ONLINE APPENDIX

Who Opts In?

Sandro Ambuehl, Axel Ockenfels, and Colin Stewart

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A Proofs

A.1 Proof of Proposition 1

We first prove part (ii) and then draw on some of the same calculations in the proof of part (i).

A.1.1 Proof of part (ii)

For simplicity of notation, we omit the arguments from $p_s(m, \lambda)$ and $p(m, \lambda)$. A direct application of Theorem 1 in Matějka and McKay (2015) shows that for each $s \in \{G, B\}$, the state-contingent participation probabilities p_s are given by

$$p_s = \left[1 + \left(\frac{1}{p} - 1\right) \exp\left\{-\frac{1}{\lambda}(\pi_s + m)\right\}\right]^{-1}.$$

Substituting these expressions into the equation $p = \mu p_G + (1 - \mu)p_B$ defining p and dividing both sides by p gives

$$1 = \frac{\mu}{p + (1-p)/g} + \frac{1-\mu}{p + (1-p)/b},$$

where $g := \exp\big((\pi_G + m)/\lambda\big)$ and $b := \exp\big((\pi_B + m)/\lambda\big)$. Note that, since $\pi_G + m > 0 > \pi_B + m$, $g > 1 > b$. Rearranging gives

$$-\mu \frac{g-1}{g\frac{p}{1-p} + 1} = (1-\mu)\frac{b-1}{b\frac{p}{1-p} + 1}.$$

Solving for $\frac{p}{1-p}$ then yields

$$\frac{p}{1-p} = -\frac{(1-\mu)(b-1) + \mu(g-1)}{(1-\mu)(b-1)g + \mu b(g-1)},$$

from which we obtain

$$p = -\frac{\mu}{b-1} - \frac{1-\mu}{g-1}. \tag{5}$$

Differentiating with respect to m gives

$$\frac{\partial p}{\partial m} = \frac{1-\mu}{(g-1)^2}\frac{g}{\lambda} + \frac{\mu}{(b-1)^2}\frac{b}{\lambda}.$$

Let A denote the first of the two terms on the right-hand side. We will show that $\frac{\partial A}{\partial \lambda} > 0$; a similar argument applies to the second term, thereby proving the result. We have

$$\frac{1}{1-\mu}\frac{\partial A}{\partial \lambda} = \frac{2g^2 \log g}{\lambda^2 (g-1)^3} - \frac{g \log g}{\lambda^2 (g-1)^2} - \frac{g}{\lambda^2 (g-1)^2},$$

which is positive if and only if

$$(g+1)\log g - g + 1 > 0.$$

The left-hand side of this inequality is equal to 0 when $g = 1$ and its derivative is positive everywhere. Therefore, the inequality holds for all $g > 1$, as needed.

A.1.2 Proof of part (i)

Lemma 1. *Let X be a continuously distributed real-valued random variable and let $f : R \longrightarrow R_+$ and $g : R \longrightarrow R_+$ be such that $\frac{f(x)}{g(x)}$ is increasing in x and $E[f(X)] > 0$ and $E[g(X)] > 0$. Then*

$$\frac{E[Xf(X)]}{E[f(X)]} > \frac{E[Xg(X)]}{E[g(X)]}.$$

Proof. Let γ be the density of X. Let $\hat{f}(x) = f(x)\gamma(x)/E[f(X)]$ and $\hat{g}(x) = g(x)\gamma(x)/E[g(X)]$. Note that $\hat{f}$ and $\hat{g}$ are probability density functions. Since $\frac{f(x)}{g(x)}$ is increasing, so is

$$\frac{f(x)\gamma(x)}{E[f(X)]} \cdot \frac{E[g(X)]}{g(x)\gamma(x)} = \frac{\hat{f}(x)}{\hat{g}(x)}.$$

That is, $\hat{f}$ and $\hat{g}$ satisfy the monotone likelihood ratio property. In particular, the distribution associated with $\hat{f}$ first-order stochastically dominates that associated with $\hat{g}$. It follows that

$$\int_{-\infty}^{\infty} x\hat{f}(x)dx > \int_{-\infty}^{\infty} x\hat{g}(x)dx.$$

By definition of $\hat{f}$ and $\hat{g}$, this last inequality is equivalent to

$$\frac{E[Xf(X)]}{E[f(X)]} = \int_{-\infty}^{\infty} x\frac{f(x)\gamma(x)}{E[f(X)]}dx > \int_{-\infty}^{\infty} x\frac{g(x)\gamma(x)}{E[g(X)]}dx = \frac{E[Xg(X)]}{E[g(X)]},$$

as needed. □

Lemma 2. *The function*

$$h(b,g) = -\left((b-1)g + b(g-1)\right)(b-1)(g-1) + (b-1)g(2b-g-1)\log g + (g-1)b(2g-b-1)\log b$$

is positive everywhere on the set $\Gamma = \{(b,g) \mid b \in (0,1) \text{ and } g \in (1,\infty)\}$.

Proof. Note that $h(1,g) \equiv 0$, so it suffices to show that $h_b(b,g)$ is negative everywhere on Γ, where h_b denotes the partial derivative of h with respect to b. We have

$$h_b(b,g) = -(g-1)(4bg-5g-b+2) + (4b-g-3)g\log g + (g-1)(2g-2b-1)\log b.$$

In particular, $h_b(b,1) \equiv 0$. Hence h_b is negative everywhere on Γ if h_{bg} is. We have

$$h_{bg}(b,g) = -8bg + 9b + 9g - 10 + (4b-2g-3)\log g + (4g-2b-3)\log b.$$

Note that $h_{bg}(b,1) \equiv b - 1 + (1-2b)\log b$, which is negative for all $b \in (0,1)$. Hence h_{bg} is negative everywhere on Γ if h_{bgg} is. We have

$$h_{bgg}(b,g) = -8b + 7 + \frac{4b-3}{g} - 2\log g + 4\log b.$$

Note that

$$h_{bgg}\left(\frac{1}{4}, g\right) \equiv 5 + 4\log\left(\frac{1}{4}\right) - \frac{2}{g} - 2\log g,$$

which is negative for all $g > 1$ since $5 + 4\log(1/4) < 0$. Now note that

$$h_{bggb}(b,g) = -8 + \frac{4}{g} + \frac{4}{b}$$

is positive whenever $b < 1/4$ and $g > 1$. It follows that h_{bgg} is negative whenever $b \in (0, 1/4]$ and $g \in (1, \infty)$.

Now consider $b > 1/4$. Note that $h_{bgg}(b,1) \equiv 4(1 - b + \log b)$, which is negative for all $b \in (0,1)$. Note also that

$$h_{bggg}(b,g) = -\frac{4b-3}{g^2} - \frac{2}{g},$$

which, for $g > 1$, is negative if and only if $g > 3/2 - 2b$, which holds if $b > 1/4$ and $g > 1$. It follows that h_{bgg} is negative whenever $b \in (1/4, 1)$ and $g \in (1, \infty)$. Combining this with the above gives that h_{bgg} is negative everywhere on Γ, as needed. □

We first argue that it suffices to show that, under the conditions stated in the proposition, $E[\lambda \mid \text{participate}]$ is increasing in m. To see this, note first that an equivalent statement of part (i) of the proposition is that if m_1 and m_2 are such that $m_2 > m_1$ and $p(m_i, \lambda) \in [0,1)$ for all $\lambda \in [\underline{\lambda}, \overline{\lambda}]$ and $i = 1, 2$, then the distribution of λ conditional on participation at m_2 first-order stochastically dominates (FOSDs) that at m_1. Let Ψ denote the distribution of λ. For each $i = 1, 2$, let F_i denote the distribution function for λ conditional on participation at m_i. Note that F_1 and F_2 are continuous since Ψ is. Suppose that F_2 does not FOSD F_1; we will show that this implies that, for some distribution of λ satisfying the conditions of the proposition,

$E[\lambda \mid \text{participate}]$ is not increasing in m. Then there exists some λ_0 such that $F_1(\lambda_0) < F_2(\lambda_0)$. By continuity of F_1 and F_2 and the fact that they agree at $\underline{\lambda}$ and $\overline{\lambda}$, there exists an interval $[a, b]$ containing λ_0 such that $F_1(a) = F_2(a)$, $F_1(b) = F_2(b)$, and $F_1(x) < F_2(x)$ for all $x \in (a, b)$. Thus, for each $\lambda \in (a, b)$,

$$F_1(\lambda|[a,b]) = \frac{F_1(\lambda) - F_1(a)}{F_1(b) - F_1(a)} = \frac{F_1(\lambda) - F_2(a)}{F_2(b) - F_2(a)} < \frac{F_2(\lambda) - F_2(a)}{F_2(b) - F_2(a)} = F_2(\lambda|[a,b]),$$

and hence $F_1(\cdot \mid [a, b])$ FOSDs $F_2(\cdot \mid [a, b])$. Note that $F_i(\cdot \mid [a, b])$ is the distribution of λ conditional on participation at m_i when the prior distribution of λ is $\Psi(\cdot \mid [a, b])$. It follows that, for the prior distribution $\Psi(\cdot \mid [a, b])$, $E\left[\lambda \mid \text{participate}\right]$ is higher at m_1 than it is at m_2, as needed.

We now show that $E[\lambda \mid \text{participate}]$ is indeed increasing in m. First suppose $p(m, \lambda) > 0$ for all $\lambda \in [\underline{\lambda}, \overline{\lambda}]$. We have

$$E\left[\lambda \mid \text{participate}\right] = \frac{E[\lambda p]}{E[p]}.$$

Differentiating with respect to m gives

$$\frac{\partial}{\partial m} E\left[\lambda \mid \text{participate}\right] = \frac{E[p]E\left[\lambda \frac{\partial p}{\partial m}\right] - E[\lambda p]E\left[\frac{\partial p}{\partial m}\right]}{(E[p])^2}.$$

This is positive if and only if the numerator is positive, which, since p and $\partial p/\partial m$ are positive for each λ, may be rewritten as

$$\frac{E\left[\lambda \frac{\partial p}{\partial m}\right]}{E\left[\frac{\partial p}{\partial m}\right]} > \frac{E[\lambda p]}{E[p]}.$$

By Lemma 1 (with $X = \lambda$, $f = \frac{\partial p}{\partial m}$, and $g = p$), it suffices to show that

$$\frac{1}{p}\frac{\partial p}{\partial m}$$

is increasing in λ. Differentiating with respect to λ gives

$$\frac{\partial}{\partial \lambda}\left(\frac{1}{p}\frac{\partial p}{\partial m}\right) = -\frac{1}{p^2}\frac{\partial p}{\partial \lambda}\frac{\partial p}{\partial m} + \frac{1}{p}\frac{\partial^2 p}{\partial \lambda \partial m}.$$

Thus it suffices to show that

$$p\frac{\partial^2 p}{\partial \lambda \partial m} > \frac{\partial p}{\partial \lambda}\frac{\partial p}{\partial m}. \tag{6}$$

Differentiating (5) gives

$$\begin{aligned}\frac{\partial p}{\partial \lambda}\frac{\partial p}{\partial m} &= \left(\frac{1-\mu}{(g-1)^2}\left(-\frac{g}{\lambda}\log g\right) + \frac{\mu}{(b-1)^2}\left(-\frac{b}{\lambda}\log b\right)\right)\left(\frac{1-\mu}{(g-1)^2}\frac{g}{\lambda} + \frac{\mu}{(b-1)^2}\frac{b}{\lambda}\right)\\ &= -(1-\mu)^2\frac{g^2\log g}{\lambda^2(g-1)^4} - \mu(1-\mu)\frac{bg\log b + bg\log g}{\lambda^2(b-1)^2(g-1)^2} - \mu^2\frac{b^2\log b}{\lambda^2(b-1)^4}, \end{aligned}\tag{7}$$

and

$$\frac{\partial^2 p}{\partial\lambda\partial m} = (1-\mu)\left(\frac{g(g+1)\log g - g(g-1)}{\lambda^2(g-1)^3}\right) + \mu\left(\frac{b(b+1)\log b - b(b-1)}{\lambda^2(b-1)^3}\right).$$

Multiplying the latter by the expression for p in (5) and expanding leads to

$$\begin{aligned}p\frac{\partial^2 p}{\partial\lambda\partial m} &= -(1-\mu)^2\left(\frac{g(g+1)\log g - g(g-1)}{\lambda^2(g-1)^4}\right)\\ &\quad - \mu(1-\mu)\left(\frac{g(g+1)\log g - g(g-1)}{\lambda^2(b-1)(g-1)^3} + \frac{b(b+1)\log b - b(b-1)}{\lambda^2(b-1)^3(g-1)}\right)\\ &\quad - \mu^2\left(\frac{b(b+1)\log b - b(b-1)}{\lambda^2(b-1)^4}\right). \end{aligned}\tag{8}$$

Comparing the $(1-\mu)^2$ terms in (7) and (8), we see that the latter is larger if and only if

$$-(g(g+1)\log g - g(g-1)) > -g^2\log g,$$

or, equivalently, if

$$g - 1 - \log g > 0,$$

which holds for all $g > 1$. Similarly, comparing the μ^2 terms in (7) and (8), we see that the latter is larger if and only if

$$b - 1 - \log b > 0,$$

which holds for all $b \in (0,1)$.

