

# Dissecting the illegal ivory trade: an analysis of ivory seizures data

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## Supporting Text S1: Details of models

### Model for number of illegal ivory transactions

Let  $y_{ikt}$  be the number of reported seizures in country  $i = 1, \dots, 68$ , ivory class  $k = 1, \dots, 6$  and year  $t = 1, \dots, 16$  and

$$y_{ikt} \sim \text{NegBin}(p_{ikt}, r_k) \text{ where } 0 < p_{ikt} < 1 \text{ and } r_k > 0$$

so that  $E[y_{ikt}] = \frac{r_k(1-p_{ikt})}{p_{ikt}} = \mu_{ikt} = \lambda_{ikt} \phi_{it} \theta_{it}$  where  $\lambda_{ikt} \geq 0$  is the expected number of unobserved class  $k$  ivory transactions in country  $i$  and year  $t$  and  $0 \leq \phi_{it} \leq 1$  is the seizure rate and  $0 \leq \theta_{it} \leq 1$  the reporting rate. Then we model the number of transactions as:

$$\log(\lambda_{ikt}) = \alpha_{0ik} + \alpha_{1ik} \zeta_1(t) + \sum_{p=2}^P \alpha_{pk} \zeta_p(t)$$

where  $\zeta_p(t)$  is the  $p^{\text{th}}$  orthogonal polynomial of year  $t$ . The random effects  $\underline{\alpha}_{0i}$  and  $\underline{\alpha}_{1i}$  are modelled as

$$\underline{\alpha}_{0i} \sim \text{MVN}(\underline{\mu}_0, \Omega_0^{-1}) \text{ and } \underline{\alpha}_{1i} \sim \text{MVN}(\underline{\mu}_1, \Omega_1^{-1})$$

where the  $\Omega$ 's are  $6 \times 6$  covariance matrices. The priors for the  $\mu$ 's and  $\Omega$ 's are non-informative so that

$$\begin{aligned} \underline{\mu}_0 &\sim \text{MVN}(\underline{0}, 10^{-4} I_6) \text{ and } \underline{\mu}_1 \sim \text{MVN}(\underline{0}, 10^{-4} I_6) \\ \Omega_0^{-1} &\sim \text{Wishart}(R_0, 6) \text{ and } \Omega_1^{-1} \sim \text{Wishart}(R_1, 6) \end{aligned}$$

Choosing suitable values for the scale matrices  $R_0$  and  $R_1$  is a little problematic and we adopted the pragmatic approach suggested by Lunn et al (2013). Specifically, we chose  $R_0 = \rho \Sigma_0$ , where  $\Sigma_0$  is a prior guess at the covariance matrix and  $\rho$  is the degrees of freedom, 6 in this case;  $R_1$  was chosen in a similar way. The values used were

$$R_0 = \text{diag}(50, 50, 5, 300, 75, 25) \text{ and } R_1 = \text{diag}(15, 10, 5, 150, 50, 10).$$

We model the seizure and reporting rates as

$$\text{logit}(\phi_{it}) = \sum_m \beta_m x_{mit} \text{ for } m = 1, \dots, M$$

$$\text{logit}(\theta_{it}) = \sum_n \gamma_n z_{nit} \text{ for } n = 1, \dots, N$$

with non-informative priors for the  $\beta$ 's and  $\gamma$ 's so that

$$\beta_m \sim N(0, 10^{-4}) \text{ and } \gamma_n \sim N(0, 10^{-4})$$

The prior for the degrees of freedom  $r_k$  are modelled on a continuous scale, so that DIC can be calculated (Lunn et al 2013), and then rounded.

$$\log(r_k^*) \sim \text{Unif}(0, 10) \text{ where } r_k = \text{round}(r_k^*)$$

After convergence, we obtained  $\lambda_{ikt}^{(s)}$  for  $s = 1, \dots, 5000$  representing 5,000 draws from the

posterior distribution of  $\lambda_{ikt}$  by calculating:  $\log(\lambda_{ikt}^{(s)}) = \alpha_{0ik}^{(s)} + \alpha_{1ik}^{(s)} \zeta_1(t) + \sum_{p=2}^P \alpha_p^{(s)} \zeta_p(t)$

### Model for weight of illegal ivory seizures

We let  $w_{ik^*t}$  be the weight of ivory of the  $i^{\text{th}}$  seizure in year  $t = 1996, \dots, 2011$  and  $k^*$  denotes whether the seizure was of raw or worked ivory. Our model for weight was then

$$\ln(w_{ik^*t}) = \delta_{k^*0} + \delta_{k^*1} t + \sigma_{k^*} \varepsilon_{ik^*t}$$

The residual  $\varepsilon_{ik^*t} \sim t_{\nu_{k^*}}$  where  $t_{\nu}$  denotes the Student t-distribution on  $\nu$  degrees of freedom.

The prior for the degrees of freedom was uniform so that  $\nu_{k^*} \sim \text{Unif}(1, 30)$ , which allows

fractional values and non-informative priors for  $\delta_{k^*0}$ ,  $\delta_{k^*1}$  and  $\sigma^2$  were used:

$$\delta_{k^*0}, \delta_{k^*1} \sim N(0, 10^4), \sigma^{-2} \sim \Gamma(0.001, 0.001).$$

After convergence, 5,000 iterations were drawn from the posterior distributions of the

parameters and the predicted weights  $w_{ik^*t}^{(s)}$  ( $s = 1, \dots, 5000$ ) computed from the parameter

values:  $\log(w_{ik^*t}^{(s)}) = \delta_{0k^*}^{(s)} + \delta_{1k^*}^{(s)} t + \sigma^{(s)} \varepsilon_{ik^*t}^{(s)}, \varepsilon_{ik^*t}^{(s)} \sim t_{\nu_{k^*}^{(s)}}$ .

### References

Lunn D, Jackson C, Best NG, Thomas A, Spiegelhalter DJ (2013) *The BUGS Book* Chapman & Hall/CRC Press, London.