## Problem 1

**a)** Rewriting the second expression for  $f(y|\lambda)$  we obtain

$$f(y|\lambda) = e^{y\ln\lambda - \ln(e^{\lambda} - 1) - \ln y!} = e^{y\theta - b(\theta) - c(y)}$$

where  $\theta = \ln \lambda$ ,  $\lambda = e^{\theta}$  and  $b(\theta) = \ln(e^{e^{\theta}} - 1)$ .

**b)** Differentiating  $b(\theta)$  we obtain

$$EY = \frac{e^{e^{\theta}}e^{\theta}}{e^{e^{\theta}} - 1} = \frac{\lambda e^{\lambda}}{e^{\lambda} - 1} = \frac{\lambda}{1 - e^{-\lambda}}$$

As  $\lambda \to \infty$ , the point mass  $P(Y = 0) = e^{-\lambda}$  that we remove when truncating the distribution becomes negligable, so we should expect the mean to approach the mean if the distribution was not trucated, that is,  $\lambda$ .

This indeed happens as

$$\lim_{\lambda \to \infty} \frac{EY}{\lambda} = \lim_{\lambda \to \infty} \frac{1}{1 - e^{-\lambda}} = 1.$$

## Problem 2

a) The model assumes that the number of covid cases

$$Y_i \sim \text{Poisson}(\mu_i)$$

where

$$\ln \mu_i = \beta_0 + \beta_1 \ln x_i$$

for at school i = 1, 2, ..., n where  $x_i$  is the number of pupils at school i.

The parameter estimates are  $\hat{\beta}_0 = -3.36$  and  $\hat{\beta}_1 = 1.037$ .

If we assume that the pupils at a particular school contract covid independently of each other with the same probability  $p_i$ , then  $Y_i$  would follow a binomial distribution. But because  $p_i$  is quite small it is reasonable to approximate this distribution with a Poisson distribution.

b) Under the null hypothesis of no overdispersion, the deviance D is chi-square with n-p = 8-2 = 6 degrees of freedom. We reject  $H_0$  for large values of D. Hence the critical value is 12.59. Since the observed value is 14.28 we reject  $H_0$  in favour of the alternative that ther is overdispersion.

An estimate of the overdisperion parameter  $\varphi$  is  $\hat{\varphi} = D/(n-p) = 2.38$ .

Adjusting for overdispersion, the standard errors of  $\hat{\beta}_0$  and  $\hat{\beta}_1$  change to  $0.77\sqrt{2.38} = 1.1888$  and  $0.1221\sqrt{2.38} = 0.1883$ , respectively.

A possible mechanism would be that different pupils (within a particular school) do not contract covid-19 independently but with positive dependency. This would inflate the binomial variance (the variance of a sum of indicator variables) (which we have approximated by a Poisson variance).

c) The estimated relationship between the expected number of cases and the number of pupils is

$$E(Y_i) = e^{\beta_0 + \beta_1 \ln x_i} = 0.03 x_i^{1.034},$$

that is, almost direct proportionality between  $E(Y_i)$  and  $x_i$ .

A possible simplification would be to build perfect proportionality into the model by instead including  $\ln x_i$  as an offset by changing the linear predictor to

$$\ln \mu_i = \beta_0 + \ln x_i.$$

An interpretation of  $\beta_0$  is that the expected rate of infection is

$$\frac{EY_i}{x_i} = e^{\beta_0}$$

Relying on the standard error adjusted for overdispersion, we can test this null hypothesis of perfect proportionality against the fitted model using the Wald test stastic

$$T = \frac{\hat{\beta}_1 - 1}{\operatorname{SE}(\hat{\beta}_1)} = \frac{0.0368}{0.1883} = 0.1954.$$

which is smaller than the  $t_{0.025,6} = 2.44$  in absolute value. Hence we do not reject  $H_0$ .

## Problem 3

a) For child  $j = 1, 2, ..., n_i$  of mother i = 1, 2, ..., m, we assume that the outcomes (birth delivered at hospital or elswhere), conditinal on the random mother effect  $\gamma_i$ , are independently distributed as

$$Y_{ii}|\gamma_i \sim \text{Bernoulli}(\pi_i)$$

where

$$\operatorname{logit} \pi_{ij} = \beta_0 + \beta_1 \ln(\operatorname{income}_{ij}) + \beta_2 \operatorname{dist}_{ij} + \beta_3 \operatorname{dropout}_i + \beta_4 \operatorname{college}_i + \gamma_i$$

where dropout<sub>i</sub> and  $college_i$  are 0/1-dummy variables indicating whether the *i*th mother dropped out of schools and finished collega education, respectively.

We also assume that the random mother effects  $\gamma_1, \ldots, \gamma_m$  are iid  $N(0, \tau^2)$ . The parameter estimates are  $\hat{\beta}_0 = -3.29, \hat{\beta}_1 = 0.55, \ldots, \hat{\beta}_4 = 1.02$  and  $\hat{\tau}^2 = 1.251$ . b) To test the signicance of the random intercept term, involves  $H_0$ :  $\tau^2 = 0$  versus  $H_1$ :  $\tau^2 > 0$ . Since  $H_0$  is on the boundary of the parameter space,

$$LRT = 2(l_1 - l_0)$$

where  $l_0$  and  $l_1$  are the maximum log-likelihoods under each alternative is distributed as a 50% : 50% mixture of chi-squares with 0 and 1 degree of freedom.