Finally, for the $\mu(1-\mu)$ terms, that in (8) is larger than that in (7) if and only if

$$-\left(\frac{g(g+1)\log g - g(g-1)}{\lambda^2(b-1)(g-1)^3} + \frac{b(b+1)\log b - b(b-1)}{\lambda^2(b-1)^3(g-1)}\right) > -\frac{bg\log b + bg\log g}{\lambda^2(b-1)^2(g-1)^2}.$$

Rearranging gives the equivalent inequality

$$\begin{aligned}(b-1)(g-1)bg(\log b+\log g)&\\ &> (b-1)^2\left(g(g+1)\log g - g(g-1)\right) + (g-1)^2\left(b(b+1)\log b - b(b-1)\right).\end{aligned}$$

Further rearranging leads to

$$-\left((b-1)g+b(g-1)\right)(b-1)(g-1)+(b-1)g(2b-g-1)\log g+(g-1)b(2g-b-1)\log b<0,$$

which, by Lemma 2, holds for all $b \in (0,1)$ and $g \in (1,\infty)$.

Combining these three comparisons, we see that (6) holds for all b and g.

Now suppose $p(m,\lambda)=0$ for some $\lambda \in [\underline{\lambda},\overline{\lambda}]$. By Lemma 2 of Matějka and McKay (2015), for any such λ, $p=0$ maximizes

$$\mu \log\left(pg+1-p\right)+(1-\mu)\log\left(pb+1-p\right).$$

The corresponding first-order condition (evaluated at $p=0$) is

$$\mu g+(1-\mu)b \leq 1. \tag{9}$$

Suppose this holds with equality; that is, suppose $\mu g+(1-\mu)b=1$. The derivative of the left-hand side of (9) with respect to λ is

$$-\mu g\frac{\log g}{\lambda}-(1-\mu)b\frac{\log b}{\lambda}.$$

Since $f(x)=-x\log x$ is a strictly concave function, Jensen's Inequality implies that

$$-\mu g\frac{\log g}{\lambda}-(1-\mu)b\frac{\log b}{\lambda}<-\frac{1}{\lambda}(\mu g+(1-\mu)b)\log\left(\mu g+(1-\mu)b\right),$$

the right-hand side of which is equal to 0 whenever (9) holds with equality. It follows that if there is some λ for which $p=0$, then there is a cutoff value $\tilde{\lambda}$ such that $p=0$ if and only if $\lambda>\tilde{\lambda}$.

Since the result holds if $p>0$ for all $\lambda \in [\underline{\lambda},\overline{\lambda}]$, it also holds if we condition on $\lambda \in [\underline{\lambda},\tilde{\lambda}]$. Removing this condition only strengthens the result since $\tilde{\lambda}$ is increasing in m (which follows from the fact that the left-hand side of (9) is increasing in m).

A.2 Proof of Proposition 2

From equation (5) we have

$$p(m, a\lambda) = -\mu f(\pi_B + m, c\eta) - (1 - \mu) f(\pi_G + m, c\eta),$$

where $\eta = 1/\lambda$, $c = 1/a$, and $f(x, \eta) = \frac{1}{e^{\eta x} - 1}$. Thus it suffices to show that

$$\left.\frac{\partial}{\partial c}\right|_{c=1} \left[-c \frac{1}{\lambda^2} \frac{\partial^2}{\partial \eta \partial m} f(x, c\eta) \right] \geq 0, \tag{10}$$

and that this inequality is strict for at least one $x \in \{\pi_B + m, \pi_G + m\}$. Differentiating the left-hand side leads to the equivalent expression

$$\left.\frac{\partial}{\partial c}\right|_{c=1} \left[-\frac{c}{\lambda^2} \frac{e^{cx\eta} \left(cx\eta + 1 + e^{cx\eta}(cx\eta - 1) \right)}{(e^{cx\eta} - 1)^3} \right]$$
$$= \frac{1}{8\lambda^2} \left(\sinh\left(\frac{z}{2}\right) \right)^{-4} \big(-1 + 2z^2 + (1 + z^2)\cosh(z) - 3z\sinh(z) \big),$$

where $z = x\eta$. Because the above expression is symmetric (in the sense that each side yields the same value, regardless of whether it is evaluated at z or at $-z$, for all z), it suffices to show that it is positive whenever z is (it holds trivially for $z = 0$). This expression is positive if and only if

$$z^2 (\cosh(z) + 2) + \cosh(z) > 1 + 3z\sinh(z).$$

Because $\cosh(z) \geq 1$ for all z, it suffices to show that $z^2\big(\cosh(z) + 2\big) > 3z\sinh(z)$, or, equivalently,

$$\cosh(z) + 2 > \frac{3}{z}\sinh(z). \tag{11}$$

To prove this inequality, we employ the fact that sinh and cosh are analytic functions. Inserting their series representations, we get

$$\frac{3}{z}\sinh(z) = \frac{3}{z}\sum_{k=0}^{\infty} \frac{z^{2k+1}}{(2k+1)!} = 3 + 3\sum_{k=1}^{\infty} \frac{z^{2k}}{(2k)!}\frac{1}{2k+1} \leq 3 + \sum_{k=1}^{\infty} \frac{z^{2k}}{(2k)!} = 2 + \cosh(z), \tag{12}$$

as needed.

Finally, the two sides of inequality (11) are equal only if $z = 1$. Because $\pi_B + m < \pi_G + m$, inequality (10) is strict for at least one $x \in \{\pi_B + m, \pi_G + m\}$.

A.3 Proof of Proposition 3

Caplin and Dean (2013) show that the agent's choice problem is equivalent to the choice of posterior beliefs $(\gamma_{\text{part}}, \gamma_{\text{abst}})$ solving

$$\max_{\gamma_{\text{part}}, \gamma_{\text{abst}}, p \in [0,1]} pN_{\text{part}} + (1-p)N_{\text{abst}} \quad \text{s.t.} \quad p\gamma_{\text{part}} + (1-p)\gamma_{\text{abst}} = \mu, \tag{13}$$

where

$$\begin{aligned} & N_{\text{abst}} := -\lambda h(\gamma_{\text{abst}}) \\ \text{and} \qquad & N_{\text{part}} := \gamma_{\text{part}}(\pi_G + m) + (1-\gamma_{\text{part}})(\pi_B + m) - \lambda h(\gamma_{\text{part}}) \end{aligned}$$

are the net utilities associated with the two posteriors (under the assumption that the agent abstains at γ_{abst} and participates at γ_{part}).

Caplin and Dean (2013) show that the solution to (13) is given by the posteriors γ_{part} and γ_{abst} that support the concavification of the upper envelope of the net utility functions, as in Aumann, Maschler, and Stearns (1995) and Gentzkow and Kamenica (2011), with $\gamma_{\text{part}} \geq \mu \geq \gamma_{\text{abst}}$. Under the assumption that each action is chosen with positive probability, these inequalities are strict, and participation is optimal at posterior γ_{part} while abstention is optimal at posterior γ_{abst}.

By concavification, the solution satisfies two conditions. First, the slopes of the tangent lines to the net utility function at γ_{abst} and γ_{part} must coincide:

$$-\lambda h'(\gamma_{\text{abst}}) = \Delta - \lambda h'(\gamma_{\text{part}}), \tag{14}$$

where $\Delta := \pi_G - \pi_B$. Second, the tangent line to the net utility function at γ_{abst} has the same value at γ_{part} as the net utility function itself:

$$-\lambda h(\gamma_{\text{abst}}) - (\gamma_{\text{part}} - \gamma_{\text{abst}})\lambda h'(\gamma_{\text{abst}}) = \Delta\gamma_{\text{part}} + \pi_B + m - \lambda h(\gamma_{\text{part}}). \tag{15}$$

To prove part (i), we start by taking derivatives of (14) and (15) with respect to λ to obtain

$$-h'(\gamma_{\text{abst}}) - \lambda h''(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial \lambda} = -h'(\gamma_{\text{part}}) - \lambda h''(\gamma_{\text{part}})\frac{\partial \gamma_{\text{part}}}{\partial \lambda} \tag{16}$$

and

$$-h(\gamma_{\text{abst}}) - \lambda h'(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial \lambda} = -h(\gamma_{\text{part}}) - \lambda h'(\gamma_{\text{part}})\frac{\partial \gamma_{\text{part}}}{\partial \lambda} + \left(\frac{\partial \gamma_{\text{part}}}{\partial \lambda} - \frac{\partial \gamma_{\text{abst}}}{\partial \lambda}\right)\lambda h'(\gamma_{\text{abst}})$$
$$+ (\gamma_{\text{part}} - \gamma_{\text{abst}})\left(h'(\gamma_{\text{abst}}) + \lambda h''(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial \lambda}\right) + \Delta\frac{\partial \gamma_{\text{part}}}{\partial \lambda}. \quad (17)$$

Cancelling $-\lambda h'(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial \lambda}$ from both sides of (17) and rearranging yields

$$h(\gamma_{\text{part}}) - h(\gamma_{\text{abst}}) = \frac{\partial \gamma_{\text{part}}}{\partial \lambda}\left[\lambda h'(\gamma_{\text{abst}}) - \lambda h'(\gamma_{\text{part}}) + \Delta\right] + (\gamma_{\text{part}} - \gamma_{\text{abst}})\left(h'(\gamma_{\text{abst}}) + \lambda h''(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial \lambda}\right).$$

By (14), the term in square brackets is equal to 0. Further rearranging yields

$$\begin{aligned}(\gamma_{\text{part}} - \gamma_{\text{abst}})\lambda h''(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial \lambda} &= h(\gamma_{\text{part}}) - h(\gamma_{\text{abst}}) - (\gamma_{\text{part}} - \gamma_{\text{abst}})h'(\gamma_{\text{abst}}) \\ &= \frac{1}{\lambda}(\Delta\gamma_{\text{part}} + \pi_B + m),\end{aligned} \quad (18)$$

where the second line follows by substituting from (15). Since participation is optimal at γ_{part}, we have $\Delta\gamma_{\text{part}} + \pi_B + m = \gamma_{\text{part}}\pi_G + (1-\gamma_{\text{part}})\pi_B + m > 0$. Because $\gamma_{\text{part}} > \bar{\gamma} > \gamma_{\text{abst}}$ and $h'' > 0$, it follows that $\frac{\partial \gamma_{\text{abst}}}{\partial \lambda} > 0$.

Rearranging (16) and substituting $h'(\gamma_{\text{part}}) - h'(\gamma_{\text{abst}}) = \frac{\Delta}{\lambda}$ from (14) leads to

$$\begin{aligned}\lambda h''(\gamma_{\text{part}})\frac{\partial \gamma_{\text{part}}}{\partial \lambda} &= \lambda h''(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial \lambda} - \frac{\Delta}{\lambda} \\ &= \frac{1}{\lambda}\left(\frac{\gamma_{\text{abst}}\pi_G + (1-\gamma_{\text{abst}})\pi_B + m}{\gamma_{\text{part}} - \gamma_{\text{abst}}}\right),\end{aligned}$$

where the second equality subsitutes for $\lambda h''(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial \lambda}$ using (18). Because $h'' > 0$ and because the quantity on the right-hand side is negative, we conclude that $\frac{\partial \gamma_{\text{part}}}{\partial \lambda} < 0$.

The proof of part (ii) proceeds similarly. Taking the derivatives of (14) and (15) with respect to m, we obtain

$$-\lambda h''(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial m} = -\lambda h''(\gamma_{\text{part}})\frac{\partial \gamma_{\text{part}}}{\partial m} \quad (19)$$

and

$$- \lambda h'(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial m} - \left(\left(\frac{\partial \gamma_{\text{part}}}{\partial m} - \frac{\partial \gamma_{\text{abst}}}{\partial m} \right) \lambda h'(\gamma_{\text{abst}}) + (\gamma_{\text{part}} - \gamma_{\text{abst}})\lambda h''(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial m} \right)$$
$$= \Delta \frac{\partial \gamma_{\text{part}}}{\partial m} + 1 - \lambda h'(\gamma_{\text{part}})\frac{\partial \gamma_{\text{part}}}{\partial m}.$$

Simplifying and rearranging this last equation gives

$$-1 - (\gamma_{\text{part}} - \gamma_{\text{abst}})\lambda h''(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial m} = \frac{\partial \gamma_{\text{part}}}{\partial m} \left(\Delta - \lambda h'(\gamma_{\text{part}}) + \lambda h'(\gamma_{\text{abst}}) \right).$$

By (14), the right-hand side of this equation is equal to zero. Which gives:

$$-1 = (\gamma_{\text{part}} - \gamma_{\text{abst}})\lambda h''(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial m}$$

Note that $\gamma_{\text{part}} > \gamma_{\text{abst}}$ and $h'' > 0$. It follows that $\frac{\partial \gamma_{\text{abst}}}{\partial m} < 0$ and, by (19), $\frac{\partial \gamma_{\text{part}}}{\partial m} < 0$ as well.

