ABSTRACT

This paper presents a time-series methodology for testing the impact of the American Academy of Pediatrics (AAP) recommendation that healthy infants be put to sleep on their side or back to reduce the risk of Sudden Infant Death Syndrome (SIDS). The effect of both this intervention and seasonality are tested using 32 months of infant mortality data from the white and non-white population from Philadelphia.

INTRODUCTION

In April 1992, the American Academy of Pediatrics (AAP) recommended that healthy infants be put to sleep on their side or back to reduce the risk of Sudden Infant Death Syndrome (SIDS). While a number of opinions exist on the efficacy of this recommendation, no statistical analysis heretofore had examined any subsequent changes in SIDS rates. However, Gibson and Fleming, et al. (1995) tested changes in SIDS rates for white and non-white populations in two major metropolitan areas using the Box and Tiao time-series intervention model.

This paper presents the SAS® programming code for both the DATA step and statistical PROC along with the model estimated, including output statistics from SAS’ PROC ARIMA to test before and after SIDS rates by quarter. Rates are normalized by the annual birth rate for the white and non-white population in Philadelphia to mitigate changes due to births. The DATA step is presented to prepare 32 quarters of SIDS data to compare rates prior to the first half of 1992 versus subsequent quarters through 1994.

The model itself is examined using PROC ARIMA to test 1) the intervention effect subsequent to the AAP recommendations; 2) the seasonality effect, i.e., the increase during the winter quarter for the first three months of the year; and 3) the autoregressive/moving average components of the error structure.

Discussion includes the theoretical ARIMA model and the results with interpretation and testing of the model parameters in relation to their standard errors. Since the model is analyzed in terms of the natural logarithm of the SIDS rates, results are interpreted through percentage changes emanating from the intervention and seasonality. This examination demonstrates how time-series intervention analysis can be used to contribute to epidemiological research.

METHODS

This paper uses time-series intervention methodology by Box and Tiao (1981) to examine the intervention’s impact on SIDS mortalities. This paper examines 32 quarters of SIDS mortality data from January, 1987 through December, 1994 to quantify the impact of the intervention.

In addition to Box and Tiao (1981), Wei (1990), McDowall et al. (1980), and Vandaele (1983) have demonstrated examples of this form of time-series intervention analysis to model the effects of some intervention factor.

Improper aggregation of data can distort conclusions used for policy analysis. Consequently, the time-series methodology in this study incorporates quarterly data that provides more exact parameter estimation, i.e., better quantification of effects, than from aggregated (annual) information (Wei, 1990).

Examination of quarterly data also provides the opportunity to quantify statistically the effects of seasonality on mortality, holding its effects constant when quantifying the effect of the intervention.

Model. The time-series model uses quarterly information to determine a “before” baseline level and “after” effect, as a “quasi-experimental” design described by Campbell and Stanley (1966). It also examines the existence of a seasonal effect, i.e., if the first
quarter of each year in Philadelphia (January through March) has a higher number of deaths than the other three quarters. The evaluation model also considers that data collected at equal intervals are autocorrelated, i.e., correlated with previous data points.

Errors (residuals) resulting from the often used ordinary least squares (OLS) regression are often times autocorrelated, a major violation of the OLS assumption. OLS estimation of parameters becomes inefficient, providing estimators without minimum error. In contrast, the Box–Tiao (Wei, 1990) intervention analysis is based on the Box–Jenkins autoregressive, integrated, moving average (ARIMA) model that specifically considers the time-dependent nature of the data to produce efficient estimation of relationships including interventions.

ARIMA specifically models dependent variables as a function of itself lagged from previous period(s) — autocorrelation; and random errors lagged from previous period(s) — moving average. A fundamental assumption that was tested in the current study, is that the time-series is stationary, i.e., has an equal mean and variance.

To quantify the impact of both the intervention and seasonality in percentage terms specifically, the natural logarithms of the dependent variable was computed from the natural logarithm of the quarterly death rate per 10,000 annual live births. In instances when no deaths occurred in the quarter, one death was assumed since there is no natural log of 0.

