

Supplemental Material 1 for Lau et al., Titi monkey neophobia and visual abilities allow for fast responses to novel stimuli

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Estimation of Marginal Contrasts

Responses to experimental stimuli in the crossover design can be contrasted in a manner that is, broadly speaking, indifferent to the order of presentation, by *marginalizing* stimulus effects over order. We estimated marginal contrasts using the full model containing all experimental effects, described here for the response variable *latency to look*. If $\lambda(t; s, o)$ is the *hazard* at time t , for stimulus s , presented in order o , then the Cox Proportional Hazards model (see *e.g.* Kalbfleisch and Prentice, 2002, Chapter 4) is

$$\log \lambda(t; s, o) = \log \lambda^*(t) + \beta_s + \phi_o + \theta_{s,o} \quad (1)$$

where $\lambda^*(t)$ is the baseline hazard, β_s is the effect of stimulus s , ϕ_o is the effect of order o and $\theta_{s,o}$ is the interaction of stimulus s and order o .

Marginalizing the hazard for stimulus s over order produces a weighted average of hazards,

$$\lambda(t; s) = q\lambda(t; s, o = \text{feather first}) + (1 - q)\lambda(t; s, o = \text{feather second}),$$

in which we set $q = 1/2$ for equal weights on order of presentation. The marginal hazard using equation 1 is then

$$\lambda(t; s) = (1/2) \lambda^*(t) [\exp\{\beta_s + \phi_o + \theta_{s,o}\} + \exp\{\beta_s + \phi_{o'} + \theta_{s,o'}\}] \quad (2)$$

where o and o' correspond to feather first and feather second, respectively, and $\phi_{o'} = \theta_{s,o'} = 0$ for model identification. The marginal log hazard-ratio for two stimuli, r and s , is subsequently

$$R(r, s) = \log \frac{\lambda(t; r)}{\lambda(t; s)} = \beta_r + \log(1 + e^{\phi_o + \theta_{r,o}}) - [\beta_s + \log(1 + e^{\phi_o + \theta_{s,o}})].$$

Estimation of $R(r, s)$ proceeds by substituting estimated effects $\hat{\beta}_r, \hat{\beta}_s, \hat{\phi}_o, \hat{\theta}_{r,o}, \hat{\theta}_{s,o}$ from the fitted survival/event time model in the equation above. We obtained an approximate standard error for $R(r, s)$ by “delta method” calculations (see, *e.g.*, Stuart and Ord 1994, sections 10.5-10.7) implemented in R Language scripts available for download.

We obtained marginal survival functions for the experimental stimuli from marginal hazards (equation 2). With $\phi_{o'} = \theta_{s,o'} = 0$, equation 2 is

$$\lambda(t; s) = (1/2) \lambda^*(t) e^{\beta_s} (1 + e^{\phi_o + \theta_{s,o}}),$$

and the corresponding marginal survival function is

$$F_s(t) = \exp\left\{ - (1/2) e^{\beta_s} (1 + e^{\phi_o + \theta_{s,o}}) \int_0^t \lambda^*(u) du \right\} = [F^*(t)]^{(1/2) e^{\beta_s} (1 + e^{\phi_o + \theta_{s,o}})},$$

where $F^*(t)$ is the baseline survival function, corresponding to the control condition, with feather presented second, for model identification.

Turning to the second response variable, suppose that Y is a *duration of looking*, and

$$\lambda_{s,o} = \mathbb{E}[Y | s, o] = \sum_y y p(y | s, o)$$

is its expected value for stimulus s , presented in order o . The full negative binomial model has the form

$$\log \lambda_{s,o} = \mu + \beta_s + \phi_o + \theta_{s,o}.$$

Marginalizing over order leads to the expression

$$\mathbb{E}[Y | s] = \sum_y y [q p(y | s, o) + (1 - q) p(y | s, o')] = q \exp\{\mu + \beta_s + \phi_o + \theta_{s,o}\} + (1 - q) \exp\{\mu + \beta_s + \phi_{o'} + \theta_{s,o'}\},$$

in which we set $\phi_{o'} = \theta_{s,o'} = 0$ for model identification, and $q = 1/2$, as for *latency to look*. The log ratio of expected *durations of looking* for two stimuli, r and s , is subsequently

$$\log \frac{\mathbb{E}[Y | r]}{\mathbb{E}[Y | s]} = \beta_r + \log(1 + e^{\phi_o + \theta_{r,o}}) - [\beta_s + \log(1 + e^{\phi_o + \theta_{s,o}})],$$

formally the same as $R(r; s)$ for *latency to look*. Estimation of marginal contrasts based on the model for *duration of looking* then proceeds as for *latency to look*.

Goodness of Fit of the Models

To check the fit of the full model for *latency to look*, we examined a graph of the cumulative hazard function of the Cox-Snell residuals (as in Figure 11.1 on page 356; Klein & Moeschberger, 2005). The graph is shown as Figure S.1 below. A comparison of the cumulative hazard with the dashed, red 45-degree line suggests that the model fits well.

To check the fit of the full model for *duration of looking*, we examined a graph of the quantiles of the squared Pearson residuals from the model, *versus* corresponding quantiles of a Chi-squared distribution on one degree of freedom. The graph is shown as Figure S.2 below. Although a few large residuals are present, the model fits reasonably well.



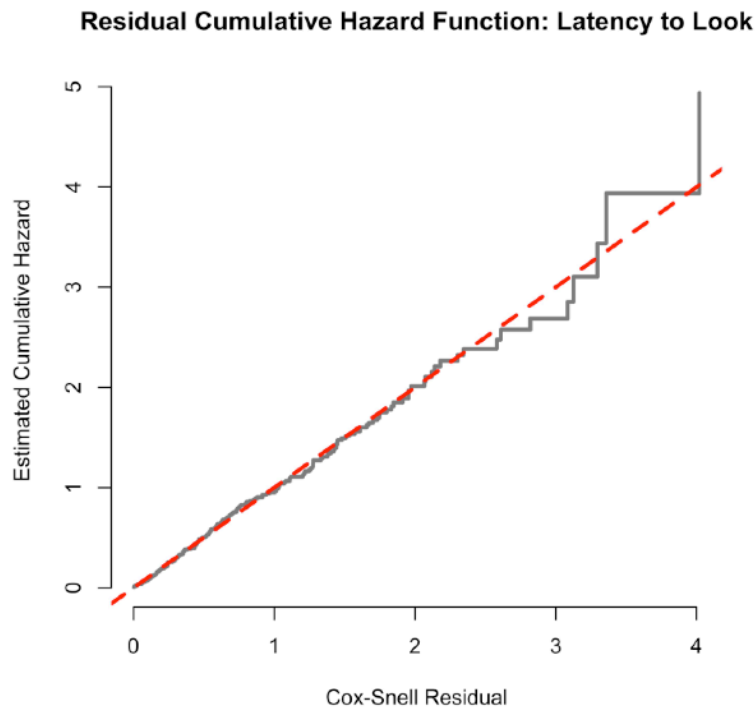


Figure S.1: Cumulative hazard function of the Cox-Snell residuals from the model for *latency to look*, along with a 45-degree line.

Figure S.2: Quantile-quantile plot, comparing squared Pearson residuals from the full model for *duration of looking* with quantiles of the Chi-squared distribution on one degree of freedom.

References

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