B Robustness

B.1 Heterogeneous priors

Our results are robust to heterogeneity in prior beliefs, as long as all types have an interior participation probability. In this case, the probability that an agent with cost parameter λ participates depends only on the mean prior amongst all agents with that cost of information acquisition. By implication, all our comparative statics on p generalize to the case of heterogeneous priors. Formally, the following result holds.

Proposition 4. *(Robustness to dispersion in prior) Fix m, π_G, and π_B. Consider a population with joint distribution of priors and costs of information $f(\mu, \lambda)$ such that $0 < p(m, \lambda, \mu) < 1$ for all $(\lambda, \mu) \in \mathrm{supp}(f)$. For each λ, let $\nu(\lambda) = \int \mu f(\mu, \lambda) d\mu$. Then,*

$$\int p(m, \lambda, \mu) f(\lambda, \mu) d\mu = p\big(\lambda, \nu(\lambda)\big)$$

Proof. Let $\gamma_{part} = P(s = G|\text{participate})$ and $\gamma_{abst} = P(s = G|\text{abstain})$ denote the optimal posteriors. By the law of iterated expectations, $\mu = p\gamma_{part} + (1 - p)\gamma_{abst}$. The participation probability can thus be written as a function of the chosen posteriors,

$$p(m, \lambda) = \frac{\mu - \gamma_{abst}}{\gamma_{part} - \gamma_{abst}} \tag{20}$$

Posterior separability implies that the optimal γ_{part} and γ_{abst} are independent of μ as long as $0 < p(m; \lambda) < 1$. The claim thus follows from the fact that (20) is linear in μ. □

B.2 Information cost functions

In this section we test the robustness of our main results, stated in Proposition 1, regarding alternative functional form assumptions on the costs of information acquisition. (Recall that Proposition 3 is formally valid for the entire class of posterior-separable cost functions.)

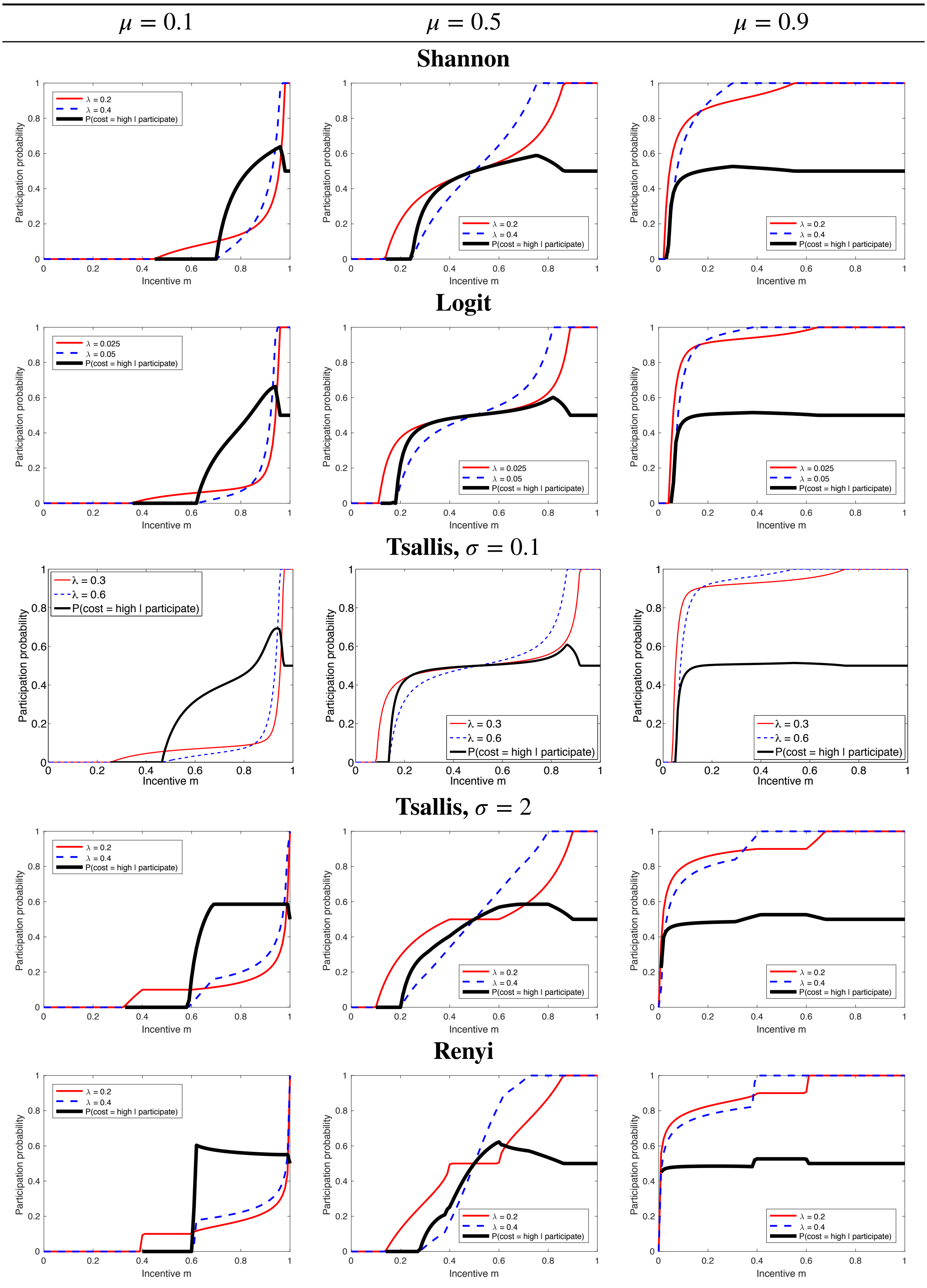


Figure B.5: Simulation tests of Proposition 1 with Shannon, logit, Tsallis, and Renyi cost functions.

We simulate the model for the following four cost-of-information functions studied in the recent theoretical literature on decision making under rational inattention (Caplin, Dean, and Leahy, 2017; Morris and Strack, 2019). In each case, the cost of the information associated with a pair of state-contingent choice probabilities (p_G, p_B) is given by $c(p_G, p_B) = \lambda(h(\mu) - ph(\gamma_{\text{part}}) - (1-p)h(\gamma_{\text{abst}}))$, where γ_{part} and γ_{abst} are the posteriors in case of participation and abstention, respectively. The cost functions differ by the functional form of h, which can take the following forms.

- Shannon costs: $h_{\text{Shannon}}(x) = -x\log(x) - (1-x)\log(1-x)$.
- Logit costs: $h_{\text{logit}}(x) = -x\text{logit}(x) - (1-x)\text{logit}(1-x)$, where $\text{logit}(y) = \log\left(\frac{y}{1-y}\right)$.
- Tsallis costs: $h_{\text{Tsallis}}(x, \sigma) = \frac{1}{\sigma-1}\left(x(1-x^{\sigma-1}) + (1-x)(1-(1-x)^{\sigma-1})\right) = \frac{1}{\sigma-1}(1 - x^{\sigma} - (1-x)^{\sigma})$ for $\sigma \in R$, $\sigma \neq 1$. Note that as $\sigma \to 1$, $h_{\text{Tsallis}}(x, \sigma) \to h_{\text{Shannon}}(x)$.
- Renyi costs: $h_{\text{Renyi}}(x, \sigma) = \frac{1}{1-\sigma}\log(x^{\sigma} + (1-x)^{\sigma})$, for $\sigma > 0$, $\sigma \neq 1$. Note that as $\sigma \to 1$, $h_{\text{Renyi}}(x, \sigma) \to h_{\text{Shannon}}(x)$.

Our analytical results apply to the case of Shannon costs, which we include here for reference. The logit case is of interest because it corresponds to the Wald (1947) sequential information acquisition problem with linear time costs (Morris and Strack, 2019). Tsallis entropy is of interest because the selection of parameter σ allows us to differentially vary the relative cost of marginal changes in the posterior depending on the distance between the posterior and the prior. In our simulations, $\sigma = 2$ is a case in which the relative cost of adjusting posteriors that are near the prior is low (h has a U-shaped appearance), and $\sigma = 0.1$ is a case in which that relative cost is high (h has more of a V-shaped appearance). Renyi entropy is of interest because it is not separable across states. We parametrize these costs with $\sigma = 2$.

The results are shown in Figure B.5, which displays participation curves and the fraction of high-cost individuals amongst participants for three different prior probabilities, $\mu \in \{0.1, 0.5, 0.9\}$. We derive the fraction of high-cost participants under the assumption that both types are equally prevalent in the population. In each of the first four cases, the participation curve is steeper for the high-cost type than for the low-cost type as soon as it is interior for both types, paralleling the analytical result for the case of Shannon costs in Proposition 1 (i). For the case of Tsallis entropy, we additionally observe that if $\sigma = 2$ and information acquisition costs are low ($\lambda = 0.2$), the participation curve is flat at the level of the prior belief μ. This indicates perfect information acquisition. The fifth case, Renyi costs, is different. For this cost function, the low-cost type sometimes responds more strongly to a change in participation payments than does the high-cost type. This tends to occur near regions of perfect information acquisition.

Regarding the robustness of part (ii) of Proposition 1, we again find in each of the first four cases that the fraction of high-cost individuals among participants monotonically increases until participation payments are so high that high-cost individuals participate with probability one. Again, behavior with Renyi costs exhibits a pattern different from that under Shannon costs; the composition of participants no longer changes monotonically as the participation payment increases, even in regions in which both types participate with an interior probability. These results are suggestive regarding the extent of the generality of the results we have analytically derived for the Shannon case.

B.3 Alternative models

There are alternative models of endogenous information acquisition with heterogeneous information acquisition costs. Some alternative models are ostensibly simpler but are analytically intractable, such as the Gaussian case we consider in detail below. While there exist simpler models that are also tractable, these models are not rich enough to capture the set of comparative statics we document in this paper. This occurs if agents cannot tailor their desired level of certainty to the incentive amount. Consider, for instance, a model in which there is a single binary information structure and agents can pay a fixed cost that is heterogeneous across individuals to access a signal from that information structure. While a higher incentive leads to the selection of higher cost participants, such selection is inconsequential in this model. The reason is that all agents observe the same information structure or abstain, so the probability of disappointment is independent of the incentive.

We now turn to exploring a model with normally distributed signals about an imperfectly known state of the world, as is often considered in the literature (e.g., Morris and Shin, 2002). We first consider the case of exogenously given signal precision. This model shares with ours the feature that the decision-maker, by choosing the threshold belief required for participation, can tailor the degree of certainty required for participation based on the incentive amount. In this model, a change in the participation payment has the same effect on the threshold belief regardless of the precision of the signal. Therefore, the effect of such a change on the participation probability is larger for individuals with less precise information. Consequently, if we associate higher cost in our model with lower precision in this model, the two models, to some extent, generate qualitatively similar comparative statics (which we verify numerically, see Appendix B.3.1). However, our main result on group composition holds only for some parameters of this model.

This difference suggests that our composition effect is driven in part by the decision-maker's ability to choose the quality of information. Therefore, we then study the case in which the agent can choose the precision of her signal at a cost. Consistent with the foregoing hypothesis, we find no violations of our results in numerical simulations of a model with normally distributed signals in which the decision-maker chooses the precision of information (with higher precision incurring greater cost).

