## **S5 Combining choice correlations and inactivation effects**

In **S3 Text** and **S4 Text**, we showed how behavioural thresholds ( $\vartheta$ ,  $\vartheta_{-\chi}$ , and  $\vartheta_{-\gamma}$ ) and multipliers on choice correlations ( $\beta_x$  and  $\beta_y$ ) depend on the relative scaling of weights ( $a_x$ ) and  $a_v$ ). Now we will combine and invert those results to provide a way to infer the scaling of weights from measurements of thresholds and choice correlations. The ratio of the multipliers  $\beta_x/\beta_y$  can be written explicitly in terms of the elements of E in **Eqn (S4.2)** in **S4 Text** as:

$$
\frac{\beta_x}{\beta_y} = \frac{(E\mathbf{a})_x}{( \mathbf{a}^{\mathrm{T}} E\mathbf{a})} \frac{(\mathbf{a}^{\mathrm{T}} E\mathbf{a})}{(E\mathbf{a})_y} = \frac{(E\mathbf{a})_x}{(E\mathbf{a})_y} = \frac{a_x \varepsilon_{xx} + a_y \varepsilon_{xy}}{a_y \varepsilon_{yy} + a_x \varepsilon_{xy}}
$$
(S5.1)

## **S5.1 Uncorrelated populations**

If populations *x* and *y* are uncorrelated, then  $\varepsilon_{xy} = 0$ . Substituting in **Eqn (S5.1)** gives

$$
\frac{\beta_x}{\beta_y} = \frac{a_x \varepsilon_{xx}}{a_y \varepsilon_{yy}} \quad \Leftrightarrow \quad \frac{a_x}{a_y} = \frac{\beta_x}{\beta_y} \frac{\varepsilon_{yy}}{\varepsilon_{xx}}
$$

If behaviour is indeed largely driven by responses along the leading modes of variance in *x* and *y*, then from **Eqn** (S3.2 – S3.3) in S3 Text, the post-inactivation thresholds are  $\vartheta_{-x}^2 \approx$  $\varepsilon_{yy}$  and  $\vartheta_{-y}^2 \approx \varepsilon_{xx}$ . This allows us to express the relative scalings of weights purely in terms of relative magnitudes of choice correlations and inactivation effects.

$$
\frac{a_x}{a_y} = \frac{\beta_x}{\beta_y} \frac{\varepsilon_{yy}}{\varepsilon_{xx}} \approx \frac{\beta_x}{\beta_y} \frac{\vartheta_{-x}^2}{\vartheta_{-y}^2}
$$
\n(S5.2)

This proves **Eqn (20)** in the main text.

## **S5.2 Correlated populations**

Let populations *x* and *y* be correlated according to  $\varepsilon_{xy} = \gamma \varepsilon_{xx}$  where  $\gamma$  denotes the strength of correlations between neurons across the populations relative to those within population *x*. We can re-write **Eqn (S5.1)** as

$$
\frac{\beta_x}{\beta_y} = \frac{a_x \varepsilon_{xx} + a_y \gamma \varepsilon_{xx}}{a_y \varepsilon_{yy} + a_x \gamma \varepsilon_{xx}} = \frac{\frac{a_x}{a_y} + \gamma}{\frac{\varepsilon_{yy}}{\varepsilon_{xx}} + \gamma \frac{a_x}{a_y}} \quad \Leftrightarrow \quad \frac{a_x}{a_y} = \left(\frac{\beta_x}{\beta_y} \frac{\varepsilon_{yy}}{\varepsilon_{xx}} - \gamma\right) \left(1 - \frac{\beta_x}{\beta_y} \gamma\right)^{-1}
$$

Once again, using  $\vartheta_{-x}^2 \approx \varepsilon_{yy}$  and  $\vartheta_{-y}^2 \approx \varepsilon_{xx}$ , we get:

$$
\frac{a_x}{a_y} = \left(\frac{\beta_x}{\beta_y} \frac{\vartheta_{-x}^2}{\vartheta_{-y}^2} - \gamma\right) \left(1 - \frac{\beta_x}{\beta_y} \gamma\right)^{-1} \tag{S5.3}
$$

This proves **Eqn (21)** in the main text.