

# Web Appendix of “Measuring Ambiguity Attitudes for All (Natural) Events”

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## Appendix WA Additional analysis of the source method

We replicate Theorem 3.5, and then give a detailed proof. AD abbreviates Abdellaoui et al. (2011) and Dimmock, Kouwenberg, & Wakker (2016).

**THEOREM 3.5.** Assume that  $a, b, p_1, p_2$  have been chosen such that Eq. 3.4 best fits the data by quadratic distance and that weak monotonicity holds. Then our index  $a$  is identical to AD’s index  $a'$ .

**PROOF.** We consider the following optimization problem:

$$\begin{aligned} \min_{\tau, \sigma, p_1, p_2} & (m_1 - \tau - \sigma p_1)^2 + (m_2 - \tau - \sigma p_2)^2 + (m_3 - \tau - \sigma(1 - p_1 - p_2))^2 \\ & + (m_{23} - \tau - \sigma(1 - p_1))^2 + (m_{13} - \tau - \sigma(1 - p_2))^2 \\ & + (m_{12} - \tau - \sigma(p_1 + p_2))^2. \end{aligned} \tag{WA.1}$$

We for now do not restrict the probabilities  $p_1, p_2$  and allow them to be any real value, so that we can apply first order conditions to them. Weak monotonicity will imply that they are still probabilities; i.e., they are nonnegative and sum to less than 1.

The first order condition of Eq. WA.1 with respect to  $\sigma$ , divided by  $-2$ , gives Eq. A.3 from the main text, renumbered here:

$$\begin{aligned} p_1(m_1 - \tau - \sigma p_1) + p_2(m_2 - \tau - \sigma p_2) + p_3(m_3 - \tau - \sigma p_3) + \\ p_{23}(m_{23} - \tau - \sigma p_{23}) + p_{13}(m_{13} - \tau - \sigma p_{13}) + \end{aligned}$$

$$p_{12}(m_{12} - \tau - \sigma p_{12}) = 0. \quad (\text{WA.2})$$

The case  $\sigma = 0$  was handled in the main text, and therefore we assume Eq. A.4 of the main text, renumbered here:

$$\sigma \neq 0. \quad (\text{WA.3})$$

To substitute the probabilities in Eq. WA.2, we consider the first order condition for  $p_1$ , divided by  $-2\sigma$ :

$$m_1 - \sigma p_1 - m_3 + \sigma(1 - p_1 - p_2) - m_{23} + \sigma(1 - p_1) + m_{12} - \sigma(p_1 + p_2) = 0. \quad (\text{WA.4})$$

That is,

$$m_1 - m_3 - m_{23} + m_{12} + 2\sigma - 2\sigma p_2 = 4\sigma p_1$$

$$4p_1 = \frac{m_1 - m_3 - m_{23} + m_{12} + 2\sigma - 2\sigma p_2}{\sigma} = \frac{m_1 - m_3 - m_{23} + m_{12}}{\sigma} + 2 - 2p_2.$$

Similarly,

$$2p_2 = \frac{m_2 - m_3 - m_{13} + m_{12}}{2\sigma} + 1 - p_1.$$

We substitute the latter formula into the preceding one:

$$4p_1 = \frac{2m_1 - 2m_3 - 2m_{23} + 2m_{12}}{2\sigma} + 2 - \frac{m_2 - m_3 - m_{13} + m_{12}}{2\sigma} - 1 + p_1.$$

$$3p_1 = \frac{2m_1 - m_2 - m_3 - 2m_{23} + m_{13} + m_{12} + 2\sigma}{2\sigma}.$$

$$3p_1 = \frac{m_{13} + m_{12} + m_{23} - m_1 - m_2 - m_3 + 3m_1 - 3m_{23} + 2\sigma}{2\sigma}.$$

$$p_1 = \frac{3(\overline{m_c} - \overline{m_s}) + 3m_1 - 3m_{23} + 2\sigma}{6\sigma} \quad (\text{WA.5})$$

(which is Eq. A.6 in the main text) and similarly Eq. A.7 of the main text is here:

$$p_2 = \frac{3(\overline{m_c} - \overline{m_s}) + 3m_2 - 3m_{13} + 2\sigma}{6\sigma}. \quad (\text{WA.6})$$

Because  $p_3 = 1 - p_1 - p_2$ , we get Eq. A.8 from the main text:

$$p_3 = \frac{3(\overline{m_c} - \overline{m_s}) + 3m_3 - 3m_{12} + 2\sigma}{6\sigma}. \quad (\text{WA.7})$$

Adding the three probabilities gives  $\frac{6\sigma}{6\sigma} = 1$ , as should be. Substituting Eqs.

