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IZA DP No. 17484

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ABSTRACT

When Transparency Fails: How Altruistic Framing Sustains Demand for Useless Advice Despite Complete Information*

This study examines whether complete transparency about the randomness of prediction-generating processes mitigates the hot hand fallacy and the conditions under which it may fail. In a pre-registered laboratory experiment (N=750), we showed that transparency about the prediction-generating processes reduced individuals' belief in the hot hand of fair coin flip predictions. However, this effect significantly weakened when we shifted from paying to donating for predictions. Participants exposed to streaks of accurate predictions under altruistic framing were more inclined to donate despite knowing the randomness involved. We explore underlying mechanisms and discuss implications for decision-making in economics and finance.

JEL Classification: C91, D03

Keywords: gambler's fallacy, hot hand, full information, altruism, random streaks, karmic investment

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1. Introduction

Both casual observation and empirical evidence suggest that there is a substantial demand for expert predictions, particularly from those with a track record of accurately forecasting stochastic and inherently hard-to-predict events.[1] This tendency is especially pronounced in financial markets, where professionals with a track record of successful stock selection often command substantial salaries and bonuses (Golec, 1996; Chevalier & Ellison, 1999) despite compelling evidence that stock prices follow a random walk (Fama, 1965; Summers, 1986) and that such success is more likely attributable to chance rather than skill (Gruber, 1996; Fama et al., 2010; Malkiel, 2003).

Why do individuals pay for expert predictions about stochastic outcomes when the intrinsic value of these predictions may be substantially lower than the price people are willing to pay? One hypothesis is the presence of asymmetric information about the underlying outcome-generating and prediction-generating processes between experts and consumers. For example, studies show that individuals with limited financial literacy are significantly less likely to invest in stocks, primarily due to the perceived complexity of the stock market (Christelis et al., 2010; Van Rooij et al., 2011). There is also evidence that individuals who believe they lack sufficient knowledge or expertise are significantly less likely to engage in sports betting (Lamont et al., 2011; Gainsbury et al., 2012). In such situations, where consumers tend to overestimate the deterministic elements (such as skill, training, and strategy) and underestimate the stochastic elements (such as luck, randomness, and uncertainty) of future

[1] The recently concluded U.S. Presidential Election serves as a compelling case study. In the lead-up to the election, as voters prepared to cast their ballots, attention was drawn to the rivalry between two prominent forecasters: Nate Silver and Alan Lichtman. Silver, a celebrated author and polling analyst, projected a victory for Donald Trump, while Lichtman, a university professor renowned for accurately predicting nine of the last ten U.S. presidential elections, forecasted Kamala Harris as the winner (Waddick, 2004). While elections are not entirely random events, they share certain parallels with the issue explored in this paper—namely, the binary nature of the outcome: a win for either Trump or Harris. Speculators closely followed these predictions, often using them to guide their bets on the election's outcome. Yet, such forecasts warrant caution. Despite their inherent limitations and the risk of being ultimately incorrect, these expert predictions continue to captivate and influence speculators, underscoring their enduring allure.

outcomes, they may be inclined to rely more heavily on expert predictions—and be willing to pay a premium for them—over their intuition (Malmendier et al., 2007; Mikhail et al., 2007).

A key question is whether transparency about the stochastic nature of events can effectively deter people from paying for predictions of random outcomes. The short answer is no. In a unique lab experiment by Powdthavee and Riyanto (2015), participants received split predictions of fair coin flips—such as forecasts of alternating sequences of Heads or Tails—which were sold at a price. Although participants understood that coin flips were random and predictions held no value, many still paid for forecasts of future flips after observing short streaks of accurate predictions. Moreover, the results indicated that their belief in the "hot hand" of the predictions did not diminish with better performance in an incentivised statistics and quantitative skill test: those who performed well were just as likely to pay for predictions as those who did not. In other words, the study by Powdthavee and Riyanto (2015), along with subsequent research, such as Sloof and Von Siemens (2017) and Cabrero et al. (2019), suggests that simply recognising the randomness of outcomes may not be sufficient to deter people from paying for blatantly useless expert advice, particularly if the underlying process behind seemingly accurate predictions remains hidden from them.

This study contributes to the literature by addressing two important research questions. First, can providing complete information about the randomness underlying the prediction-generating process effectively reduce people's belief in the hot hand of predictions? Empirical insights into this research question can help inform educational and policy interventions. If statistical and financial education that directly explains how experts generate predictions can help individuals better evaluate the value of these forecasts, it may lead to more informed decision-making regarding whether to invest in such predictions in the context of stochastic events. Moreover, enhancing public understanding of prediction-generating processes could serve as a protective measure, reducing the likelihood of individuals falling victim to scams or fraudulent schemes that exploit misguided beliefs in streaks or patterns.

The second research question, which builds naturally on the first, asks under what conditions complete information fails to reduce the hot hand of the predictions. Specifically, we investigate whether reframing the motivation from *expertise*—paying experts for the predictions—to *altruism*—donating money to a charity in exchange for the predictions—sustains people's belief that a streak of correct predictions of explicitly random events, such as a series of fair coin flips, will continue as long as they maintain altruistic and pro-social behaviour—a behaviour resembling the psychological concepts of "illusion of control" (Langer, 1975) and "karmic investment" (Burger & Lynn, 2005; Pronin et al., 2006). If evidence of such tendencies exists, then standard awareness interventions may not be as effective as we might have previously thought as a tool to protect people from succumbing to the predictive illusions of stochastic events.[2]

We conducted a pre-registered laboratory experiment to investigate the extent to which people are willing to pay for transparently useless advice under varying conditions. Specifically, we extended Powdthavee and Riyanto's (2015) unique experimental design, which involves distributing split predictions on fair coin flips, to examine whether fully disclosing the randomness underlying the prediction process would completely discourage individuals from purchasing forecasts of purely random events, particularly after witnessing a streak of improbably accurate predictions in real-time within the lab. Additionally, we investigated whether reframing the concept from "paying for predictions" to "donating in exchange for predictions" could significantly weaken the influence of complete information on individuals' belief in the hot-hand effect. Our findings provide evidence in support of both hypotheses. Under complete information, we found that individuals were significantly less

[2] One could imagine, for example, scammers exploiting charitable donations as a guise for selling predictions.

willing to pay for predictions after having witnessed a streak of correct predictions. Nevertheless, when the framing shifted to donations, participants became more likely to donate in exchange for predictions after observing a streak of correct predictions despite knowing the underlying randomness of the prediction-generating process.

This paper is organised as follows: Section 2 briefly outlines the background literature. Section 3 describes the experimental setup. Section 4 discusses theories and hypotheses. Section 5 outlines the empirical strategy. Section 6 presents the results. In Section 7, we discuss the implications of our findings and provide concluding remarks.

2. Background Literature

In their seminal paper, Rabin and Vayanos (2010) developed a theoretical model that links two cognitive biases: the gambler's fallacy—the erroneous expectation of mean reversion following a streak of random sequence (e.g., anticipating a tail after a series of heads in coin flips)—and the hot hand fallacy—the belief in streak persistence (e.g., assuming a basketball player will continue scoring after making several consecutive shots). In the context of prediction markets—such as finance, sports betting, or forecasting—they argued that individuals observing a short streak of accurate experts' predictions initially display behaviour consistent with the gambler's fallacy, i.e., expecting the streak to end. However, as the streak becomes longer, the hot hand fallacy takes over, leading people to believe the streak of correct predictions will continue due to the experts' underlying skills.

One of the fundamental assumptions in Rabin and Vayanos's (2010) model is that the belief in the hot hand of experts arises primarily in contexts where there exists some uncertainty or ambiguity about the randomness of the outcome-generating process, such as stock movements and sporting events. In contrast, for **purely and explicitly** random events—like predicting lottery numbers or consecutive coin flips—individuals' behaviour will be shaped solely by the gambler's fallacy (a luck-based perception) rather than the hot hand fallacy (a performance-based perception) attributed to the experts. This is because any rational observer should recognise that no system exists for predicting transparently independent and identically distributed (i.i.d.) events, and any streak of correct predictions by experts, no matter how long, can only be attributed to experts' luck and not skill.

However, contrary to Rabin and Vayanos's (2010) assumption, a small but growing body of evidence suggests that beliefs in the hot hand of experts' predictions can still occur despite individuals being fully aware of the randomness of the outcome-generating process. For example, in a lab experiment by Huber et al. (2010), participants could choose to bet on the outcomes of computer-generated coin flips, follow advice from randomised "experts," or select a risk-free alternative. They found that participants who relied on randomised experts were more likely to pick experts who had been successful in the past, which is consistent with the hot hand fallacy.

Using actual rather than computer-generated coin flips, Powdthavee and Riyanto (2015) also demonstrated that participants in a lab experiment were willing to pay for predictions of fair coin flips after observing only a short streak of correct predictions live in the lab. In a natural experimental setting, Yuan et al. (2014) demonstrated that participants in a popular Chinese lottery were willing to pay commission fees to emulate the number choices of previous winners despite the fact that selecting winning lottery numbers is purely a matter of chance. Similarly, Bou et al. (2016) found that participants in a laboratory experiment were significantly more likely to pay for the opportunity to place bets on players with a strong track record of accurate guesses in a coin flip task. Overall, these empirical studies suggest that, instead of exhibiting the gambler's fallacy, individuals have a strong tendency to develop belief in the hot hand of experts after witnessing only a brief streak of successful predictions. This tendency persists even when the outcomes are independently drawn, and the randomness of the context is explicitly and universally known to the individuals.

A potential explanation for why people are willing to pay for transparently useless information is that they do not have sufficient awareness or insight into the experts' ability to generate consecutive correct predictions of random sequences. When Powdthavee and Riyanto (2015, p. 268) asked their laboratory subjects why they decided to pay for predictions of coin flips, many responded that the predictions had been more successful than their bets. However, they offered no further justification or explanation for why this was the case, which suggests that individuals may have been unable to rationalise how such an improbable streak of successful predictions of fair coin flips was possible and happening live in front of them.[3] This inability to explain the streak may have evoked a sense of wonder or awe toward the experts' ability to predict future random events (Keltner & Haidt, 2003; Rudd et al., 2012), which can diminish rational scepticism and ultimately foster behaviours consistent with the hot hand fallacy.

Empirical evidence on the extent to which enhancing people's understanding of experts' prediction-generating process can effectively reduce belief in the experts' hot hand remains scarce. However, a few notable studies have shown that providing explanations can potentially mitigate overreliance on experts' predictions. For example, Kelly et al. (2012) demonstrated that providing explicit warnings about potential biases in stock analysts' recommendations can reduce investors' overreliance on overly optimistic recommendations to buy certain stocks. More recently, Vasconcelos et al. (2023) demonstrated through an experiment that when artificial intelligence (AI) provides simple explanations for its

[3] In Powdthavee and Riyanto's (2015) study, the probability of correctly predicting two consecutive coin flips is calculated as 25%. Similarly, the probability of correctly predicting three consecutive flips drops to 12.5%. For four successive correct predictions, the probability becomes 6.25%. Finally, the likelihood of predicting five consecutive coin flips accurately is 3.125%.

predictions to participants, it reduces their overreliance on the AI's predictions. One potential mechanism is that transparency lowers the perceived competence of experts relative to individuals, prompting people to favour their judgments over those of the experts (Heath & Tversky, 1991). Nevertheless, the existing literature is small, and the extent to which transparency can effectively mitigate the hot hand effect is not entirely clear.

A related research question is whether full disclosure of the randomness inherent in both the outcomes and prediction-generating processes is less effective in specific contextual settings than in others. For instance, if people are fully informed that luck, not skill, determines the success rate in guessing i.i.d. outcomes, they may accept that an expert's hot hand is merely a product of chance and, as a result, cease paying for their predictions. However, suppose the predictions are framed as an opportunity for altruistic behaviour. In that case, individuals may begin to rationalise donating to follow a hot hand as a means of influencing future random outcomes and sustaining the streaks despite being fully aware of the randomness in both the outcomes and prediction-generating processes. This behaviour is consistent with Langer's (1975) concept of the "illusion of control," which refers to people's tendency to overestimate their ability to influence outcomes that are determined by chance or random events (see also Burger & Lynn, 2005; Pronin et al., 2006).

The behaviour also aligns with the psychological concept of "karmic investment," which refers to people's tendency to attempt to influence uncontrollable outcomes by proactively performing good deeds, believing that positive actions will yield favourable results (Risen & Gilovich, 2008; Converse et al., 2012). For example, Converse et al. (2012) found that individuals facing uncertainty—such as awaiting test results, job offers, or other significant personal outcomes beyond their control—were more likely to engage in prosocial behaviour, such as donating money or volunteering time, compared to those not experiencing such uncertainty. We hypothesise that similar tendencies would emerge if people were given an opportunity to behave prosocially in the hope of sustaining a streak of correct predictions. In this context, reframing the predictions from being expert-driven to altruism-focused might suffice to preserve belief in the hot hand effect—not in spite of, but precisely because individuals are fully aware that the predictions are entirely random and that luck, not skills, determines their successes.

3. Experimental Setup

To empirically investigate whether (i) individuals pay for transparently useless advice after observing a streak of correct or incorrect predictions, replicating the earlier findings by Powdthavee and Riyanto (2015), (ii) an intervention aimed at raising awareness of the randomness in the prediction-generating process reduces their willingness to pay for such predictions, and (iii) shifting the framing to altruism increases the likelihood of engaging in altruistic behaviour in exchange for a prediction following a streak, we conducted a pre-registered, 2×2 randomised laboratory experiments (https://osf.io/2dg8x/) with students at Nanyang Technological University (NTU) in Singapore between September and November 2024. Once recruited, we randomised participants into the following four treatments:

1. **Control Group (Expert-No Info)**
2. **Awareness Intervention (Expert-Full Info)**
3. **Altruism Framing (Charity-No Info)**
4. **Combined Intervention (Charity-Full Info)**

In the **Control Group (Expert-No Info)**, replicating the experimental design of Powdthavee and Riyanto (2015), participants were randomly assigned to individual cubicles upon arrival at the lab. Once seated, they were instructed to complete two tasks.

In the first task, participants placed bets on the outcomes of five rounds of "fair" coin flips. To ensure transparency and emphasise the fairness of the process, the following rules were clearly communicated to participants from the outset:

- **Participant-Supplied Coins**: The participants, not the experimenters, would provide the coins used for the flips. Experimenters only supplied one if none of the participants had a coin with them.[4]
- **Volunteer Flipper**: A volunteer participant would be randomly selected to step forward and flip the coin in full view of all participants.
- **Rotation of Flippers**: To ensure impartiality, a different volunteer would flip the coin in each round.

This setup was designed to minimise the participants' perceptions of manipulation by the experimenters and maintain their trust in the fairness of the coin flips.

Participants were given an initial endowment of 300 points to place bets across the five rounds of coin flips. A minimum bet of 10 points was required per round, and participants were not permitted to exhaust their endowment entirely before the final round, ensuring that they could participate in all five rounds. A correct bet was worth double, and an incorrect bet was worth 0 in return. At the start of the experiment, each participant received five numbered envelopes, which were taped to the table within their respective cubicles. They were informed that each envelope contained a prediction for the outcome of a coin flip, corresponding to one of the upcoming rounds. Before each round, participants had the option to pay a fixed fee of 10 points to reveal the prediction inside the relevant envelope prior to placing their bet and flipping the coin. They were also informed at the start that if they chose not to pay, they could open the corresponding envelope immediately **<u>for free</u>** after the coin flip. This allowed them to compare the prediction with the actual outcome and satisfy any curiosity they had about the

[4]Participants supplied their own coins in all but two sessions.

prediction's accuracy. To ensure that all participants clearly observed the coin flip outcome, we projected the result onto a screen and announced it aloud at the end of each round. We also made sure that participants were not primed about the source of the predictions by withholding any information regarding their origin. Participants were told that any remaining endowment at the end of the experiment would be converted to Singapore dollars (SG$) at the exchange rate of 50 points = SG$1.

