NATIONAL FORUM OF MULTICULTURAL ISSUES JOURNAL
VOLUME 7, NUMBER 1, 2010

An Empirical Infusion of Time Series Crime Forecasting Modeling into Crime Prevention Approach for Use by Law Enforcement Agencies: An Econometrics Perspective

G. Solomon Osho, PhD
Prairie View A&M University
The Texas A&M University System
Prairie View, Texas

Ayodeji Daramola, MS
Prairie View A&M University
The Texas A&M University System
Prairie View, Texas

ABSTRACT

Time series is one of the most important tools for research in the social sciences, and forecasting is one of the most interesting and vital part of everyday life in all societies. The statistical forecasting tool is time series. Crime prediction is an emerging approach in criminal justice studies and criminological research. Since crime is universal, time series have been an effective statistical tool used to forecast crime rates in many countries of the world. The general main of this study is examine how to infuse time series as a forecasting technique to predict crime rate in Harris County for the over specific period of time. Crime rate is a useful statistic for many purposes, such as evaluating the effectiveness of crime prevention measures or the relative safety of a particular city and neighborhood. Hence, accurate forecast of crime rate could be used by policy makers to advocate for or against policies designed to deal with crime.

Introduction

Time series forecast is one of the most important tools for research in the field of social sciences and forecasting has become one of the most integral parts of everyday life in all societies. The main statistical forecasting tool is time series. Crime prediction is an emerging approach in criminal justice studies and criminological research. By reviewing historical data over time, researchers, criminologists and justice practitioners can better understand the pattern of past behavior of crime variables and better predict the future crime behavior. A time series is a set of observations on a variable measured over successive points in time or over successive periods of time, usually obtained at equally spaced intervals; it could be: daily, monthly, quarterly, or yearly data.

The goal of time series forecasting technique is to discover a trend and pattern in the historical data and then extrapolate the pattern into the future. The forecast is usually based on past values of the variable and past forecast errors. Time series forecasting treats the system as black box and makes no attempt to discover the factors affecting its behavior. It explains only what will happen, not why something happens. The common goal in the application of forecasting techniques is to minimize these deviations or errors in the forecast. The errors are defined as the differences between the actual value and what was predicted.

Time series is used by governments all over the world to forecast unemployment, interest rates, and expected revenues from income taxes for policy purposes. It is also used by crime mapping with GIS software to make prediction and for strategic police budgeting. In addition, time series, is also used by administrators to forecast for recruitment. However, probably one of the greatest uses of time series is to predict crime rates. Since crime is universal, time series have been an effective statistical tool used to forecast crime rates in many countries of the world. The general main of this study is examine how to infuse time series as a forecasting technique to predict crime rate in Harris County for the over specific period of time.

Prior Research

Time series has been used in both government and private sectors, and it has been used extensively in research in the social sciences. Cantor and Land (1985) investigated the relationship between unemployment rates and crime rates in the United States by using annual data. This study has provided new direction for other criminal studies in time series forecasting. However, Hale and Sabbagh (1991) and Hale (1991) have provided rigorous critical suggestions regarding the methods used in for their study (Land *et al.*, 1995). Cantor and Land (1985) argue that earlier research dealing with the impact of unemployment on crime rates has led to weak and inconsistent findings because it has failed to take into consideration two possible ways unemployment might influence crime.

Furthermore in their study they noted that “unemployed are expected to have greater motivation to violate the law, they might also spend more time at home, preventing burglaries and reducing their vulnerability to robbery, assault, and homicide (an opportunity effect)”. Cantor and Land (1985) concluded that the two possibilities are not necessarily being mutually exclusive: unemployment may reduce the opportunity to violate the law, while at the same time, may increase the motivation. If both effects are instantaneous, a coefficient representing the net effect of unemployment on crime might be small and insignificant even though both effects are substantial. Using a linear function to establish the rate at which individual *i* commits crimes $C_{(i)}$, and that individual's lawful opportunities and motivation at time *t* can be represented in the form of a regression equation with residual e_i:

$$C_{it} = \beta_0 + \beta_1(\text{opportunity})_{it} + \beta_2(\text{motivation})_{it} + \ldots + e_{it} \quad \ldots\ldots\ldots\ldots\ldots\ldots(1)$$

