Risk and Rationality: The Relative Importance of Probability Weighting and Choice Set Dependence

— Online Appendix —

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Contents

1 Qualitative Predictions for ST

1.1 Binary Choices to Trigger Common Consequence Allais Paradoxes: Independent Payoffs

CC1.independent

$$X = \begin{cases} 2500, & p_1 \\ z, & p_2 \\ 0, & p_3 \end{cases} \quad vs \quad Y = \begin{cases} 2400, & p_1 + p_3 \\ z, & p_2 \end{cases}$$

where $z \in \{0, 2400\}$.

If $z = 2400$ the choice is:

$$X = \begin{cases} 2500, & p_1 \\ 2400, & p_2 \\ 0, & p_3 \end{cases} \quad vs \quad Y = \{2400$$

The salience rankings are $\sigma(0, 2400) > \sigma(2500, 2400) > \sigma(2400, 2400)$ since $\sigma(0, 2400) > \sigma(0, 100) = \sigma(100, 0) > \sigma(2500, 2400)$. This makes lottery Y more attractive.

If $z = 0$ the choice is:

$$X = \begin{cases} 2500, & p_1 \\ 0, & p_2 + p_3 \end{cases} \quad vs \quad Y = \begin{cases} 2400, & p_1 + p_3 \\ 0, & p_2 \end{cases}$$

The salience rankings are $\sigma(2500, 0) > \sigma(0, 2400) > \sigma(2500, 2400) > \sigma(0, 0)$ since $\sigma(2500, 0) = \sigma(0, 2500) > \sigma(0, 2400)$. This makes lottery X more attractive.

CC2.independent

$$X = \begin{cases} 5000, & p_1 \\ z, & p_2 \\ 0, & p_3 \end{cases} \quad vs \quad Y = \begin{cases} 4800, & p_1 + p_3 \\ z, & p_2 \end{cases}$$

where $z \in \{0, 4800\}$. The stake size is double relative to gambles A1.1 so the salience rankings will be the same.

If $z = 4800$ the choice is:

$$X = \begin{cases} 5000, & p_1 \\ 4800, & p_2 \\ 0, & p_3 \end{cases} \quad vs \quad Y = 4800$$

The salience rankings are $\sigma(0,4800) > \sigma(5000,4800) > \sigma(4800,4800)$ since $\sigma(0,4800) > \sigma(0,200) = \sigma(200,0) > \sigma(5000,4800)$. This makes lottery Y more attractive.

If $z = 0$ the choice is:

$$X = \begin{cases} 5000, & p_1 \\ 0, & p_2 + p_3 \end{cases} \quad vs \quad Y = \begin{cases} 4800, & p_1 + p_3 \\ 0, & p_2 \end{cases}$$

The salience rankings are $\sigma(5000,0) > \sigma(0,4800) > \sigma(5000,4800) > \sigma(0,0)$ since $\sigma(5000,0) = \sigma(0,5000) > \sigma(0,4800)$. This makes lottery X more attractive.

CC3.independent

$$X = \begin{cases} 3000, & p_1 \\ z, & p_2 \\ 500, & p_3 \end{cases} \quad vs \quad Y = \begin{cases} 2600, & p_1 + p_3 \\ z, & p_2 \end{cases}$$

where $z \in \{500, 2600\}$.

If $z = 2600$ the choice is:

$$X = \begin{cases} 3000, & p_1 \\ 2600, & p_2 \\ 500, & p_3 \end{cases} \quad vs \quad Y = 2600$$

The salience rankings are $\sigma(500,2600) > \sigma(3000,2600) > \sigma(2600,2600)$. This makes lottery Y more attractive.

If $z = 500$ the choice is:

$$X = \begin{cases} 3000, & p_1 \\ 500, & p_2 + p_3 \end{cases} \quad vs \quad Y = \begin{cases} 2600, & p_1 + p_3 \\ 500, & p_2 \end{cases}$$

The salience rankings are $\sigma(3000,500) > \sigma(500,2600) > \sigma(3000,2600) > \sigma(500,500)$ since $\sigma(3000,500) = \sigma(500,3000) > \sigma(500,2600)$. This makes lottery X more attractive.

CC4.independent

$$X = \begin{cases} 2500, & p_1 \\ z, & p_2 \\ 0, & p_3 \end{cases} \quad vs \quad Y = \begin{cases} 2400, & p_1 + p_3 \\ z, & p_2 \end{cases}$$

where $z \in \{0, 2000\}$.

If $z = 2000$ the choice is:

$$X = \begin{cases} 2500, & p_1 \\ 2000, & p_2 \\ 0, & p_3 \end{cases} \quad vs \quad Y = \begin{cases} 2400, & p_1 + p_3 \\ 2000, & p_2 \end{cases}$$

The salience rankings are $\sigma(0,2400) > \sigma(0,2000) > \sigma(2500,2000) > \sigma(2000,2400) > \sigma(2500,2400) > \sigma(2000,2000)$, since $\sigma(2500,2000) = \sigma(2000,2500) > \sigma(2000,2400)$ and $\sigma(2000,2400) > \sigma(2100,2500) = \sigma(2500,2100) > \sigma(2500,2400)$. This makes lottery Y more attractive.

If $z = 0$ the choice is:

$$X = \begin{cases} 2500, & p_1 \\ 0, & p_2 + p_3 \end{cases} \quad vs \quad Y = \begin{cases} 2400, & p_1 + p_3 \\ 0, & p_2 \end{cases}$$

The salience rankings are $\sigma(2500,0) > \sigma(0,2400) > \sigma(2500,2400) > \sigma(0,0)$ since $\sigma(2500,0) = \sigma(0,2500) > \sigma(0,2400)$. This makes lottery X more attractive.

CC5.independent

$$X = \begin{cases} 5000, & p_1 \\ z, & p_2 \\ 0, & p_3 \end{cases} \quad vs \quad Y = \begin{cases} 4800, & p_1 + p_3 \\ z, & p_2 \end{cases}$$

where $z \in \{0, 4000\}$. The stake size is double relative to gambles B1.1 so the salience rankings will be the same.

If $z = 4000$ the choice is:

$$X = \begin{cases} 5000, & p_1 \\ 4000, & p_2 \\ 0, & p_3 \end{cases} \quad vs \quad Y = \begin{cases} 4800, & p_1 + p_3 \\ 4000, & p_2 \end{cases}$$

The salience rankings are $\sigma(0,4800) > \sigma(0,4000) > \sigma(5000,4000) > \sigma(4000,4800) > \sigma(5000,4800) > \sigma(4000,4000)$ since $\sigma(0,4000) = \sigma(4000,0) > \sigma(5000,100) > \sigma(5000,4000)$ and $\sigma(4000,4800) > \sigma(4200,5000) = \sigma(5000,4200) > \sigma(5000,4800)$. This makes lottery Y more attractive.

If $z = 0$ the choice is:

$$X = \begin{cases} 5000, & p_1 \\ 0, & p_2 + p_3 \end{cases} \quad vs \quad Y = \begin{cases} 4800, & p_1 + p_3 \\ 0, & p_2 \end{cases}$$

The salience rankings are $\sigma(5000,0) > \sigma(0,4800) > \sigma(5000,4800) > \sigma(0,0)$. This makes lottery X more attractive.

CC6.independent

$$X = \begin{cases} 3000, & p_1 \\ z, & p_2 \\ 500, & p_3 \end{cases} \quad vs \quad Y = \begin{cases} 2600, & p_1 + p_3 \\ z, & p_2 \end{cases}$$

where $z \in \{500, 2000\}$.

If $z = 2000$ the choice is:

$$X = \begin{cases} 3000, & p_1 \\ 2000, & p_2 \\ 500, & p_3 \end{cases} \quad vs \quad Y = \begin{cases} 2600, & p_1 + p_3 \\ 2000, & p_2 \end{cases}$$

The salience rankings are $\sigma(500, 2600) > \sigma(500, 2000) > \sigma(3000, 2000) > \sigma(2000, 2600) > \sigma(3000, 2600) > \sigma(2000, 2000)$ since $\sigma(500, 2000) > \sigma(1000, 2000) = \sigma(2000, 1000) > \sigma(3000, 2000)$ and $\sigma(2000, 2600) = \sigma(2600, 2000) > \sigma(3000, 2400) > \sigma(3000, 2600)$. This makes lottery Y more attractive.

If $z = 500$ the choice is:

$$X = \begin{cases} 3000, & p_1 \\ 500, & p_2 + p_3 \end{cases} \quad vs \quad Y = \begin{cases} 2600, & p_1 + p_3 \\ 500, & p_2 \end{cases}$$

The salience rankings are $\sigma(3000, 500) > \sigma(2600, 500) > \sigma(3000, 2600) > \sigma(500, 500)$. This makes lottery X more attractive.

1.2 Binary Choices to Trigger Common Consequence Allais Paradoxes: Dependent Payoffs

CC1.dependent

p_s	p_1	p_2	p_3
x_s	2500	z	0
y_s	2400	z	2400

where $z \in \{0, 2400\}$. The salience rankings are $\sigma(0, 2400) > \sigma(2500, 2400) > \sigma(z, z)$ for $z \in \{0, 2400\}$. This makes lottery Y more attractive.

CC2.dependent

p_s	p_1	p_2	p_3
x_s	5000	z	0
y_s	4800	z	4800

where $z \in \{0, 4800\}$. The salience rankings are $\sigma(0, 4800) > \sigma(5000, 4800) > \sigma(z, z)$ for $z \in \{0, 4800\}$. This makes lottery Y more attractive.

CC3.dependent

p_s	p_1	p_2	p_3
x_s	3000	z	500
y_s	2600	z	2600

where $z \in \{500, 2600\}$. The salience rankings are $\sigma(500, 2600) > \sigma(3000, 2600) > \sigma(z, z)$ for $z \in \{500, 2600\}$. This makes lottery Y more attractive.

CC4.dependent

p_s	p_1	p_2	p_3
x_s	2500	z	0
y_s	2400	z	2400

where $z \in \{0, 2000\}$. The salience rankings are $\sigma(0, 2400) > \sigma(2500, 2400) > \sigma(z, z)$ for $z \in \{0, 2000\}$. This makes lottery Y more attractive.

CC5.dependent

p_s	p_1	p_2	p_3
x_s	5000	z	0
y_s	4800	z	4800

where $z \in \{0, 4000\}$. The salience rankings are $\sigma(0, 4800) > \sigma(5000, 4800) > \sigma(z, z)$ for $z \in \{0, 4000\}$. This makes lottery Y more attractive.

CC6.dependent

p_s	p_1	p_2	p_3
x_s	3000	z	500
y_s	2600	z	2600

where $z \in \{500, 2000\}$. The salience rankings are $\sigma(500, 2600) > \sigma(3000, 2600) > \sigma(z, z)$ for $z \in \{500, 2000\}$. This makes lottery Y more attractive.

1.3 Binary Choices to Trigger Common Ratio Allais Paradoxes: Independent Payoffs

CR1.independent

$$X = \begin{cases} 6000 & p = \frac{1}{2}q \\ 0 & 1 - p = 1 - \frac{1}{2}q \end{cases} \quad \text{vs.} \quad Y = \begin{cases} 3000 & q \\ 0 & 1 - q \end{cases}$$

The salience rankings are $\sigma(6000,0) > \sigma(0,3000) > \sigma(6000,3000) > \sigma(0,0)$. Hence, the decision maker evaluates lottery X as

$$\begin{aligned} V^{ST}(X) &= \left[\omega_1^{ST}(6000,0) + \omega_3^{ST}(6000,3000)\right] \ v(6000) \\ &\quad + \left[\omega_2^{ST}(0,3000) + \omega_4^{ST}(0,0)\right] \ v(0) \,. \end{aligned}$$

and lottery Y as

$$\begin{aligned} V^{ST}(Y) &= \left[\omega_2^{ST}(0,3000) + \omega_3^{ST}(6000,3000)\right] \ v(3000) \\ &\quad + \left[\omega_1^{ST}(6000,0) + \omega_4^{ST}(0,0)\right] \ v(0) \,. \end{aligned}$$

Using $v(0) = 0$ and the decision weights given by equation (2) in the paper, the decision maker prefers Y over X when

$$\begin{aligned} v(3000)\left[\delta(1-p)q + \delta^2 pq\right] &> v(6000)\left[p(1-q) + \delta^2 pq\right] \\ v(3000)\, 2\delta\left[1 - p(1-\delta)\right] &> v(6000)\left[1 - 2p(1-\delta^2)\right] \\ \frac{1-p(1-\delta)}{1-2p(1-\delta^2)} &> \frac{v(6000)}{2\delta v(3000)} \,. \end{aligned}$$

Note that when p is scaled down, the right hand side of the above inequality remains unchanged, while the left hand side decreases. Hence, for a sufficiently low λ the sign of the above inequality may change, and the decision maker prefers X to Y and exhibits the Common Ratio Allais Paradox.

CR2.independent

$$X = \begin{cases} 5500 & p = \frac{1}{2}q \\ 500 & 1-p = 1-\frac{1}{2}q \end{cases} \quad \text{vs.} \quad Y = \begin{cases} 3000 & q \\ 500 & 1-q \end{cases}$$

The salience rankings are $\sigma(5500,500) > \sigma(500,3000) > \sigma(5500,3000) > \sigma(500,500)$. Hence, the decision maker evaluates lottery X as

$$\begin{aligned} V^{ST}(X) &= \left[\omega_1^{ST}(5500,500) + \omega_3^{ST}(5500,3000)\right] \ v(5500) \\ &\quad + \left[\omega_2^{ST}(500,3000) + \omega_4^{ST}(500,500)\right] \ v(500) \,. \end{aligned}$$

and lottery Y as

$$\begin{aligned} V^{ST}(Y) &= \left[\omega_2^{ST}(500, 3000) + \omega_3^{ST}(5500, 3000)\right] \, v(3000) \\ &\quad + \left[\omega_1^{ST}(5500, 500) + \omega_4^{ST}(500, 500)\right] \, v(500) \,. \end{aligned}$$

Using the decision weights given by equation (2) in the paper, the decision maker prefers Y over X when

$$\begin{aligned} v(3000)\,[\delta(1-p)q + \delta^2 pq] + v(500)\,p(1-q) &> v(5500)\,[p(1-q) + \delta^2 pq] + v(500)\,\delta(1-p)q \\ 2p &> \frac{v(5500) - 2\delta v(3000) - (1-2\delta)v(500)}{(1-\delta^2)v(5500) - \delta(1-\delta)v(3000) - (1-\delta)v(500)} \,. \end{aligned}$$

Note that when p is scaled down, the right hand side of the above inequality remains unchanged, while the left hand side decreases. Hence, for a sufficiently low λ the sign of the above inequality may change, and the decision maker prefers X to Y and exhibits the Common Ratio Allais Paradox.