Our prediction-generating process involves strategically distributing split predictions across the envelopes to ensure that a sufficient number of participants experienced at least three consecutive correct and incorrect predictions. For any given session with *N* participants, half (*N*/2) will randomly receive a prediction of "heads," while the other half (*N*/2) will receive a prediction of "tails" in the first round. This approach guarantees that at least half of the participants receive a correct prediction in the first round, irrespective of the coin-flip outcome. The same split prediction allocation is applied in the second round, ensuring that approximately *N*/4 participants randomly receive two consecutive correct predictions, while another *N*/4 receive two consecutive incorrect predictions. This process is repeated up to round five, making it likely that in each session, at least one participant receives four consecutive correct predictions, and at least one receives four consecutive incorrect predictions (see Figure 1). Of 750 participants, 363 participants (48%) received a correct prediction in the first round. In the second round, 178 (23.73%) received two consecutive correct predictions, and 190 (25.33%) received two consecutive incorrect predictions. In the third round, 85 (11.33%) received three consecutive correct predictions, and 95 (12.67%) received three consecutive incorrect predictions. In the fourth round, 44 (5.87%) received four consecutive correct predictions, and 45 (6%) received four consecutive incorrect predictions.[5]

[5] There is a slight variation in the number of participants with streaks of correct or incorrect predictions in each experimental session, depending on the total number of participants in that session. While we aimed for 24

The **Awareness Intervention (Expert-Full Info)** treatment is identical to the **Control Group (Expert-No Info)** but with an additional component: Participants were explicitly informed about the randomness of the prediction-generating process, raising their awareness of the predictions' stochastic nature. Notably, participants were presented with a coin tree diagram shown in Figure 1 illustrating how split predictions were randomly assigned to individuals in each round. This allowed participants to understand how the predictions were generated before the first round of betting and assured them that no trickery or magic was involved in the prediction process.

The **Altruism Framing (Charity-No Info)** treatment is also identical to the **Control Group (Expert-No Info)** but with one key difference: the predictions were presented as an opportunity to engage in altruistic behaviour. Rather than paying the experimenter, we specifically told participants that, before each round of the coin toss, they will be given an option to donate a fixed portion of their endowment (10 points) to CARE International (https://www.care-international.org) in exchange for the predictions.[6]

Finally, the **Combined Intervention (Charity-Full Info)** treatment combines the awareness intervention with altruism framing, allowing us to determine whether the impact of altruistic framing completely offsets the effect of increased awareness.

In the second task of the experiment, participants completed a series of incentivised probability tests, earning 15 points (SG$0.30) for each correct answer, losing 15 points for each incorrect answer, and neither gaining nor losing points for unanswered questions. They also responded to standard control questions and shared their beliefs about karma, locus of control: external, intolerance of uncertainty. We also elicited their risk preferences using the standard

participants per session—the capacity of our lab—not all sessions reached this number due to fewer registrations or no-shows on the day of the experiment.

[6] The total donation to CARE International was SG$72.40 (US$53.81). Of 363 participants in the altruistic framing conditions, 183 (50.4%) donated at least once. To ensure participants were aware that the donation was made and that no deception occurred, we sent them a 'Thank you for your support' email from CARE International two weeks after the experiment.

Holt-Laury multiple price list method (Holt and Laury, 2002). Finally, we incorporated questions on their comprehension of the experiment's purpose.

A total of 750 participants took part in the study[7]. Of those, 349 (46.53%) were males, 384 (51.20%) were females, and 17 (2.27%) preferred not to say. The average age of participants was 20.82 (S.D.=2.12). The average score, out of the possible 10, in the incentivised statistics and quantitative skill test was 6.99 (S.D.=2.43). The average earnings from the betting task was SG$6 (US$4.5), with a standard deviation of SG$3.80 (US$2.87). A few participants earned an incredible amount from the betting task, with maximum earnings of SG$43.60 (US$32.95). In terms of random assignment, 187 participants were allocated to the **Control Group (Expert-No Info)**, 200 to the **Awareness Intervention (Expert-Full Info)**, 175 to the **Altruistic Framing (Charity-No Info)**, and 188 to the **Combined Intervention (Charity-Full Info)**. See Table 1A and Table 2A in the Appendix A for the descriptive statistics of the variables used in the analysis and the behaviour pattern, both overall and across treatment conditions.

4. Theory and Empirical Strategy

4.1. Dynamic-Inference Model

Prior to placing a bet on the outcome of a coin flip in period *t*, each participant observes two sequences of signals whose probability distributions depend on some underlying states (Rabin & Vayanos, 2010; Powdthavee & Riyanto, 2015). The first signal, s_t, is the result of

a fair coin flip, and is common across all subjects in period *t*. For simplicity, we assume that the outcome is binary, s_t (1) and $1 - s_t$ (0). The second signal, a_{it}, reflects the accuracy of an

[7] As recommended by G*Power and stated in our pre-registered document, we originally planned to collect a sample size of 816 participants. However, we were unable to recruit more undergraduate students who would be willing to take part in the experiment and had not already participated in it before. We also required at least 10 people in each session to ensure that a random person receives a streak of correct prediction. Given that we were able to collect 92% of the planned sample, we applied the stoppage rule at 750 participants.

expert's prediction provided to participant i in period t, taking a value of 1 if the prediction matches the coin flip outcome and 0 otherwise. This signal is private and idiosyncratic. For all subjects, the common signal s_t in periods $t = 1, 2, \ldots, T$ is

$$s_t = \mu + \varepsilon_t, \tag{1}$$

and the idiosyncratic signal a_{it} in rounds $t = 1, 2, \ldots, T$ is

$$a_{it} = \varphi + \upsilon_{it}, \tag{2}$$

where μ is the long-run mean of the signals, which is fixed at 0.5, corresponding to the expected outcome of i.i.d. events with binary outcomes. For individuals, the envelopes' long-run predictability of these binary outcomes, denoted as φ, is also assumed a priori to be fixed at 0.5. This assumption reflects the intuitive and straightforward conclusion that, for anyone familiar with basic probabilistic reasoning, there is no systematic way to accurately predict pure random outcomes, such as coin flips. The terms ε_t and υ_{it} are i.i.d. normal shocks with means 0 and variances σ_ε^2 and σ_υ^2, respectively, where both variances are positive ($\sigma_\varepsilon^2, \sigma_\upsilon^2 > 0$). The shock υ_{it} can be interpreted as individual i's expert's luck in predicting s_t in period t. We assume that s_t is determined independently of a_{it}. In a betting market, there are no physical costs incurred by individuals when deciding to switch their bet from s_t to $1 - s_t$ in any given period. However, each individual must pay a fixed fee to an expert if they want to obtain their prediction of the random event in the corresponding period before placing their bet.

Since μ is transparently and universally known to be fixed at 0.5, it should not be influenced by a streak of s_t or $1 - s_t$ observed up to period $t - 1$. However, because μ is fixed at 0.5, participants' betting behaviours will generally be influenced by the gambler's fallacy, i.e., betting against the streak—driven by the belief in mean reversion after having witnessed a streak of s_t or $1 - s_t$.

By contrast, given the ambiguity surrounding how envelopes' predictions are generated, we assume participants' beliefs about the prediction-generating process, φ, to be flexible and influenced by a streak of either a_{it} (correct predictions) or $1 - a_{it}$ (incorrect predictions) observed up to period $t-1$ (Powdthavee & Riyanto, 2015). Specifically, we allow φ, initially fixed at 0.5 in period $t = 1$, to vary across individuals and rounds, evolving dynamically according to the following autoregressive process:

$$\varphi_{it} = 0.5 + \rho(\varphi_{it-1} - 0.5) + \eta_{it}, \tag{3}$$

where $\rho \in [0,1)$ is the reversion rate to the long-run average of 0.5 and η_{ij} is an i.i.d. normal shock with mean 0 and variance σ_η^2 that is independent of v_{it}. As empirically demonstrated by Powdthavee and Riyanto (2015), there is a tendency for subjects to develop a belief in serially correlated variation in φ (i.e., $\rho > 0$) after having observed a streak of correct predictions (a). Given these assumptions, we can write our first set of testable hypotheses on people's betting behaviours as follows:

Hypothesis 1: Following a streak of coin flip outcomes (s_{t-1}) up to period $t-1$, individuals who did not pay for the prediction will exhibit behaviour consistent with the gambler's fallacy, i.e., betting against the streak by choosing $1 - s_t$, in period t. Conversely, when they observe a streak of $1 - s_t$ up to period $t-1$, they will bet on s_t in period t.

Hypothesis 2: Based on the prediction in period t, those who paid for it will place a bet that corresponds to the hot hand of the expert's prediction rather than being influenced by the gambler's fallacy.

Hypothesis 3: Following a streak of correct predictions (a) up to period $t-1$, the hot hand effect will take over, leading individuals to pay to see the expert's prediction for the next period and place their bet according to the prediction.

Hypothesis 4: Following a streak of incorrect predictions $(1 - a)$ up to period $t - 1$, the cold hand effect will take over, leading individuals to pay to see the expert's prediction in the next period and then bet against it.[8]

Both Hypotheses 3 and 4 also imply that

Hypothesis 5: Individuals who pay for a prediction in period t will take the information seriously by placing a higher bet in the corresponding period.

4.2. Intervention to Raise Awareness of the Prediction-Generating Process's Randomness

The assumption that individuals become more inclined to pay for predictions following a streak of correct forecasts reflects real-world behaviour. In practice, individuals often pay "experts" for predictions about inherently uncertain events—such as short-term fluctuation in stock market prices or political outcomes—particularly after witnessing a series of accurate predictions. This tendency persists because individuals assume that experts possess insights into the prediction-generating process; as a result, they interpret the streak as evidence of a "hot hand," even though the previous correct predictions were merely the product of chance.

In this study, we hypothesise that an intervention aimed at raising awareness of the prediction-generating process's randomness can diminish the perceived hot-hand effect from observing a streak of correct predictions, bringing it closer to zero. More formally, we assume that participants' awareness level increases, α, with the intervention, as follows:

$$\alpha_t = \alpha_{t-1} + \beta I_t, \;\; \alpha_t \in [0,1], \;\; \beta > 0, \tag{4}$$

[8] Powdthavee and Riyanto (2015) found the estimated coefficient on the streaks of incorrect predictions to be positive and statistically significant in the final round, j=5. This suggests that participants who observed a streak of incorrect predictions leading up to the final round were inclined to pay for the final prediction, only to then place their bet in opposition to the prediction's recommendation.

where I_t is an intervention to raise participants' awareness of the prediction-generating process's randomness, which takes the value of 1 if an intervention occurs and 0 otherwise. The revised belief evolution with awareness can then take the following form:

$$\varphi_{it} = 0.5 + (1 - \alpha_t) \cdot \rho(\varphi_{it} - 1) + \eta_{it}. \tag{5}$$

Eq. (5) suggests that as awareness, α_t, increases, individuals reduce their belief in streaks. When $\alpha_t = 1$, participants fully understand that predictions are independent, and the predictability belief resets to 0.5. The intervention can also be interpreted as imposing *rationality costs* on participants, whereby they experience cognitive dissonance if they continue to act on predictions despite knowing the randomness underlying the prediction-generating process. This produces the following hypothesis:

> ***Hypothesis 6***: Following an intervention, neither a streak of correct predictions (a) nor a streak of incorrect predictions $(1 - a)$ up to period $t - 1$ will have a positive impact on individuals' demand for the expert's prediction of a binary i.i.d. outcome in period t.

Hypothesis 6 is also consistent with the notion that enhancing financial literacy, statistical literacy, and critical thinking skills can mitigate individuals' vulnerability to financial fraud (see, e.g., Lusardi & Mitchell, 2014; Gamble et al., 2015) and reduce overreliance on experts (Kelly et al., 2012; Vasconcelos et al., 2023).

B. Shifting the Framing from Experts to Altruism

Eq. (5) suggests that increasing individuals' awareness in the prediction-generating process can reduce their inclination to pay for what could only be described as useless information. However, we further posit that, even with efforts to raise awareness of the randomness underlying the predictions, individuals may continue to exhibit behaviour consistent with a belief in streaks of correct outcomes if the framing shifts from expertise to altruism. This hypothesis builds on psychological research suggesting that individuals are more likely to engage in altruistic behaviour when confronted with the outcomes of significant events beyond their control (Risen & Gilovich, 2008; Converse et al., 2012). Furthermore, drawing on the illusion of control theory (Langer, 1975), we hypothesise that individuals believe a streak of luck will continue as long as they sustain altruistic and pro-social behaviour (Burger & Lynn, 2005; Pronin et al., 2006).

To clarify our framework, we assume that even with full awareness of the randomness underlying the prediction-generating process, individuals continue to engage with predictions for two key reasons:

1. **Altruistic motivation**: Individuals derive intrinsic satisfaction from the act of altruism.
2. **Streak-influenced motivation**: Streaks of correct predictions continue to influence individuals; however, rather than being driven solely by belief in the predictive ability of future i.i.d. outcomes, they reinterpret these streaks as a rationale for contribution. In this context, donating functions symbolically, akin to an investment in *good karma*, with the aim of sustaining positive outcomes.

We assume individuals engage in altruistic behaviour if the total utility from doing so exceeds their baseline utility, given by

$$U_A(A_t, \varphi_{it}) = u \cdot A_t + \upsilon \cdot \varphi_{it} - \tau(\alpha_t), \qquad (6)$$

where $u \cdot A_t$ represents the altruistic utility derived from altruistic behaviours, such as donating to a charity. This utility may include the warm glow utility from the act of donating or the satisfaction derived from seeing the donation benefit the recipient (Andreoni, 1989).

Here, $\upsilon \cdot \varphi_{it}$ reflects the influence of streak-based belief in predictability, even under awareness; and $\tau(\alpha_t)$ represents the rationality cost, which increases with awareness.[9] Subjects then decide to donate if:

$$U_A(A_t, \varphi_{it}) > \pi(0.5), \tag{7}$$

where $\pi(0.5)$ is the baseline utility a participant expects if they do not behave altruistically. This produces the following testable hypothesis:

> ***Hypothesis** 7*: Despite the intervention aimed at raising awareness of the prediction-generating process, a shift in framing increases the likelihood that individuals will engage in altruistic behaviour in exchange for a prediction in period t, following a streak of either correct or incorrect predictions up to period $t-1$.

5. Empirical Strategy

5.1. Testing Participants' Beliefs in the Gambler's Fallacy (H1 and H2)

To test whether participants' betting behaviours are generally influenced by the gambler's fallacy across all treatment conditions, we estimate for round j the following betting equation:

$$\begin{aligned} BH_{ij} = \alpha_j + \beta_{1j}SH_{j-1} + \beta_{2j}ST_{j-1} + \delta_j P_{ij} + \gamma_{1j}\left(SH_{j-1} \times P_{ij}\right) \\ +\gamma_{2j}\left(ST_{j-1} \times P_{ij}\right) + \textstyle\sum_{k=1}^{K} \mu_k TR_{ik} + \rho_j BH_{ij-1} + X_i'\sigma + \varepsilon_{ij}, \end{aligned} \tag{8}$$

where BH_{ij} is an indicator variable equal to 1 if individual i bets on head in round j, and 0 otherwise. SH_{j-1} is a dummy variable indicating a streak of heads up to round $j-1$, while

[9] We can consider this term of rationality as a factor that heightens cognitive dissonance. As awareness grows, the cognitive dissonance between the desire to invest in good deeds to maintain the streak (+ve) and the realization that the predictions are ineffective (-ve) also intensifies.

ST_{j-1} represents a streak of tails up to same round. P_{ij} is a dummy variable denoting whether individual i either paid for or donated to receive the prediction in round j. TR_{ik} is a set of dummy variables representing the randomised treatments, k, assigned to individual i. BH_{ij-1} is a dummy variable denoting whether individual i bet on head in the previous round, which captures the inertia in betting behaviour. X_i' is a vector of control variables, and ε_{ij} is the error term. According to Hypothesis 1, we expect $\beta_{1j} < 0$ and $\beta_{2j} > 0$. We will also estimate Eq. (8) separately for participants who received "head" and those who received "tail" as the prediction in the corresponding round. For those who received "head" as the prediction, we expect $\gamma_{1j} > 0$. Conversely, for those who received "tail" as the prediction, we anticipate $\gamma_{2j} < 0$.

