UNSW THE UNIVERSITY OF NEW SOUTH WALES

TARS Research

Never Stand Still | Science | Transport and Road Safety (TARS) Research

A Comparison of Statistical Methods in Interrupted Time Series Analysis to Estimate an Intervention Effect

Joanna Wang

Research Fellow at Transport & Road Safety (TARS)

University of New South Wales

Road Safety Research, Policing and Education (RSRPE) Conference

August, 2013

Co-authors

- Scott Walter, Centre for Health Systems and Safety Research, University of New South Wales

- Raphael Grzebieta, Transport and Road Safety, University of New South Wales

- Jake Olivier, School of Mathematics and Statistics, University of New South Wales

UNSW THE UNIVERSITY OF NEW SOUTH WALES

TARS Research

Outline

- Mandatory Helmet Legislation in NSW
- Interrupted Time Series Analysis
- Full Bayesian and Empirical Bayes methods
- Conclusions

Mandatory Helmet Law (MHL) in NSW

MHL in NSW

- Applies to all age groups
- Came into effect in two stages
  - Adults (>16): January 1, 1991
  - Children: July 1, 1991
- MHL led to much greater helmet wearing rate (>80% post law)
- Associated with fewer bicycle related head injuries
  - Solid evidence for helmet wearing in lowering bicycle related head injuries from biomechanical and epidemiological studies

A Simple Analysis

- Comparing single pre- and post-intervention does not give the full picture:
  - Ignores any trends before and after intervention
  - Ignores any cyclical patterns
  - Variances around the mean before and after intervention may be different
  - Intervention may be immediate or delayed
  - Doesn't take into account any possible autocorrelation

Interrupted Time Series (ITS)

- A type of time series where we know the specific point at which an intervention (interruption) occurred
  - ➢ No randomisation
  - ➢ Definitive pre- and post-intervention periods

- Type of quasi-experimental design
  - ➢ ‘Strongest, quasi-experimental approach for evaluating longitudinal effects of intervention’ (Wagner et al. 2002)

- Important comparisons can be made between pre- and post intervention
  - ➢ Change in level (immediate effect)
  - ➢ Change in slope (gradual effect)

A Basic Model

- Using segmented regression (Wagner et al., 2002),

$$Y_t = \beta_0 + \beta_1 \times T_t + \beta_2 \times I + \beta_3 \times T_t \times I + \varepsilon_t$$

Where

- Y_t is the outcome of interest
- T_t = ..., -2.5, -1.5, -0.5, 0.5, 1.5, 2.5,... (intervention occurs when T_t = 0
- I is a dummy variable = $\begin{cases} 0 \text{ pre-intervention} \\ 1 \text{ post-intervention} \end{cases}$
- ε_t is the random error

A Basic Model (cont'd)

- Using segmented regression (Wagner et al., 2002),

$$Y_t = \beta_0 + \beta_1 \times T_t + \beta_2 \times I + \beta_3 \times T_t \times I + \varepsilon_t$$

Where

- β_0 estimates the base level of the outcome
- β_1 estimates the base trend of the outcome (change with time in pre-intervention period)
- β_2 estimates the **change in level** in the post-intervention period (H_0: $\beta_2 = 0$)
- β_3 estimates the **change in trend** in the post-intervention period (H_0: $\beta_3 = 0$)

ITS

Threats to Internal Validity

- Factors other than the intervention may influence the dependent variable

- For instance, changes in head injury rate may due to
  - Decline in the number of cyclists
  - Construction of cycling infrastructure

- Use of a dependent, non-equivalent, no-intervention control group to account for unmeasured confounding
  - We use arm injury

- More discussion found in Olivier et al. (2013)

Model Specification for Injury Counts

- Log-linear negative binomial regression model expressed using Poisson-Gamma mixture

$$Y_i \mid \eta_i \sim Poisson\,(\eta_i \mu_i)$$

$$\eta_i \sim Gamma(\alpha, \alpha)$$

$$\begin{aligned}\log(\mu_i) = \beta_0 + \beta_1 TIME + \beta_2 INJURY + \beta_3 LAW + \beta_4 TIME \times INJURY + \beta_5 TIME \times LAW \\ + \beta_6 INJURY \times LAW + \beta_7 TIME \times INJURY \times LAW + \log(\text{exposure}), \qquad (1)\end{aligned}$$

where

-$TIME$ = -17.5, … , -0.5, 0.5, … , 17.5

-$INJURY$ is a dummy variable = $\begin{cases} 0 \text{ arm injury} \\ 1 \text{ head injury} \end{cases}$