CR3.independent

$$X = \begin{cases} 7000 & p = \frac{1}{2}q \\ 1000 & 1-p = 1-\frac{1}{2}q \end{cases} \quad \text{vs.} \quad Y = \begin{cases} 4000 & q \\ 1000 & 1-q \end{cases}$$

The salience rankings are $\sigma(7000, 1000) > \sigma(1000, 4000) > \sigma(7000, 4000) > \sigma(1000, 1000)$. Hence, the decision maker evaluates lottery X as

$$\begin{aligned} V^{ST}(X) &= \left[\omega_1^{ST}(7000, 1000) + \omega_3^{ST}(7000, 4000)\right] \, v(7000) \\ &\quad + \left[\omega_2^{ST}(1000, 4000) + \omega_4^{ST}(1000, 1000)\right] \, v(1000) \,. \end{aligned}$$

and lottery Y as

$$\begin{aligned} V^{ST}(Y) &= \left[\omega_2^{ST}(1000, 4000) + \omega_3^{ST}(7000, 4000)\right] \, v(4000) \\ &\quad + \left[\omega_1^{ST}(7000, 1000) + \omega_4^{ST}(1000, 1000)\right] \, v(1000) \,. \end{aligned}$$

Using the decision weights given by equation (2) in the paper, the decision maker prefers Y over X when

$$
\begin{aligned}
v(4000)\left[\delta(1-p)q+\delta^2 pq\right]+v(1000)\,p(1-q) &> v(7000)\left[p(1-q)+\delta^2 pq\right]+v(1000)\,\delta(1-p)q \\
2p &> \frac{v(7000)-2\delta v(4000)-(1-2\delta)v(1000)}{(1-\delta^2)v(7000)-\delta(1-\delta)v(4000)-(1-\delta)v(1000)}\,.
\end{aligned}
$$

Note that when p is scaled down, the right hand side of the above inequality remains unchanged, while the left hand side decreases. Hence, for a sufficiently low λ the sign of the above inequality may change, and the decision maker prefers X to Y and exhibits the Common Ratio Allais Paradox.

1.4 Binary Choices to Trigger Common Ratio Allais Paradoxes: Dependent Payoffs

CR1.dependent

p_s	p	p	$1-2p$
x_s	6000	0	0
y_s	3000	3000	0

The salience rankings are $\sigma(0,3000) > \sigma(6000,3000) > \sigma(0,0)$. Hence, the decision maker evaluates lottery X as

$$
V^{ST}(X)=\omega_2^{ST}(6000,3000)\,v(6000)+\left[\omega_1^{ST}(0,3000)+\omega_3^{ST}(0,0)\right]\,v(0)
$$

and evaluates lottery Y as

$$
V^{ST}(Y)=\left[\omega_1^{ST}(0,3000)+\omega_2^{ST}(6000,3000)\right]\,v(3000)+\omega_3^{ST}(0,0)\,v(0)
$$

Using $v(0)=0$ and the decision weights given by equation (2) in the paper, the decision maker prefers X over Y when

$$
\begin{aligned}
v(6000)\,\delta p &> v(3000)\,(\delta p+p) \\
v(6000)\,\delta p &> v(3000)\,(\delta p+p) \\
\frac{v(6000)}{v(3000)} &> \frac{1+\delta}{\delta}\,.
\end{aligned}
$$

Hence, regardless of the value of p, the decision maker always prefers X over Y when the above inequality holds, and otherwise always prefers Y over X. Consequently, the decision maker never exhibits the Common Ratio Allais Paradox when the lotteries' payoffs are dependent of each other.

CR2.dependent

p_s	p	p	$1-2p$
x_s	5500	500	500
y_s	3000	3000	500

The salience rankings are $\sigma(500,3000) > \sigma(5500,3000) > \sigma(500,500)$. Hence, the decision maker evaluates lottery X as

$$V^{ST}(X) = \omega_2^{ST}(5500,3000)\,v(5500) + \left[\omega_1^{ST}(500,3000) + \omega_3^{ST}(500,500)\right]\,v(500)$$

and evaluates lottery Y as

$$V^{ST}(Y) = \left[\omega_1^{ST}(500,3000) + \omega_2^{ST}(5500,3000)\right]\,v(3000) + \omega_3^{ST}(500,500)\,v(500)$$

Using the decision weights given by equation (2) in the paper, the decision maker prefers X over Y when

$$\begin{aligned} v(5500)\,\delta p + v(500)\,p &> v(3000)\,(p+\delta p) \\ v(5500)\,\delta + v(500) &> v(3000)\,(1+\delta) \\ \delta &> \frac{v(3000)-v(500)}{v(5500)-v(3000)}\,. \end{aligned}$$

Hence, regardless of the value of p, the decision maker always prefers X over Y when the above inequality holds, and otherwise always prefers Y over X. Consequently, the decision maker never exhibits the Common Ratio Allais Paradox when the lotteries' payoffs are dependent of each other.

CR3.dependent

p_s	p	p	$1-2p$
x_s	7000	1000	1000
y_s	4000	4000	1000

The salience rankings are $\sigma(1000,4000) > \sigma(7000,4000) > \sigma(1000,1000)$. Hence, the decision maker evaluates lottery X as

$$V^{ST}(X) = \omega_2^{ST}(7000,4000)\,v(7000) + \left[\omega_1^{ST}(1000,4000) + \omega_3^{ST}(1000,1000)\right]\,v(1000)$$

and evaluates lottery Y as

$$V^{ST}(Y) = \left[\omega_1^{ST}(1000, 4000) + \omega_2^{ST}(7000, 4000)\right] \, v(4000) + \omega_3^{ST}(1000, 1000) \, v(1000)$$

Using the decision weights given by equation (2) in the paper, the decision maker prefers X over Y when

$$\begin{aligned} v(7000)\,\delta p + v(1000)\,p &> v(4000)\,(p + \delta p) \\ v(7000)\,\delta + v(1000) &> v(4000)\,(1 + \delta) \\ \delta &> \frac{v(4000) - v(1000)}{v(7000) - v(4000)}\,. \end{aligned}$$

Hence, regardless of the value of p, the decision maker always prefers X over Y when the above inequality holds, and otherwise always prefers Y over X. Consequently, the decision maker never exhibits the Common Ratio Allais Paradox when the lotteries' payoffs are dependent of each other.

2 Occurrence of Preference Reversals in ST

This section describes under which conditions ST describes preference reversals in the 6 binary choices of the experiment's additional part.

2.1 Choices 1 and 2

The binary lottery choices 1 and 2 are as follows:

$$\tilde{X} = \begin{cases} x \text{ with } & p \\ 0 \text{ with } & 1-p \end{cases} \quad \text{vs.} \quad \tilde{Y} = \begin{cases} 4x \text{ with } & q = p/4 \\ 0 \text{ with } & 1-q = 1-p/4 \end{cases},$$

where for choice 1 $x = 400$ and $p = 0.96$ whereas for choice 2 $x = 1600$ and $p = 0.24$. In this case we can have two possible salience rankings:

(i) $\sigma(0, 4x) > \sigma(x, 4x) > \sigma(x, 0) > \sigma(0, 0)$

(ii) $\sigma(0, 4x) > \sigma(x, 0) > \sigma(x, 4x) > \sigma(0, 0)$

We consider each case separately.

(i) If the salience ranking is $\sigma(0, 4x) > \sigma(x, 4x) > \sigma(x, 0) > \sigma(0, 0)$, then

$$\begin{aligned} V^{ST}(\tilde{X}|\{\tilde{X},\tilde{Y}\}) &= [\pi_2^{ST}(x,4x) + \pi_3^{ST}(x,0)]v(x) + [\pi_1^{ST}(0,4x) + \pi_4^{ST}(0,0)]v(0) \\ &= \left[\frac{pq\delta^2}{D} + \frac{p(1-q)\delta^3}{D}\right]v(x) + \left[\frac{(1-p)q\delta}{D} + \frac{(1-p)(1-q)\delta^4}{D}\right]v(0) \\ &= \left[\frac{pq\delta^2}{D} + \frac{p(1-q)\delta^3}{D}\right]v(x) \end{aligned}$$

and

$$\begin{aligned} V^{ST}(\tilde{Y}|\{\tilde{X},\tilde{Y}\}) &= [\pi_1^{ST}(0,4x) + \pi_2^{ST}(x,4x)]v(4x) + [\pi_3^{ST}(x,0) + \pi_4^{ST}(0,0)]v(0) \\ &= \left[\frac{(1-p)q\delta}{D} + \frac{pq\delta^2}{D}\right]v(4x) + \left[\frac{p(1-q)\delta^3}{D} + \frac{(1-p)(1-q)\delta^4}{D}\right]v(0) \\ &= \left[\frac{(1-p)q\delta}{D} + \frac{pq\delta^2}{D}\right]v(4x) \end{aligned}$$

where $D = (1-p)q\delta + pq\delta^2 + p(1-q)\delta^3 + (1-p)(1-q)\delta^4$. The ST decision maker prefers $\tilde{X}$ to $\tilde{Y}$ when

$$\left[\frac{pq\delta^2}{D} + \frac{p(1-q)\delta^3}{D}\right]v(x) > \left[\frac{(1-p)q\delta}{D} + \frac{pq\delta^2}{D}\right]v(4x),$$

or

$$p\left[q\delta + (1-q)\delta^2\right]v(x) > q\left[(1-p) + p\delta\right]v(4x),$$

or

$$\frac{p\delta\left[q + (1-q)\delta\right]}{q\left[(1-p) + p\delta\right]} > \frac{v(4x)}{v(x)},$$

or

$$\frac{p\delta\left[\frac{p}{4}+\left(1-\frac{p}{4}\right)\delta\right]}{\frac{p}{4}\left[(1-p)+p\delta\right]}>\frac{v(4x)}{v(x)},$$

or

$$\frac{\delta\left[p+(4-p)\,\delta\right]}{1-p+p\delta}>\frac{v(4x)}{v(x)}. \tag{1}$$

(ii) If the salience ranking is $\sigma(0,4x)>\sigma(x,0)>\sigma(x,4x)>\sigma(0,0)$, then

$$\begin{aligned}
V^{ST}(\tilde{X}|\{\tilde{X},\tilde{Y}\}) &= [\pi_3^{ST}(x,4x)+\pi_2^{ST}(400,0)]v(x)+[\pi_1^{ST}(0,4x)+\pi_4^{ST}(0,0)]v(0)\\
&= \left[\frac{pq\delta^3}{D}+\frac{p(1-q)\delta^2}{D}\right]v(x)+\left[\frac{(1-p)q\delta}{D}+\frac{(1-p)(1-q)\delta^4}{D}\right]v(0)\\
&= \left[\frac{pq\delta^3}{D}+\frac{p(1-q)\delta^2}{D}\right]v(x),
\end{aligned}$$

and

$$\begin{aligned}
V^{ST}(\tilde{Y}|\{\tilde{X},\tilde{Y}\}) &= [\pi_1^{ST}(0,4x)+\pi_3^{ST}(x,4x)]v(4x)+[\pi_2^{ST}(x,0)+\pi_4^{ST}(0,0)]v(0)\\
&= \left[\frac{(1-p)q\delta}{D}+\frac{pq\delta^3}{D}\right]v(4x)+\left[\frac{p(1-q)\delta^2}{D}+\frac{(1-p)(1-q)\delta^4}{D}\right]v(0)\\
&= \left[\frac{(1-p)q\delta}{D}+\frac{pq\delta^3}{D}\right]v(4x)
\end{aligned}$$

where $D=(1-p)q\delta+p(1-q)\delta^2+pq\delta^3+(1-p)(1-q)\delta^4$. The ST decision maker prefers $\tilde{X}$ to $\tilde{Y}$ when

$$\left[\frac{pq\delta^3}{D}+\frac{p(1-q)\delta^2}{D}\right]v(x)>\left[\frac{(1-p)q\delta}{D}+\frac{pq\delta^3}{D}\right]v(4x),$$

or

$$p\left[q\delta^2+(1-q)\delta\right]v(x)>q\left[(1-p)+p\delta^2\right]v(4x),$$

or

$$\frac{p\delta\left[q\delta+(1-q)\right]}{q\left[(1-p)+p\delta^2\right]}>\frac{v(4x)}{v(x)},$$

or

$$\frac{p\delta\left[\frac{p}{4}\delta+(1-\frac{p}{4})\right]}{\frac{p}{4}\left[(1-p)+p\delta^2\right]}>\frac{v(4x)}{v(x)},$$

or

$$\frac{\delta\left[p\delta+(4-p)\right]}{1-p+p\delta^2}>\frac{v(4x)}{v(x)}. \tag{2}$$

Let us now determine the value of the certainty equivalent of lottery $\tilde{X}$. This means that now we need to find out the value of lottery $\tilde{X}$ with respect to the series of sure amounts $\{0,...,x/2,...,x\}$:

$$\tilde{X}=\begin{cases} x \text{ with } & p\\ 0 \text{ with } & 1-p\end{cases} \quad \text{vs} \quad \{0,...,x/2,...,x\}.$$

Denote by $CE_{\tilde{X}}$ the certainty equivalent of lottery $\tilde{X}$. If $\sigma(x, CE_{\tilde{X}}) > \sigma(0, CE_{\tilde{X}})$, then

$$\begin{aligned} v(CE_{\tilde{X}}) &= V^{ST}(\tilde{X}|\sigma(x, CE_{\tilde{X}}) > \sigma(0, CE_{\tilde{X}})) \\ &= \pi_1^{ST}(x, CE_{\tilde{X}})v(x) + \pi_2^{ST}(0, CE_{\tilde{X}})v(0) \\ &= \frac{p\delta}{p\delta + (1-p)\delta^2}v(x) + \frac{(1-p)\delta^2}{p\delta + (1-p)\delta^2}v(0) \\ &= \frac{p\delta}{p\delta + (1-p)\delta^2}v(x) = \frac{p}{p + (1-p)\delta}v(x). \end{aligned}$$

If $\sigma(x, CE_{\tilde{X}}) = \sigma(0, CE_{\tilde{X}})$, then

$$\begin{aligned} v(CE_{\tilde{X}}) &= V^{ST}(\tilde{X}|\sigma(x, CE_{\tilde{X}}) = \sigma(0, CE_{\tilde{X}})) \\ &= \pi_1^{ST}(x, CE_{\tilde{X}})v(x) + \pi_1^{ST}(0, CE_{\tilde{X}})v(0) \\ &= \frac{p\delta}{p\delta + (1-p)\delta}v(x) + \frac{p\delta}{p\delta + (1-p)\delta}v(0) = pv(x). \end{aligned}$$

If $\sigma(x, CE_{\tilde{X}}) < \sigma(0, CE_{\tilde{X}})$, then

$$\begin{aligned} v(CE_{\tilde{X}}) &= V^{ST}(\tilde{X}|\sigma(x, CE_{\tilde{X}}) < \sigma(0, CE_{\tilde{X}})) \\ &= \pi_2^{ST}(x, CE_{\tilde{X}})v(x) + \pi_1^{ST}(0, CE_{\tilde{X}})v(0) \\ &= \frac{p\delta^2}{(1-p)\delta + p\delta^2}v(x) + \frac{(1-p)\delta}{(1-p)\delta + p\delta^2}v(0) \\ &= \frac{p\delta^2}{(1-p)\delta + p\delta^2}v(x) = \frac{p\delta}{(1-p) + p\delta}v(x). \end{aligned}$$

Hence, the value of $CE_{\tilde{X}}$ is

$$v(CE_{\tilde{X}}) = \begin{cases} \frac{p}{p+(1-p)\delta}v(x), & \text{if } \sigma(0, CE_{\tilde{X}}) < \sigma(x, CE_{\tilde{X}}) \\ pv(x), & \text{if } \sigma(0, CE_{\tilde{X}}) = \sigma(x, CE_{\tilde{X}}) \\ \frac{p\delta}{(1-p)+p\delta}v(x), & \text{if } \sigma(0, CE_{\tilde{X}}) > \sigma(x, CE_{\tilde{X}}) \end{cases}.$$

Defining as $CE_g^{\tilde{X}}$ the $CE_{\tilde{X}}$ that solves $\sigma(0, CE_{\tilde{X}}) = \sigma(x, CE_{\tilde{X}})$ we have

$$v(CE_{\tilde{X}}) = \begin{cases} \frac{p}{p+(1-p)\delta}v(x), & \text{if } p < \frac{\delta\frac{v(CE_g^{\tilde{X}})}{v(x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{X}})}{v(x)}} \\ v(CE_g^{\tilde{X}}), & \text{if } p = \frac{v(CE_g^{\tilde{X}})}{v(x)} \\ \frac{p\delta}{(1-p)+p\delta}v(x), & \text{if } p > \frac{\frac{v(CE_g^{\tilde{X}})}{v(x)}}{\delta+(1-\delta)\frac{v(CE_g^{\tilde{X}})}{v(x)}} \end{cases}. \quad (3)$$

