# PAYING FOR INATTENTION

ALA AVOYAN* AND GIORGIA ROMAGNOLI†

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**Abstract**

We consider a discrete-choice rational inattention model in which the decision-maker can influence the payoff distribution across success and failure states. By reducing the gap between payoffs in different states—buying insurance to dampen the damage in case of failure—the decision-maker changes his incentives to pay attention. The smaller the gap between success/failure payoffs, the less attentive the decision-maker needs to be. The extreme example of complete equalization of payoffs over all states leaves the decision-maker with no incentive to exert costly attention. Using the novel framework with endogenous incentives we derive a method for eliciting the attention level solely by observing the decision maker's incentive redistribution choice. As a result, we have two ways of observing the same variable of interest—targeted success probability: (i) through actual performance (a method used in the literature); and (ii) through our model estimation, using insurance choices. Having two ways of identifying the targeted probability of success allows us to examine aspects of the rational inattention models without making assumptions on the cost of attention function.

**JEL Classification:** C72, C91, C92, D83;

**Keywords:** rational inattention, experiment, attention cost function, endogenous incentives.

*Department of Economics, Indiana University. E-mail: aavoyan@iu.edu

†Department of Economics, University of Amsterdam. E-mail: g.romagnoli@uva.nl

# 1 Introduction

The seminal work of Sims (1998, 2003) built the foundations of the concept of rational inattention (RI), the idea that the decision maker optimally chooses the level of attention based on a trade-off between attention costs and expected monetary gains. This concept has been explored theoretically and applied to various areas of economics.[1] In the typical setup of RI, the decision maker chooses among actions with state-dependent payoffs and he is uncertain about the actual state realization (Matejka and McKay (2014), Caplin and Dean (2015)). By being more attentive the agent can refine his posterior distribution over states and improve his choice of the payoff-maximizing action. Models in this literature have typically assumed that the agent takes the payoff structure as exogenously given. That is, while attention is endogenous, incentives to be attentive have been kept outside of the control of the decision maker. In this paper we endogenize the payoff structure.

The motivation for this work is twofold. First, the model seeks to capture the real-life circumstances in which the decision maker chooses his own incentives to exert costly attention. Examples include insurance choices (with full-coverage contracts reducing the incentives to pay attention,[2] compared to partial coverage), and financial choices (certain portfolios requiring more monitoring than others), among others. Second, our new framework provides a way to examine the rational inattention models without typical assumptions on the cost function. The existing tests of rational inattention can be categorized into two strands. On the one hand, there are tests concerned with special versions of the rational inattention model where certain parametric assumptions are made about the attention cost function. These tests posit one functional form against the other, or derive, from the chosen functional form, additional predictions that allow to compare rational inattention to other paradigms, such as the random utility models (see Dean and Neligh (2017)). These tests are well fit to compare various theories; however, parametric assumption are needed and testing general predictions are not feasible with this method.

In this paper, we extend the discrete-choice RI model to the case in which the decision maker can influence the payoff distribution across states. There is an interesting interplay between the choice of attention levels and the choice of payoff distribution. The extreme example of full equalization of payoffs over all

[1] See, for example, Woodford (2008), Bartoš et al. (2016), Mondria et al. (2010), Matějka (2015), Matějka and Tabellini (2017), Martinelli (2006), Martin (2017), Mackowiak and Wiederholt (2009), Kacperczyk et al. (2016), Gaballo (2016), De Oliveira et al. (2017), Caplin et al. (2014), Andrade and Le Bihan (2013).

[2] For example, if one has health insurance that covers the cost of visiting the doctor, one may be less likely to take precautions against catching an illness that might require a doctor's visit. While one has more incentive to pay attention to their health status with partial or no insurance coverage.

states leaves the agent with no incentive to exert costly attention and learn the true state. In general, the more the payoffs are smoothed out across states, the lower the incentives to pay attention and refine beliefs about the true state. By observing how the decision maker chooses to redistribute payoffs across states, we can identify the underlying targeted attention.

There are studies concerned with the general rational inattention model, making minimal assumptions about the shape of the cost function. Caplin and Dean (2015) show that, under these minimal assumptions, as long as attention is increasing in incentives (difference between payoffs in distinct states), the RI model holds in that a cost function can be found that rationalizes the data. These assumptions assess the monotonic response of attention to incentives and corroborate RI. However, the generality and unobservability of the cost function can make these types of tests not fully satisfactory. For example, attention may be monotonically responsive to incentives while having systematic departures from the assumption of optimal trade-off, which is at the heart of the RI model. As a proof of concept, imagine a decision-maker who, faced with two tasks, say A and B, systematically underestimates the attention required to succeed in task A and overestimates the attention needed by task B. As a result, this decision-maker may allocate less attention than it is optimal to task A and more attention to task B. This would violate the optimality of the trade-off inherent in the RI paradigm. However, so long as the decision-maker monotonically responds to incentives, his non-optimal behavior would still be rationalized within the RI paradigm.

By endogenizing payoffs, in this paper, we elicit an additional choice: insurance. We use this choice to predict the level of accuracy that the decision-maker is targeting. We then compare these estimates to the actual level of accuracy attained during the execution of the task. This comparison allows for a test of the RI model without making restrictive assumptions about the parametric form of the attention costs function. We present the extension of the RI model with endogenous payoffs followed by the identification of insurance choices and costs that this model enables. Next, we conduct a lab experiment to validate the method.

We find that 94% of subjects choose to smooth out payoffs at least once. Moreover, in 87% of all possible cases, payoff redistribution is strictly positive. Furthermore, more insurance a participant buyers, worse their performance in the task. We conclude that subjects are willing to pay to avoid paying more attention. Furthermore, some participants even fully insure by completely equalizing the payoffs in both states, thus avoiding the need to pay attention to the task at all. We investigate attention choices during the task after payoff distribution has been chosen. We observe that attention is monotonically increasing in incentives, confirming that our data pass the standard tests of the general RI model currently in use in the literature (Caplin and Dean (2015)). Furthermore, our data satisfies further two tests: harder the task more insurance the participants acquire and cheaper insurance gets insurance levels go up.

Finally, we provide an exploration of our test of RI. We measure attention in three different ways. First, as it is standard, we observe actual performance in the task. Second, we use insurance choices and estimate the targeted probability of success through our model. Finally, we ask subjects to assess how well they did, which results in an ex-post subjective measure of the targeted likelihood of success. We find that model-estimated probability has a significant and sizable prediction power for performance. At the same time, we observe that targeted and observed probabilities do not fully align.

# 2 The Model

In the typical setup of the costly information acquisition model (Sims (2003)), the decision maker chooses among actions with state-dependent payoffs and he is uncertain about the actual state realization (Matejka and McKay (2014), Caplin and Dean (2015)).

Our model builds on the costly information acquisition framework of Matejka and McKay (2014) and Caplin and Dean (2015) and endogenizes the payoff structure. Here the decision maker maximizes utility by choosing an information structure and a payoff redistribution function at the same time. The decision maker's action set is $A = \{1, ..., N\}$. The state of nature is a vector $\mathbf{v} \in S \subset \mathbb{R}^N$, where $v_i$ is the payoff of action $i \in A$ (let $S = \{\mathbf{v}_1, \mathbf{v}_2, ..., \mathbf{v}_M\}$) and $\mu \in \Gamma$ is the prior belief with $\Omega^\mu$ support and $\gamma \in \Gamma$ posterior belief. $\Pi^\mu$ is the set of feasible attention strategies of all mappings $\pi : \Omega^\mu \to \Delta(\Gamma)$ with finite support and that satisfy Bayes' law. Let $\Pi = \cup_\mu \Pi^\mu$. Let $G : \Gamma \times \Pi \to \mathbb{R}$ be the gross payoff of using some information structure:

$$G(\mu, \pi) = \sum_{\gamma \in \Gamma(\pi)} \left[ \sum_{j=1}^{M} \mu(\mathbf{v}_j) \pi(\gamma | \mathbf{v}_j) \right] g(\gamma) \tag{1}$$

where

$$g(\gamma) = \max_{i \in A} \sum_{i=1}^{M} \mathbf{v}_i \, \gamma(\mathbf{v}_i)$$

The gross expected payoff in (1) can be rewritten in terms of induced probability of selecting an action given a state. That is, let $\mathcal{P}_i(\mathbf{v})$ be

$$\mathcal{P}_i(\mathbf{v}) := \sum_{\gamma \in S_i} \pi(\gamma|\mathbf{v})$$

where $S_i$ is a set of all signals for which optimal action is $i$ (formally, $S_i := \{\gamma \in \mathbb{R}^N : \arg\max_{j \in A} \mathbb{E}_{\pi(\gamma|\mathbf{v})}[v_j] = i\}$). Again, $\mathcal{P}_i(\mathbf{v})$ is the induced probability of selecting action $i$ conditional on state $\mathbf{v}$. Expected payoff in terms of $\mathcal{P}_i(\mathbf{v})$ is as follows

$$G(\mu, \mathcal{P}) = \sum_{i=1}^{N} \sum_{j=1}^{M} v_j^i \mathcal{P}_i(\mathbf{v_j}) \mu(\mathbf{v_j})$$

and $\mathcal{P} := \{\mathcal{P}_i(\mathbf{v})\}_{i=1}^N$. Optimal choice given cost $K$:

$$\hat{\mathcal{P}}(\mu, K) = \arg\max_{\mathcal{P}} \{G(\mu, \mathcal{P}) - K(\mu, \mathcal{P})\}$$

**Introducing Redistribution.** Now, let us introduce the payoff redistribution function $X : \mathbb{R}^{N \times M} \to \mathbb{R}^{N \times M}$. Let $V$ be $(N \times M)$ matrix such that $V_{ij}$ is agent's payoff for action $i$ and state $\mathbf{v}_j$. Function $X$ redistributes $V$ to $\tilde{V}$, $X(V) = \tilde{V}$.

$$G(\mu, \mathcal{P}, X) = \sum_{i=1}^{N} \sum_{j=1}^{M} \tilde{V}_{ij} \mathcal{P}_i(\mathbf{v_j}) \mu(\mathbf{v_j})$$

Optimal information structure and optimal redistribution given attention cost and redistribution cost:

$$(\hat{\mathcal{P}}, \hat{X}) := \arg\max_{(\mathcal{P}, X)} \{G(\mu, \mathcal{P}, X) - K(\mu, \mathcal{P}) - \mathcal{Q}(X)\} \tag{2}$$

## 2.1 Matching-the-state task with endogenous payoffs

In this section, we focus on the simplest environment that delivers our identification results. This is also the setup that most closely matches our experimental design. The setup is a symmetric two-state and two-action environment, with matching-the-state task. In the Appendix A, we show how our method can be easily extended to the case with $N$ states, incorporate risk-preferences and involve continuous actions and payoffs.

