Online Appendix for Ambiguity & Enforcement

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Abstract

This document contains the online appendix materials for the paper "Ambiguity & Enforcement". Section A details the theoretical model used in the paper. Section B formalizes the equilibrium of the model. Section C provides some additional empirical results. Section D contains the instructions used in the experiment. The replication material for the study is available at `https://doi.org/10.7910/DVN/VHS9OT`.

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A Theoretical model

This section outlines the formal theoretical model and discusses the identification of preferences given driver behavior. The section begins by focusing on the axiomatic foundations for driver behavior, given the officer's choice of monitoring (m_A, m_B and $m = m_A + m_B$). The following section establishes the equilibrium of the game.

Let $U^{\text{Obs}}(X, m_A, m_B)$ denote the driver's utility of choosing strategy $X \in \{A, B, C\}$ when monitoring is fully observable, and $U^{\text{Unobs}}(X, m)$ denote utility in the case where only m is observable.[1] For convenience, and without loss of generality, we normalize the utility of choosing C to be 50 for all levels of monitoring (i.e. $U^{\text{Obs}}(C, m_A, m_B) = U^{\text{Unobs}}(C, m) = 50$ for all m_a, m_b, m).

The first assumption, Monotonicity, implies that driver utility is decreasing in monitoring levels. In particular, in the observed case, the utility from choosing road A (B) is decreasing in m_A (m_B). In the unobserved case, the utility of choosing either A or B is decreasing in the sum of monitoring across the two roads.

Definition 1 (Monotonicity – observable monitoring)**.**

For all $m_B \in [0, 0.9]$, $m_A < m'_A \Rightarrow U^{\text{Obs}}(A, m_A, m_B) > U^{\text{Obs}}(A, m'_A, m_B)$; and for all $m_A \in [0, 0.9]$, $m_B < m'_B \Rightarrow U^{\text{Obs}}(B, m_A, m_B) > U^{\text{Obs}}(B, m_A, m'_B)$.

Definition 2 (Monotonicity – unobservable monitoring)**.**

$m < m' \Rightarrow U^{\text{Unobs}}(A, m) > U^{\text{Unobs}}(A, m')$ and $U^{\text{Unobs}}(B, m) > U^{\text{Unobs}}(B, m')$.

The second assumption, Symmetry, has two components. In the observed case, it ensures that the utility of choosing one road is not affected by the monitoring level on the other road, that road A and B are treated symmetrically, and that the driver is indifferent between speeding and not speeding when monitoring on a given road is observed to be 0.4. In the unobserved case it ensures that the utility of road A and road B are always equal, and that the utility depends only on the sum of the monitoring across the two roads.

Definition 3 (Symmetry – observable monitoring)**.**

For all $m', m_A, m_B \in [0, 0.9]$, $U^{\text{Obs}}(A, m', m_B) = U^{\text{Obs}}(B, m_A, m')$; and for all m_A, m_B, $U^{\text{Obs}}(A, 0.4, m_B) = U^{\text{Obs}}(B, m_A, 0.4) = 50$.

Definition 4 (Symmetry – unobservable monitoring)**.**

$m = m' \Rightarrow U^{\text{Unobs}}(A, m) = U^{\text{Unobs}}(B, m')$.

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[1] The axiomatic structure is not dependent on whether the driver payoff is probabilistic or not, and therefore we do not introduce additional notation to make this distinction here.

The Non-triviality assumption is straightforward.

Definition 5 (Non-triviality)**.**
$U^{\text{Obs}}(A,0,0) > U^{\text{Obs}}(C,0,0)$; $U^{\text{Obs}}(A,0.9,0.9) < U^{\text{Obs}}(C,0.9,0.9)$; $U^{\text{Unobs}}(A,0) > U^{\text{Unobs}}(C,0)$; and $U^{\text{Unobs}}(A,1.8) < U^{\text{Unobs}}(C,1.8)$.

Notice that Non-triviality follows immediately from Monotonicity and Symmetry when $I = \text{Obs}$ but imposes weak additional restrictions when $I = \text{Unobs}$. Practically, Non-triviality ensures that when monitoring is maximal the driver always prefer C and when monitoring is minimal the driver will never prefer C.

Further, continuity of the utility function implies that there exists a value of $\overline{m}_t \in (0,1.8)$ such that $U_t^{\text{Unobs}}(A,\overline{m}_t) = U_t^{\text{Unobs}}(B,\overline{m}_t) = U_t^{\text{Unobs}}(C,\overline{m}_t)$. That is, there exists a level of monitoring that induces indifference in the driver.

Lemma 1, presented in the main text, provides the best response correspondence for drivers. The proof of Lemma 1 is presented below, and makes use of the definitions above.

Proof of Lemma 1. For the case where $I = \text{Obs}$, the final row follows directly from symmetry. The three preceding rows each follow from the final row after applying monotonicity. The third row follows from rows four, six and monotonicity. The second row follows from rows four and five and monotonicity. The first row follows from rows five, six and monotonicity.

For the case where $I = \text{Unobs}$, the existence of $\overline{m}$ is guaranteed by non-triviality and continuity of the utility function. The first row then follows from the third row and monotonicity, and the second row follows from the third row, monotonicity and symmetry. $\square$

The indifference point for the driver, $\overline{m}$, provides a measure of the uncertainty preferences of the driver. To see this, consider first an EU agent in the *EV* treatment. In this treatment, choosing C provides a sure payoff of 50 points. Note also that given total monitoring, m, the expected value of choosing A or B is $90 - \frac{100m}{2}$ points. When facing monitoring level of exactly $\overline{m}$ the driver subjectively considers the prospect of choosing A or B to have a certainty equivalent of 50 points. For the case where $\overline{m} > 0.8$ the expected value of choosing A or B is less than 50 and, therefore, less than the certainty equivalent of choosing A or B. The driver is, by definition, risk seeking in this case. By a similar argument, the driver is risk neutral when $\overline{m} = 0.8$ and risk averse when $\overline{m} < 0.8$.

For the *Prob* treatment the logic is the same. In this case, however, C provides a lottery that pays 100 points with probability 0.5 (and nothing otherwise). When facing monitoring level of exactly $\overline{m}$ the driver subjectively considers the prospect of choosing A or B to have a probability equivalent of $\frac{1}{2}$. For the case where $\overline{m} > 0.8$ the expected probability of earning 100 points when choosing A or B is less than $\frac{1}{2}$ and, therefore, less than the probability equivalent of choosing A or B. The driver is, by definition, uncertainty seeking in this case. By a similar argument, the driver is uncertainty neutral when $\overline{m} = 0.8$ and uncertainty averse when $\overline{m} < 0.8$. Further, if we assume that the driver has Expected Utility preferences over risk, then we can, in the *Prob* treatment, identify uncertainty aversion with ambiguity aversion.