Let us now determine the value of the certainty equivalent of lottery $\tilde{Y}$. This means that now we need to find out the value of lottery $\tilde{Y}$ with respect to the series of sure amounts $\{0, ..., 2x, ..., 4x\}$:

$$\tilde{Y} = \begin{cases} 4x \text{ with } & q = p/4 \\ 0 \text{ with } & 1-q = 1-p/4 \end{cases} \quad \text{vs} \quad \{0, ..., 2x, ..., 4x\}.$$

Denote by $CE_{\tilde{Y}}$ the certainty equivalent of lottery $\tilde{Y}$. If $\sigma(4x, CE_{\tilde{Y}}) > \sigma(0, CE_{\tilde{Y}})$, then

$$\begin{aligned} v(CE_{\tilde{Y}}) &= V^{ST}(\tilde{Y}|\sigma(4x, CE_{\tilde{Y}}) > \sigma(0, CE_{\tilde{Y}})) \\ &= \pi_1^{ST}(4x, CE_{\tilde{Y}})v(4x) + \pi_2^{ST}(0, CE_{\tilde{Y}})v(0) \\ &= \frac{q\delta}{q\delta + (1-q)\delta^2}v(4x) + \frac{(1-q)\delta^2}{q\delta + (1-q)\delta^2}v(0) \\ &= \frac{q\delta}{q\delta + (1-q)\delta^2}v(4x) = \frac{q}{q + (1-q)\delta}v(4x). \end{aligned}$$

If $\sigma(4x, CE_{\tilde{Y}}) = \sigma(0, CE_{\tilde{Y}})$, then

$$\begin{aligned} v(CE_{\tilde{Y}}) &= V^{ST}(\tilde{Y}|CE_{\tilde{Y}} < 2x, \sigma(4x, CE_{\tilde{Y}}) = \sigma(0, CE_{\tilde{Y}})) \\ &= \pi_1^{ST}(4x, CE_{\tilde{Y}})v(4x) + \pi_1^{ST}(0, CE_{\tilde{Y}})v(0) \\ &= \frac{q\delta}{q\delta + (1-q)\delta}v(4x) + \frac{q\delta}{q\delta + (1-q)\delta}v(0) \\ &= qv(4x). \end{aligned}$$

If $\sigma(4x, CE_{\tilde{Y}}) < \sigma(0, CE_{\tilde{Y}})$, then

$$\begin{aligned} v(CE_{\tilde{Y}}) &= V^{ST}(\tilde{Y}|\sigma(4x, CE_{\tilde{Y}}) < \sigma(0, CE_{\tilde{Y}})) \\ &= \pi_2^{ST}(4x, CE_{\tilde{Y}})v(4x) + \pi_1^{ST}(0, CE_{\tilde{Y}})v(0) \\ &= \frac{q\delta^2}{(1-q)\delta + q\delta^2}v(4x) + \frac{(1-q)\delta}{(1-q)\delta + q\delta^2}v(0) \\ &= \frac{q\delta^2}{(1-q)\delta + q\delta^2}v(4x) = \frac{q\delta}{(1-q) + q\delta}v(4x). \end{aligned}$$

Hence, the value of $CE_{\tilde{Y}}$ is

$$v(CE_{\tilde{Y}}) = \begin{cases} \frac{q}{q+(1-q)\delta}v(4x), & \text{if } \sigma(0, CE_{\tilde{Y}}) < \sigma(4x, CE_{\tilde{Y}}) \\ qv(4x), & \text{if } \sigma(0, CE_{\tilde{Y}}) = \sigma(4x, CE_{\tilde{Y}}) \\ \frac{q\delta}{(1-q)+q\delta}v(4x), & \text{if } \sigma(0, CE_{\tilde{Y}}) > \sigma(4x, CE_{\tilde{Y}}) \end{cases}.$$

Defining as $CE_g^{\tilde{Y}}$ the $CE_{\tilde{Y}}$ that solves $\sigma(0, CE_{\tilde{Y}}) = \sigma(4x, CE_{\tilde{Y}})$ we have

$$v(CE_{\tilde{Y}}) = \begin{cases} \frac{q}{q+(1-q)\delta}v(4x), & \text{if } q < \frac{\delta\frac{v(CE_g^{\tilde{Y}})}{v(4x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(4x)}} \\ v(CE_g^{\tilde{Y}}), & \text{if } q = \frac{v(CE_g^{\tilde{Y}})}{v(4x)} \\ \frac{q\delta}{(1-q)+q\delta}v(4x), & \text{if } q > \frac{\frac{v(CE_g^{\tilde{Y}})}{v(4x)}}{\delta+(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(4x)}} \end{cases}.$$

Since $q = p/4$ we have

$$v(CE_{\tilde{Y}}) = \begin{cases} \frac{p}{p+(4-p)\delta} v(4x), & \text{if } \frac{p}{4} < \frac{\delta \frac{v(CE_g^{\tilde{Y}})}{v(4x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(4x)}} \\ v(CE_g^{\tilde{Y}}), & \text{if } \frac{p}{4} = \frac{v(CE_g^{\tilde{Y}})}{v(4x)} \\ \frac{p\delta}{(4-p)+p\delta} v(4x), & \text{if } \frac{p}{4} > \frac{\frac{v(CE_g^{\tilde{Y}})}{v(4x)}}{\delta+(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(4x)}} \end{cases}. \tag{4}$$

For a preference reversal to exist the decision maker must prefer lottery $\tilde{X}$ to lottery $\tilde{Y}$ and his certainty equivalent of lottery $\tilde{Y}$ must be greater than his certainty equivalent of lottery $\tilde{X}$, that is, $v(CE_{\tilde{Y}}) > v(CE_{\tilde{X}})$. From (3) and (4) we see that, apart from the knife-hedge cases $p = v(CE_g^{\tilde{X}})/v(x)$ and $p/4 = v(CE_g^{\tilde{Y}})/v(4x)$, we can have $v(CE_{\tilde{Y}}) > v(CE_{\tilde{X}})$ when either

$$p < \frac{\delta \frac{v(CE_g^{\tilde{X}})}{v(x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{X}})}{v(x)}} \text{ and } \frac{p}{4} < \frac{\delta \frac{v(CE_g^{\tilde{Y}})}{v(4x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(4x)}}, \tag{5}$$

or

$$p > \frac{\frac{v(CE_g^{\tilde{X}})}{v(x)}}{\delta+(1-\delta)\frac{v(CE_g^{\tilde{X}})}{v(x)}} \text{ and } \frac{p}{4} < \frac{\delta \frac{v(CE_g^{\tilde{Y}})}{v(4x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(4x)}}. \tag{6}$$

From (1), (3), and (4), a preference reversal exists when (5) holds and when the salience ranking is (i) $\sigma(0,4x) > \sigma(x,4x) > \sigma(x,0) > \sigma(0,0)$ if and only if

$$\frac{\delta\left[p+(4-p)\,\delta\right]}{1-p+p\delta} > \frac{v(4x)}{v(x)} > \frac{\frac{p}{p+(1-p)\delta}}{\frac{p}{p+(4-p)\delta}} = \frac{p+(4-p)\delta}{p+(1-p)\delta}.$$

In this case a preference reversal does not exist since the term on the LHS, $\frac{\delta[p+(4-p)\delta]}{1-p+p\delta}$, is smaller than the term on the RHS, $\frac{p+(4-p)\delta}{p+(1-p)\delta}$. From (2), (3), and (4), a preference reversal exists when (5) holds and when the salience ranking is (ii) $\sigma(0,4x) > \sigma(x,0) > \sigma(x,4x) > \sigma(0,0)$ if and only if

$$\frac{\delta\left[p\delta+(4-p)\right]}{1-p+p\delta^2} > \frac{v(4x)}{v(x)} > \frac{\frac{p}{p+(1-p)\delta}}{\frac{p}{p+(4-p)\delta}} = \frac{p+(4-p)\delta}{p+(1-p)\delta}.$$

In this case a preference reversal exists when the term on the LHS is greater than the term on the RHS. From (1), (3), and (4) a preference reversal exists when (6) holds and when the salience ranking is (i) $\sigma(0,4x) > \sigma(x,4x) > \sigma(x,0) > \sigma(0,0)$ if and only if

$$\frac{\delta\left[p+(4-p)\,\delta\right]}{1-p+p\delta} > \frac{v(4x)}{v(x)} > \frac{\frac{p\delta}{(1-p)+p\delta}}{\frac{p}{p+(4-p)\delta}} = \frac{\delta\left[p+(4-p)\delta\right]}{1-p+p\delta}.$$

In this case a preference reversal does not exist since the term on the LHS is equal to the term on the RHS. From (2), (3), and (4), a preference reversal exists when (6) holds and when the salience ranking is (ii) $\sigma(0,4x) > \sigma(x,0) > \sigma(x,4x) > \sigma(0,0)$ if and only if

$$\frac{\delta\left[p\delta + (4-p)\right]}{1-p+p\delta^2} > \frac{v(4x)}{v(x)} > \frac{\frac{p\delta}{(1-p)+p\delta}}{\frac{p}{p+(4-p)\delta}} = \frac{\delta\left[p + (4-p)\delta\right]}{1-p+p\delta}.$$

In this case a preference reversal exists since the term on the LHS is always greater than the term on the RHS.

2.2 Choice 3

The binary lottery choice 3 is as follows:

$$\tilde{X} = \begin{cases} x \text{ with } & p \\ 0 \text{ with } 1-p \end{cases} \quad \text{vs.} \quad \tilde{Y} = \begin{cases} 16x \text{ with } & q = p/16 \\ 0 \text{ with } 1-q = 1-p/16 \end{cases},$$

where $x = 400$ and $p = 0.96$. In this case we can have two possible salience rankings:

(i) $\sigma(0,16x) > \sigma(x,16x) > \sigma(x,0) > \sigma(0,0)$

(ii) $\sigma(0,16x) > \sigma(x,0) > \sigma(x,16x) > \sigma(0,0)$

We consider each case separately.

(i) If the salience ranking is $\sigma(0,16x) > \sigma(x,16x) > \sigma(x,0) > \sigma(0,0)$, then

$$\begin{aligned} V^{ST}(\tilde{X}|\{\tilde{X},\tilde{Y}\}) &= [\pi_2^{ST}(x,16x) + \pi_3^{ST}(x,0)]v(x) + [\pi_1^{ST}(0,16x) + \pi_4^{ST}(0,0)]v(0) \\ &= \left[\frac{pq\delta^2}{D} + \frac{p(1-q)\delta^3}{D}\right] v(x) + \left[\frac{(1-p)q\delta}{D} + \frac{(1-p)(1-q)\delta^4}{D}\right] v(0) \\ &= \left[\frac{pq\delta^2}{D} + \frac{p(1-q)\delta^3}{D}\right] v(x), \end{aligned}$$

and

$$\begin{aligned} V^{ST}(\tilde{Y}|\{\tilde{X},\tilde{Y}\}) &= [\pi_1^{ST}(0,16x) + \pi_2^{ST}(x,16x)]v(16x) + [\pi_3^{ST}(x,0) + \pi_4^{ST}(0,0)]v(0) \\ &= \left[\frac{(1-p)q\delta}{D} + \frac{pq\delta^2}{D}\right] v(16x) + \left[\frac{p(1-q)\delta^3}{D} + \frac{(1-p)(1-q)\delta^4}{D}\right] v(0) \\ &= \left[\frac{(1-p)q\delta}{D} + \frac{pq\delta^2}{D}\right] v(16x) \end{aligned}$$

where $D = (1-p)q\delta + pq\delta^2 + p(1-q)\delta^3 + (1-p)(1-q)\delta^4$. The ST decision maker prefers $\tilde{X}$ to $\tilde{Y}$ when

$$\left[\frac{pq\delta^2}{D} + \frac{p(1-q)\delta^3}{D}\right] v(x) > \left[\frac{(1-p)q\delta}{D} + \frac{pq\delta^2}{D}\right] v(16x)$$

or

$$\left[pq\delta + p(1-q)\delta^2\right] v(x) > \left[(1-p)q + pq\delta\right] v(16x)$$

or

$$p\delta\left[q+(1-q)\delta\right]v(x) > q\left[(1-p)+p\delta\right]v(16x)$$

or

$$\frac{p\delta\left[q+(1-q)\delta\right]}{q\left[(1-p)+p\delta\right]} > \frac{v(16x)}{v(x)},$$

or

$$\frac{p\delta\left[\frac{p}{16}+(1-\frac{p}{16})\delta\right]}{\frac{p}{16}\left[(1-p)+p\delta\right]} > \frac{v(16x)}{v(x)},$$

or

$$\frac{\delta\left[p+(16-p)\delta\right]}{1-p+p\delta} > \frac{v(16x)}{v(x)}. \tag{7}$$

(ii) If the salience ranking is $\sigma(0,16x) > \sigma(x,0) > \sigma(x,16x) > \sigma(0,0)$, then

$$\begin{aligned} V^{ST}(\tilde{X}|\{\tilde{X},\tilde{Y}\}) &= [\pi_3^{ST}(x,16x)+\pi_2^{ST}(x,0)]v(x)+[\pi_1^{ST}(0,16x)+\pi_4^{ST}(0,0)]v(0) \\ &= \left[\frac{pq\delta^3}{D}+\frac{p(1-q)\delta^2}{D}\right]v(x)+\left[\frac{(1-p)q\delta}{D}+\frac{(1-p)(1-q)\delta^4}{D}\right]v(0) \\ &= \left[\frac{pq\delta^3}{D}+\frac{p(1-q)\delta^2}{D}\right]v(x), \end{aligned}$$

and

$$\begin{aligned} V^{ST}(\tilde{Y}|\{\tilde{X},\tilde{Y}\}) &= [\pi_1^{ST}(0,16x)+\pi_3^{ST}(x,16x)]v(16x)+[\pi_2^{ST}(x,0)+\pi_4^{ST}(0,0)]v(0) \\ &= \left[\frac{(1-p)q\delta}{D}+\frac{pq\delta^3}{D}\right]v(16x)+\left[\frac{p(1-q)\delta^2}{D}+\frac{(1-p)(1-q)\delta^4}{D}\right]v(0) \\ &= \left[\frac{(1-p)q\delta}{D}+\frac{pq\delta^3}{D}\right]v(16x) \end{aligned}$$

where $D=(1-p)q\delta+p(1-q)\delta^2+pq\delta^3+(1-p)(1-q)\delta^4$. The ST decision maker prefers $\tilde{X}$ to $\tilde{Y}$ when

$$\left[\frac{pq\delta^3}{D}+\frac{p(1-q)\delta^2}{D}\right]v(x) > \left[\frac{(1-p)q\delta}{D}+\frac{pq\delta^3}{D}\right]v(16x),$$

or

$$p\delta\left[q\delta+(1-q)\right]v(x) > q\left[(1-p)+p\delta^2\right]v(16x),$$

or

$$\frac{p\delta\left[q\delta+(1-q)\right]}{q\left[(1-p)+p\delta^2\right]} > \frac{v(16x)}{v(x)},$$

or

$$\frac{p\delta\left[\frac{p}{16}\delta+(1-\frac{p}{16})\right]}{\frac{p}{16}\left[(1-p)+p\delta^2\right]} > \frac{v(16x)}{v(x)},$$

or

$$\frac{\delta\left[p\delta+(16-p)\right]}{1-p+p\delta^2} > \frac{v(16x)}{v(x)}. \tag{8}$$

