy:

A Method for Time-Series Analysis of

Deterrent Impacts

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by

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During the past decade, state legislatures have increasingly adopted crime legislation based on the deterrence doctrine. The doctrine maintains that lawbreaking is deterred to the extent that punishments are perceived to be certain, swift, and severe (see e.g., Blumstein et al., 1978; Gibbs, 1975). Through stricter penalties, for the most part, lawmakers are seeking to prevent further crimes by potential offenders and future crimes by those convicted. The penalties emanate from a rationale that sufficient punishment can be meted out or threatened so as to create the incentive to not commit the undesired behavior. Punishment often means mandatory imprisonment and longer sentences with fewer possibilities for early release. Inevitably, lawmakers have credited recent decreases in reported crimes to these policy changes.

The idea that persons can be deterred from crimes simply by the fear of punishment has long been debated among criminologists. Since the early 1970s, this controversy and the emphasis on deterrence in crime policy has generated a considerable surge in related research. Tittle (1980) concludes that the explosion of research has nevertheless only reiterated what is commonly accepted among criminologists: that some punishments deter some individuals from some crimes in some situations. Such an understanding seems to provide little justification for the emphasis on deterrence-based policies. Yet lawmakers continue to create laws that reflect an absolute faith in the deterrent effect of punishment.

One source of this situation may be the paucity of usable information that would result from applied investigations of the efficacy of deterrence-based laws and policies. If the agreed state of knowledge is that some punishments deter some individuals from some crimes in some situations, then, to have any impact on public policy, criminal justice researchers must determine which punishments, which individuals, which crimes, and which situations. The number and variety of laws of recent years constitute a natural laboratory for doing so. This paper will discuss and demonstrate a proven means for rigorous, scientific assessment of these laws and their effect.

THE INTERRUPTED TIME-SERIES QUASI-EXPERIMENT

Problems of methodology are largely responsible for the general lack of definitve research on the deterrence doctrine (Tittle, 1980; Blumstein et al., 1978; Gibbs, 1975). The research methodology is crucial since, as Gibbs (1975) points out, deterrence is inherently unobservable and can be known only inferentially. Deterrence studies have widely used cross-sectional data in correlational research designs to compare crime rates and sanctions across different jurisdictions. Using this method, deterrence is generally established when the analyst finds significantly lower crime rates in those jurisdictions with sanctions that are perceived as relatively more severe. Analyses of this kind are flawed because, from them, it is extremely difficult to adequately infer causality. Nevertheless, reviewers of deterrence studies have also consistently noted the prowess and potential of a particular methodology: interrupted time-series analysis (see again Blumstein et al., 1978; Gibbs, 1975). Using interrupted time-series analysis, the analyst seeks to establish the effect of a deterrence-based intervention by measuring change in the proscribed behavior due to a change in sanctions. Consider, for example, that a law is enacted in a jurisdiction which imposes a mandatory five-year prison sentence for robberies where a firearm is used. If robberies with a firearm are significantly reduced at the onset of the new law and plausible alternative explanations have been ruled out, then general deterrence, the omission of an illegal act in response to a threatened punishment, has been achieved. This impact may be described more simply as a significant change in the level of firearm robberies from the pre- to post-law state. The causal structure of such an effect is inherently understood.

The interrupted time-series research design is a form of the simple pretest-postest quasi-experiment. Using the notation of Campbell and Stanley (1966), the time-series quasi-experiment is diagrammed:

$$O_1 \quad O_2 \quad O_3 \quad O_4 \; X \; O_5 \quad O_6 \quad O_7 \quad O_8$$

where O_1, O_2, ... ,O_8 denote the observations of a dependent variable and X is an intervention. If X has an impact on the dependent variable, the post-intervention observations (O_5 ... O_8) will change in contrast to the pre-intervention observations (O_1 ... O_4). An interrupted time-series analysis provides a statistical comparison of differences between the pre- and post-intervention segments. The statistical analysis of a time-series quasi-experiment is also referred to as impact assessment. The most widely used statistical models for impact assessment are the AutoRegressive Intergrated Moving Average (ARIMA) models of Box and Jenkins (1976). Two such models are developed in this paper to demonstrate the analysis of deterrent impact using the interrupted time-series methodology.

Alternative explanations to the finding of a deterrent impact pose the greatest threat to causal interpretation (for a detailed discussion of threats to the time-series quasi-experiment, see Ross and McCleary, 1983; Ross, 1973;

and Campbell, 1969). For the most part, however, rival explanations may be ruled out by the addition of an appropriate "control" time series to the research design. Following Campbell and Stanley (1966) again, the resulting multiple time-series design is diagrammed:

$$\begin{array}{ccccccccc} O_{1a} & O_{2a} & O_{3a} & O_{4a} & X & O_{5a} & O_{6a} & O_{7a} & O_{8a} \\ O_{1b} & O_{2b} & O_{3b} & O_{4b} & & O_{5b} & O_{6b} & O_{7b} & O_{8b} \end{array}$$

Here $O_{1a}, O_{2a}, \ldots ,O_{8a}$ represent an "experimental" time series, and O_{1b}, $O_{2b}, \ldots ,O_{8b}$ represent the appropriate control counterpart. The quasi-experimental logic of this design is based on a priori expectations derived from the relationship between the experimental and control series. To illustrate, the gun law example from above would not be expected to reduce robberies where a weapon other than a firearm is used. A quasi-experimental contrast may be created by using robberies with a firearm as the experimental series and robberies without a firearm as the control series. The logic of this contrast implies that the intervention must produce a significant reduction in the experimental series and not in the control series to assert that the gun law had a general deterrent effect. Moreover, the same quasi-experiment may also be used for contrary interpretations. If similar reductions were found in both series, for example, then the analyst could conclude that the decrease in firearm robberies was no greater than the decrease expected as a result of a general decline in robberies. If, however, the contrast revealed a significant reduction in firearm robberies and a significant increase in non-firearm robberies, the analyst might then conclude that the legal intervention had only shifted the type of weapon used to commit robberies. Obviously, this quasi-experiment is much stronger than the simple interrupted time-series design.

A more traditional form of the multiple time-series quasi-experiment involves the use of control populations. In other words, time-series data from one population are contrasted with the same time-series data from another population. Suppose, for instance, that the hypothetical gun law was imposed in city A and not in city B. One would then expect a reduction in gun-armed robberies in city A but not in city B, with analysis of the general deterrent effect of the law. A note of caution, however; the validity of such a finding under these conditions is highly dependent upon the degree of equivalency between the two populations.

Still another form of the multiple time-series quasi-experiment has been used most notably to detect the general deterrent impact of drinking-and-driving laws. In this case, the control series is subject to the same intervention as the experimental series. But based on some theoretically prescribed relationship between the two series, the degree of impact on each must again be predicted a priori (see Cook and Campbell, 1979). This form of the time-series quasi-experiment is useful when direct contrasts are unavailable or unreliable. It would seem most appropriate, for example, to use a quasi-experimental contrast of official drinking and non-drinking traffic statistics to evaluate the effect of a new drunk driving law. Because these data rely heavily on subjective police reports, though, they may contain many "dark figures" and are therefore unreliable (Waller, 1971). Quasi-experimental contrasts are instead constructed from known relationships among variables of alcohol consumption and traffic accidents. The drinking-and-driving literature (for a review, see Jones and Joscelyn, 1978) describes a close association between the seriousness of a crash, the time of day it occurred, and whether or not alcohol was involved. As a result of this research, it is customarily accepted that crashes involving drinking drivers are more severe than those involving sober drivers and occur more often at night than during the day. A time series of nighttime traffic crashes resulting in deaths and injuries should then be quite sensitive to a deterence-based drunk-driving intervention. On the other hand, the same intervention should produce little, if any, impact on a series of daytime fatal and injury crashes. The analysis of this quasi-experiment will be demonstrated below.

Of course, crime statistics (i.e., Uniform Crime Reports) are not without dark figures of their own. For instance, the impact of a new anti-shoplifting policy may be more precisely measured using weekly or monthly inventory records than by using UCR offense or arrest data. This does not imply, however, that time-series analysis of crime statistics should be avoided. To the contrary, longitudinal analyses may provide the most valid means of assessing UCR statistics. UCR data are subject to dark figures that are relatively constant over time and thus may be a valid indicator of crime trends (McCleary et al., 1982).