Consider the case in which there are two states of the world $S = \{\mathbf{w}, \mathbf{b}\}$ to which the agent's prior assigns *equal probability*. The agent can take two possible actions $A = \{W, B\}$. The initial payoff structure describes a typical "matching-the-state" task: An agent receives payoff $Y$ if he matches the state (that is, he picks action $W$ in state $\mathbf{w}$ and action $B$ in state $\mathbf{b}$) and 0 otherwise. An agent can choose to change the payoff structure by purchasing insurance that guarantees a portion $x$ of total payoff $Y$ (that is, a dollar amount equal to $xY$) in the event he fails to match the state. Insurance costs are given by the function $q(x)$. Hence, the initial payoff structure is given by the matrix $V$, where the element $v_{ij}$ is the payoff of playing action $i \in \{W, B\}$ in state $j \in \{\mathbf{w}, \mathbf{b}\}$.

$$V = \begin{bmatrix} Y & 0 \\ 0 & Y \end{bmatrix}$$

By purchasing insurance $x \in [0, 1]$ at cost $q(x)$, the agent has the ability to alter the initial payoff matrix and replace it with any of the following final payoff matrices $\tilde{V}(x)$ net of insurance costs:

$$\tilde{V}(x) = \begin{bmatrix} Y - q(x) & xY - q(x) \\ xY - q(x) & Y - q(x) \end{bmatrix}$$

By paying attention, the agent targets a certain posterior probability of matching the state $\{\mathcal{P}_W, \mathcal{P}_B\}$, where $\mathcal{P}_W$ is the probability of taking action $W$ when the state is $\mathbf{w}$ and $\mathcal{P}_B$ is the probability of taking action $B$ when the state is $\mathbf{b}$. We assume that (i) only symmetric posterior probabilities can be selected (that is, agents can only choose posterior probabilities such that $\mathcal{P}_W = \mathcal{P}_B = \mathcal{P}$ and (ii) posterior probabilities $\mathcal{P}$ that can be chosen by the agent vary in the continuum, $\mathcal{P} \in [0, 1]$. Let $K(\mu, \mathcal{P})$ be the *mental cost function*, which is the cost of the attention required to target a posterior probability $\mathcal{P}$ of matching the state;[3] $K(\mu, \mathcal{P})$ is assumed to be differentiable.

The agent has utility $u$ defined over monetary outcomes and is rationally inattentive, that is, he chooses $x$ and $\mathcal{P}$ by taking into account both the monetary rewards and his mental costs. The objective function is given by the expected utility of the monetary payoffs as given by matrix $\tilde{V}(x)$, weighted by the probability of success $\mathcal{P}$, minus the mental costs of targeting $\mathcal{P}$.

[3] Mental effort is conceived of as the minimum utility loss required to target a probability of success of $\mathcal{P}$ or larger.

## Identification of $\mathcal{P}$

An external observer cannot identify the targeted probability of success $\mathcal{P}$ or the mental cost function $K(\mu, \mathcal{P})$ from the standard maximization problem with exogenous payoffs.[4] Here we show how, in the augmented maximization problem, where the payoff distribution is made endogenous, $\mathcal{P}$ and $K'_{\mathcal{P}}(\mu, \hat{\mathcal{P}})$ can be inferred from observing $x$ and $q(x)$.

The agent's maximization problem 2 with 2 states, 2 actions and risk-neutral utility function leads to the first order conditions:[5]

$$(1 - \mathcal{P})Y - q'(x) = 0 \tag{3}$$

$$Y - xY - K'_{\mathcal{P}}(\mu, \mathcal{P}) = 0 \tag{4}$$

Let $(x_q^*, \hat{\mathcal{P}}_q)$ be the solution to the FOC conditions given by 3 and 4 and let the pair $\left(x_q^*, q'(x_q^*)\right)$ be the observable output of the decision problem. The FOC can be rewritten in terms of observables as follows:

$$\hat{\mathcal{P}}_q = 1 - q'(x_q^*)Y^{-1} \tag{5}$$

$$K'_{\mathcal{P}}(\mu, 1 - q'(x_q^*)Y^{-1}) = Y(1 - x_q^*) \tag{6}$$

Hence, the optimal probability of success, $\hat{\mathcal{P}}_q = 1 - q'(x_q^*)Y^{-1}$, and the value of the derivative of the mental cost function at that point, $K'_{\mathcal{P}} = Y(1 - x_q^*)$, can all be expressed in terms of observables. By adopting a family of insurance cost functions $q(x) \in \mathbb{Q}$ and observing one choice of insurance level for each cost function in set $\mathbb{Q}$, we obtain values of the derivative of the cost function $K'_{\mathcal{P}}(\mu, \hat{\mathcal{P}})$ for several values of $\hat{\mathcal{P}}$. An interpolation method could be used to obtain an estimate of the derivative of the cost function, called $\hat{K}'_{\mathcal{P}}$. The domain $[\underline{\mathcal{P}}, \overline{\mathcal{P}}]$, on which the derivative of the cost function can be interpolated, depends upon the specific task being executed and the number of alternatives available for choice. For example, in multiple-choice tasks with 2 options, a utility-maximizing agent can secure a probability of $\underline{\mathcal{P}} = 1/2$ by exerting no

[4] In the standard problem the agent chooses $\mathcal{P}$ to maximize revenues minus the cost of mental effort. The maximization is $\max_{\mathcal{P}} \mathcal{P}Y - K(\mu, \mathcal{P})$ with FOC $Y = K'_{\mathcal{P}}(\mu, \hat{\mathcal{P}})$. The only flexible variable available to the experimenter is $Y$. However, varying $Y$ does not lead to identification because both $\mathcal{P}$ and $K(\mu, \mathcal{P})$ remain unobserved.

[5] For the sake of clean illustration we assume risk neutrality. However, the model generalizes to the case of risk aversion. In this case identification is reached provided that we specify a utility function and separately estimate the coefficient of risk aversion. See Appendix A.

attention and choosing one option randomly. Hence, in this case the mental cost function can be recovered over a range contained in the interval $(\frac{1}{2}, 1]$. (In general, in multiple choice tasks with uniform prior and $n$ options, the mental cost function can be interpolated over a range contained in the interval $(\frac{1}{n}, 1]$.) Notice also that all interior solutions must satisfy $K'_{\mathcal{P}}(\mu, \hat{\mathcal{P}}) \leq Y$, which implies that the mental cost function cannot be estimated for values of $\mathcal{P}$ such that $K'_{\mathcal{P}}(\mu, \hat{\mathcal{P}}) > Y$.

# 3 Experimental Design

All experimental sessions were conducted at the Center for Experimental Social Science (CESS) laboratory at New York University (NYU) during the Spring of 2017, using the software z-Tree (Fischbacher (2007)). All participants were NYU students. The experiment lasted about 90 minutes, and subjects earned, on average, \$22, which included a \$7 show-up fee. The experiment consists of four sessions with 51 subjects. In each session, written instructions were distributed to the subjects and also read aloud.[6]

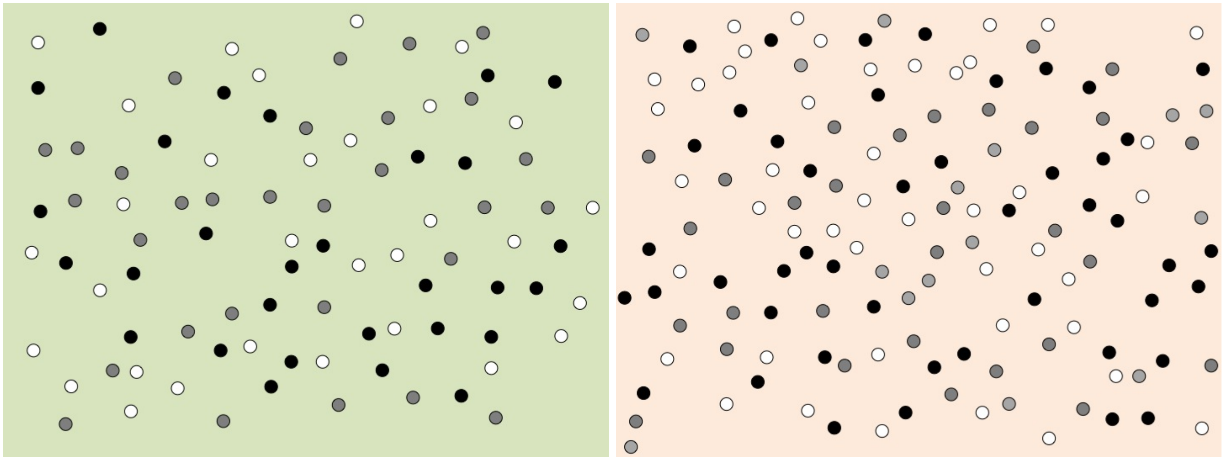
The experiment consists of four phases. In Phase 1, the incentives are provided exogenously and subjects are asked to perform four match-the-state tasks with two levels of task difficulty and two incentive. This Phase allows subjects to familiarize themselves with the environment and better understand the stakes and effort involved in Phase 2. In Phase 2, after subjects have been familiarized with the task and the difficulty of performing it, we ask them to choose their insurance for six tasks they will perform in the next phase. The first three questions are for one level of difficulty, and the second three questions are for the other level of difficulty. The level of difficulty for the first set of questions (order of the task difficulty) is randomized at the session level. In Phase 3, subjects perform the tasks with the incentives they chose in Phase 2. The order of task execution is randomized at the session level. In Phase 4, we elicit subjects' risk and ambiguity attitudes using well-established measures in the literature.

In the experiment, subjects solve a matching-the-state task in 10 consecutive rounds. The task requires subjects to look at screens filled with white, gray and black balls and determine which of the three colors is the most numerous. Subjects earn a larger payoff for a correct answer and a lower payoff for an incorrect answer. Tasks alternate between two difficulty levels, *easy* and *difficult*, whereby the screens of the *easy* task contain 90 balls and the screens of the *difficult* task contain 135 balls.[7]

Tasks also differ in terms of how payoffs are determined. In the first four rounds, payoffs for succeeding

[6] Experimental instructions are in Appendix B.