5.2. *Testing the Treatment Effects as Moderators of the Streak Effects (H3-H4, H6-H7)*

To test the effectiveness of the awareness intervention and the counterbalancing effect of the altruistic framing, we estimate the following buying/donating equation:

$$P_{ij} = a_j + b_{1j}SC_{ij-1} + b_{2j}SI_{ij-1} + \sum_{k=1}^{K} c_k TR_{ik} + \sum_{k=1}^{K} d_{1jk}\left(SC_{ij-1} \times TR_{ik}\right) + \textstyle\sum_{k=1}^{K} d_{2jk}\left(SI_{ij-1} \times TR_{ik}\right) + X_i'f + \epsilon_{ij}, \qquad (9)$$

where P_{ij} is individual i either paying or donating for the prediction in round j. SC_{ij-1} is a dummy variable that represents a streak of correct predictions up to $j-1$. SI_{ij-1} is a dummy variable that represents a streak of incorrect predictions up to $j-1$. Let $TR_i^{Control}$ be the reference group, we anticipate $b_{1j} > 0$. We also expect $b_{2j} > 0$ if—and only if—participants pay/donate for the prediction and then bet against the streak. We also anticipate the main treatment effects for the Altruistic Framing, $c^{Altruistic}$, and the Combined

Intervention, $c^{Combined}$, to be positive due to the altruistic motivation in these treatments, i.e., $u \cdot A_t > 0$ in Eq. (6).[10]

With respect to the interaction terms, we expect $d_1^{Awareness} < 0$ and $d_2^{Awareness} < 0$ due to the awareness effect. Conversely, we anticipate $d_1^{Altruistic} > 0$ because of the streak-influenced motivation, i.e., $\upsilon \cdot \varphi_{it} > 0$ in Eq. (6). If the size of the awareness effect is larger than the effect of streak-influenced motivation, then $d_1^{Combined} \leq 0$. However, if streak-influence motivation dominates, then $d_1^{Combined} \geq 0$. If participants plan to bet against the streak of incorrect predictions, then we can also expect $d_2^{Altruistic} > 0$. Additionally, the sign of $d_2^{Combined}$ is likely to align with that of $d_1^{Combined}$ under the same betting behaviour.

5.3. Testing Whether Participants Bet the Same or Against the Predictions (H2-H4)

To test whether the subjects who received the predictions bet according to or against the predictions, we estimate the following equation:

$$SP_{ij} = \theta_j + \tau_{1j} SC_{ij-1} + \tau_{2j} SI_{ij-1} + \phi_{1j}\left(SC_{ij-1} \times P_{ij}\right)$$
$$+\phi_{2j}\left(SI_{ij-1} \times P_{ij}\right) + \textstyle\sum_{k=1}^{K} \varpi_k TR_{ik} + X_i' o + u_{ij}, \qquad (10)$$

where SP_{ij} is a dummy variable that takes the value of 1 if the individual bets the same as the predicted envelope in round *j* and 0 otherwise. The hypothesis is that subjects who purchased or donated for the prediction in round *j* after witnessing a streak of correct predictions will believe in the hot hand and bet according to the envelope, $\phi_{1j} > 0$. In contrast, subjects who purchased or donated for the prediction in round *j* after witnessing a streak of incorrect predictions will believe in the cold hand and bet against the envelope, $\phi_{2j} < 0$. We also

[10] Note that we deviated from the pre-registered analysis plan by excluding the lagged dependent variable, Pij-1 , from the regression. This decision was based on the understanding that the participant's previous decision to purchase or donate for a prediction would already be influenced by the streaks of correct or incorrect predictions up to j-2. Since these streak effects are incorporated in the streaks up to j-1, including the lagged dependent variable would likely result in an underestimation of the influence of streaks up to j-1 on the decision to purchase or donate in round j.

estimate a three-way interaction model between the streaks, previous purchase/donation, and treatment dummies to test whether participants' betting behaviours following the purchase/donation vary by treatment and illustrate the results as predicted margins.

5.4. Testing the Buying Predictions on Betting Exuberance (H5)

To investigate whether participants who purchased or donated for predictions treated them seriously by placing larger bets, we estimate the following equation for bet amounts:

$$AB_{ij} = \mu_j + \pi_j P_{ij} + \sum_{k=1}^{K} \zeta_k TR_{ik} + X_i'\vartheta + \nu_{ij}, \tag{11}$$

where AB_{ij} denotes the amount of endowment that individual i allocated to their bet in round j. According to Hypothesis 7, participants who purchased or donated for prediction in round j are expected to place larger bets than those who did not, i.e., $\pi_j > 0$. In subsequent analyses, we further examine whether participants' bet amounts differ across treatments and illustrate them as predicted margins.

5.5. Estimator and Control Variables

We estimate all the regression equations mentioned above using a linear probability model with robust standard errors. This enables the coefficients to be directly interpreted as marginal effects. Depending on the outcome variable, the control variables, X_i', may include gender, age, endowment in the current round, the proportion of correct answers in an incentivised statistical and quantitative skill test, a dummy variable representing whether the individual made a wrong bet in the previous round, a dummy variable representing whether the individual followed a fixed betting strategy by betting either head or tail in every round, and factor scores of the individual's belief in karma, authority, and tolerance of uncertainty.

6. Results

6.1. Are Participants' Betting Behaviours Influenced by the Gambler's Fallacy?

One of the initial findings reported by Powdthavee and Riyanto (2015, p.263) was that participants exhibited betting behaviours consistent with the gambler's fallacy. Specifically, they were 28 to 31 percentage points less likely to bet on heads in round j after observing a streak of heads up to $j-1$ (where $j=3$ and 4). Conversely, they were 17 percentage points more likely to bet on heads in round j after witnessing a streak of tails leading up to round $j-1$ (where $j=3$ and 4). These findings were based on 118 observations of two consecutive heads and 152 observations of two consecutive tails following the first two rounds, as well as 23 observations of three consecutive heads and 48 observations of three consecutive tails following the first three rounds.

In the current experiment, there were 191 observations of two consecutive heads and 149 observations of two consecutive tails after the first two coin flips; 131 observations of three consecutive heads and 52 observations of three consecutive tails after the first three coin flips; and 74 observations of four consecutive heads and 12 observations of four consecutive tails after the first four coin flips. To test whether participants' betting behaviours align with the gambler's fallacy following a streak of heads or tails, we estimate Eq. 8 and present the results in Table 1. The dependent variable in this model is a binary indicator that takes the value of 1 if the participant placed a bet on heads and 0 if they bet on tails in round j. We estimated the regression model for rounds $j = 3, 4, 5$.

First, column 1 of Table 1 provides evidence that participants exhibit betting behaviour consistent with the gambler's fallacy after observing a short streak of either heads or tails. Participants were, on average, 15.6 percentage points less likely to bet on heads in round 3 after seeing two consecutive heads in the first two rounds, with this result being highly significant (*$p<0.001$*). Conversely, they were around 6.5 percentage points more likely to bet on heads in round $j = 3$ following two consecutive tails in the first two rounds, although the estimate is not statistically significantly different from zero. This replicates Powdthavee and Riyanto's (2015) original findings and aligns with Rabin and Vayanos's (2010) theory, which suggests that people are more likely to exhibit behaviour consistent with the gambler's fallacy after observing a short streak of signals.

However, as the streak of either heads or tails becomes longer, there is evidence that participants begin to exhibit behaviour consistent with the hot hand fallacy. While a streak of three consecutive heads has no significant effect on participants' likelihood of betting on heads in round $j = 4$ (see column 4), participants are significantly more likely to bet on heads in round $j = 5$ after observing four consecutive heads in the first four rounds (see column 7). The shift from the gambler's fallacy—betting against the streak—after observing a short streak to the hot hand fallacy—betting with the streak—as the streak lengthens is consistent with Rabin and Vayanos (2010). This is also the first indication that participants may be inclined to believe in the hot hand of coins despite knowing that coin flip outcomes exhibit i.i.d. properties.

Did the betting behaviours differ for participants who bought or donated in exchange for the predictions? Conditioning on the prediction in round j being heads, we observe from round $j = 3$ an offsetting effect to the gambler's fallacy among participants who purchased or donated for the prediction after recently observing two consecutive heads: these individuals were $-0.203 + 0.279 + 0.120 = 0.196$ $[S.E. = 0.110], p = 0.077$ or 19.6 percentage points more likely to bet on heads, even when the previous two outcomes had also been heads; see Column 2. Conditioning on the prediction in round j being tails, a similar offsetting effect to the gambler's fallacy emerges among participants who bought or donated for the prediction in round $j = 3$ after observing two consecutive tails. These individuals were $0.076 - 0.394 - 0.161 = -0.478$ $[S.E. = 0.117], p < 0.000$ or 47.8 percentage points less likely to bet on heads, even when the preceding two outcomes had been tails; see Column 3.

On the other hand, there is evidence of an offsetting effect to the hot hand fallacy among participants who purchased or donated for the prediction in round $j = 5$ after witnessing a streak of four consecutive heads or tails. For example, conditioned on the prediction in round $j = 5$ being tails in Column 9, participants were $0.092 - 0.377 - 0.115 = -0.399$ $[S.E. = 0.202], p = 0.048$ or 39.9 percentage points less likely to bet on heads, even after observing a streak of four consecutive heads in the first four rounds; see Column 5. Overall, these estimates, which are consistent with H1, H2, and the findings of Powdthavee and Riyanto (2015), suggest that individuals who purchased or donated for predictions were significantly more inclined to use these predictions as a guide for their betting decisions rather than relying on intuition influenced by the gambler's fallacy or the hot hand fallacy.

6.2. Under what conditions would people pay or donate for useless predictions?

In what follows, we examine whether: i) people are generally more inclined to pay for predictions after observing a streak of correct (or incorrect) predictions; ii) demand for predictions approaches zero following an awareness intervention; and iii) reframing the act from 'paying for predictions' to 'donating to a charity for predictions' fully mitigates the effect of complete information.

Figure 1 provides a first pass to these questions. Looking across treatments and rounds, we can see raw data evidence that:

- Participants in the **Control Group (Expert-No Info)** who observed a streak of correct predictions up to round $j - 1$ were, on average, significantly more likely to purchase a prediction in round j. This replicates the findings of Powdthavee and Riyanto (2015) and is consistent with H3.
- In the **Control Group (Expert-No Info)**, the proportion of participants who purchased the prediction increased with each consecutive streak of correct predictions. For

instance, 22.2% of participants who observed a streak of two correct predictions opted to purchase the prediction in round $j = 3$. This proportion rose to 27.3% for those who observed a streak of three correct predictions and paid in round $j = 4$, and further increased to 36.3% for those with a streak of four correct predictions in round $j = 5$.

- In the **Awareness Intervention (Expert-Full Info)** group, we can see that participants became less inclined to follow the streak of correct predictions as the streak lengthened. For instance, only 12% of participants who observed a streak of three correct predictions purchased the prediction in round $j = 4$, and 16% of those who observed a streak of four correct predictions paid for the prediction in round $j = 5$. The wide standard errors indicate that these proportions are not statistically significantly different from zero, offering initial raw data evidence that the awareness intervention effectively reduced participants' beliefs in the hot hand effect and diminished their demand for useless predictions. The results are also consistent with H6.
- Consistent with the concept of the illusion of control and karmic investment (H7), the **Altruism Framing (Charity-No Info)** group showed the highest proportion of participants donating to acquire predictions following a streak of correct predictions. Specifically, 28.8% of participants donated after a streak in round $j = 2$, increasing to 40% in $j = 3$, 68.4% in $j = 4$, and reaching 90% in $j = 5$.
- In the **Combined Intervention (Charity-Full Info)** treatment, there is evidence that participants continued to believe in the hot hand effect despite having complete information about the prediction-generating process's randomness. For instance, 27.9% of participants who observed a streak of two correct predictions donated for a prediction in round $j = 3$. This proportion rose to 31.6% in round $j = 4$ after observing three consecutive correct predictions and further increased to 45.5% in round $j = 5$ after four consecutive correct predictions. These figures provide the first evidence that

a shift in the framing from 'paying for predictions' to 'donating for predictions' can completely offset the effect that full awareness has on the demand for useless predictions.

- Compared to the hot hand effect, the cold hand effect, i.e., paying or donating for predictions after observing a streak of incorrect predictions, is relatively weaker across all four treatments. Hence, we do not have strong evidence to partially support H4.

We analyse and report Eq. 9's regression results of the interaction model in Table 2. Overall, the results are predominantly consistent with the previous raw data evidence. For example, in round $j = 4$, we can see that the coefficient on "all predictions up to $j - 1$ had been correct" is positive and statistically significantly different from zero at the 5% level. Specifically, a streak of three correct predictions increased the probability of paying for the prediction in round j for participants in the **Control Group (Expert-No Info)** by 18 percentage points; see Column 3. By contrast, the implied effect of having observed a streak of three correct predictions for the average participant in the **Awareness Intervention (Expert-Full Info)** treatment is small and statistically insignificantly different from zero: $-0.032 + 0.180 - 0.089 = -0.003$ $[S.E. = 0.046], p = 0.952$. This finding suggests that providing participants with complete information was successful in reducing their belief in the hot hand effect to zero in this round.

Conversely, the implied effect of having observed a streak of three correct predictions for an average participant in the **Combined Intervention (Charity-Full Info)** condition is positive, sizeable, and statistically significantly different from zero at the 5% level. For people in this group, a streak of three correct predictions increased the probability of donating in round $j = 4$ by 23.5 percentage points ($0.049 + 0.180 + 0.007 = 0.235$ $[S.E. = 0.114], p = 0.040$). This result implies that, despite the awareness intervention, a shift in framing increases the likelihood that individuals will continue to exhibit behaviour consistent with the hot hand fallacy following a streak of correct predictions up to period $t-1$. This finding is consistent with H7.

To better illustrate how different treatments impact the influence of streaks on the demand for predictions, Figure 2 displays the predicted margins of streaks on individuals' willingness to pay or donate for predictions across different treatments, drawing on the estimates from Table 2. Here, we can see that each predicted margin of the streak of correct predictions is the most positive and statistically significant for participants in the **Altruistic Framing (Charity-No Info)** groups in each round. By contrast, we can also see that the predicted margin of the streak of correct predictions is statistically insignificantly different from zero in the **Awareness Intervention (Expert-Full Info)**. Finally, it is evident that, even with full awareness of the predictions' randomness, demand for predictions in the **Combined Intervention (Charity-Full Info)** remains positive and statistically significantly different from zero after participants observed a streak of correct predictions.

6.3. Did participants treat the paid-for or donated-for predictions seriously by betting according to the predictions?

An interesting question for participants who either purchased or donated for predictions is whether they bet according to or contrary to the predictions they received. If participants believe in the hot hand effect of the predictions, the hypothesis is that they will consistently place their bets in line with the paid-for or donated-for predictions for each round. Similarly, if participants believe in the cold hand effect of the predictions, then they will consistently place their bets against the paid-for or donated-for predictions for each round.

To examine this, Table 3 presents the regression results for Eq. 10, where the dependent variable is a binary indicator that takes the value of 1 if the participant places the same bet as the prediction and 0 otherwise. Looking across columns, we can see strong evidence from the implied effects in each round that participants who purchased or donated for the prediction in round j were significantly more likely to bet in line with the prediction after observing a streak of correct predictions up to round $j-1$. This is consistent with the hot hand fallacy, i.e., H3. However, statistically significant evidence of behaviour consistent with the cold hand fallacy (H4)—where participants purchase or donate for the prediction after observing a streak of incorrect predictions but then subsequently bet against it—appears only in round $j=4$.[11] Here, we can see that a streak of incorrect predictions reduced the probability of betting in alignment with the prediction among participants who paid or donated for it by 30 percentage points ($\mathit{0.043}+0.275-0.621=-0.300$ $[S.E.=132], p=0.023$); see Column 3. We can also see from the predicted margins illustrated in Figure 1A in the Appendix that the probabilities of betting according to the predictions are much closer to 0.5 for those who did not pay or donate for them.

As an exploratory analysis to understand why the cold hand effect does not appear consistently across rounds, we estimated a three-way interaction model (Treatment × Decision to purchase/donate in round j × Streaks of predictions) to examine whether the effect varies by treatment. We then calculated the predicted margins, which we illustrated in Figure 3. Here, we observe some evidence that participants in the **Combined Intervention (Charity-Full Info)** group who donated for predictions were significantly more likely in every round to bet in accordance with the prediction in round j, even after witnessing a streak of incorrect predictions up to round $j-1$. One possible explanation for this behaviour might be as follows. Firstly, it is essential to recall that these individuals are fully aware that the predictions are entirely random, with any streaks of correct or incorrect predictions arising purely by chance.