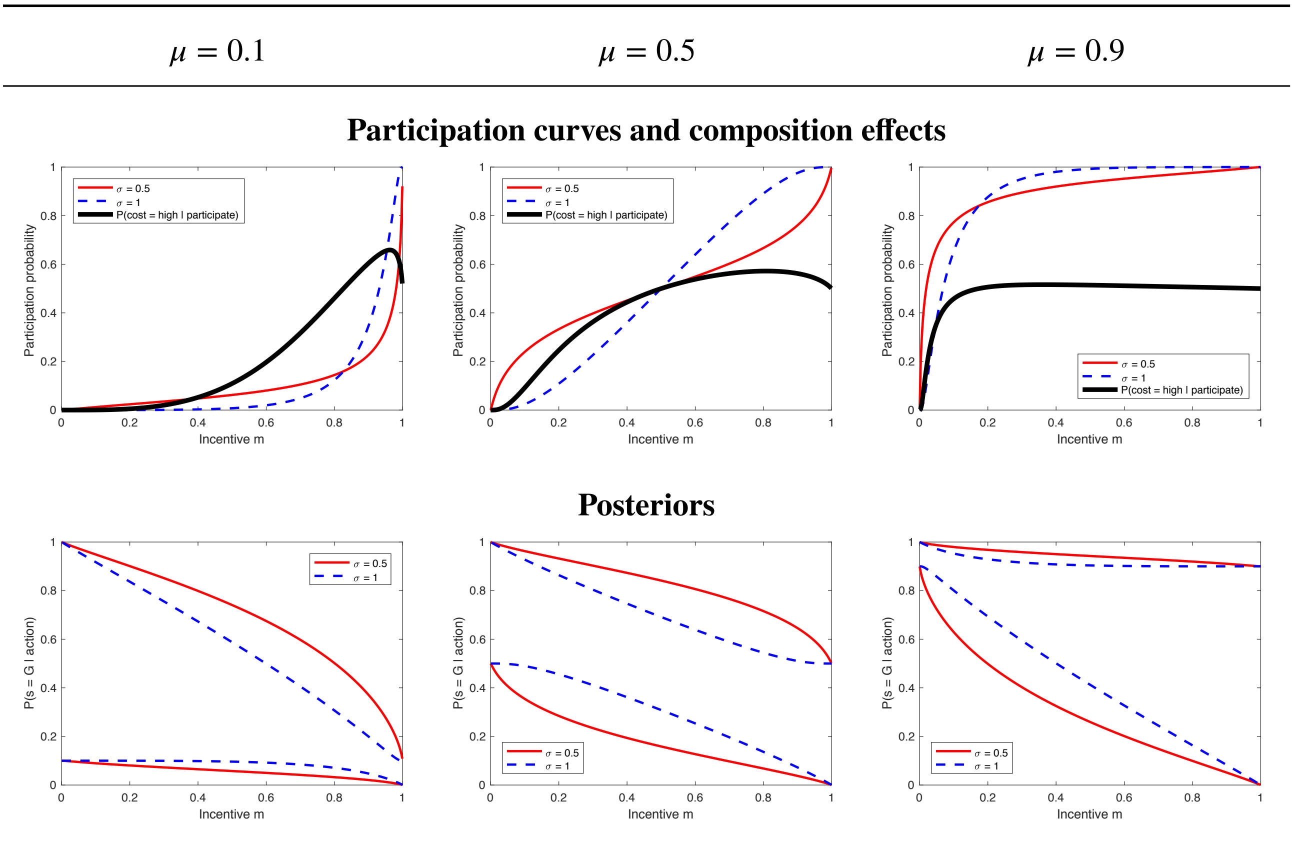


Figure B.6: Comparative statics similar to those of Proposition 1 in a model with exogenous Gaussian signals. Graphs in the top row depict participation curves for each level of the signal precision, as well as the fraction of high-cost types amongst participants, assuming equal population frequencies of the types. Graphs in the bottom row depict posteriors $P(s = G|$ participate) and $P(s = G|$ abstain).

B.3.1 Exogenous Gaussian signals

As in the main text, an agent decides whether or not to participate in a transaction in exchange for a payment m. There are two states $s \in \{G, B\}$ with prior distribution $P(s = G) = \mu$. If the agent participates in state s, she receives utility $\pi_s + m$, which is positive if $s = G$ and negative otherwise. Non-participation gives utility 0.

The information acquisition technology differs from that in the main text. The agent observes a stochastic signal n that is normally distributed. If $s = G$, the mean of the signal is 1, if $s = B$, the mean is 0. The variance of the signal is σ^2, and is heterogeneous across subjects. While the normal signal is free to observe, the fact that this signal provides only incomplete information about the state, and the fact that the extent of incompleteness varies across agents corresponds to an implicit assumption that information is costly, and that information costs are heterogeneous across subjects.

Conditional on signal realization n, the agent will participate if $(\pi_G + m)Pr(s = G|n) + (\pi_B + m)Pr(s = B|n) \geq 0$, or equivalently, if

$$Pr(s = G|n) \geq \frac{-(\pi_B + m)}{\pi_G - \pi_B}. \tag{21}$$

As noted in the main text, this threshold belief is independent of the signal variance σ^2.

To derive the participation probability, observe that the posterior belief of the agent after observing signal realization n is given by

$$Pr(s = G|n) = \frac{\mu \frac{1}{\sqrt{2\pi\sigma}} \exp(-\frac{(n-1)^2}{2\sigma^2})}{\mu \frac{1}{\sqrt{2\pi\sigma}} \exp(-\frac{(n-1)^2}{2\sigma^2}) + (1-\mu)\frac{1}{\sqrt{2\pi\sigma}} \exp(-\frac{n^2}{2\sigma^2})} = \frac{\mu}{\mu + (1-\mu)\exp(\frac{1-2n}{2\sigma^2})}.$$

By (21), the agent will thus participate if

$$n \geq \frac{1}{2} - \sigma^2 \log \gamma, \tag{22}$$

where $\gamma = -\frac{\mu(\pi_G+m)}{(1-\mu)(\pi_B+m)}$. This yields the state-dependent participation probabilities $p_G = 1 - \Phi\left(\frac{-\frac{1}{2}-\sigma^2 \log\gamma}{\sigma}\right)$ and $p_B = 1 - \Phi\left(\frac{\frac{1}{2}-\sigma^2 \log\gamma}{\sigma}\right)$.

Figure B.6 shows the participation curves implied by this model for $\mu \in \{0.1, 0.5, 0.9\}$, and two levels of σ each. Over a part of the domain, the figures are consistent with both parts of Proposition 1. First, participation increases more steeply for the high-cost type whenever the prior-based expected value of the gamble is sufficiently close to zero. Second, as long as m is sufficiently small, the probability that a participant is a high-cost type increases with the payment m.

The figure also shows posterior probabilities that $s = G$ conditional on each action (the upper two curves in each graph correspond to $P(s = G|\text{accept})$, and the lower two curves correspond to $P(s = G|\text{reject})$). Mechanically, a lower variance of the signal corresponds to more dispersed posteriors (that is, posteriors that incorporate more information), which parallels Proposition 3.

B.3.2 Choice of Gaussian signal precision

We consider the same information technology as in Section B.3.1, with the exception that the agent can now choose the precision of the Gaussian signal at a cost. Specifically, the agent pays cost $c(\sigma) = \lambda/\sigma$ to observe a signal with variance σ^2. As in the main text, λ captures individual heterogeneity in information acquisition costs, and information acquisition costs are discounted from the agent's utility.

Conditional on the signal variance σ^2, the analysis parallels that of Section B.3.1. Specifically, if the agent finds it optimal to base her decision on a signal with precision σ^2, she will participate for signal realizations that weakly exceed the bound in equation (22). If the agent finds it optimal to reach a decision without acquiring any information, she will participate with probability 1 if $\mu(\pi_G + m) + (1 - \mu)(\pi_B + m) \geq 0$, and abstain otherwise. The condition determining whether the agent acquires information is somewhat complicated; if she does, one can show that the optimal signal precision satisfies the first-order condition

$$\frac{(\frac{1}{2} + \sigma^2 \log \gamma)^2}{2\sigma^2} = \log \frac{\mu(\pi_G + m)}{\sqrt{2\pi}\lambda},$$

where $\gamma = -\frac{\mu(\pi_G+m)}{(1-\mu)(\pi_B+m)}$. When combined with the above expressions for the participation probability, the second derivatives required for our comparative statics results become analytically intractable. We therefore solve the model numerically.

Figure B.7 shows the participation curves implied by this model for $\mu \in \{0.1, 0.5, 0.9\}$, and two levels of λ each. The figures are consistent with both parts of Proposition 1. First, participation increases more steeply for the high-cost type whenever it is interior. Second, as long as neither type participates with probability 1, the probability that a participant is a high-cost type increases with the payment m. We have not found any counterexamples for a wide range of alternative parameter values we have checked.

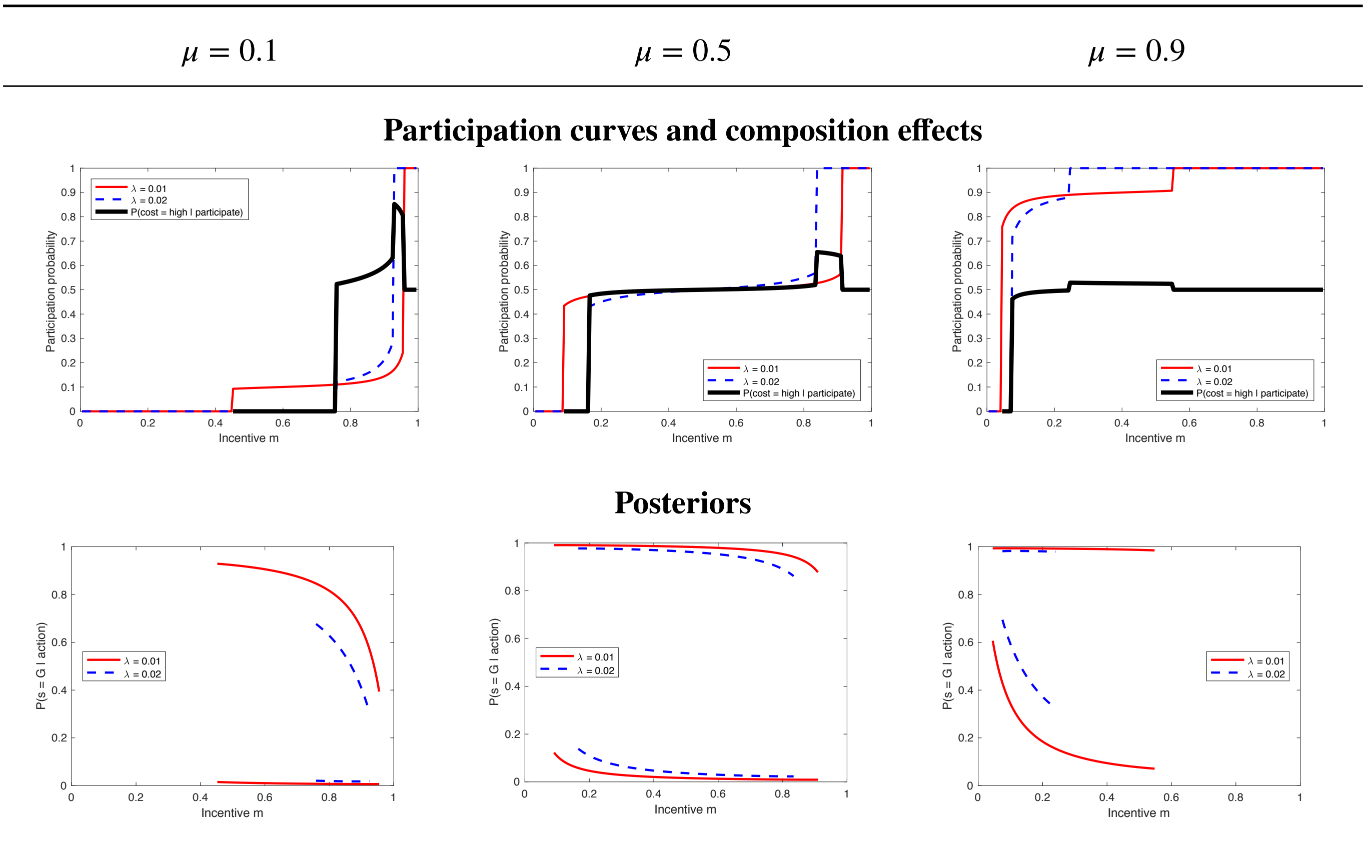


Figure B.7: Comparative statics similar to those of Proposition 1 in a model with Gaussian signals with optimally chosen costly precision. Graphs in the top row depict participation curves for each cost level, as well as the fraction of high-cost types amongst participants, assuming equal population frequencies of the types. Graphs in the bottom row depict posteriors $P(s = G|$ participate) and $P(s = G|$ abstain) and are drawn over the domain on which the agent chooses based on information rather than on priors alone.

C Experiment: Additional Materials

C.1 Laboratory sessions

Table C.5 presents details regarding each session. All sessions were conducted by a doctoral student research assistant in Cologne. We recruited subjects from the existing subject pool of the University of Cologne's Laboratory for Economic Research without any targeting of particular demographics.

The experiment was computerized, based on the Qualtrics survey platform and javascript. Lists of additions such as in Figure 2 were displayed in a graphic format (HTML5 canvas) rather than as text in order to prevent computerized checking and searching.

After analyzing the data from the sessions in May, we decided to replicate the results, using a condition in which performance on the IQ test was incentivized. In sessions 18 and 19, a clerical error caused an inconsistency in the instructions the experimenter read aloud and the IQ-incentive condition subjects were actually given. Since responses to incentives can depend significantly on expectations (Abeler, Falk, Goette, and Huffman, 2011), we discard the IQ data from these sessions.

C.2 Summary statistics

Data overview Table C.6 presents an overview of our data. Each subject provides us with 18 observations, leading to 7,008 observations across the task difficulty levels and 3,504 observations in the Exogenous Information condition. A handful of subjects choose to take the bet in all rounds of a condition, or in none of them. The latter behavior is more frequent in the Exogenous Information condition. Given the limits on information acquisition in that condition, we would expect such behavior from risk averse individuals.