BEGINNING THE ANALYSIS

Combining the interrupted time-series quasi-experiment with ARIMA time-series models provides a uniquely powerful method for assessing the deterrent impact of laws and policies. The results of an analysis are nevertheless uninterpretable if the analyst has not constructed an appropriate quasi-experiment. Interpretation of the impact assessment must always evolve from a priori specification of the onset of a discrete and notable event. And all conclusions that are thereafter drawn must conform to an existing theory in the substantive area (McCleary and Hay, 1980). The results of an impact analysis subsequently rest in the knowledge and skills of the analyst.

A recent law strengthening provisions of the driving-while-intoxicated (DWI) statute in Arizona is used to illustrate some of the methodological issues peculiar to the impact assessment of deterrence-based interventions. Briefly, the new law explicitly prohibited the practice of plea bargaining to lesser charges, and established harsher penalties, mandatory jail sentences, compulsory record keeping, and a per se level of intoxication. Like other DWI laws recently adopted throughout the United States, the Arizona legislation resulted from major state and national movements to reduce the tragic consequences of drunk driving. In this enviroment, the law and other anti-drunk-driving efforts accompanying it received much notoriety. The events important to this discussion are therefore exaggerated in comparison with similar events that might occur with another legal or policy intervention. Nevertheless, most of the conceptual and procedural issues arising from analysis may be generalized to other investigations of deterrent impact.

Figure 1 presents the time series of state-wide daytime and nighttime fatal and injury crashes from the proposed quasi-experiment described above. These data are monthly, from January 1978 to December 1983, and the nighttime series reflects crashes occurring between 8:00 pm and 4:00 am, and the daytime series between 6:00 am and 6:00 pm. An analyst should visually inspect each time-series before modeling. Visual clarification of an impact should not be the motivation for doing so, however, nor should it be expected since impacts are often indistinguishable from other variances in the time series. Rather, a visual examination of the series may be most useful in fitting an ARIMA model to the data (see McCleary and Hay, 1980) and in detecting sources of confounding influence to the expected impact. Even so, visual inspection should be used only for exploratory purposes and never to confirm a hypothesis.

The broken, vertical line in Figure 1 represents the official implementation of the new DWI law in August 1982. According to the quasi-experiment, the onset of the deterrence-based intervention is expected to significantly impact the experimental series (i.e., nighttime fatal and injury crashes) but not the control series (i.e., daytime fatal and injury crashes). Previous investigations of DWI laws (see e.g., Ross et al., 1982) indicate that the analyst should also specify an abrupt and temporary impact; though, in this case it seems that an impact of permanent duration would best fit the relatively short post-law period. A visual comparison of the two series suggests that the experimental series has indeed been impacted. The onset of this impact appears to have occured gradually, however, and some time prior to the legal intervention.

It would be a mistake for this investigation to strictly follow the previous research and limit the intervention analysis to the formal effective date of the legislation. Other explanations not withstanding, a finding of no impact from such an analysis does not consider the informal process of legal intervention (see e.g., Musheno, 1980), and a finding of impact may likely result from measuring the aftermath of some prior impact (if one exists). In either case, the finding is invalid because the analyst failed to rule out rival explanations to the onset of the expected impact.

There are at least five factors known from prior research that could possibly confound the impact of the law. First, with driving costing what it does, a weak economy generally leads to less driving and thereby reduces traffic crashes and casualties. People also tend to stay home rather than driving to costly leisure activities. Second, drinking and driving may drop because of a reduction in alcohol sales. Decreased alcohol sales, which can result in fewer drunk drivers on the road, may be the product of economic, social, or political factors, or may coincide with DWI laws or laws seeking to reduce or regulate drinking. Such laws that do so indirectly and others that may directly affect traffic safety, represent a third source of confounding influence to the DWI intervention. A fourth may result from visible law enforcement efforts to apprehend DWI violaters that occur before or coterminously with the law's inception. And finally, publicity in the form of media coverage or public information campaigns is also known to affect the impact of deterrence-based laws. This will be discussed below.

Key to the onset of deterrent impact, though, are the perceptual variables of the deterrence doctrine. Ross (1982) restates the doctrine: the greater the perceived likelihood of apprehension, prosecution, conviction, and punishment, the more severe the perceived eventual penalty, and the more swiftly it is perceived to be administered, the greater will be the deterrent effect of the legal threat. Past studies of deterrence-based DWI laws have generally found that immediate but temporary deterrent effects resulted from drivers' "exaggerated" perceptions of the risk of being apprehended if drinking and driving. These perceptions were attributed to increased media attention surrounding the new laws. Apparently, the intensified coverage produced a corresponding public awareness of the state's desire to crackdown on drunk driving. This led drivers to initially overestimate enforcement efforts and the risk of being caught, thereby causing potential offenders to restrain their behavior until they learned or experienced otherwise (Ross, 1982). In other words, the new law generated publicity, the publicity enhanced perceptions, and the perceptions caused deterrence. The onset of deterrent impact was therefore set at the legal intervention.

Could a similar effect occur, however, absent the threat of a new law? Ross (1977) cites the example of a well-publicized drunk-driving enforcement blitz that temporarily deterred drivers on the basis of existing law. Suppose that such an effect occurred prior to inception of the DWI law in Arizona. Obviously, the state had an existing law with penalties and the apparatus for imposing them. The next step should determine whether significant DWI-enforcement efforts and coinciding media coverage occurred at some point before the legal intervention. A visual examination of Figure 2 indicates a fairly constant level of drunk-driving enforcement in the two years prior to the law. Nevertheless, the ultimate source of information concerning publicized enforcement efforts is the daily newspaper. In this case, a content analysis of major daily newspapers in Arizona was conducted to provide a sense of the scope and intensity of publicity surrounding the relevant events preceding the inception of the state's new DWI law.

The content analysis revealed that newspaper coverage of DWI-related issues increased dramatically at the start of the state's 1982 legislative session in January. Most of the media attention in early 1982 surrounded the legislative debate over bills to revise the DWI law and other drinking-and-driving policies.

More importantly, however, the analysis discovered that the cities of Phoenix and Tucson initiated large-scale anti-drunk-driving publicity campaigns in late February and March of 1982. These campaigns were centered around tough anti-drunk-driver themes such as "Drunk drivers should be barred" rather than the appeals to the conscience found in earlier campaigns like "Friends don't let friends drive drunk." The clear message from the multimedia campaigns was that drunk drivers would be caught and prosecuted to the maximum extent of the law. Disseminated through the Phoenix and Tucson media markets, this message was directed at a potential audience that represents about 85 percent of the state's population.

The information provided by the content analysis suggests a quite plausible rival hypothesis to the legal intervention. It is proposed that the publicity blitz caused a significant deterrent impact on drinking and driving in Arizona. It is further proposed that the onset and aftermath of this effect was of sufficient dimension to have masked the expected impact of the new law.

Figure 3 indicates that an increased level of reactive newspaper coverage also continued into March 1982. With addition of the combined publicity campaigns, the hypothesis assumes that March was a watershed month of publicity of the intensity necessary to alter drivers' perceptions of DWI enforcement. Thus, the onset of deterrent impact for time-series analysis should be set in March and presumed to occur immediately. Furthermore, because reactive media coverage and elements of the publicity campaigns remained active through the end of the study period, an impact of permanent duration is predicted.

A demonstration of the ARIMA model-building and impact assessment process is presented below. It is not intended as inclusive. Those interested in the detailed mechanics of impact assessment models are encouraged to review McCleary and Hay (1980: Chap. 3) and McCain and McCleary (1979), which are closely followed in this paper.

ANALYSIS OF THE EXPERIMENTAL TIME SERIES

Figure 4 presents a revised picture of the present quasi-experiment. Shown here are both the hypothesized intervention of March 1982 and the legal intervention of August 1982. Although increased enforcement efforts were assumedly perceived, the March intervention marks only the onset of the anti-drunk-driving publicity campaigns. (DWI arrests were subsequently analyzed as a rival explanation, but no significant rise was measured at either intervention.) For visual clarification of the impact, the data displayed in Figure 4 have been adjusted to remove seasonal characteristics of the time series.