[11] The implied effect of paying/donating for prediction and having received a streak of incorrect predictions up to round 4 is -0.090, though statistically insignificantly different from zero. However, given that very few people (N=7) received four consecutive predictions and paid/donated for the final round's prediction, the statistically insignificant result could be a Type II error.

Secondly, they were in a condition that provided opportunities to "turn their luck around" by investing in karma. Having recently experienced a series of "bad luck" with a streak of incorrect predictions, they might believe that their decision to donate for a prediction will result in a correct prediction in the current round.

6.4. Did people bet more after paying or donating for predictions?

Another way to test whether people took the predictions seriously is to assess whether they placed higher bets after paying or donating for them. Table 4 investigates this by presenting the regression estimates from Equation 11, where the dependent variable is the logarithm of the bet amount in round j.

Looking across columns, we can see that participants who purchased or donated for the prediction in round j also placed a higher bet than those who did not purchase or donate for it. For instance, participants who paid or donated for the prediction in round $j = 3$ placed bets approximately 27.1% higher than those who did not. This figure increased to 28% in round $j = 4$ and 40.3% in round $j = 5$. This evidence suggests that, in line with H5, participants who paid or donated for the predictions not only treated them seriously in their betting behaviour but also tended to place higher bets as a result.

Finally, Figure 4 explores whether the predicted margins of the effects of predictions on bet amounts differ across treatments. Here, we observe that bet amounts are generally higher among participants who paid or donated for the prediction compared to those who did not across all treatments, suggesting that they generally trusted the predictions they received before placing their bets.

7. Discussion and Conclusion

When Powdthavee and Riyanto's (2015) working paper first appeared online in 2012, it attracted considerable media attention for an economics paper about coin flipping.[12] This was highly unusual, though perhaps understandable, considering that one of the paper's key results was that people were willing to pay for coin flip predictions after observing a streak of correct predictions live in the laboratory. This surprising finding captured many people's imagination, as it challenges rational choice theory, which assumes that utility-maximising agents would never allocate resources to obtain something they recognise as obviously worthless.

One possible explanation for why participants in Powdthavee and Riyanto's study fell prey to the hot hand fallacy after observing a streak of correct predictions of fair coin flips is the ambiguity surrounding the processes behind prediction generation. Despite being fully aware that the outcome-generating processes, such as coin flips, were random, they could not have been as confident that the processes generating predictions of these outcomes were also random. This is consistent with most expert predictions, where consumers typically lack the necessary insight to know how these predictions are generated, especially when the likelihood of a streak of correct predictions is highly improbable. Had they been aware, for instance, that the predictions were generated using the split prediction system, it is doubtful whether they would have continued to pay for these blatantly useless forecasts—even after witnessing a sufficiently long streak of live, accurate predictions.

This paper builds upon the foundation laid by Powdthavee and Riyanto (2015). Specifically, we adopt their experimental framework to replicate and reassess their findings from over a decade ago. The replication findings reaffirm that participants are willing to pay

[12] The working paper's results were discussed at length on the Freakonomics blog (www.freakonomics.com/blog/ ("Paying for 'Transparently Useless Advice,'" June 6, 2012), *New Statesman* ("If You've Got Lucky, It's Easy to Convince People You're a Sage," June 6, 2012), *The Economist* ("Buttonwood: Not So Expert," June 9, 2012), *The Financial Times* ("Heads or Tails? Just Don't Bet on It," June 15, 2012), and *The Wall Street Journal* ("People Will Pay for 'Transparently Useless Advice' about Chance Events," June 18, 2012), among others.

for predictions of random events after witnessing a streak of accurate predictions, even when they are fully aware that coin flips are inherently random.

We then extend their work by addressing the first premise of our study: assessing whether providing individuals with complete information about the underlying split prediction system significantly diminishes their demand for useless predictions. Our findings confirm this hypothesis. When participants are fully informed about the mechanism behind the prediction generation, their willingness to pay for these predictions decreases significantly even after observing a sufficiently long streak of accurate forecasts, e.g., four consecutive correct predictions of fair coin flips.

This suggests that complete transparency about the prediction-generating process is crucial in curbing people's willingness to pay for—and rely on—forecasts of random events that are accurate merely by chance. Our results indicate that simply being aware of the randomness of outcomes is insufficient to deter individuals from seeking and paying for useless advice. A deeper understanding of the randomness inherent in the prediction process itself is equally essential.

The second premise of our study was to explore the conditions under which transparency about the underlying prediction-generating processes might prove ineffective. Drawing on psychological theories such as the illusion of control (Langer, 1975) and karmic investment (Risen & Gilovich, 2008; Converse et al., 2012), we investigated whether reframing the act from 'paying for predictions' to 'donating for predictions' would sustain individuals' demand for these useless predictions after observing a streak of correct forecasts.

Our findings indicate that it did indeed sustain—and surprisingly even significantly increase—the demand for predictions. For example, 90% of participants who observed a streak of four accurate predictions chose to donate for the prediction in the final round. Based on

Table 2's estimates, this is almost 80 percentage points higher than participants who received a mixed pattern of predictions. This willingness to donate following a streak of correct predictions remained substantial, even when individuals were fully aware that the split prediction system was used to generate the prediction patterns.

These findings suggest that the act of donating may trigger psychological mechanisms that mitigate the deterrent effect of transparency in the prediction-generating processes on people's willingness to pay for predictions. Even when participants were aware that the predictions were generated randomly, reframing the transaction as a donation seemed to preserve their belief in the value of the predictions. This effect could arise from individuals perceiving that performing a good deed, such as donating, increases their likelihood of experiencing positive events—a form of karmic investment—or from a misplaced sense of control over inherently random outcomes.

There are two main policy implications to our results. The first is that improving citizens' statistical literacy may not be enough to protect them from falling victim to potential prediction scams—such as stock market prediction scams, betting tipster frauds, and cryptocurrency scams—where initial rounds often feature improbable streaks of correct predictions generated by split prediction systems[13]. Our results suggest that a more effective policy would be to raise public awareness about the prediction-generating processes these businesses may use and the considerable role that luck, rather than skill, often plays in creating streaks of correct predictions in inherently random outcomes. It may also be essential to educate people on how scammers frequently exploit social media platforms to conduct these schemes.

[13] A recent and well-known example of a stock market prediction scam involves NatWest Forex Scammer Gurvin Singh and his "forex guru" schemes on Instagram. He sent different forex trading predictions to various followers using a split prediction system. One group would receive a prediction for a currency pair to increase, while another group would receive a prediction for it to decrease. After a currency moved, he would only publicise the "correct" predictions to create the impression of accurate foresight. Consequently, thousands of people, mostly young adults, invested significant sums in these trading signals, and many ultimately suffered substantial losses. For reference, see https://www.bbc.com/news/articles/cn5z5z753wgo (last accessed November 9th, 2024).

For instance, scammers can use these platforms to segment audiences into different private groups or direct messaging lists, allowing them to send varying predictions to each group and manage the process more effectively.

Secondly, while evidence suggests that providing the general public with complete information about how predictions are made can help reduce beliefs in the hot hand effect, policymakers should also be mindful of the conditions under which this broad transparency approach may prove ineffective or, in some cases, even backfire. One hypothesis is that by informing participants that both outcomes and predictions are randomly generated, we may have inadvertently generated a demand for control from other external sources. Prediction providers could strategically leverage this demand through a 'charity-linked marketing' approach, pledging a portion of their earnings to specific charities or causes. While similar methods have been explored previously (e.g., Elfenbein and McManus, 2010; Owens et al., 2018), our study highlights that a streak of correct predictions can significantly boost sales of charity-linked predictions by enhancing consumers' willingness to invest in good deeds to sustain the streak. Consequently, certain regulations governing charity-linked prediction products or services may be warranted.

There are several possible objections to our findings. The first is that the cost associated with each prediction—10 points (SG$0.20)—was too low. Given that participants played with house money, it is not surprising that they would spend a small portion of their endowment on predictions for fun. However, since participants could view the unpurchased or undonated predictions after each round's coin flip for free, there was no incentive to pay the fee, irrespective of how small it was. Furthermore, if participants did not trust the predictions they paid for or donated for fun, they would not have placed their bets that aligned with the predictions or chosen to place a larger bet only after having paid or donated in the corresponding round.[14]

Second, the illusion of control and karmic investment may not be the sole mechanisms driving people to donate to a charity in exchange for predictions. We consider this a valid objection. For example, studies on the link between positive emotions and prosocial behaviours suggest that getting a streak of correct predictions may have induced feelings of exuberance or a "feel good" state. This elevated mood can, in turn, increase a person's propensity to be generous or altruistic, leading them to donate (Drouvelis and Grosskopf, 2016). Another potential explanation is reciprocity (Fehr and Schmidt, 2006). Even when aware that the predictions are random, individuals may feel a subconscious obligation to reciprocate after witnessing a streak of correct predictions, prompting them to donate. In both scenarios, we would expect little evidence of individuals consistently aligning their bets with the predictions or increasing their betting amounts after donating for the predictions. However, we find that participants who donated took the predictions seriously, as they not only aligned their bets with the predictions but also tended to increase their betting amounts based on them. These behaviours align more closely with theories of the illusion of control and karmic investment.

Third, the results may not be generalisable to individuals in Western societies, where belief in karma is relatively less prevalent compared to Eastern societies. While this remains an empirical question that requires further replication studies on WEIRD (Western, Educated, Industrialised, Rich, and Democratic) samples to be conclusive, studies examining the behavioural implications of karmic beliefs among individuals in the UK and US indicate that

[14] It is also worth noting that although the prediction fee was small, the prediction providers can stand to gain substantial revenue from selling them at a low price. In the context of this experiment, there were 750 people across 5 rounds = 3,750 decisions. Before making these decisions, people paid for envelopes 387 times and donated for envelopes 363 times. Each envelope cost 10 points = SG$0.2. This implies that experts would have received SG$77.4 (US$58.4), whilst the charity would have received SG$72.6 (US$54.7). It might appear cheap to the consumers, but the revenue from selling these worthless predictions is substantial compared to the cost of producing them.

karmic investment is not a phenomenon unique to Eastern societies (Converse et al., 2012; Wiese, 2023). It is worth noting that although our sample primarily consisted of young Singaporeans (aged 18–28), it embodies most of the WEIRD characteristics—namely, being educated, industrialised, rich, and democratic.

Fourth, the experimental setup oversimplifies real-world situations, such as finance or sports, where events are often perceived as having at least some level of predictability, even if minimal. This is not necessarily a strong objection, as, similar to the counter-arguments presented in Powdthavee and Riyanto (2015), belief in the hot hand effect after a streak of correct predictions is likely to be stronger in real-world settings than in a controlled laboratory environment. In everyday situations, the line between luck and skill in predicting future events is often more ambiguous than in a laboratory setting, where predictions usually focus on outcomes that are universally recognised as random, such as fair coin flips, as discussed in this paper. However, we acknowledge that explaining how predictions are made in real-world contexts may be more challenging than describing the split predictions system used in this study. Future research should return to investigate whether explaining how predictions of future stock price movements or sports outcomes are made, as well as outlining the limitations and risks associated with these systems, can reduce people's overreliance on such predictions.

Fifth, the experimenter demand effect could potentially explain why participants chose to pay or donate for seemingly useless advice. However, if this effect were the sole driver of these decisions, we would expect uniform purchasing and donating rates across all groups, regardless of prior prediction accuracy. In contrast, our findings reveal distinct patterns in participants' purchasing and donating behaviours, which had been primarily influenced by streaks of previous correct predictions.

In conclusion, this paper experimentally investigates when transparency about the processes that generate predictions helps to reduce people's beliefs in the hot hand of useless predictions and when it does not. We hope our findings can contribute to shaping policies on statistical and financial literacy, as well as informing potential market regulations concerning charity-linked marketing practices related to prediction-based products or services.

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Figure 1: **The coin tree (source: Powdthavee and Riyanto, 2015)**

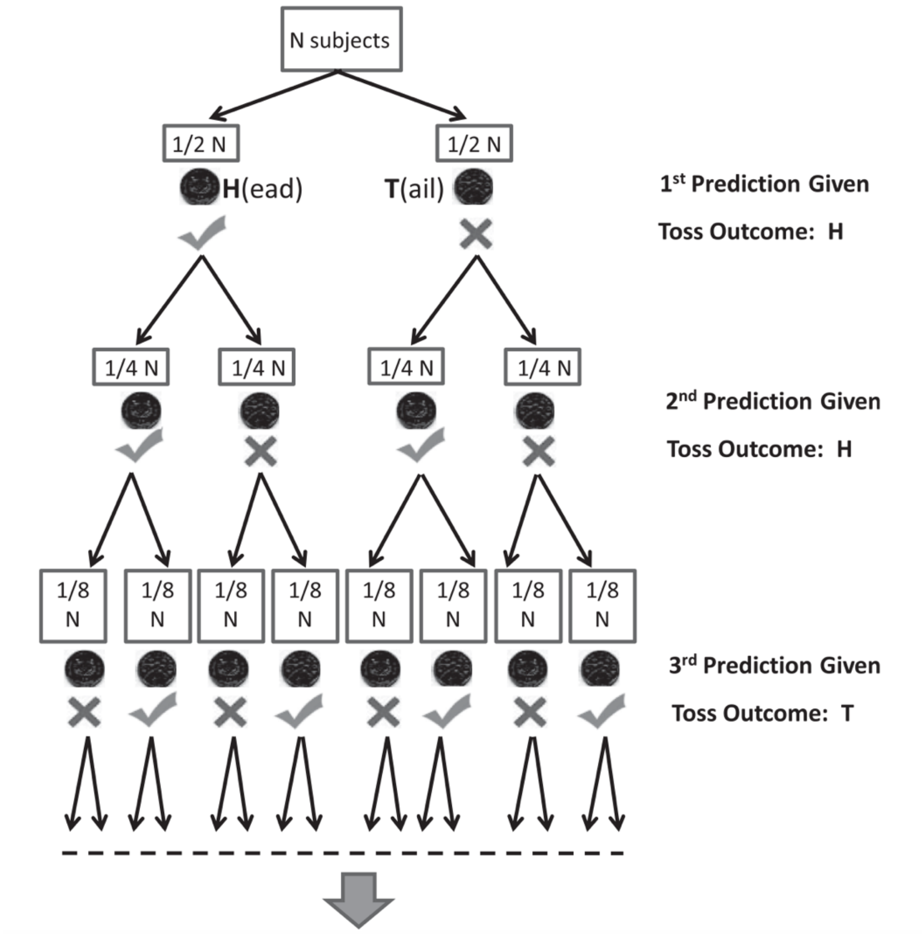
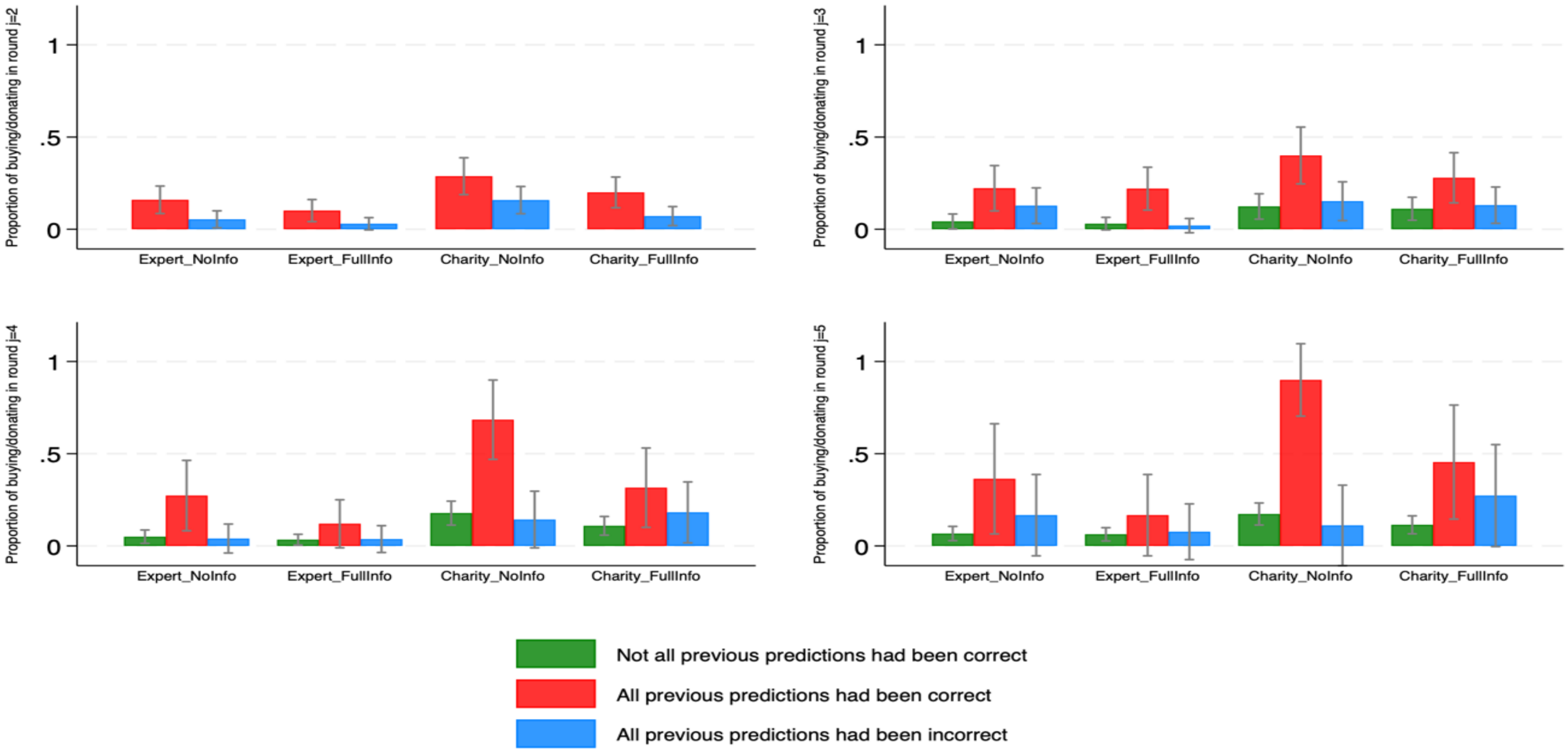