Subjects' background characteristics The average subject is 24.5 years of age. 53.3% are female. 54.8% of our subjects are enrolled in a STEM major. Amongst those, 11.8% have taken an honors class in both mathematics and German, 29.9% have taken neither, 33.6% have taken

Session	Date	Weekday	Time	#Subjects	Low-cost condition # correct if $s = G$	# incorrect if $s = G$	IQ incentives
1	4/27/17	Mon	10 AM	19	12	8	No
2	5/3/17	Wed	10 AM	32	18	12	No
3	5/3/17	Wed	1 PM	29	18	12	No
4	5/3/17	Wed	4:30 PM	31	18	12	No
5	5/10/17	Wed	10 AM	32	15	10	No
6	5/10/17	Wed	1 PM	31	15	10	No
7	5/11/17	Thur	10 AM	30	15	10	No
8	5/11/17	Thur	1 PM	32	15	10	No
9	5/12/17	Fri	10 AM	32	15	10	No
10	5/12/17	Fri	1 PM	32	15	10	No
11	7/7/17	Fri	1 PM	29	15	10	Yes
12	7/10/17	Mon	10 AM	32	15	10	Yes
13	7/10/17	Mon	1 PM	32	15	10	Yes
14	7/17/17	Mon	10 AM	32	15	10	Yes
15	7/17/17	Mon	1 PM	32	15	10	Yes
16	7/18/17	Tue	10 AM	32	15	10	Yes
17	7/18/17	Tue	1 PM	32	15	10	Yes
18	7/24/17	Mon	10 AM	32	15	10	N.A.
19	7/24/17	Mon	1 PM	31	15	10	N.A.

Table C.5: Laboratory Sessions.

Information condition	Subjects	Decisions	% bet	Always take bet in condition	Never take bet in condition
Endogenous information	584	7008	37.74%	4	6
Exogenous information	584	3504	33.19%	4	91

Table C.6: Data overview. Each subject participated in each treatment, in random order. One subject chose to never bet in either condition.

only mathematics, and 24.7% have taken only German. Amongst those not enrolled in a STEM major, the respective numbers are 10.5%, 31.9%, 19.8%, and 37.9%.

Correlations between individual-level measures Table C.7 displays pairwise correlations between our individual-level measures.

C.3 Auxiliary analysis

Order effects There are pronounced order effects regarding the time subjects take to complete each decision. On average, they examine the first picture for over 2.7 minutes, whereas they examine the last one for just 1.2 minutes (with standard deviations in the population test subjects of 2 and 1.3 minutes, respectively). The fraction of betting-decisions that are aligned with the state is 79.5% for the first round, and 71.2% for the last round. Regressing the fraction of decisions that align with the state on the decision order yields a slope coefficient of 0.38 percentage points per round (SE 0.10). While this change is statistically significant, it is less pronounced than one might expect from a 60% drop in examination time. We conclude that the drop in examination time includes a substantial learning component and reflects to a lesser extent a change in how careful subjects make decisions.

Implementation of the reservation price elicitation task Of the subjects selected to check a given number of calculations (according to the reservation price elicitation stage), 90.23% of subjects verified 90% or more correctly, and thus exceeded the quality required for receiving

Table C.7: Pairwise correlations between subject characteristics.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CE rank	Res. price rank	Raven's test rank Non-inc.	Raven's test rank Inc.	High school mathematics Honors	High school mathematics Grade rank	STEM	HS German Honors
CE rank	1.0000							
Reservation price rank	-0.0225	1.0000						
	(0.5878)							
Raven's test rank								
Non-incentivized	-0.1241	-0.1449	1.0000					
	(0.0316)	(0.0120)						
Incentivized	-0.0564	-0.0240	.	1.0000				
	(0.4039)	(0.7224)	.					
High school mathematics								
Honors	0.0258	-0.0735	0.0416	0.2199	1.0000			
	(0.5442)	(0.0841)	(0.4929)	(0.0011)				
Grade rank	-0.0560	-0.0712	0.1527	0.2352	0.2284	1.0000		
	(0.2026)	(0.1048)	(0.0123)	(0.0010)	(0.0000)			
STEM	0.0686	0.0010	0.0935	0.1687	0.1566	0.1479	1.0000	
	(0.0977)	(0.9802)	(0.1062)	(0.0120)	(0.0002)	(0.0007)		
High school German								
Honors	-0.0302	0.0485	-0.0585	-0.2071	-0.2047	-0.1018	-0.1197	1.0000
	(0.4793)	(0.2551)	(0.3355)	(0.0022)	(0.0000)	(0.0225)	(0.0049)	
Grade rank	-0.0195	0.0531	-0.0283	-0.0872	-0.1021	0.1734	-0.1547	0.1841
	(0.6597)	(0.2288)	(0.6518)	(0.2206)	(0.0223)	(0.0001)	(0.0004)	(0.0000)

Notes: CE rank is the percentile rank of a subjects' mean certainty equivalent in the risk elicitation task. Higher ranks correspond to lower risk aversion. Numbers in parentheses display *p*-values.

payment for this task (and avoiding punishment). This statistic is based solely on sessions 5–19; sessions 1–4 are excluded as there was an error with recording the fraction of correctly verified calculations.

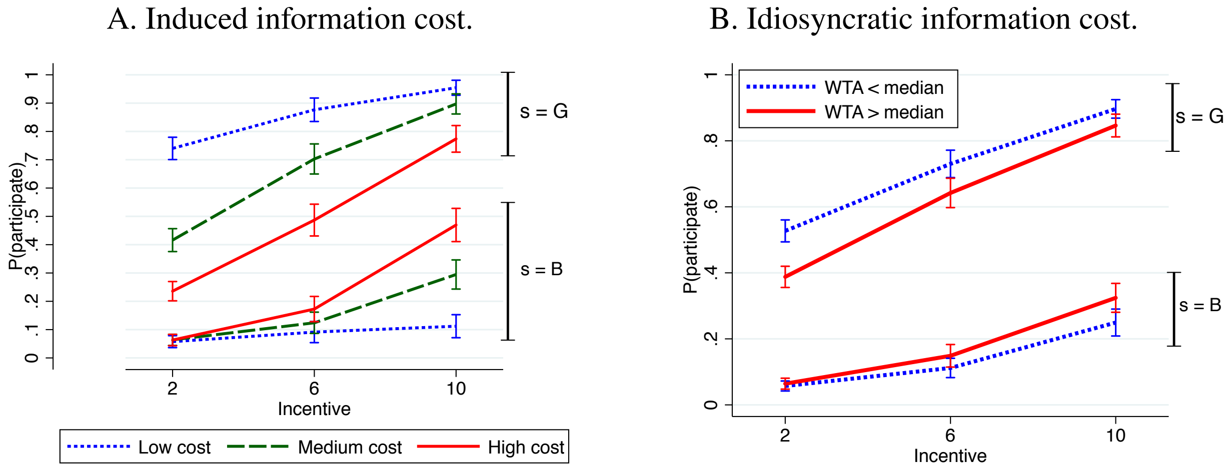
Decision reversals After stating their posterior beliefs, subjects had the opportunity to return to the previous screen to change their decision of whether to accept or refuse the bet. Overall, 1.05% of all decisions were changed, and 15.6% of subjects changed their decision at least once over the 18 rounds of the experiment.

C.4 Robustness of the empirical results

Participation by state Figure C.8 shows the effect of incentives on participation separately by state as an additional check whether our results arise for the right reasons. Panel A splits the data by information cost condition. It that our results are consistent with the intuition outlined in Section 2. A subject who participates in the good state avoids a false negative error; a subject who participates in the bad state commits a false positive error. The graph shows that a higher participation payment leads to an increase in the false positive probability and to a decrease in the false negative probability within each information cost condition, and that this change is larger in magnitude for higher information costs, leading to more elastic participation in these conditions. Panel B shows that the same result obtains if we instead split the data by whether a subject has an above or below median reservation price for checking a given number of calculations.

First-order stochastic dominance Proposition 1 (i) predicts that the distribution of information costs amongst those who elect to participate first-order stochastically increases in the incentive. Section 4.1 shows that average costs increase, which is a weaker statement than an increase in distribution. Here we examine the stronger claim by plotting empirical cumulative distribution functions of the information costs amongst subjects who chose to participate in the gamble, by incentive amount. Panel A of Figure C.9 uses the information cost index as the measure of cost. A FOSD-increase is readily apparent. Panel B uses our measure of idiosyn-

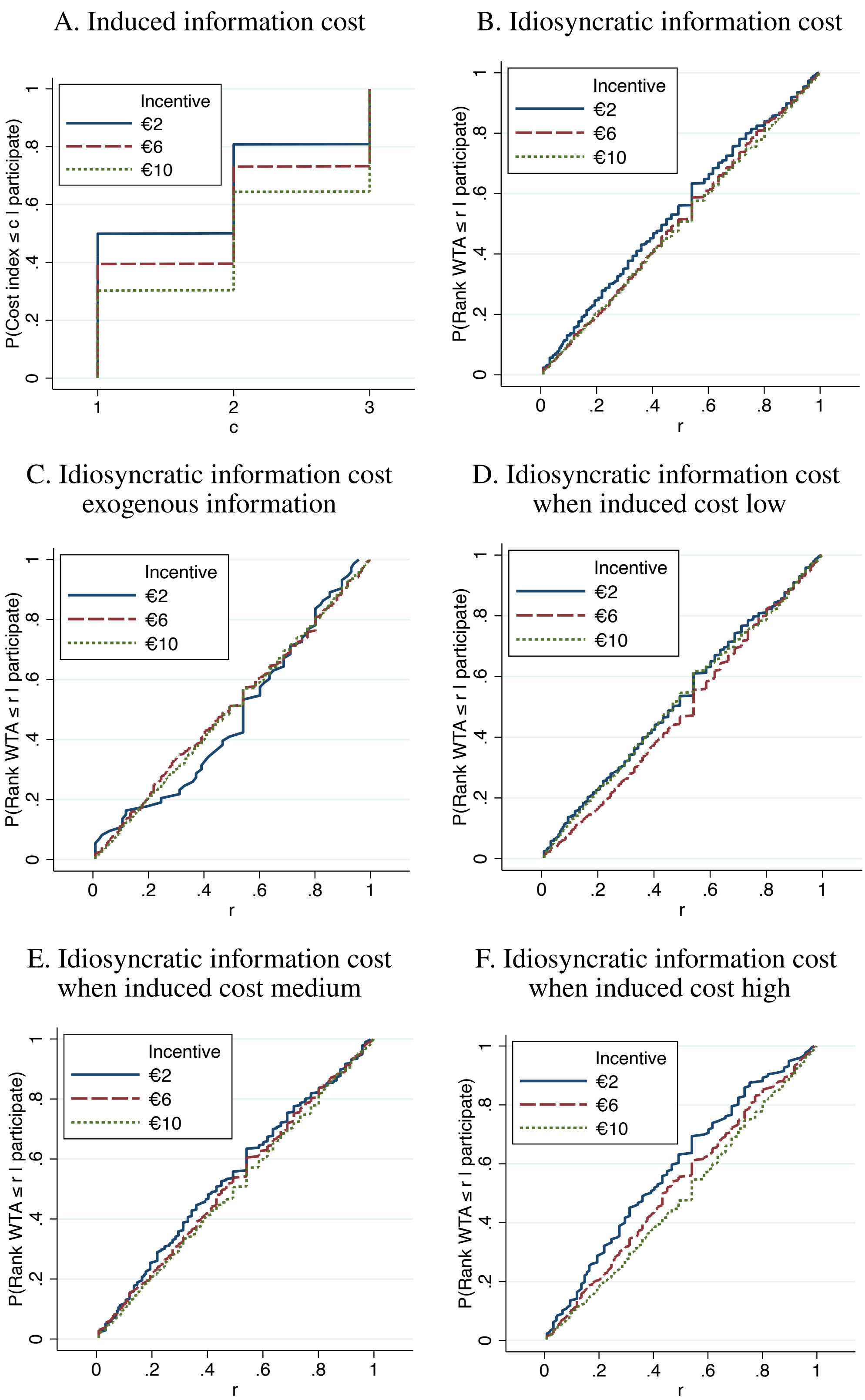
Figure C.8: State-dependent participation by information cost.



cratic information costs. We observe an FOSD shift as the incentive rises from €2 to €6 but only small effects as it changes from €6 to €10. Panel C displays corresponding results for the exogenous information condition. Consistent with our expectations, we observe no FOSD-shift in that treatment. Finally, Panels D, E, and F split the information contained in Panel B according to whether the induced cost is low, medium, or high, respectively. We observe clear FOSD shifts in the latter case (Panel F).

Alternative regression specifications Table C.8 replicates our main table, Table 2, including a control for subjects' percentile rank of their mean certainty equivalent to the risk preference elicitation questions, as well as the interaction between that variable and the incentive amount. The parameter estimates and significance levels generally remain similar to Table 2.

Figure C.9: Empirical cumulative distribution function of cost measures amongst subjects who chose to participate in the gamble



Notes: All panels except for panel C exclude observations from the exogenous information condition. Panel C only includes observations from that condition.