The experimental series is analyzed first by testing the hypothesis that a certain event (the onset of the anti-drunk-driving publicity campaigns) caused a change in time series (nighttime fatal and injury crashes). The intervention of the publicity blitz in March, 1982 is represented in the impact assessment model as a "dummy" variable or step function where

$$I_t = 0 \text{ prior to March, 1982}$$
$$= 1 \text{ in March and thereafter.}$$

The impact assessment model for analysis of this time series is written as

$$Y_t = N_t + \omega_0 I_t.$$

Here N_t is the noise component, an empirically identified ARIMA model, and $\omega_0 I_t$ is an intervention component that denotes the zero-order transfer function of

I_t. The intervention component describes the deterministic relationship between the variable I_t and the time series, while the noise component describes the systematic behavior of the time series around this relationship (see McCleary and Hay, 1980). Each N_t is a function of autoregressive and moving average operators,

$$\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p, \text{ and}$$
$$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q$$

where B is the backshift operator defined such that $B^n Y_t = Y_{t-n}$, In the general case, N_t will be of the form

$$N_t = \phi_p(B)^{-1}\theta_q(B)a_t$$

where a_t is a white noise random shock. Following the Box-Jenkins philosophy, seasonal variance in the time series is accommodated by multiplicative autoregressive and moving average operators of degree S. Therefore,

$$N_t = \phi_p(B)^{-1}\phi_{pS}(B)^{-1}\theta_q(B)\theta_{qS}(B^S)$$

for the period S. Since the data are monthly, S = 12.

In the present analysis, the intervention component is modeled as a zero-order transfer function which determines an abrupt an permanent shift in the series level from pre- to postintervention with the impact pattern

$$\begin{array}{llllllll} \text{Before} & 0 & 0 & 0 & 0 & & & \\ & & & & \uparrow & & & \\ & & & & \omega_0 & & & \\ & & & & \downarrow & & & \\ & & & & 0 & 0 & 0 & 0 \quad \text{After.} \end{array}$$

Thus, at the onset of the publicity campaigns, the level of nighttime fatal and injury crashes is expected to drop immediately by amount ω_0, to a permanent, new level that is significantly lower than before the March intervention.

The BMDP2T Box-Jenkins time-series program (Liu, 1981) is used to identify, estimate, diagnose, and demonstrate the impact assessment model. Construction of a model begins with the observed time series, with which the model is empirically identified through a model-building strategy where appropriate filters and parameters are fit to estimate the noise and intervention components and to produce an output series of white noise residuals. It is from this white noise process only that a change in level can be determined. To start an analysis, the autocorrelation function (ACF) of the observed time series is examined to test for white noise and to identify the model. A partial autocorrelation function (PACF) is used to distinguish processes indicated by the ACF.

Figure 5 shows the ACF and PACF of the raw nighttime fatal and injury crash series. The lines of plusses (+) mark two standard errors, where lags that fall over the lines contribute significantly to a nonstationary output series in which residuals are not white noise. In general terms, a primary goal of model building is to appropriately restrict all lags to values well within these lines. The pattern of this ACF clearly indicates a nonstationary series. While the nonstationary ACF of a raw time series is not uncommon, examination of the PACF suggests that it is unusally nonstationary and would require an elaborate model. As McCleary and Hay (1980) point out, however, the rule of ARIMA modeling is parsimony, and complex models should be avoided. The authors also demonstrate that a very large impact in the time series may sometimes distort the ACF and PACF. In such a case, they advise the analyst to estimate ACFs and PACFs from the preintervention series only. A look at Figure 4 confirms that the impact may indeed overwhelm the ACF and PACF. Thus, the preintervention series of 50 observations, from January 1978 through February 1982, is tested for white noise. The resulting ACF and PACF in Figure 6 reveal a substantially different series. A single significant spike at lag-12 in the ACF suggests a simple seasonal, twelfth-order moving average process. The full impact assessment model is tentatively set as

$$Y_t = \theta_0 + (1 - \theta_{12}B^{12})a_t + \omega_0 I_t.$$

This model is applied to the total time series (72 observations). The resulting estimates for the full impact assessment model are reported in Table 1. In the BMDP notation: NIGHT is the Y_t series; the noise component (N_t) is MA, the moving average parameter (AR for autoregressive), and MEAN, or θ_0, the preintervention level of the stationary series; and the intervention component ($\omega_0 I_t$) is UP, the U-Polynomial where U is analagous to the ω parameter of Box-Jenkins notation, and MARCH82, or I_t.

Generally, to accept the impact assesment model, three diagnostic tests must be passed. First, all parameters are significant (probability of t at $P < .05$ is $\pm$ 1.96 or greater) and, therefore, may be kept in the model. Second, the residual ACF, presented in Figure 7, should indicate that the residuals of this model are not different than white noise and does. And finally, a third diagnostic test, the Ljung-Box Q-statistic (L.-B. Q), also shows that the residuals are not different than white noise. The value of Q, 30.0, at 24 degrees of freedom (df = k (lags) - n (all autoregressive and moving average factors)) is not statistically significant at the $P < .05$ level of the chi-square distribution and, thereby, suggests a white noise process.

Based on the diagnostic tests, the impact assessment model is accepted. Moreover, the hypothesis of a March 1982 intervention and impact is confirmed. The ω_0 value indicates a drop of 129 nighttime fatal and injury crashes from a preintervention series level of 725, an 18 percent decrease. Furthermore, since the effect conforms to a permanent impact pattern, an estimate of the total impact may be made by simply multiplying ω_0 by the number of postintervention months in the time series (i.e., -129 x 22). The onset and aftermath of the March 1982 publicity campaigns therefore resulted in 2,847 fewer nighttime fatal and injury crashes.

At least two other hypothesis should be examined with the accepted impact assessment model. First, it should be determined if the legal intervention caused any further deterrent impact relative to the publicity blitz. This is easily done by adding a second intervention component to the impact assessment model. Assuming a $\omega_0 I_t$ intervention component for the impact of the new DWI law, the parameter estimates and diagnotic tests of the model are reported in Table 2 and Figure 8. Because the August 1982 impact is so trivial, the hypothesis of further impact is rejected and the intervention component may be dropped from the model.

A second additional hypothesis rests on the possibility that the change in series level beginning in March was gradually realized before reaching a new, permanent level. Figure 4 seems to suggest this possibility. In fact, it may be more arguable that drivers became only increasingly aware of the anti-drunk-driving message as the publicity blitz diffused through the media. To test this hypothesis, then, a different type of intervention component must be fit to the impact assessment model. A change in series level that is gradual in onset and permanent in duration is modeled with the first-order transfer function

$$\frac{\omega_0}{1 - \delta_1 B} I_t$$

where parameter δ_1 is restricted to the interval

$$-1 < \delta_1 < +1.$$

Parameter δ_1 may be interpreted as a rate. When δ_1 is large, near the value 1, the change from pre- to postintervention level is slow. When δ_1 is small, on the other hand, near zero, the change to postintervention level is rapid.

With the new intervention component, the full impact assessment model is

$$Y_t = \theta_0 + (1 - \theta_{12}B^{12})a_t + \frac{\omega_0}{1 - \delta_1 B} I_t$$

Table 3 and Figure 9 present the results of this model. Here, SP refers the S-Polynomial, where S is equivalent to δ_1. The value of δ_1 suggests a somewhat gradual but rapid change to the new level. Because the parameter is statistically insignificant, however, it may be dropped from the model in favor of the abrupt and permanent impact pattern. The argument that an immediate and significant deterrent impact was effected in March, a watershed month of publicity, is once again confirmed as the correct hypothesis.