We summarize this intuition in the lemmas below, using the smooth ambiguity aversion functional form to illustrate the role of ambiguity in our experimental design. To distinguish between the *Prob* and *EV* treatments we introduce an additional piece of notation, $\overline{m}_t$, which denotes the driver's indifference point in treatment $t \in \{\text{Prob}, \text{EV}\}$. An empirical analysis of the effects of non-EU risk preferences (i.e. non-linear probability weighting) is found in Section A.1, concluding that non-EU risk preferences can only generate small deviations of $\overline{m}$ from 0.8.

Lemma 1. If a driver has Expected Utility preferences that satisfy Symmetry, then $\overline{m}_{\text{Prob}} = 0.8$. If, in addition, the driver is

- risk neutral, then $\overline{m}_{\text{EV}} = 0.8$;
- risk averse, then $\overline{m}_{\text{EV}} < 0.8$;
- risk seeking, then $\overline{m}_{\text{EV}} > 0.8$.

Proof of Lemma 1. The driver knows that $m_A + m_B = m$ and assume that the driver believes the distribution of m_A has probability density function $\mu(x)$. Further, suppose that the driver has expected utility preferences with Bernoulli utility function $u(\cdot)$. Definition 3 implies that $\mu(x)$ is symmetric (i.e. $\mu(x) = \mu(m - x)$ for $x \leq \frac{m}{2}$). Then, in the *Prob* treatment the expected utility of the driver playing A is given by:

$$\begin{aligned}
EU(A) &= \int_0^m \big[u(100)(0.9 - x) + u(0)(0.1 + x)\big]\mu(x)dx \\
&= u(100)\Big[\int_0^m 0.9\mu(x)dx - \int_0^m x\mu(x)dx\Big] + u(0)\Big[\int_0^m 0.1\mu(x)dx + \int_0^m x\mu(x)\Big] \\
&= u(100)[0.9 - \frac{m}{2}] + u(0)[0.1 + \frac{m}{2}]
\end{aligned}$$

where the third line has used the symmetry assumption. The expected utility of B is calculated similarly, and $EU(C) = \frac{u(100)+u(0)}{2}$. Clearly, $EU(A) = EU(B) = EU(C)$ when $m = 0.8$.

In the EV treatment, the expected utility of the driver playing A is given by:

$$EU(A) = \int_0^m u(100(0.9 - x))\mu(x)dx$$

and note also that the expected value of playing A is given by $EV(A) = 100(0.9 - \frac{m}{2})$. If the driver is risk averse then $EU(A) \leq u(EV(A))$. At $m = 0.8$, $EV(A) = EV(C)$ and $u(EV(C)) = u(C)$ because C generates a fixed payment. Therefore, if the driver is risk averse then $EU(A) \leq u(C)$, so that $\overline{m} \leq 0.8$. The opposite conclusion holds if the driver is risk seeking. □

Before presenting Lemma 2, we provide a brief introduction to the smooth ambiguity model (Klibanoff et al., 2005) in the context of our game. In the smooth ambiguity model preferences are represented by a double expectational form, where the inner expectation is taken with respect to objective uncertainty and the outer expectation with respect to subjective uncertainty. When m_A and m_B are observable to the driver, $I =$ Obs, there is no subjective uncertainty and the smooth ambiguity model collapses to expected utility. We therefore focus on the case where m_A and m_B are unobservable, $I =$ Unobs, where we can write the driver's utility from choosing A as

$$U(A) = \int \phi\Big(u(100)[0.9 - m_A] + u(0)[0.1 + m_A]\Big)d\mu(m_A)$$

in the *Prob* treatment where u is a Bernoulli utility function, $\mu(m_A)$ is the agent's subjective belief regarding the distribution of m_A, and ϕ is a mapping from $\mathbb{R}$ to $\mathbb{R}$ that encapsulates ambiguity preferences. The utility of choosing C can be expressed as

$$U(C) = u(100)[0.5] + u(0)[0.5]$$

because C involves no subjective uncertainty. Notice that normalizing $u(100) = 100$ and $u(0) = 0$ is consistent with our previous normalization that $U(C) = 50$. Applying this normalization to the utility of choosing A, $U(A)$, we have

$$U(A) = \int \phi\big(100[0.9 - m_A]\big)d\mu(m_A). \tag{1}$$

Equation 1 is independent of the curvature of the utility function, u. Intuitively utility in the *Prob* treatment is independent of risk preferences because there are only two possible outcomes. Uncertainty preferences in the *Prob* treatment are, therefore, entirely determined by the curvature of ϕ, the ambiguity preferences of the agent.

This does not hold in the EV treatment where the utility of choosing A is given by

$$U(A) = \int \phi\big(u(100[0.9 - m_A])\big) d\mu(m_A).$$

in this case, the utility of A, and aggregate uncertainty preferences are determined by both the curvature of u and ϕ.

Lemma 2. Assume that the driver has risk neutral "smooth" ambiguity preferences (Klibanoff et al., 2005) that satisfy Symmetry. If, in addition, the driver is

- ambiguity neutral, then $\overline{m}_t = 0.8$;
- ambiguity averse, then $\overline{m}_t < 0.8$;
- ambiguity seeking, then $\overline{m}_t > 0.8$.

for $t \in \{\text{EV}, \text{Prob}\}$.

Proof of Lemma 2. The driver knows that $m_A + m_B = m$ and assume that the driver believes the distribution of m_A has probability density function $\mu(x)$. Further, suppose that the driver has smooth ambiguity preferences with Bernoulli utility function $u(c) = c$. Definition 3 implies that $\mu(x)$ is symmetric (i.e. $\mu(x) = \mu(m - x)$ for $x \leq \frac{m}{2}$). The utility of choosing A is therefore given by:

$$\begin{aligned} U(A) &= \int \phi\big(u(100)[0.9 - m_A] + u(0)[0.1 + m_A]\big) d\mu(m_A) \\ &= \int \phi\big(100[0.9 - m_A]\big) d\mu(m_A) \end{aligned}$$

Note that the expected value of playing A is given by $EV(A) = 100(0.9 - \frac{m}{2})$. If ϕ is linear (i.e. the driver is ambiguity neutral) then $U(A) = EV(A)$. If ϕ is concave (i.e. the driver is ambiguity averse) then $U(A) \leq EV(A)$ and if ϕ is convex (i.e. the driver is ambiguity seeking) then $U(A) \geq EV(A)$. At $m = 0.8$, $EV(A) = EV(C)$ and $U(EV(C)) = U(C)$ because C generates a fixed payment. Therefore, if the driver is ambiguity averse and $U(A) \leq EV(A)$ then $U(A) \leq U(C)$, so that $\overline{m} \leq 0.8$. The opposite conclusion holds if the driver is ambiguity seeking. ☐

A.1 The effects of non-linear probability weighting

So far, we have assumed Expected Utility over risk. In this section we consider the effect of non-linear probability weighting on the driver's indifference point, $\overline{m}$. The overall conclusion of this section is that, for realistic amounts of curvature, probability weighting has only a small effect on $\overline{m}$. Therefore, substantial deviations from $\overline{m} = 0.8$ in the *Prob* treatment must be generated by non-neutral ambiguity preferences. We reach this conclusion by simulating $\overline{m}$ for a hypothetical driver with linear utility function and Prelec probability weighting function (with parameter $0.4 < \alpha < 1.2$). We assume that the hypothetical driver has beliefs that are consistent with the true distribution of monitoring levels in the *Prob* treatment of our experiment.