Table 1: Do People Follow the Gambler's Fallacy or the Hot Hand Fallacy? A linear probability model of betting behaviour following a streak of signals

Dependent variable: Betting Head in Round j	$j=3$			$j=4$			$j=5$		
	(1) All	(2) Prediction =H	(3) Prediction =T	(4) All	(5) Prediction =H	(6) Prediction =T	(7) All	(8) Prediction =H	(9) Prediction =T
A streak of H up to $j-1$	-0.156***	-0.203**	-0.199**	-0.0236	-0.0753	0.111	0.139*	0.248**	0.0926
	(0.0450)	(0.0708)	(0.0668)	(0.0529)	(0.0712)	(0.0887)	(0.0605)	(0.0793)	(0.102)
A streak of T up to $j-1$	0.0649	0.0652	0.0765	-0.00943	0.0873	-0.105	-0.172	-0.0453	-0.360
	(0.0488)	(0.0734)	(0.0689)	(0.0757)	(0.0979)	(0.127)	(0.149)	(0.216)	(0.192)
Purchased/donated for round j's prediction		0.279***	-0.394***		0.249***	-0.287**		0.202**	-0.377***
		(0.0811)	(0.0820)		(0.0609)	(0.101)		(0.0670)	(0.0762)
A streak of H up to $j-1$ × Purchased/donated for round j's prediction		0.120	0.158		-0.251	-0.157		-0.399	-0.115
		(0.145)	(0.159)		(0.231)	(0.193)		(0.294)	(0.231)
A streak of T up to $j-1$ × Purchased/donated for round j's prediction		-0.392	-0.161		0.0627	0.0266			
		(0.238)	(0.146)		(0.111)	(0.252)			
Treatments									
Expert-Full Info	0.107*	0.0919	0.118	-0.0409	-0.0115	-0.0905	0.0137	-0.0289	0.0677
	(0.0506)	(0.0739)	(0.0692)	(0.0522)	(0.0689)	(0.0799)	(0.0509)	(0.0675)	(0.0767)
Charity-No Info	0.0871	0.101	0.0633	0.00688	0.0195	0.00472	0.0665	0.0569	0.147
	(0.0522)	(0.0731)	(0.0732)	(0.0520)	(0.0675)	(0.0827)	(0.0514)	(0.0691)	(0.0760)
Charity-Full Info	0.124*	0.0768	0.142*	-0.0438	-0.0831	0.00855	0.00777	0.0264	0.0243
	(0.0523)	(0.0755)	(0.0710)	(0.0537)	(0.0704)	(0.0814)	(0.0525)	(0.0693)	(0.0789)
Implied effect of streaks on betting H by the decision to purchase/donate for round j's prediction									
A streak of H up to $j-1$ and purchased/donated for round j's prediction		0.196 (0.110)	-0.434*** (0.129)		-0.076 (0.217)	-0.332* (0.152)		0.052 (0.278)	-0.399* (0.202)
A streak of T up to $j-1$ and purchased/donated for round j's prediction		-0.048 (0.218)	-0.478*** (0.117)		0.399*** (0.065)	-0.365 (0.207)		0.156 (0.229)	
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	750	351	399	750	428	322	750	409	341
Adjusted R^2	0.030	0.064	0.107	-0.001	0.025	0.036	0.006	0.011	0.079

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors are in parentheses. The dependent variable is an indicator variable that takes the value of 1 if the individual places a bet on heads (H) in round *j*. P=H indicates that the prediction in round *j* is head. P=T indicates that the prediction in round *j* is tail. Estimates of the control variables are reported in Table 3A in the Appendix.

Figure 1: Proportion of people purchasing or donating for predictions by treatments and types of prediction streaks



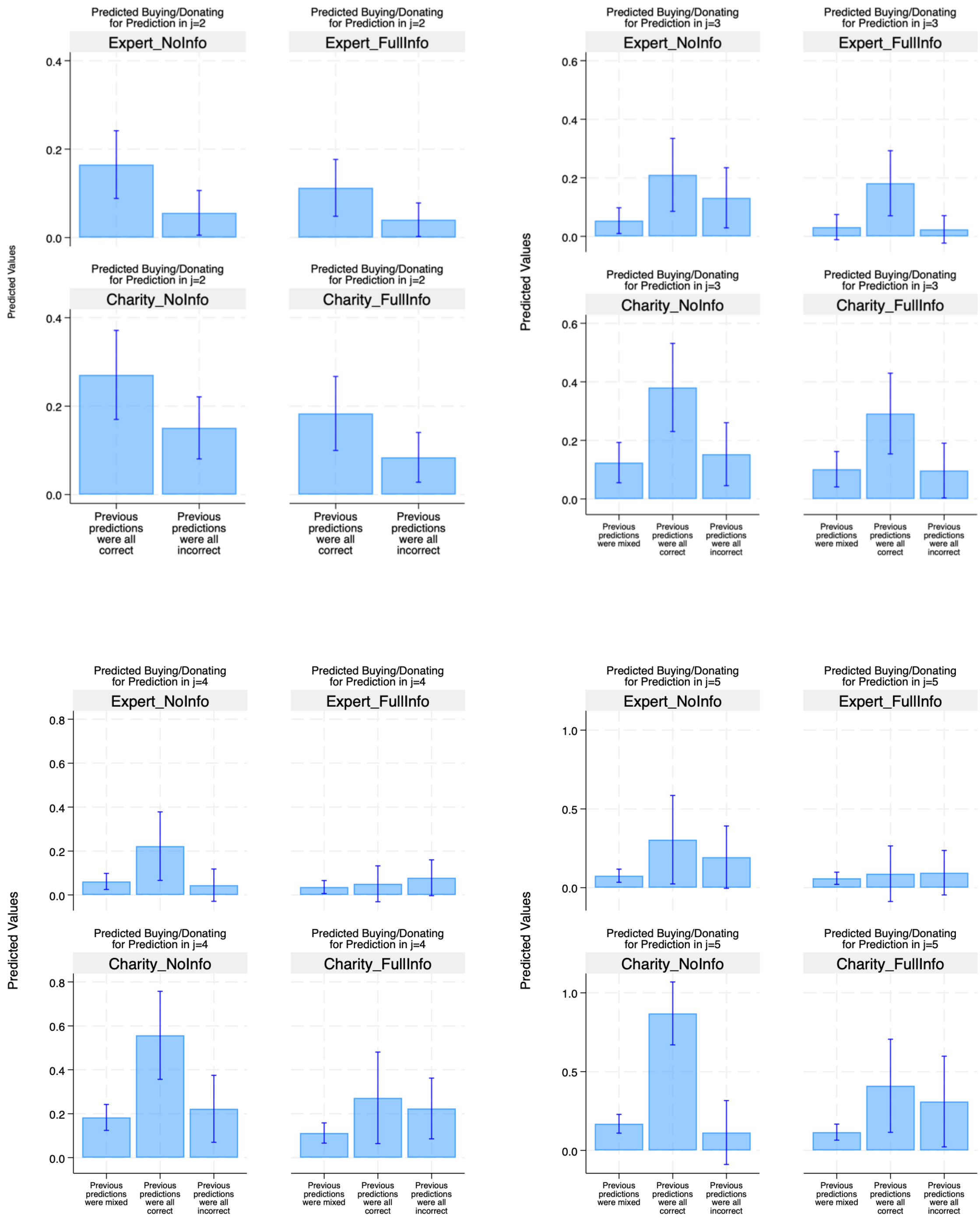
Note: Standard errors represent 95% confidence intervals.

Table 2: Linear probability model estimates of factors predicting buying or donating for predictions decisions per round

Dependent variable: Purchased or donated for the prediction in j	(1) $j = 2$	(2) $j = 3$	(3) $j = 4$	(4) $j = 5$
Treatments				
Expert-Full Info	-0.0190	-0.0222	-0.0321	-0.00638
	(0.0298)	(0.0291)	(0.0264)	(0.0285)
Charity-No Info	0.0990*	0.0755	0.123**	0.0977**
	(0.0441)	(0.0410)	(0.0393)	(0.0368)
Charity-Full Info	0.0252	0.0697	0.0489	0.0421
	(0.0363)	(0.0387)	(0.0331)	(0.0326)
All predictions up to $j-1$ had been correct	0.105*	0.157*	0.180*	0.246
	(0.0450)	(0.0637)	(0.0866)	(0.146)
All predictions up to $j-1$ had been incorrect		0.0814	-0.00282	0.114
		(0.0541)	(0.0467)	(0.105)
Expert-Full Info × All predictions up to $j-1$ had been correct	-0.0268 (0.0572)	0.0520 (0.0883)	-0.0892 (0.107)	-0.154 (0.182)
Expert-Full Info × All predictions up to $j-1$ had been incorrect		-0.0841 (0.0620)	0.0241 (0.0613)	-0.0885 (0.127)
Charity-No Info × All predictions up to $j-1$ had been correct	0.0160 (0.0782)	0.0903 (0.106)	0.298* (0.144)	0.455* (0.180)
Charity-No Info × All predictions up to $j-1$ had been incorrect		-0.0553 (0.0843)	-0.0327 (0.0941)	-0.174 (0.151)
Charity-Full Info × All predictions up to $j-1$ had been correct	0.0100 (0.0680)	-0.000420 (0.0970)	0.00732 (0.143)	0.0624 (0.213)
Charity-Full Info × All predictions up to $j-1$ had been incorrect		-0.0638 (0.0826)	0.0857 (0.0986)	0.0507 (0.173)
Implied effect of streaks on the decision to purchase or donate by treatment				
Expert-No Info: all previous predictions had been correct	0.104* (0.044)	0.157* (0.064)	0.180* (0.086)	0.246 (0.146)
Expert-No Info: all previous predictions had been incorrect		0.081 (0.054)	-0.003 (0.046)	0.114 (0.105)
Expert-Full Info: all previous predictions had been correct	0.058 (0.039)	0.186** (0.062)	0.058 (0.063)	0.085 (0.107)
Expert-Full Info: all previous predictions had been incorrect		-0.024 (0.030)	-0.011 (0.040)	0.019 (0.071)
Charity-No Info: all previous predictions had been correct	0.219*** (0.056)	0.322*** (0.080)	0.599*** (0.113)	0.799*** (0.104)
Charity-No Info: all previous predictions had been incorrect		0.101 (0.059)	0.087 (0.079)	0.037 (0.105)
Charity-Full Info: all previous predictions had been correct	0.139** (0.048)	0.226** (0.071)	0.235* (0.114)	0.350* (0.154)
Charity-Full Info: all previous predictions had been incorrect		0.087 (0.056)	0.132 (0.082)	0.207 (0.137)
Control variables	Yes	Yes	Yes	Yes
Observations	750	750	750	750
Adjusted R^2	0.047	0.086	0.133	0.109

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors are in parentheses. The dependent variable is an indicator variable that takes the value of 1 if the individual either purchased or donated for the prediction in round j and 0 otherwise. Estimates of the control variables are reported in Table 4A in the Appendix.

Figure 2: Predicted margins of streaks on the decision to purchase or donate for predictions across different treatments



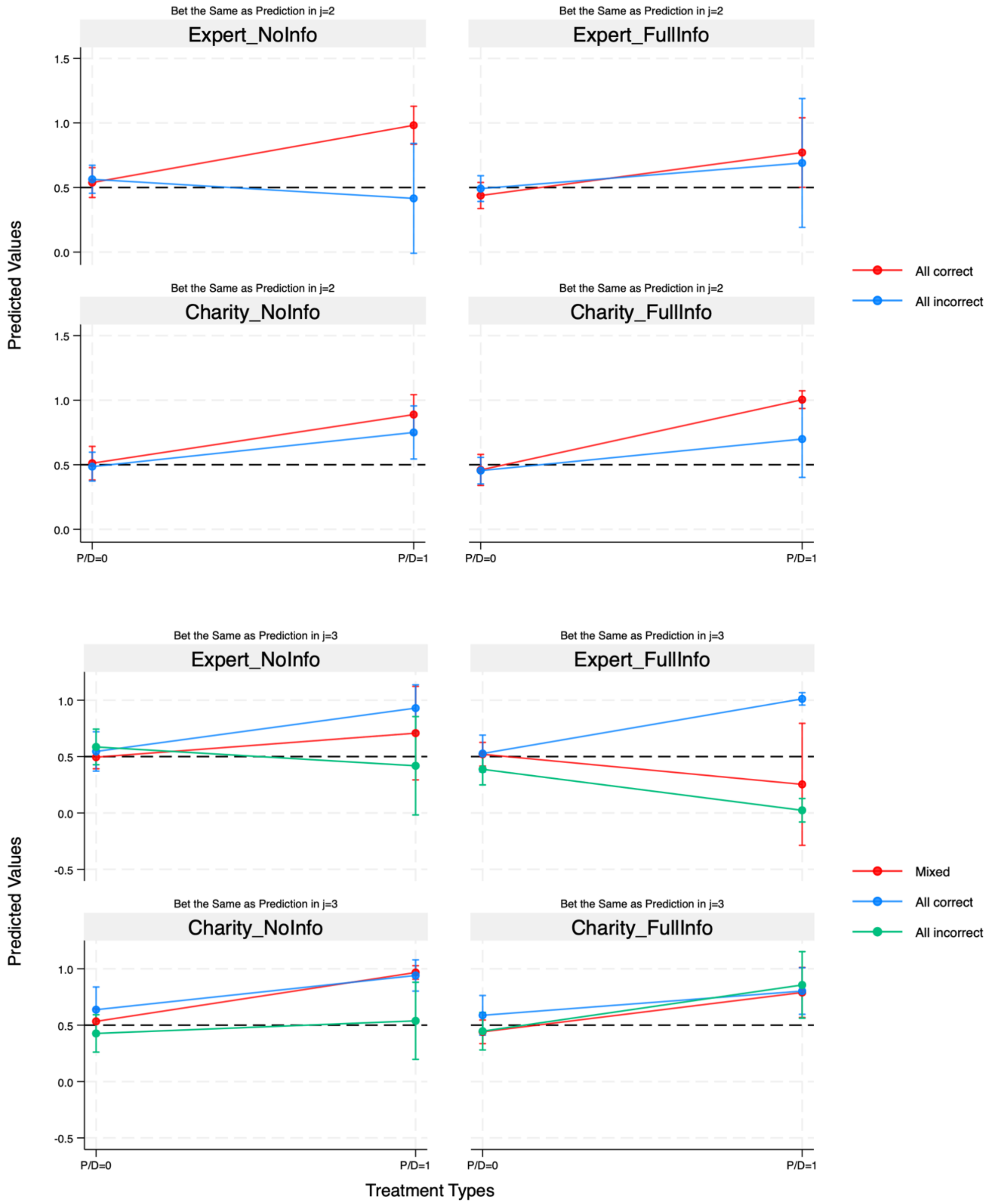
Note: Standard errors represent 95% confidence intervals.

