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CAN VECTOR-AUTOREGRESSION METHODOLOGY HELP IN AN UNDERSTANDING OF THE CAUSAL DYNAMICS OF THE UNEMPLOYMENT-CRIME RELATIONSHIP?

We apply a dynamic time-series method called Vector-autoregression (VAR) to studying the dynamic linkages between unemployment and crime rates in Virginia. The promise of the VAR methodology lies in its ability to provide information on the dynamic and the feedback properties in systems of variables (Sims, 1980).[1]

We studied the dynamic relationship between unemployment and crime for monthly data from Virginia for the period between January 1983 to December 1992. The basic system studied consisted of the following variables:

- Virginia Unemployment Rates (VAUN)
- Property Crimes Rates: property crimes studied included burglaries (BURG), larcenies (LARC) and robberies (ROB).
- Total part 1 and part 2 arrest rates (TTLAR)
- Jail Crowding (CROWD): Jail crowding was defined as the percentage of jail capacity that was occupied by local responsible jail inmates in any given month.

We confined our study to property crimes because the literature suggests that the linkages between unemployment and crime are more likely to occur for property crimes (Cantor and Land, 1985).[2] Similarly, as we were focusing on crimes of lesser seriousness we restricted our study to jails.

We focusssed on the following research questions:

(1) What were the causal properties of the above system? In other words, which variables could be considered "causes" of other variables in the system?

(2) VAR methodology explores the dynamic linkages in the system by addressing the following question: How would a shock (innovation) in one of the variables affect the other variables in the system over time ?

CAUSAL CONCEPTS IN THE VAR FRAMEWORK:

Vector-autoregression are multivariate generalizations of the Granger-Causality framework (Granger, 1969) . There are four causal notions that are basic in the Granger-Causality framework: Causality, Feedback, Instantaneous Causality and Causality Lag.

Definitions:

Let U_t be the "information accumulated in the Universe since time t-1. $U_t - Y_t$ denotes all information apart from the specified series Y_t" (Granger, 1969, p. 428).[3] Let A_p represent the set of past values, and A_{pp} represent the set of past and present values.

Causality:

If $Var(X/U) < Var(X/(U-Y)_p)$, we say that Y is causing X; this is denoted by $Y_t => X_t$. "We say that Y_t is causing X_t, if we are better able to predict X_t using all variable information than if the information apart from Y_t had been used" (ibid, p. 428).

Feedback:

If $Var(X/U_p) < Var(X/(U-Y)_p)$
and $Var(Y/U_p) < Var(Y/(U-X)_p)$

then we say that feedback is occuring. More generally, "feedback is said to occur when X_t is causing Y_t and also Y_t is causing X_t" (ibid. , p. 428).

Instantaneous Causality:

If $(Var(X/U_p, Y_{pp}) < Var(X/U_p)$
then we say that instantaneous causality $Y_t => X_t$ is occurring.
" In other words, the current value of X_t is better 'predicted' if the present value of Y_t is included in the prediction than if it is not" (ibid., p. 429).

Causality Lag:

"We define the (integer) causality 'lag m' to be the least value of k such that $Var(X/U-Y(k)) < Var(X/U-Y(k+1))$. Thus knowing the values Y_{t-j}, $j = 0,1,2...m-1$, will be of no help in improving the prediction of X_t" (ibid., p. 429).

Definition of VAR:

Let y_t be a m x 1 matrix of random variables. A VAR of order p (denoted by VAR(p)) is defined as:

$y_t = A(L)y_{t-1} + u_t$
$A(L) = A_1 + A_2L + A_3L^2 + ... + A_p L^{p-1}$
where $A_1, A_2, ... A_p$ are mxm matrices of coefficients and u_t is a white noise vector process with the following properties:

$E(u_t) = 0$
$E(u_t u_s') = \Sigma$ for $s=t$
$E(u_t u_s') = 0$ for $s \neq t$

Σ is the variance-covariance matrix of u_t.
u_s' is the transpose of u_s.

Methodology:

The lag-length to determine the order of the VAR is fixed using the modified likelihood-ratio test (Sims, 1980).

Multivariate generalizations of granger causality tests are used to study the causal relationships . These tests are known as Block-exogeneity tests (Freeman et al., 1989).

Impulse response functions study the response of the system to "innovations" (random shocks) in each of the endogenous variable. Impulse response functions can be used to simulate the effects of policy-intervention. As an example, consider Freeman et al. (1989, pp. 848-849)[4]:

> The VAR approach to public policy analysis treats governmental decision making in some respects as "reactive" and in other respects "unpredictable." VAR modelers almost always treat policy variables as endogenous in that they place them on both the left- and right-hand sides of their equation systems. At the same time, VAR modelers understand that policies fluctuate in seemingly random ways, or that governments make novel, surprise decisions. These decisions presumably can be represented as econometric innovations in the policy variables. The impact of these shocks or "policy innovations" presumably are reflected in the respective, recursive moving average responses of the system.

RESULTS:

Sims likelihood-ratio test indicated that eight lags would be better than four lags. However, given the large number of coefficients involved in estimating VAR models with eight lags, we restricted the number of lags to four.