The following ARIMA equation includes the effect of the intervention on the dependent variables after June 30, 1992:

\[ Z_t = \mu + \phi \omega I_t + \omega S S_t + \frac{\theta}{\phi} a_t \]

\( Z_t \) is the dependent variable representing the natural logarithm of SIDS deaths per 10,000 annual births and \( \omega \) is the average number of deaths in the non-winter, prior to the intervention. \( \omega \) is the abrupt effect of the intervention on the dependent variable during the subsequent ten quarters, i.e., the percentage change after the intervention. \( I_t \) is a dummy vector with a value of 0 for quarters prior to June, 1992 and 1 thereafter for the ten quarters through December, 1994.

Intervention effects were modelled for quarters using a dummy vector where:

\[ I_t = 0, t <= 22 \text{ (January, 1987 - June, 1992) } \]

\[ 1, t >= 23 \text{ (July, 1992 - December, 1994) } \]

\( S_t \) is the effect of seasonality comparing the effect of winter on the dependent variable to non-winter quarters, i.e., the percentage change from non-winter to winter. \( S_t \) is the dummy vector coded for months in winter quarters according to:

\[ S_t = 1, \text{(January - March) } \]

\[ 0, \text{(April - December) } \]

The right-hand side of the right-hand part of the equation represents the ARIMA noise process. The \( a_t \) represents a stationary (with 0 mean and constant variance), white noise (0 covariance between error lags) process. \( B \) is the backshift operator, and the \( \phi \) and \( \theta \) are the coefficients of the noise model moving average and autoregressive factors, respectively. Values of the coefficients are subject to requirements of invertibility and stationarity. See, e.g., Wei (1990); Vandaele (1983).

The right-hand side of the right-hand part of the equation represents the ARIMA noise process. The \( a_t \) represents a stationary (with 0 mean and constant variance), white noise (0 covariance between error lags) process. The program uses a method based on maximum likelihood to estimate parameters after obtaining initial values from conditional least squares (SAS Institute, 1988). The program uses a method based on maximum likelihood to estimate parameters after obtaining initial values from conditional least squares (SAS Institute, 1988). \( \chi^2 \) statistics are presented for each model that test the model's goodness-of-fit, i.e., the lack of autocorrelation in the residuals and remaining white noise process.
in the estimated residuals in accordance with the Ljung–Box \( Q \)-statistic.

**DATA STEP.** The following program code was used to input the data for whites and non-whites, including the mortality statistics by quarter. IF-THEN statements were used to provide annual births for the mortality rate computations. Date functions were used to create the intervention and seasonality variables. The ..... is used to represent data from 1969 through 1993, for purposes of brevity.