WA.5-WA.7 in Eq. WA.2 and multiplying by  $6\sigma$  gives:

$$\begin{aligned}
& (3(\overline{m}_c - \overline{m}_s) + 3m_1 - 3m_{23} + 2\sigma) \left( m_1 - \tau - \frac{3(\overline{m}_c - \overline{m}_s) + 3m_1 - 3m_{23} + 2\sigma}{6} \right) + \\
& (3(\overline{m}_c - \overline{m}_s) + 3m_2 - 3m_{13} + 2\sigma) \left( m_2 - \tau - \frac{3(\overline{m}_c - \overline{m}_s) + 3m_2 - 3m_{13} + 2\sigma}{6} \right) + \\
& (3(\overline{m}_c - \overline{m}_s) + 3m_3 - 3m_{12} + 2\sigma) \left( m_3 - \tau - \frac{3(\overline{m}_c - \overline{m}_s) + 3m_3 - 3m_{12} + 2\sigma}{6} \right) + \\
& (4\sigma - 3(\overline{m}_c - \overline{m}_s) + 3m_{23} - 3m_1) \left( m_{23} - \tau - \frac{4\sigma - 3(\overline{m}_c - \overline{m}_s) - 3m_1 + 3m_{23}}{6} \right) + \\
& (4\sigma - 3(\overline{m}_c - \overline{m}_s) + 3m_{13} - 3m_2) \left( m_{13} - \tau - \frac{4\sigma - 3(\overline{m}_c - \overline{m}_s) - 3m_2 + 3m_{13}}{6} \right) + \\
& (4\sigma - 3(\overline{m}_c - \overline{m}_s) + 3m_{12} - 3m_3) \left( m_{12} - \tau - \frac{4\sigma - 3(\overline{m}_c - \overline{m}_s) - 3m_3 + 3m_{12}}{6} \right) \\
& = 0.
\end{aligned}$$

Multiplying by 6:

$$\begin{aligned}
& (3(\overline{m}_c - \overline{m}_s) + 3m_1 - 3m_{23} + 2\sigma)(3m_1 - 6\tau - 3(\overline{m}_c - \overline{m}_s) + 3m_{23} - 2\sigma) + \\
& (3(\overline{m}_c - \overline{m}_s) + 3m_2 - 3m_{13} + 2\sigma)(3m_2 - 6\tau - 3(\overline{m}_c - \overline{m}_s) + 3m_{13} - 2\sigma) + \\
& (3(\overline{m}_c - \overline{m}_s) + 3m_3 - 3m_{12} + 2\sigma)(3m_3 - 6\tau - 3(\overline{m}_c - \overline{m}_s) + 3m_{12} - 2\sigma) + \\
& (4\sigma - 3(\overline{m}_c - \overline{m}_s) - 3m_1 + 3m_{23})(3m_{23} - 6\tau - 4\sigma + 3(\overline{m}_c - \overline{m}_s) + 3m_1) + \\
& (4\sigma - 3(\overline{m}_c - \overline{m}_s) - 3m_2 + 3m_{13})(3m_{13} - 6\tau - 4\sigma + 3(\overline{m}_c - \overline{m}_s) + 3m_2) + \\
& (4\sigma - 3(\overline{m}_c - \overline{m}_s) - 3m_3 + 3m_{12})(3m_{12} - 6\tau - 4\sigma + 3(\overline{m}_c - \overline{m}_s) + 3m_3) \\
& = 0.
\end{aligned}$$

