MODELING TRENDS IN EMERGENCY ROOM DRUG ABUSE EPISODES

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1 Introduction

The Drug Abuse Warning Network (DAWN) is a reporting system designed to be an early warning indicator of the nature and extent of the drug abuse problem in the United States. Data on hospital emergency room (ER) episodes involving the abuse of licit and illicit drugs are processed monthly by the Substance Abuse and Mental Health Services Administration (SAMHSA). The DAWN sample consists of a panel of approximately 500 participating hospitals located throughout the coterminous United States. The panel sample has virtually 100-percent overlap from month to month, with exceptions due primarily to sample attrition (non-response and ER closings) and the recruitment of newly eligible hospitals. The current sample has a 50-percent overlap with the hospital sample used prior to 1988, and preliminary weighted estimates have been produced for the 1978-87 period. For additional information, see Fairchild, Hughes, and Gruberg (1993) and NIDA (1992).

The secular trends and seasonal variations have long been important issues requiring attention when examining data collected from the DAWN ER sample. The purpose of this research is to apply time series analysis methods to the DAWN data to identify seasonal patterns, trends, or cycles in the data. The research reported in this paper led to the development of seasonal adjustment factors, examination of the auto-correlation structure of the data, and the development of a time series model. This research was supported by the National Institute on Drug Abuse (NIDA) under Contract Number NO1DA-3-5100.

2 Historical Data

The key data used in this analysis are episodes motivated by suicide, mentions of cocaine, and mentions of heroin/morphine in ER episodes. Suicide episodes are about half of all episodes, and cocaine and heroin/morphine are mentioned in about half of the non-suicide episodes. As shown in Figure 1 (left scale), suicide episodes have grown slowly over the years from around 13,000 per month in the early years to around 16,000 in the later years, with large month to-month variations. Monthly heroin mentions in episodes hovered around 1,000 in the early years of the survey, gradually rose to 4,000 by the middle of 1989, and after a decline to 3,000 in 1991, nearly

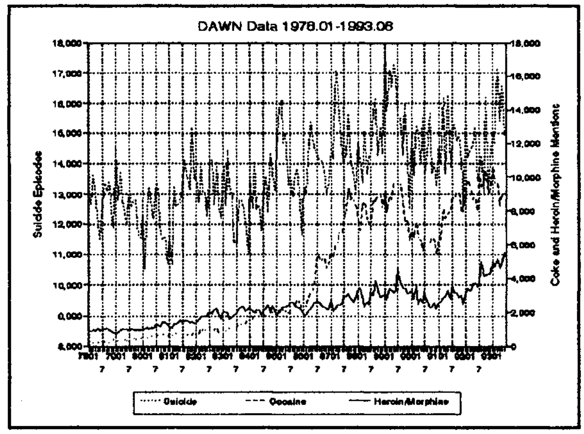

Figure 1

doubled to over 6,000 in early 1993. Heroin mentions outnumbered cocaine mentions by a margin of 2 to 1 from 1978 through the end of 1982.

Cocaine mentions grew at the same rate as heroin/morphine mentions from 1978 through 1982. They increased rapidly in 1983 and 1984 and were equal in number to heroin mentions by March of 1984, and the increasing trend continued through the end of 1985. Then in 1986, cocaine mentions exploded. In less than 18 months, mentions more than tripled, from under 3,000 to over 9,000, a level reached in several months from September 1987 through August 1989. This reflects the crack cocaine epidemic widely reported in the press. Heroin/morphine mentions rose more gradually, doubling over a 36 month period. After declines from the middle of 1989 through the end of 1990, mentions of both cocaine and heroin/morphine have increased again. While there has been an increasing trend in suicide episodes, it is neither as sharp or as dramatic as the increase in heroin/morphine and cocaine mentions.

3 Methodology

One goal of time series analysis of survey data is to increase the precision of the estimates through the use of analysis of repeated surveys, modeling seasonality and trends, and sampling error in a single model. The application of time series methods to periodic surveys was pioneered by Scott and Smith (1974) and was extended by Scott, Smith, and Jones (SSJ) (1977) to cover complex survey designs, including partially overlapping surveys. This methodology has been extended and applied in the United States to develop new methods for estimating monthly employment and unemployment for 39 States and the District of Columbia for the Current Population Survey (CPS) (Tiller 1992a). The model adopted by Bell and Hillmer (1987) and by Tiller (1992a, 1992b) is a basic structural model (BSM) as defined by Harvey (1989). This paper analyzes both the standard ARIMA model and the BSM, following the approach set forth by Bell (1993).