**SAS PROGRAM CODE.** NOTE THAT DATA HAVE BEEN REPLACED BY 'X' BECAUSE PUBLICATION IS PENDING FOR THIS RESEARCH.

```
DATA RESID.SIDS; /*CREATING THE DATA SET TO BE ANALYZED*/;
  INPUT DATE WHITE NONWHITE;
  INFORMAT DATE YYQ4.;
  IF DATE GT '30JUN92' THEN INTER=1; ELSE INTER=0; /*CREATING INTERVENTION*/;
  IF QTR(DATE)=1 THEN SEASON=1; ELSE SEASON=0; /*CREATING SEASONALITY*/;
  IF YEAR(DATE)=1987 THEN WBIRTH=XXXXX;
  ELSE IF YEAR(DATE)=1988 THEN WBIRTH=XXXXX;
  ELSE IF YEAR(DATE)=1989 THEN WBIRTH=XXXXX;
  ELSE IF YEAR(DATE)=1990 THEN WBIRTH=XXXXX;
  ELSE IF YEAR(DATE)=1991 THEN WBIRTH=XXXXX;
  ELSE IF YEAR(DATE)=1992 THEN WBIRTH=XXXXX;
  ELSE IF YEAR(DATE)=1993 THEN WBIRTH=XXXXX;
  ELSE IF YEAR(DATE)=1994 THEN WBIRTH=XXXXX;
  IF WHITE=0 THEN LWRAT=LOG(1/WBIRTH*10000); /*ADJUSTING FOR 0 DEATHS*/;
  ELSE LWRAT=LOG(WHITE/WBIRTH*10000); /*CREATING WHITE DEP VAR*/;
  IF YEAR(DATE)=1987 THEN NBIRTH=XXXXX;
  ELSE IF YEAR(DATE)=1988 THEN NBIRTH=XXXXX;
  ELSE IF YEAR(DATE)=1989 THEN NBIRTH=XXXXX;
  ELSE IF YEAR(DATE)=1990 THEN NBIRTH=XXXXX;
  ELSE IF YEAR(DATE)=1991 THEN NBIRTH=XXXXX;
  ELSE IF YEAR(DATE)=1992 THEN NBIRTH=XXXXX;
  ELSE IF YEAR(DATE)=1993 THEN NBIRTH=XXXXX;
  ELSE IF YEAR(DATE)=1994 THEN NBIRTH=XXXXX;
  IF NONWHITE=0 THEN LBRATIO=LOG(1/NBIRTH*10000); /*ADJUSTING FOR 0 DEATHS*/;
  ELSE LBRATIO=LOG(NONWHITE/NBIRTH*10000); /*CREATING NON-WHI DEP VAR*/;
CARDS:
87Q1 X XX
87Q2 X XX
87Q3 X XX
87Q4 X XX
88Q1 X XX
88Q2 X XX
88Q3 X XX
88Q4 X XX
.... X XX
.... X XX
.... X XX
```
The following program code was used to test the effect of the intervention and seasonality for the white population. A macro variable DEPVAR was created for generalized testing. This first model for whites includes a test without the autoregressive and moving average terms. The second model for whites includes a test with the autoregressive terms, lags 1 and 7 that were found to be statistically significant. This demonstrates the need for the Box–Jenkins error specification. The 0 in parentheses indicates that no differencing is needed to create stationarity.

OPTIONS PAGENO=1;
%LET DEPVAR=LWRATIO;
PROC ARIMA DATA=RESID.SIDS;
IDENTIFY VAR=&DEPVAR(O) CROSSCOR=(INTER(O) SEASON(O)) NLAG=4 NOPRINT;
ESTIMATE INPUT=(INTER SEASON) ML;
TITLE1 "ANALYSIS OF LWRATIO FOR LOG OF WHITE DEATHS PER 10,000";
TITLE2 "ANALYSIS WITHOUT ANY AR/MA TERMS";
RUN;

PROC ARIMA DATA=RESID.SIDS;
IDENTIFY VAR=&DEPVAR(O) CROSSCOR=(INTER(O) SEASON(O)) NLAG=4 NOPRINT;
ESTIMATE P=(1)(7) INPUT=(INTER SEASON) ML;
TITLE2 "ANALYSIS WITH ANY AR/MA TERMS";
RUN;

Similarly, the following program code was used to test the effect of the intervention and seasonality for the non–white population. This first model for non–whites includes a test without the autoregressive and moving average terms. The second model for non–whites includes a test with the moving average term, lag 3 that was found to be statistically significant. This also demonstrates the need for the Box–Jenkins error specification.

PROC ARIMA DATA=RESID.SIDS;
IDENTIFY VAR=&DEPVAR(O) CROSSCOR=(INTER(O) SEASON(O)) NLAG=4 NOPRINT;
ESTIMATE INPUT=(INTER SEASON) ML;
TITLE1 "ANALYSIS OF LWRATIO FOR LOG OF NON–WHITE DEATHS PER 10,000";
TITLE2 "ANALYSIS WITHOUT ANY AR/MA TERMS";
PROC ARIMA DATA=RESID.SIDS;
IDENTIFY VAR=&DEPVAR(O) CROSSCOR=(INTER(0) SEASON(0)) NLAG=4 NOPRINT;
ESTIMATE Q=(3) INPUT=(INTER SEASON) ML;
TITLE2 "ANALYSIS WITH AR/MA TERMS";
RUN;

RESULTS

Whites. The results for the white population can be seen in Appendix 1. Page 1 presents the results without correcting autocorrelation. The $\chi^2$ statistics are presented in the Autocorrelation Check of Residuals that test the model's goodness-of-fit, i.e., the lack of autocorrelation in the residuals. The p-values reveal at each lag of 6 reveal statistically significant autocorrelation that should be corrected. Page 2 presents the results after the autocorrelation has been corrected.

