

estimates of the precision using the `boot()` function. These GLM-based time series models are extensively used with longitudinal time series (Li, 1994).

As an illustration, we consider the late night fatality data discussed in Vingilis et al. (2005). The purpose of this analysis was to investigate the effect of the extension of bar closing hours to 2:00 AM that was implemented May 1, 1996. This type of intervention analysis (Box and Tiao, 1975) is known as an interrupted time series design in the social sciences (Shadish et al., 2001). The total fatalities per month for the period starting January 1992 and through to December 1999, corresponding to a time series of length $n = 84$, are shown in Figure 17.

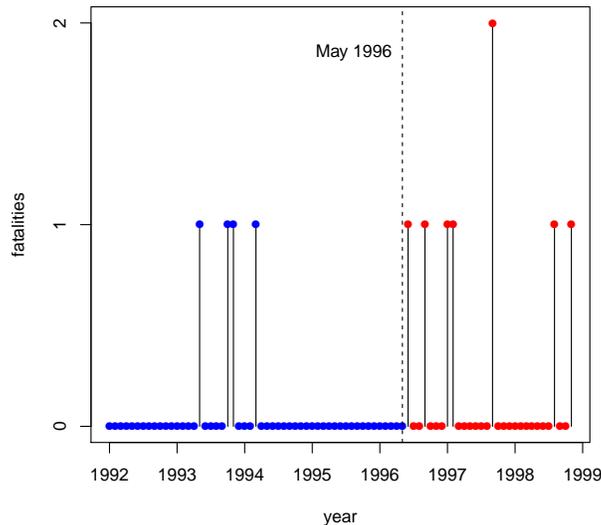


Figure 17: Late night car fatalities in Ontario. Bar closing hours were extended May 1996.

The output from the `glm()` function using `y` as the dependent variable, `y1` as the lagged dependent variable⁹, and `x` as the step intervention defined as 0 before May 1, 1996 and 1 after.

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R >summary(ans)$coefficients
```

⁹ `y` and `y1` are the vectors containing the sequence of observed fatalities and its lagged values.

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-2.53923499	0.5040873	-5.03729193	4.721644e-07
x2	1.16691417	0.6172375	1.89054329	5.868534e-02
y1	-0.06616152	0.6937560	-0.09536712	9.240232e-01

The resulting GLM model may be summarized as follows. The total fatalities per month, y_t , are Poisson distributed with mean μ_t , where $\hat{\mu}_t = \exp\{\hat{\beta}_0 + \hat{\beta}_1 x_t + \hat{\beta}_2 y_{t-1}\}$, $\hat{\beta}_0 \doteq -2.54$, $\hat{\beta}_1 \doteq 1.17$, and $\hat{\beta}_2 \doteq -0.07$. There is no evidence of lagged dependence but the intervention effect, β_2 is significant with $p < 0.10$.

We verified the standard deviation estimates of the parameters by using a non-parametric bootstrap with 1000 bootstrap samples. This computation takes less than 10 seconds on most current PC's. Table 1, produced directly from the R output using the package **xtable**, compares the asymptotic and bootstrap standard deviations. As seen from the table the agreement between the two methods is reasonably good.

	(Intercept)	x2	y1
asymptotic	0.50	0.62	0.69
bootstrap	0.49	0.66	0.75

Table 1: Comparison of asymptotic and bootstrap estimates of the standard deviations in the GLM time series regression

Hidden Markov models provide another time series generalization of Poisson and binomial GLM models (Zucchini and MacDonald, 2009).

5. Nonlinear time series models

Volatility models including the GARCH family of models are one of the newest types on nonlinear time series models. Nonlinear regression models can sometimes be applied to time series. GLM models provide an extension of linear models that is useful for modeling logistic and count time series (Kedem and Fokianos, 2002). Ritz and Streibig (2008) provides an overview of nonlinear regression models using R. Loess regression in R provides a flexible nonparametric regression approach to handling up to three inputs. Using generalized additive models (GAM), many more inputs could be