Traditional time series methods model survey data as if there were no sampling error using ARIMA methods. To illustrate, let Y_t be the observations in a time series, where $t = 1, ..., n$, which will be the logarithms of the original series in this paper. Let the structure of the time series be

$$Y_t = x_t \beta + Z_t \qquad (1)$$

where $x'_t\beta$ is a linear regression function and Z_t is the stochastic part of Y_t. The regression variables in this function may be used as needed to account for outliers and shifts in the level of a series. The ARIMA model of the stochastic term (Z_t) used in the analysis is written in the form

$$\phi(B)(1-B)(1-B^{12})Z_t = \theta(B)(1-\theta_{12}B^{12})a_t \qquad (2)$$

where B is the backshift operator (i.e., $BZ_t = Z_{t-1}$), ϕB and θB are the nonseasonal AR and MA operators, $(1-B^{12})$ and $(1-\theta_{12}B^{12})$ are the seasonal operators, and a_t is white noise. The specific differencing and seasonal forms are explored using standard diagnostics for each data series.

Harvey (1989) shows that each ARIMA model has a BSM counterpart of the form

$$Z_t = S_t + T_t + I_t \qquad (3)$$

where the stochastic term is decomposed explicitly into seasonal (S), trend (T), and irregular components (I). Tiller (1992b) expands this model to include regressor components as in Eq. (1) above, to allow for outliers, trend shifts due to changes in survey design, and the like. A central advantage of the BSM over the ARIMA is that alternative models of the components can be tested explicitly to incorporate prior information on sampling variance (Bell and Hillmer, 1987, Tiller, 1992a and 1992b) or alternative specifications of seasonality (Bell 1993). The structural equations models are estimated using the Kalman filter technique.

The BSM models have been shown to be powerful in modeling series that include sampling error, but are not necessarily superior for seasonal adjustment of data. Tiller (1992b) tested alternative models that included sampling error, ignored sampling error, and assumed that sampling error followed a first order autoregressive process. Not surprisingly, he found the models ignoring sampling error to overstate the trend variance, and the model using a first order autoregressive process to overstate the noise. He concluded that the results might have important implications for seasonal adjustments. On the other hand, Bell (1993) concluded that the BSM models provided a poor fit to the time series subjected to seasonal adjustment by the Census Bureau. Thus the relative merits of ARIMA and BSM models may differ with the data analyzed and the purposes of the analysis.

4 Tests of Stationary

Stationarity is essential to the estimation of ARIMA models. Stationarity means that the mean, variance, and autocovariances of the data series are constant over time and do not depend on the time period (t) (Harvey 1989). Most time series can be reduced to stationarity by appropriate differencing. In annual data, first differences may suffice, while in monthly data, differences of other orders may be needed. In this analysis, the stationarity of the series was assessed by use of the augmented Dicky-Fuller test (ADF) and by examination of the correlogram or autocorrelation function of the data. The autocorrelation function is

$$r(\tau) = c(\tau)/c(0), \tau = 0,1,2,... \qquad (4)$$

$$c(\tau) = T^{-1}\sum (y_t - \bar{y})(y_{t-\tau} - \bar{y}), \tau = 1,2,3,... \qquad (5)$$

$$c(0) = T^{-1}\sum (y_t - \bar{y})^2 \qquad (6)$$

The sample autocorrelation for a given time period (Eq 4) is the covariance function for that time period (Eq 5) divided by variance of sample as a whole (Eq 6). If the sample is stationary, then autocorrelations for successive time periods should converge to zero quickly.

To illustrate the autocorrelation analysis, Figure 2 presents three correlograms of the autocorrelations