[7] In the instructions the two types of task were not referred to as difficult and easy, but rather as the 90-task and the 135-task



(a) Easy task (b) Difficult task

Figure 1

and failing the task are exogenously determined. In the last six rounds payoffs are determined by the subjects themselves by means of a transfer choice. Starting off with an extreme payoff distribution that awards \$20 if they succeed and \$0 if they fail the task, subjects can choose to transfer any percentage of their payoffs from a successful to a failed outcome, up to the point at which payoffs are completely equalized. An underlying transfer function determines the cost of operating such a transfer. Subjects do not see the transfer function but are given a calculator which they can use by entering any transfer level to obtain the resulting success and failure payoffs. Subjects can familiarize with the transfer function for as long as they wish to. Once they identify their preferred transfer level, their choice is finalized by pressing the confirm button.

Transfer functions vary across rounds and are associated with three cost levels: low, medium and high. The three transfer functions $q_i(x)$ with $i \in \{low,\ medium,\ high\}$, are summarized in Figure 2. Upon choosing a level of transfer $x \in [0, 1]$, payoffs are given by $20 - q_i(x)$ in the event of success, and by $20x - q_i(x)$ in the event of failure. The left panel of Figure 2 shows the accumulated costs for increasing transfer levels for each of the three transfer functions. Notice that moving from low to medium costs, and similarly from medium to high costs, is associated with an increase in both the total and the marginal costs for each transfer level. The right panel of Figure 2 shows all possible payoffs of success and failure for each transfer level. For example, if insurance level chosen is 100%, the participant would get about \$13, \$11, \$8 in low, medium, and high cost cases, respectively, regardless of whether they succeed or fail in the task. If insurance level chosen is 0%, subject gets \$20 or \$0, depending on whether they succeed or fail in the task, regardless of the insurance cost level.

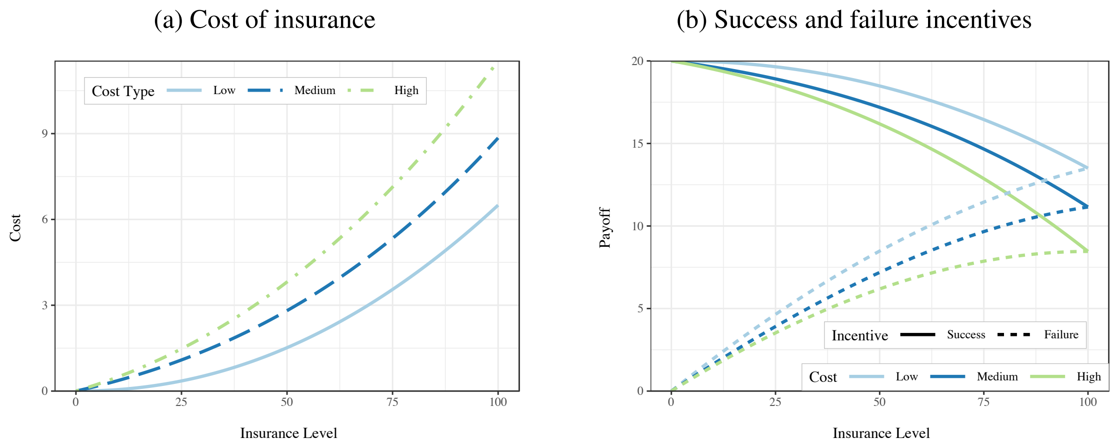



Figure 2: Transfer functions and payoff redistribution

At the end of the experiment, we elicit subjects' attitudes toward risk, ambiguity, and compound lotteries. We first elicit their attitudes towards risk using two procedures: the classic procedure developed by Holt and Laury (2002), and a second developed by Gneezy and Potters (1997) and Charness and Gneezy (2010). We then build on these tests to elicit subjects' attitudes towards ambiguity and compound lotteries (Agranov and Ortoleva (2017)). In the first task, developed by Gneezy and Potters (1997) and Charness and Gneezy (2010), subjects are endowed with 100 tokens, any number of which can be invested in a risky asset that has a 0.5 chance of success and, if successful, a payoff of 2.5 times the investment. Whatever is not invested is kept. The number of tokens not invested is proportional to the degree of risk- aversion of a subject who obeys expected utility. The second investment task was identical to the first, except that the success of the investment was determined by a compound lottery which reduces to a 0.5 chance of success. A subject with no aversion nor attraction to compound lotteries should invest the same number of tokens in both questions, while a subject who dislikes (likes) compound lotteries might decide to invest less (more) in the second rather than in the first investment task.

The Holt and Laury (2002) method for eliciting risk aversion elicitation presents subjects with a list of choices between sure payments and a lottery performed on a bag with a 50-50 composition of blue and red chips. Subjects choose the color they want to bet on. The lottery pays \$4 if their chosen color is extracted from the bag and \$0 otherwise. Risk aversion is measured by the certainty equivalent of the lottery. We further incorporate the elicitation of ambiguity aversion in this setting by adopting a procedure similar to that of Halevy (2007) and Dean and Ortoleva (2015). Subjects are presented with a second bag containing blue and red chips in unknown proportions. Subjects choose the color they want to bet on and receive \$4 if the chosen color is extracted from the bag with unknown composition and \$0 otherwise. The certainty equivalent of this gamble is elicited with the same choice list approach. Under subjective expected utility, the certainty equivalent for the ambiguous bet should be at least as high as the certainty equivalent for the risky lottery. Ambiguity aversion is therefore measured as the difference between the certainty equivalent of the risky bet and the certainty equivalent of the ambiguous bet.

# 4 Preliminaries and comparative statics predictions

In this section, we provide some definitions and details for clear exposition of comparative statics and theoretical predictions.

## 4.1 Definitions

**Definition 1** *An Assignment is a triple $\{T, Y, q(x)\}$ consisting of a task $T$, a payoff $Y$ for the successful completion of the task, and an insurance cost function $q(x)$ specifying the cost of each level of coverage $x$.*

**Definition 2** *A Sequence is a set $S = \{T, Y, \{q_1(x), ...q_k(x)\}\}$ consisting of a task $T$, a payoff $Y$ for the successful completion of the task, and a set of $k$ insurance cost functions $q_j(x)$, $j \in \{1, ..., k\}$. In other words, a sequence is a series of k assignments, all sharing the same task and payoff structure.*

Next, let $x^*_{hj}$ denote the choice of insurance performed by a subject facing sequence $h$ and insurance function $q_j(x)$. Similarly, let $\hat{\mathcal{P}}_{hj}$ denote the predicted probability of success in the same assignment. $\hat{\mathcal{P}}_{hj}$ is obtained by plugging $x^*_{hj}$ in the first order condition, that is $\hat{\mathcal{P}}_{hj} = 1 - q_j\left(x^*_{hj}\right)$. A subject's answer to sequence $h$, is a $k$-tuple of insurance choices $\{x^{h*}_1, ..., x^{h*}_k\}$, one for each insurance function.

## 4.2 Comparative statics

The following comparative statics results can be derived from the first order conditions and provide a testing ground for our elicitation technique.

1. **Variation of the degree of complexity of the task.** Consider two sequences, $A$ and $B$, which have the same payoff structure $Y$ and the same set of insurance functions $\{q_1(x), ..., q_k(x)\}$. However, the task in sequence $A$ is more difficult, that is $K_A(\mu, \hat{\mathcal{P}}) > K_B(\mu, \hat{\mathcal{P}})$ for all $\hat{\mathcal{P}}$. Then the model predicts that for each insurance cost functions $q_j(x)$: (i) Subjects buy more insurance for the sequence

with larger attention costs, $x_j^{A*} > x_j^{B*}$, and (ii) Agents target a lower probability of success for the sequence with larger attention costs, that is $\hat{\mathcal{P}}_j^A < \hat{\mathcal{P}}_j^B$.

2. **Variation of the cost of insurance.** Fixing a sequence (e.g. for fixed task and payoff structure) consider two insurance costs functions $q_1(x)$ and $q_2(x)$, such that insurance 1 is more expensive than 2, that is $q_1(x) > q_2(x), \forall x \in X$. Then the model predicts that: (i) Subjects buy more insurance when it is cheaper, $x_2^* > x_1^*$, and (ii) Subjects target a lower probability of success for the assignment with cheaper insurance, that is $\hat{\mathcal{P}}_1 > \hat{\mathcal{P}}_2$. This prediction can be tested by comparing answers given by an individual subject and for a given sequence.

Assuming that the two comparative statics results are supported by the data, we can move to test the following prediction.

3. **Correspondence between targeted and observed probability of success**. The probability of success derived from the first order conditions, $\hat{\mathcal{P}} = 1 - q'(x^*)$, should have predictive power for the success rate observed in the actual execution of the assignment.

# 5 Results

In this section we examine the comparative statics results from Section 4.2 and evaluate the resulting predictions. After presenting the determinants of insurance choices and their effect on attention, we proceed to probability measures and we find significant explanatory power of model estimated targeted probability of success on performance.

## 5.1 Insurance and attention

Let us first examine whether attention responds to incentives as predicted by the theory. First, we determine the effect of task difficulty and the insurance cost on the choice of insurance and, subsequently, the effect on success probability. Let us re-state the theoretical predictions and examine the insurance choices.

**Prediction 1** *As the underlying task becomes more difficult, the decision maker buys more insurance and targets a lower probability of success.*

**Prediction 2** *As insurance gets more expensive, the decision maker buys less insurance and targets a higher probability of success.*

To test these predictions, let us first consider the average insurance bought when the task is easy and when it is hard. Subjects on average choose lower insurance, $37.3\%$, when the task is easy than when it is hard, $54.2\%$ (Mann-Whitney U (MWU) test with $p < 0.001$). The averages provide support for the prediction, and when we examine insurance distribution we find more support for it. Insurance bought under a difficult task first-order stochastically dominates the easy task: Subjects insure themselves more in the harder task (Figure 3b).