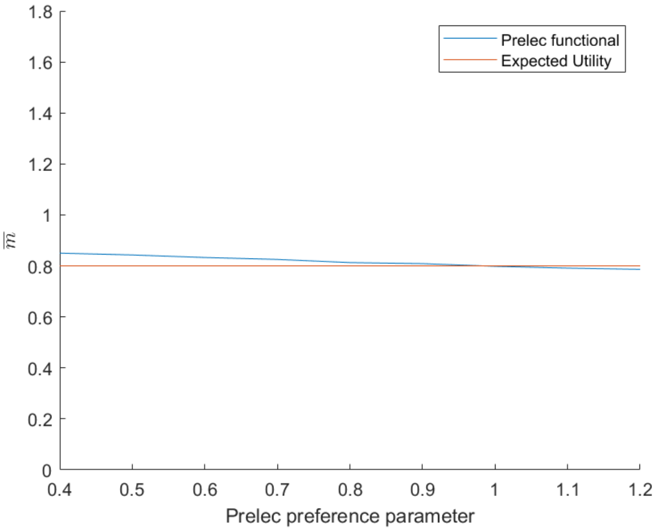

Figure 1: The effects of probability weighting on the driver's indifference point, $\overline{m}$. We assume that driver's preferences satisfy Rank Dependent Expected Utility with Prelec weighting function $w(p) = e^{-(-\ln(p))^{\alpha}}$, and plot $\overline{m}$ as a function of α. Expected Utility is the special case of $\alpha = 1$.

To estimate the empirical distribution of monitoring levels, in the unobserved case, we consider the distribution of $\hat{m}_A = \frac{m_A}{m}$ in the data, and in doing so we restrict our attention to the middle 80% of observations of total monitoring (that is, observations with $0.13 < m < 1.33$).[2] In approximately

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[2] When monitoring is above, or below, this level the level of total monitoring is so far away from the driver's indifference point that we do not expect the distribution of monitoring in this region to affect beliefs near the indifference point.

20% of rounds (139 out of 694) we observe $\hat{m}_A = 0.5$, and in approximately 25% of rounds (171 out of 694) we observe either $\hat{m}_A = 0$ or $\hat{m}_A = 1$. For the remaining observations, $\hat{m}_A$ is approximately normally distributed with mean 0.5 and standard deviation 0.2.

In our simulations, therefore, we assume that the driver has beliefs over $\hat{m}_A$ that follow a mixture distribution that places weight of 0.2 on $\hat{m}_A = 0.5$, 0.125 on $\hat{m}_A = 0$, 0.125 on $\hat{m}_A = 1$, and is otherwise governed by a normal distribution $N(0.5, 0.2)$ that is truncated at 0 and 1. Given this belief distribution we calculate, via numerical simulation, the indifference point for a driver with Rank Dependent Expected Utility preferences with $u(x) = x$ and $w(p) = e^{-(-\ln(p))^\alpha}$ for $0.4 < \alpha < 1.2$.[3] Notice that $\alpha = 1$ recovers the standard case of Expected Utility.

As can be seen from Figure 1, the effect of probability weighting on $\overline{m}$ is minor. Recall that an Expected Utility agent will have $\overline{m} = 0.8$ in the *Prob* treatment, and note that even at the rather extreme value of $\alpha = 0.4$ we estimate that $\overline{m}$ increases to only 0.85. At more realistic values of α the effect is even smaller, with $\overline{m} \approx 0.83$ at $\alpha = 0.7$ and $\overline{m} \approx 0.82$ at $\alpha = 0.8$.

B Complete equilibrium characterization

This section provides a complete equilibrium characterization. Because the equilibrium structure, and proof thereof, are the same for the *Prob* and *EV* treatments, we suppress the treatment notation in what follows.

As stated in Section 3 of the main text the officer's strategy can be summarized by the vector $M = (m, m_A, m_B, I)$ and the driver's strategy can be summarized by the pair of functions $D^{\text{Obs}} : [0, 0.9]^2 \to \{A, B, C\}$ and $D^{\text{Unobs}} : [0, 1.8] \to \{A, B, C\}$. In some cases, when the choice of information strategy is clear, we abuse notation and shorten the officer's strategy to $M = (m, m_A, m_B)$.

We impose the following technical assumption on the driver's strategy.

Assumption 1. *Either the set $\{(x, y) : D^{Obs}(x, y) = C\}$ is closed, or the set $\{(x, y) : D^{Obs}(x, y) \in \{A, B\}\}$ is closed.*

This assumption rules out several pathological driver strategies including, for example, the case where $D(0.4, y) = C$ if $y > 0.4$ is rational and $D(0.4, y) = A$ if $y > 0.4$ is irrational. Recall that each choice of m and I defines the start of a new subgame, and we use subgame perfect Nash

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[3] The range of α was chosen to be consistent with a similar robustness exercise in Baillon and Placido (2019).

equilibrium to solve the game.

Proposition 1. In the *CrimMin* treatment in the subgame where $I = \text{Obs}$, if M and D^{Obs} form an equilibrium then $M = (0.8, 0.4, 0.4)$ and $D^{\text{Obs}}(0.4, 0.4) = C$.

In the *RevMax* treatment in the subgame where $I = \text{Obs}$, if M and D^{Obs} form an equilibrium then $M = (0.8, 0.4, 0.4)$ and $D^{\text{Obs}}(0.4, 0.4) \in \{A, B\}$.

Proof. We begin with the *CrimMin* case. Subgame perfection requires that $D(m_A, m_B)$ is consistent with Lemma 1. If, in addition, $D(0.4, 0.4) = C$, then it follows immediately that the officer's best response is $M = (0.8, 0.4, 0.4)$. Therefore there exists an equilibrium with $M = (0.8, 0.4, 0.4)$ and $D(0.4, 0.4) = C$. To show that there are no other equilibrium, we consider two cases. First, if the set of (x, y) values such that $D(x, y) = C$ is closed then any best response function for the driver satisfies $D(0.4, 0.4) = C$. Second, if the set of (x, y) values such that $D(x, y) \in \{A, B\}$ is closed then the set of (x, y) such that $D(x, y) = C$ is open from below. There does not exist a best response for the officer who seeks to minimize $m_A + m_B$ subject to $D(m_A, m_B) = C$ and, therefore, no equilibrium exists.