Table C.8: Composition and slope effects controlling for risk preferences.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Type	**Composition effect**				**Slope effect**			
VARIABLES	Info. cost index	Res. price %ile	Res. price %ile	Res. price %ile	Gamble accepted	Gamble accepted	Gamble accepted	Gamble accepted
Proposition tested	1(ii)	1(ii)	-	2[a)]	1(i)	1(i)	-	2
Sample								
Endogenous Information	✓	✓		✓	✓	✓		✓
Exogenous Information			✓				✓	
Panel A. Main regressions								
	Gamble accepted				1 ×			
× Incentive	0.577***	0.064***	0.007	-0.053	-0.073	0.350***	0.785***	-0.008
	(0.049)	(0.019)	(0.042)	(0.036)	(0.069)	(0.051)	(0.065)	(0.091)
× Cost index				-0.040***	-0.167***			
				(0.012)	(0.012)			
× Incentive × cost index				0.065***	0.239***			
				(0.018)	(0.025)			
	Gamble rejected				Res. Price > median			
× Incentive	-0.208***	-0.023**	-0.009	0.030		0.099**	-0.042	-0.130
	(0.033)	(0.011)	(0.016)	(0.028)		(0.047)	(0.054)	(0.112)
× Cost index				0.007				-0.053**
				(0.005)				(0.024)
× Incentive × cost index				-0.026**				0.115**
				(0.013)				(0.050)
× 1	0.559***	0.064***	0.001	-0.020		-0.072***	0.024	0.034
	(0.039)	(0.016)	(0.036)	(0.034)		(0.025)	(0.025)	(0.057)
CE rank								
×1	0.033*	-0.011	-0.010	-0.011	0.026	0.022	-0.026	0.022
	(0.018)	(0.041)	(0.041)	(0.041)	(0.044)	(0.044)	(0.049)	(0.044)
× Incentive	-0.061**	-0.005	-0.013	-0.005	0.151*	0.157**	0.336***	0.157**
	(0.026)	(0.005)	(0.009)	(0.005)	(0.078)	(0.078)	(0.102)	(0.078)
Observations	7,008	7,008	3,504	7,008	7,008	7,008	3,504	7,008
Subjects	584	584	584	584	584	584	584	584

[a)] Proposition 2 is stated in terms of slopes on the participation curves only, as tested in Column (8). If there are no countervailing level effects, proposition 2 implies the comparative statics on composition effects tested in column 4.

Notes: This table replicates Table 2 including controls for a subject's risk-preference percentile (CE rank) and its interaction with the incentive amount, as well as an indicator of the cost condition for cases in which information costs are measured as reservation price for checking a given number of calculations. Standard errors in parentheses, clustered by subject. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

C.5 Experiment instructions

Note: Horizontal lines represent screen breaks. The instructions reproduced here concern the unincentivized IQ condition. In the incentivized IQ condition, subjects were told that there are three parts, that they could earn money in each of them, and that the chance of each of the parts counting for payment was 80%, 10% and 10%, respectively.

Welcome to this experiment!

Study structure and time involvement

This study has 3 parts:
1. Decision making part A
2. Logical puzzles
3. Decision making part B

Parts 1 and 2 will take you between 30 and 40 minutes to complete, and part 3 will take you approximately 10 minutes.

Payments

At the end of this study, you will be paid cash for your participation.

You start this experiment with a **budget** of **€15.** Depending on your decisions, and on luck, you can win or lose money. Money that you win will be added to your budget of €15. Money that you lose will be subtracted from your budget. The final sum of money will be paid to you in cash.

Whether you win or lose money depends on **a single decision** that you will make in one of the two decision making parts. The computer will **randomly** select the decision for which you will be paid.

Hence, you **should make every decision as if it was the one that counts – it could be the one!**

You will probably be paid for a decision from **decision making part A**. The exact probability of being paid according to that part is **80%**. The probability of being paid for a decision made in **decision making part B** is **20%**.

<< >>

ABOUT CHANCE

Some of your decision, as well as your payout, may be partially determined by chance.

We guarantee, that when we tell you that something will happen with some chance out of 100, it will happen with exactly that chance.

Rules

This is a study about individual decision making. This means that you must not talk during this study. If you have questions, raise your hand. We will come to you and answer your questions privately.

Please do not use cell phones or other electronic devices until the study is finished. Do not surf the internet and do not check your emails. Should we ascertain that you do one of these things, the rules of this study prescribe that we deduct €10 from your payout.

(Sometimes, the continue button will appear only after a few seconds.)

To start the study, please enter the password given to you by the administrator of this experiment.

losgehts

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Instructions for part 1

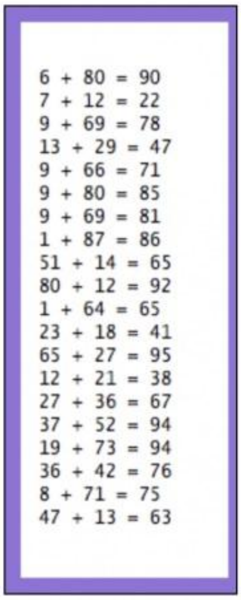
You will be able to continue with the study only if you correctly answer multiple test questions about these instructions. Therefore, it is in your best interest to pay close attention.

Part 1 one of this study has 18 rounds. Each round has two steps, the betting decision and the probability assessment.

<< >>

In each round, you will see a NEW picture like this, consisting of multiple calculations. Some calculations are CORRECT, others are WRONG.

For example, in this picture, the first two calculations are wrong and the third one is correct.



A picture can be GOOD or BAD. A picture is Good if it has more correct calculations than it has wrong calculations. Otherwise, it is Bad.

In each round, you will decide whether to bet on the picture or not. If you bet on the picture and the picture is Good, you win money. If you bet and the picture is Bad, you will lose money.

Important: A picture can be Good, even if it has many wrong calculations, as long as it has more correct calculations than wrong ones. Similarly, a picture can be Bad if it has some correct calculations, as long as it has more wrong calculations that correct ones.

In each round, it is **exactly equally likely** that you see a Good picture or a Bad picture. Each round, the computer will randomly decide which is the case.

The calculations in a picture appear in a **completely random order**!

None of this depends at all on what happened in previous rounds.

<< >>

Betting decision

This is how your betting decision works:

If you **bet** on on a picture and the **picture is Good** (i.e. it has more correct calculations than wrong ones), you **win** money.

If you **bet** on a picture and the **picture is Bad** (i.e. it has more wrong calculations than correct ones), you **lose** money.

If you do **not bet** on the picture, you **neither** win **nor** lose money.

Before deciding whether to bet on the picture or not, you may inspect the picture as long **as you wish** to get an idea of whether the picture is Good or Bad.

In a table like this one you will be able to see how much money you can win or lose if you bet on the picture in the current round. You can also see exactly how many correct and wrong calculations a Good or Bad picture contains.

	Good picture (probability 50%)	Bad picture (probability 50%)
Correct calculations	12	8
Wrong calculations	8	12
If you bet on the picture	***WIN €5***	***LOSE €5***

In each round, you will see a different picture.

How much money to win or lose by betting can differ from round to round!

If you are getting paid for a round of this part, the probability is 80% that your payment is determined by a betting decision. The remaining 20% are the probability of being paid for your answer in a probability assessment, which we will explain now.

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Probability assessment

After inspecting the picture and deciding whether to bet on the picture or not, we will ask you in each round how certain you are that the picture that you just saw was Good or Bad by showing you a question like this:

definitely good	most likely good	very likely good	quite likely good	fairly likely good	slightly likely good	slightly likely bad	fairly likely bad	quite likely bad	very likely bad	most likely bad	definitely bad
100%	90-99%	80-90%	70-80%	60-70%	50-60%	40-50%	30-40%	20-30%	10-20%	1-10%	0%
○	○	○	○	○	○	○	○	○	○	○	○

The number below each possible choice is the probability in percent with which you believe that the picture was Good.

There is a 1 in 5 chance that your earnings from this study are determined by your answer to such a question. Depending on your answer, the picture you have seen, and luck, your bonus may rise by €3 or fall by €3.

The payment procedure is designed such that it in your best interest to give your best, genuine answer to this question.

If you believe, for example, that it is about 75% likely that you have seen a good picture, it is in your best interest to select “quite likely good (70 - 80%)”. If you believe, for example that it is about 25% likely that you have seen a good picture (that is, you believe it is about 75% likely that you have seen a bad picture), then it is in your best interest to select “quite likely bad (20 - 30%)".

One of your decisions from this study will be randomly selected for payment. Thus, you will be paid for EITHER for your bet on a picture (with a 4 in 5 chance), OR for the answer you give to the questions explained above, but never for both.

Read this if you would like to know more about the payment mechanism and about WHY it is in your best interest to answer this questions according to you true beliefs.

(We will ***not*** ask you test questions about the remaining content on this page.)

The payment procedure works like this.

For most choices you can select, there is a range of chances (for example 50 - 60%). Your payment is determined by the number in middle of the range you select (for example 55%, if you select the range 50 - 60 %).

Suppose you select a choice for which the middle of the range is some number X. The computer will randomly and secretly draw another number Y between 0 and 100. If the number the computer randomly draws is the larger one, that is if Y > X, then you will win €3 with chance Y in 100 (and lose €3 if you don't win). If the number you stated is the larger one, that is, if X > Y, then you will win if the picture you have seen is good. So if X is your genuine belief that the picture you have seen was good, you will win with chance X or with chance Y, whichever of the two is larger.

WHY is it in my best interest to answer this question according to my genuine beliefs?

Simply, the reason is that you lower your chance of winning if you state a chance that is lower than you genuinely believe, and you also lower your chance of winning if you state something that is higher than you genuinely believe. So the best you can do is state what you genuinely believe.

To see why, it's best to go through an example.

Here's why you lose from stating a chance that is higher than you genuinely think is true. For example, suppose you genuinely believe the chance that the picture is good 60%, but in the survey question you select a higher chance, say 90%. Suppose the number Y that the computer draws is between 60% and 90%, let's say it is 80%. This is lower than what you've told us (you've told us 90%), so you will not play the computers' bet. Instead, you will win if the picture is good, which you genuinely think only occurs with 60% chance. The computers' bet would have given you a higher, 80%, chance instead. Hence, you hurt your chance of winning by stating the picture was more likely good than you genuinely think.

And here's why you lose from stating a lower chance than you genuinely think is true. For example, suppose again you genuinely believe the chance that the picture is good 60%, but in the survey question you select a lower chance, say 10%. Suppose the number Y that the computer draws is between 10% and 60%, let's say it is 30%. That is higher than what you told us (which is 10%), so you will play the computers' bet and win with chance 30%. That is lower than if you had instead received the bet on the picture, which, according to your genuine belief, has a 60% chance. Hence, you hurt your chance of winning by stating the picture was less likely good than you genuinely think.

Therefore, the best you can possibly do is to select exactly the answer that corresponds to your genuine beliefs.

If you have any questions about this payment mechanism, please raise your hand.

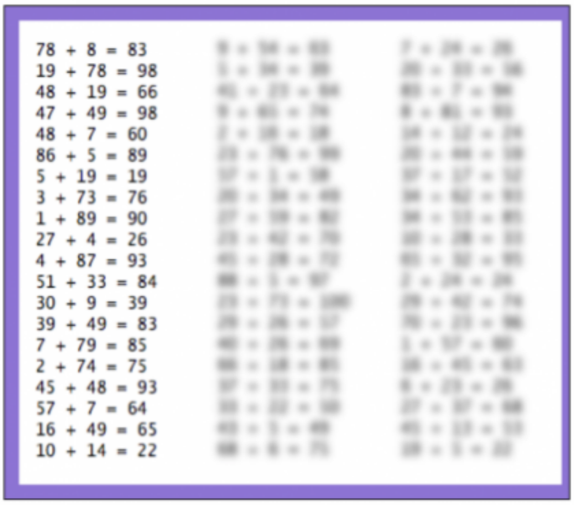
<< >>

Blurry Calculations

In some rounds, a part of the picture will be blurred, such as in the one below.

Amongst the area that is *not* blurred, the computer will automatically count for you how many correct and incorrect calculations there are, as below.

Number of CORRECT calculations in the visible part: 7
Number of WRONG calculations in the visible part: 13



You cannot see the other calculations, but they are just as relevant for winning or losing should you decide to bet on the picture. This means that winning or losing the bet depends on how many correct and wrong calculations are in the *whole* picture, counting those calculations that you cannot see.
Apart from what you can see and are told about the picture, these rounds are like all others.

<< >>

To make sure you got all of this, check all statements below that are true. You can only continue if you tick all boxes correctly.

Use the back button on the bottom if you would like to revisit the instructions.

(Do not try random combinations, there are far too many possible combinations. If you feel you understand the instructions, but still cannot continue, or have some other question, please raise your hand.)

- [ ] A picture is bad ONLY if ALL the calculations in that picture are incorrect.
- [x] A bad picture has both correct and incorrect calculations (but more incorrect ones).
- [x] At the end of the study, the computer will randomly select one decision I made. I will be paid for that and only that decision.
- [ ] When I am asked about how certain I am about a picture, I will earn most from this study if I state something a little lower than I truly think.
- [x] I can examine the picture FOR AS LONG AS I LIKE before I make a decision.
- [ ] If a part of the picture is blurred, whether I will win or lose from taking the lottery ONLY depends on those calculations that I can see, not on those that are blurred.
- [x] A good picture has both correct and incorrect calculations (but more correct ones).
- [ ] A picture is good ONLY if ALL the calculations in that picture are correct.
- [ ] When I am asked about how certain I am about a picture, I will earn most from this study if I state something a little higher than I truly think.
- [x] f a part of the picture is blurred, whether I will win or lose from taking the lottery depends on all calculations in the picture, even those that are blurry.
- [x] When I am asked about how certain I am about a picture, I will earn most from this study if I state exactly what I truly think.
- [x] If I am paid for a part with a picture, I will be paid EITHER for the bet I take on that picture, OR for the my answer to the question how certain I am about the picture I have seen, but NOT for BOTH.