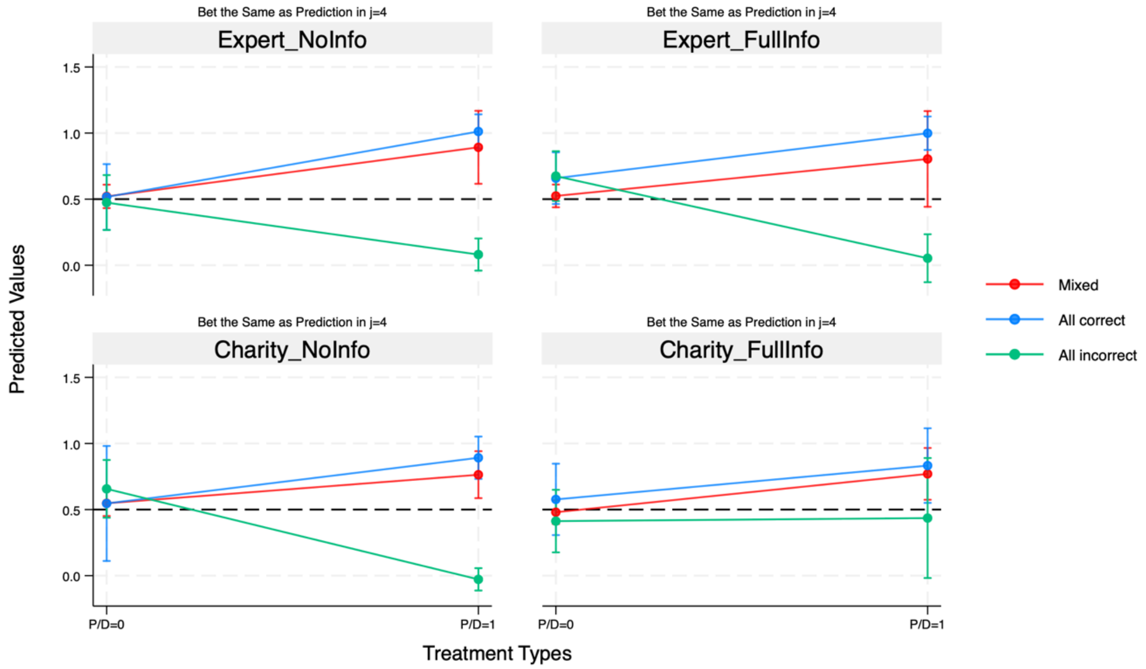
Table 3: Did people who purchased or donated for predictions treat them seriously? A linear probability model of following the prediction

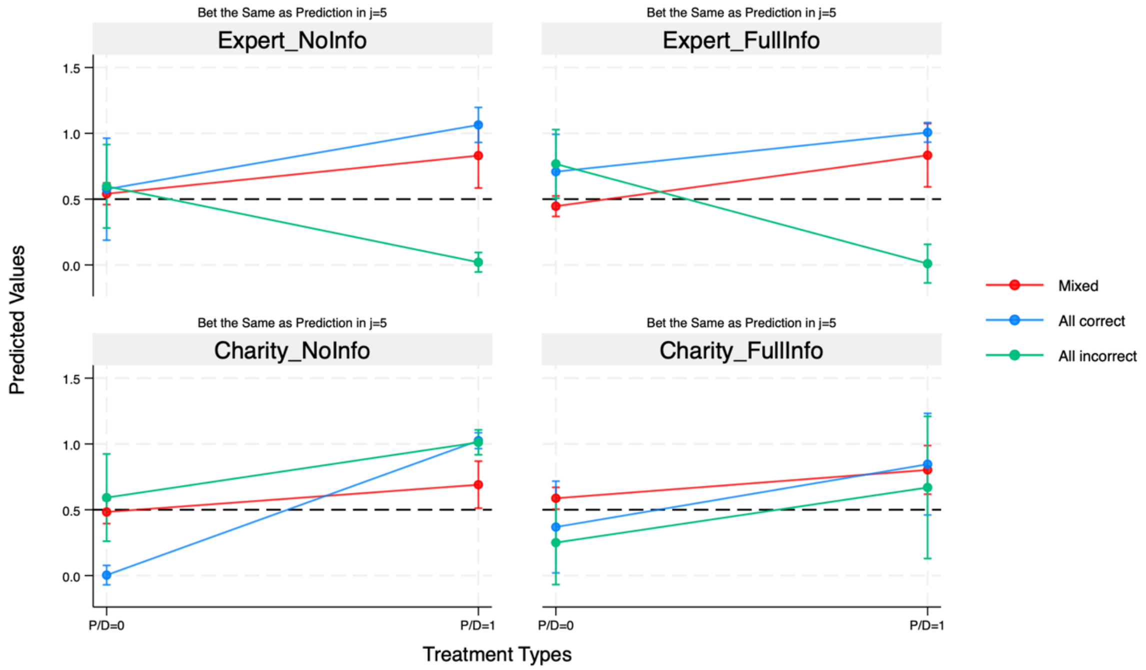
Dependent variable: Bet the same as the prediction in round j	(1) $j = 2$	(2) $j = 3$	(3) $j = 4$	(4) $j = 5$
All predictions up to $j - 1$ had been correct	-0.0164	0.0729	0.0663	0.0440
	(0.0405)	(0.0523)	(0.0682)	(0.104)
All predictions up to $j - 1$ had been incorrect		-0.0391	0.0426	0.0629
		(0.0476)	(0.0583)	(0.0877)
Purchased/donated for round j's prediction	0.174*	0.290***	0.275***	0.258***
	(0.0860)	(0.0768)	(0.0634)	(0.0576)
Purchased/donated for round j's prediction × All predictions up to $j - 1$ had been correct	0.261** (0.0982)	0.0571 (0.0961)	0.0549 (0.103)	0.177 (0.131)
Purchased/donated for round j's prediction × All predictions up to $j - 1$ had been incorrect		-0.186 (0.140)	-0.621*** (0.153)	-0.411 (0.215)
Treatments				
Expert-Full Info	-0.0809	-0.0378	0.0357	-0.0574
	(0.0508)	(0.0511)	(0.0522)	(0.0511)
Charity-No Info	-0.0471	0.0130	0.0261	-0.0558
	(0.0530)	(0.0520)	(0.0526)	(0.0524)
Charity-Full Info	-0.0734	-0.0387	-0.0338	0.0149
	(0.0509)	(0.0528)	(0.0537)	(0.0522)
Implied effect of streaks on betting the same as the prediction by the decision to purchase/donate for round *j*'s prediction				
Purchased/donated for round j's prediction and all predictions up to $j - 1$ had been correct	0.417*** (0.051)	0.419*** (0.050)	0.392*** (0.061)	0.483*** (0.065)
Purchased/donated for round j's prediction and all predictions up to $j - 1$ had been incorrect		0.064 (0.115)	-0.300* (0.132)	-0.090 (0.192)
Control variables	Yes	Yes	Yes	Yes
Observations	750	750	750	750
Adjusted R^2	0.074	0.053	0.046	0.031

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors are in parentheses. The dependent variable is an indicator variable that takes the value of 1 if the individual bets the same as the prediction in round j and 0 otherwise. Estimates of the control variables are reported in Table 4A in the Appendix.

Figure 3: Predicted margins of streaks on the decision to bet the same as the prediction by purchasing/donating decision in round *j* and treatment







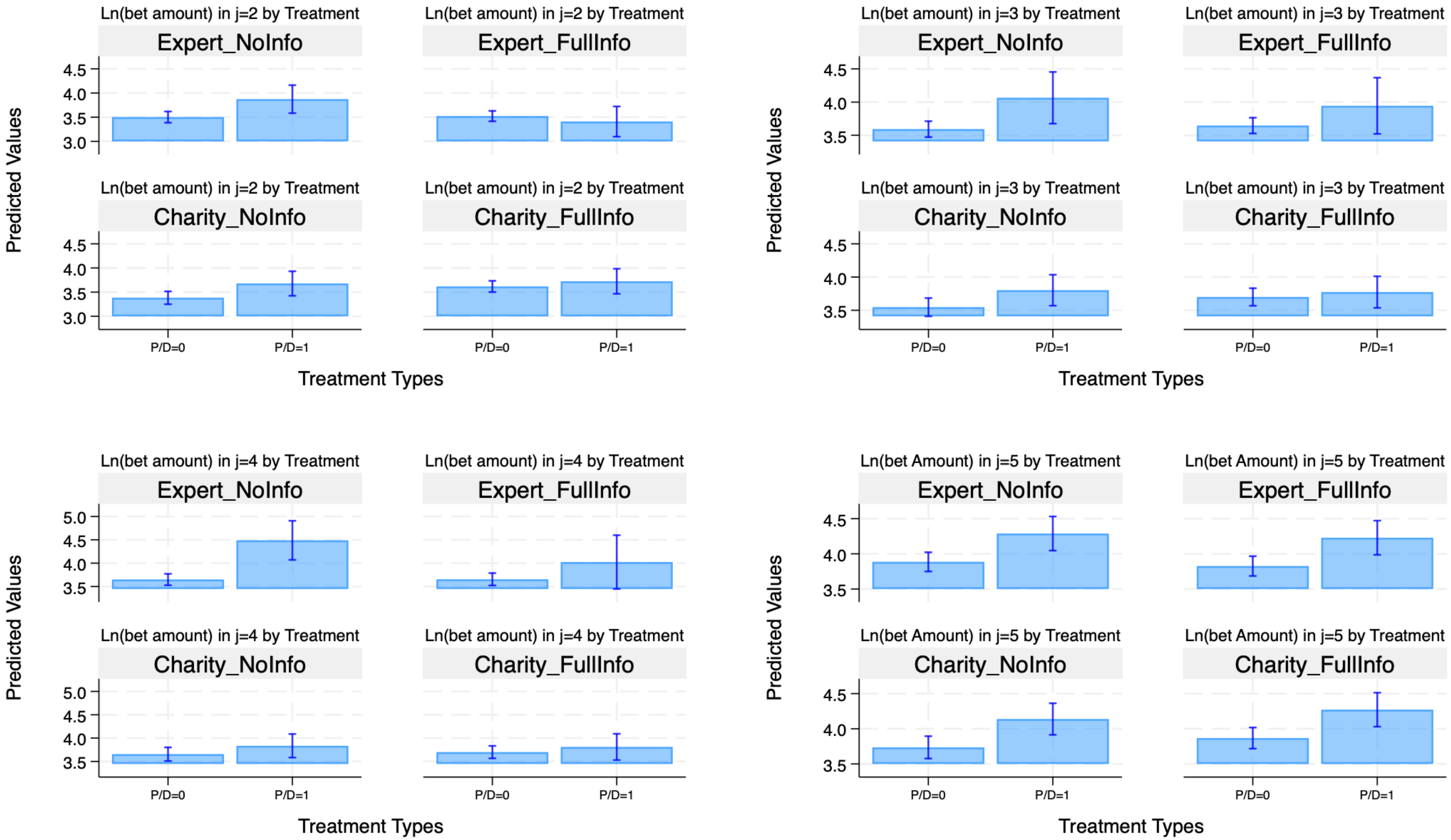
Note: Standard errors represent 95% confidence intervals. The dotted horizontal line represents the 50% mark. The predicted margins are based on a three-way interaction regression model (Decision to purchase/donate for predictions#Streaks of the predictions#Treatments).

Table 4: OLS estimates of the log of bet amount placed in each round

Dependent variable: Log(bet amount in round j)	(1) $j = 2$	(2) $j = 3$	(3) $j = 4$	(4) $j = 5$
Purchased/donated=1	0.199*	0.271**	0.280**	0.403***
	(0.0783)	(0.0832)	(0.0943)	(0.110)
Treatments				
Expert-Full Info	-0.0160	0.0372	-0.0286	-0.0571
	(0.0758)	(0.0823)	(0.0898)	(0.0988)
Charity-No Info	-0.115	-0.0668	-0.0527	-0.144
	(0.0823)	(0.0836)	(0.0880)	(0.103)
Charity-Full Info	0.0813	0.0461	-0.0264	-0.0279
	(0.0780)	(0.0866)	(0.0908)	(0.103)
Control variables	Yes	Yes	Yes	Yes
Observations	750	750	750	750
Adjusted R^2	0.092	0.079	0.100	0.077

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors are in parentheses. The dependent variable is a log of the bet amount in the round j. Estimates of the control variables are reported in Table 5A in the Appendix.

Figure 4: Predicted margins of the decision to purchase/donate for the prediction in round *j* on the log of bet amount by treatment



Note: Standard errors represent 95% confidence intervals.

Online Appendix

Online Appendix A

Table 1A: Descriptive Statistics of Participants

	All	Control	Awareness	Altruism	Combined	Balance test: p-values					
		(0)	(1)	(2)	(3)	(0) = (1)	(0) = (2)	(0) = (3)	(1) = (2)	(1) = (3)	(2) = (3)
Social-demographic characteristics											
Age	20.83	20.68	20.90	20.76	20.96	*0.33*	*0.72*	*0.18*	*0.56*	*0.77*	*0.36*
	(2.13)	(1.86)	(2.36)	(2.14)	(2.10)						
Gender											
Male	46.5%	46.0%	43.5%	47.4%	49.5%	*0.75*	*0.68*	*0.31*	*0.46*	*0.17*	*0.56*
Female	51.2%	50.8%	54.0%	50.3%	49.5%						
Prefer not to say	2.3%	3.2%	2.5%	2.3%	1.1%						
Year of Study											
Year 1	44.3%	46.0%	41.5%	44.6%	45.2%	*0.02*	*0.16*	*0.08*	*0.42*	*0.65*	*0.73*
Year 2	23.5%	28.9%	21.5%	24.0%	19.7%						
Year 3	13.9%	11.8%	15.5%	12.6%	15.4%						
Year 4	13.1%	10.7%	15.5%	12.6%	13.3%						
Year 5	0.3%			1.1%							
Postgraduate	5.1%	2.7%	6.0%	5.1%	6.4%						
Field of Study											
Social Sciences	14.8%	9.6%	16.0%	16.6%	17.0%	*0.09*	*0.46*	*0.01*	*0.41*	*0.40*	*0.11*
Arts and Humanities	5.7%	5.3%	6.5%	4.6%	6.4%						
Business	21.1%	23.5%	19.0%	18.3%	23.4%						

Natural Sciences	13.6%	12.3%	16.5%	8.6%	16.5%						
Engineering	44.8%	49.2%	42.0%	52.0%	36.7%						
Ethnicity											
Chinese	78.0%	80.2%	75.0%	77.1%	79.8%	*0.17*	*0.81*	*0.82*	*0.27*	*0.11*	*0.64*
Malay	5.3%	4.3%	3.5%	7.4%	6.4%						
Indian	9.2%	8.0%	11.5%	9.1%	8.0%						
Others	4.1%	4.8%	6.0%	2.9%	2.7%						
Prefer not to say	3.3%	2.7%	4.0%	3.4%	3.2%						
Performance in Probability Test											
# of Questions Answered Correctly	7.00	7.30	6.84	7.06	6.81	*0.06*	*0.35*	*0.05*	*0.39*	*0.90*	*0.33*
	(2.43)	(2.31)	(2.45)	(2.53)	(2.42)						
Psychological Traits											
Belief in Karma (5 point Likert scale, 1='Strongly disagree', 5='Strong agree'.)											
When people are met with misfortune, they have brought it upon themselves by previous behaviour in their life.	2.99	3.00	3.01	2.95	2.97	*0.93*	*0.71*	*0.83*	*0.65*	*0.77*	*0.88*
	(1.21)	(1.16)	(1.16)	(1.21)	(1.30)						
When people experience good fortune, they have brought it upon themselves by previous behaviour in their life.	3.17	3.17	3.29	3.17	3.06	*0.33*	*0.97*	*0.38*	*0.32*	*0.07*	*0.42*
	(1.20)	(1.14)	(1.14)	(1.20)	(1.33)						
In life, everyone eventually gets what they deserve based on their deeds.	3.22	3.17	3.27	3.18	3.27	*0.40*	*0.90*	*0.42*	*0.49*	*0.99*	*0.51*
	(1.25)	(1.24)	(1.21)	(1.25)	(1.30)						
Locus of Control (7 point Likert scale, 1='Strongly disagree', 7='Strong agree'.)											