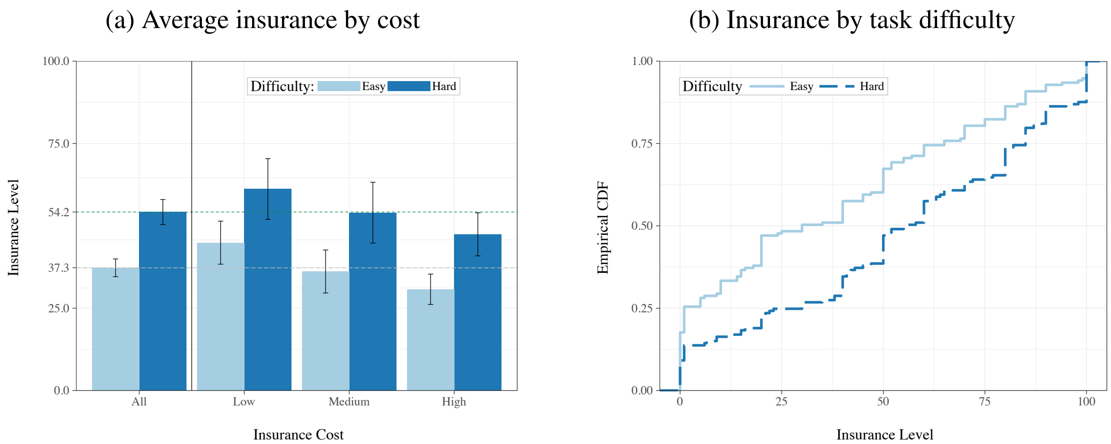



Figure 3: Effect of the task type and cost on insurance

The comparative statics results about the difficulty of the task are averaged over all levels of insurance costs (in the experiment, buying insurance—i.e., transferring a fraction of a winning prize to a fail prize—has low, medium, or high cost). We first break down the insurance choice by how expensive each was (Figure 3a). For each insurance cost, the same pattern emerges for task difficulty of the task: The harder the task, the more insurance subjects buy. Now, what happens when we make insurance more expensive? As expected, subjects buy less insurance when it is more expensive. To better understand subject' insurance choices, we run a regression that includes the task difficulty and insurance cost, as well as two types of subjects' personal characteristics. We include economic characteristics elicited during the experiment and information about the subjects provided in the exit survey (the results are in Table 1).

The results in Table 1 provide further support for Propositions 1 and 2. In addition to the effects of task type and cost level, the regression reveals a significant effect of risk and ambiguity attitudes of people on their insurance choices. The more risk averse a person is (measured by a commonly used procedure developed by Holt and Laury (2002)), the more they insure themselves and consequently, lower probability

Table 1: Insurance Choice Regressions

| | *Dependent variable: Insurance* | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Difficulty: Easy | $-16.938^{***}$ | $-16.938^{***}$ | $-16.938^{***}$ |
| | (2.658) | (2.658) | (2.663) |
| Cost: Low | $13.956^{***}$ | $13.956^{***}$ | $13.956^{***}$ |
| | (3.213) | (3.213) | (3.219) |
| Cost: Medium | $5.985^{**}$ | $5.985^{**}$ | $5.985^{**}$ |
| | (2.369) | (2.369) | (2.373) |
| Ambiguity Attitude | $16.620^{**}$ | $15.873^{**}$ | $16.553^{**}$ |
| | (8.122) | (7.939) | (7.944) |
| Risk Aversion HL | $4.033^{**}$ | | $4.463^{**}$ |
| | (2.029) | | (1.816) |
| Risky Investment | | 0.173 | 0.211 |
| | | (0.147) | (0.146) |
| Compound Lottery | 7.125 | 8.015 | 7.315 |
| | (9.509) | (9.570) | (9.359) |
| GPA | 19.317 | 14.478 | 16.876 |
| | (15.883) | (16.022) | (15.606) |
| Gender | $-4.565$ | $-0.035$ | $-1.057$ |
| | (7.794) | (8.988) | (8.790) |
| GameTheory | $-11.974$ | $-11.783$ | $-13.931$ |
| | (9.106) | (9.643) | (8.918) |
| Constant | $-53.228$ | $-24.362$ | $-59.327$ |
| | (60.585) | (57.564) | (58.653) |

*Note*: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$; errors are clustered at the subject level.

of success they target. An interesting implication of this result is that risk averse individuals perform worse in this tasks.

If a subject is ambiguity averse, they buy about 15% more insurance than subjects that have neutral ambiguity attitudes. This is a significant effect both statistically and economically. The quantitative effect is similar to the impact of task difficulty going from easy to hard. A possible interpretation of this result is that exerting attention may be perceived as an ambiguous act, with a degree of uncertainty surrounding the mapping from paying attention to success probabilities. If this is true, then an ambiguity averse person will express a desire to hedge against such ambiguity by choosing a larger payoff redistribution. Finally, we notice that payoff redistribution and attention choices do not correlate with attitudes towards compound lotteries, GPA, Gender or familiarity with Game Theory.

Table 2: Performance Regressions

| | *Dependent variable: Performance* | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Incentives | $0.022^{***}$ | $0.017^{***}$ | $0.018^{***}$ |
| | (0.004) | (0.004) | (0.004) |
| Difficulty: Easy | $0.179^{***}$ | $0.209^{***}$ | $0.206^{***}$ |
| | (0.040) | (0.039) | (0.040) |
| Exogenous | $-0.218^{***}$ | $-0.183^{***}$ | $-0.189^{***}$ |
| | (0.041) | (0.041) | (0.042) |
| Response Time | | $0.001^{***}$ | $0.001^{***}$ |
| | | (0.000) | (0.000) |
| Ambiguity Attitude | | | $-0.029$ |
| | | | (0.043) |
| Risk Aversion HL | | | 0.023 |
| | | | (0.015) |
| Risky Investment | | | 0.0001 |
| | | | (0.001) |
| Compound Lottery | | | 0.001 |
| | | | (0.001) |
| GPA | | | 0.090 |
| | | | (0.063) |
| Gender | | | $0.097^{*}$ |
| | | | (0.051) |
| GameTheory | | | 0.058 |
| | | | (0.053) |
| Constant | $0.374^{***}$ | $0.279^{***}$ | $-0.356$ |
| | (0.063) | (0.074) | (0.288) |

*Note*: $^{*}p$ <0.1; $^{**}p$ <0.05; $^{***}p$ <0.01; errors are clustered at the subject level.

## 5.2 Attention and performance

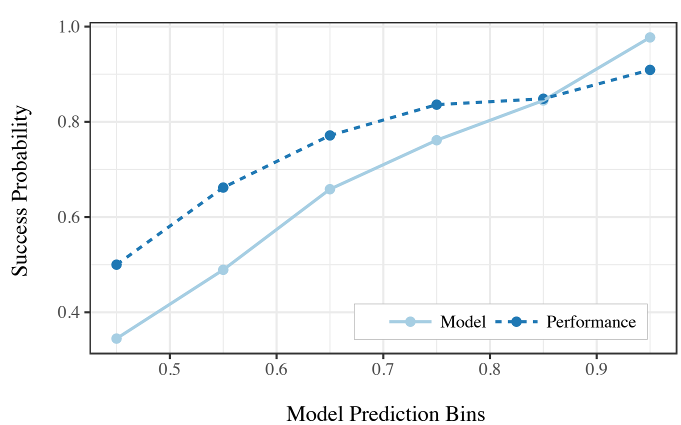
The second part of the propositions concerns the targeted probabilities. Let us start by looking at the probability of success of all subjects by difficulty. On average, in 60.8% of the time subjects are successful at the hard task, while they reach on average 79.7% success rate with an easy task. Table 2 presents regression analyses for the variables of interest—performance, which is variable that takes values: 1 or 0, depending on whether the subject correctly responded to the task or not. As explanatory variables we use Incentives (difference between payoffs in success and failure states), difficulty of the task, and whether the task had exogenous or endogenous choice of payoff distribution. In addition, we include Response Time variable, that measures the number of seconds the participant took to provide an answer to the task. We also incorporate in the analysis a series of control variables, including gender, GPA, and measures of risk and ambiguity aversion. The theory is silent on the effect of time on the performance in a task; however, it is fairly intuitive to think that successful performance in a task would relate to longer time spent on it.

The results in Table 2 provide further support for Propositions 1 and 2. Higher the incentive—more sizable the difference between success and failure payoffs—better the performance. Likelihood of success (higher performance) is greater in the Easy task than Difficult task. And unsurprisingly, response time has a positive effect on performance. Control variables, such as risk and ambiguity attitudes, do not have an effect on performance directly. Though, recall that incentives in endogenous case are affected by these variables as seen in Table 1. That is because the incentives in exogenous cases are determined by the choice of insurance. There is one effect in Table 2 that we did not expect and the theory does not account for. The coefficient on variable Exogenous is significant and negative. Consider an example of the following incentives: $16 and $8 under success and failure, respectively. The result implies that that for the same level of incentives ($16-$8), if this distribution was chosen by subjects they performed better than if the same distribution was given endogenously. Further research could shed light on the possible reasons behind such effect, which is out of the scope of the current paper.

Combining the results above, we conclude that the two predictions of the rational inattention model with endogenous incentives are confirmed: (1) when the task is more difficult, subjects buy more insurance and perform worse; and (2) as insurance becomes more expensive, subjects buy less of it and target a higher probability of success.

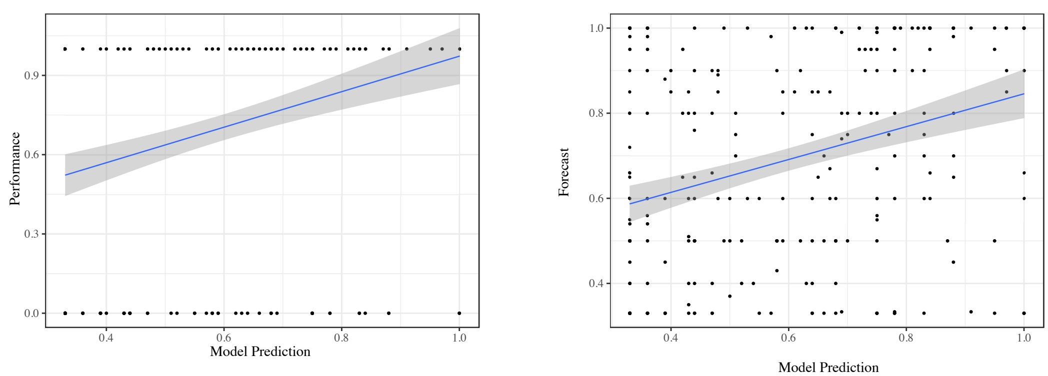
## 5.3 Attention Measures

Figure 4: Model Predictions vs actual performance




Since the data strongly supports the theoretical predictions on incentive reactions we can proceed and investigate the targeted probability. Given our experimental design, for given incentives set by the subjects we observe one repetition of the task. Hence, we know whether a subject was successful or not in that particular setting. To estimate the frequency of successes we use the standard method in the literature and aggregate the data in decile bins, in the following way. First, we take all the cases in which the model estimate of targeted probability was within a certain decile, for example, between $0.6$ and $0.7$. For all those instances, we calculate the frequency of actual successes. Figure 4 presents the results of this exercise. We can see the model average and performance in each interval starting from the minimal success probability of 1/3 (i.e., the success probability of a subject exerting no attention and choosing one of the three actions at random).[8] We observe that the predicted probabilities by the model track the actual probabilities of success quite closely. We also observe the actual performance being almost everywhere higher than the model predicts, suggesting that the subjects may have been under-confident about their ability to succeed and therefore over-insured themselves, except at the highest levels of estimated and actual success probabilities.