ANALYSIS OF THE CONTROL TIME SERIES

The expectation of the quasi-experiment must still be confirmed to rule out other explanations of the measured impact in the experimental series. This is accomplished by contrasting the impact assessment model of the control series. The same model-building process of identification, estimation, and diagnosis is followed to analyze this time series. Based on the proposed quasi-experiment, the impact that ocurred in the experimental series should not occur in the control series. Thus, the $\omega_0 I_t$ intervention component is added to the impact assessment model of the control time series with the expectation that it will not fit and parameter ω_0 will be statistically insignificant. Like the experimental series, then, the impact assessment model for analysis of this time series is

$$Y_t = N_t + \omega_0 I_t.$$

Figure 10 shows the ACF and PACF of the raw time series. The lags of the ACF are quite similar to a pattern indicating that seasonal, twelfth-order differencing is required (see McCleary and Hay, 1980: Chap. 2). An analyst should try differencing the time series if it is indicated. But, perhaps because of its short length, this time series is more adequately (and parsimoniously) modeled as a seasonal autoregressive process and does not require differencing. To start this model, the significant single-spike at lag-1 in the PACF suggests a first-order autoregressive factor when contrasted with the steady decay from lag-1 shown in the ACF. The impact assessment model at this point is tentatively designated

$$Y_t = \theta_0 + (1 - \phi_1 B)a_t + \omega_0 I_t.$$

Estimates of the model are reported in Table 4. The residual ACF, presented in Figure 11, reveals significant spikes at seasonal lags -12 and -24. The tentative model must be rejected. In the PACF, on Figure 11, the single-spike at lag-12 indicates that a seasonal twelfth-order autoregressive factor should be added to the model. This leads to a new impact assessment model, tentatively set as

$$Y_t = \theta_0 + (1 - \phi_1 B)(1 - \phi_{12} B^{12})a_t + \omega_0 I_t.$$

Table 5 shows that the model parameters are significant with the exception of ω_0. Furthermore, the residual ACF in Figure 12 suggests a white noise process and is supported by a statistically insignificant Q-statistic. As expected, the March 1982 impact did not affect the control time series. The ω_0 value represents a statistically insignificant drop of only 47 daytime fatal and injury crashes from a preintervention series level of 1,714, a 3 percent decrease. (Note: observed data in this series were reduced by a factor of 10 to allow for more efficient computation). The impact assessment model is therefore accepted as confirmation of the proposed quasi-experiment.

As a final note, the analyst should always be aware of methodological, statistical, and substantive limitations of the analysis. In this particular analysis, at least two major problems remain unresolved. First, while the conclusion provided by analysis of this single quasi-experiment is compelling, it is nevertheless thin. The finding of deterrent impact would be far more compelling if a number of quasi-experimental contrasts supported the same conclusion. And second, some of the plausible alternative hypotheses previously discussed can not be addressed fully by the quasi-experiment. In this case, Cook and Campbell (1979: Chap. 6) suggest that time series reflecting these hypotheses (i.e., nonequivalent dependent variables) should also be assessed for impact, much like a conventional control series. By resolving such problems and understanding other limitations of the analysis, the analyst can add considerable strength to interpretations and conclusions.

CONCLUSION

This paper is concerned more with the issues of measuring deterrence and suggesting a method for doing so than with the issue of deterrence itself. The deterrence doctrine stands on reasonable grounds and must now be rigorously tested in an applied setting. A search through the criminology literature yields relatively few analyses of deterrent impact and fewer that are methodologically sound. The paucity of research persists even while deterrence-based policy is emphasized in current criminal law. Moreover, uniquely-suited statistical methods for analysis are now available in popular, user-friendly computer software programs. An opportunity thus exists for criminal justice researchers to become more involved in the creation of criminal justice policy. Interrupted time-series analyses are easily explained and can provide understandable yet scientifically valid policy evaluations. There is no obvious reason to assume that policymakers will not respond to well-conceived impact assessments of their policies.

The preceding discussion and demonstration has been offered to facilitate the use of interrupted time-series analysis for impact assessment of deterrence-based laws and policies. It attempts to pull together, into one package, the most important elements of the full impact assessment strategy. In taking this approach, however, each aspect is discussed only briefly and many questions are surely left unanswered. The interested reader is encouraged to refer to those sources indicated which may present further explication of the methodological and statistical issues discussed in this essay. The utility of interrupted time-series methods in deterrence research is as much or more evident in these works as in the present paper.

REFERENCES

Blumstein, A., J. Cohen, and D. Nagin, eds. (1978) Deterrence and Incapacitation: Estimating the Effects of Criminal Sanctions on Crime Rates. Washington, D.C.: National Academy of Sciences.

Box, G.E.P. and G.M. Jenkins (1976) Times Series Analysis: Forecasting and Control. San Francisco: Holden-day.

Campbell, D.T. (1969) "Reforms as experiments." Amer. Psychologist 24: 409-429.

Campbell, D.T. and J.C. Stanley (1966) Experimental and Quasi-Experimental Designs for Research. Chicago: Rand McNally.

Cook, T.D. and D.T. Campbell, eds. (1979) Quasi-Experimentation: Design and Analysis Issues for Field Settings. Chicago: Rand McNally.

Gibbs, J.P. (1975) Crime, Punishment, and Deterrence. New York: Elsevier Scientific.

Jones, R.K. and K.B. Joscelyn (1978) Alcohol and Highway Safety 1978: Review of the State of Knowledge. Washington D.C.: U.S. Department of Transportation, Technical Report DOT HS-5-01217.

Liu, L.M. (1981) "P2T; Box-Jenkins time series analysis." in W.J. Dixon, J.W. Frane, M.A. Hill, R.I. Jennrich, and J.D. Toporeh (eds.) BMDP Statistical Software 1981. Berkely; University of California Press.

McCain, L.J. and R. McCleary (1979) "The statistical analysis of the simple interrupted time series quasi-experiment," chap. 6 in T.D. Cook and D.T. Campbell (eds.) Quasi-Experimentation: Design and Analysis Issues for Field Settings. Chicago: Rand McNally.

McCleary, R., B.C. Nienstedt, and J.M. Erven (1982) "Uniform Crime Reports as organizational outcomes: three time series quasi-experiments." Social Problems 29: 361-372.

McCleary, R. and R.A. Hay, Jr. (1980) Applied Time Series Analysis for the Social Sciences. Beverly Hills, California: Sage.

Musheno, M.C. (1980) "On the hazards of selecting intervention points: time-series analysis of mandated policies." Policy Studies Review 3: 1134-1145.

Ross, H.L. (1982) Deterring the Drinking Driver: Legal Policy and Social Control. Lexington and Toronto: D.C. Heath and Company.

Ross, H.L. (1977) "Deterrence regained: the Cheshire constabulary's "breathalyser blitz." J. Legal Studies 6: 241-249.

Ross, H.L. (1973) "Law, science and accidents: the British Road Safety Act of 1967." J. Legal Studies 2: 1-78.

Ross, H.L. and R. McCleary (1983) "Methods for studying the impact of drunk driving laws." Accid. Anal. and Prev 15: 415-428.

Ross, H.L., R. McCleary, and T. Epperlein (1982) "Deterrence of drinking and driving in France: an evaluation of the law of July 12, 1978." Law and Society Review 16: 345-374.

Tittle, C.R. (1980) Sanctions and Social Deviance. New York: Praeger Publishers.

Waller, J.A. (1971) "Factors associated with police evaluation of drinking in fatal highway crashes." J. of Safety Research 3: 35-41.

Figure 1. Contrast of Daytime and Nighttime Fatal and Injury-Producing Crashes in Arizona