We continue with the *RevMax* case. Subgame perfection requires that $D(m_A, m_B)$ is consistent with Lemma 1. If, in addition, $D(0.4, 0.4) \in \{A, B\}$, then it follows immediately that the officer's best response is $M = (0.4, 0.4)$. Therefore there exists an equilibrium with $M = (0.8, 0.4, 0.4)$ and $D(0.4, 0.4) \in \{A, B\}$. To show that there are no other equilibrium, we consider two cases. First, if the set of (x, y) values such that $D(x, y) \in \{A, B\}$ is closed then any best response function for the driver satisfies $D(0.4, 0.4) \in \{A, B\}$. Second, if the set (x, y) of values such that $D(m, x, y) = C$ is closed then the set of (x, y) such that $D(x, y) \in \{A, B\}$ is open from above. There does not exist a best response for the officer who seeks to maximize $\min\{m_A, m_B\}$ subject to $D(m_A, m_B) \in \{A, B\}$ and, therefore, no equilibrium exists. ☐

Proposition 2. In the *CrimMin* treatment with $I = \text{Unobs}$, if M and D^{Unobs} form an equilibrium then $M = (\overline{m}, m_A, m_B)$ and $D^{\text{Unobs}}(\overline{m}) = C$ with $\overline{m}$ as defined in Lemma 1.

In the *RevMax* treatment with $I = \text{Unobs}$, if M and D^{Unobs} form an equilibrium then $M = (\overline{m}, m_A, m_B)$ and $D^{\text{Unobs}}(\overline{m}) \in \{A, B\}$ with $\overline{m}$ as defined in Lemma 1.

Proof. We begin with the *CrimMin* case. Subgame perfection requires that $D(m, m_A, m_B)$ is consistent with Lemma 1. If, in addition, $D(\overline{m}) = C$, then it follows immediately that the officer's best response is any m_A and m_B such that $m_A + m_B = \overline{m}$. Therefore there exists an equilibrium with $M = (\overline{m}, m_A, m_B)$ and $D(\overline{m}) = C$. To show that there are no other equilibrium consider the case where $D(\overline{m}) \in \{A, B\}$. There does not exist a best response for the officer who seeks to minimize $m_A + m_B$ subject to $D(m_A + m_B) = C$ and, therefore, no equilibrium exists.

We continue with the *RevMax* case. Subgame perfection requires that $D(m)$ is consistent with Lemma 1. If, in addition, $D(\overline{m}) \in \{A, B\}$, then it follows immediately that the officer's best response is any m_A and m_B such that $m_A + m_B = \overline{m}$. Therefore there exists an equilibrium with $M = (\overline{m}, m_A, m_B)$ and $D(\overline{m}) \in \{A, B\}$. To show that there are no other equilibrium consider the case where $D(\overline{m}) = C$. There does not exist a best response for the officer who seeks to maximize $\min\{m_A, m_B\}$ subject to $D(\min\{m_A, m_B\}) \in \{A, B\}$ and, therefore, no equilibrium exists. $\square$

Clearly in the case of endogenous information the officer will select $I \in \{\text{Obs}, \text{Unobs}\}$, conditional on the driver's uncertainty preferences, to maximize her payoff.

Proposition 3. In the *CrimMin* treatment, there are three classes of equilibrium:

- if $\overline{m} < 0.8$, then $I^* = \text{Unobs}$ and $M^* = (\overline{m}, m_A, m_B)$ and $D^{*\text{Unobs}}(\overline{m}) = C$ in every equilibrium.
- if $\overline{m} = 0.8$, then $I^* = \text{Unobs}$ and $M^* = (0.8, m_A, m_B)$ and $D^{*\text{Unobs}}(0.8) = C$ or $I^* = \text{Obs}$ and $M^* = (0.8, 0.4, 0.4)$ and $D^{*\text{Obs}}(0.4, 0.4) = C$ in every equilibrium.
- if $\overline{m} > 0.8$, then $I^* = \text{Obs}$ and $M^* = (0.8, 0.4, 0.4)$ and $D^{*\text{Obs}}(0.4, 0.4) = C$ in every equilibrium.

In the *RevMax* treatment, there are three classes of equilibrium:

- if $\overline{m} < 0.8$, then $I^* = \text{Obs}$ and $M^* = (0.8, 0.4, 0.4)$ and $D^{*\text{Obs}(0.4,0.4)} \in \{A, B\}$ in every equilibrium.
- if $\overline{m} = 0.8$, then $I^* = \text{Unobs}$ and $M^* = (0.8, m_A, m_B)$ and $D^{*\text{Unobs}}(0.8) \in \{A, B\}$ or $I = \text{Obs}$ and $M = (0.8, 0.4, 0.4)$ and $D^{\text{Obs}}(0.4, 0.4) \in \{A, B\}$ in every equilibrium.
- if $\overline{m} > 0.8$, then $I^* = \text{Unobs}$ and $M^* = (\overline{m}, m_A, m_B)$ and $D^{*\text{Unobs}}(\overline{m}) \in \{A, B\}$ in every equilibrium.

Proof. Follows immediately from Proposition 1 and Proposition 2. $\square$

C Supplementary Results

This section documents the demographics of our subjects, and shows that our main results are robust to demographic controls. Table 1 displays the mean values of our demographic variables by treatment. There is little variation in demographics across treatments. The largest difference is the difference in gender composition of Officers (36% female) and Drivers (53% female) within the Prob treatment, although this difference is not statistically significant at standard levels of significance ($p = 0.08$).

Table 2 recreates Table 7 from the main paper, and also includes demographic controls. The parameter estimates are almost unchanged when demographic controls are included. Further, the coefficients on the demographic controls are all small in magnitude. For example, the effect of being an Engineering or Science major, relative to "Other" majors, is equivalent to an increase in the level of monitoring, $V_{i,r}^{I}(m_A, m_B)$, of approximately 0.06 in the EV treatment and 0.07 in the Prob treatment with observed monitoring. The relative effects are even smaller in the case of unobserved monitoring (0.01 and 0.02 for the EV and Prob treatments, respectively).

	EV treatment	Prob treatment		
		Aggregated	Officers	Drivers
$\mathbb{1}(Female)$	0.46	0.45	0.36	0.53
	(0.50)	(0.50)	(0.49)	(0.50)
$\mathbb{1}(BusEcMajor)$	0.21	0.28	0.25	0.31
	(0.41)	(0.45)	(0.44)	(0.47)
$\mathbb{1}(EngSciMajor)$	0.56	0.52	0.58	0.45
	(0.50)	(0.50)	(0.50)	(0.50)
$\mathbb{1}(OtherMajor)$	0.24	0.20	0.16	0.24
	(0.43)	(0.40)	(0.37)	(0.24)
Age	21.2	21.0	20.8	21.1
	(2.2)	(3.0)	(2.5)	(3.6)
Number of Econ Classes	2.0	2.0	1.9	2.1
	(2.0)	(3.1)	(3.3)	(2.9)
GPA	3.38	3.44	3.49	3.40
	(0.58)	(0.62)	(0.76)	(0.44)

Table 1: Summary of demographic variables by treatment. $\mathbb{1}(X)$ denotes an indicator variable that takes on a value of 1 if X is true, and 0 otherwise. Values presented are means. Standard errors are in parentheses.