Figure 5: Model Prediction, Performance and Forecast




(a) Model Prediction and Performance

(b) Model Prediction and Forecast

Let us look at the relationship between model estimated probability and subjects' actual performance and forecast (see Figure 5). Model prediction of targeted probability and subject forecast range from $\frac{1}{3}$ to 1. Subject's performance is a variable that takes values 1 or 1 depending on whether a subject executes the task correctly or not. Simply looking at fitted lines in Figure 5 suggest that model estimated probability has a predictive power on performance and subject's forecast similar to result in Figure 4. To further explore this relationship we run a regression using performance as a dependent variable and model prediction as an explanatory variable. We find that, the coefficient of model prediction is .82 with $p$-value less than 0.001.

[8] In the experiment, the buttons for answers to the task (black, gray, white) were randomized to ensure that if a subject always chose the first option when they were 'randomizing,' we did not get always get the same color answer.

# 6 Discussion and Conclusion

This paper examines how the decision-makers ability to influence the payoff distribution across states affects attention choices. Our framework takes the standard discrete choice information acquisition model and makes the payoff structure endogenous, enabling us to study the joint determination of attention strategies and payoff redistribution. This is done by introducing the insurance to protect against the state in which the payoff is relatively lower. There is an interesting interplay between insurance choice and attention. The extreme example of full equalization of payoffs over all states leaves the agent with no incentive to exert costly attention. By observing how the decision-maker chooses to redistribute payoffs across states, we can identify the underlying attention choices and infer specific properties of the underlying unobservable attention costs.

The model leads to comparative static results, which we examine using data from an experiment. Firstly, we find that subjects have a demand for attention insurance as 94% of subjects buy insurance at least once. Moreover, in 87% of all possible cases, insurance purchased towards the failed state was strictly positive. Therefore, subjects are willing to pay to avoid paying more attention. Second, insurance and attention respond to task difficulty and insurance cost as predicted by the model, which allows us to calculate the probability from our identification procedure. Finally, we find that model-estimated probability has a significant and sizable predictive power for actual performance.

In the theoretical framework or the conditions of the experiment, we have not made any parametric restrictions on the attention cost function. Therefore, the conditions we get from the agent's maximization problem can be applied to any cost function, and then the predictions can be tested using the existing data. Therefore, the data generated by this experiment can be used to test specific cost functions of theoretical or applied interest.

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# Appendices

## A Proofs and Extension

### A.1 Risk preferences

In what follows, we extend the model to the case of a decision maker with general risk attitude. The basic setup remains unchanged and the only addition is represented by the introduction of a possibly non-linear utility function over monetary payoffs. The new maximization is as follows:

$$\max_{\mathcal{P},x} \mathcal{P} \cdot u\left(Y - q(x)\right) + (1-\mathcal{P}) \cdot u\left(xY - q(x)\right) - c(\mathcal{P})$$

leading to the following first order conditions:

$$\begin{aligned}
&- \mathcal{P}u'(Y - q(x))q'(x) + (1-\mathcal{P})u'(xY - q(x))(Y - q'(x)) = 0 \\
&u(Y - q(X)) - u(xY - q(x)) - K'(\mathcal{P}) = 0
\end{aligned}$$

which, after rearrangment, lead to:

$$\mathcal{P} = \frac{u'(xY - q(x))(Y - q'(x))}{u'(Y - q(x))q'(x) + u'(xY - q(x))(Y - q'(x))} \tag{7}$$

$$K'(\mathcal{P}) = u(Y - q(x)) - u(xY - q(x)) \tag{8}$$

We can still obtain identification of $p$ and $K'(p)$ if we make parametric assumptions about the utility function and separately estimate its parameters. For example, we can impose the CRRA utility function:

$$u(m) = \begin{cases} \frac{m^{1-\rho}}{1-\rho} & \text{for} \quad \rho \neq 1 \\ \ln(m) & \text{for} \quad \rho = 1 \end{cases}$$

and, after the appropriate substitutions, the identification equations in (7) and (8) become:

$$\mathcal{P} = \frac{(xY - q(x))^{-\rho}(Y - q'(x))}{(Y - q(x))^{-\rho} \cdot q'(x) + (xY - q(x))^{-\rho} \cdot (Y - q'(x))}$$

$$K'(\mathcal{P}) = \frac{(Y - q(x))^{1-\rho}}{1-\rho} - \frac{(xY - q(x))^{1-\rho}}{1-\rho}$$

The model is still identified, provided that we obtain a separate estimation for the risk parameter $\rho$.

### A.2 Continuous payoffs

The method outlined in the main body of the text can be extended to settings where the decision maker is executing an assignment characterized by continuous actions and payoffs. Consider a DM that chooses one action $a$ to play with $a \in \mathbb{R}$. Payoffs are determined as $-(a - a^*)^2$ where $a^*$ is a normal random variable $a^* \sim N(0, \sigma_a)$ whose realization is unknown to the decision maker. The DM draws a signal $s = a^* + \epsilon$ with $\epsilon \sim N(0, \sigma_\epsilon)$ and chooses the precision of the signal.

There is a monotonically increasing relationship between $\sigma_\epsilon$ and the average loss $L = E((a - a*)^2)$, therefore we can re-parametrize the choice problem and say that the DM is choosing $L$. A signal with higher precision (lower variance) is more costly. It follows that we can express the attention cost function $k(\sigma_\epsilon)$ as a function of the average loss $c(-L)$. Finally the DM can purchase insurance $x$ by paying a cost of $q(x)$. $x$ is the percentage of $L$ which is returned to the DM, i.e. when the DM buys $x$ units of insurance his payoffs are given by $(x-1)L - q(x)$.

Under risk neutrality the maximization problem is as follows:[9]

$$\begin{aligned} \max_{x,L} \quad & -L + xL - q(x) - c(-L) \\ & \text{s.t.} \\ & 0 \leq x \leq 1 \\ & 0 \leq L \end{aligned}$$

The first order conditions are:

[9] In Appendix A we provide the extension of the method to general risk attitude.

$$(1-x) = c'(x) \tag{9}$$

$$L = q'(x) \tag{10}$$

The second order conditions for a maximum are:

$$-q''(x) < 0$$

$$c''(p)q''(x) > 1$$

Here again we can express the FOC only in terms of observables:

$$c'(-q'(x)) = 1 - x \tag{11}$$

The derivation of the cost of attention can be obtained following the same procedure outlined in the main body of paper.

### A.3 N actions

Maximization problem

$$V = \begin{bmatrix} v_1 & 0 & ... & 0 \\ 0 & v_2 & ... & 0 \\ . & . & . & . \\ 0 & 0 & ... & v_N \end{bmatrix}$$

$$\tilde{V} = \begin{bmatrix} v_1 & xv_2 & ... & xv_N \\ xv_1 & v_2 & ... & xv_N \\ . & . & . & . \\ xv_1 & xv_2 & ... & v_N \end{bmatrix}$$

$$X = \begin{bmatrix} v_{11} & v_{12} & ... & v_{1M} \\ v_{21} & v_{22} & ... & v_{2M} \\ . & . & . & . \\ v_{N1} & v_{N2} & ... & v_{NM} \end{bmatrix}$$

$\mu$ : prior probability of each state $\begin{bmatrix} \mathbf{v_1} & \mathbf{v_2} & ... & \mathbf{v_N} \\ p_1 & p_2 & ... & p_N \end{bmatrix}$

$\mathcal{P}_i(\mathbf{v_j})$ : probability of choosing an action $i$ given the state $\mathbf{v_j}$

$$\mathcal{P} = \begin{bmatrix} q_{11} & q_{12} & \cdots & q_{1M} \\ q_{21} & q_{22} & \cdots & q_{2M} \\ . & . & . & . \\ q_{N1} & q_{N2} & \cdots & q_{NM} \end{bmatrix}$$

$$\sum_i q_{ij} = 1, \forall j$$

$$G(\mu, \mathcal{P}, x) = \sum_{i=1}^{N} \sum_{j=1}^{N} \tilde{V}_{ij} \mathcal{P}_i(\mathbf{v_j}) \mu(\mathbf{v_j}) = \sum_{i=1}^{N} \sum_{j=1}^{N} \tilde{V}_{ij} q_{ij} p_j = \sum_{i=1}^{N} \sum_{\substack{j=1 \\ j \neq i}}^{N} x v_j q_{ij} p_j + \sum_{i=1}^{N} v_i q_{ii} p_i$$

$$C(\mu, \mathcal{P}, x) = \kappa(\mu, \mathcal{P}) + q(x)$$

## Instructions

# B Instructions

This is an experiment in decision making funded by Indiana University. If you follow instructions and make good decisions you may earn a SUBSTANTIAL AMOUNT of money. Money you earn will be paid to you in CASH at the end of the experiment. The entire session will take place through computer terminals.

The experiment is divided in three parts:

- Part 1: Four periods (16 minutes)
- Part 2: Six periods (24 minutes)
- Part 3: Four tasks (15 minutes)

You will be paid according to one period out of the ten that you play combining Parts 1 and 2. To this amount we will add your earnings in one randomly chosen task among the four you will play in Part 3, plus 7 dollars of show-up fee. The whole experiment will take about 2 hours.

## Part 1

In each of the four periods, you will see a screen containing colored balls. **Your main task is to decide which color of balls is more represented on a given screen** - whether there are "more black", "more grey" or "more white" balls.

Before executing the task of counting the balls, you will be shown a screen like the one below. At the top of the screen you can monitor *which period* you are in. You then read: "If you SUCCEED in the task you will earn" and "If you FAIL the task you will earn", followed by dollar amounts. Every period the payoffs for success and failure may be different. *Make sure you carefully examine payoffs before pressing the Reveal Button.*

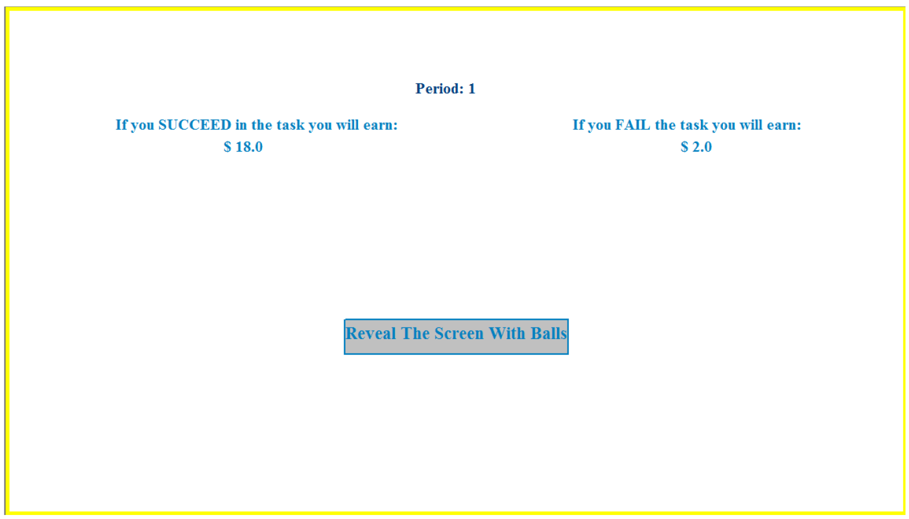



**Figure 1** – Success/Failure Payoffs

After you press the *Reveal Button* your screen will appear as in Figure 2. On the screen you can see some black, white and grey balls. Your task is to determine whether there are "More Black", "More Grey" or "More White" balls.