-LAW is a dummy variable = $\begin{cases} 0 \text{ pre−MHL} \\ 1 \text{ post−MHL} \end{cases}$

- NSW population size is used as exposure

ITS

Model Specification for Injury Counts

- Log-linear negative binomial regression model expressed using Poisson-Gamma mixture

$$Y_i \mid \eta_i \sim Poisson\ (\eta_i \mu_i)$$
$$\eta_i \sim Gamma(\alpha, \alpha)$$
$$\log(\mu_i) = \beta_0 + \beta_1 TIME + \beta_2 INJURY + \beta_3 LAW + \beta_4 TIME \times INJURY + \beta_5 TIME \times LAW$$
$$+ \beta_6 INJURY \times LAW + \beta_7 TIME \times INJURY \times LAW + \log(\text{exposure}),$$

where

- β_6: any differential changes in head injuries as compared to arm injuries from pre- to post MHL
- β_7: any differences in the rate of change of head and arm injuries between pre- and post MHL

ITS

Full Bayesian Method

- The above model can be estimated using maximum likelihood approach in SAS (Walter et al., 2011)
- **Full Bayesian (FB) method** as a powerful alternative
  - ➢ Combining likelihood and prior belief to generate posterior distribution of unknown parameters
  - ➢ A non-informative prior distribution is adopted in the absence of specific prior information
- Advantages
  1. Allow estimation of models with smaller sample sizes since Bayesian methods do not depend on their asymptotic properties
  2. Ability to include prior knowledge on parameter values into the model
  3. Enables one to implement very complex hierarchical models where the likelihood function is intractable

Full Bayesian Model Estimation

- Disadvantages
  1. Posterior distributions only analytically tractable for only a small number of simple models → simulation-based Markov chain Monte Carlo (MCMC) methods
  2. MCMC methods can be computationally intensive
- We will use MCMC techniques, in particular, Gibbs sampling, by implementing the model in the WinBUGS package
- The Gibbs sampler generates a sample from the joint posterior distribution by iteratively sampling from each of the univariate full conditional distributions
- For our model (1), we assign the following non-informative prior distributions:

Regression coefficients: $\beta_i \sim Normal\,(0, 1000), \qquad i = 0, 1, \ldots, 7$

Dispersion parameter: $\alpha \sim Uniform\,(0.5, 200)$

Empirical Bayes Method

- Related to the FB method in combining current data with prior information to obtain an estimate
- The parameters of the prior distribution are estimated from existing data and then used assuming there is no uncertainty
- Extensively used in the analysis of traffic safety data, particularly for before-after evaluation of road safety treatments; need to evaluate Safety Performance Functions
- Advantage:
  - Easy to implement
  - Less computationally costly than FB
- Disadvantages:
  - Do not fully account for all uncertainties as in FB
  - May result in unrealistically small standard errors

Empirical Bayes Method

- We apply a particular EB procedure by French and Heagerty (2008)

- Fit a regression model to data prior to policy intervention and use the model to form a trajectory of outcomes in periods after intervention

$$Y_i \mid \eta_i \sim Poisson\ (\eta_i \mu_i)$$
$$\eta_i \sim Gamma(\alpha, \alpha)$$
$$\log(\mu_i) = \delta_0 + \delta_1 TIME_{PRE} + \delta_2 INJURY + \delta_3 TIME_{PRE} \times INJURY + \log(\text{exposure})$$

- Contrast post-intervention observations with their expected outcomes under the absence of a policy intervention

$$\Delta_i = \log(Y_i) - \log(\hat{\mu}_i)$$

Empirical Bayes Method

- We then model this contrast to obtain estimates for a policy effect and assess its significance by using standard statistical test

$$\Delta = \delta_4 + \delta_5 TIME_{POST} + \delta_6 INJURY + \delta_7 TIME_{POST} \times INJURY + \varepsilon$$

- δ_4 and δ_5 : baseline level and slope change for arm injuries after intervention respectively
- δ_6 and δ_7 : differential level and slope changes in head and arm injuries post-law respectively