The value of the certainty equivalent of lottery $\tilde{X}$ is given by (3). Let us now determine the value of the certainty equivalent of lottery $\tilde{Y}$. This means that we need to find out the value of lottery $\tilde{Y}$ with respect to the series of sure amounts $\{0, ..., 8x, ..., 16x\}$:

$$\tilde{Y} = \begin{cases} 16x \text{ with} & q = p/16 \\ 0 \text{ with} & 1-q = 1-p/16 \end{cases} \quad \text{vs} \quad \{0, ..., 8x, ..., 16x\}$$

If $\sigma(16x, CE_{\tilde{Y}}) > \sigma(0, CE_{\tilde{Y}})$, then

$$\begin{aligned} v(CE_{\tilde{Y}}) &= V^{ST}(\tilde{Y}|\sigma(16x, CE_{\tilde{Y}}) > \sigma(0, CE_{\tilde{Y}})) \\ &= \pi_1^{ST}(16x, CE_{\tilde{Y}})v(16x) + \pi_2^{ST}(0, CE_{\tilde{Y}})v(0) \\ &= \frac{q\delta}{q\delta + (1-q)\delta^2}v(16x) + \frac{(1-q)\delta^2}{q\delta + (1-q)\delta^2}v(0) \\ &= \frac{q\delta}{q\delta + (1-q)\delta^2}v(16x) = \frac{q}{q + (1-q)\delta}v(16x). \end{aligned}$$

If $\sigma(16x, CE_{\tilde{Y}}) = \sigma(0, CE_{\tilde{Y}})$, then

$$\begin{aligned} v(CE_{\tilde{Y}}) &= V^{ST}(\tilde{Y}|\sigma(16x, CE_{\tilde{Y}}) = \sigma(0, CE_{\tilde{Y}})) \\ &= \pi_1^{ST}(16x, CE_{\tilde{Y}})v(16x) + \pi_1^{ST}(0, CE_{\tilde{Y}})v(0) \\ &= \frac{q\delta}{q\delta + (1-q)\delta}v(16x) + \frac{q\delta}{q\delta + (1-q)\delta}v(0) = qv(16x). \end{aligned}$$

If $\sigma(16x, CE_{\tilde{Y}}) < \sigma(0, CE_{\tilde{Y}})$, then

$$\begin{aligned} v(CE_{\tilde{Y}}) &= V^{ST}(\tilde{Y}|\sigma(16x, CE_{\tilde{Y}}) > \sigma(0, CE_{\tilde{Y}})) \\ &= \pi_2^{ST}(16x, CE_{\tilde{Y}})v(16x) + \pi_1^{ST}(0, CE_{\tilde{Y}})v(0) \\ &= \frac{q\delta^2}{(1-q)\delta + q\delta^2}v(16x) + \frac{(1-q)\delta}{(1-q)\delta + q\delta^2}v(0) \\ &= \frac{q\delta^2}{(1-q)\delta + q\delta^2}v(16x) = \frac{q\delta}{(1-q) + q\delta}v(16x). \end{aligned}$$

Hence, the value of $CE_{\tilde{Y}}$ is

$$v(CE_{\tilde{Y}}) = \begin{cases} \frac{q}{q+(1-q)\delta}v(16x), & \text{if } \sigma(0, CE_{\tilde{Y}}) < \sigma(16x, CE_{\tilde{Y}}) \\ qv(16x), & \text{if } \sigma(0, CE_{\tilde{Y}}) = \sigma(16x, CE_{\tilde{Y}}) \\ \frac{q\delta}{(1-q)+q\delta}v(16x), & \text{if } \sigma(0, CE_{\tilde{Y}}) > \sigma(16x, CE_{\tilde{Y}}) \end{cases}.$$

Defining as $CE_g^{\tilde{Y}}$ the $CE_{\tilde{Y}}$ that solves $\sigma(0, CE_{\tilde{Y}}) = \sigma(16x, CE_{\tilde{Y}})$ we have

$$v(CE_{\tilde{Y}}) = \begin{cases} \frac{q}{q+(1-q)\delta}v(16x), & \text{if } q < \frac{\delta\frac{v(CE_g^{\tilde{Y}})}{v(16x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(16x)}} \\ v(CE_g^{\tilde{Y}}), & \text{if } q = \frac{v(CE_g^{\tilde{Y}})}{v(16x)} \\ \frac{q\delta}{(1-q)+q\delta}v(16x), & \text{if } q > \frac{\frac{v(CE_g^{\tilde{Y}})}{v(16x)}}{\delta+(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(16x)}} \end{cases}.$$

Since $q = p/16$ we have

$$v(CE_{\tilde{Y}}) = \begin{cases} \frac{p}{p+(16-p)\delta} v(16x), & \text{if } \frac{p}{16} < \frac{\delta \frac{v(CE_g^{\tilde{Y}})}{v(16x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(16x)}} \\ v(CE_g^{\tilde{Y}}), & \text{if } \frac{p}{16} = \frac{v(CE_g^{\tilde{Y}})}{v(16x)} \\ \frac{p\delta}{(16-p)+p\delta} v(16x), & \text{if } \frac{p}{16} > \frac{\frac{v(CE_g^{\tilde{Y}})}{v(16x)}}{\delta+(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(16x)}} \end{cases} . \tag{9}$$

For a preference reversal to exist the decision maker must prefer lottery $\tilde{X}$ to lottery $\tilde{Y}$ and his certainty equivalent of lottery $\tilde{Y}$ must be greater than his certainty equivalent of lottery $\tilde{X}$, that is, $v(CE_{\tilde{Y}}) > v(CE_{\tilde{X}})$. From (3) and (9) we see that, apart from the knife-hedge cases $p = v(CE_g^{\tilde{X}})/v(x)$ and $p/16 = v(CE_g^{\tilde{Y}})/v(16x)$, we can have $v(CE_{\tilde{Y}}) > v(CE_{\tilde{X}})$ when either

$$p < \frac{\delta \frac{v(CE_g^{\tilde{X}})}{v(x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{X}})}{v(x)}} \text{ and } \frac{p}{16} < \frac{\delta \frac{v(CE_g^{\tilde{Y}})}{v(16x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(16x)}}, \tag{10}$$

or

$$p > \frac{\frac{v(CE_g^{\tilde{X}})}{v(x)}}{\delta+(1-\delta)\frac{v(CE_g^{\tilde{X}})}{v(x)}} \text{ and } \frac{p}{16} < \frac{\delta \frac{v(CE_g^{\tilde{Y}})}{v(16x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(16x)}}. \tag{11}$$

From (7), (3), and (9), a preference reversal exists when (10) holds and when the salience ranking is (i) $\sigma(0,16x) > \sigma(x,16x) > \sigma(x,0) > \sigma(0,0)$ if and only if

$$\frac{\delta\left[p+(16-p)\delta\right]}{1-p+p\delta} > \frac{v(16x)}{v(x)} > \frac{\frac{p}{p+(1-p)\delta}}{\frac{p}{p+(16-p)\delta}} = \frac{p+(16-p)\delta}{p+(1-p)\delta}.$$

In this case a preference reversal does not exist since the term on the LHS, $\frac{\delta[p+(16-p)\delta]}{1-p+p\delta}$, is smaller than the term on the RHS, $\frac{p+(16-p)\delta}{p+(1-p)\delta}$. From (8), (3), and (9), a preference reversal exists when (10) holds and when the salience ranking is (ii) $\sigma(0,16x) > \sigma(x,0) > \sigma(x,16x) > \sigma(0,0)$ if and only if

$$\frac{\delta\left[p\delta+(16-p)\right]}{1-p+p\delta^2} > \frac{v(16x)}{v(x)} > \frac{\frac{p}{p+(1-p)\delta}}{\frac{p}{p+(16-p)\delta}} = \frac{p+(16-p)\delta}{p+(1-p)\delta}.$$

In this case a preference reversal exists when the term on the LHS is greater than the term on the RHS. From (7), (3), and (9) a preference reversal exists when (11) holds and when the salience ranking is (i) $\sigma(0,16x) > \sigma(x,16x) > \sigma(x,0) > \sigma(0,0)$ if and only if

$$\frac{\delta\left[p+(16-p)\delta\right]}{1-p+p\delta} > \frac{v(16x)}{v(x)} > \frac{\frac{p\delta}{(1-p)+p\delta}}{\frac{p}{p+(16-p)\delta}} = \frac{\delta\left[p+(16-p)\delta\right]}{1-p+p\delta}.$$

In this case a preference reversal does not exist since the term on the LHS is equal to the term on the RHS. From (8), (3), and (9), a preference reversal exists when (11) holds and when the salience ranking is (ii) $\sigma(0,16x) > \sigma(x,0) > \sigma(x,16x) > \sigma(0,0)$ if and only if

$$\frac{\delta\left[p\delta + (16-p)\right]}{1-p+p\delta^2} > \frac{v(16x)}{v(x)} > \frac{\frac{p\delta}{(1-p)+p\delta}}{\frac{p}{p+(16-p)\delta}} = \frac{\delta\left[p + (16-p)\delta\right]}{1-p+p\delta}.$$

In this case a preference reversal exists since the term on the LHS is always greater than the term on the RHS.

2.3 Choices 4, 5, and 6

The binary lottery choices 4, 5, and 6 are as follows:

$$\tilde{X} = \begin{cases} x \text{ with prob. } & p \\ 0 \text{ with prob. } & 1-p \end{cases} \quad \text{vs.} \quad \tilde{Y} = \begin{cases} 2x \text{ with prob. } & q = p/2 \\ 0 \text{ with prob. } & 1-q = 1-p/2 \end{cases},$$

where $x = 3000$, $p = 0.9$ for choice 4, $p = 0.8$ for choice 5, and $p = 0.7$ for choice 6. The salience ranking is:

$$\sigma(0,2x) > \sigma(x,0) > \sigma(x,2x) > \sigma(0,0).$$

Hence, we have

$$\begin{aligned} V^{ST}(\tilde{X}|\{\tilde{X},\tilde{Y}\}) &= [\pi_3^{ST}(x,2x) + \pi_2^{ST}(x,0)]v(x) + [\pi_1^{ST}(0,2x) + \pi_4^{ST}(0,0)]v(0) \\ &= \left[\frac{pq\delta^3}{D} + \frac{p(1-q)\delta^2}{D}\right]v(x) + \left[\frac{(1-p)q\delta}{D} + \frac{(1-p)(1-q)\delta^4}{D}\right]v(0) \\ &= \left[\frac{pq\delta^3}{D} + \frac{p(1-q)\delta^2}{D}\right]v(x), \end{aligned}$$

and

$$\begin{aligned} V^{ST}(\tilde{Y}|\{\tilde{X},\tilde{Y}\}) &= [\pi_1^{ST}(0,2x) + \pi_3^{ST}(x,2x)]v(2x) + [\pi_2^{ST}(x,0) + \pi_4^{ST}(0,0)]v(0) \\ &= \left[\frac{(1-p)q\delta}{D} + \frac{pq\delta^3}{D}\right]v(2x) + \left[\frac{p(1-q)\delta^2}{D} + \frac{(1-p)(1-q)\delta^4}{D}\right]v(0) \\ &= \left[\frac{(1-p)q\delta}{D} + \frac{pq\delta^3}{D}\right]v(2x) \end{aligned}$$

where $D = (1-p)q\delta + p(1-q)\delta^2 + pq\delta^3 + (1-p)(1-q)\delta^4$. The ST decision maker prefers $\tilde{X}$ to $\tilde{Y}$ when

$$\left[\frac{pq\delta^3}{D} + \frac{p(1-q)\delta^2}{D}\right]v(x) > \left[\frac{(1-p)q\delta}{D} + \frac{pq\delta^3}{D}\right]v(2x),$$

or

$$p\left[q\delta^2 + (1-q)\delta\right]v(x) > q\left[(1-p) + p\delta^2\right]v(2x),$$

or

$$\frac{p\delta\left[q\delta+(1-q)\right]}{q\left[(1-p)+p\delta^2\right]}>\frac{v(2x)}{v(x)},$$

or

$$\frac{p\delta\left[\frac{p}{2}\delta+\left(1-\frac{p}{2}\right)\right]}{\frac{p}{2}\left[(1-p)+p\delta^2\right]}>\frac{v(2x)}{v(x)},$$

or

$$\frac{\delta\left[(2-p)+p\delta\right]}{(1-p)+p\delta^2}>\frac{v(2x)}{v(x)}. \tag{12}$$

The value of the certainty equivalent of lottery $\tilde{X}$ is given by (3). Let us now determine the value of the certainty equivalent of lottery $\tilde{Y}$. This means that we need to find out the value of lottery $\tilde{Y}$ with respect to the series of sure amounts $\{0,...,x,...,2x\}$:

$$\tilde{Y}=\begin{cases} 2x \text{ with } & q=p/2 \\ 0 \text{ with } & 1-q=1-p/2 \end{cases} \quad \text{vs} \quad \{0,...,x,...,2x\}$$

If $\sigma(2x,CE_{\tilde{Y}})<\sigma(0,CE_{\tilde{Y}})$, then

$$\begin{aligned} v(CE_{\tilde{Y}}) &= V^{ST}(\tilde{Y}|\sigma(2x,CE_{\tilde{Y}})<\sigma(0,CE_{\tilde{Y}})) \\ &= \pi_2^{ST}(2x,CE_{\tilde{Y}})v(2x)+\pi_1^{ST}(0,CE_{\tilde{Y}})v(0) \\ &= \frac{q\delta^2}{(1-q)\delta+q\delta^2}v(2x)+\frac{(1-q)\delta}{(1-q)\delta+q\delta^2}v(0) \\ &= \frac{q\delta^2}{(1-q)\delta+q\delta^2}v(2x)=\frac{q\delta}{(1-q)+q\delta}v(2x). \end{aligned}$$

If $\sigma(2x,CE_{\tilde{Y}})>\sigma(0,CE_{\tilde{Y}})$, then

$$\begin{aligned} v(CE_{\tilde{Y}}) &= V^{ST}(\tilde{Y}|\sigma(2x,CE_{\tilde{Y}})>\sigma(0,CE_{\tilde{Y}})) \\ &= \pi_1^{ST}(2x,CE_{\tilde{Y}})v(2x)+\pi_2^{ST}(0,CE_{\tilde{Y}})v(0) \\ &= \frac{q\delta}{q\delta+(1-q)\delta^2}v(2x)+\frac{(1-q)\delta^2}{q\delta+(1-q)\delta^2}v(0) \\ &= \frac{q\delta}{q\delta+(1-q)\delta^2}v(2x)=\frac{q}{q+(1-q)\delta}v(2x). \end{aligned}$$

If $\sigma(2x,CE_{\tilde{Y}})=\sigma(0,CE_{\tilde{Y}})$, then

$$\begin{aligned} v(CE_{\tilde{Y}}) &= V^{ST}(\tilde{Y}|\sigma(2x,CE_{\tilde{Y}})=\sigma(0,CE_{\tilde{Y}})) \\ &= \pi_1^{ST}(2x,CE_{\tilde{Y}})v(2x)+\pi_1^{ST}(0,CE_{\tilde{Y}})v(0) \\ &= \frac{q\delta}{q\delta+(1-q)\delta}v(2x)+\frac{q\delta}{q\delta+(1-q)\delta}v(0)=qv(2x). \end{aligned}$$

Hence, the value of $CE_{\tilde{Y}}$ is

$$v(CE_{\tilde{Y}}) = \begin{cases} \frac{q}{q+(1-q)\delta}v(2x), & \text{if } \sigma(0, CE_{\tilde{Y}}) < \sigma(2x, CE_{\tilde{Y}}) \\ qv(2x), & \text{if } \sigma(0, CE_{\tilde{Y}}) = \sigma(2x, CE_{\tilde{Y}}) \\ \frac{q\delta}{(1-q)+q\delta}v(2x), & \text{if } \sigma(0, CE_{\tilde{Y}}) > \sigma(2x, CE_{\tilde{Y}}) \end{cases}.$$