You succeed at the task if you guess the color correctly, that is you click the button "More White" if indeed the number of white balls on the screen exceeds the number of black and grey balls, if you click on "More Black" if there are more black than white or grey balls, and if you click on "More Grey" if grey is the most represented color. For example, in Figure 2 there are 31 white, 29 black and 30 grey balls. Hence the white balls outnumber the other two colors. If on that screen you press "More White" you succeed and your payoff is $18. If instead you press "More Black" or "More Grey" you fail and your payoff is $2.

You enter your choice by pressing the corresponding button. The order of the buttons may change, pay attention and make sure you read the labels in each period.

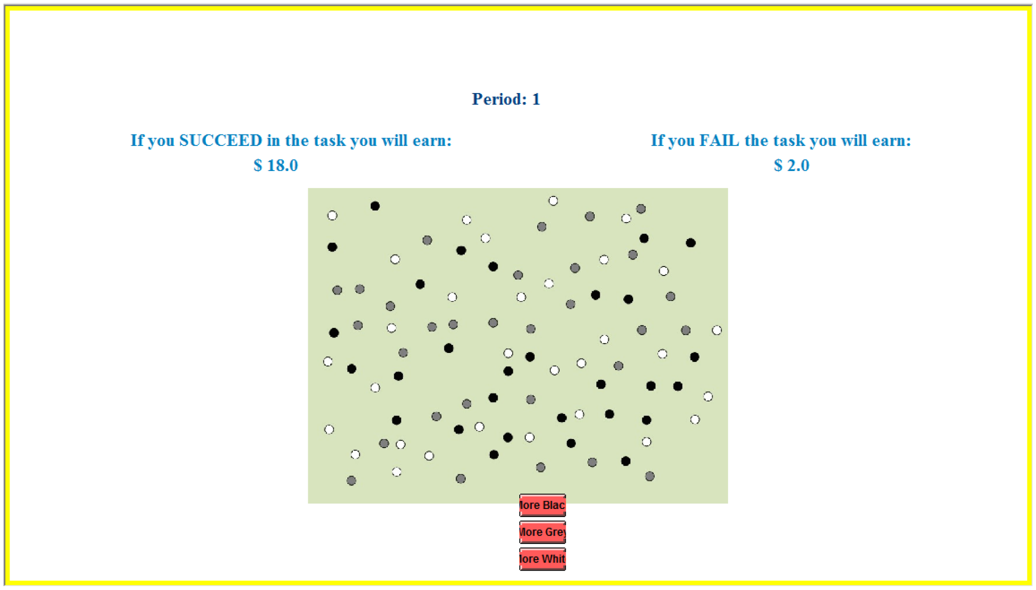



**Figure 2** – Black/Grey/White balls

## 90-Task and 135-Task

There are two types of tasks (90–Task and 135–Task) that vary in the number of total balls. In a 90–Task, there are **approximately** 90 balls (more precisely there are between 87 and 93 total balls). In a 135–Task there are approximately 135 balls (more precisely there are between 131 and 139 total balls). **Remember, the proportion of each color is approximately 1/3 in each period.** Figure 2 is an example of a 90–Task.

There are a total of 4 periods in Part 1. You will start with two periods where you play the 90–Task followed by two periods where you play the 135–Task.

## Review Questions

1. If your screen is like the one in Example 1, and you are successful in the task, how much do you earn? How much do you earn if you fail the task?

2. If your screen is like the one in Example 2, and you are successful in the task, how much do you earn? How much do you earn if you fail the task?

| If you SUCCEED in the task you will earn: | If you FAIL the task you will earn: |
|---|---|
| 9.00 | 3.00 |

Example 1

| If you SUCCEED in the task you will earn: | If you FAIL the task you will earn: |
|---|---|
| 11.00 | 11.00 |

Example 2

## Time limit

In each period you have a maximum of 4 minutes to enter your choices. A timer at the top of the screen will remind you how much time you have left. You cannot carry over unused time to the next period.

### Chance Assessment

After you execute the colored-balls task, and before proceeding to the subsequent period, you will guess the chance that you were succesful in the task you just performed. We ask you to enter a number between 33.3% (which stands for "I have the same chances to be correct as someone who picks one option at random") to 100% (which stands for "I am entirely sure that my answer was correct"). The number you type will remain anonymous, you will not receive a payment for it, nor it will be used to determine any payoff relevant outcome for you. When the chance assessment screen is on, the clock is stopped so you can take your time and get ready for the next period.

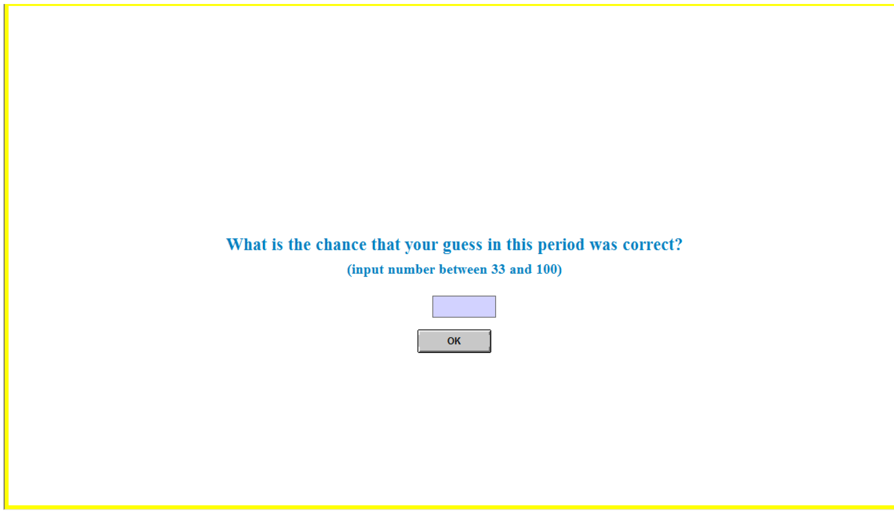



**Figure 3** – Guess the Chance

## Periods overview

- **Period 1 and Period 2: 90-Task**

- **Period 3 and Period 4: 135-Task**

You can go at your own pace until the end of Part 1. Before moving to Part 2 we will wait for all participants to finish Part 1. You are free to use your phone or engage in other activities after you finish Part 1 and before we collectively move to Part 2.

One period, out of the 10 periods you play combining Part 1 and Part 2, will be randomly chosen and you will be payed the amount you earned in that period.

## Part 2

In Part 2 you face 6 periods. In each period you will perform the same task you performed in Part 1, that is you have to determine whether on the screen there are more black, more grey or more white balls. The difference with respect to Part 1 is that the payoffs that you receive in the case of SUCCESS and FAILURE **are decided by you.**

You will choose your payoffs by looking at a table similar to the one in Figure 4. As you see, there is a list of payoffs under success and failure that you can choose from. Please have a good look at the list.

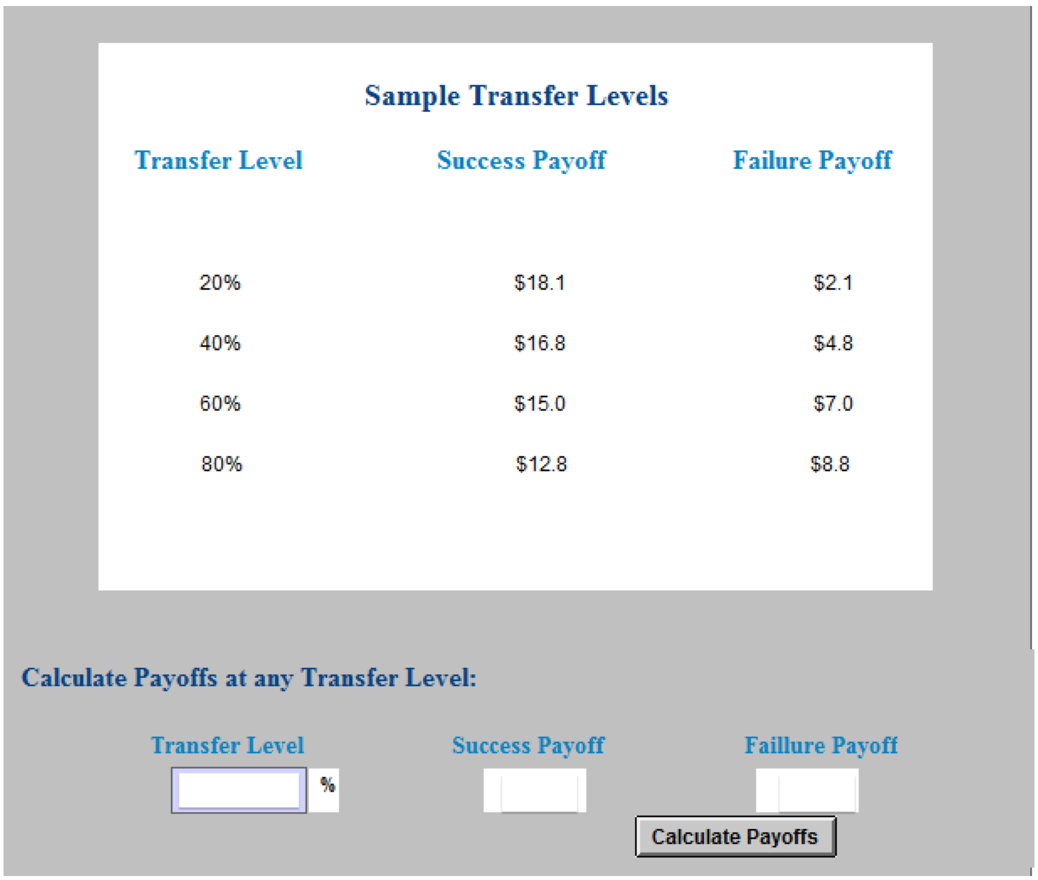



**Figure 4** – Choice of the payoffs screen

As you notice, the payoffs under success and failure are like two communicating vessels: **You can increase the amount of money you receive if you fail only if you reduce the amount received if you succeed**. For example, according to the option on top of the list, you get $18.1 if you succeed and $2.1 if you fail. As you scroll down the list, the payoff under success decreases and the payoff under failure increases, that is, they get closer and closer to each other until they are completely equalized.