	EV treatment		Prob treatment	
	(1)	(2)	(3)	(4)
Constant	-3.94^{***}	-4.04^{***}	-3.09^{***}	-3.42^{**}
	(0.41)	(0.75)	(0.33)	(1.20)
$\mathbb{1}(\text{Obs})$	-30.77^{**}	-31.47^{**}	-5.80^{***}	-5.81^{***}
	(8.99)	(9.29)	(1.14)	(1.12)
$V^I_{i,r}(m_A, m_B)$	9.43^{***}	9.68^{***}	6.00^{***}	6.12^{***}
	(0.91)	(0.92)	(0.72)	(0.73)
$\mathbb{1}(\text{Obs})V^I_{i,r}(m_A, m_B)$	77.01^{**}	78.83^{**}	14.52^{***}	14.60^{***}
	(22.28)	(23.04)	(2.77)	(2.70)
$\mathbb{1}(Female)$		0.27		0.20
		(0.18)		(0.22)
$\mathbb{1}(BusEcMajor)$		0.14		0.05
		(0.25)		(0.29)
$\mathbb{1}(EngSciMajor)$		0.58^{*}		0.42
		(0.23)		(0.28)
Age		-0.02		0.02
		(0.03)		(0.04)
Number of Econ Classes		0.10		0.08^{*}
		(0.06)		(0.04)
GPA		0.02		-0.18
		(0.14)		(0.23)
Observations	1728	1728	1980	1980
Subjects	72	72	55	55

Table 2: Population average GEE parameter estimates, as shown in Table 7 of the main paper, with robust standard errors in parentheses. Columns (1) and (3) replicate the main paper, and columns (2) and (4) add demographic controls. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

D Instructions

The instructions for the Expected Value treatment are reproduced below, followed by the payoff guide provided to subjects. The instructions for the Probabilistic treatment are very similar, and are not reproduced below for space reasons.

Experimental Overview (V2)

You will be participating in an experiment on human decision making. There are two roles in the experiment: a Worker and a Supervisor. You will play one role for the first half of the experiment, and then the other role for the remainder of the experiment. Your computer screen indicates which role you will have in the first half of the experiment. Your computer screen will display useful information. Remember that the information on your computer screen is private. Please do not communicate with the other participants at any point during the experiment. If you have any questions, or need assistance of any kind, raise your hand and the experimenter will come and help you.

Please switch your phones off and place them away. The only materials you will need for this experiment are the computer and the calculator in front of you. We will also provide you with some paper if you wish to take notes.

This experiment will consist of multiple rounds. In each round there will be three tasks. The choice of the supervisor will affect the payoffs for each of the tasks. The worker will then decide which of the three tasks to implement. The points earned in each round will be added together and converted to USD at the end of the experiment at an exchange rate of 100 points = \$0.90. You will also receive, in addition, a \$5 show up fee.

Supervisor's decision

The supervisor will set the values of two variables, O_A and O_B. The supervisor will input their decisions using slider bars. To help fine tune your choice, you may click on the slider and then use the arrow keys to adjust your decision. While the Supervisor is making their decision, the Worker will see a wait screen. Each variable will take a value between 0 and 0.9, with increments of 0.01. The variables will affect the payoffs for each of task A, task B and task C as follows.

Effect on worker's payoffs

The worker will always earn 50 points if task C is implemented.

For task A, the worker's payoff will decrease as O_A increases. If $O_A = 0$, then the worker earns 90 points. If $O_A = 0.9$, the worker earns 0 points. The rate of decrease is linear, so that increasing O_A by 0.1 reduces the worker's payoff by 10 points. Equivalently, the formula is given by $W_A = 90 - 100O_A$, where W_A is the points earned by the worker.

For task B, the worker's payoff will decrease as O_B increases. If $O_B = 0$, then the worker earns 90 points. If $O_B = 0.9$, the worker earns 0 points. The rate of decrease is linear, so that increasing O_B by 0.1 reduces the worker's payoff by 10 points. Equivalently, the formula is given by $W_B = 90 - 100O_B$, where W_B is the points earned by the worker.

You may also view the supplemental payoff guide that was given to you as a visual representation of the payoffs.

Effect on supervisor's payoffs: Payment scheme 1

There are two payment schemes that will be used for the supervisor.

In payment scheme 1, increases in O_A will increase the supervisor's payoff for task A, but decrease their payoff for tasks B and C. Increases in O_B will increase the supervisor's payoff for task B, but decrease their payoff for tasks A and C. The formulas are given by:

$$S_A = 20 + 80O_A - 20O_B,$$

$$S_B = 20 - 20O_A + 80O_B$$

and

$$S_C = 20 - 20O_A - 20O_B$$

where S_A, S_B and S_C are the points earned by supervisor in each task.

Note that if O_A and O_B are each increased by the same amount, then the supervisor's payoff for task A and B increases, and their payoff for task C decreases.

You may also view the supplemental payoff guide that was given to you as a visual representation of the payoffs.

Effect on supervisor's payoffs: Payment scheme 2

In payment scheme 2, increases in either O_A or O_B will decrease the supervisor's payoff for tasks A, B and C with the payoff for task C always being larger than either tasks A or B.

$$S_A = 40 - 20O_A - 20O_B,$$

$$S_B = 40 - 20O_A - 20O_B$$

and

$$S_C = 80 - 20O_A - 20O_B$$

where S_A, S_B and S_C are the points earned by supervisor in each task.

You may also view the supplemental payoff guide that was given to you as a visual representation of the payoffs.

A picture of the Supervisor's decision screen is shown in figure 1.

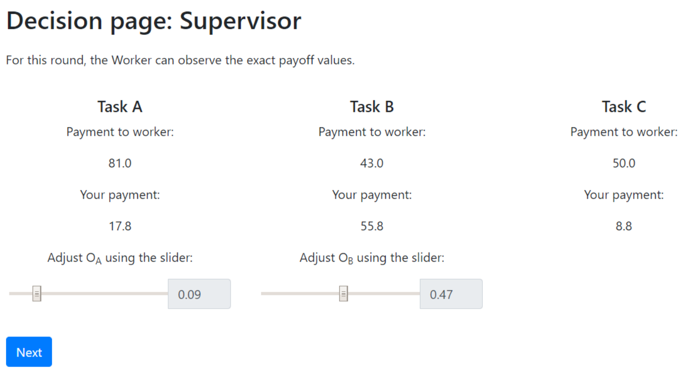
The Worker's decision

In each round the Worker will choose either Task A, Task B, or Task C using a drop down menu. While the worker is making their decision, the supervisor will see a wait screen. The worker will only be able to see their payoffs, and not the supervisors payoffs, when making their decision (figure 2).

Information schemes

There will be three information schemes. The information scheme will affect what the worker can see when making their decision:

1. The Worker can see the exact payoffs of all outcomes at the time they make their decision.
2. The Worker can see only a range of possible payoffs, as described below.