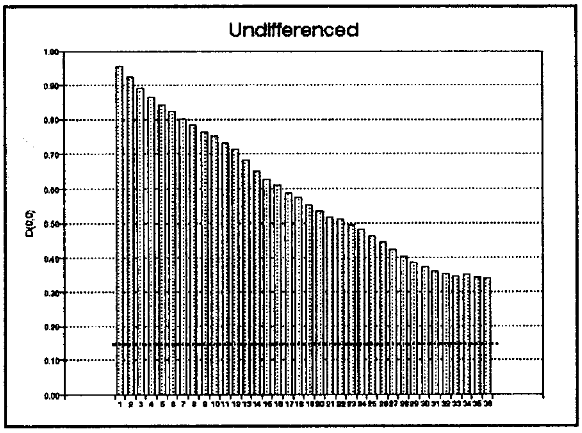

Figure 2a

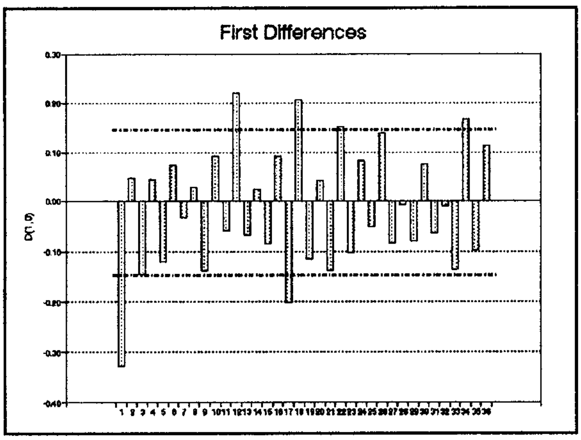

Figure 2b

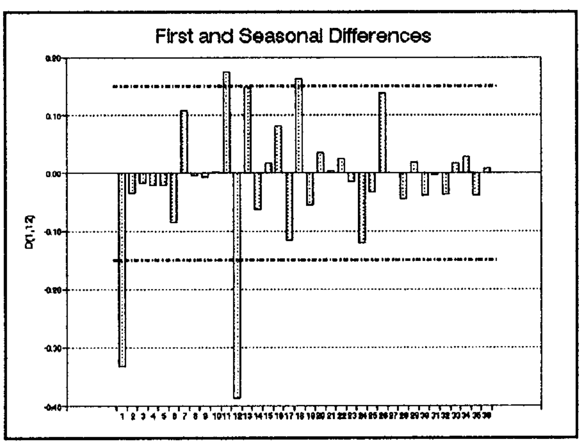

Figure 2c

and partial autocorrelations for heroin/morphine mentions: the undifferenced series (Fig 2a), the series differenced once (*B)* (Fig 2b), and the series differencing once and seasonally (*B, B^{12}*) (Fig 2c). The null hypothesis is that all autocorrelations are zero, implying that the series is white noise. One standard test is the Box-Pierce Q statistic, defined as

$$Q=n\sum r_j^2$$

where *n* is the number of observations, *r* is the j-th correlation, and the summation is from j-1 to *p*, the total number of correlations. The statistic is distributed as chi-squared with *p* degrees of freedom.

In the undifferenced series, the autocorrelations do not decay at all. In the first differenced series, the autocorrelations do decay but the Q test, shows the presence of residual autocorrelation. The seasonally-differenced series (1,12) show strong negative residual correlations, especially at lags 1 and 12. Similar analyses were conducted for cocaine mentions and suicide episodes, with similar results.

5 ARIMA Models

The three data series shown in Figure 1 have quite different time trend patterns, and one might expect standard time series (ARIMA) models to have quite different results. This section of the paper compares model estimates across the series. Models that fit all of the data well are ARIMA(1,1,0) with a seasonal component. That is, the models after differencing once have a strong first order autoregressive term AR(1) and a seasonal autoregressive term SAR(12). No moving average terms improve either the overall model or the forecasts. A separate analysis of seasonality (Fairchild, et al., 1993) showed modest but similar patterns of seasonality in all drug-related ER visits.

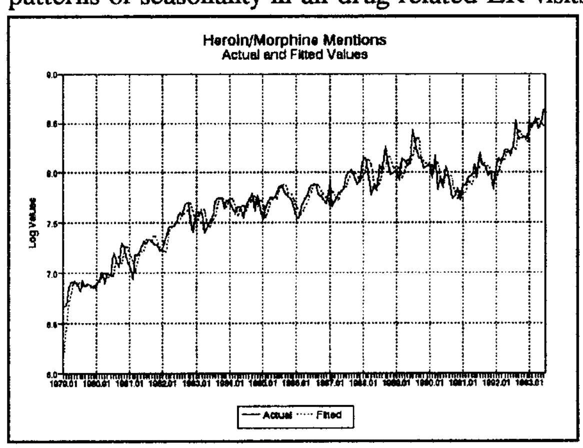

Figure 3

Figure 3 shows, for heroine/morphine, the actual and fitted values for the series to the data for 1979.01 through 1992.12. The fitted values show in Figure 3 are one-step ahead forecasts, using the actual values from all prior periods to fit each period. The charts suggest that the fits are quite close for all three series, and by the analysis of residuals (not shown here) showed that all residuals lie within three standard errors. The residuals for suicide episodes and their standard error were smaller than for heroin/morphine or cocaine. The models were then used to prepare both fitted and forecast values for the out-of-sample period from 1993.01 to 1993.06. Whereas the fitted values use the actual data for each prior period to estimate the current month (and fitting errors are self-correcting), the forecast values use the forecast data for each period (and forecast errors are cumulative).