NUM1 and NUM2 representing the intervention and seasonality effects, respectively, are statistically significant p<.005 for the one-tailed tests. The t-ratio is computed as the ratio of the estimated parameter to its approximate standard error.

The intervention caused a significant reduction in the SIDS rate. Winter SIDS rates are higher than those in other seasons. A supplemental analysis revealed that no statistical interaction exists between the intervention and seasonality, i.e., the effect of winter did not change after the intervention.

The percentage impact of the intervention can be estimated with this coding scheme by subtracting (e raised to the estimated parameter for NUM1) from 1. Conversely, the percentage impact of seasonality can be estimated with this coding scheme by subtracting 1 from (e raised to the estimated parameter for NUM2).

Non-whites. The results for the white population can be seen in Appendix 2. Page 1 presents the results without correcting autocorrelation. The $\chi^2$ statistics are presented in the Autocorrelation Check of Residuals that test the model's goodness-of-fit. The p-values reveal at each lag of 6 reveal statistically significant autocorrelation that should be corrected. Page 2 presents the results after the autocorrelation has been corrected.

NUM1 and NUM2 representing the intervention and seasonality effects, respectively, are statistically significant p<.005 and p<.01 for the one-tailed tests.

As found for whites, the intervention caused a significant reduction in the SIDS rate. Winter SIDS rates are higher than those in other seasons. A supplemental analysis revealed that no statistical interaction exists between the intervention and seasonality, i.e., the effect of winter did not change after the intervention.

CONCLUSIONS

This study demonstrates how a methodology traditionally used in economic analyses on observational data can be used for epidemiological purposes. This particular study presents a policy analysis using the powerful tool of intervention analysis and PROC ARIMA. The methodology provides a more exact quantification of an intervention. Hopefully, further epidemiologic research will use this tool with observational data when pure "experimental design" is not feasible due to practical and ethical considerations.

REFERENCES


Statistics, Data Analysis, and Modeling


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APPENDIX 1

ANALYSIS OF IMRATIO FOR LOG OF WHITE DEATHS PER 10,000
ANALYSIS WITHOUT ANY ARIMA TERMS

ARIMA Procedure

Maximum Likelihood Estimation

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Std Error</th>
<th>T Ratio</th>
<th>Lag</th>
<th>Variable Shift</th>
</tr>
</thead>
<tbody>
<tr>
<td>MU</td>
<td>0.70963</td>
<td>0.13957</td>
<td>5.08</td>
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<td>IMRATIO 0</td>
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<tr>
<td>NUM1</td>
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<td>0.22183</td>
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<td>INTER 0</td>
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<tr>
<td>NUM2</td>
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<td>0.23746</td>
<td>1.58</td>
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</table>

Constant Estimate = 0.70962809

Variance Estimate = 0.33626756

Std Error Estimate = 0.7999852

AIC = 58.7668439

BIC = 63.1840515

Number of Residuals = 32

Correlations of the Estimates

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter</th>
<th>IMRATIO</th>
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<td>MU</td>
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<td>0.078</td>
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<td>SEASON</td>
<td>NUM2</td>
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<td>0.078</td>
<td>1.000</td>
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</table>

Autocorrelation Check of Residuals

<table>
<thead>
<tr>
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</tr>
<tr>
<td>24</td>
<td>27.04</td>
<td>24</td>
<td>0.025</td>
</tr>
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</table>

Model for variable IMRATIO

Estimated Intercept = 0.70962809

Input Number 1 is INTER.

Overall Regression Factor = -0.29885

Input Number 2 is SEASON.