Defining as $CE_g^{\tilde{Y}}$ the $CE_{\tilde{Y}}$ that solves $\sigma(0, CE_{\tilde{Y}}) = \sigma(2x, CE_{\tilde{Y}})$ we have

$$v(CE_{\tilde{Y}}) = \begin{cases} \frac{q}{q+(1-q)\delta}v(2x), & \text{if } q < \frac{\delta\frac{v(CE_g^{\tilde{Y}})}{v(2x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(2x)}} \\ v(CE_g^{\tilde{Y}}), & \text{if } q = \frac{v(CE_g^{\tilde{Y}})}{v(2x)} \\ \frac{q\delta}{(1-q)+q\delta}v(2x), & \text{if } q > \frac{\frac{v(CE_g^{\tilde{Y}})}{v(2x)}}{\delta+(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(2x)}} \end{cases}.$$

Since $q = p/2$ we have

$$v(CE_{\tilde{Y}}) = \begin{cases} \frac{p}{p+(2-p)\delta}v(2x), & \text{if } \frac{p}{2} < \frac{\delta\frac{v(CE_g^{\tilde{Y}})}{v(2x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(2x)}} \\ v(CE_g^{\tilde{Y}}), & \text{if } \frac{p}{2} = \frac{v(CE_g^{\tilde{Y}})}{v(2x)} \\ \frac{p\delta}{(2-p)+p\delta}v(2x), & \text{if } \frac{p}{2} > \frac{\frac{v(CE_g^{\tilde{Y}})}{v(2x)}}{\delta+(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(2x)}} \end{cases}. \tag{13}$$

For a preference reversal to exist the decision maker must prefer lottery $\tilde{X}$ to lottery $\tilde{Y}$ and his certainty equivalent of lottery $\tilde{Y}$ must be greater than his certainty equivalent of lottery $\tilde{X}$, that is, $v(CE_{\tilde{Y}}) > v(CE_{\tilde{X}})$. From (3) and (13) we see that, apart from the knife-hedge cases $p = v(CE_g^{\tilde{X}})/v(x)$ and $p/2 = v(CE_g^{\tilde{Y}})/v(2x)$, we can have $v(CE_{\tilde{Y}}) > v(CE_{\tilde{X}})$ when either

$$p < \frac{\delta\frac{v(CE_g^{\tilde{X}})}{v(x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{X}})}{v(x)}} \text{ and } \frac{p}{2} < \frac{\delta\frac{v(CE_g^{\tilde{Y}})}{v(2x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(2x)}}, \tag{14}$$

or

$$p > \frac{\frac{v(CE_g^{\tilde{X}})}{v(x)}}{\delta+(1-\delta)\frac{v(CE_g^{\tilde{X}})}{v(x)}} \text{ and } \frac{p}{2} < \frac{\delta\frac{v(CE_g^{\tilde{Y}})}{v(2x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(2x)}}. \tag{15}$$

From (12), (3), and (13), a preference reversal exists when (14) holds if and only if

$$\frac{\delta\left[p\delta+(2-p)\right]}{1-p+p\delta^2} > \frac{v(2x)}{v(x)} > \frac{\frac{p}{p+(1-p)\delta}}{\frac{p}{p+(2-p)\delta}} = \frac{p+(2-p)\delta}{p+(1-p)\delta}.$$

In this case a preference reversal exists when the term on the LHS is greater than the term on the RHS. From (12), (3), and (13), a preference reversal exists when (15) holds if and only if

$$\frac{\delta\left[p\delta+(2-p)\right]}{1-p+p\delta^2} > \frac{v(2x)}{v(x)} > \frac{\frac{p\delta}{(1-p)+p\delta}}{\frac{p}{p+(2-p)\delta}} = \frac{\delta\left[p+(2-p)\delta\right]}{1-p+p\delta}.$$

In this case a preference reversal exists since the term on the LHS is always greater than the term on the RHS.

3 Relationship between Type-Membership and Individual Characteristics

This section shows the results of a multinomial logit regression investigating the relationship between the subjects' type-membership and their individual characteristics. The dependent variable is an indicator for the subjects' type-membership – EUT, CPT, or ST – which follows form equation (7) in the paper. The independent variables comprise the subjects' gender, cognitive ability score based on 12 Raven's matrices, scores in the five main categories of the Big 5 personality questionnaire, and average decision time. The basis category is membership in the EUT-type. Two subjects are missing as they did not complete the Big 5 personality questionnaire.

Online Table 1 shows the results. All characteristics are insignificant, both when tested individually and jointly. Hence there is no correlation between the subjects' type-membership and their individual characteristics.

This null result may be surprising at first glance – in particular, the fact that cognitive ability is not correlated with individual type-membership. We may hypothesize that ST-types have lower cognitive ability than the other types since they are local thinkers unable to take all possible states of the world into account. However, the following argument weakens this hypothesis. Cognitive ability is measured with 12 Raven's matrices which require subjects to recognize repeated patterns that stand out. Hence, ST-types who overweight salient states where the payoffs stand out relative to other states may not have a disadvantage in this test at all.

Online Table 1: Multinomial Logit of Type-Membership and Individual Characteristics

Individual characteristic	CPT	ST
Female	0.203	-0.020
	(0.346)	(0.362)
Cognitive ability score	0.090	-0.028
	(0.075)	(0.074)
Big 5: Extraversion	-0.005	-0.021
	(0.042)	(0.044)
Big 5: Agreeableness	0.077	0.064
	(0.054)	(0.056)
Big 5: Conscenciousness	0.015	0.035
	(0.049)	(0.051)
Big 5: Neuroticism	-0.038	0.005
	(0.037)	(0.039)
Big 5: Openness	-0.016	-0.105
	(0.036)	(0.037)
Average Decision Time (in seconds)	-0.000	0.000
	(0.000)	(0.000)
Constant	-0.606	1.410
	(1.523)	(1.554)
Number of subjects/observations	281	
Log Likelihood	-296.09	
P-values of joint tests		
H_0 : all coefficients = 0	0.205	
H_0 : all type-specific coefficients = 0	0.722	0.201
H_0 : all Big 5 coefficients = 0	0.642	0.067

2 of the 283 subjects are missing as they did not complete the Big 5 personality questionnaire.

4 Monte Carlo Simulations

This section presents a series of Monte Carlo Simulations. They allow us to assess (i) the structural model's power to recover a wide range of parameters and discriminate between the three preference types as well as its robustness against (ii) potential serial correlations in the error term and (iii) heterogeneity in preferences within types.

4.1 General Set-up

All Monte Carlo Simulations share an identical general set-up. First, we define the true number of subjects in each type, N_{EUT}, N_{CPT}, and N_{ST}, and the vector

$$\Psi = (\theta_{EUT}, \theta_{CPT}, \theta_{ST}, \sigma_{EUT}, \sigma_{CPT}, \sigma_{ST}, \pi_{EUT}, \pi_{CPT})$$

which contains the true preference parameters, choice sensitivities, and relative sizes for each type. We use these true parameters to simulate the subjects' choices. The types' relative sizes π_M follow from the true number of subjects in each type.

After defining the number of subjects in each type and the vector of true parameters, we conduct $R = 1,000$ simulation runs. Each simulation run r consists of two steps.

1. We simulate the choices of all $N = N_{EUT} + N_{CPT} + N_{ST}$ subjects in the main part of the experiment (see Section 3.1 of the paper) based on the true type-specific parameters Ψ and the random utility model presented in Section 5.1 of the paper. To represent the experiment as closely as possible, we simulate that in each type, one half of the subjects is exposed to the 87 choices in the canonical presentation while the other half is exposed to the 78 choices in the states of the world presentation.

   As in the experiment, the order in which the simulated subjects make their choices is randomized. Simulating this random order is important, as we also intend to assess the extent to which serial correlation in the random errors errors across choices can bias our results. Thus, the simulated random errors in a subject's utility follow an AR(1) process across choices with serial correlation ρ and type-1-extreme-value-distributed innovations. The simulations in Section 4.2 use independent errors ($\rho = 0$) as assumed by the structural model. However, the simulations in Section 4.4 use serially correlated errors ($\rho > 0$) to test whether the structural model is robust against this type of misspecification.

2. We try to recover the true parameters by estimating the structural model on the simulated choices. This yields a vector of estimated parameters $\hat{\Psi}^{(r)}$ for each simulation run r.

   Moreover, we classify the subjects into types according to their behavior and the model's estimated parameters by using the individual ex-post probabilities of type-membership $\tau_{i,M}^{(r)}$ (see equation (7) in the paper). This yields the fraction of correctly classified subjects, $f_{correct,M}^{(r)}$, in each type.

After finishing all R simulation runs, we compare the true and the estimated parameters to assess the potential bias and the overall accuracy of our estimators. The bias in the estimator of the j-th parameter,

$$Bias(\hat{\Psi}_j) = \frac{1}{R}\sum_{r=1}^{R} \hat{\Psi}_j^{(r)} - \Psi_j \,,$$

indicates whether, on average, we can recover the true parameter, or whether the estimated parameter systematically deviates from the true value. The overall accuracy of the estimator is given by its Mean Squared Error (MSE),

$$MSE(\hat{\Psi}_j) = Bias(\hat{\Psi}_j)^2 + Var(\hat{\Psi}_j) = \frac{1}{R}\sum_{r=1}^{R} \left(\hat{\Psi}_j^{(r)} - \Psi_j\right)^2 ,$$

and corresponds to the sum of the estimator's squared bias plus its variance - an inverse measure for its precision. A MSE close to zero indicates great overall accuracy, while a large MSE indicates a low overall accuracy due to a bias in the estimator and/or a high variance. Considering the overall accuracy and not just bias is relevant, as a biased estimator with a relatively low variance may be overall more accurate than an unbiased estimator with a relatively high variance.

We also assess how well the structural model performs at classifying subjects into types. To do so, we calculate the average fraction of correctly classified subjects,

$$f_{correct,M} = \frac{1}{R}\sum_{r=1}^{R} f_{correct,M}^{(r)} \,,$$

for each type.

4.2 Parameter Recovery and Discriminatory Power

This section discusses the set-up and the results of four Monte Carlo Simulations to assess the structural model's power to recover a wide range of parameters and discriminate between the three preference types in the choices of our experiment.

4.2.1 Set-up

Online Table 2 shows the types' sizes and the true parameters in the four simulations.

- In simulations S1 to S3, the simulated types are increasingly difficult to discriminate. Each of the simulated types consists of 80 subjects who exhibit the same mildly concave utility function ($\beta = 0.2$) and low choice sensitivity ($\rho = 0.3$). The only systematic differences between the simulated types lie in the CPT-type's degree of likelihood sensitivity (α) and the ST-type's degree of local thinking (δ). However, these differences decrease from S1 to S3, making the types increasingly difficult to discriminate. From S1 to S3, the CPT-type gets increasingly similar to the EUT-type as its degree of likelihood sensitivity increases in three equally sized steps from $\alpha = 0.4$ to $\alpha = 0.8$. Similarly, the ST-type also gets increasingly similar to the EUT-types as its degree of local thinking increases in three equally sized steps from $\delta = 0.5$ to $\delta = 0.9$. Consequently, simulations S1 to S3 allow us to assess the structural model's power at discriminating the types in our experiment when this task becomes increasingly difficult.

- In simulation S4, the simulated types are very similar to the ones uncovered in the paper. Hence, simulation S4 gives us an idea about the structural model's power at discriminating the types in a situation similar to the one in the actual experiment.

4.3 Results

Online Table 3 shows the results of simulations S1 to S4.

- In simulations S1, S2, and S4, there is virtually no bias in the estimated parameters and the MSEs indicate great overall precision. Moreover, the structural model classifies almost all subjects into the correct type.

- In simulation S3 – i.e., the simulation where the CPT- and ST-types are almost indistinguishable from the EUT-type – there is some bias in the estimated parameters

Online Table 2: Types' Sizes and True Parameters in Simulations to Assess Discriminatory Power

S1					
Type	N (π)	β	α	δ	σ
EUT	80 (0.3333)	0.2000			0.3000
CPT	80 (0.3333)	0.2000	0.4000		0.3000
ST	80 (0.3333)	0.2000		0.5000	0.3000
S2					
Type	N (π)	β	α	δ	σ
EUT	80 (0.3333)	0.2000			0.3000
CPT	80 (0.3333)	0.2000	0.6000		0.3000
ST	80 (0.3333)	0.2000		0.7000	0.3000
S3					
Type	N (π)	β	α	δ	σ
EUT	80 (0.3333)	0.2000			0.3000
CPT	80 (0.3333)	0.2000	0.8000		0.3000
ST	80 (0.3333)	0.2000		0.9000	0.3000
S4					
Type	N (π)	β	α	δ	σ
EUT	80 (0.2963)	0.1000			0.0100
CPT	100 (0.3704)	0.5500	0.4500		0.3000
ST	90 (0.3333)	0.8500		0.9000	2.5000

In S1 to S3, the types differ only in the degrees of likelihood sensitivity (α) and local thinking (δ). They become increasingly similar in preferences, i.e., hard to discriminate. In S4, the types are similar to the ones uncovered in the paper. Simulation results can be found in Online Table 3.

Online Table 3: Results of Simulations to Assess Discriminatory Power

S1	Bias					Mean Squared Error (MSE)					
Type	π	β	α	δ	σ	π	β	α	δ	σ	$f_{correct}$
EUT	0.0000	0.0003			0.0020	0.0000	0.0001			0.0004	1.0000
CPT	0.0000	-0.0092	0.0016		-0.0079	0.0000	0.0011	0.0001		0.0054	1.0000
ST	0.0000	-0.0014		-0.0009	-0.0006	0.0000	0.0002		0.0000	0.0008	1.0000

S2	Bias					Mean Squared Error (MSE)					
Type	π	β	α	δ	σ	π	β	α	δ	σ	$f_{correct}$
EUT	0.0000	0.0002			0.0020	0.0000	0.0001			0.0004	1.0000
CPT	0.0000	-0.0002	0.0002		0.0001	0.0000	0.0000	0.0000		0.0003	1.0000
ST	0.0000	0.0005		0.0027	0.0111	0.0000	0.0002		0.0002	0.0021	1.0000

S3	Bias					Mean Squared Error (MSE)					
Type	π	β	α	δ	σ	π	β	α	δ	σ	$f_{correct}$
EUT	0.0135	0.0015			-0.0008	0.0097	0.0013			0.0008	0.9338
CPT	0.0140	0.0000	0.0001		0.0012	0.0093	0.0001	0.0001		0.0002	1.0000
ST	-0.0275	-0.1836		-0.0188	-0.0036	0.0377	1.6935		0.0170	0.0023	0.9362

S4	Bias					Mean Squared Error (MSE)					
Type	π	β	α	δ	σ	π	β	α	δ	σ	$f_{correct}$
EUT	-0.0002	-0.0083			0.0000	0.0000	0.0836			0.0000	0.9949
CPT	0.0002	0.0002	-0.0003		0.0014	0.0000	0.0003	0.0001		0.0008	0.9984
ST	0.0000	-0.0002		-0.0002	0.0005	0.0000	0.0001		0.0001	0.0180	0.9989

Simulated number of subjects and true parameters for all four simulations can be found in Online Table 2. In each simulation, biases and Mean Squared Errors (MSE) are calculated based on $R = 1,000$ simulation runs. $f_{correct}$ denotes the fraction of correctly classified subjects in each type.

of the ST-type. The MSEs also indicate that the ST-type's parameters are estimated only with low overall precision, in particular the estimator for the concavity of the utility function is quite imprecise. However, the model still manages to classify almost all subjects into the correct type.

