

# A Bayesian Meta-Analysis of Longitudinal Data in Placebo Controlled Studies with Naproxen

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## Introduction

- Naproxen is an NSAID used in the treatment of pain.
- We want to understand the time profile response for Naproxen versus placebo for the WOMAC pain endpoint in subjects with osteoarthritis (OA) pain.
- Aim to incorporate all available, relevant data into a meta-database.
- A comprehensive systematic literature search was carried out to identify suitable studies.
- Total of 15 references identified with 5 external and 10 internal studies.
- Different teams interested in responses at different time points so makes sense to apply a longitudinal model from which the relevant contrasts can be pulled.
- Using summary level (mean) data.
- Ninety four summary observations corresponding to a total of 4121 subjects (sample size range: 41-280 per group) across the 15 studies.
- A Bayesian approach is applied to meta-analysis using non-informative priors to enable probabilistic statements to be made about contrasts and parameters of interest.

## Model and Methods

A Bayesian  $E_{max}$  model was applied to the 15 studies with the basic structure given below:

$$\overline{Response}_i = E_0 - \frac{(E_{max} * time_i)}{(te_{50} + time_i)}$$

Response<sub>i</sub> = Womac pain score (0-20) for observation i.  
 $E_{max} = E_{maxp} + I(\text{naproxen}) * E_{maxn} + \beta$  (bsl - mean(bsl)).  
 $te_{50} = te_{50p} + I(\text{naproxen}) * te_{50n}$ .  
 $E_0 = \text{Base} + \eta(j)$ , where j is the study number (1-15).

Where I(Naproxen) = 1 for naproxen and 0 for placebo.  
 bsl - observed baseline WOMAC pain score.

A random effect,  $\eta(j)$ , was fitted to baseline such that  $\eta(j)$  is normally distributed mean 0, variance  $\tau^2$ .

Modelling was carried out using WinBUGS. A burn-in of 10000 iterations was used and a subsequent update of 50000 to get posterior distributions.

In addition to diagnostic plots, the WinBUGS DIC tool was used to compare 2 models for model selection by assessing the difference in Dbar for each model. This is equivalent to the difference in residual deviance.

## Priors

- All prior knowledge of naproxen/placebo response is effectively contained within the dataset being modelled.
- Expert prior knowledge would inevitably be a function of some of these data hence non-informative priors were used for the parameters (Table 1).

## Results

Table 1 also presents the posterior medians of each parameter of interest from the  $E_{max}$  model and also gives the corresponding classical parameter estimates based on the same model. Note that posterior distributions are available for each  $\eta$  (not listed here for brevity reasons as there are 15  $\eta$ 's).

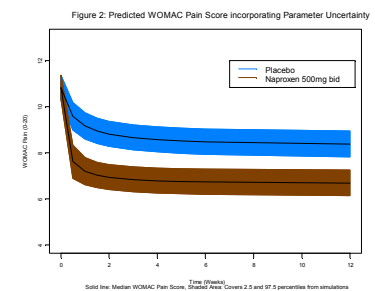
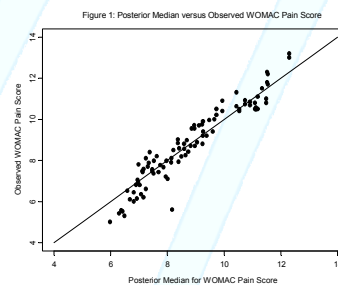
Figure 1 shows a plot of each posterior median versus the observed value which gives an overall good fit.

Figure 2 presents model predictions over time for naproxen and placebo. The bands represent the 2.5 and 97.5 percentiles.

Table 1 – Prior Distributions and Posterior Medians with Classical parameter estimates for comparison

Parameter	Prior	Bayesian Posterior Median (95% CRI*)	Classical parameter estimates (95% CI)
Base	Uniform(0, 20)	10.8 (10.3, 11.4)	10.8 (10.3, 11.3)
$E_{maxp}$	Uniform(-20, 20)	-2.6 (-2.9, -2.3)	-2.5 (-3.2, -1.8)
$E_{maxn}$	Uniform(-20, 20)	-1.6 (-1.9, -1.3)	-1.5 (-2.1, -0.9)
$te_{50p}$	Uniform(0, 24)	0.54 (0.25, 0.92)	0.67 (0.39, 0.94)
$te_{50n}$	Uniform(- $te_{50p}$ , 24) *	-0.39 (-0.76, -0.09)	-0.51 (-0.82, -0.20)
$\beta$	Normal (0, 1600)	-1.0 (-1.2, -0.8)	-0.8 (-1.5, -0.1)
tau	Uniform(0, 10)	1.02 (0.70, 1.62)	0.72 (?)

\*ensures an overall positive  $te_{50}$



- We are interested in the expected week 12, baseline adjusted, contrast for naproxen versus placebo for say 100 subjects per treatment group.
- This predictive distribution will include between study variation ( $\tau$ ) but will also take into account the uncertainty in  $\tau$ .
- The probabilities of naproxen beating placebo by at least 1, 1.5 and 2 points are summarised in Table 2.

Table 2: Probabilistic statements around the contrast (naproxen – placebo)

Difference to detect ( $\delta$ )	-1	-1.5	-2
$P(N-P) < \delta$	0.999	0.838	0.052

## Conclusions

- A Bayesian approach to a longitudinal model gave a good fit to the data and comparable parameter estimates to the classical approach.
- Direct probabilistic statements were made from the resultant posterior distributions. This was done simultaneously to the modelling itself rather than by post modelling simulation.
- Based on the posterior distribution, the median difference between naproxen and placebo at week 12 is approximately 1.7 points on a 0-20 scale with 95% credible interval (1.2, 2.2).

## Discussion

This poster covers the very first steps in developing a Bayesian  $E_{max}$  model and further work might focus on looking at:

- Subjectively weighting the evidence (e.g. giving more weight to internal studies than external ones, or weighting according to age of study).
- Internal database includes patient level data. We could combine individual and summary level data to get a better idea about covariates.
- A Bayesian approach allows for indirect treatment comparisons so could look at other studies with either placebo and naproxen where there is some other positive comparator in common.
- Assessing literature bias.