Overall Regression Factor = 0.374571

1323
### Analysis of LWRatio for Log of White Deaths per 10,000

**Analysis with any AR/MA terms**

**ARIMA Procedure**

**Maximum Likelihood Estimation**

<table>
<thead>
<tr>
<th>Parameter</th>
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<th>T Ratio</th>
<th>Log</th>
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<tr>
<td>AR1,1</td>
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<td>0.17237</td>
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**Constant Estimate** = 1.33074802

**Variance Estimate** = 0.23105655

**Std Error Estimate** = 0.48068342

**AIC** = 51.7234367

**BIC** = 59.0521162

**Number of Residuals** = 22

#### Correlations of the Estimates

<table>
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<th>Variable</th>
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#### Autocorrelation Check of Residuals

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<tbody>
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<tr>
<td>24</td>
<td>23.05</td>
<td>22</td>
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**Model for variable LWRatio**

Estimated Intercept = 0.60925805

**Autoregressive Factors**

Factor 1: $1 + 0.36771 B^{(1)}$

Factor 2: $1 + 0.59699 B^{(7)}$
**APPENDIX 2**

**ANALYSIS OF LBRATIO FOR LOG OF NON-WHITE DEATHS PER 10,000**

**ANALYSIS WITHOUT ANY AR/MA TERMS**

**ARIMA Procedure**

**Maximum Likelihood Estimation**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
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<th>t Ratio</th>
<th>Lag</th>
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<tr>
<td>NUM2</td>
<td>0.28713</td>
<td>0.11450</td>
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<td>0</td>
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**Constant Estimate = 2.35425234**

**Variance Estimate = 0.07818731**

**Std Error Estimate = 0.27961991**

**AIC = 12.1052494**

**SBC = 16.5024572**

**Number of Residuals = 32**

**Correlations of the Estimates**

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**Autocorrelation Check of Residuals**

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<td>-0.199 -0.007 0.002 0.149 0.021 -0.245</td>
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</tbody>
</table>

**Model for variable LNRATIO**

**Estimated Intercept = 2.35425234**

**Input Number 1 is INTER.**

**Overall Regression Factor = -0.21567**

**Input Number 2 is SEASON.**

**Overall Regression Factor = 0.287123**
ANALYSIS OF LBRATIO FOR LOG OF NON-WHITE DEATHS PER 10,000 ANALYSIS WITH AR/MA TERMS

ARIMA Procedure

Maximum Likelihood Estimation

<table>
<thead>
<tr>
<th>Approx. Parameter</th>
<th>Estimate</th>
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Variance Estimate = 0.0670655
Std Error Estimate = 0.26055948
AIC = 9.38669619
SBC = 15.2499128
Number of Residuals = 32

Correlations of the Estimates

<table>
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<tr>
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<th>Parameter</th>
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<th>LBRATIO</th>
<th>INTER</th>
<th>SEASON</th>
</tr>
</thead>
<tbody>
<tr>
<td>LBRATIO</td>
<td>MU</td>
<td>1.000</td>
<td>0.197</td>
<td>-0.497</td>
<td>-0.735</td>
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<tr>
<td>LBRATIO</td>
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<td>0.197</td>
<td>1.000</td>
<td>-0.359</td>
<td>-0.094</td>
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<tr>
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<td>NUM1</td>
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<td>-0.359</td>
<td>1.000</td>
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<tr>
<td>SEASON</td>
<td>NUM2</td>
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<td>-0.094</td>
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</table>

Autocorrelation Check of Residuals

<table>
<thead>
<tr>
<th>Lag</th>
<th>Chi Square DF</th>
<th>Prob</th>
<th>Autocorrelations</th>
</tr>
</thead>
<tbody>
<tr>
<td>6</td>
<td>1.41</td>
<td>5</td>
<td>0.923 -0.097 0.001 0.057 -0.033 0.117 -0.093</td>
</tr>
<tr>
<td>12</td>
<td>3.48</td>
<td>11</td>
<td>0.983 -0.102 0.087 -0.010 -0.095 -0.042 -0.128</td>
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<tr>
<td>18</td>
<td>5.88</td>
<td>17</td>
<td>0.994 -0.011 0.021 -0.122 -0.046 0.132 0.002</td>
</tr>
<tr>
<td>24</td>
<td>15.50</td>
<td>23</td>
<td>0.876 -0.132 0.077 -0.088 0.083 0.029 -0.210</td>
</tr>
</tbody>
</table>

Model for variable LBRATIO

Estimated Intercept = 2.34124775

Moving Average Factors

Factor 1: 1 - 0.51516 B**(3)

Input Number 1 is INTER.
Overall Regression Factor = -0.21981