Results

Table 1. Negative binomial model estimates using MLE, FB and EB methods

	Frequentist MLE	Full Bayesian	Empirical Bayes
Variable	Estimate (95% CI)	Estimate (95% CI)	Estimate (95% CI)
Intercept (β_0 or δ_0)	-11.470 (-11.613,-11.326)	-11.470 (-11.630,-11.320)	-11.470 (-11.601, -11.337)
TIME (β_1 or δ_1)	-0.005 (-0.019,0.009)	-0.005 (-0.020,0.009)	-0.005 (-0.018,0.007)
INJURY (β_2 or δ_2)	0.072 (-0.128,0.272)	0.071 (-0.136,0.287)	0.077 (-0.111,0.255)
LAW (β_3 or δ_4)	-0.112 (-0.318,0.093)	-0.111 (-0.330,0.106)	-0.145 (-0.314,0.024)
TIME×INJURY (β_4 or δ_3)	-0.003 (-0.022,0.016)	-0.003 (-0.023,0.017)	-0.003 (-0.021,0.014)
TIME×LAW (β_5 or δ_5)	0.015 (-0.005,0.034)	0.015 (-0.006,0.036)	0.017 (0.000,0.033)
INJURY×LAW (β_6 or δ_6)	-0.322 (-0.618,-0.027)	-0.323 (-0.635,-0.014)	-0.302 (-0.514,-0.064)
TIME×INJURY×LAW (β_7 or δ_7)	0.010 (-0.018,0.038)	0.010 (-0.021,0.040)	0.007 (-0.016,0.030)

Results

Table 1. Negative binomial model estimates using MLE, FB and EB methods

	Frequentist MLE	**Full Bayesian**	**Empirical Bayes**
Variable	Estimate (95% CI)	Estimate (95% CI)	Estimate (95% CI)
Intercept (β_0 or δ_0)	[illegible]	[illegible]	11.470 [illegible]
TIME (β_1 or δ_1)	[illegible]	[illegible]	[illegible]
INJURY (β_2 or δ_2)	[illegible] (-0.128,0.272)	0.071 (-0.136,0.287)	0.077 (-0.111,0.255)
LAW (β_3 or δ_4)	**-0.112** (-0.318,0.093)	**-0.111** (-0.330,0.106)	**-0.145** (-0.314,0.024)
TIME×INJURY (β_4 or δ_3)	-0.003 (-0.022,0.016)	-0.003 (-0.023,0.017)	-0.003 (-0.021,0.014)
TIME×LAW (β_5 or δ_5)	0.015 (-0.005,0.034)	0.015 (-0.006,0.036)	0.017 (0.000,0.033)
INJURY×LAW (β_6 or δ_6)	-0.322 (-0.618,-0.027)	-0.323 (-0.635,-0.014)	-0.302 (-0.514,-0.064)
TIME×INJURY×LAW (β_7 or δ_7)	0.010 (-0.018,0.038)	0.010 (-0.021,0.040)	0.007 (-0.016,0.030)

Negative estimate of β_3 and δ_4 indicate overall injury counts decreased after the law

FB and EB methods

Results

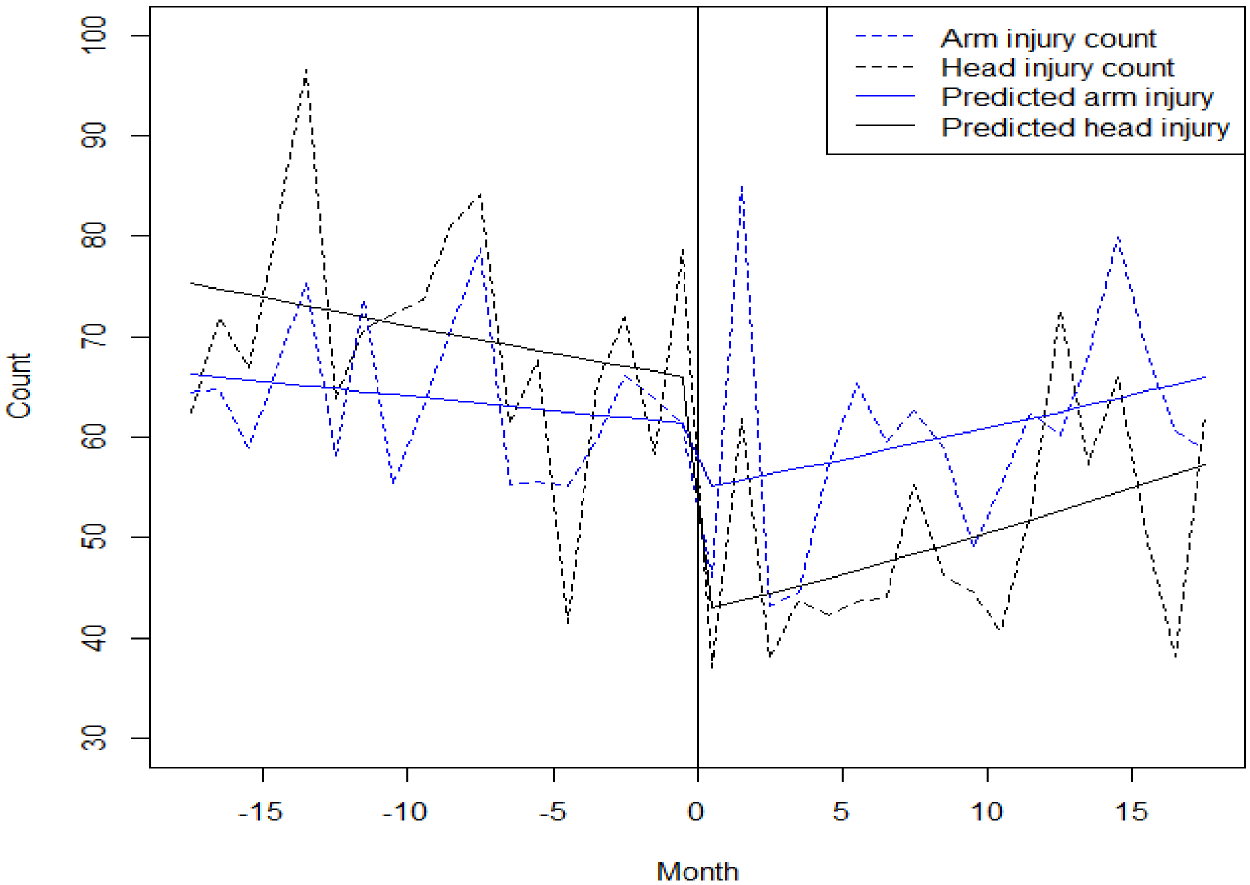
Table 1. Negative binomial model estimates using MLE, FB and EB methods