We substitute  $\tau = (\overline{m}_c + \overline{m}_s - \sigma)/2$  from Eq. A.2:

$$\begin{aligned}
& (3(\overline{m}_c - \overline{m}_s) + 3m_1 - 3m_{23} + 2\sigma)(3m_1 + 3m_{23} - 6\overline{m}_c + \sigma) + \\
& (3(\overline{m}_c - \overline{m}_s) + 3m_2 - 3m_{13} + 2\sigma)(3m_2 + 3m_{13} - 6\overline{m}_c + \sigma) + \\
& (3(\overline{m}_c - \overline{m}_s) + 3m_3 - 3m_{12} + 2\sigma)(3m_3 + 3m_{12} - 6\overline{m}_c + \sigma) + \\
& (4\sigma - 3(\overline{m}_c - \overline{m}_s) - 3m_1 + 3m_{23})(3m_{23} + 3m_1 - 6\overline{m}_s - \sigma) + \\
& (4\sigma - 3(\overline{m}_c - \overline{m}_s) - 3m_2 + 3m_{13})(3m_{13} + 3m_2 - 6\overline{m}_s - \sigma) + \\
& (4\sigma - 3(\overline{m}_c - \overline{m}_s) - 3m_3 + 3m_{12})(3m_{12} + 3m_3 - 6\overline{m}_s - \sigma) \\
& = 0.
\end{aligned}$$

It implies:

$$\begin{aligned}
& 3(\overline{m}_c - \overline{m}_s)(9\overline{m}_s + 9\overline{m}_c - 18\overline{m}_c + 3\sigma - 9\overline{m}_c - 9\overline{m}_s + 18\overline{m}_s + 3\sigma) \\
& + 9m_1^2 + 9m_1m_{23} - 18m_1\overline{m}_c + 3m_1\sigma - 9m_1m_{23} - 9m_1^2 + 18m_1\overline{m}_s + 3m_1\sigma
\end{aligned}$$

$$\begin{aligned}
& +9m_2^2 + 9m_2m_{13} - 18m_2\overline{m}_c + 3m_2\sigma - 9m_2m_{13} - 9m_2^2 + 18m_2\overline{m}_s + 3m_2\sigma \\
& +9m_3^2 + 9m_3m_{12} - 18m_3\overline{m}_c + 3m_3\sigma - 9m_3m_{12} - 9m_3^2 + 18m_3\overline{m}_s + 3m_3\sigma \\
& -9m_1m_{23} - 9m_{23}^2 + 18m_{23}\overline{m}_c - 3m_{23}\sigma + 9m_{23}^2 + 9m_1m_{23} - 18m_{23}\overline{m}_s - 3m_{23}\sigma \\
& -9m_2m_{13} - 9m_{13}^2 + 18m_{13}\overline{m}_c - 3m_{13}\sigma + 9m_{13}^2 + 9m_2m_{13} - 18m_{13}\overline{m}_s - 3m_{13}\sigma \\
& -9m_3m_{12} - 9m_{12}^2 + 18m_{12}\overline{m}_c - 3m_{12}\sigma + 9m_{12}^2 + 9m_3m_{12} - 18m_{12}\overline{m}_s - 3m_{12}\sigma \\
& +6m_1\sigma + 6m_{23}\sigma - 12\overline{m}_c\sigma + 2\sigma^2 \\
& +6m_2\sigma + 6m_{13}\sigma - 12\overline{m}_c\sigma + 2\sigma^2 \\
& +6m_3\sigma + 6m_{12}\sigma - 12\overline{m}_c\sigma + 2\sigma^2 \\
& +12m_{23}\sigma + 12m_1\sigma - 24\overline{m}_s\sigma - 4\sigma^2 \\
& +12m_{13}\sigma + 12m_2\sigma - 24\overline{m}_s\sigma - 4\sigma^2 \\
& +12m_{12}\sigma + 12m_3\sigma - 24\overline{m}_s\sigma - 4\sigma^2 \\
& = 0.
\end{aligned}$$