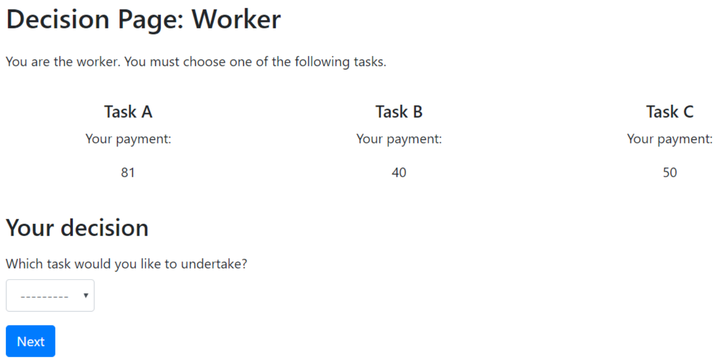


Decision page: Supervisor

For this round, the Worker can observe the exact payoff values.

Task A	Task B	Task C
Payment to worker:	Payment to worker:	Payment to worker:
81.0	43.0	50.0
Your payment:	Your payment:	Your payment:
17.8	55.8	8.8
Adjust O_A using the slider:	Adjust O_B using the slider:	
0.09	0.47	

Figure 1: The Supervisor's decision screen



Decision Page: Worker

You are the worker. You must choose one of the following tasks.

Task A	Task B	Task C
Your payment:	Your payment:	Your payment:
81	40	50

Your decision

Which task would you like to undertake?

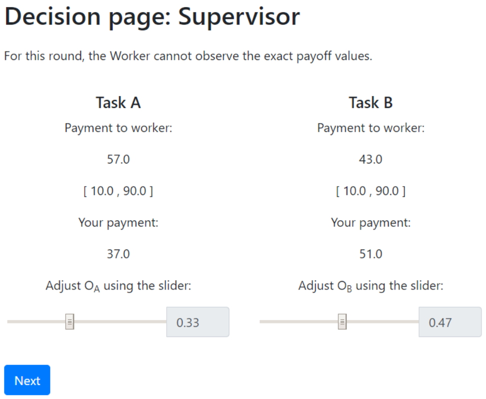
Figure 2: The Supervisor's decision screen

3. The Supervisor can decide whether the information scheme is number 1 or number 2.

In information scheme 2, the worker observes a range of possible payoffs for tasks A and B. The range will be presented as [min, max], where min is the smallest possible payoff and max is the largest possible payoff. The range shown will be the same for task A and task B, but the true payoffs may differ between task A and task B. **The sum of the true payoffs for task A and task B will always equal the sum of the minimum possible payoff plus the maximum possible payoff.**

The size of the range shown will depend on the sum of $O_A + O_B$. The supplemental payoff guide that was given to you shows how the range varies with O_A and O_B.

To illustrate an example, figure 3 shows the supervisor's screen under information scheme 2. The supervisor can see the exact payoff that the worker would receive, as well as the range of possible payoffs that will be shown to the worker. Note that the worker's payoff for task A, plus the payoff for task B, equals the sum of the minimum and maximum possible payoffs. Figure 4 shows the workers screen for the same round.



Decision page: Supervisor

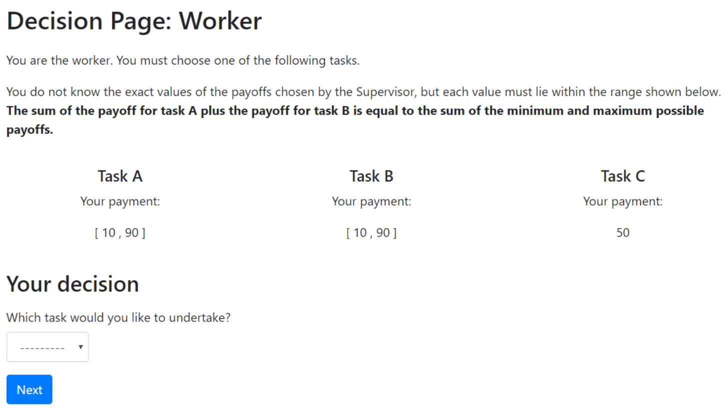
For this round, the Worker cannot observe the exact payoff values.

Task A	Task B	Task C
Payment to worker:	Payment to worker:	Payment to worker:
57.0	43.0	50.0
[10.0 , 90.0]	[10.0 , 90.0]	
Your payment:	Your payment:	Your payment:
37.0	51.0	4.0
Adjust O_A using the slider:	Adjust O_B using the slider:	
0.33	0.47	

Figure 3: The Supervisor's decision screen

Rounds

There will be a total of 48 rounds. Each round you will be randomly and anonymously matched with another person in the room. You will maintain the same role (i.e. worker or supervisor) for



Decision Page: Worker

You are the worker. You must choose one of the following tasks.

You do not know the exact values of the payoffs chosen by the Supervisor, but each value must lie within the range shown below.
The sum of the payoff for task A plus the payoff for task B is equal to the sum of the minimum and maximum possible payoffs.

Task A	Task B	Task C
Your payment:	Your payment:	Your payment:
[10 , 90]	[10 , 90]	50

Your decision

Which task would you like to undertake?

Figure 4: The Supervisor's decision screen

the first 24 rounds, and then switch to the other role for the next 24 rounds.

The first 12 rounds will be conducted using Payoff Scheme 1. Of these 12 rounds, the first 4 will use Information Structure 2, rounds 5-8 will use Information Structure 1, and rounds 9-12 will use Information Structure 3.

Rounds 13-24 will be conducted using Payoff Scheme 2. Of these 12 rounds, rounds 13-16 will use Information Structure 2, rounds 17-20 will use Information Structure 1, and rounds 21-24 will use Information Structure 3.

Rounds 25-36 will be conducted using Payoff Scheme 1. Of these 12 rounds, rounds 25-28 will use Information Structure 2, rounds 29-32 will use Information Structure 1, and rounds 33-36 will use Information Structure 3.

Rounds 37-48 will be conducted using Payoff Scheme 2. Of these 12 rounds, rounds 37-40 will use Information Structure 2, rounds 41-44 will use Information Structure 1, and rounds 45-48 will use Information Structure 3.

Feedback

At the end of each round, you will receive feedback on the round. The feedback for the supervisor will show the choice made by the worker and the payoffs of both parties. The feedback for the worker will include only the worker's payoff.

Note on earnings

Your total earnings will be the sum of your earnings in each round. It is possible to earn negative points in some rounds. In the unlikely event that someone has a negative points total after 48 rounds then their earnings will be set to 0 points.

Demographic survey

At the end of the experiment there will be a brief demographic survey. Please fill the survey in accurately. Once you have completed the survey your total earnings will be displayed. You should then sit quietly until an experimenter arrives at your terminal.

Summary

- In each round the Supervisor will select values for O_A and O_B.
- In each round the Worker will select one task; either A, B or C.
- In some rounds the Worker will be able to see their exact payoffs, in other rounds they will observe only a range of possible payoffs.
- The task chosen by the Worker will be implemented.
- Points will be summed across all rounds, and converted to dollars at the end of the experiment.
- Each round you will be randomly re-matched with another player in the room.