	Frequentist MLE	**Full Bayesian**	**Empirical Bayes**
Variable	Estimate (95% CI)	Estimate (95% CI)	Estimate (95% CI)
Intercept (β_0 or δ_0)	-11.470 (-11.613,-11.326)	-11.470 (-11.630,-11.320)	-11.470 (-11.601, -11.337)
TIME (β_1 or δ_1)	-0.005 (-0.019,0.009)	-0.005 (-0.020,0.009)	-0.005 (-0.018,0.007)
INJURY (β_2 or δ_2)	0.072 [illegible]	0.071 [illegible]	0.077 [illegible]
LAW (β_3 or δ_4)	[illegible]	[illegible]	[illegible]
TIME×INJURY (β_4 or δ_3)	[illegible]	[illegible]	[illegible] (-0.021,0.014)
TIME×LAW (β_5 or δ_5)	0.015 (-0.005,0.034)	0.015 (-0.006,0.036)	0.017 (0.000,0.033)
INJURY×LAW (β_6 or δ_6)	**-0.322** (-0.618,-0.027)	**-0.323** (-0.635,-0.014)	**-0.302** (-0.514,-0.064)
TIME×INJURY×LAW (β_7 or δ_7)	0.010 (-0.018,0.038)	0.010 (-0.021,0.040)	0.007 (-0.016,0.030)

Significant and negative estimate of β_6 and δ_6: head injuries dropped by more than arm injuries post-law

Results

Figure 1. Head vs. arm injury counts and fitted model (FB) for 18 months prior and post MHL