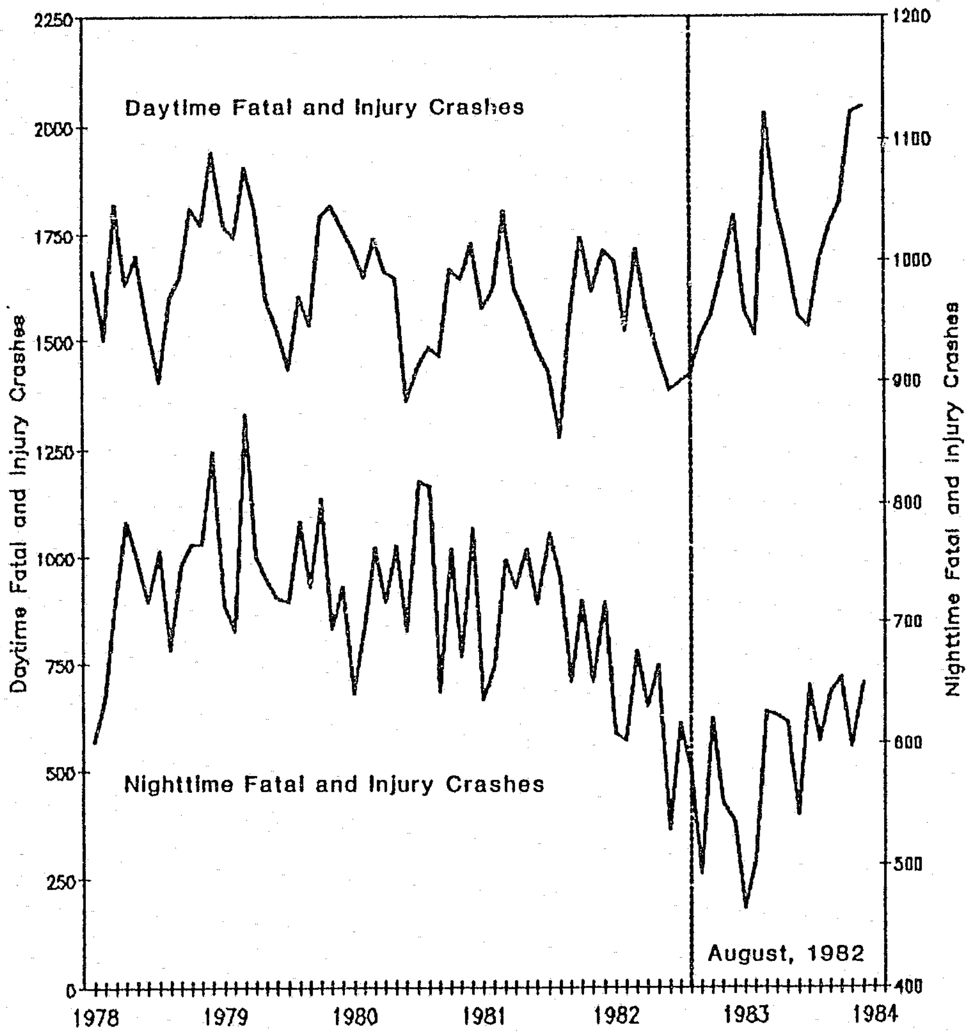

Figure 2. DWI Arrests in Arizona

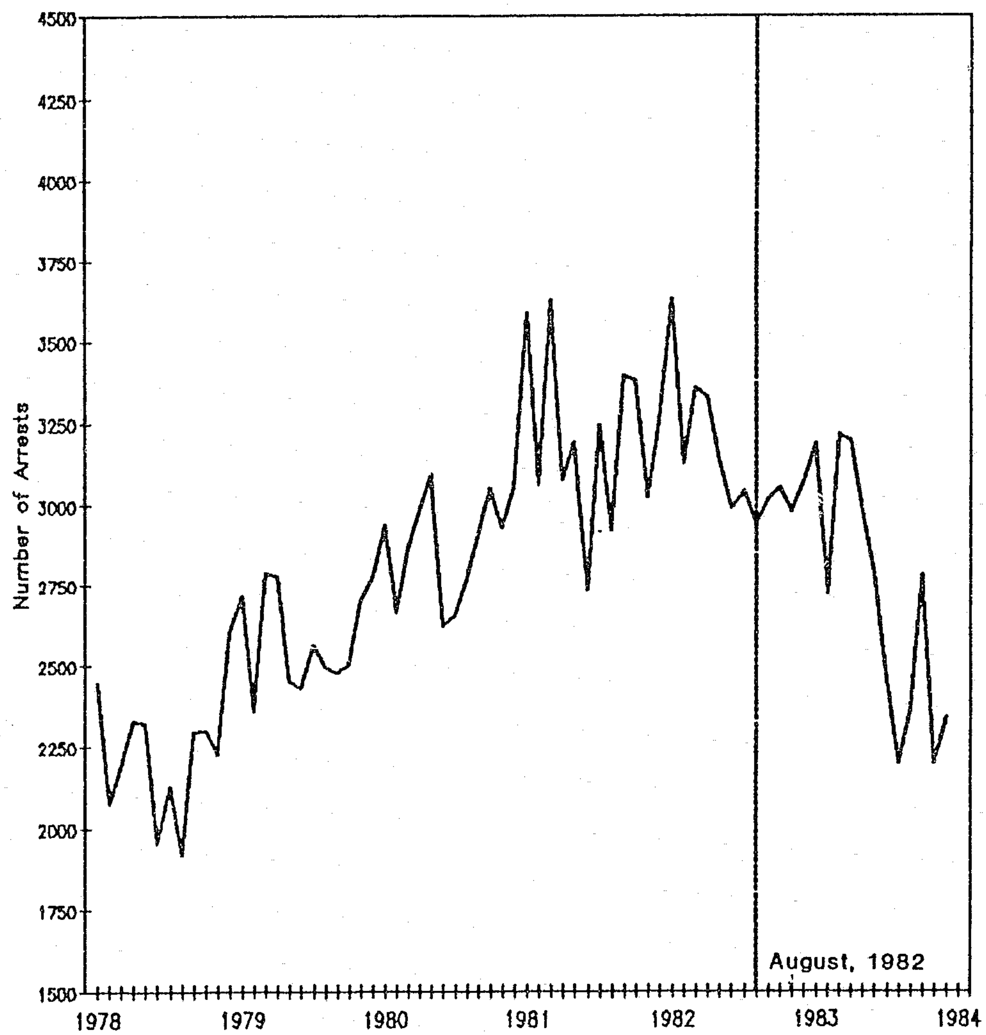

Figure 3. DWI–Related Coverage by the Phoenix Newspapers

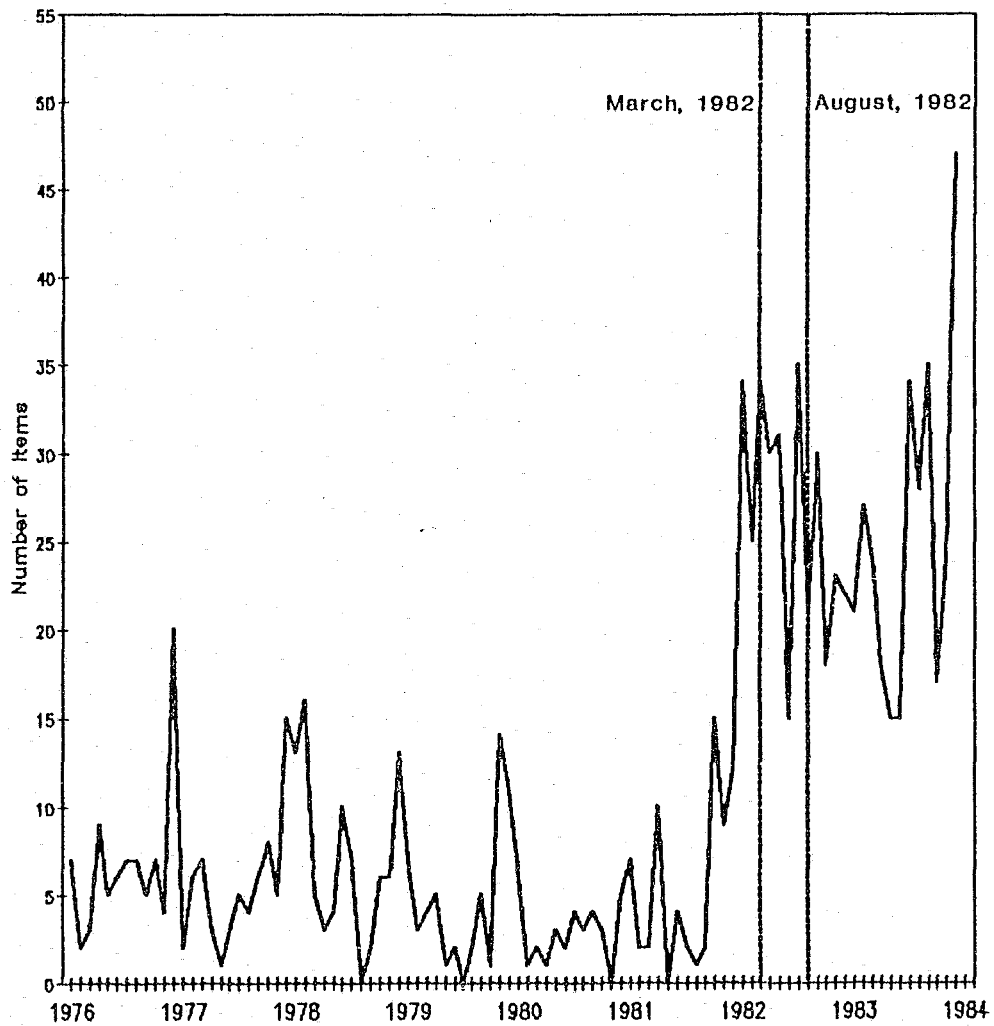

Figure 4. Contrast of Daytime and Nighttime Fatal and Injury–Producing Crashes in Arizona, Seasonal Variation Removed