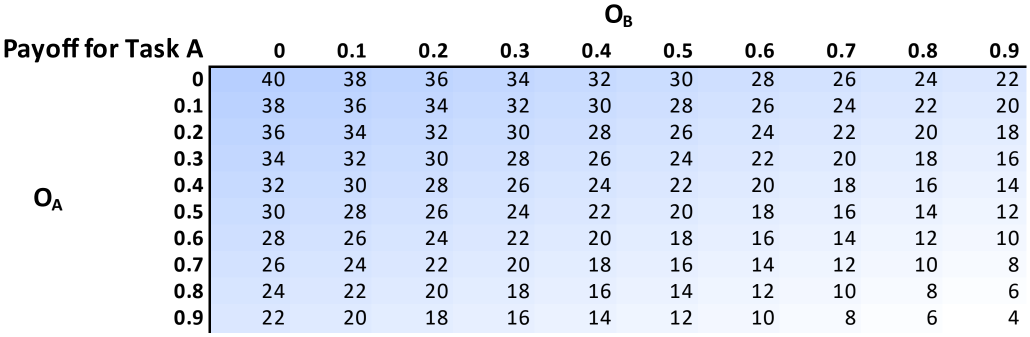
Supervisor Payoff Guide -- Scheme 1

		O_B									
Payoff for Task A		**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
	0	20	18	16	14	12	10	8	6	4	2
	0.1	28	26	24	22	20	18	16	14	12	10
	0.2	36	34	32	30	28	26	24	22	20	18
	0.3	44	42	40	38	36	34	32	30	28	26
O_A	**0.4**	52	50	48	46	44	42	40	38	36	34
	0.5	60	58	56	54	52	50	48	46	44	42
	0.6	68	66	64	62	60	58	56	54	52	50
	0.7	76	74	72	70	68	66	64	62	60	58
	0.8	84	82	80	78	76	74	72	70	68	66
	0.9	92	90	88	86	84	82	80	78	76	74

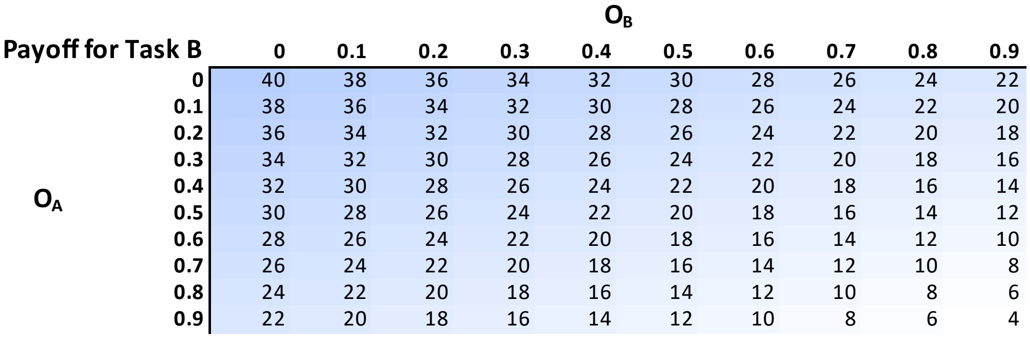
		O_B									
Payoff for Task B		**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
	0	20	28	36	44	52	60	68	76	84	92
	0.1	18	26	34	42	50	58	66	74	82	90
	0.2	16	24	32	40	48	56	64	72	80	88
	0.3	14	22	30	38	46	54	62	70	78	86
O_A	**0.4**	12	20	28	36	44	52	60	68	76	84
	0.5	10	18	26	34	42	50	58	66	74	82
	0.6	8	16	24	32	40	48	56	64	72	80
	0.7	6	14	22	30	38	46	54	62	70	78
	0.8	4	12	20	28	36	44	52	60	68	76
	0.9	2	10	18	26	34	42	50	58	66	74

		O_B									
Payoff for Task C		**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
	0	20	18	16	14	12	10	8	6	4	2
	0.1	18	16	14	12	10	8	6	4	2	0
	0.2	16	14	12	10	8	6	4	2	0	-2
	0.3	14	12	10	8	6	4	2	0	-2	-4
O_A	**0.4**	12	10	8	6	4	2	0	-2	-4	-6
	0.5	10	8	6	4	2	0	-2	-4	-6	-8
	0.6	8	6	4	2	0	-2	-4	-6	-8	-10
	0.7	6	4	2	0	-2	-4	-6	-8	-10	-12
	0.8	4	2	0	-2	-4	-6	-8	-10	-12	-14
	0.9	2	0	-2	-4	-6	-8	-10	-12	-14	-16

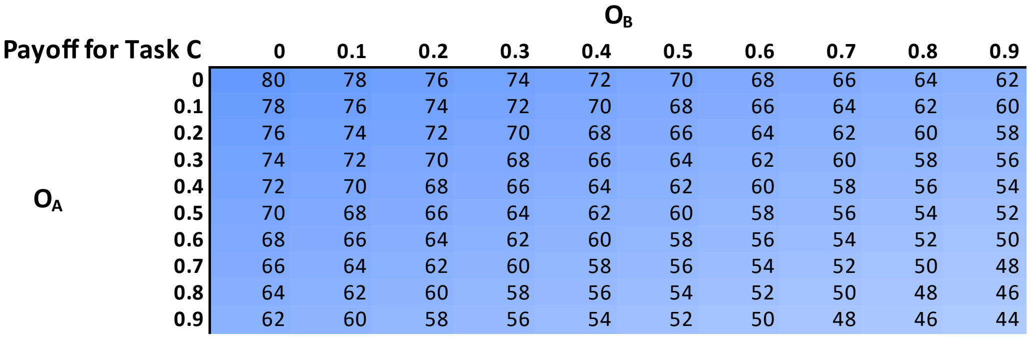
Supervisor Payoff Guide -- Scheme 2



					O_B						
	Payoff for Task A	**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
	0	40	38	36	34	32	30	28	26	24	22
	0.1	38	36	34	32	30	28	26	24	22	20
	0.2	36	34	32	30	28	26	24	22	20	18
	0.3	34	32	30	28	26	24	22	20	18	16
O_A	**0.4**	32	30	28	26	24	22	20	18	16	14
	0.5	30	28	26	24	22	20	18	16	14	12
	0.6	28	26	24	22	20	18	16	14	12	10
	0.7	26	24	22	20	18	16	14	12	10	8
	0.8	24	22	20	18	16	14	12	10	8	6
	0.9	22	20	18	16	14	12	10	8	6	4



					O_B						
	Payoff for Task B	**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
	0	40	38	36	34	32	30	28	26	24	22
	0.1	38	36	34	32	30	28	26	24	22	20
	0.2	36	34	32	30	28	26	24	22	20	18
	0.3	34	32	30	28	26	24	22	20	18	16
O_A	**0.4**	32	30	28	26	24	22	20	18	16	14
	0.5	30	28	26	24	22	20	18	16	14	12
	0.6	28	26	24	22	20	18	16	14	12	10
	0.7	26	24	22	20	18	16	14	12	10	8
	0.8	24	22	20	18	16	14	12	10	8	6
	0.9	22	20	18	16	14	12	10	8	6	4