FB and EB methods

UNSW THE UNIVERSITY OF NEW SOUTH WALES

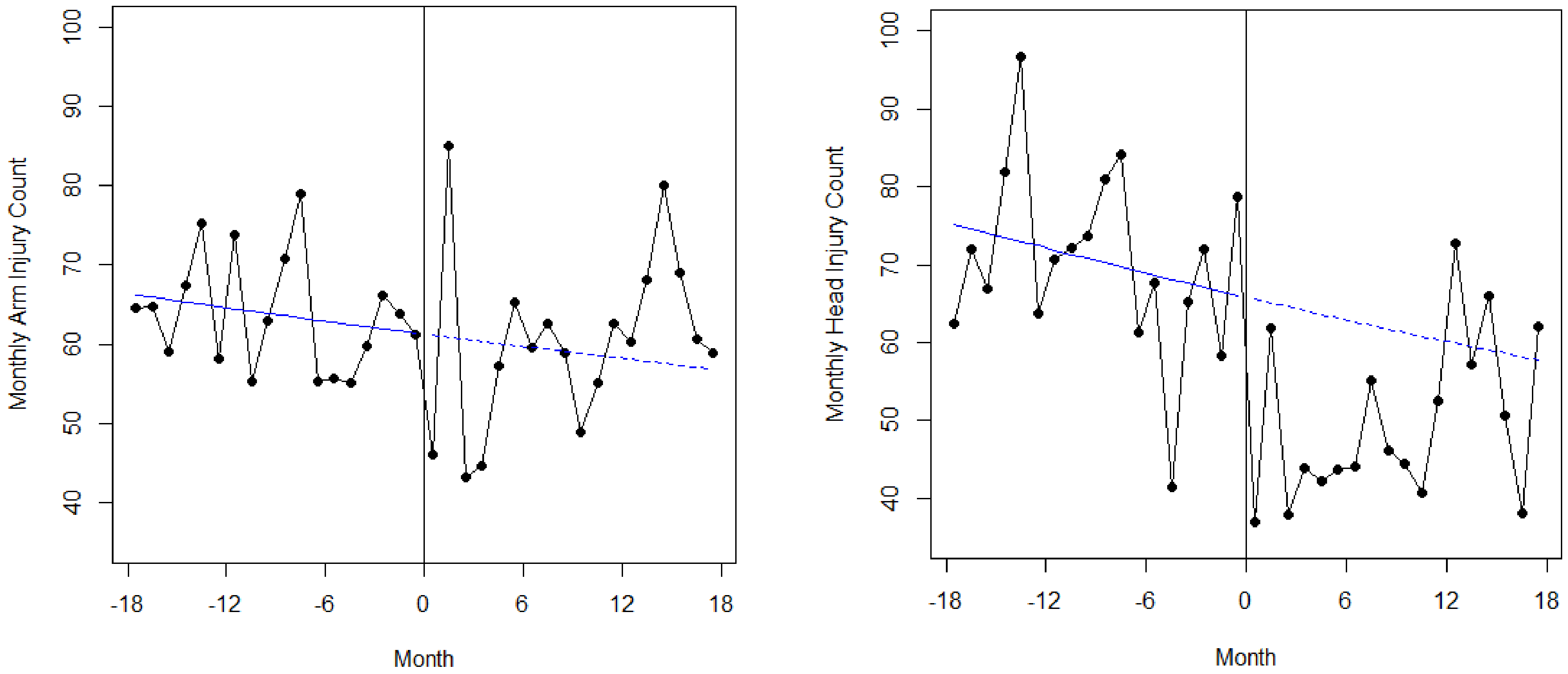
TARS Research

Empirical Bayes Results

- Parameter estimates similar to MLE and FB
- Standard errors are not directly comparable
- Mean contrasts for arm injuries does not significantly differ from zero($\hat{\delta}_4$ = -0.145, s.e.= 0.086, *p* value = 0.102)
- Mean contrasts for head injuries is significantly different from zero ($\hat{\delta}_4 + \hat{\delta}_6$ = -0.447, s.e.= 0.086, *p* value = 1.14×10^{-5})
- Significant difference between head and arm contrasts ($\hat{\delta}_6$ = -0.302, s.e.=0.122, *p*=0.019)

Results

Figure 2. Head and arm injury counts with pre-policy estimation (solid line) and post-policy prediction (dashed line)



FB and EB methods

Summary of Analysis

Conclusions

- Three estimation methods give similar results
- Statistically significant drop in cycling head injuries after MHL
- Estimated legislation attributable drop in head injuries are 27.6% and 26.1% using FB and EB methods, comparable to 27.5% in the study by Walter et al. (2011)
- Comparing to frequentist maximum likelihood and EB approaches, the FB method
  - ➢ Better accounts for uncertainty in the sample
  - ➢ Models negative binomial distribution as a hierarchical Poisson-Gamma mixture distribution; allows other distributions (eg. Poisson-Lognormal) to be implemented
  - ➢ May be computationally costly and may have convergence issues

UNSW THE UNIVERSITY OF NEW SOUTH WALES

TARS Research

References

- French, B., Heagerty, P.J. (2008) Analysis of longitudinal data to evaluate a policy change. *Statistics in Medicine* 27, 5005-5025.

- Walter, S., Olivier, J., Churches, T., Grzebieta, R. (2011). The impact of compulsory cycle helmet legislation on cyclist head injuries in New South Wales, Australia. *Accident Analysis and Prevention* 43, 2064-2071.

- Wagner, A.K., Soumerai, S.B., Zhang, F., Ross-Degnan, D. (2002). Segmented regression analysis of interrupted time series studies in medication use research. *Journal of Clinical Pharmacy and Therapeutics* 27, 299-309.

Thank you!