I have little control over the things that happen to me.	3.48	3.52	3.41	3.51	3.51	*0.47*	*0.98*	*0.93*	*0.50*	*0.53*	*0.96*
	(1.55)	(1.54)	(1.56)	(1.56)	(1.55)						
There is really no way I can solve some of the problems I have.	3.31	3.50	3.41	3.09	3.23	*0.61*	*0.02*	*0.14*	*0.06*	*0.31*	*0.41*
	(1.70)	(1.70)	(1.70)	(1.67)	(1.73)						
There is little I can do to change many of the important thing.	2.86	2.86	2.71	3.00	2.88	*0.33*	*0.40*	*0.92*	*0.08*	*0.29*	*0.47*
	(1.57)	(1.50)	(1.55)	(1.65)	(1.60)						
I often feel helpless in dealing with the problems of life.	3.42	3.55	3.43	3.41	3.29	*0.47*	*0.41*	*0.12*	*0.91*	*0.40*	*0.48*
	(1.65)	(1.58)	(1.68)	(1.64)	(1.69)						
Sometimes I feel that I'm being pushed around in life.	3.99	3.95	4.13	4.06	3.84	*0.30*	*0.51*	*0.57*	*0.72*	*0.11*	*0.23*
	(1.73)	(1.74)	(1.65)	(1.64)	(1.89)						
What happens to me in the future mostly depends on me.	5.77	5.76	5.63	5.76	5.94	*0.29*	*1.00*	*0.13*	*0.30*	*0.01*	*0.14*
	(1.17)	(1.10)	(1.28)	(1.12)	(1.15)						
I can do just about anything I really set my mind to do.	5.35	5.27	5.30	5.23	5.58	*0.81*	*0.78*	*0.02*	*0.62*	*0.04*	*0.01*
	(1.36)	(1.32)	(1.39)	(1.37)	(1.32)						
Tolerance of Uncertainty (5 point Likert scale, 1='Not at all characteristic of me', 5='Entirely characteristic of me'.)											
Unforeseen events upset me greatly.	2.82	2.87	2.82	2.90	2.71	*0.63*	*0.74*	*0.13*	*0.42*	*0.31*	*0.08*
	(1.04)	(1.00)	(1.06)	(1.05)	(1.04)						

It frustrates me not having all the information I need.	3.29	3.32	3.32	3.27	3.25	*0.96*	*0.68*	*0.53*	*0.72*	*0.57*	*0.83*
	(1.10)	(1.03)	(1.14)	(1.08)	(1.13)						
One should always look ahead so as to avoid surprises.	3.23	3.29	3.27	3.29	3.08	*0.87*	*0.98*	*0.06*	*0.85*	*0.11*	*0.07*
	(1.11)	(1.04)	(1.17)	(1.07)	(1.14)						
A small, unforeseen event can spoil everything, even with the best of planning.	2.72	2.78	2.72	2.79	2.61	*0.59*	*0.95*	*0.17*	*0.55*	*0.40*	*0.16*
	(1.20)	(1.18)	(1.21)	(1.18)	(1.21)						
I always want to know what the future has in store for me.	3.35	3.43	3.36	3.28	3.32	*0.55*	*0.24*	*0.37*	*0.55*	*0.77*	*0.75*
	(1.19)	(1.16)	(1.22)	(1.20)	(1.17)						
I can't stand being taken by surprise.	2.23	2.21	2.27	2.30	2.13	*0.57*	*0.42*	*0.48*	*0.81*	*0.21*	*0.15*
	(1.07)	(1.02)	(1.10)	(1.09)	(1.05)						
I should be able to organize everything in advance.	3.17	3.16	3.20	3.19	3.13	*0.76*	*0.77*	*0.81*	*1.00*	*0.60*	*0.61*
	(1.13)	(1.05)	(1.19)	(1.15)	(1.13)						
Uncertainty keeps me from living a full life.	2.45	2.43	2.40	2.51	2.46	*0.81*	*0.52*	*0.77*	*0.37*	*0.58*	*0.71*
	(1.15)	(1.18)	(1.12)	(1.20)	(1.13)						
When it's time to act, uncertainty paralyses me.	2.53	2.55	2.54	2.46	2.57	*0.89*	*0.46*	*0.84*	*0.53*	*0.73*	*0.34*
	(1.13)	(1.16)	(1.12)	(1.10)	(1.13)						
	2.71	2.62	2.76	2.70	2.74	*0.25*	*0.52*	*0.30*	*0.63*	*0.93*	*0.69*

When I am uncertain I can't function very well.	(1.15)	(1.13)	(1.19)	(1.13)	(1.17)						
The smallest doubt can stop me from acting.	2.55	2.59	2.64	2.49	2.46	*0.67*	*0.43*	*0.31*	*0.22*	*0.14*	*0.86*
	(1.20)	(1.21)	(1.17)	(1.26)	(1.16)						
I must get away from all uncertain situations.	2.31	2.29	2.34	2.30	2.29	*0.73*	*0.94*	*0.99*	*0.79*	*0.72*	*0.94*
	(1.18)	(1.14)	(1.14)	(1.22)	(1.23)						
N	750	187	200	175	188						

Table 2A: Descriptive Statistics of Behavioural Patterns

	All	Treatments			
		Control Group	**Awareness Intervention**	**Altruism Framing**	**Combined Intervention**
Round j = 2					
Correct Predictions up to j-1	363	94	99	80	90
% of all predictions	48.40%	50.27%	49.95%	45.71%	47.87%
Purchased/Donated in j = 2	66	15	10	23	18
% of all correct predictions up to j-1	18.18%	15.96%	10.10%	28.75%	20.00%
Round j = 3					
Correct Predictions up to j-1	178	45	50	40	43
% of all predictions	23.73%	24.06%	25.00%	22.86%	22.87%
Purchased/Donated in j = 3	49	10	11	16	12
% of all correct predictions up to j-1	27.53%	22.22%	22.00%	40.00%	27.91%
Round j = 4					
Correct Predictions up to j-1	85	22	25	19	19
% of all predictions	11.33%	11.76%	12.50%	10.86%	10.11%
Purchased/Donated in j = 4	28	6	3	13	6
% of all correct predictions up to j-1	32.94%	27.27%	12.00%	68.42%	31.58%
Round j = 5					
Correct Predictions up to j-1	44	11	12	10	11
% of all predictions	5.87%	5.88%	6.00%	5.71%	5.85%
Purchased/Donated in j = 5	20	4	2	9	5
% of all correct predictions up to j-1	45.45%	36.36%	16.67%	90.00%	45.45%

Table 3A: Estimates of Table 1's control variables

Dependent variable: Betting Head in Round *j*	$j = 3$			$j = 4$			$j = 5$		
	(1) All	(2) P=H	(3) P=T	(4) All	(5) P=H	(6) P=T	(7) All	(8) P=H	(9) P=T
Control variables									
Female	-0.0502	-0.0162	-0.0636	-0.0230	-0.0784	0.0683	-0.0109	-0.0260	-0.0292
	(0.0378)	(0.0556)	(0.0512)	(0.0389)	(0.0515)	(0.0581)	(0.0387)	(0.0519)	(0.0567)
I would prefer not to say	-0.00405	-0.344*	0.120	0.114	0.0212	0.283	0.0859	0.0573	0.0542
	(0.121)	(0.163)	(0.141)	(0.120)	(0.124)	(0.264)	(0.120)	(0.151)	(0.219)
Age	0.00686	0.0206	-0.00102	0.00184	0.00882	0.00114	0.00967	0.00254	0.0239
	(0.00880)	(0.0125)	(0.0119)	(0.00899)	(0.0110)	(0.0148)	(0.00897)	(0.0131)	(0.0123)
Proportion of correct answers in the statistical/quantitative skill test	-0.00857	-0.000494	-0.0129	0.00832	-0.00415	0.0278*	0.000752	0.00424	-0.00408
	(0.00744)	(0.0110)	(0.0101)	(0.00782)	(0.0103)	(0.0119)	(0.00750)	(0.00956)	(0.0117)
Factor: Belief in karma	-0.0163	-0.0619	0.0111	-0.0154	0.0165	-0.0424	-0.0150	-0.0167	0.000793
	(0.0216)	(0.0315)	(0.0291)	(0.0216)	(0.0278)	(0.0339)	(0.0217)	(0.0301)	(0.0324)
Factor: Locus of control: external	0.00705	0.0222	-0.00260	0.0372	0.0331	0.0425	0.00340	-0.0410	0.0743*
	(0.0223)	(0.0322)	(0.0297)	(0.0222)	(0.0282)	(0.0349)	(0.0230)	(0.0289)	(0.0362)
Factor: Tolerance of uncertainty	-0.0196	-0.00356	-0.0237	-0.0490*	-0.0737*	-0.0155	-0.0382	0.00361	-0.0898*
	(0.0212)	(0.0300)	(0.0273)	(0.0212)	(0.0291)	(0.0318)	(0.0214)	(0.0268)	(0.0348)
Risk score: risk-aversion	-0.0117	-0.00246	-0.0154	0.00803	0.0248	-0.0240	0.0352	0.0136	0.0507
	(0.0180)	(0.0264)	(0.0237)	(0.0184)	(0.0230)	(0.0311)	(0.0185)	(0.0247)	(0.0272)
Constant	0.487*	0.164	0.713*	0.512*	0.472	0.360	0.301	0.485	0.00368
	(0.209)	(0.307)	(0.280)	(0.217)	(0.270)	(0.356)	(0.212)	(0.301)	(0.302)
Observations	750	351	399	750	428	322	750	409	341
Adjusted R^2	0.031	0.067	0.108	0.001	0.025	0.037	0.002	0.013	0.071

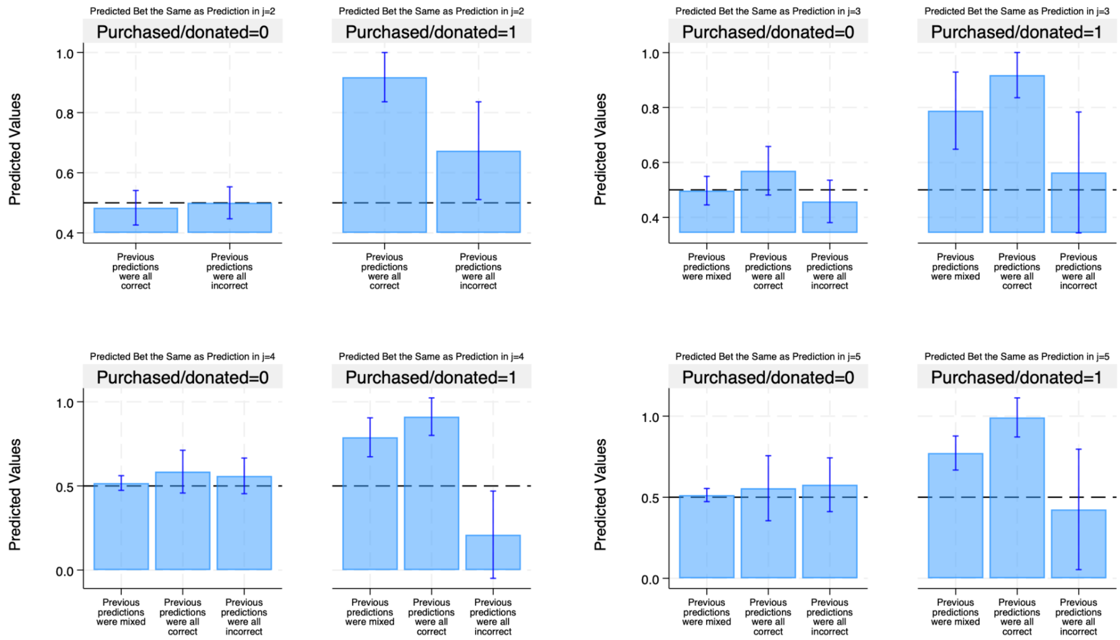
Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors are in parentheses. The dependent variable is an indicator variable that takes the value of 1 if the individual places a bet on heads (H) in round *j*. P=H indicates that the prediction in round *j* is head. P=T indicates that the prediction in round *j* is tail.

Table 4A: Estimates of Table 2's control variables

Dependent variable: Purchased or donated for the prediction in j	(1) $j = 2$	(2) $j = 3$	(3) $j = 4$	(4) $j = 5$
Control variables				
Female	0.0188	0.00498	0.0337	0.0160
	(0.0256)	(0.0259)	(0.0236)	(0.0246)
I would prefer not to say	-0.0455	-0.0238	-0.0247	0.0148
	(0.0545)	(0.0617)	(0.0729)	(0.0697)
Age	-0.00498	0.0135*	0.00653	0.0131*
	(0.00579)	(0.00615)	(0.00593)	(0.00635)
Proportion of correct answers in the statistical/quantitative skill test	-0.00419	0.00214	-0.00155	0.00189
	(0.00472)	(0.00438)	(0.00430)	(0.00444)
Endowment in j	0.0000447	0.000117	0.000325*	0.0000861
	(0.000421)	(0.000204)	(0.000148)	(0.000103)
A streak of heads up to $j - 1$	0.0232	-0.00926	0.00128	-0.0159
	(0.0286)	(0.0305)	(0.0327)	(0.0368)
A streak of tails up to $j - 1$		-0.00858	0.0581	-0.0735**
		(0.0331)	(0.0486)	(0.0265)
Made wrong bet in $j - 1$	0.00129	-0.00880	0.0346	-0.0102
	(0.0435)	(0.0301)	(0.0266)	(0.0255)
Fixed betting strategy	-0.0337	-0.0596*	-0.0785***	-0.0716**
	(0.0246)	(0.0250)	(0.0212)	(0.0230)
Bet the same as the prediction in $j - 1$	0.0607**	0.0667**	0.0327	0.0284
	(0.0232)	(0.0246)	(0.0219)	(0.0227)
Factor: Belief in karma	0.000424	0.00497	0.00935	0.00118
	(0.0136)	(0.0138)	(0.0130)	(0.0134)
Factor: Locus of control: external	0.00851	0.0139	0.00469	0.000968
	(0.0143)	(0.0147)	(0.0135)	(0.0142)
Factor: Tolerance of uncertainty	0.00485	0.00549	0.00747	-0.00105
	(0.0150)	(0.0150)	(0.0139)	(0.0131)
Risk score: risk-aversion	-0.00270	0.0273**	-0.0176	-0.00423
	(0.0125)	(0.0103)	(0.0124)	(0.0121)
Constant	0.126	-0.337*	-0.169	-0.230
	(0.205)	(0.156)	(0.155)	(0.144)
Observations	750	750	750	750
Adjusted R^2	0.047	0.086	0.133	0.109

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors are in parentheses. The dependent variable is an indicator variable that takes the value of 1 if the individual either purchased or donated for the prediction in round j and 0 otherwise.

Figure 1A: **Predicted margins of streaks on the decision to bet the same as the prediction by purchasing/donating decision in round *j***



Note: Standard errors represent 95% confidence intervals.