The critical value c satisfies

$$P(LRT > c) = \frac{1}{2}(\chi_0^2 > c) + \frac{1}{2}(\chi_0^2 > c) = \alpha$$

implying that  $c = \chi^2_{1,2\alpha} = 6.63$ .

Based on the observed value of

$$LRT = 2(-524.6 - (-537.5)) = 25.8$$

we thus reject  $H_0$  and conclude that there is evidence in the data for a difference between the different mothers.

c) For a given mother, that is, conditional on  $\gamma_i$ , we have

logit 
$$P(Y_{ij} = 1 | \gamma_i) = \mathbf{x}_{ij}^T \boldsymbol{\beta} + \gamma_i.$$

Hence, the effect of a unit change in  $\text{college}_{ij}$ , is that the log odds of birth delivery to a hospital changes by  $\beta_4$ , and the odds changes by a odds ratio of  $e^{\beta_4} = e^{1.023} = 2.78$ , that is, the odds increases by 178%. This interpretation is exact.

If we consider the average effect, we have the approximate relation

$$P(Y_{ij} = 1) = \int P(Y_{ij} = 1|\gamma_i) f(\gamma_i) d\gamma_i$$
$$= \int \frac{1}{1 + e^{-(\mathbf{x}_{ij}^T \boldsymbol{\beta} + \gamma_i)}} f(\gamma_i) d\gamma_i$$
$$\approx \frac{1}{1 + e^{-\mathbf{x}_{ij}^T \boldsymbol{\beta} / \sqrt{1 + .6\tau^2}}}$$

or equivalently,

logit 
$$P(Y_{ij} = 1) \approx \mathbf{x}_{ij}^T \boldsymbol{\beta} / \sqrt{1 + .6\tau^2}$$

see Agresti (2002), p. 499. Thus, marginally, the odds of birth sdelivery at hospital changes approximately by a factor of  $e^{1.023/\sqrt{1+0.6\cdot 1.25}} = 2.16$ , that is, under the marginal model, the odds increases by 116% (as opposed to by 178% conditionally for a given mother).

## Problem 4

a) Assuming equal strengths of both players, the probability of a white win is

$$P(Y_i = 1) = P(Y_i \le 1) = \Phi(\theta_1) = \Phi(-.2894) = 0.3861,$$

the probability of a draw is

 $P(Y_i = 2) = P(Y_i \le 2) - P(Y_i \le 1) = \Phi(\theta_2) - \Phi(\theta_1) = \Phi(0.8827) - \Phi(-.2894) = 0.4251,$ 

and a black win has

$$P(Y_i = 3) = 1 - P(Y \le 2) = 1 - \Phi(\theta_2) = 0.1886.$$

**b)** The model corresponds to the assumption that the event  $Y_i = r$  occurs if  $\theta_{r-1} < u_i \le \theta_r$ ,  $u_i = \alpha_{j(i)} - \alpha_{k(i)} + \varepsilon_i$ ,  $\varepsilon_i \sim N(0, 1)$  and  $\theta_0 = -\infty$  and  $\theta_3 = \infty$ , since this implies  $P(Y_i \le r) = \Phi(\theta_r + \alpha_{j(i)} - \alpha_{k(i)})$ .

If a white and black win has equal probabilities  $(H_0)$ ,

$$\Phi(\theta_1) = 1 - \Phi(\theta_2).$$

The cdf of the standard normal has the property  $\Phi(x) = 1 - \Phi(-x)$ . Thus the null hypothesis corresponds to the linear hypothesis

$$\theta_1 = -\theta_2.$$

This can also be seen from the latent variable interpretation of the model, the latent variable

$$u_i = \underbrace{\alpha_{j(i)} - \alpha_{k(i)}}_{=0} + \underbrace{\varepsilon_i}_{\sim N(0,1)}$$

clearly falls below  $\theta_1$  (win to white) or above  $\theta_2$  (a win black) when  $\theta_1$  and  $\theta_2$  are located symmetrically around 0. This null hypothesis can be written on the form

$$C\beta = d$$

where  $\mathbf{C} = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}$  and  $\mathbf{d} = 0$ .

To test this null hypothesis we use

$$\mathbf{C}\hat{\boldsymbol{\beta}} - \mathbf{d} = \hat{\theta}_1 + \hat{\theta}_2$$

as the starting point. This random variable has

$$\operatorname{Var}(\hat{\theta}_1 + \hat{\theta}_2) = \operatorname{Var}\hat{\theta}_1 + \operatorname{Var}\hat{\theta}_2 + 2\operatorname{Cov}(\hat{\theta}_1, \hat{\theta}_2)$$

Hence, relying on approximate/asymptotic normality of  $\hat{\boldsymbol{\beta}}$ ,

$$Z = \frac{\hat{\theta}_1 + \hat{\theta}_2}{\sqrt{\operatorname{Var}(\hat{\theta}_1 + \hat{\theta}_2)}}$$

is asymptotically/approximately N(0,1) under  ${\cal H}_0.$  The observed value becomes

$$\frac{-.2894 + .8827}{\sqrt{0.0417 + 0.0528 + 2 \cdot 0.0176}} = 1.64$$

which is not in the critical region |Z| > 1.96 of a two sided test. Hence, the data do not provide sufficient evidence to conclude that there is any difference in the winning chances when playing with white versus black pieces.