That is,

$$\begin{aligned}
& 3(\overline{m}_c - \overline{m}_s)(-18\overline{m}_c + 18\overline{m}_s + 6\sigma) \\
& -18m_1(\overline{m}_c - \overline{m}_s) + 6m_1\sigma \\
& -18m_2(\overline{m}_c - \overline{m}_s) + 6m_2\sigma \\
& -18m_3(\overline{m}_c - \overline{m}_s) + 6m_3\sigma \\
& +18m_{23}(\overline{m}_c - \overline{m}_s) - 6m_{23}\sigma \\
& +18m_{13}(\overline{m}_c - \overline{m}_s) - 6m_{13}\sigma \\
& +18m_{12}(\overline{m}_c - \overline{m}_s) - 6m_{12}\sigma \\
& +6m_1\sigma + 6m_{23}\sigma - 12\overline{m}_c\sigma + 2\sigma^2 \\
& +6m_2\sigma + 6m_{13}\sigma - 12\overline{m}_c\sigma + 2\sigma^2 \\
& +6m_3\sigma + 6m_{12}\sigma - 12\overline{m}_c\sigma + 2\sigma^2 \\
& +12m_{23}\sigma + 12m_1\sigma - 24\overline{m}_s\sigma - 4\sigma^2 \\
& +12m_{13}\sigma + 12m_2\sigma - 24\overline{m}_s\sigma - 4\sigma^2 \\
& +12m_{12}\sigma + 12m_3\sigma - 24\overline{m}_s\sigma - 4\sigma^2 \\
& = 0,
\end{aligned}$$

implying

$$\begin{aligned}
& 3(\overline{m}_c - \overline{m}_s)(6\sigma) + 6m_1\sigma + 6m_2\sigma + 6m_3\sigma - 6m_{23}\sigma - 6m_{13}\sigma - 6m_{12}\sigma \\
& +6m_1\sigma + 6m_{23}\sigma - 12\overline{m}_c\sigma + 2\sigma^2 \\
& +6m_2\sigma + 6m_{13}\sigma - 12\overline{m}_c\sigma + 2\sigma^2
\end{aligned}$$

$$\begin{aligned}
&+6m_3\sigma + 6m_{12}\sigma - 12\overline{m}_c\sigma + 2\sigma^2 \\
&+12m_{23}\sigma + 12m_1\sigma - 24\overline{m}_s\sigma - 4\sigma^2 \\
&+12m_{13}\sigma + 12m_2\sigma - 24\overline{m}_s\sigma - 4\sigma^2 \\
&+12m_{12}\sigma + 12m_3\sigma - 24\overline{m}_s\sigma - 4\sigma^2 \\
&= 0,
\end{aligned}$$

or, combining terms  $\sigma^2$  and dividing by 6,

$$\begin{aligned}
&3(\overline{m}_c - \overline{m}_s)\sigma + m_1\sigma + m_2\sigma + m_3\sigma - m_{23}\sigma - m_{13}\sigma - m_{12}\sigma \\
&+m_1\sigma + m_{23}\sigma - 2\overline{m}_c\sigma \\
&+m_2\sigma + m_{13}\sigma - 2\overline{m}_c\sigma \\
&+m_3\sigma + m_{12}\sigma - 2\overline{m}_c\sigma \\
&+2m_{23}\sigma + 2m_1\sigma - 4\overline{m}_s\sigma \\
&+2m_{13}\sigma + 2m_2\sigma - 4\overline{m}_s\sigma \\
&+2m_{12}\sigma + 2m_3\sigma - 4\overline{m}_s\sigma - \sigma^2 \\
&= 0,
\end{aligned}$$

which yields

$$\sigma(3\overline{m}_c - 3\overline{m}_s - \sigma) = 0.$$

Eq. WA.3 precludes  $\sigma = 0$ , and therefore the solution is

$$\sigma = 3\overline{m}_c - 3\overline{m}_s,$$

implying  $a' = 1 - \sigma = 1 - (3\overline{m}_c - 3\overline{m}_s) = a$ .

In the appendix in the main text it is shown that  $\sigma > 0$  and that the  $p_j$ 's are probabilities, which concludes the proof.  $\square$

The following lemma may be useful. It considers optimization w.r.t.  $\sigma, \tau$ , without assuming anything about the probabilities (other than that they add to 1).

LEMMA WA.1. To minimize the distance in Eq. A.1, the sign of  $\sigma$  is equal to the sign of the correlation between the probabilities  $p$  and their  $m$  values.

