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## I. Introduction

The time series quasi experiment is often a useful design in cases where randomization is impossible but data can be collected across time. If there are  $n_1$  observation points before an intervention to the time series process and  $n_2$  observation points after the intervention, there is generally interest in analyzing pre-post changes in the process. Among the methods of analysis available for this interrupted time series design are those suggested by Box and Tiao (1965 and 1975), Glass, Willson and Gottman (1975) and Jones, Crowell and Kapuniai (1969).

A basic problem with this design is that events concomitant with the planned intervention must be considered as alternative explanations of the change. One method of dealing with this interpretation problem is to employ one or more control series in which the intervention is not applied. If the change in the control series is not the same as the change in the basic series, evidence for the effect of the intervention is strengthened.

A method of analyzing change in the basic series which is free, in a linear sense, of the change in one or more concomitant series is described in this paper. The procedure involves

(1) regressing the basic time series on the concomitant series for the preintervention data,

(2) fitting a first order autoregressive (Markov) model to the residuals of (1) and

(3) testing differences in the postintervention phase between observed points and points predicted from information contained in (a) the concomitant series and (b) autoregression in the residuals of the fitted regression.

Certain aspects of this procedure are extensions of the Jones model.

II. The Model

The proposed model for the time series process is  $Y_T = \mu_Y + \beta_{1,2,3}, \dots, m(X_{1,T} - \mu_{X_1}) + \beta_{2,1,3}, \dots, m(X_{2,T} - \mu_{X_2}) \dots + \beta_{m+1,2}, \dots, m-1(X_{m,T} - \mu_{X_m}) + \alpha \left[Y_{T-1} - (Y | X_1, X_2, \dots, X_m)_{T-1}\right] + \varepsilon_T$ where

 $\mathbf{Y}_{T}$  is the dependent variable score at time T which is any of the equally spaced observation points,

 $\mu_{\mbox{Y}}$  is the process mean for the basic (dependent variable) series,

 $\mu_{X1}$  through  $\mu_{Xm}$ , are the means of the concomitant series (i.e., covariates) one through m,  $\beta_{1.2}$ , 3...m through  $\beta_{m.1,2}$ ,...,m-1 are the partial regression coefficients obtained from re-

partial regression coefficients obtained from regressing  $Y_T$  on covariates  $X_{1,T}, X_{2,T}, \dots, X_{m,T}$  $X_{1,T}, X_{2,T}, \dots, X_{m,T}$  are scores on covariates

 $x_1, T, x_2, T, \cdots, x_m, T$  are scores on covariates 1,2,..., m measured at time T. These scores are obtained from any available set of concomitant time series and may be in the form of continuous scores or dummy values which indicate the presence or absence of a condition.

 $\alpha$  is the first order autoregression parameter relating the residuals  $y_{T-1} - (y | x_1, y_2, \dots, x_m)_{T-1}$ 

and 
$$\begin{bmatrix} Y_T - (Y | X_1, X_2, \cdots X_m) \end{bmatrix}$$
 and

 $\epsilon_{T}$  is the error which is NID(0,  $\sigma^{2}$ ). III. Estimation

The parameters of the model are estimated as follows:

 $\mu_{\mathbf{Y}}$  is estimated using

$$\hat{\mu} = \frac{1}{n} \frac{\sum_{i=1}^{n} Y}{T=1} T$$

where  $\mathbf{n}_1$  is the number of preintervention observations,

 $\mu_{X_1}$  through  $\mu_{X_m}$  are estimated using

$$\hat{\mu}_{\mathbf{X}_{\mathbf{i}}} = \frac{1}{n} \sum_{T=1}^{n} X_{\mathbf{i}},$$

the partial regression coefficients are estimated using ordinary least squares on the  ${\bf n}_1$  preintervention points and the first order autoregression parameter is estimated using

$$\hat{\alpha} = \frac{SP_1}{SS_c} =$$

$$\frac{\prod_{T=2}^{n_1} \left[ \mathbf{Y}_{T-1} - (\mathbf{Y} | \mathbf{X}_1, \mathbf{X}_2, \cdots, \mathbf{X}_m)_{T-1} \right] \left[ \mathbf{Y}_T - (\mathbf{Y} | \mathbf{X}_1, \mathbf{X}_2, \cdots, \mathbf{X}_m)_T \right]}{\left( \frac{n_1 - 1}{n_1} \right) \prod_{T=1}^{n_1} \left[ \mathbf{Y}_T - (\mathbf{Y} | \mathbf{X}_1, \mathbf{X}_2, \cdots, \mathbf{X}_m) \right]_T^2}$$

where  $SP_1$  is the lag one sum of products of the residuals of the regression and  $SS_c$  is the zero lag sum of squares corrected by a term that allows for the difference between the number of observations that are associated with the sum of products and sum of squares.

IV. Testing for Intervention Effects

Two related tests are suggested for testing for change in the time series following the intervention.