Overall, simulations S1 to S4 reveal that the structural model's power to recover parameters and discriminate between the different types is very high. Even in simulation S3, where the three types are so similar that they are at the edge of being indistinguishable, the model still manages to classify almost all subjects into the correct type. These results also confirm that the experimental choices contain rich information about a subjects' type-membership and that the structural model exploits this information efficiently.

4.4 Effects of Serially Correlated Errors

This section discusses the set-up and the results of four simulations to investigate the robustness of the structural model against potential serial correlation in the errors. This investigation is important since, in the experiment, subjects make a series of binary choices. Thus, the random errors subjects make when evaluating the lotteries may be serially correlated across the binary choices. Such serial correlation would imply that our structural model is misspecified as it assumes independent errors and, thus, could yield biased parameter estimates. However, as explained in the paper, the order of the binary choices was randomized across subjects. Hence, since the structural model does not estimate at the individual level but takes into account the choices of all subjects simultaneously, the serial correlations in the subjects' errors may average out due to the random order in which the choices were presented.

4.4.1 Set-up

Online Table 4 shows the types' sizes and the true parameters in the four simulations. Across all four simulations S5-S8, the simulated types are identical. They are very similar in terms of relative size and parameters to the ones uncovered in the paper. However, the serial correlation across choices in the random errors the simulated subjects make when evaluating the lotteries increases in four equally sized steps from $\rho = 0$ to $\rho = 0.6$.

Online Table 4: Types' Sizes, True Parameters, and Serial Correlation (ρ) in Simulations to Assess the Effects of Serially Correlated Errors

Types' sizes & true parameters: common in simulations **S5-S8**					
Type	N (π)	β	α	δ	σ
EUT	80 (0.2963)	0.1000			0.0100
CPT	100 (0.3704)	0.5500	0.4500		0.3000
ST	90 (0.3333)	0.8500		0.9000	2.5000
Serial correlation of errors		**S5**	**S6**	**S7**	**S8**
ρ		0.0	0.2	0.4	0.6

In S4-S7, the types are similar in size and parameters to the ones uncovered in the paper. Simulation results can be found in Online Table 5.

Online Table 5: Results of Simulations to Assess the Effects of Serially Correlated Errors

S5 ($\rho = 0.0$)	Bias					Mean Squared Error (MSE)					
Type	π	β	α	δ	σ	π	β	α	δ	σ	$f_{correct}$
EUT	-0.0002	-0.0083			0.0000	0.0000	0.0836			0.0000	0.9949
CPT	0.0002	0.0002	-0.0003		0.0014	0.0000	0.0003	0.0001		0.0008	0.9984
ST	0.0000	-0.0002		-0.0002	0.0005	0.0000	0.0001		0.0001	0.0180	0.9989

S6 ($\rho = 0.2$)	Bias					Mean Squared Error (MSE)					
Type	π	β	α	δ	σ	π	β	α	δ	σ	$f_{correct}$
EUT	-0.0005	-0.0001			-0.0003	0.0000	0.0012			0.0000	0.9930
CPT	0.0003	0.0018	-0.0009		-0.0031	0.0000	0.0002	0.0001		0.0007	0.9974
ST	0.0001	-0.0006		0.0009	-0.0591	0.0000	0.0001		0.0001	0.0196	0.9988

S7 ($\rho = 0.4$)	Bias					Mean Squared Error (MSE)					
Type	π	β	α	δ	σ	π	β	α	δ	σ	$f_{correct}$
EUT	-0.0010	0.0023			-0.0010	0.0000	0.0022			0.0000	0.9878
CPT	0.0011	0.0035	-0.0020		-0.0229	0.0000	0.0003	0.0001		0.0012	0.9950
ST	-0.0002	0.0010		-0.0002	-0.2305	0.0000	0.0001		0.0001	0.0675	0.9976

S8 ($\rho = 0.6$)	Bias					Mean Squared Error (MSE)					
Type	π	β	α	δ	σ	π	β	α	δ	σ	$f_{correct}$
EUT	-0.0039	-0.0061			-0.0022	0.0001	0.1725			0.0000	0.9676
CPT	0.0053	0.0022	-0.0021		-0.0622	0.0001	0.0004	0.0001		0.0045	0.9855
ST	-0.0014	0.0011		-0.0003	-0.5564	0.0000	0.0001		0.0001	0.3210	0.9914

Simulated number of subjects and true parameters for all four simulations can be found in Online Table 4. In each simulation, biases and Mean Squared Errors (MSE) are calculated based on $R = 1,000$ simulation runs. $f_{correct}$ denotes the fraction of correctly classified subjects in each type.

4.4.2 Results

Online Table 5 shows the results of the four simulations. Simulations S5 to S8 reveal that, regardless of the degree of serial correlation in the errors, the types' estimated relative sizes and preference parameters are virtually unbiased and highly precise. The structural model also classifies the vast majority of subjects into the correct type. Only the estimated choice sensitivities exhibit an increasing downward bias when the serial correlation in the errors increases.

In sum, the structural model turns out to be remarkably robust against serial correlation in the subjects' errors. Hence, even if the subjects' errors in the experiment were serially correlated across choices, this would neither bias the types' estimated sizes, nor their preference parameters, nor the classification of subjects into types. Note that we also use cluster-robust standard errors in the paper to ensure that our inferences about the structural model's parameters remain valid even if the subjects' errors in the experiment were serially correlated across choices.

Again, we suppose the reason why the structural model is so robust against serial correlation in the subjects' errors is because the order of the choices is randomized across subjects. Since the finite mixture model does not operate at the individual level but uses the choices of all subjects simultaneously when estimating its parameters, the random order of the choices across subjects may cause the serial correlations in the errors to average each other out.

4.5 Effects of Within-Type Heterogeneity

This section discusses the set-up and the results of a simulation to investigate the robustness of the structural model against within-type heterogeneity in the preference parameters. This investigation is relevant as, in reality, there may be substantial preference heterogeneity not only between types but also within types. Thus, it is important to know to what extent such within-type heterogeneity could bias the estimated parameters.

4.5.1 Set-up

Online Table 6 shows the uniform distributions from which the individual parameters to simulate the choices are drawn. The uniform distributions all have the same expectations as the true parameters in in Simulation S4 – and, thus, are similar in expectations to the estimated parameters in the paper. However, they lead to substantial individual heterogeneity within types.

Online Table 6: Types' Sizes and Distribution of True Parameters in the Simulation to Assess the Effects of Within-Type Heterogeneity

S9					
Type	N (π)	β	α	δ	σ
EUT	80 (0.2963)	U(0.0000, 0.2000)			0.0100
CPT	100 (0.3704)	U(0.4500, 0.6500)	U(0.3500, 0.5500)		0.3000
ST	90 (0.3333)	U(0.7500, 0.9500)		U(0.8500, 0.9500)	2.5000

The table shows the lower and upper limit of the uniform distributions from which the true individual parameters are drawn. The types' sizes and choice sensitivities correspond to the ones in simulation S4. Simulations results can be found in Online Table 7.

4.5.2 Results

Online Table 7 displays the results of the simulation. It shows the biases and MSE relative to the expected true parameters.

In sum, the finite mixture model recovers the average true parameters remarkably well as the biases and the MSE are negligible for all parameters. Moreover, it also classifies the vast majority of simulated subjects into the correct type. Hence, within-type heterogeneity does not induce bias in the estimated average parameters.

Online Table 7: Results of the Simulation to Assess the Effects of Within-Type Heterogeneity

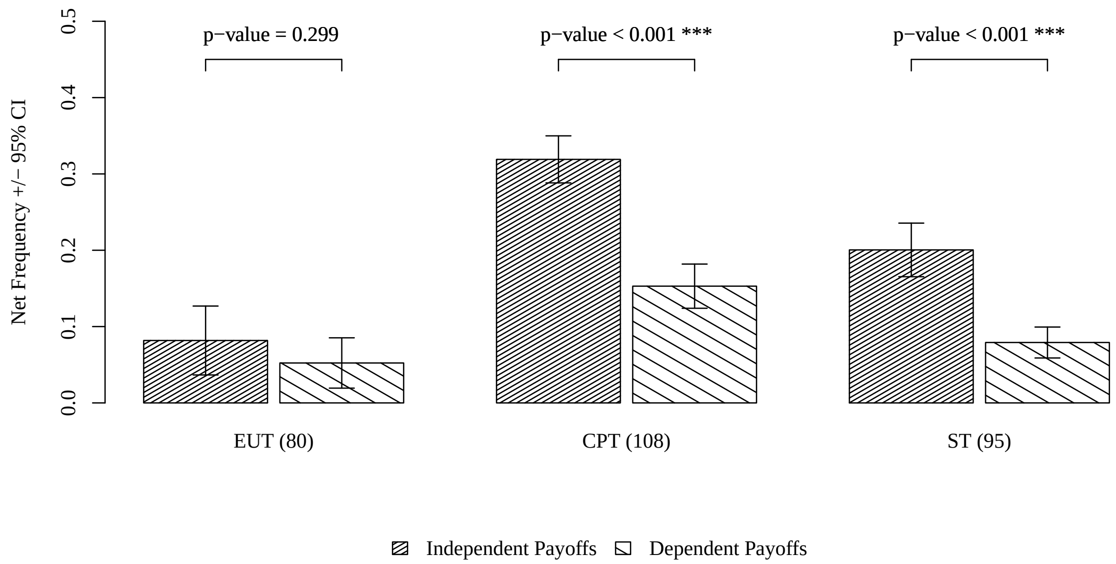
S9	Bias					Mean Squared Error (MSE)					
Type	π	β	α	δ	σ	π	β	α	δ	σ	$f_{correct}$
EUT	0.018	-0.011			-0.001	0.000	0.000			0.000	0.994
CPT	-0.017	-0.030	0.001		-0.052	0.000	0.001	0.000		0.003	0.953
ST	0.000	0.019		-0.002	0.182	0.000	0.000		0.000	0.048	0.996

Simulated number of subjects and the distributions of the true parameters can be found in Online Table 6. Biases and Mean Squared Errors (MSE) relative to the expected true parameters are calculated based on $R = 1,000$ simulation runs. $f_{correct}$ denotes the fraction of correctly classified subjects in each type.

5 Net Frequency of Allais Paradoxes per Type

An interesting question that the structural model cannot directly address is whether probability weighting and salience exclusively drive the choices of the CPT- and ST-types, or whether they influence the choices of all types to a varying degree. To answer this question, we turn to Online Figure 1 which shows the net frequency of Allais Paradoxes separately for subjects classified as EUT-, CPT-, and ST-types. First, the net frequency of Allais Paradoxes for EUT-types is the lowest and, more importantly, does not significantly differ across independent and dependent payoffs. This justifies the classification of these subjects as EUT-types. Second, the CPT-types' net frequency of Allais Paradoxes always exceeds those of the other two types, in particular with dependent payoffs. For this reason, the finite mixture model classifies these subjects as CPT-types. Third, the ST-types' net frequency of Allais Paradoxes is 2.53 times higher with independent than with dependent payoffs. Moreover, with dependent payoffs, the ST-types' net frequency of Allais Paradoxes is indistinguishable from the EUT-types'. This is why the finite mixture model classifies these subjects as ST-types. In sum, the ST-types' choices are mainly driven by choice set dependence while the CPT-types' choices are driven by primarily by probability weighting.

Online Figure 1: Net Frequency of Allais Paradoxes by Preference Type



The figure shows the net frequency of Allais Paradoxes for lotteries with independent and dependent payoffs, separately for EUT-, CPT-, and ST-types. Net frequency of Allais Paradoxes refers to the difference in the relative frequencies of Allais Paradoxes in the expected and the inverse directions. The numbers in parentheses indicate the number of subjects in each of the three types.

6 Finite Mixture Models with Only Two Types

6.1 Finite Mixture Model with EUT- and CPT-Types

Online Table 8: Type-Specific Parameter Estimates of the Finite Mixture Model

Type-specific estimates	EUT	CPT
Relative size (π)[a]	0.349	0.651
	(0.042)	(0.042)
Concavity of utility function (β)	0.875***	0.358***
	(0.018)	(0.057)
Likelihood sensitivity (α)		0.660°°°
		(0.043)
Choice sensitivity (σ)	2.908***	0.061***
	(0.363)	(0.022)
Number of subjects[b]	99	184
	(12.270)	(12.270)
Number of observations	23,316	
Log Likelihood	-11,832.58	
AIC	23,677.15	
BIC	23,725.50	

Subject cluster-robust standard errors are reported in parentheses and based on 1,000 bootstrap replications. Significantly different from 0 (1) at the 1% level: *** (°°°).

[a] The relative group sizes are not tested against zero, since under the null hypothesis that a type's relative size is zero, the preference parameters are meaningless. Consequently, the test statistic would exhibit an unknown distribution. The distribution of the test statistic could be bootstrapped under the null hypothesis. However, since the estimates of the relative group sizes are sufficiently far from the edges of the parameter space, this is not done here.

[b] Subjects are assigned to the best-fitting model according to their ex-post probabilities of type-membership. The number of assigned subjects is not tested against zero, for the same reason as the relative group sizes are not tested against zero.

6.2 Finite Mixture Model with EUT- and ST-Types

Online Table 9: Type-Specific Parameter Estimates of the Finite Mixture Model

Type-specific estimates	EUT	ST
Relative size (π)[a]	0.560	0.440
	(0.037)	(0.037)
Concavity of utility function (β)	0.053***	0.884***
	(0.012)	(0.012)
Degree of local thinking (δ)		0.904°°°
		(0.013)
Choice sensitivity (σ)	0.010***	2.388***
	(0.001)	(0.243)
Number of subjects[b]	158	125
	(10.841)	(10.841)
Number of observations	23,316	
Log Likelihood	-12,015.27	
AIC	24,042.55	
BIC	24,090.89	

Subject cluster-robust standard errors are reported in parentheses and based on 1,000 bootstrap replications. Significantly different from 0 (1) at the 1% level: *** (°°°).

[a] The relative group sizes are not tested against zero, since under the null hypothesis that a type's relative size is zero, the preference parameters are meaningless. Consequently, the test statistic would exhibit an unknown distribution. The distribution of the test statistic could be bootstrapped under the null hypothesis. However, since the estimates of the relative group sizes are sufficiently far from the edges of the parameter space, this is not done here.

[b] Subjects are assigned to the best-fitting model according to their ex-post probabilities of type-membership. The number of assigned subjects is not tested against zero, for the same reason as the relative group sizes are not tested against zero.

6.3 Finite Mixture Model with CPT- and ST-Types

Online Table 10: Type-Specific Parameter Estimates of the Finite Mixture Model

Type-specific estimates	CPT	ST
Relative size (π)[a]	0.620	0.380
	(0.044)	(0.044)
Concavity of utility function (β)	0.334***	0.880***
	(0.059)	(0.017)
Likelihood sensitivity (α)	0.670°°°	
	(0.045)	
Degree of local thinking (δ)		0.919°°°
		(0.013)
Choice sensitivity (σ)	0.052***	2.644***
	(0.020)	(0.360)
Number of subjects[b]	177	106
	(13.486)	(13.486)
Number of observations	23,316	
Log Likelihood	-11,790.12	
AIC	23,594.24	
BIC	23,650.64	

Subject cluster-robust standard errors are reported in parentheses and based on 1,000 bootstrap replications. Significantly different from 0 (1) at the 1% level: *** (°°°).

[a] The relative group sizes are not tested against zero, since under the null hypothesis that a type's relative size is zero, the preference parameters are meaningless. Consequently, the test statistic would exhibit an unknown distribution. The distribution of the test statistic could be bootstrapped under the null hypothesis. However, since the estimates of the relative group sizes are sufficiently far from the edges of the parameter space, this is not done here.