If opportunity at time *t* and motivation at time *t* are both proportional to unemployment at time *t* (U_t), a regression of C_i against U_t will yield an estimate of the sum β_1 and β_2 (Greenberg, 2001). Greenberg (2001) updated the data used by Cantor and Land (1985), added additional variables to it, and analyzed homicide and robbery rates in the United States during the years 1946-1997. He used regression equation given above in the time series study. He found that the regression equations do not adequately represent the theoretical ideas they were designed to test, and the variables in the theory were not adequately represented by those available in official employment statistics. Greenberg (2001) found that aggregate data were less ideal when estimating relationships posited by theory to hold for individuals.

Furthermore, Corman and Mocan (2000) used a time series analysis to investigate the interrelationship between crime, drug use, police, and arrests in New York City. The study provided more refined evidence on the crime-deterrence relationship using monthly data observations from1970 through 1990 in New York City, and plotting the individual time series for five different non-drug crimes, arrest rates for these crimes, drug deaths, number of police officers, and drug arrests in New York City.

Corman and Mocan (2000) found that law enforcement has a significant deterrent effect on robberies, burglaries, and motor vehicle theft. Their study concluded that "an increase in the growth rate of police officers is associated with a reduction in the growth rate of burglaries and robberies, although the relationship is only significant at the 11 percent level in the latter. Murder and assault rates are not related to changes in the growth rate of drug use". This result, which is also unique because it is in line with that of Corman, Joyce, and Mocan (1991) that was based on an intervention analysis, since they did not include a structural upturn in the time-series trends of murders in New York City during 1985.

However, one explanation of the fact that murder and assault growth rates are not related to changes in the growth of drug use, is that the increase in the supply of drugs that constituted the crack cocaine epidemic reduced the producer surplus fought over, offsetting other effects of drugs on violent crime. Another explanation is that drug related violence stems mostly from the interaction between sellers. Increase in the growth of drug use, however, is associated with increases in the growth rate of robberies and burglaries (Corman & Mocan, 2000).

Model Specification

A time series $x_{(t)}$; t=1 is stationary if its statistical properties do not depend on time t. A time series may be stationary in respect to one characteristic, that is the mean, but not stationary in respect to another, hence the variance

$$M(x_{(t)}) = \text{constant} \quad (2)$$

The mean does not depend on time t.

$$\text{Var}(x_{(t)}) = v_{(t)} \quad (3)$$

The variance depends on time t; where M(.) is the mean and Var(.) is the variance. The white noise is a stationary time series or a stationary random process with zero autocorrelation: $N_{(t)}$ any pair of values, $N_{(t1)}$ and $N_{(t2)}$ taken at different moments t_1 and t_2 of time are not correlated, Correlation Coefficient—$r(N_{(t1)}, N_{(t2)})$ is equal to null, White noise is the most common model of noise in time series analysis and signal processing

Autoregressive (AR) Models

Autoregressive Models —AR is used in time series analysis to describe stationary time series, and they could also be used to represent time series generated by passing the white noise through a recursive linear filter. AR model of a random process—$y_{(t)}$ in discrete time t is expressed thus:

$$y_{(t)} = \Sigma\alpha_{(1)} y_{(t-1)} + \epsilon_{(t)} \quad (4)$$

where α_1, $\alpha_2 \ldots \alpha_m$ are the coefficients of the recursive filter, m is the order of the model $\epsilon_{(t)}$ are output uncorrelated errors. There are three types of autoregressive models—AR(1), AR(2), and AR(3), and each one is expressed by the following equations:

$$\text{AR}(1)\ y_{(t)} = \alpha_o + \alpha_1 y_{(t-1)} + \epsilon_{(t)} \quad (5)$$

$$\text{AR}(2)\ y_{(t)} = \alpha_o + \alpha_1 y_{(t-1)} + \alpha_2 y_{(t-2)} + \epsilon_{(t)} \quad (6)$$

$$\text{AR}(3)\ y_{(t)} = \alpha_0 + \alpha_1 y_{(t-1)} + \alpha_2 y_{(t-2)} + \alpha_3 y_{(t-3)} + \epsilon_{(t)} \quad (7)$$