<<   >>

Before we begin the study, please conform your participation, if you still want to participate.

Protocol officers: Axel Ockenfels, Professor, Department of Economics, University of Cologne and Sandro Ambuehl, Assistant Professor for Management, Department of Management UTSC, Rotman School of Management, University of Toronto

PAYMENT: On average, you will receive **€10 per hour** as payment for your participation, depending on luck and the decisions that you and other participants make. All participants will receive a payment. The minimum payment is €4 show-up fee. (To understand the next paragraph, please keep in mind that the payment is *not* to be understood to be utility. You will definitely receive a payment as described in the next paragraph.)

RISKS AND BENEFITS: We do not promise that you derive any kind of benefit from this study. There are no other risks relating to this study.

SCHEDULE: Your participation in this study will take between **60 and 120 minutes**.

YOUR RIGHTS: If, after reading this form and deciding to participate in this study, know that your participation is voluntary and that you can abort the study without any consequences or loss of due payments at all times. You have the right to not give an answer to individual questions. Your privacy will be protected in all published or written works that result from this study. If you have questions about your rights as a participant, you can contact the Research Oversight and Compliance Office - Human Research Ethics Program at ethics.review@utoronto.ca, 416-946-3273.

ACCESS TO INFORMATION, PRIVACY AND PUBLICATION OF RESULTS: At the end of the experiment, you have the opportunity to enter your email address should you want to receive information about the hypotheses and results of this study as soon as it is finished. This email address is the sole identifiable information that we elicit from you and it is your right to withhold this information. All of your information will be stored on an encrypted and password protected computer for up to five years. An anonymized version of the data will be shared with coauthors and published on the Harvard dataverse platform indefinitely. The results of this study will be published in academic seminars and journals. The study in which you take part may be subjected to a quality control to ensure that applicable laws and regulations are fulfilled. Should it be selected, (one) representative(s) of the Human Research Ethics Program (HREP) may review data related to this study and/or declarations of consent as part of the audit. All informations accessed by HREP are governed by the same level of privacy as the level indicated by the research team.

CONFLICTS OF INTEREST:

None of the researchers that are involved with this study have any conflict of interest. This study is financed by the University of Cologne (Chair Prof. Dr. Axel Ockenfels).

CONTACT INFORMATION:

***If you believe that you were injured by participating in this study, please contact Sandro Ambuehl, University of Toronto, Rotman School of Management, 105 St. George Street, Toronto, M5S 3E6, sandro.ambuehl@utoronto.ca, (647) 981 63 84.**

*Questions, concerns or complaints: If you have any kind of questions, concerns or complaints, the procedure, risks or benefits regarding this **research study**, please ask protocol officer Sandro Ambuehl, University of Toronto, Rotman School of Management, 105 St. George Street, Toronto, M5S 3E6, sandro.ambuehl@utoronto.ca, (647) 981 63 84.

*Independent contact: If you disagree with how this study was conducted or if you have any concerns, complaints or general questions about this research or your rights, please contact the University of Toronto Research Ethics Board, McMurrich Building, 2nd Floor, 12 Queen's Park Crescent W, Toronto, ON, M5S 1S8, ethics.review@utoronto.ca, 416-946-3273, to talk to someone who is independent of the research team.

I do **NOT** agree to participate in this study and would like to withdraw from my participation now.	I agree to participate in this experiment and would like to continue.
○	●

<< >>

The study starts now.

Your decisions are about real money.

<< >>

	Good picture (probability 50%)	Bad picture (probability 50%)
Correct calculations	55	45
Wrong calculations	45	55
If you bet on the picture	***WIN €2***	***LOSE €10***

3 + 47 = 55	62 + 11 = 73	49 + 44 = 93	23 + 31 = 54	5 + 37 = 41
23 + 50 = 73	60 + 31 = 91	31 + 64 = 95	33 + 42 = 72	19 + 71 = 90
83 + 7 = 90	77 + 5 = 82	20 + 63 = 83	40 + 2 = 40	18 + 49 = 63
66 + 8 = 78	4 + 74 = 82	3 + 77 = 77	17 + 5 = 22	20 + 43 = 64
2 + 58 = 60	8 + 49 = 55	54 + 25 = 79	35 + 39 = 72	18 + 73 = 91
31 + 61 = 92	53 + 23 = 71	5 + 39 = 48	67 + 12 = 79	32 + 52 = 89
53 + 17 = 70	11 + 5 = 14	51 + 47 = 103	38 + 12 = 49	17 + 14 = 31
18 + 38 = 60	33 + 51 = 82	21 + 69 = 85	29 + 16 = 45	33 + 7 = 44
1 + 96 = 97	34 + 59 = 92	42 + 53 = 96	62 + 15 = 77	18 + 9 = 27
13 + 73 = 86	9 + 67 = 76	7 + 40 = 47	11 + 27 = 38	5 + 22 = 27
3 + 36 = 43	11 + 23 = 34	8 + 30 = 38	15 + 74 = 92	32 + 58 = 91
7 + 68 = 70	46 + 6 = 52	5 + 33 = 38	21 + 19 = 40	62 + 29 = 91
2 + 80 = 84	38 + 49 = 87	64 + 25 = 89	51 + 30 = 81	49 + 47 = 99
25 + 33 = 58	9 + 76 = 82	32 + 16 = 43	12 + 15 = 22	15 + 28 = 38
27 + 43 = 70	53 + 16 = 69	79 + 10 = 85	57 + 28 = 87	58 + 26 = 84
34 + 7 = 36	53 + 40 = 93	29 + 4 = 33	41 + 43 = 84	71 + 18 = 84
12 + 79 = 87	68 + 27 = 95	47 + 16 = 63	8 + 17 = 30	17 + 65 = 82
48 + 41 = 89	21 + 44 = 68	3 + 74 = 77	55 + 19 = 74	18 + 75 = 96
75 + 18 = 93	17 + 81 = 95	93 + 2 = 95	64 + 23 = 86	11 + 86 = 97
28 + 50 = 83	21 + 30 = 51	80 + 17 = 97	32 + 11 = 43	35 + 22 = 56

Look at the purple image as long as you like to see if you want to bet on the image or not.

Click CONTINUE to make your decision.

(You can NOT return to this page once you have clicked CONTINUE.)

<< >>

	Good picture (probability 50%)	Bad picture (probability 50%)
Correct calculations	55	45
Wrong calculations	45	55
If you bet on the picture	***WIN €2***	***LOSE €10***

Make a decision.

- ● I bet on the picture. I WIN €2 if the purple picture is Good, and LOSE €10 if it is Bad.
- ○ I do not bet on the purple picture.

<< >>

How certain are you that the purple picture is Good?

It is...

definitely good	most likely good	very likely good	quite likely good	fairly likely good	slightly likely good	slightly likely bad	fairly likely bad	quite likely bad	very likely bad	most likely bad	definitely bad
100%	90-99%	80-90%	70-80%	60-70%	50-60%	40-50%	30-40%	20-30%	10-20%	1-10%	0%
○	○	○	●	○	○	○	○	○	○	○	○

(The number below each option is the probability in percent that you think the purpurrote image is good.)

If you like, you can go back now to change your decision whether you want to bet on the picture.

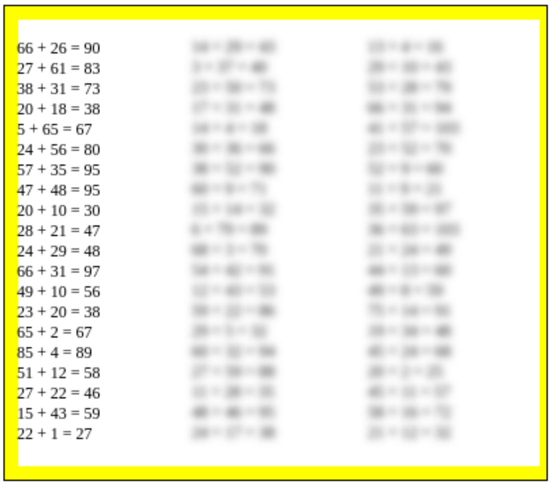
<< >>

Round 6 out of 18

	Good picture (probability 50%)	Bad picture (probability 50%)
Correct calculations	35	25
Wrong calculations	25	35
If you bet on the picture	***WIN €10***	**LOSE €2**

This picture also has 60 calculations, but you can only see 20 of them as the remainder is blurred.

Number of CORRECT calculations in the visible area: 7
Number of WRONG calculations in the visible area: 13



Look at the yellow image for as long as you like to see if you want to bet on the picture or not.

Click CONTINUE to make your decision.

(You can NOT return to this page once you have clicked CONTINUE.)

<< >>

[The subject completes all 18 rounds]

Additional calculation tasks for bonus payment

You now have the option of solving additional calculations to earn a bonus.

You will receive this bonus payment *in addition* to your other payouts from this study.

To determine the amount of your bonus payment, you will complete four decision lists like the one below.

Are you willing to solve
60 calculations
in exchange for the given amount of money?

(One of your decisions will be randomly selected and executed!)

Solve calculations, receive €0	○	○	Don't solve, receive no bonus
Solve calculations, receive €0.25	○	○	Don't solve, receive no bonus
Solve calculations, receive €0.50	○	○	Don't solve, receive no bonus
Solve calculations, receive €0.75	○	○	Don't solve, receive no bonus
Solve calculations, receive €1	○	○	Don't solve, receive no bonus
Solve calculations, receive €1.50	○	○	Don't solve, receive no bonus
Solve calculations, receive €2	○	○	Don't solve, receive no bonus
Solve calculations, receive €2.50	○	○	Don't solve, receive no bonus
Solve calculations, receive €3	○	○	Don't solve, receive no bonus
Solve calculations, receive €3.50	○	○	Don't solve, receive no bonus
Solve calculations, receive €4	○	○	Don't solve, receive no bonus

When we speak of "60 calculations", each of these tasks is like the ones you saw in the picture before. This means that each task has a calculation like "45 + 37 = 67" and it is your task to indicate if the calculation is right or wrong. (In this example, the calculation is wrong.)

<< >>

Once you have completed all four decision lists, the computer will **randomly pick one of these lists and one of the decisions** you made. This decision will then be executed at the very end of the experiment, after you finish the part with the logic puzzle. (Your decisions have absolutely no effect on the choice that the computer makes!)

This means that if you have decided not to solve the calculations for the amount of money offered, you will end the study without having to perform further calculations. If you have agreed to solve the specified amount of calculations for the amount of money offered, you will complete the tasks and receive the corresponding additional bonus.

You will **only receive the estimated amount for the additional tasks if you solve the tasks well enough**. This means that you are allowed to solve 1 out of 10 calculations incorrectly. (For example, if you solve 30 tasks, that means you can answer three of them incorrectly.) **If you solve more than 1 in 10 tasks incorrectly**, you will not only lose the extra bonus you would have got if you had completed the task correctly but there are an additional **€** deducted from your bonus.

Example: Suppose that in the randomly chosen task you decided to solve 30 calculations for €2. If you solve at least 90% of them correctly, €2 will be added to your bonus. But if you solve less than 90% correctly, you will (i) *not* receive the 2€ you would have received had you solved at least 90% correctly and (ii) €10 will be deducted from your bonus.

A second example: Suppose that in the randomly chosen task you decided to solve 30 calculations for €8. If they solve at least 90% of them correctly, €8 will be added to your bonus. But if you solve less than 90% correctly, you will (i) *not* receive the €8 you would have received had you solved at least 90% correctly and (ii) €10 will be deducted from your bonus.

Therefore, it is in your best interests to agree to solving the additional tasks only if you are genuinely willing to solve them well, and otherwise refuse to solve the additional tasks.

Please complete the following four lists according to your true preferences.

<< >>

Are you willing to solve

30 calculations

in exchange for the given amount of money?

(One of your decisions will be randomly selected and executed!)