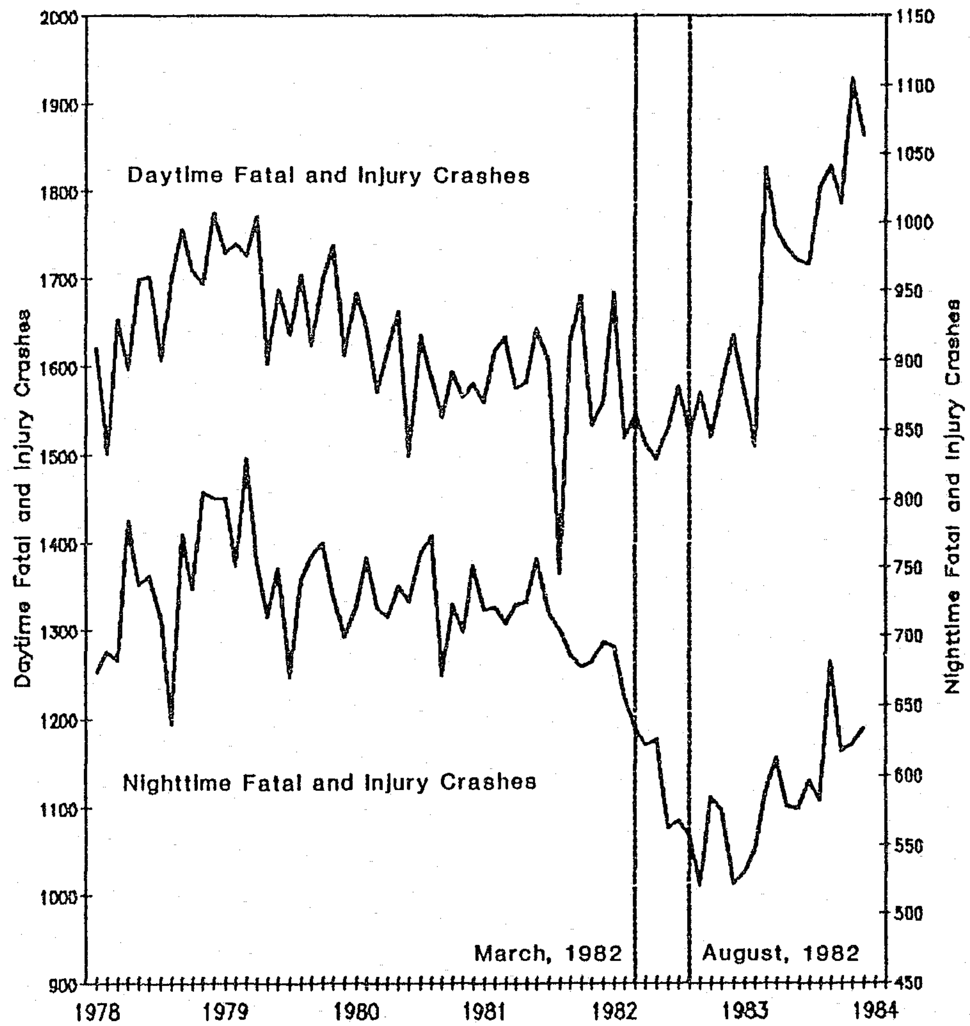

FIGURE 5.

PLOT OF AUTOCORRELATIONS

```
          -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
LAG   CORR. +----+----+----+----+----+----+----+----+----+----+
                                     I
  1   0.598                    +     IXXXXX+XXXXXXXXX
  2   0.605                  +       IXXXXXXX+XXXXXXX
  3   0.568                 +        IXXXXXXXX+XXXXX
  4   0.539                +         IXXXXXXXXX+XXX
  5   0.639               +          IXXXXXXXXXX+XXXXX
  6   0.390              +           IXXXXXXXXXX +
  7   0.527             +            IXXXXXXXXXXXXX
  8   0.404             +            IXXXXXXXXXX  +
  9   0.381            +             IXXXXXXXXXX   +
 10   0.353            +             IXXXXXXXXX    +
 11   0.273            +             IXXXXXXX      +
 12   0.413           +              IXXXXXXXXXX    +
 13   0.106           +              IXXX           +
 14   0.142           +              IXXXX          +
 15   0.102           +              IXXX           +
 16   0.113           +              IXXX           +
 17   0.138           +              IXXX           +
 18  -0.098           +            XXI              +
 19   0.066           +              IXX            +
 20  -0.025           +             XI              +
 21  -0.023           +             XI              +
 22  -0.030           +             XI              +
 23  -0.099           +            XXI              +
 24   0.058           +              IX             +
 25  -0.124           +           XXXI              +
```

PLOT OF PARTIAL AUTOCORRELATIONS

```
          -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
LAG   CORR. +----+----+----+----+----+----+----+----+----+----+
                                     I
  1   0.598                    +     IXXXXX+XXXXXXXXX
  2   0.386                    +     IXXXXX+XXXX
  3   0.210                    +     IXXXXX+
  4   0.122                    +     IXXX  +
  5   0.322                    +     IXXXXX+XX
  6  -0.287                   X+XXXXXI     +
  7   0.193                    +     IXXXXX+
  8  -0.126                    +  XXXI     +
  9  -0.044                    +    XI     +
 10  -0.122                    +  XXXI     +
 11   0.074                    +     IXX   +
 12   0.109                    +     IXXX  +
 13  -0.400                XXXX+XXXXXI     +
 14  -0.072                    +   XXI     +
 15  -0.015                    +     I     +
 16   0.100                    +     IXX   +
 17  -0.040                    +    XI     +
 18  -0.073                    +   XXI     +
 19   0.116                    +     IXXX  +
 20   0.045                    +     IX    +
 21  -0.026                    +    XI     +
 22   0.062                    +     IXX   +
 23   0.030                    +     IX    +
 24   0.099                    +     IXX   +
 25   0.010                    +     I     +
```

FIGURE 6.

PLOT OF AUTOCORRELATIONS

```
           -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
LAG   CORR.  +----+----+----+----+----+----+----+----+----+----+
                                      |
  1    0.104                   +      |XXX   +
  2    0.095                   +      |XX    +
  3    0.040                   +      |X     +
  4   -0.013                   +      |      +
  5    0.215                   +      |XXXXX +
  6   -0.251                   +XXXXXX|      +
  7    0.106                  +       |XXX    +
  8   -0.003                  +       |       +
  9   -0.026                  +      X|       +
 10    0.007                  +       |       +
 11   -0.048                  +      X|       +
 12    0.365                  +       |XXXXXXX+X
 13   -0.160                 +    XXXX|        +
 14   -0.108                 +     XXX|        +
 15   -0.070                 +      XX|        +
 16    0.033                 +        |X       +
 17    0.106                 +        |XXX     +
 18   -0.299                 + XXXXXXX|        +
 19    0.023                 +        |X       +
 20   -0.000                 +        |        +
 21   -0.048                 +       X|        +
 22    0.012                 +        |        +
 23   -0.069                 +      XX|        +
 24    0.211                 +        |XXXXX   +
 25   -0.004                +         |         +
```

PLOT OF PARTIAL AUTOCORRELATIONS

```
           -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
LAG   CORR.  +----+----+----+----+----+----+----+----+----+----+
                                      |
  1    0.104                   +      |XXX   +
  2    0.085                   +      |XX    +
  3    0.022                   +      |X     +
  4   -0.028                   +     X|      +
  5    0.218                   +      |XXXXX +
  6   -0.310                  X+XXXXXX|      +
  7    0.170                   +      |XXXX  +
  8   -0.023                   +     X|      +
  9   -0.018                   +      |      +
 10   -0.065                   +    XX|      +
 11    0.126                   +      |XXX   +
 12    0.260                   +      |XXXXXXX
 13   -0.274                   XXXXXXX|      +
 14   -0.097                   +    XX|      +
 15   -0.009                   +      |      +
 16    0.125                   +      |XXX   +
 17   -0.096                   +    XX|      +
 18   -0.119                   +   XXX|      +
 19    0.006                   +      |      +
 20    0.058                   +      |X     +
 21   -0.101                   +   XXX|      +
 22    0.065                   +      |XX    +
 23    0.018                   +      |      +
 24    0.012                   +      |      +
 25    0.121                   +      |XXX   +
```

TABLE 1.