A. Testing for Postintervention Change at Individual Postintervention Points

The test statistic for evaluating the change in the time series at a post intervention point specified  $a \ priori$  is

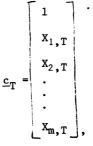
$$t = \sqrt{\frac{SS_{c} (1-R^{2} - \hat{\alpha}(1-R^{2}))}{n_{1}-m-3}} \left[ 1 + \underline{c'_{T}}(\underline{x}'\underline{x})^{-1}\underline{c_{T}} \right]$$

where

Y is the predicted postintervention value based on the fitted model,

 $R^2$  is the coefficient of multiple determination based on the fitted model,

 $\underline{c}_T$  is the unity augmented column vector of covariate scores measured at time T, i.e.,



X is the unity augmented covariate score matrix based on the n preintervention data points, i.e., X =

The test statistic t is compared with the critical value of the conventional t statistic based on  $n_1$ -m-3 degrees of freedom.

B. Testing for Overall Change in the Whole Postintervention Series

If interest lies in evaluating the intervention points, the following approximate test is suggested

$$z = \frac{\frac{n_1 + n_2}{\sum t_T}}{\frac{n_1 + 1}{n_2 [(n_1 - m - 3)/(n_1 - m - 5)]}}$$

If the first order autoregressive model fits the residuals of the regression, the individual ttests will be approximately independent and the test statistic z will be approximately a standard normal variable.

V. Example

Drunkenness arrest data from two Michigan counties are plotted in Figures A and B. A program that was expected to have an effect on the arrests in the first county (Kalamazoo) is the intervention that occurs after week 39. A comparison of the data from the experimental county with the covariate data from the control county (Calhoun) which was not exposed to the program, reveals a somewhat disturbing pattern. The arrests appear to drop for both the experimental and control counties. In order to evaluate whether or not the postintervention change is significant for the experimental county after controlling for change in the control county, we apply the tests of Section IV.

Individual tests:

Week	t
40	-1.48
41	-1.41
42	63
43	-1.45
44	-1.11
45	-1.74
46	63
47	-1.25

Overall test:

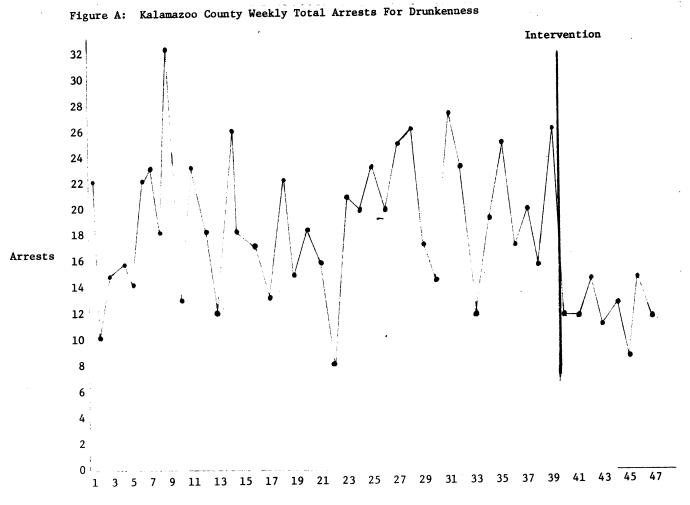
$$z = \frac{-9.70}{\sqrt{8(35/33)}} = -3.33.$$

None of the individual t tests are significant using  $\alpha$  = .05, but the observed values associated with these tests are all less than the predicted values. This is indicated by the negative signs associated with the t values. As would be

expected, when the combined information from these individual t values is employed in the overall test, the conclusion is that significant postintervention change, beyond that which is found in the control county, took place in the experimental county.

## References

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  - Jones, R. H., Crowell, D. H., and Kapuniai, L. E. Change detection model for serially correlated data. Psychological Bulletin, 1969, 71, 352-358.



Week

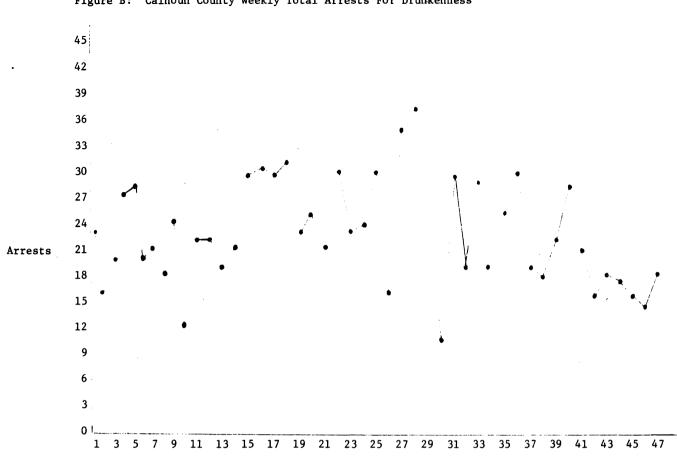


Figure B: Calhoun County Weekly Total Arrests For Drunkenness

Week