Moving Average (MA) Models

Moving Average —MA models are used in time series analysis to describe stationary time series and represent time series generated by passing the white noise through a non-recursive linear filter. Also, there are three moving average models—

MA(1), MA(2), and MA(3). A moving average model of a random process $y_{(t)}$ in discrete time (t) is defined thus:

$$y_{(t)} = \Sigma\beta_{(i)}x_{(t-i)} + \epsilon_{(t)}, \quad \ldots\ldots\ldots\ldots (8)$$

where $\beta_{i,\ i}=0, 1\ldots., n$ are coefficients of the linear non-recursive filter, n is the order of the MA model, $x_{(t)}$ are elements of the (input) white noise, and $\epsilon_{(t)}$ are the output uncorrelated errors. Autoregressive Moving Average (ARMA) Model is also called Box-Jenkins Model, named after George Box and Gwilym Jenkins in 1970. Autoregressive moving average—ARMA consists of two parts, an autoregressive (AR) part, and a moving average (MA) part.

The model is referred to as the ARMA(p, q) model, where p =1,2,3... is the order of the autoregressive part and q=1,2,3… is the order of the moving average part.

$$\text{ARMA}(1,2) \quad y_{(t)} =\alpha_0 + \alpha_1 y_{(t-1)} +\alpha_2 e_{(t-1)} +\alpha_3 e_{(t-2)} + u_{(t)} \quad \ldots\ldots\ldots\ldots (8)$$

The original Box-Jenkins modeling procedure involved an interactive three-stage process of model selection, parameter estimation, and model checking. Recent explanations of the process (Makridakis, Wheelwright, & Hyndman, 1998) often add a preliminary stage of data preparation and a final stage of model application or forecasting.

Data Preparation

Data preparation involves transformations and differencing. Transformation of the data such as square roots or logarithms can help stabilize the variance in a series where the variance changes with the level. This often happens with business and economic data; then the data are differenced until there are no obvious patterns such as trend or seasonality left in the data. “Differencing” means taking the difference between consecutive observations a year apart; hence, the differenced data are often easier to model than the original data.

Model Selection

Model selection in the Box-Jenkins framework uses various graphs based on the transformed and differenced data to try to identify potential ARIMA processes which might provide a good fit to the data. Later developments have led to other model selection tools such as Schwartz Bayesian Criterion (SBC), and Akaike Information Criterion (AIC).

Parameter Estimation

Parameter estimation means finding the values of the model coefficients which provide the best fit to the data. There are sophisticated computational algorithms designed for this specific purpose.

Model Checking

Model checking involves testing the assumptions of the model to identify any areas where the model is inadequate. If the model is found to be inadequate, it is necessary to go back to model selection and try to identify a better model. The model with the lowest or minimum summation of SBC and AIC, is the best model to use. Finally, forecasting is what the whole Box-Jenkins procedure is designed to accomplish. Once the model has been selected, estimated, and checked, it is usually easy to compute forecasts. This of course is done by a computer. Although originally designed for modeling time series with ARIMA processes, the underlying strategy of Box-Jenkins is applicable to a wide variety of statistical modeling situations. It provides a convenient framework which allows an analyst to think about the data, and to find an appropriate statistical model which can be used to answer relevant questions about the data (Makridakis, Wheelwright, & Hyndman, 1998).

Testing for Data Stability

When a time series is not stationary, special; procedures are needed. Consequently, one of the first issues a researcher must confront when analyzing time series is the question whether it is stationary or not. Unit root tests also called Dickey-Fuller Unit Root Tests, allow one to determine whether a series is stationary, and if it is not, whether it is a random walk, a random walk with drift, or a random walk with drift and trend (Banerjee, Dolado, Galbraith, & Hendry, 1993; Holden & Perman, 1994; Harris, 1995).