SUMMARY OF THE MODEL

OUTPUT VARIABLE -- NIGHT
INPUT VARIABLES -- NOISE   MARCH82

VARIABLE	VAR. TYPE	MEAN	TIME	DIFFERENCES
NIGHT	RANDOM		1- 72	
MARCH82	BINARY		1- 72	

PARAMETER	VARIABLE	TYPE	FACTOR	ORDER	ESTIMATE	ST. ERR.	T-RATIO
1	NIGHT	MA	1	12	-0.8411	0.0434	-19.37
2	NIGHT	MEAN	1	0	724.9	10.3176	70.26
3	MARCH82	UP	1	0	-129.4	14.8944	-8.69

RESIDUAL SUM OF SQUARES = 142952.437500
DEGREES OF FREEDOM = 69
RESIDUAL MEAN SQUARE = 2071.774414
(BACKCASTS EXCLUDED)

FIGURE 7.

AUTOCORRELATIONS

1- 12	.16	.16	.14	-.04	.15	-.08	.03	-.08	-.05	-.12	-.02	-.02
ST.E.	.12	.12	.12	.13	.13	.13	.13	.13	.13	.13	.13	.13
L.-B. Q	1.9	3.7	5.3	5.4	7.2	7.7	7.7	8.2	8.5	9.7	9.7	9.7

13- 24	-.17	-.02	-.21	.10	.08	-.26	.06	-.07	-.02	.08	-.01	.19
ST.E.	.13	.13	.13	.14	.14	.14	.15	.15	.15	.15	.15	.15
L.-B. Q	12.	12.	16.	17.	18.	25.	25	26.	26.	26.	26.	30.

25- 25	-.01
ST.E.	.15
L.-B. Q	30.

PLOT OF AUTOCORRELATIONS

```
          -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
LAG   CORR. +----+----+----+----+----+----+----+----+----+----+
                                     I
  1   0.158                    +     IXXXX +
  2   0.156                    +     IXXXX +
  3   0.141                    +     IXXXX +
  4  -0.042                    +    XI     +
  5   0.148                    +     IXXXX +
  6  -0.078                    +   XXI     +
  7   0.030                    +     IX    +
  8  -0.077                    +   XXI     +
  9  -0.055                    +    XI     +
 10  -0.117                    +  XXXI     +
 11  -0.020                    +    XI     +
 12  -0.024                    +    XI     +
 13  -0.165                    + XXXXI     +
 14  -0.024                   +     XI      +
 15  -0.211                   + XXXXXI      +
 16   0.097                   +      IXX    +
 17   0.081                   +      IXX    +
 18  -0.264                   XXXXXXXI      +
 19   0.065                   +      IXX    +
 20  -0.066                   +    XXI      +
 21  -0.016                   +      I      +
 22   0.075                   +      IXX    +
 23  -0.010                   +      I      +
 24   0.186                   +      IXXXXX +
 25  -0.009                   +      I      +
```

TABLE 2.

SUMMARY OF THE MODEL

OUTPUT VARIABLE -- NIGHT
INPUT VARIABLES -- NOISE MARCH82 AUGUST82

VARIABLE	VAR. TYPE	MEAN	TIME	DIFFERENCES
NIGHT	RANDOM		1- 72	
MARCH82	BINARY		1- 72	
AUGUST82	BINARY		1- 72	

PARAMETER	VARIABLE	TYPE	FACTOR	ORDER	ESTIMATE	ST. ERR.	T-RATIO
1	NIGHT	MA	1	12	-0.8371	0.0455	-18.42
2	NIGHT	MEAN	1	0	725.8	10.4888	69.20
3	MARCH82	UP	1	0	-123.1	18.4664	-6.67
4	AUGUST82	UP	1	0	-9.828	17.7317	-0.55

RESIDUAL SUM OF SQUARES = 142252.062500
DEGREES OF FREEDOM = 68
RESIDUAL MEAN SQUARE = 2091.942139
(BACKCASTS EXCLUDED)

FIGURE 8.

AUTOCORRELATIONS

1- 12	.16	.16	.15	-.03	.17	-.06	.05	-.06	-.04	-.11	-.01	-.02
ST.E.	.12	.12	.12	.13	.13	.13	.13	.13	.13	.13	.13	.13
L.-B. Q	1.8	3.8	5.6	5.6	8.0	8.2	8.4	8.7	8.8	9.8	9.8	9.9
13- 24	-.17	-.03	-.23	.08	.06	-.29	.04	-.09	-.03	.06	-.02	.19
ST.E.	.13	.13	.14	.14	.14	.14	.15	.15	.15	.15	.15	.15
L.-B. Q	13.	13.	18.	18.	19.	27.	27.	28.	28.	28.	28.	32.
25- 25	0.0											
ST.E.	.15											
L.-B. Q	32.											

PLOT OF AUTOCORRELATIONS

```
           -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
LAG   CORR.  +----+----+----+----+----+----+----+----+----+----+
                                      I
 1    0.155                     +     IXXXX +
 2    0.160                     +     IXXXX +
 3    0.153                     +     IXXXX +
 4   -0.032                     +    XI     +
 5    0.170                     +     IXXXX +
 6   -0.057                     +    XI     +
 7    0.048                     +     IX    +
 8   -0.056                     +    XI     +
 9   -0.041                     +    XI     +
10   -0.108                     +  XXXI     +
11   -0.012                     +     I     +
12   -0.024                     +    XI     +
13   -0.172                     + XXXXI     +
14   -0.032                    +     XI      +
15   -0.227                    +XXXXXXI      +
16    0.082                    +      IXX    +
17    0.062                    +      IXX    +
18   -0.289                    XXXXXXXI      +
19    0.044                    +      IX     +
20   -0.088                    +    XXI      +
21   -0.033                    +     XI      +
22    0.063                    +      IXX    +
23   -0.023                    +     XI      +
24    0.188                    +      IXXXXX +
25   -0.001                   +       I       +
```

TABLE 3.

SUMMARY OF THE MODEL

OUTPUT VARIABLE -- NIGHT
INPUT VARIABLES -- NOISE   MARCH82

VARIABLE	VAR. TYPE	MEAN	TIME	DIFFERENCES
NIGHT	RANDOM		1- 72	
MARCH82	BINARY		1- 72	

PARAMETER	VARIABLE	TYPE	FACTOR	ORDER	ESTIMATE	ST. ERR.	T-RATIO
1	NIGHT	MA	1	12	-0.6782	0.0803	-8.45
2	NIGHT	MEAN	1	0	724.8	10.1717	71.26
3	MARCH82	UP	1	0	-91.91	32.0449	-2.87
4	MARCH82	SP	1	1	0.3077	0.2414	1.27

RESIDUAL SUM OF SQUARES = 160894.687500
DEGREES OF FREEDOM = 68
RESIDUAL MEAN SQUARE = 2366.098389
(BACKCASTS EXCLUDED)

FIGURE 9.

AUTOCORRELATIONS

1- 12	.17	.14	.11	-.06	.15	-.10	.05	-.03	-.03	-.06	-.01	-.02
ST.E.	.12	.12	.12	.13	.13	.13	.13	.13	.13	.13	.13	.13
L.-B. Q	2.2	3.8	4.9	5.1	7.0	7.8	8.0	8.1	8.2	8.5	8.5	8.5
13- 24	-.19	-.04	-.19	.12	.10	-.27	.02	-.14	-.04	.02	-.04	.25
ST.E.	.13	.13	.13	.14	.14	.14	.15	.15	.15	.15	.15	.15
L.-B. Q	12.	12.	15.	17.	18.	25.	25.	27.	27.	27.	27.	34.
25- 25	-.01											
ST.E.	.16											
L.-B. Q	34.											

PLOT OF AUTOCORRELATIONS

```
          -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
LAG   CORR. +----+----+----+----+----+----+----+----+----+----+
                                     |
  1   0.173                    +     |XXXX +
  2   0.145                    +     |XXXX +
  3   0.115                    +     |XXX  +
  4  -0.060                    +   XX|     +
  5   0.152                    +     |XXXX +
  6  -0.097                    +   XX|     +
  7   0.055                    +     |X    +
  8  -0.026                    +    X|     +
  9  -0.034                    +    X|     +
 10  -0.061                    +   XX|     +
 11  -0.014                    +     |     +
 12  -0.018                    +     |     +
 13  -0.188                    +XXXXX|     +
 14  -0.041                   +     X|      +
 15  -0.190                   + XXXXX|      +
 16   0.122                   +      |XXX   +
 17   0.105                   +      |XXX   +
 18  -0.273                   XXXXXXX|      +
 19   0.022                   +      |X     +
 20  -0.137                   +   XXX|      +
 21  -0.041                   +     X|      +
 22   0.019                   +      |      +
 23  -0.036                   +     X|      +
 24   0.250                   +      |XXXXXX+
 25  -0.013                  +       |       +
```

FIGURE 10.