[b] Subjects are assigned to the best-fitting model according to their ex-post probabilities of type-membership. The number of assigned subjects is not tested against zero, for the same reason as the relative group sizes are not tested against zero.

7 Alternative Error Specification and Modeling of Choice Set Dependence

This section of the Online Appendix explores how an alternative specification using a Fechner-type error and modeling choice set dependence by RT instead of ST affects the structural model's fit.

7.1 Fechner-Type Errors

Although the random utility approach presented in Section 5.1.1 of the paper offers an intuitive way to estimate preference parameters in binary choices, an alternative approach is to specify a Fechner-type error that directly affects a subject's choices instead of her utility. With a normally distributed Fechner-type error ν_g with standard deviation σ_M, the probability that subject i of type M chooses lottery X_g in binary choice g, i.e. X_g, i.e., $C_{ig} = X$, is given by

$$\begin{aligned} Pr(C_{ig} = X; \theta_M, \sigma_M) &= Pr\left[V^M(X_g, \theta_M) - V^M(Y_g, \theta_M) + \nu \geq 0\right] \\ &= \Phi\left(\frac{V^M(X_g, \theta_M) - V^M(Y_g, \theta_M)}{\sigma_M}\right), \end{aligned}$$

where Φ is the cdf of the standard normal distribution. By using this probability in equation (6), we obtain subject i's type-specific density contribution to the structural model.

Online Table 11 shows the estimation results of the structural model when we specify such a Fechner-type error instead of applying the random utility approach. Although the parameter estimates and the percentage of correctly predicted choices remain remarkably similar, the AIC and BIC indicate that the model with a Fechner-type error fits the data substantially worse than the one applying the random utility approach.[1] Moreover, when we compare the individual classification of subjects into types between the two models, they are mostly identical as 94.7% of subjects are classified into the same type. In conclusion, even though the two models yield essentially the same results, we select the model using the random utility approach in the paper due to its superior fit.

[1]Since the two models have the same number of parameters, we can also directly compare the achieved log likelihood which is substantially lower for the model with the Fechner-type error.

Online Table 11: Type-Specific Parameter Estimates of the Finite Mixture Model with a Fechner-Type Error

Type-specific estimates	EUT	CPT	ST
Relative size (π)[a]	0.294	0.362	0.345
	(0.037)	(0.037)	(0.037)
Concavity of utility function (β)	0.095***	0.554***	0.860***
	(0.030)	(0.052)	(0.014)
Likelihood sensitivity (α)		0.474°°°	
		(0.027)	
Degree of local thinking (δ)			0.922°°°
			(0.013)
Standard deviation of Fechner-type error (σ)	172.056***	6.158***	0.707***
	(45.854)	(2.371)	(0.069)
Number of subjects[b]	84	100	99
	(11.246)	(10.755)	(10.836)
Number of observations		23,316	
Log Likelihood		-11527.18	
AIC		23,074.35	
BIC		23,154.92	
Share of correctly predicted choices[c]		0.745	

Subject cluster-robust standard errors are reported in parentheses and based on 1,000 bootstrap replications. Significantly different from 0 (1) at the 1% level: *** (°°°).

[a] The relative group sizes are not tested against zero, since under the null hypothesis that a type's relative size is zero, the preference parameters are meaningless. Consequently, the test statistic would exhibit an unknown distribution. The distribution of the test statistic could be bootstrapped under the null hypothesis. However, since the estimates of the relative group sizes are sufficiently far from the edges of the parameter space, this is not done here.

[b] Subjects are assigned to the best-fitting model according to their ex-post probabilities of type-membership (see equation (7)). The number of assigned subjects is not tested against zero, for the same reason as the relative group sizes are not tested against zero.

[c] Choices are predicted by using the subjects' classification into types and by calculating the lotteries' values, $V^M(X_g, \hat{\theta}_M)$ and $V^M(Y_g, \hat{\theta}_M)$, for the type-specific parameter estimates $\hat{\theta}_M$.

7.2 Modeling Choice Set Dependence by RT

Now we investigate how the fit of our model changes if we model choice set dependence by RT instead of ST. The main difference between ST and RT is how they operationalize choice set dependence. ST focuses on payoff differences while RT focuses on utility differences. To specify the RT-types we use a power regret function, i.e. $Q(\Delta v) = \Delta v^{\zeta}$ if $\Delta v \geq 0$ and $Q(\Delta v) = -(-\Delta v)^{\zeta}$ if $\Delta v < 0$, with $\zeta \geq 0$. Moreover, since RT does not directly provide individual values of the lotteries under consideration, we have to use a Fechner-type error instead of the random utility approach. Thus, the probability of RT-type i choosing lottery X_g in binary choice g, i.e., $C_{ig} = X$, is given by

$$\begin{aligned} Pr(C_{ig} = X; \theta_{RT}, \sigma_{RT}) &= Pr\left(\sum_{s=1}^{S} p_s\, Q[v(x_s, \beta_{RT}) - v(y_s, \beta_{RT}), \zeta] + \nu_g \geq 0\right) \\ &= \Phi\left(\frac{\sum_{s=1}^{S} p_s\, Q[v(x_s, \beta_{RT}) - v(y_s, \beta_{RT}), \zeta]}{\sigma_{RT}}\right), \end{aligned}$$

where θ_{RT} contains the preference parameters β_{RT} and ζ. In this model, RT-type i's contribution to the finite mixture model's likelihood is

$$f_{RT}(C_i; \theta_{RT}, \sigma_{RT}) = \prod_{g=1}^{G} Pr(C_{ig} = X; \theta_{RT}, \sigma_{RT})^{I(C_{ig}=X)}\, Pr(C_{ig} = Y; \theta_{RT}, \sigma_{RT})^{1-I(C_{ig}=X)},$$

which replaces $f_{ST}(C_i; \theta_{ST}, \sigma_{ST})$ in equation (6).

Online Table 12 shows the estimation results of the model replacing ST with RT when we use a Fechner-type error for all three types. Comparing these results to the model in Online Table 11 reveals the following.

1. Although the model replacing ST with RT yields a similar percentage of correctly predicted choices, it fits the data substantially worse in terms of the AIC (23,135.17 vs. 23,074.35) and BIC (23,215.74 vs. 23,154.92) and achieves a considerably lower log likelihood (-11,557.59 vs. 11,527.18).

2. The model fails to pick up any choice set dependence as the subjects classified as RT-types exhibit on average a linear regret function ($\hat{\zeta} = 1.003$). Thus, combined with their almost linear utility function, the RT-types essentially maximize the expected payoff. We suspect that the model's failure to pick up the choice set dependence behind the observed Allais Paradoxes in our data is due to the regret function's convexity which violates diminishing sensitivity.

3. When we analyze how the individual classification of subjects into types changes, the following result emerges: 99.1% of subjects originally classified as CPT-types remain in this type. However, 88.8% of subjects originally classified as EUT-types with an almost linear utility function are now classified as RT-types, and 93.7% of subjects originally classified as ST-types with a strongly concave utility function are now classified as EUT-types.

In conclusion, we prefer the model using ST due to its superior fit and ability to pick the choice set dependence in our data – which is essential to explain the non-parametric results in Section 4 of the paper as well as the pattern in the subjects' preference reversals in Section 5.4 of the paper.

To rule out that this conclusion is driven by imposing a Fechener-type error on all types – i.e. the EUT- and CPT-types as well – we also estimated a model replacing ST with RT in which only the RT-types exhibit a Fechner-type error but the other two types follow the random utility approach. Online Table 13 shows the estimation results. When we compare these results with our baseline model in Table 2 of the paper, the conclusion prevails: the model using ST exhibits a superior fit and, in contrast to the model using RT, picks up the choice set dependence in our data.

Online Table 12: Type-Specific Parameter Estimates of the Finite Mixture Model using RT instead of ST with a Fechner-Type Error for all Types

Type-specific estimates	EUT	CPT	RT
Relative size (π)[a]	0.325	0.366	0.309
	(0.037)	(0.042)	(0.043)
Concavity of utility function (β)	0.858***	0.571***	0.098***
	(0.016)	(0.049)	(0.030)
Likelihood sensitivity (α)		0.469°°°	
		(0.027)	
Exponent of regret function (ζ)[b]			1.098
			(0.075)
Standard deviation of Fechner-type error (σ)	0.651***	5.494***	345.392
	(0.064)	(1.969)	(228.251)
Number of subjects[c]	93	100	90
	(10.892)	(12.331)	(12.622)
Number of observations		23,316	
Log Likelihood		-11557.59	
AIC		23,135.17	
BIC		23,215.74	
Share of correctly predicted choices[d]		0.752	

Subject cluster-robust standard errors are reported in parentheses and based on 1,000 bootstrap replications. Significantly different from 0 (1) at the 1% level: *** (°°°).

[a] The relative group sizes are not tested against zero, since under the null hypothesis that a type's relative size is zero, the preference parameters are meaningless. Consequently, the test statistic would exhibit an unknown distribution. The distribution of the test statistic could be bootstrapped under the null hypothesis. However, since the estimates of the relative group sizes are sufficiently far from the edges of the parameter space, this is not done here.

[b] The specification of RT uses a power regret function, $Q(\Delta v) = \Delta v^{\zeta}$ if $\Delta v \geq 0$ and $Q(\Delta v) = -(-\Delta v)^{\zeta}$ if $\Delta v < 0$, with $\zeta \geq 0$.

[c] Subjects are assigned to the best-fitting model according to their ex-post probabilities of type-membership (see equation (7)). The number of assigned subjects is not tested against zero, for the same reason as the relative group sizes are not tested against zero.

[d] Choices are predicted by using the subjects' classification into types and by calculating the lotteries' values, $V^M(X_g, \hat{\theta}_M)$ and $V^M(Y_g, \hat{\theta}_M)$, for the type-specific parameter estimates $\hat{\theta}_M$.

Online Table 13: Type-Specific Parameter Estimates of the Finite Mixture Model using RT instead of ST with a Fechner-Type Error for the RT-Types and a Random Utility Approach for the EUT- and CPT-types

Type-specific estimates	EUT	CPT	RT
Relative size (π)[a]	0.315	0.427	0.259
	(0.046)	(0.053)	(0.055)
Concavity of utility function (β)	0.866***	0.582***	0.082***
	(0.021)	(0.063)	(0.053)
Likelihood sensitivity (α)		0.487°°°	
		(0.030)	
Exponent of regret function (ζ)[b]			1.003
			(0.122)
Choice sensitivity (σ)	2.938***	0.323***	
	(0.367)	(0.168)	
Standard deviation of Fechner-type error (σ)			193.298 (344.017)
Number of subjects[c]	91	119	73
	(13.621)	(15.908)	(15.936)
Number of observations		23,316	
Log Likelihood		-11,510.36	
AIC		23,040.72	
BIC		23,121.29	
Share of correctly predicted choices[d]		0.747	

Subject cluster-robust standard errors are reported in parentheses and based on 1,000 bootstrap replications. Significantly different from 0 (1) at the 1% level: *** (°°°).

[a] The relative group sizes are not tested against zero, since under the null hypothesis that a type's relative size is zero, the preference parameters are meaningless. Consequently, the test statistic would exhibit an unknown distribution. The distribution of the test statistic could be bootstrapped under the null hypothesis. However, since the estimates of the relative group sizes are sufficiently far from the edges of the parameter space, this is not done here.

[b] The specification of RT uses a power regret function, $Q(\Delta v) = \Delta v^{\zeta}$ if $\Delta v \geq 0$ and $Q(\Delta v) = -(-\Delta v)^{\zeta}$ if $\Delta v < 0$, with $\zeta \geq 0$.

[c] Subjects are assigned to the best-fitting model according to their ex-post probabilities of type-membership (see equation (7)). The number of assigned subjects is not tested against zero, for the same reason as the relative group sizes are not tested against zero.

[d] Choices are predicted by using the subjects' classification into types and by calculating the lotteries' values, $V^M(X_g, \hat{\theta}_M)$ and $V^M(Y_g, \hat{\theta}_M)$, for the type-specific parameter estimates $\hat{\theta}_M$.

8 Instructions

The following pages contain translations of the instructions that were handed out to the subjects. The original instructions in French are available on request.

The subjects received printed instructions regarding the general explanations on the experiment, the main part of the experiment (Part 1), and the additional part of the experiment (Part 2). Note that the instructions of the main part of the experiment differ, depending on whether the subject was exposed to the canonical presentation or the states of the world presentation.

The instructions of the remaining Parts 3-5 were shown on screen and are available on request.

General explanations on the experiment

You are about to participate in an economic experiment. The experiment is conducted by the departement d'économetrie et économie politique (DEEP) of the university of Luasanne and funded by the Swiss National Science Foundation (SNSF). It aims at better understanding individual decision making under risk.

For your participation in the experiment you will earn a lump sum payment of 10 CHF for sure. The experiment consists of five parts in some of which you can earn points that depend on your decisions. At the end of the experiment, you get an additional payment of one CHF for every 100 points you earned during the course of the experiment. In other words, each point corresponds to one centime. **Thus, it is to your own benefit to read these explanations carefully.**

You can take your decisions at your own speed. The amount of points you earn only depends on your own decisions.

It is prohibited to communicate with the other participants during the whole course of the experiment. If you do not abide by this rule you will be excluded from the experiment and all payments. However, if you have questions you can always ask one of the experimenters by raising your hand.

You can also abort the experiment anytime you wish without giving any reasons. To do so, please raise your hand and tell the experimenter that you wish to abort the experiment. The experimenter will then guide you outside the laboratory. Note that if you abort the experiment, you are not entitled to any payments.

We will ask you about your personal information and contact address in the fifth part of the experiment. We will only use this information in an anonymized way for scientific purposes or to contact you again with respect this experiment, if necessary. **Thus, your anonymity is guaranteed.**

The backside of these explanations gives you an overview of the experiment. If you have any questions please raise your hand. Otherwise, you can now begin with the instructions of first part of the experiment.

Thank you very much for your participation!

Overview of the experiment

Part 1:
Choosing between two risky options

↓

Part 2:
Choosing between a risky option and a sure amount

↓

Part 3:
Pattern supplementation

↓

Part 4:
Personality questionnaire

↓

Part 5:
Personal Data

↓

Payment

Part 1: Choosing between two risky options [Canonical Presentation]

In this part of the experiment, you first draw a sealed envelope that contains one of 93 decision situations in which you have to choose between two risky options. The possible payoffs of the two risky options are either correlated with each other or independent of each other.

The decision situation in the sealed envelope is the only one relevant for your payoff in this part of the experiment. **However, you are not allowed to open the envelope before the end of the experiment (if you do, you will be excluded from the experiment and all payments).** Instead, you should give us instructions on the computer screen, for each of the 93 decision situations that may be in you sealed envelope, which of the two risky options you choose.

These explanations first contain two examples of the decision situations for which you have to give us instructions on the computer screen. In the first example the possible payoffs of the two risky options are correlated, while in the second example they are independent. Subsequently, the explanations illustrate how your payoff for this part of the experiment is calculated. Finally, they contain some questions that verify your understanding.

Examples of decision situations

In each of the 93 decision situations that may be in your sealed envelope you have the choice between two risky options X and Y. In 45 out of these 93 decision situations the possible payoffs of the two risky options are correlated with each other, while in the remaining 48 decision situations the possible payoffs are independent of each other.

Correlated payoffs

First, consider the following example of a decision situation in which the possible payoffs of the two risky options are correlated. There are three possible payoff states which are realized with probabilities 10.50%, 19.50%, and 70.00%, respectively. Option X pays either 0, 500, or 2400 points depending on the realized payoff state. Option Y yields either 500, 500, or 1500 points depending on the realized payoff state. Hence, the realized payoff state determines the payoff of *both* risky options. For example, if the rightmost payoff state is realized, option X yields 2400 and option Y pays 1500 points.