The significance levels of the F-tests for the block exogeneity tests are presented in table 1. At the 0.01 level of significance VAUN is exogenous to the system. At the 0.05 level of significance, TTLAR is a predictor of VAUN. At the 0.05 level of significance, VAUN is a predictor of ROB and BURG. TTLAR is a statistically significant predictor of ROB and BURG ($p< 0.01$). Significant predictors of TTLAR include VAUN ($p<0.05$), LARC($p<0.01$), ROB($p<0.05$) and BURG ($p<0.05$). BURG is a significant predictor of CROWD ($p< 0.05$). We find feedback effects between TTLAR and each of the following variables: VAUN, ROB and BURG.

Impulse Response Functions help in an understanding of the direction of the above relationships (figure 1 plots the response of TTLAR to shocks in the variables of the system). An increase in arrest rates leads to a drop in unemployment rates . This decrease is strongest 3 months after the shock in arrest rates. An increase in unemployment rate is accompanied by small increases in the burglary and robbery rates. For robberies, the effect is strongest 7 months after a shock to the unemployment rate; for burglaries the response is strongest 3 months after the shock. A shock in the arrest rates initially leads to drops in robbery and burglary rates; however, after 6 months ,such a shock leads to an increase in burglary and robbery rates. An increase in the unemployment rate results in a decrease in arrest rates. This effect is strongest eight months after the initial shock (see figure 1). Similar impulse response functions were obtained for the other variables.

DISCUSSION/CONCLUSION:

We recommend an application of VAR methodology in criminal justice settings with a few cautions: VAR have been criticized for their robustness properties (Runkle, 1987).[5] In addition, there are problems with the interpretation of impulse response functions (Lutkepohl, 1993).[6] However, despite these problems, we still recommend VAR methodology for the following reasons:

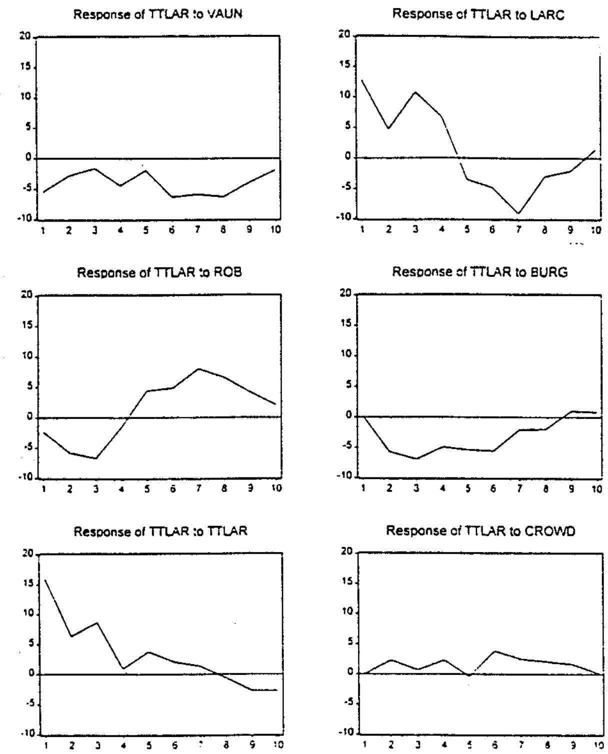
(1) they have the potential to provide information on the feedback processes in criminal justice. The concept of feedback has yet to be fully appreciated in criminal justice settings.

(2) More broadly, the VAR framework has the potential to help the theorist as well as the policy-maker focus on the "dynamics" of relationships between variables in criminal justice.

Table 1: Block-exogeneity tests : Significance of F-tests

Equation	Vaun	Larc	Rob	Burg	Ttlar	Crowd
Variable						
Vaun	0.00**	0.12	0.03*	0.03*	0.03*	0.18
Larc	0.05	0.03*	0.02*	0.04*	0.00**	0.45
Rob	0.13	0.48	0.02*	0.60	0.04*	0.45
Burg	0.33	0.02*	0.71	0.00**	0.02*	0.04*
Ttlar	0.01*	0.31	0.00**	0.00**	0.00**	0.96
Crowd	0.07	0.80	0.33	0.50	0.58	0.00**

Figure 1· Response of TTLAR to One S.D Innovations



[1] Sims, C.A. (1980). Macroeconomics and Reality. Econometrica. 48: 1-40.
[2] Cantor, D. and Land, K.C. (1985). Unemployment and Crime Rates in the Post-World War II United States: A Theoretical and Empirical Analysis. American Sociological Review. 50: 317-332.
[3] Granger, C.W.J. (1969). Investigating Causal Relations by Econometric Models and Cross-Spectral Methods. Econometrica 37: 424-438.
[4] Freeman, J.R., Williams, J.T., and Lin, T.-m. (1989). Vector Autoregression and the Study of Politics. American Journal of Political Science. 33: 842:877.
[5] Runkle, D. (1987). Vector Autoregression and Reality. Journal of Business and Economic Statistics. 5: 437:442.
[6] Lutkepohl, H. (1993). Introduction to Multiple Time Series Analysis, Springer-Verlag, Berlin.