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Appendix

Appendix to: Young JM, Stacey I, Dobbins TA, et al. Association between tobacco plain packaging and Quitline calls: a population-based, interrupted time-series analysis. *Med J Aust* 2014; 200: 29-32. doi: 10.5694/mja13.11070.

Association between tobacco plain packaging and Quitline calls: a population-based, interrupted time series analysis.

Supplementary material: Expanded statistical methods

Overview of ARIMA modelling

We used an ARIMA approach to model calls to the Quitline. An ARIMA model is a combination of auto-regressive (AR) and moving-average (MA) models, combined with differencing (or "Integration"). The model is specified as an ARIMA (p, d, q) model. An auto-regressive model of order p predicts a current value of an outcome from linear combinations of the p previous values, plus a residual. A moving-average model of order q predicts a value of an outcome from linear combinations of the previous q residuals, plus a residual estimated for the current observation. Both auto-regressive and moving-average models assume *stationarity*, where the series has a constant mean and variance over time. Time series can be *differenced*, where previous values of the outcome are subtracted from the current value, to induce stationarity. The number of difference operators required to induce stationarity is denoted d, and can be determined through visual inspection of the series.

We used the approach of model investigation, estimation and diagnostic checking suggested by Box, Jenkins and Reinsel.[1] We assessed stationarity of the Quitline series from plots of the series and from the augmented Dickey-Fuller test. Call volume data were differenced if required to induce series stationarity. Model diagnostics obtained from univariate models were used to nominate candidate autoregressive or moving average terms, or the SAS automated options MINIC, ESACF and SCAN were used if a combined AR and MA model (an ARMA model) was suspected. Candidate models were estimated using values of p, d and q from the previous investigation steps. Adequacy of candidate models was assessed visually and with Ljung-Box chi-square tests to test for normally distributed white noise residuals. White noise is defined as "a sequence of mutually independent and identically distributed random variables".[2]

Selection of study periods

The residuals from single ARIMA models fitted to the entire 7 year period of Quitline call data did not meet the distributional assumption of white noise. This led to selection of an eighteen month period surrounding the introduction of plain packaging for analysis,

comprising twelve months prior to and six months after 1 October 2012. This was the longest duration of Quitline calls that was available at the time of the study. As a comparator, the same period surrounding the introduction of graphic health warnings on 1 March 2006 was analysed. This provided a comparable six month period following the intervention of interest and twelve months prior to this intervention.

Model fitting strategy

The same modelling approach was used for fitting models to both data subsets. Indicator terms were created to represent the week of the introduction of plain packaging and graphic health warnings. A pulse transfer function with exponential decay was then diagnosed for each intervention using the cross-correlation plot and this was used to add the intervention term to the model.

A seasonal New Year's Eve term was created to allow for an increase in calls around the New Year period. The potential confounders of New Year's Eve, TARPs, cigarette price and number of smokers in the population were included in the models using the same approach. Where appropriate, each potential confounder was differenced to induce stationarity, and pre-whitened to remove any auto-correlation. Pre-whitening avoids spurious associations with the outcome due to both series being associated with time.[3] Suitable transfer functions were determined by assessing cross-correlation plots with the outcome variable. Where several candidate transfer functions were indicated, the most appropriate was chosen on the basis of the AIC and SBC. Potential confounders were retained in the ARIMA models regardless of their statistical significance on the basis of face validity.

The adequacy of each ARIMA model was assessed by examining the correlation plots of the model residuals, with normality of residuals assessed graphically through histograms and normal-probability plots. The white-noise assumption was assessed using Ljung-Box chi-square tests.

For the period before and after the introduction of tobacco plain packaging (Box 2), an ARIMA(1,0,0) model fitted the data as the data were stationary (d=0) with each value (number of weekly calls) correlated with the previous value (p=1, q=0). For the period before and after the introduction of graphic health warnings (Box 2), an ARIMA(2,1,0)

model fitted the data with each value correlated with the two previous values (p=2, q=0) after stationarity was induced by differencing the current and previous values (d=1). For both models, the residuals were uncorrelated and normally distributed, and all other model diagnostics indicated a suitably fitted model.

References

1. Box GEP, Jenkins GM, Reinsel GC. Time series analysis: forecasting and control. Hoboken, N.J.: John Wiley; 2008.

2. Pankratz A. Forecasting with dynamic regression models. New York: Wiley; 1991.

3. Metcalfe D, Price C, Powell J. Media coverage and public reaction to a celebrity cancer diagnosis. J Public Health. 2011 Mar 1;33(1):80–5.