ARIMA Models

ARIMA(p,d,q) models are the most general class of models for forecasting a time series which can be stationarized by transformations such as differencing and logging. The acronym ARIMA stands for "Auto-Regressive Integrated Moving Average." Lags of the differenced series appearing in the forecasting equation are called "auto-regressive" terms, lags of the forecast errors are called "moving average" terms, and a time series which needs to be differenced to be made stationary is said to be an "integrated" version of a stationary series. In ARIMA(p,d,q): where p is the number of autoregressive terms, d is the number of nonseasonal differences, and q is the number of lagged forecast errors in the prediction equation. To identify the appropriate ARIMA model for a time series, you begin by identifying the order(s) of the differencing needed to stationarize the series and remove the gross features of seasonality, perhaps in conjunction with a variance-stabilizing transformation such as logging or deflating.

Conclusions

Time series is a useful statistical tool used to forecast the future behavior of a variable by using past historical data of the variable. The objective of time series methods is to discover a pattern in the historical data and then extrapolate the pattern into the future. The forecast is based solely on past values of the variable and/ or past forecast errors. Time series forecasting treats the system as black box and makes no attempt to discover the factors affecting its behavior. It explains only what will happen, not why something happens. The common goal in the application of forecasting techniques is to minimize these deviations or errors in the forecast. The errors are defined as the differences between the actual value and what was predicted.

Forecast is used by governments all over the world to forecast unemployment, interest rates, and expected revenues from income taxes for policy purposes. It is also used by marketing executives to forecast demand, sales, and consumer preferences for strategic planning. In addition, time series, is also used by college administrators to forecast enrollments to plan for facilities and for faculty recruitment. It is used by retail stores to forecast demand to control inventory levels, hire employees and provide training. But, probably one of the greatest uses of time series is to predict crime rates. Since crime is universal, time series have been an effective statistical tool used to forecast crime rates in many countries of the world. Crime rate is a useful statistic for many purposes, such as evaluating the effectiveness of crime prevention measures or the relative safety of a particular city or neighborhood. Forecasting and crime rate statistics are usually used by policy makers to advocate for or against a particular program and legislation designed to deal with crime.

References

Banerjee, A., Dolado, J., Galbraith, J., & Hendry, D. (1993). *Co-integration, error, correction, and the econometric analysis of non-stationary data*. New York, New York: Oxford University Press.

Cantor, D., & Land, K. C. (1985). Unemployment and crime rates in the post-World War II United States: A theoretical and empirical analysis. *American Social Review, 50,* 317-332.

Corman, H., & Mocan, H. (2000, June). "A time-series analysis of crime, deterrence, and drug abuse in New York City." *American Economic Review, 90,* 584-604.

Greenberg, D. F. (2001, December). Time series analysis of crime rates. *Journal of Quantitative Criminology, 17*(4), 291-327.

Hale, C. (1991). Unemployment and crime: Differencing is no substitute modeling. *Journal of Research Crime and Delinquency, 28,* 426-429.

Hale, C., & Sabbagh, D. (1991). *Testing the relationship between unemployment and crime: A methodological comment and empirical analysis using time series data from England and Wales. Journal of Research Crime and Delinquency, 28,* 400-417.

Harris, R. (1995). *Using cointegration analysis in econometric modeling*. New York: Prentice-Hall.

Holden, D., & Perman R. (1994). *"Unit roots and cointegration for the economist."* In B. B. Rao (Ed.), *Cointegration for the applied economist* (pp.47-112). New York, New York: St. Martin's.

Land, K., Cantor, D., & Russell, S. (1995). *Unemployment and crime rate fluctuations in the post-World War II United States: Statistical time series properties and alternative models*. In Hagan, J. & R. Peterson. (Eds.), *Crime and inequality*. Stanford, CA: Stanford University Press.

Makridakis, S., Wheelwright, S. C., & Hyndman, R. J. (1998). *Forecasting: Methods and applications*. New York, New York: John Wiley & Sons.