The payoffs under success and failure are related by a **transfer function**, that is a mathematical formula that determines how money is transferred from the event of success to the event of failure. The first column in the list, called “Transfer Level”, reports the percentage of funds that you are transferring.

The transfer functions **will change** across periods. That is, sometimes transferring money from the event of success to the event of failure *will be cheaper*, and sometimes it will be *more expensive* (Figure 5 reports another screen. Take a few seconds to inspect it and verify that transferring funds in this case is cheaper than it is in the table of Figure 4).

**With a more expensive transfer functions it becomes increasingly more costly to transfer funds**, that is, choosing a high transfer level will come at an increasingly higher cost as compared to a cheaper transfer function. Compare again figure 4 and 5. The more expensive transfer function in Figure 4 lists payoffs that are lower than those in figure 5 for all transfer levels. Moreover, the difference in payoff between the two figures is small at the top and increases as you move down the list of transfer levels.

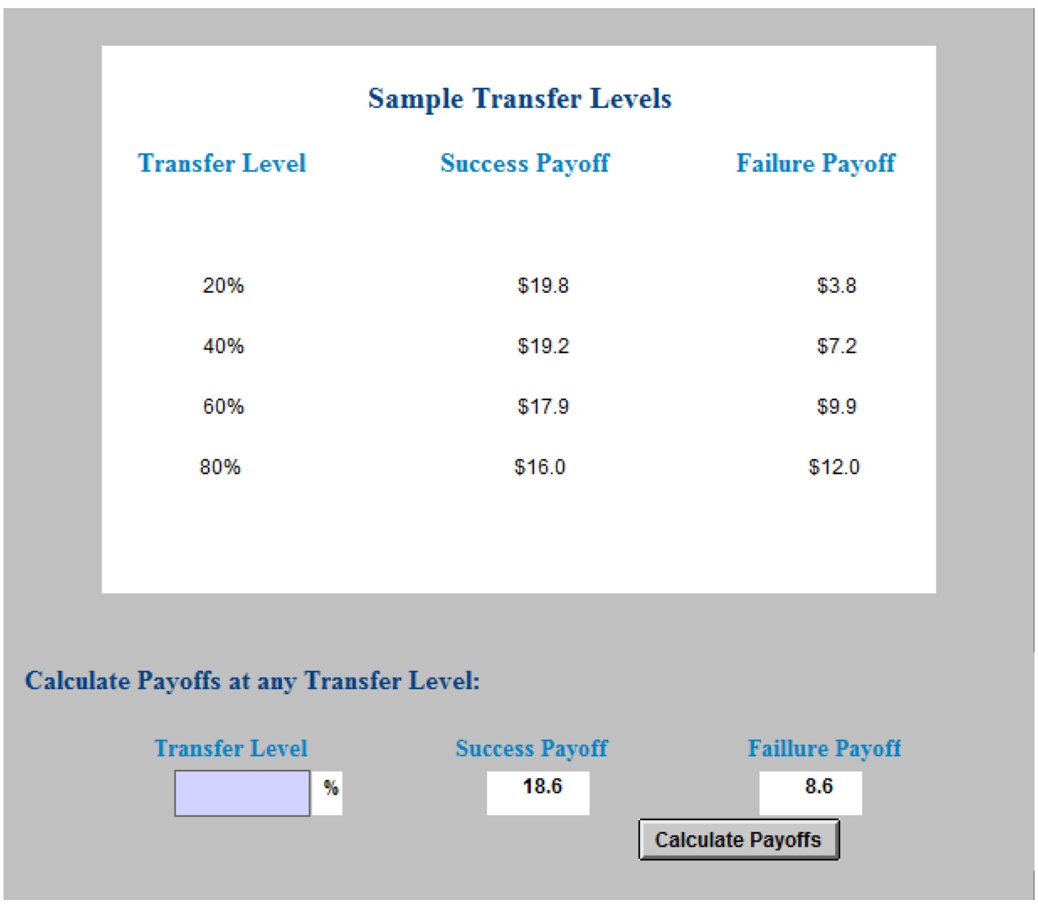



**Figure 5** – A cheaper transfer function

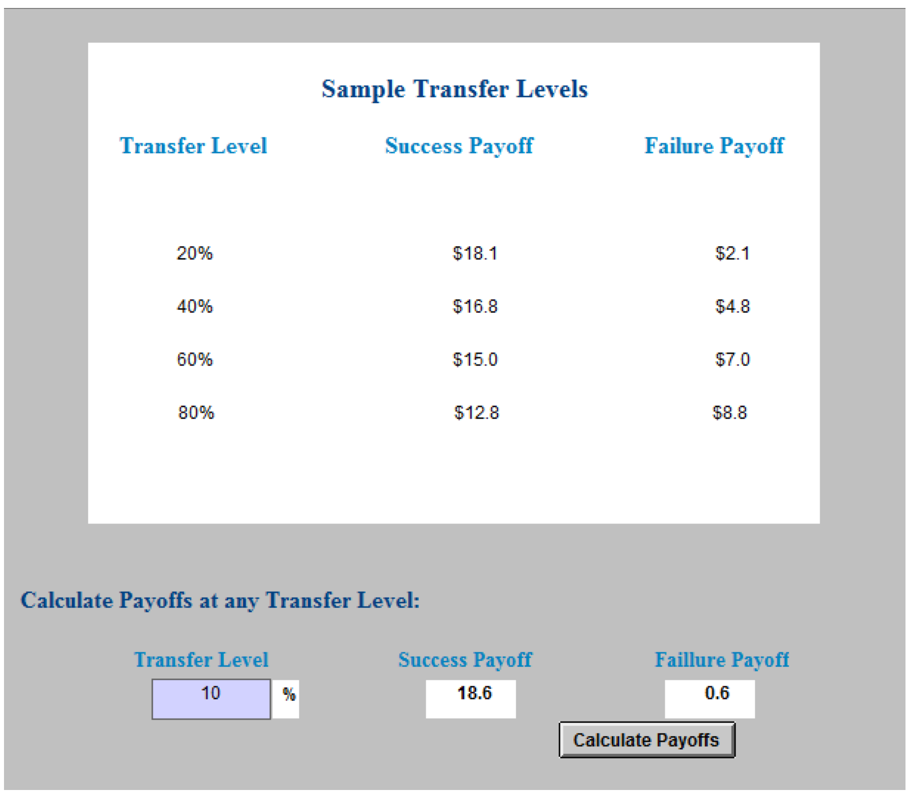
**Review question:**

If you choose a transfer of 40% how much would your payoffs under success and failure be in Figure 4? And in Figure 5?

### How to choose your preferred payoff pair

The choice of your preferred payoff pair is made by typing a number in the box below the table in the bottom left corner, and, after you are satisfied with the outcome, by pressing the Continue button. The number you have to type is a value between 0 and 100, corresponding to the percentage you wish to transfer. Recall that the list above the box reports payoffs for transfer levels equal to 20%, 40%, 60% , 80%. However, **you can actually choose this percentage to be any number between** 0 **and** 100**.**

To find your preferred transfer, we recommend that you follow this procedure: **Look at the list to identify the ranges where your preferred transfer lies. Type in the calculator different numbers in these ranges until you find your preferred option. You can calculate as many options as you want.**


Sample Transfer Levels

| Transfer Level | Success Payoff | Failure Payoff |
|---|---|---|
| 20% | $18.1 | $2.1 |
| 40% | $16.8 | $4.8 |
| 60% | $15.0 | $7.0 |
| 80% | $12.8 | $8.8 |

Calculate Payoffs at any Transfer Level:

| Transfer Level | Success Payoff | Faillure Payoff |
|---|---|---|
| 10 % | 18.6 | 0.6 |

Calculate Payoffs

**Figure 6** – Choosing your preferred payoffs under success and failure

In the example in Figure 6 the player has entered the payoff level 10% and calculated her payoff pair to be \$18.6 under success and \$0.6 under failure. **When you are satisfied with the resulting payoff pair, you can click on the Continue button. Only then the payoffs that you have calculated will become final.** That is they become the payoffs that you will be playing for in that period.

## Choosing the payoffs for all six periods

Remember you will play six periods, three periods for the 90-Task and three periods for the 135-Task. For each period you will make a separate choice regarding your preferred payoff pair as we just explained. You will make the payoff choices for all the periods at the same time, and only afterwards you will play the six colored-balls task given the payoff that you have chosen.

You will make choices on a screen as in Figure 7. **The first three screens contain choices which will be relevant for the periods where you play the 90-Task. The last three screens contain choices which will be relevant for the periods where you play the 135-Task.** The box on the left of the screen will remind you whether you are choosing payoffs for the 135-Tasks or for the 90-Tasks.

Within the first three screens and within the last three screens, **transfer functions are presented in order from cheapest to most expensive**. Remember, with a more expensive transfer function it becomes increasingly more costly to transfer funds.

There is no time limit, you can take as much time as you want to explore the transfer functions and make your choices. We will wait for all participants to choose their payoffs in all six periods before proceeding to the colored balls task.