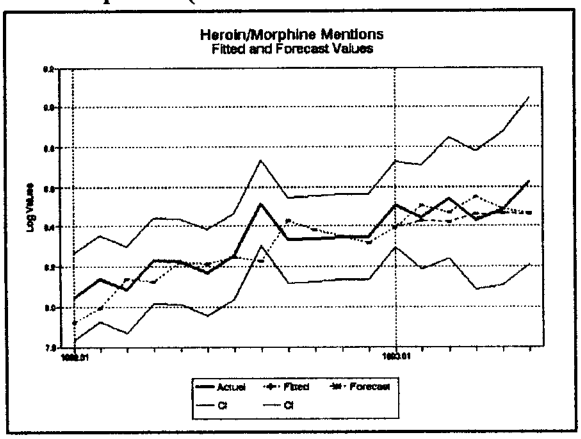

Figure 4

The results for heroin/morphine are shown in Figure 4, which shows fitted values from 1992.01 through 1993.06 and out-of-sample forecasts for 1993.01 through 1993.06. The out-of-sample forecasts were nearly as good as the fitted values. The root mean square error (RMSE) of estimate for the fitted values in the out-of-sample period was 0.093. While the RMSE of the forecast was only slightly higher (0.108), but as can be seen in Figure 4, the forecasts were biased below the actual values. Nonetheless, the mean absolute error (MAE) was 0.077 for the fitted values and only slightly higher (0.090) for the forecast values. For cocaine mentions and suicide episodes (not shown here), the RMSEs and MAEs of the forecast values were nearly double those of the fitted values. Prior analysis (Fairchild, et al., 1993) suggests that the accuracy of the forecast depends on the starting month, with some starting months producing more bias than others.

6 Discussion

The simple ARIMA models presented in this paper show that time series models can fit the DAWN data for drug-related emergency room visits with accuracy that differs by substance (heroin/morphine or cocaine) and by motivation for drug use (suicide). The differences in forecast accuracy are not surprising. Indeed, given the quite different time patterns of the data, it is surprising that the model accuracy is so similar. The end goal of this analysis is to combine the time series modeling with sampling error modeling to produce a consistent method of estimation that can improve the accuracy of DAWN estimates for individual metropolitan areas, drugs, and population subgroups. That analysis will fit BSM models and use autocorrelation functions and error estimates each group separately.

REFERENCES

Bell, W.R., and Hillmer, S.C., (1987), "Time Series Methods for Survey Estimation," Bureau of the Census Statistical Research Division Report Series, #CENSUS/SRD/RR-87/20.

Bell, W.R., (1993), "Empirical Comparisons of Seasonal ARIMA and ARIMA Component (Structural) Time Series Models", *American Statistical Association: 1993 Proceedings of the Business and Economic Statistics Section*, pp. 226-231.

Box, G.E.P. and Jenkins, G.M. (1976) *Time Series Analysis: Forecasting and Control.* San Francisco: Holden Day.

Brookoff, D., Campbell, E.A., and Shaw, L.M. (1993), "The Underreporting of Cocaine-Related Trauma: Drug Abuse Warning Network Reports vs. Hospital Toxicology Tests," *American Journal of Public Health*, 83, 3, 369-371.

Dickey, E.B., and Fuller, W.A. (1979), "Distribution of the Estimators for Autoregressive Time Series with Unit Root," *Journal of the American Statistical Association*, 74, 427-431.

Fairchild, C.K., Hughes, A.L., and Gruberg, R.E., (1993), "Estimating time series models for emergency room episodes involving drugs," *1992 Proceedings of the Section on Survey Research Methods, American Statistical Association*, 892-7.

Harvey, A.C., (1989), *Forecasting, structural time series models and the Kalman filter.* (Cambridge: Cambridge University Press).

Judge, G.G., Griffiths, W.E., Hill, R.C., Lutkepol, H., and Lee, T.C.,1985, *The Theory and Practice of Econometrics.* New York, John Wiley and Sons.

Kendall, M. and Ord, J.K. *Time Series Third Edition.* New York: Oxford University Press.

National Institute on Drug Abuse (NIDA, 1992), *Annual Emergency Room Data 1991*, DHHS No. (ADM) 92-1955, Series 1, Number 11-A.

QMS (1990), *MicroTSP User's Manual.* Irvine, California: Quantitative Micro Software.

Scott, A.J. and Smith, T.M.F. (1974), "Analysis of Repeated Surveys Using Time Series Methods," *Journal of the American Statistical Association*, 69, 674-678.

Scott, A.J., Smith, T.M.F., and Jones, R.G. (1977), "The Application of Time Series Methods to the Analysis of Repeated Surveys," *International Statistical Review*, 45, 13-28.

Tiller, R. (1992a), "A Kalman Filter Approach to Labor Force Estimation Using Survey Data", *1992 Proceedings of the Business and Economic Statistics Section, American Statistical Association*, 16-25.

Tiller, R. (1992b), "A Time Series Approach to Small Area Estimation", *1992 Proceedings of the Section on Survey Research Methods, American Statistical Association*, 10-17.