					O_B						
	Payoff for Task C	**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
	0	80	78	76	74	72	70	68	66	64	62
	0.1	78	76	74	72	70	68	66	64	62	60
	0.2	76	74	72	70	68	66	64	62	60	58
	0.3	74	72	70	68	66	64	62	60	58	56
O_A	**0.4**	72	70	68	66	64	62	60	58	56	54
	0.5	70	68	66	64	62	60	58	56	54	52
	0.6	68	66	64	62	60	58	56	54	52	50
	0.7	66	64	62	60	58	56	54	52	50	48
	0.8	64	62	60	58	56	54	52	50	48	46
	0.9	62	60	58	56	54	52	50	48	46	44

Worker Payoff Guide -- exact payoffs

		O_B									
Payoff for Task A		**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
O_A	**0**	90	90	90	90	90	90	90	90	90	90
	0.1	80	80	80	80	80	80	80	80	80	80
	0.2	70	70	70	70	70	70	70	70	70	70
	0.3	60	60	60	60	60	60	60	60	60	60
	0.4	50	50	50	50	50	50	50	50	50	50
	0.5	40	40	40	40	40	40	40	40	40	40
	0.6	30	30	30	30	30	30	30	30	30	30
	0.7	20	20	20	20	20	20	20	20	20	20
	0.8	10	10	10	10	10	10	10	10	10	10
	0.9	0	0	0	0	0	0	0	0	0	0

		O_B									
Payoff for Task B		**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
O_A	**0**	90	80	70	60	50	40	30	20	10	0
	0.1	90	80	70	60	50	40	30	20	10	0
	0.2	90	80	70	60	50	40	30	20	10	0
	0.3	90	80	70	60	50	40	30	20	10	0
	0.4	90	80	70	60	50	40	30	20	10	0
	0.5	90	80	70	60	50	40	30	20	10	0
	0.6	90	80	70	60	50	40	30	20	10	0
	0.7	90	80	70	60	50	40	30	20	10	0
	0.8	90	80	70	60	50	40	30	20	10	0
	0.9	90	80	70	60	50	40	30	20	10	0

		O_B									
Payoff for Task C		**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
O_A	**0**	50	50	50	50	50	50	50	50	50	50
	0.1	50	50	50	50	50	50	50	50	50	50
	0.2	50	50	50	50	50	50	50	50	50	50
	0.3	50	50	50	50	50	50	50	50	50	50
	0.4	50	50	50	50	50	50	50	50	50	50
	0.5	50	50	50	50	50	50	50	50	50	50
	0.6	50	50	50	50	50	50	50	50	50	50
	0.7	50	50	50	50	50	50	50	50	50	50
	0.8	50	50	50	50	50	50	50	50	50	50
	0.9	50	50	50	50	50	50	50	50	50	50

Worker Payoff Guide -- range

Range for Task A						O_B					
		0	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
	0	[90,90]	[80,90]	[70,90]	[60,90]	[50,90]	[40,90]	[30,90]	[20,90]	[10,90]	[0,90]
	0.1	[80,90]	[70,90]	[60,90]	[50,90]	[40,90]	[30,90]	[20,90]	[10,90]	[0,90]	[0,80]
	0.2	[70,90]	[60,90]	[50,90]	[40,90]	[30,90]	[20,90]	[10,90]	[0,90]	[0,80]	[0,70]
	0.3	[60,90]	[50,90]	[40,90]	[30,90]	[20,90]	[10,90]	[0,90]	[0,80]	[0,70]	[0,60]
O_A	**0.4**	[50,90]	[40,90]	[30,90]	[20,90]	[10,90]	[0,90]	[0,80]	[0,70]	[0,60]	[0,50]
	0.5	[40,90]	[30,90]	[20,90]	[10,90]	[0,90]	[0,80]	[0,70]	[0,60]	[0,50]	[0,40]
	0.6	[30,90]	[20,90]	[10,90]	[0,90]	[0,80]	[0,70]	[0,60]	[0,50]	[0,40]	[0,30]
	0.7	[20,90]	[10,90]	[0,90]	[0,80]	[0,70]	[0,60]	[0,50]	[0,40]	[0,30]	[0,20]
	0.8	[10,90]	[0,90]	[0,80]	[0,70]	[0,60]	[0,50]	[0,40]	[0,30]	[0,20]	[0,10]
	0.9	[0,90]	[0,80]	[0,70]	[0,60]	[0,50]	[0,40]	[0,30]	[0,20]	[0,10]	[0,0]

Range for Task B						O_B					
		0	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
	0	[90,90]	[80,90]	[70,90]	[60,90]	[50,90]	[40,90]	[30,90]	[20,90]	[10,90]	[0,90]
	0.1	[80,90]	[70,90]	[60,90]	[50,90]	[40,90]	[30,90]	[20,90]	[10,90]	[0,90]	[0,80]
	0.2	[70,90]	[60,90]	[50,90]	[40,90]	[30,90]	[20,90]	[10,90]	[0,90]	[0,80]	[0,70]
	0.3	[60,90]	[50,90]	[40,90]	[30,90]	[20,90]	[10,90]	[0,90]	[0,80]	[0,70]	[0,60]
O_A	**0.4**	[50,90]	[40,90]	[30,90]	[20,90]	[10,90]	[0,90]	[0,80]	[0,70]	[0,60]	[0,50]
	0.5	[40,90]	[30,90]	[20,90]	[10,90]	[0,90]	[0,80]	[0,70]	[0,60]	[0,50]	[0,40]
	0.6	[30,90]	[20,90]	[10,90]	[0,90]	[0,80]	[0,70]	[0,60]	[0,50]	[0,40]	[0,30]
	0.7	[20,90]	[10,90]	[0,90]	[0,80]	[0,70]	[0,60]	[0,50]	[0,40]	[0,30]	[0,20]
	0.8	[10,90]	[0,90]	[0,80]	[0,70]	[0,60]	[0,50]	[0,40]	[0,30]	[0,20]	[0,10]
	0.9	[0,90]	[0,80]	[0,70]	[0,60]	[0,50]	[0,40]	[0,30]	[0,20]	[0,10]	[0,0]

Payoff for Task C						O_B					
		0	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
	0	50	50	50	50	50	50	50	50	50	50
	0.1	50	50	50	50	50	50	50	50	50	50
	0.2	50	50	50	50	50	50	50	50	50	50
	0.3	50	50	50	50	50	50	50	50	50	50
	0.4	50	50	50	50	50	50	50	50	50	50
O_A	**0.5**	50	50	50	50	50	50	50	50	50	50
	0.6	50	50	50	50	50	50	50	50	50	50
	0.7	50	50	50	50	50	50	50	50	50	50
	0.8	50	50	50	50	50	50	50	50	50	50
	0.9	50	50	50	50	50	50	50	50	50	50

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