

## Chapter 8

# Random Effects Models for Repeated Binary Data

The models and methods for repeated binary data which were considered in Chapter 7 are most appropriate when the data are balanced, that is, there are  $n$  common occasions of measurement and imbalance ( $n_i \neq n$  for some  $i$ ) arises because of missing observations. When the unequal  $n_i$  arise because of inherently unbalanced data or because of clustered designs, the most natural approach is to consider extending the LMM using random effects to the GLM setting.

By analogy to the linear case, we assume each subject has a vector of subject-specific effects,  $b_i$ , and we add  $Z_i b_i$  to the linear predictor  $X_i \beta$ . Letting  $Y_i$  denote the  $n_i \times 1$  vector of binary outcomes, we have

$$E(Y_i | b_i, X_i) = \mu_i^* = g(X_i \beta^* + Z_i b_i) \quad (8.1)$$

where

$$\ell(\mu_i^*) = X_i \beta^* + Z_i b_i, \quad (8.2)$$

$\ell$  is the link function, and  $g$  the inverse link function. As before, we assume that  $E(b_i) = 0$  and  $\text{var}(b_i) = D$ . Generally, we also assume that given  $b_i$ , the  $Y_{ij}$ 's are independent.

We use the  $\mu_i^*, \beta^*$  notation to emphasize that  $\mu_i^*$  and  $\beta^*$  are conditional and not marginal parameters. Recall that for  $\mu_i, \beta$  defined in Chapters 6 and 7, we assume that

$$E(Y_i | X_i) = \mu_i = g(X_i \beta).$$

But here we have

$$E(Y_i | X_i, b_i) = \mu_i^* = g(X_i \beta^* + Z_i b_i)$$