PLOT OF AUTOCORRELATIONS

```
          -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
LAG   CORR. +----+----+----+----+----+----+----+----+----+----+
                                     I
  1    0.532                   +     IXXXXX+XXXXXXX
  2    0.253                  +      IXXXXXX+
  3    0.067                 +       IXX     +
  4   -0.102                 +    XXXI       +
  5   -0.122                 +    XXXI       +
  6   -0.130                 +    XXXI       +
  7   -0.061                 +     XXI       +
  8   -0.075                 +     XXI       +
  9    0.001                 +       I       +
 10    0.059                 +       IX      +
 11    0.278                 +       IXXXXXXX+
 12    0.441                 +       IXXXXXXX+XXX
 13    0.207                +        IXXXXX   +
 14    0.057                +        IX       +
 15   -0.159                +    XXXXI        +
 16   -0.290                + XXXXXXXI        +
 17   -0.203                +   XXXXXI        +
 18   -0.265               +  XXXXXXXI         +
 19   -0.220               +    XXXXXI         +
 20   -0.202               +    XXXXXI         +
 21   -0.124               +      XXXI         +
 22    0.003               +         I         +
 23    0.204               +         IXXXXX    +
 24    0.310               +         IXXXXXXXX +
 25    0.146              +          IXXXX      +
```

PLOT OF PARTIAL AUTOCORRELATIONS

```
          -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
LAG   CORR. +----+----+----+----+----+----+----+----+----+----+
                                     I
  1    0.532                   +     IXXXXX+XXXXXXX
  2   -0.042                   +    XI     +
  3   -0.072                   +   XXI     +
  4   -0.141                   + XXXXI     +
  5    0.009                   +     I     +
  6   -0.046                   +    XI     +
  7    0.050                   +     IX    +
  8   -0.096                   +   XXI     +
  9    0.083                   +     IXX   +
 10    0.030                   +     IX    +
 11    0.324                   +     IXXXXX+XX
 12    0.220                   +     IXXXXXX
 13   -0.259                   XXXXXXI     +
 14   -0.087                   +   XXI     +
 15   -0.161                   + XXXXI     +
 16   -0.068                   +   XXI     +
 17    0.139                   +     IXXX  +
 18   -0.266                  X+XXXXXI     +
 19   -0.101                   +  XXXI     +
 20   -0.084                   +   XXI     +
 21    0.052                   +     IX    +
 22    0.138                   +     IXXX  +
 23    0.062                   +     IXX   +
 24   -0.013                   +     I     +
 25   -0.103                   +  XXXI     +
```

TABLE 4.

SUMMARY OF THE MODEL

OUTPUT VARIABLE -- DAY
INPUT VARIABLES -- NOISE   MARCH82

VARIABLE	VAR. TYPE	MEAN	TIME	DIFFERENCES
DAY	RANDOM		1- 72	
MARCH82	BINARY		1- 72	

PARAMETER	VARIABLE	TYPE	FACTOR	ORDER	ESTIMATE	ST. ERR.	T-RATIO
1	DAY	AR	1	1	0.5947	0.1050	5.66
2	DAY	MEAN	1	0	162.3	4.6970	34.55
3	MARCH82	UP	1	0	7.935	7.7712	1.02

RESIDUAL SUM OF SQUARES = 12460.576172
DEGREES OF FREEDOM = 68
RESIDUAL MEAN SQUARE = 183.243774

FIGURE 11.

AUTOCORRELATIONS

1- 12	.01	.04	.02	-.13	-.03	-.12	.03	-.11	-.01	-.02	.11	.39
ST.E.	.12	.12	.12	.12	.12	.12	.12	.12	.12	.12	.12	.13
L.-B. Q	0.0	.10	.20	1.5	1.6	2.8	2.9	3.9	3.9	3.9	4.9	18.
13- 24	.01	.09	-.11	-.26	.05	-.18	-.07	-.14	-.09	-.03	.12	.32
ST.E.	.14	.14	.14	.14	.15	.15	.15	.15	.16	.16	.16	.16
L.-B. Q	18.	19.	20.	27.	27.	30.	30.	32.	33.	33.	35.	46.
25- 25	.02											
ST.E.	.17											
L.-B. Q	46.											

PLOT OF AUTOCORRELATIONS

```
          -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
LAG   CORR. +----+----+----+----+----+----+----+----+----+----+
                                     I
  1   0.010                    +     I     +
  2   0.037                    +     IX    +
  3   0.025                    +     IX    +
  4  -0.132                    +  XXXI     +
  5  -0.026                    +    XI     +
  6  -0.124                    +  XXXI     +
  7   0.032                    +     IX    +
  8  -0.111                    +  XXXI     +
  9  -0.006                    +     I     +
 10  -0.021                    +    XI     +
 11   0.106                    +     IXXX  +
 12   0.392                    +     IXXXXX+XXXX
 13   0.010                   +      I      +
 14   0.095                   +      IXX    +
 15  -0.110                   +   XXXI      +
 16  -0.256                   +XXXXXXI      +
 17   0.053                   +      IX     +
 18  -0.177                   +  XXXXI      +
 19  -0.066                  +     XXI       +
 20  -0.136                  +    XXXI       +
 21  -0.087                  +     XXI       +
 22  -0.026                  +      XI       +
 23   0.117                  +       IXXX    +
 24   0.318                  +       IXXXXXXXX
 25   0.019                  +       I       +
```

TABLE 5.

SUMMARY OF THE MODEL

OUTPUT VARIABLE -- DAY
INPUT VARIABLES -- NOISE   MARCH82

VARIABLE	VAR. TYPE	MEAN	TIME	DIFFERENCES
DAY	RANDOM		1- 72	
MARCH82	BINARY		1- 72	

PARAMETER	VARIABLE	TYPE	FACTOR	ORDER	ESTIMATE	ST. ERR.	T-RATIO
1	DAY	AR	1	1	0.6126	0.1148	5.34
2	DAY	AR	2	12	0.6478	0.1223	5.30
3	DAY	MEAN	1	0	171.4	12.4333	13.79
4	MARCH82	UP	1	0	-4.672	7.5246	-0.62

RESIDUAL SUM OF SQUARES = 6924.665527
DEGREES OF FREEDOM = 55
RESIDUAL MEAN SQUARE = 125.903008

FIGURE 12.

AUTOCORRELATIONS

1- 12	-.08	-.12	.27	.16	-.14	.11	.20	.04	.10	-.03	.11	-.08
ST.E.	.13	.13	.13	.14	.15	.15	.15	.15	.15	.15	.15	.16
L.-B. Q	.40	1.3	6.0	7.8	9.1	9.9	13.	13.	14.	14.	15.	15.
13- 24	.04	.12	-.10	-.12	.16	.01	-.25	.17	-.14	-.07	.12	.04
ST.E.	.16	.16	.16	.16	.16	.16	.16	.17	.17	.17	.17	.18
L.-B. Q	15.	16.	17.	18.	21.	21.	26.	29.	30.	31.	32.	33.
25- 25	-.06											
ST.E.	.18											
L.-B. Q	33.											

PLOT OF AUTOCORRELATIONS

```
          -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
LAG   CORR. +----+----+----+----+----+----+----+----+----+----+
                                     I
  1  -0.080                    +   XXI     +
  2  -0.122                    +  XXXI     +
  3   0.271                   +      IXXXXXXX
  4   0.163                   +      IXXXX  +
  5  -0.140                   +   XXXI      +
  6   0.110                   +      IXXX   +
  7   0.204                   +      IXXXXX +
  8   0.036                  +       IX      +
  9   0.101                  +       IXXX    +
 10  -0.026                  +      XI       +
 11   0.109                  +       IXXX    +
 12  -0.076                  +     XXI       +
 13   0.039                  +       IX      +
 14   0.120                  +       IXXX    +
 15  -0.096                  +     XXI       +
 16  -0.124                  +    XXXI       +
 17   0.164                  +       IXXXX   +
 18   0.009                  +       I       +
 19  -0.246                  + XXXXXXI       +
 20   0.168                  +       IXXXX   +
 21  -0.135                  +    XXXI       +
 22  -0.071                 +      XXI        +
 23   0.119                 +        IXXX     +
 24   0.044                 +        IX       +
 25  -0.061                 +      XXI        +
```