PROOF. We reproduce the distance to be minimized from Eq. A.1:

$$(m_1 - \tau - \sigma p_1)^2 + (m_2 - \tau - \sigma p_2)^2 + (m_3 - \tau - \sigma p_3)^2 \\ + (m_{23} - \tau - \sigma p_{23})^2 + (m_{13} - \tau - \sigma p_{13})^2 + (m_{12} - \tau - \sigma p_{12})^2.$$

The average value of the  $m$ 's, i.e.  $(\overline{m_c} + \overline{m_s})/2$ , is denoted  $\overline{m}$ . Eq. A.2 implies  $\tau = \overline{m} - \sigma/2$ . Substituting this in Eq. WA.2 implies

$$\sigma = \frac{p_1 m_1 + p_2 m_2 + p_3 m_3 + p_{23} m_{23} + p_{13} m_{13} + p_{12} m_{12} - 3\overline{m}}{(p_1^2 + p_2^2 + p_3^2 + p_{23}^2 + p_{13}^2 + p_{12}^2 - 3/2)}.$$

The denominator is always positive, taking its minimum ( $\frac{1}{6}$ ) at  $p_1 = p_2 = 1/3$ . The numerator is the covariance between the  $p$ 's and  $m$ 's.  $\square$

## Appendix WB Results excluding violations of weak monotonicity

Weak monotonicity was violated was violated by 8 subjects in part 1 only, by 4 subjects in part 2 only, and by 2 subjects in both parts. Hence, excluding the indexes when weak monotonicity is violated results in dropping 16 observations. Tables WB.1 and WB.2 below are equivalent to Tables 3 and 4 of the paper when these 16 observations are dropped. Unlike in Table 3, part 2 \* control treatment (capturing learning effects in the control treatment) is not significant anymore.

TABLE WB.1: ambiguity aversion indexes  $b$

	Model 1	Model 2
intercept	-0.07*	0.03
	(0.04)	(0.06)
<b>part 1 * TP treatment</b>	<b>-0.03</b>	<b>-0.04</b>
	<b>(0.05)</b>	<b>(0.05)</b>
part 2 * control treatment	-0.04	-0.04
	(0.02)	(0.02)
part 2 * TP treatment	-0.01	-0.02
	(0.05)	(0.05)
male		-0.09*
		(0.04)
Dutch		-0.08
		(0.05)
age – 20		0.01
		(0.01)
Chi2	3.89	14.40*
N	182	182

+  $p < 0.1$ , \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ . Point estimates are followed by standard errors between brackets. The impact of TP is in bold. The variable age has been recoded as age – 20 so that the intercept corresponds to the  $b$  index of a 20 year-old subject (median age)

TABLE WB.2: a-insensitivity indexes  $a$ 

	Model 1	Model 2
intercept	0.10 (0.06)	0.20* (0.10)
<b>part 1 * TP treatment</b>	<b>0.19*</b> <b>(0.08)</b>	<b>0.18*</b> <b>(0.09)</b>
part 2 * control treatment	0.06 (0.05)	0.06 (0.05)
part 2 * TP treatment	0.01 (0.08)	0.00 (0.09)
male		-0.08 (0.08)
Dutch		-0.08 (0.09)
age – 20		0.01 (0.02)
Chi2	17.72***	20.24**
N	182	182

+  $p < 0.1$ , \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ . Point estimates are followed by standard errors between brackets. The impact of TP is in bold. The variable age has been recoded as age – 20 so that the intercept corresponds to the  $a$  index of a 20 year-old subject (median age)



## Appendix WC Impact of TP on index $b$

We tested whether TP would make index  $b$  more or less extreme by running the same regressions as described in the main text on the absolute value of  $b$ . TP did not have any impact on the magnitude of  $b$ .

TABLE WC.1: absolute value of the ambiguity aversion indexes  $b$

	Model 1	Model 2
intercept	0.18*** (0.02)	0.15*** (0.04)
<b>part 1 * TP treatment</b>	<b>0.01</b> <b>(0.03)</b>	<b>0.01</b> <b>(0.03)</b>
part 2 * control treatment	0.02 (0.02)	0.02 (0.02)
part 2 * TP treatment	0.02 (0.03)	0.02 (0.03)
male		0.02 (0.03)
Dutch		0.02 (0.03)
age – 20		0.00 (0.01)
Chi2	1.19	1.94
N	198	198

<sup>+</sup>  $p < 0.1$ , \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ . Point estimates are followed by standard errors between brackets. The impact of TP is in bold. The variable age has been recoded as age – 20 so that the intercept corresponds to the  $b$  index of a 20 year-old subject (median age)