Probability:	10.50%	19.50%	70.00%	Your Choice
Option X	0	500	2400	❑
Option Y	500	500	1500	❑

If you indicate on the computer screen that you prefer option X and if the decision situation in this example corresponds to the one in your envelope, you get either 0 points with probability 10.50%, 500 points with probability 19.50%, or 2400 points with probability 70.00%. If you indicate that you prefer option Y instead and if the decision situation in this example corresponds to the one in your envelope, you get either 500 points with probability 10.50%, 500 points with probability

19.50%, or 1500 points with probability 70.00%.

Independent payoffs

Now, consider the following example of a decision situation in which the possible payoffs of the two risky options are independent. Option X pays either 0, 500, or 2400 points with probability 10.50%, 19.50%, or 70.00%, respectively. Option Y yields either 500 or 1500 points with probability 30.00% or 70.00%, respectively. Since the possible payoffs are independent, the payoff of one option does not determine the payoff of the other. For example, if the realized payoff of option X is 2400 points, option Y still pays either 500 points with probability 30.00% or 1500 points with probability 70.00%.

Probability:	10.50%	19.50%	70.00%		Probability:	30.00%	70.00%
Option X	0	500	2400	VS.	Option Y	500	1500
Your Choice:		❑				❑	

If you indicate on the computer screen that you prefer option X and if the decision situation in this example corresponds to the one in your envelope, you get either 0 points with probability 10.50%, 500 points with probability 19.50%, or 2400 points with probability 70.00%. If you indicate that you prefer option Y instead and if the decision situation in this example corresponds to the one in your envelope, you get either 500 points with probability 30.00%, or 1500 points with probability 70.00%.

Possible payoffs and probabilities

In each decision situation, you always have to indicate your choice between the two risky options X and Y. However, the number and the size of the possible payoffs as well as the corresponding probabilities differ across the 93 decision situations.

- The number of possible payoffs of a risky option is always between 1 and 3.
- The size of the payoffs varies between 0 and 7000 points.
- The corresponding probabilities of the payoffs range from 1% to 100%.

Calculation of your payoff

At the end of the experiment, you will hand in the sealed envelope to the experimenter who will open it together with you. For the decision situation that is inside your envelope, you will then get the option you have previously indicated on the computer screen.

Correlated payoffs

For instance, let's assume that the decision situation in your envelope is the one with the correlated payoffs from before, and you instructed us on the computer screen that you prefer option X:

Probability:	10.50%	19.50%	70.00%	Your Choice
Option X	0	500	2400	✓
Option Y	500	500	1500	❑

After opening the envelope, you will have to roll four 10-sided dice to generate a random number between 0000 and 9999. The first die indicates the first digit corresponding to thousands. The second die indicates the second digit corresponding to hundreds. The third die indicates the third digit corresponding to tens. Finally, the fourth die indicates the last digit corresponding to units. This random number determines the realized payoff state, as shown in the table below.

Random number				
between	*0000*	*1050*	*3000*	
and	*1049*	*2999*	*9999*	
Probability:	10.50%	19.50%	70.00%	Your Choice
Option X	0	500	2400	✓
Option Y	500	500	1500	❑

With probability 10.50% the random number lies between 0000 and 1049, and the first payoff state is realized. With probability 19.50%, the random number is between 1050 and 2999, and the second payoff state is realized. Finally, with probability 70.00% the random number is between 3000 and 9999, and the third payoff state is realized.

For example, assume that the random number you roll is 4276. Since 4276 is between 3000 and 9999, the third payoff state is realized, and your resulting payoff is 2400 points.

Thus, if you indicate the option you want on the computer screen, you will get the option you want. However, if you give us wrong instructions on the computer screen, you won't get the option you want.

Independent payoffs

Now, assume that the decision situation in your envelope is the one with the independent payoffs from before, and you instructed us on the computer screen that you prefer option Y:

Probability:	10.50%	19.50%	70.00%		Probability:	30.00%	70.00%
Option X	0	500	2400	VS.	Option Y	500	1500
Your Choice:		❑				✓	

After opening the envelope, you will have to roll the four 10-sided dice twice to generate two random numbers between 0000 and 9999. Since the risky options are independent, the first random number determines the payoff of option X, while the second random number determines the payoff of option Y.

First random number					*Second random number*		
between	*0000*	*1050*	*3000*		*between*	*0000*	*3000*
and	*1049*	*2999*	*9999*		*and*	*2999*	*9999*
Probability:	10.50%	19.50%	70.00%		Probability:	30.00%	70.00%
Option X	0	500	2400	VS.	Option Y	500	1500
Your Choice:		❑				✓	

With probability 30.00% the second random number lies between 0000 and 2999, and option Y pays 500 points. With probability 70.00% the second random number is between 3000 and 9999, and option Y yields 1500 points.

For instance, assume that the second random number you roll is 1387. As 1387 is between 0000 and 2999, your resulting payoff from choosing option Y is 500 points.

Again, if you indicate the option you want on the computer screen, you will get the option you want. However, if you give us wrong instructions on the computer screen, you won't get the option you want.

Questions to verify your understanding

The following questions test whether you correctly understood the explanations for the first part of the experiment.

Let's assume that at the end of the experiment your envelope contains the following decision situation:

Random number					
between	*0000*	*0525*	*1800*	*3800*	
and	*0524*	*1799*	*3799*	*9999*	
Probability:	5.25%	12.75%	20.00%	62.00%	Your Choice
Option X	0	1000	1500	3500	❑
Option Y	100	1000	2000	2500	❑

If you indicated on the computer screen that you prefer option Y, what are the possible payoffs and corresponding probabilities?

____

If you roll the number 2845, which of these payoffs will you get?

____

To how many CHF does this payoff correspond?

____

Now, assume that at the end of the experiment your envelope contains the following decision situation:

First random number					*Second random number*		
between	*0000*	*1550*	*3450*		*between*	*0000*	*3450*
and	*1549*	*3449*	*9999*		*and*	*3449*	*9999*
Probability:	15.50%	19.00%	65.50%		Probability:	34.50%	65.50%
Option X	100	1500	2400	VS.	Option Y	1500	2000
Your Choice:		❑				❑	

What is your payoff if you indicated on the computer screen that you prefer option X, and the first random number you rolled is 1201, while the second random number is 5498?

After finishing these questions, please raise your hand and wait for the experimenter to correct them. Thank you.

Part 1: Choosing between two risky options
[States of the World Presentation]

In this part of the experiment, you first draw a sealed envelope that contains one of 84 decision situations in which you have to choose between two risky options.

The decision situation in the sealed envelope is the only one relevant for your payoff in this part of the experiment. **However, you are not allowed to open the envelope before the end of the experiment (if you do, you will be excluded from the experiment and all payments).** Instead, you should give us instructions on the computer screen, for each of the 84 decision situations that may be in you sealed envelope, which of the two risky options you choose.

These explanations first contain an example of one of the decision situations for which you have to give us instructions on the computer screen. Subsequently, they illustrate how your payoff for this part of the experiment is calculated. Finally, they contain some questions to verify that you understood the explanations correctly.

Example of a decision situation

In each of the 84 decision situations that may be in your sealed envelope you have the choice between two risky options X and Y.

Consider the following example. There are three possible payoff states which are realized with probabilities 10.50%, 19.50%, and 70.00%, respectively. Option X pays either 0, 500, or 2400 points depending on the realized payoff state. Option Y yields either 500, 500, or 1500 points depending on the realized payoff state.

Probability:	10.50%	19.50%	70.00%	Your Choice
Option X	0	500	2400	❑
Option Y	500	500	1500	❑

Thus, if you indicate on the computer screen that you prefer option X and if the decision situation in this example corresponds to the one in your envelope, you get either 0 points with probability 10.50%, 500 points with probability 19.50%, or 2400 points with probability 70.00%. If you indicate that you prefer option Y instead and if the decision situation in this example corresponds to the one in your envelope, you get either 500 points with probability 10.50%, 500 points with probability 19.50%, or 1500 points with probability 70.00%.

In each of the 84 decision situation, you always have to indicate your choice between two risky options X and Y. However, the number of payoff states as well as the corresponding probabilities and sizes of the payoffs differ across the 84 decision situations.

- The number of payoff states is always either 3 or 4.
- The probabilities of the payoff states range from 0.02% to 97.02%.
- The sizes of the payoffs vary between 0 and 7000 points.

Calculation of your payoff

At the end of the experiment, you will hand in the sealed envelope to the experimenter who will open it together with you. For the decision situation that is inside your envelope, you will then get the option you have previously indicated on the computer screen.

For instance, let's assume that the decision situation in your envelope is the one from before, and you instructed us previously on the computer screen that you prefer option X:

Probability:	10.50%	19.50%	70.00%	Your Choice
Option X	0	500	2400	✓
Option Y	500	500	1500	❑

After opening the envelope, you will have to roll four 10-sided dice to generate a random number between 0000 and 9999. The first die indicates the first digit corresponding to thousands. The second die indicates the second digit corresponding to hundreds. The third die indicates the third digit corresponding to tens. Finally, the fourth die indicates the last digit corresponding to units. This random number determines the realized payoff state, as shown in the table below.

Random number				
between	*0000*	*1050*	*3000*	
and	*1049*	*2999*	*9999*	
Probability:	10.50%	19.50%	70.00%	Your Choice
Option X	0	500	2400	✓
Option Y	500	500	1500	❑

With probability 10.50% the random number lies between 0000 and 1049, and the first payoff state is realized. With probability 19.50%, the random number is between 1050 and 2999, and the second payoff state is realized. Finally, with probability 70.00% the random number is between 3000 and 9999, and the third payoff state is realized.

For example, assume that the random number you roll is 4276. Since 4276 is between 3000 and 9999, the third payoff state is realized, and your resulting payoff is 2400 points.

Thus, if you indicate the option you want on the computer screen, you will get the option you want. However, if you give us wrong instructions on the computer screen, you won't get the option you want.

Questions to verify your understanding

The following three questions test whether you correctly understood the explanations for the first part of the experiment.

Let's assume that at the end of the experiment your envelope contains the following decision situation:

Random number					
between	*0000*	*0525*	*1800*	*3800*	
and	*0524*	*1799*	*3799*	*9999*	
Probability:	5.25%	12.75%	20.00%	62.00%	Your Choice
Option X	0	1000	1500	3500	❑
Option Y	100	1000	2000	2500	❑

If you indicated on the computer screen that you prefer option Y, what are the possible payoffs and corresponding probabilities?

If you roll the number 2845, which of these payoffs will you get?

To how many CHF does this payoff correspond?

After finishing these questions, please raise your hand and wait for the experimenter to correct them. Thank you.

Part 2: Choosing between a risky option and a sure amount

In this part of the experiment, you first draw a sealed envelope that contains one of 180 decision situations in which you have to choose between a risky option and a sure amount.

The decision situation in the sealed envelope is the only one relevant for your payoff in this part of the experiment. **However, you are not allowed to open the envelope before the end of the experiment (if you do, you will be excluded from the experiment and all payments).** Instead, you should give us instructions on the computer screen, for each of the 180 decision situations that may be in you sealed envelope, whether you choose the risky option or the sure amount.

These explanations first contain an example of a computer screen on which you have to give us instructions about your choice. Subsequently, they illustrate how your payoff for this part of the experiment is calculated. Finally, they contain a question to verify that you understood the explanations correctly.

Example of a computer screen

There will be nine computer screens each containing 20 decision situations. In each of these decision situations, you have to chose between either a risky option A or a sure amount B.

Consider the example below of such a computer screen. The risky option remains the same across all 20 decision situations. However, the sure amount increases from the lowest possible payoff of the risky option, 0, to its highest possible payoff, 6400, in twenty equally sized steps.

	Option A	Your Choice	Option B
1	6400 with probability 10 % or 0 with probability 90%	A ❑ ❑ B	0
2		A ❑ ❑ B	320
3		A ❑ ❑ B	640
4		A ❑ ❑ B	960
5		A ❑ ❑ B	1280
6		A ❑ ❑ B	1600
7		A ❑ ❑ B	1920
8		A ❑ ❑ B	2240
9		A ❑ ❑ B	2560
10		A ❑ ❑ B	2880
11		A ❑ ❑ B	3200
12		A ❑ ❑ B	3520
13		A ❑ ❑ B	3840
14		A ❑ ❑ B	4160
15		A ❑ ❑ B	4480
16		A ❑ ❑ B	5120
17		A ❑ ❑ B	5440
18		A ❑ ❑ B	5760
19		A ❑ ❑ B	6080
20		A ❑ ❑ B	6400

For each of these 20 decision situations on the computer screen, you have to give us instructions whether you choose the risky option A or the sure amount B, if that decision is in your sealed envelope. For instance, you may start by choosing the risky option in the first decision situation where the sure amount is zero. But at some decision situations further down the list, where the sure amount is larger, you may switch to choosing the sure amount instead of the risky option.

Across the nine computer screens, the risky option differs: It always has two possible payoffs, but the probabilities and sizes of these two possible payoffs vary.

- The probabilities range from 4.00% to 96.00%.
- The lower of the two possible payoffs is always 0, while higher one varies between 400 and 6000 points.

Calculation of your payoff

At the end of the experiment, you will hand in the sealed envelope to the experimenter who will open it together with you. For the decision situation that is inside your envelope, you will then get the option you have previously chosen on the computer screen.

For example, consider you gave us the following instructions on the computer screen from before:

	Option A	Your Choice	Option B
1	6400 with probability 10 % or 0 with probability 90%	A ✓ ❑ B	0
2		A ✓ ❑ B	320
3		A ✓ ❑ B	640
4		A ✓ ❑ B	960
5		A ✓ ❑ B	1280
6		A ✓ ❑ B	1600
7		A ✓ ❑ B	1920
8		A ❑ ✓ B	2240
9		A ❑ ✓ B	2560
10		A ❑ ✓ B	2880
11		A ❑ ✓ B	3200
12		A ❑ ✓ B	3520
13		A ❑ ✓ B	3840
14		A ❑ ✓ B	4160
15		A ❑ ✓ B	4480
16		A ❑ ✓ B	5120
17		A ❑ ✓ B	5440
18		A ❑ ✓ B	5760
19		A ❑ ✓ B	6080
20		A ❑ ✓ B	6400

Moreover, assume that your envelope contains the following decision situation which corresponds to the *sixth row* in the above computer screen:

- Option A: 6400 with probability 10% (random number between 0000 and 0999), or 0 with probability 90% (random number between 1000 and 9999).
- Option B: 1600 for sure.

Since in this example, you chose the risky option A over the sure amount of 1600 in the sixth row of the computer screen, you will get the risky option A. As in the first part of the experiment, you will have to roll four 10-sided dice to generate a random number between 0000 and 9999 that will determine the realized payoff of the risky option A. If you had chosen the sure amount instead of the risky option, you would have gotten 1600 points for sure.

Thus, if you indicate the option you want on the computer screen, you will get the option you want. However, if you give us wrong instructions on the computer screen, you won't get the option you want.

Question to verify your understanding

The following question tests whether you correctly understood the explanations for the second part of the experiment.

Let's assume that the decision situation in your envelope corresponds to the *sixteenth row* of the example of the computer screen as shown on the previous page, i.e.:

- Option A: 6400 with probability 10% (random number between 0000 and 0999), or 0 with probability 90% (random number between 1000 and 9999).
- Option B: 5120 for sure.

If you gave the same instructions as in the example of the computer screen on the previous page, does your payoff depend on the random number you roll? If yes, what are the possible payoffs? If not, which payoff do you get?

After finishing these questions, please raise your hand and wait for the experimenter to correct them. Thank you.