Solve calculations, receive €0	○	●	Don't solve, receive no bonus
Solve calculations, receive €0.25	○	●	Don't solve, receive no bonus
Solve calculations, receive €0.50	○	●	Don't solve, receive no bonus
Solve calculations, receive €0.75	○	●	Don't solve, receive no bonus
Solve calculations, receive €1	○	●	Don't solve, receive no bonus
Solve calculations, receive €1.50	○	●	Don't solve, receive no bonus
Solve calculations, receive €2	○	●	Don't solve, receive no bonus
Solve calculations, receive €2.50	●	○	Don't solve, receive no bonus
Solve calculations, receive €3	●	○	Don't solve, receive no bonus
Solve calculations, receive €3.50	●	○	Don't solve, receive no bonus
Solve calculations, receive €4	●	○	Don't solve, receive no bonus
Solve calculations, receive €4.50	●	○	Don't solve, receive no bonus
Solve calculations, receive €5	●	○	Don't solve, receive no bonus
Solve calculations, receive €5.50	●	○	Don't solve, receive no bonus
Solve calculations, receive €6	●	○	Don't solve, receive no bonus
Solve calculations, receive €6.50	●	○	Don't solve, receive no bonus
Solve calculations, receive €7	●	○	Don't solve, receive no bonus
Solve calculations, receive €7.50	●	○	Don't solve, receive no bonus
Solve calculations, receive €8	●	○	Don't solve, receive no bonus
Solve calculations, receive €8.50	●	○	Don't solve, receive no bonus
Solve calculations, receive €9	●	○	Don't solve, receive no bonus
Solve calculations, receive €9.50	●	○	Don't solve, receive no bonus
Solve calculations, receive €10	●	○	Don't solve, receive no bonus

<< >>

(Note: The selection of options in the above list is illustration purposes only. For all subjects, no options were selected until the subject made a selection. Subjects had to make an active choice on each line, but could only switch from the option on the right to the option on the left once, or never, and never in the opposite direction. Subjects also saw corresponding lists for

totals of 60, 100, and 200 calculations)

Part 2

of this study will now start. You can take as much time as you like.

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Logic Puzzles

In this task, please select the answer that best suits each of the 32 questions on the following pages.

(Your answers to these questions will not affect your payout in this experiment.)

>>

Note: At this stage, subjects solve the Raven's matrices (not reproduced here for copyright reasons).

Part 3

Note: There is a 20% chance that your payout in this study will be determined solely by a decision in this section. (With the remaining probability of 80%, it is determined by a decision you made in Part 1).

In this part of the experiment, you will complete 9 decision lists. Here is an example of a decision list.

What exactly "Lottery X" is will vary from round to round.

Would you rather participate in the following lottery or receive / lose the certain amount on the right-hand side?

Lottery X

In each line, choose the option that you prefer.

Participate in the lottery	O	O	Lose €10 with certainty
Participate in the lottery	O	O	Lose €9 with certainty
Participate in the lottery	O	O	Lose €8 with certainty
Participate in the lottery	O	O	Lose €7 with certainty
Participate in the lottery	O	O	Lose €6 with certainty
....	O	O	....
....	O	O	....
Participate in the lottery	O	O	Win €6 with certainty
Participate in the lottery	O	O	Win €7 with certainty
Participate in the lottery	O	O	Win €8 with certainty
Participate in the lottery	O	O	Win €9 with certainty
Participate in the lottery	O	O	Win €10 with certainty

Each line is a separate decision.

In each line, you can either select the option on the right or left side.

If, at the end, the computer randomly decides that your payout in this experiment is determined by a decision list, the following will happen:

The computer will randomly pick a line from the decision list. Your payout will then match the decision you made in this line. Your decision has absolutely no influence on which line the computer selects.

So it's in your best interest to pick the option that fits your true preferences in each line.

There are no correct or wrong decisions!

>>

For example, suppose you completed the decision list as follows:

Would you rather participate in the following lottery or receive / lose the certain amount on the right-hand side?

Win €6 with a probability of **50%**,
lose €6 with a probability of **50%**.

In each line, choose the option that you prefer.

Participate in the lottery	Lose €10 with certainty
Participate in the lottery	Lose €9 with certainty
Participate in the lottery	Lose €8 with certainty
Participate in the lottery	Lose €7 with certainty
Participate in the lottery	Lose €6 with certainty
....	....
....	....
Participate in the lottery	Win €6 with certainty
Participate in the lottery	Win €7 with certainty
Participate in the lottery	Win €8 with certainty
Participate in the lottery	Win €9 with certainty
Participate in the lottery	Win €10 with certainty

Suppose that the computer randomly selects the decision on the third line. In this line you have chosen the possibility on the left side. Therefore, your payout for this experiment will depend on Lottery X (described in more detail later) and whether you win or lose it.

Instead, assume that the computer randomly selects the decision in the third-bottom line. In this line you have chosen the possibility on the right side. That's why you will win €8.

Most people start such a decision-making list by making a choice on the left side and eventually switching to the right side (as in the example above).

<< >>

WHY is it in my best interest to answer that question with my true valuation?

Simply put, the reason is that you will receive a worse payout if you choose anything other than what you actually prefer.

For example, suppose you would rather lose €2 in a certain round than participate in the lottery. Also, suppose that you state that you would prefer the lottery to the safe loss of €2 (for example, because you can lose a lot of money in the lottery). If, by chance, the computer chooses this decision to determine your payout, you will play the lottery, although you would have preferred to lose €2 with certainty.

Simply put, if at the end of the experiment a particular decision is chosen from this part of the experiment to determine your payout, you will receive exactly what you have selected. But you have no influence on which decision will be selected.

Therefore, the best thing you can do is to pick exactly the option on each line of each decision list that you would rather be paid for.

If you have questions about this payout mechanism, please raise your hand.

<< >>

Part 3 of the experiment starts now.

Your decisions are about real money.

<< >>

Would you rather participate in the following lottery or receive / lose the certain amount on the right-hand side?

Win €6 with a probability of **50%**,
lose €6 with a probability of **50%**.

In each line, choose the option that you prefer.

Participate in the lottery	●	○	Lose €10 with certainty
Participate in the lottery	●	○	Lose €9 with certainty
Participate in the lottery	●	○	Lose €8 with certainty
Participate in the lottery	●	○	Lose €7 with certainty
Participate in the lottery	●	○	Lose €6 with certainty
Participate in the lottery	●	○	Lose €5 with certainty
Participate in the lottery	●	○	Lose €4 with certainty
Participate in the lottery	●	○	Lose €3 with certainty
Participate in the lottery	●	○	Lose €2 with certainty
Participate in the lottery	●	○	Lose €1 with certainty
Participate in the lottery	○	●	Win €0 with certainty
Participate in the lottery	○	●	Win €1 with certainty
Participate in the lottery	○	●	Win €2 with certainty
Participate in the lottery	○	●	Win €3 with certainty
Participate in the lottery	○	●	Win €4 with certainty
Participate in the lottery	○	●	Win €5 with certainty
Participate in the lottery	○	●	Win €6 with certainty
Participate in the lottery	○	●	Win €7 with certainty
Participate in the lottery	○	●	Win €8 with certainty
Participate in the lottery	○	●	Win €9 with certainty
Participate in the lottery	○	●	Win €10 with certainty

<< >>

(Note: The selection of options in the above list is illustration purposes only. For all subjects, no options were selected until the subject made a selection. Subjects had to make an active choice on each line, but could only switch from the option on the right to the option on the left once, or never, and never in the opposite direction. Subjects decided for 8 further lotteries, in random order.

We would like to ask you some questions about yourself.

Please answer truthfully.

What is your gender?

[male; female; other (e.g. genderqueer)]

How old are you?

At which faculty do you study?

[Faculty of Economics, Management and Social Science; Faculty of Law; Faculty of Medicine; Faculty of Philosophy; Faculty of Mathematics and Natural Sciences; Faculty of the Humanities; I am not a student]

Which state conferred your Abitur (university entrance diploma)?

[Baden-Württemberg; Bayern; Berlin; Brandenburg; Bremen; Hamburg; Hesse; Mecklenburg-Vorpommern; Niedersaxen; Nordrhein-Westfalen; Rheinland-Pfalz; Saarland; Sachsen; Sachsen-Anhalt; Schleswig-Holstein; Thüringen; I received the International Baccalaureate; I do not have an Abitur; I prefer not to say]

What was your Grade Point Average in the Abitur?

[1.0, 1.1, 1.2, …, 3.9, 4.0; I do not have an Abitur; I do not remember; I prefer not to say]

What was your Abitur grade in Mathematics?

[15 points (1+), 14 points (1), 13 points (1-), 12 points (2+), 11 points (2), 10 points, (2-), …, 3 points (5+), 2 points (2), 1 point (2-), 0 points; I do not have an Abitur; I do not remember; I prefer not to say]

What was your Abitur grade in German?

[15 points (1+), 14 points (1), 13 points (1-), 12 points (2+), 11 points (2), 10 points, (2-), …,

3 points (5+), 2 points (2), 1 point (2-), 0 points; I do not have an Abitur; I do not remember; I prefer not to say]

Have you taken an honors class in Mathematics in high school (Leistungskurs im Abitur)?

[Yes; No; I do not have an Abitur]

Have you taken an honors class in German in high school (Leistungskurs im Abitur)?

[Yes; No; I do not have an Abitur]

How much money do you spend on average each month (incl. rent, food, transportation, etc.)

[€ 0 - € 150; € 150 - € 300; € 300 - € 450; € 450 - € 600; € 600 - € 750; € 750 - € 900; € 900 - € 1050; € 1050 - € 1200; € 1200 - € 1350; € 1350 - € 1500; € 1500 - € 2000; € 2000 - € 2500; € 2500 - € 3000; more than € 3000; I prefer not to say]

How much money do you earn each month through your own labor?

[€ 0 - € 50; € 50 - € 100; € 100 - € 150; € 150 - € 200; € 200 - € 250; € 250 - € 300; € 300 - € 350; € 350 - € 400; € 400 - € 450; € 450 - € 500; € 500 - € 600; € 600 - € 700; € 700 - € 800; € 800 - € 900; € 900 - € 1000; € 1000 - € 1250; € 1250 - € 1500; € 1500 - € 1750; € 1750 - € 2000; € 2000 - € 2500; € 2500 - € 3000; more than € 3000; I prefer not to say]

How much money do you receive from your parents each month?

[€ 0 - € 50; € 50 - € 100; € 100 - € 150; € 150 - € 200; € 200 - € 250; € 250 - € 300; € 300 - € 350; € 350 - € 400; € 400 - € 450; € 450 - € 500; € 500 - € 600; € 600 - € 700; € 700 - € 800; € 800 - € 900; € 900 - € 1000; € 1000 - € 1250; € 1250 - € 1500; € 1500 - € 1750; € 1750 - € 2000; € 2000 - € 2500; € 2500 - € 3000; more than € 3000; I prefer not to say]

What is the net wealth of your parents (incl. real estate)?

[€ 0k - € 25k; € 25k - € 50k; € 50k - € 75k; € 75k - € 100k; € 100k - € 125k; € 125k -

€ 150k; € 150k - € 175k; € 175k - € 200k; € 200k - € 250k; € 250k - € 300k; € 300k - € 350k; € 350k - € 400k; € 400k - € 450k; € 450k - € 500k; € 500k - € 600k; € 600k - € 700k; € 700k - € 800k; € 800k - € 900k; € 900k - € 1 mio.; € 1 mio. - € 1.5 mio.; € 1.5 mio. - € 2 mio.; € 2 mio. - € 2.5 mio.; € 2.5 mio. - € 3 mio.; € 3 mio. - € 3.5 mio.; € 3.5 mio. - € 4 mio.; more than € 4 mio.; I prefer not to say]

Would you like to be informed by e-mail about the results and hypotheses of this study?

If yes, please enter your email address here.
(You are also allowed to leave this field blank.)

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As a reminder, you have made various decisions about whether you want to solve extra calculations for additional bonuses in decision lists.

The computer has randomly selected a list and one of your decisions, which is now being executed.

The decision that was randomly chosen is the following:

Solve 200 calculations for €2.5.

You decided to REJECT this transaction.

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We're done!

Thank you for your participation in this study!

Again, on behalf of the University of Cologne and the University of Toronto, we guarantee that your payout is exactly as we described it to you. Specifically, this means that if we told you something would happen with a certain probability out of 100, then it was with that very probability.

As explained in the introduction, you will receive €15 for your participation in this experiment, plus any winnings you made in this experiment and less any losses you have suffered. Your total payout is calculated as follows.

Your payout is determined by your probability assessment in part 1, round 11 so that you receive €3.

You do not receive a bonus payment for solving additional calculations.

Now, therefore, your final payout is €18.

You have completed the experiment now. Please go quietly to the experimenter room to receive your payout. Bring the completed receipt with you.

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References

Abeler, J., A. Falk, L. Goette, and D. Huffman (2011). Reference points and effort provision. *American Economic Review 101*(2), 470–92.

Aumann, R. J., M. Maschler, and R. E. Stearns (1995). *Repeated Games with Incomplete Information*. MIT Press.

Caplin, A. and M. Dean (2013). Rational inattention, entropy, and choice: The posterior-based approach. Working paper.

Caplin, A., M. Dean, and J. Leahy (2017). Rationally inattentive behavior: Characterizing and generalizing Shannon entropy. NBER Working Paper.

Gentzkow, M. and E. Kamenica (2011). Bayesian persuasion. *American Economic Review 101*(6), 2590–2615.

Matějka, F. and A. McKay (2015). Rational inattention to discrete choices: A new foundation for the multinomial logit model. *American Economic Review 105*(1), 272–98.

Morris, S. and H. S. Shin (2002). Social value of public information. *American Economic Review 92*(5), 1521–1534.

Morris, S. and P. Strack (2019). The Wald problem and the relation of sequential sampling and ex-ante information costs. Working paper.

Wald, A. (1947). *Sequential Analysis*. New York: Wiley.