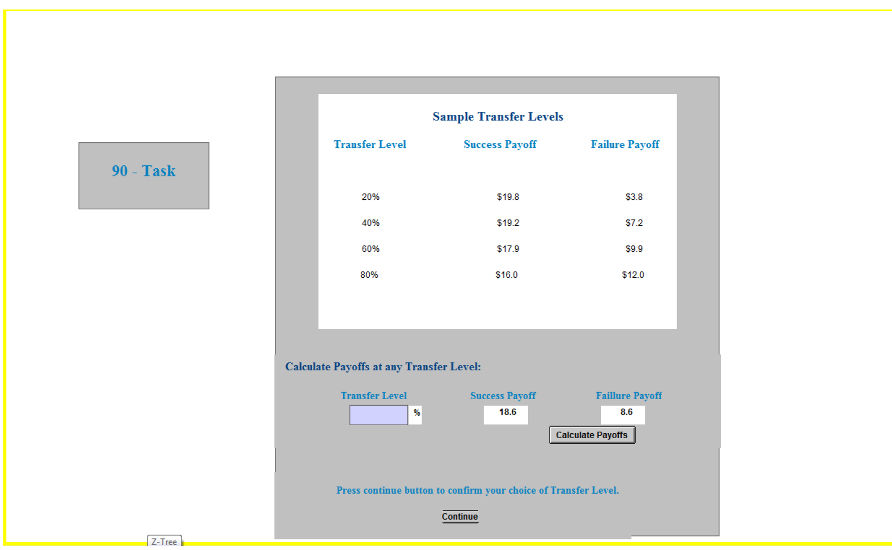



**Figure 7** – Payoff choice screen

After you are done selecting your payoffs for all 6 periods you will move to the colored-balls tasks. From this point onwards, the sequence of screens will be similar to the one you saw in Part 1, **except for the payoffs under success and failure which will be the ones that you chose.**
First, a screen will remind you your selected payoff pair for the period you are about to play. After pressing the Reveal button, the colored balls will appear and you can start counting balls (see Figure 9). **The order in which you will play the colored balls task is randomized.**

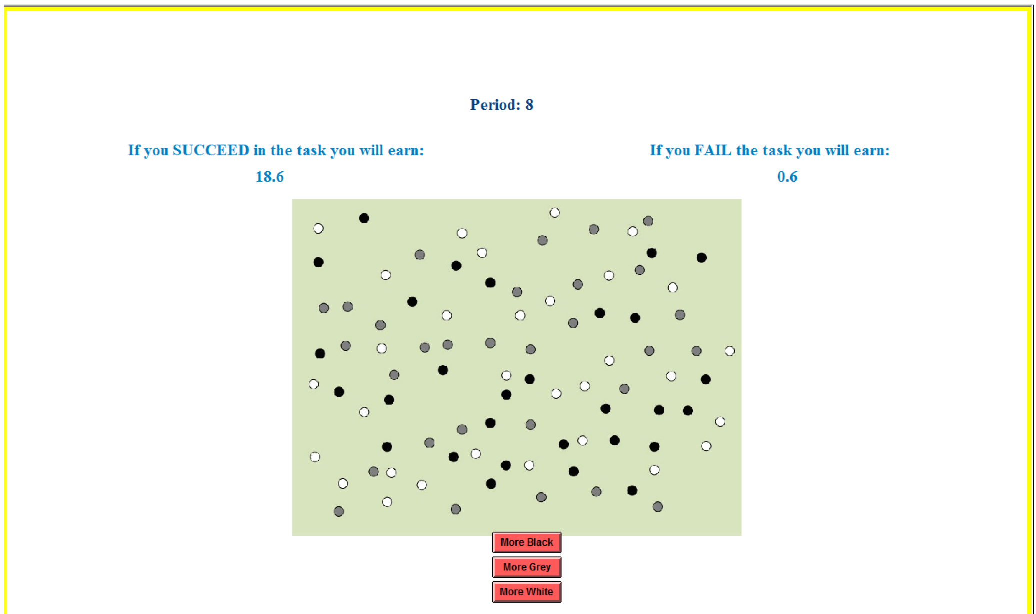



**Figure 8** – Screen reminding your payoffs after the choice is taken

### Chance Assessment

After you execute the colored-balls task, we ask you to guess the chance that you were successful in the task you just performed. Again, you will enter a number between 33.3% to 100%. This question is unincentivized. When the chance assessment screen is on, the clock is stopped so you can take your time and get ready for the next period.

**Timeline**

- **Payoff choices for all 6 periods**

  1. **90-Task** Cheap transfer function
  2. **90-Task** Medium transfer function
  3. **90-Task** Expensive transfer function

  4. **135-Task** Cheap transfer function
  5. **135-Task** Medium transfer function
  6. **135-Task** Expensive transfer function

- **Colored-balls task**

  **Six periods in randomized order**

  Time limit: 4 minute per period

  Payoffs: Chosen by you

There is no time limit to choose the six payoff pairs. After all participants are done with choosing their payoffs, we will move to the colored-balls task. You are free to use your phone or engage in other activities after you have reached the end of Part 2 and before we move to Part 3.

One period, out of the 10 periods you will play combining Part 1 and Part 2, will be randomly chosen and you will be payed the amount you earned in that period.

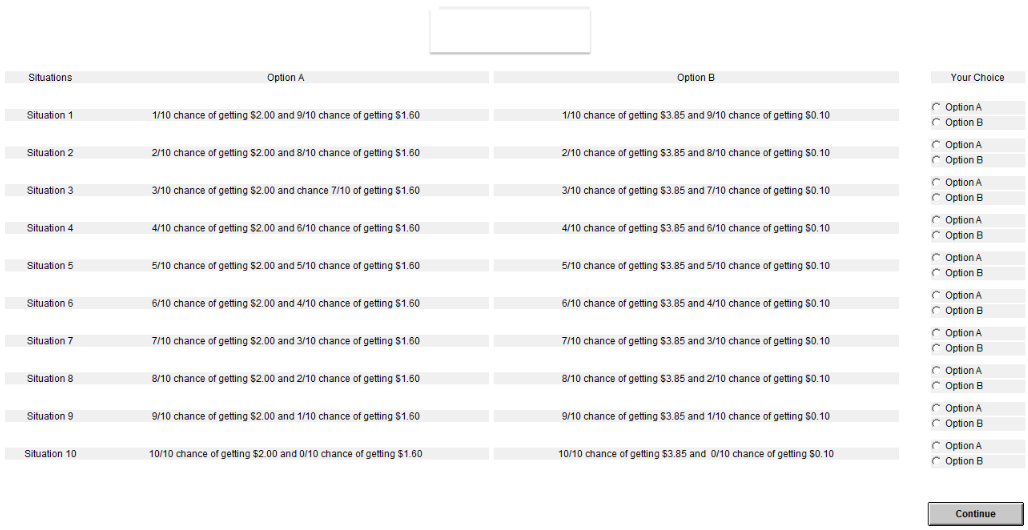
## Part 3

This part is structured in four tasks. At the end of Part 3 we will randomly extract one of the four tasks and pay you according to your choices in that task.

We will read instructions for each task and let you complete the task before moving to the next.

### Task 1

You are presented with 10 questions and in each question you choose, between two lotteries, the one that you prefer. Choices will be presented to you in a list as in Figure 7.



| Situations | Option A | Option B | Your Choice |
|---|---|---|---|
| Situation 1 | 1/10 chance of getting $2.00 and 9/10 chance of getting $1.60 | 1/10 chance of getting $3.85 and 9/10 chance of getting $0.10 | Option A<br>Option B |
| Situation 2 | 2/10 chance of getting $2.00 and 8/10 chance of getting $1.60 | 2/10 chance of getting $3.85 and 8/10 chance of getting $0.10 | Option A<br>Option B |
| Situation 3 | 3/10 chance of getting $2.00 and chance 7/10 of getting $1.60 | 3/10 chance of getting $3.85 and 7/10 chance of getting $0.10 | Option A<br>Option B |
| Situation 4 | 4/10 chance of getting $2.00 and 6/10 chance of getting $1.60 | 4/10 chance of getting $3.85 and 6/10 chance of getting $0.10 | Option A<br>Option B |
| Situation 5 | 5/10 chance of getting $2.00 and 5/10 chance of getting $1.60 | 5/10 chance of getting $3.85 and 5/10 chance of getting $0.10 | Option A<br>Option B |
| Situation 6 | 6/10 chance of getting $2.00 and 4/10 chance of getting $1.60 | 6/10 chance of getting $3.85 and 4/10 chance of getting $0.10 | Option A<br>Option B |
| Situation 7 | 7/10 chance of getting $2.00 and 3/10 chance of getting $1.60 | 7/10 chance of getting $3.85 and 3/10 chance of getting $0.10 | Option A<br>Option B |
| Situation 8 | 8/10 chance of getting $2.00 and 2/10 chance of getting $1.60 | 8/10 chance of getting $3.85 and 2/10 chance of getting $0.10 | Option A<br>Option B |
| Situation 9 | 9/10 chance of getting $2.00 and 1/10 chance of getting $1.60 | 9/10 chance of getting $3.85 and 1/10 chance of getting $0.10 | Option A<br>Option B |
| Situation 10 | 10/10 chance of getting $2.00 and 0/10 chance of getting $1.60 | 10/10 chance of getting $3.85 and 0/10 chance of getting $0.10 | Option A<br>Option B |

Continue

Figure 7

At the end of Part 3, if this task is selected for payment, we will randomly extract one question from the list and we will play the lottery that you picked in that question, and adding to your earnings the resulting payoffs.

Please go ahead and complete Task 1.

Prior to describing Task 2 and Task 3, let us introduce two bags, A and B. Bag A contains 10 red and 10 blue chips, Bag B contains a total of 20 chips, each of which can be either red or blue in unknown proportions. Before opening this session, with a volunteer, we drew one chip from each bag and recorded the extracted color. If you want, at the end of the experiment, you can check the content of the bags and the colors extracted. In task 2 and 3 you will bet on the colors of the chips that have been extracted from the two bags.

### Task 2

Task 2 involves **choices between gambles on bag A and sure amounts**. Remember, Bag A contains 10 red and 10 blue chips. In this task, first you choose the color you bet on. This choice will define your gamble. If the color extracted from bag A was the color you placed your bet on, you win 4 dollars, if we extracted the other color you win 0 dollars. Next you are presented with a list of questions where you have the option to trade your gamble for a sure payment. Choices will again be presented in a list and for each question you need to state if you prefer the gamble or the sure payment.

At the end of Part 2, if this task is selected for payment, we will randomly extract one question from the list and we will pay you according to your choice in that question. If you picked the sure amount, you will receive that amount irrespectively of the color drawn from bag A. If you picked the gamble, you will win 4 dollars if the color you bet on is drawn and 0 dollars otherwise.

Please go ahead and complete Task 2.

### Task 3

Task 3 involves **choices between gambles on bag B and sure amounts**. Remember, bag B contains a total of 20 chips, each of which can be either red or blue in unknown proportions. In this task, first you choose the color you bet on. This choice will define your gamble. If the color extracted from bag B was the color you placed your bet on, you win 4 dollars, if we extracted the other color you win 0 dollars. Next you are presented with a list of questions where you have the option to trade your gamble for a sure payment. Choices will again be presented in a list and for each question you need to state if you prefer the gamble or the sure payment.

At the end of Part 3, if this task is selected for payment, we will randomly extract one question from the list and we will pay you according to your choice in that question. If you picked the sure amount, you will receive that amount irrespectively of the color drawn from bag B. If you picked the gamble, you will win 4 dollars if the color you bet on is drawn and 0 dollars otherwise. Please go ahead and complete Task 3.

You can now move to the fourth task, the instructions of which appear on the terminal.