Table 4A: Estimates of Table 3's control variables

Dependent variable: Bet the same as the prediction in round j	(1) $j = 2$	(2) $j = 3$	(3) $j = 4$	(4) $j = 5$
Female	-0.0735	0.0269	-0.0901*	-0.00576
	(0.0378)	(0.0386)	(0.0385)	(0.0388)
I would prefer not to say	-0.0188	-0.200	0.00229	0.0117
	(0.127)	(0.111)	(0.115)	(0.131)
Age	0.000582	0.0124	0.00364	-0.0101
	(0.00844)	(0.00875)	(0.00862)	(0.00888)
Number of Questions Answered Correctly in Probability Test	-0.0220**	0.00412	-0.0169*	0.00495
	(0.00736)	(0.00785)	(0.00759)	(0.00775)
Endowment in j	-0.000820	-0.00076**	0.000164	-0.000241
	(0.000564)	(0.000278)	(0.000177)	(0.000128)
A streak of heads up to $j-1$	-0.0157	0.0264	-0.0909	0.0848
	(0.0405)	(0.0451)	(0.0522)	(0.0643)
A streak of tails up to $j-1$		-0.0314	0.127	0.0990
		(0.0504)	(0.0745)	(0.154)
Made wrong bet in $j-1$	0.00221	-0.0873*	-0.0157	0.00596
	(0.0590)	(0.0441)	(0.0421)	(0.0392)
Fixed betting strategy	-0.0355	-0.0147	-0.0220	-0.0408
	(0.0406)	(0.0423)	(0.0424)	(0.0421)
Bet the same as the prediction in $j-1$	0.0252	0.0219	-0.00168	-0.0135
	(0.0382)	(0.0365)	(0.0362)	(0.0368)
Factor: Belief in karma	0.0206	-0.0331	0.0176	-0.0104
	(0.0214)	(0.0215)	(0.0220)	(0.0219)
Factor: Locus of control: external	-0.0537*	0.00649	-0.00179	-0.0392
	(0.0216)	(0.0223)	(0.0223)	(0.0224)
Factor: Tolerance of uncertainty	0.0240	0.0125	-0.0315	0.0316
	(0.0203)	(0.0200)	(0.0212)	(0.0216)
Risk score: risk-aversion	0.00567	0.00648	0.0133	-0.0165
	(0.0176)	(0.0182)	(0.0181)	(0.0179)
Constant	0.969***	0.471*	0.552*	0.821***
	(0.277)	(0.224)	(0.217)	(0.217)
Observations	750	750	750	750
Adjusted R^2	0.074	0.053	0.046	0.031

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors are in parentheses. The dependent variable is an indicator variable that takes the value of 1 if the individual bets the same as the prediction in round j and 0 otherwise.

Table 5A: Estimates of Table 4's control variables

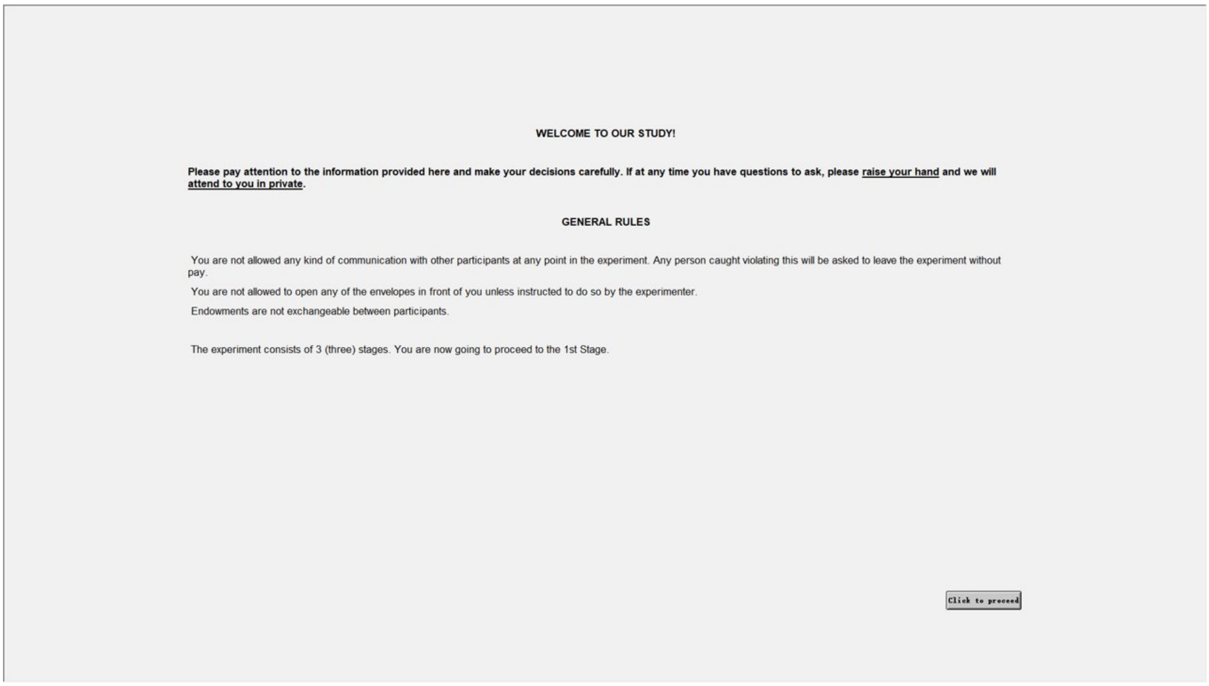
Dependent variable: Log(bet amount in round j)	(1) $j = 2$	(2) $j = 3$	(3) $j = 4$	(4) $j = 5$
Control variables				
Female	-0.375***	-0.402***	-0.394***	-0.390***
	(0.0577)	(0.0621)	(0.0651)	(0.0772)
I would prefer not to say	-0.0343	-0.249	-0.266	-0.392
	(0.207)	(0.222)	(0.276)	(0.272)
Age	0.0215	-0.00990	-0.00563	-0.0114
	(0.0134)	(0.0149)	(0.0157)	(0.0181)
Number of Questions Answered Correctly in Probability Test	-0.00271	-0.00351	-0.0121	-0.000176
	(0.0115)	(0.0122)	(0.0133)	(0.0153)
Endowment in j	0.00192	0.00143*	0.00184***	0.000869**
	(0.00114)	(0.000628)	(0.000429)	(0.000305)
A streak of heads up to $j-1$	-0.000552	-0.119	-0.159	-0.108
	(0.0631)	(0.0766)	(0.0884)	(0.126)
A streak of tails up to $j-1$		-0.0412	0.0345	0.443*
		(0.0825)	(0.137)	(0.200)
Made wrong bet in $j-1$	-0.0870	0.172*	0.218**	0.0532
	(0.100)	(0.0773)	(0.0791)	(0.0807)
Fixed betting strategy	-0.0484	-0.0393	-0.0919	-0.0663
	(0.0635)	(0.0693)	(0.0747)	(0.0819)
Bet the same as the prediction in $j-1$	-0.0259	0.0791	-0.00798	0.0858
	(0.0585)	(0.0610)	(0.0618)	(0.0727)
Factor: Belief in karma	-0.00396	0.0146	-0.0160	-0.00567
	(0.0338)	(0.0358)	(0.0401)	(0.0458)
Factor: Locus of control: external	0.00935	0.0188	0.0168	-0.0307
	(0.0350)	(0.0368)	(0.0382)	(0.0473)
Factor: Tolerance of uncertainty	-0.0419	-0.0710*	-0.0729*	-0.0644
	(0.0310)	(0.0340)	(0.0353)	(0.0412)
Risk score: risk-aversion	-0.0305	-0.0631*	-0.0814*	-0.0980**
	(0.0312)	(0.0303)	(0.0348)	(0.0377)
Constant	2.828***	3.647***	3.626***	4.171***
	(0.495)	(0.424)	(0.415)	(0.429)
Observations	750	750	750	750
Adjusted R^2	0.092	0.079	0.100	0.077

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors are in parentheses. The dependent variable is a log of the bet amount in the round j.

Online Appendix B
Screenshots of Experiments

Stage 1: Coin Flip Prediction Task

Page 1: Welcome



Page 2: Introduction

STAGE 1

In stage 1, you will be asked to play a game of predicting the outcomes of coin tosses, i.e., head or tail (H-T). The game will consist of tossing the coin a total of **five (5) times**. Participants will be asked to make a bet on the outcome of each of the subsequent coin tosses.

For every **1 point** you use to bet correctly, i.e., the bet matches the actual outcome of the coin toss, **your return will be 1 point *2 = 2 points**. For every **1 point** you use to bet incorrectly, **you will lose the point you used to bet**.

However, before each round of the coin toss, you will be given the option to buy a prediction containing the coin toss outcome in numbered envelopes, which we will set out for you and will cost a fixed price of **10 points per prediction**. You will be given the opportunity to open and view the prediction **before** placing the bet in that round.

Note that the decision to buy the prediction enables you to view the prediction **BEFORE THE COIN TOSS TAKES PLACE**. However, regardless of whether you bought the prediction or not, it will be revealed to you **for free** **AFTER** the coin toss of that round **HAS ALREADY TAKEN PLACE**.

Please click the button below to see details about the envelopes.

Click to proceed

(Expert - No Info and Expert - Full Info Condition)

STAGE 1

In stage 1, you will be asked to play a game of predicting the outcomes of coin tosses, i.e., head or tail (H-T). The game will consist of tossing the coin a total of **five (5) times**. Participants will be asked to make a bet on the outcome of each of the subsequent coin tosses.

For every **1 point** you use to bet correctly, i.e., the bet matches the actual outcome of the coin toss, **your return will be 1 point *2 = 2 points**. For every **1 point** you use to bet incorrectly, **you will lose the point you used to bet**.

However, before each round of the coin toss, you will be given the option to donate to **CARE International**, a leading global humanitarian organization that fights poverty and social injustice. It focuses on a wide range of issues, including poverty eradication, emergency response, women's empowerment, health, education and sustainable development. In appreciation of your charitable action, you will be rewarded with a prediction contained in numbered envelopes about the coin toss that has not happened yet. If you choose to donate, a fix amount of **10 points per prediction** will be withdrawn from your account, and you will be granted the privilege to open and view the prediction **before** placing the bet in that round.

Note that the decision to donate enables you to view the prediction **BEFORE THE COIN TOSS TAKES PLACE**. However, regardless of whether you bought the prediction or not, it will be revealed to you **for free** **AFTER** the coin toss of that round **HAS ALREADY TAKEN PLACE**.

Please click the button below to see details about the envelopes.

Click to proceed

(Charity - No Info and Expert - Full Info Condition)

Page 3: Information about prediction generation

STAGE 1

The numbered envelope contains a prediction of either H (head) or T (tail) for that round.

The predictions enclosed in the envelopes are **entirely unknown**, and the method by which the predictions are made **remains undisclosed**.

Click to proceed

(Expert - No Info and Charity - No Info Condition)

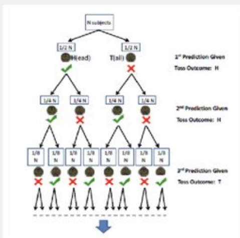
STAGE 1

The numbered envelope contains a prediction of either H (head) or T (tail) for that round.

The predictions given in the envelopes are **completely random** and that the envelopes' success and failure at predicting the coin flips are **purely luck-based**.

The figure below illustrates the random distribution of the predictions. Imagine there are **N** number of participants (including you) in this room. **N/2** will receive a prediction of H in the first round, while **the other N/2** will receive a prediction of T. The same process applies in Round 2, i.e., N/2 will receive a prediction of H in the second round, while the other N/2 will receive a prediction of T. In other words, any given prediction is completely random, with no way to predict whether a participant will receive a correct prediction or not.

Note that, because predictions are randomly allocated, some of you will receive **a streak of correct predictions** by chance, while some will receive **a streak of incorrect predictions**, also by chance.

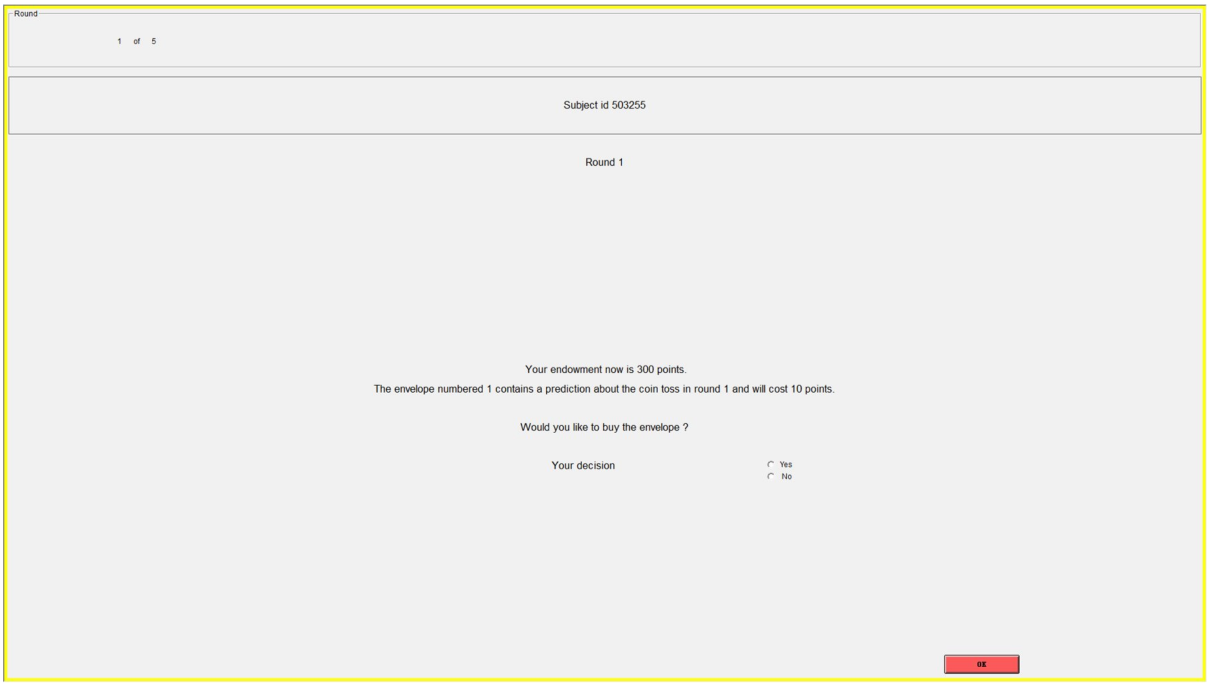


This is the end of the instructions for stage 1; you will be given the instruction for the next stages once you have completed stage 1.

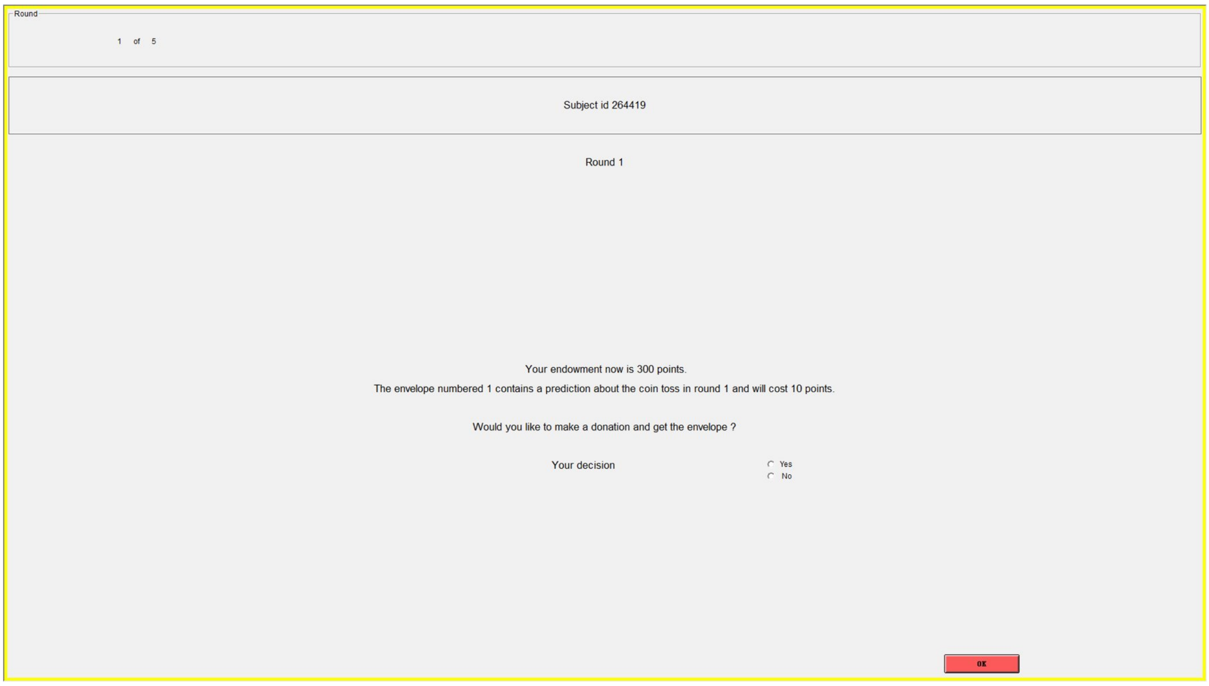
Click to proceed

(Expert - Full Info and Charity - Full Info Condition)

Page 4: Decision Making for Envelope

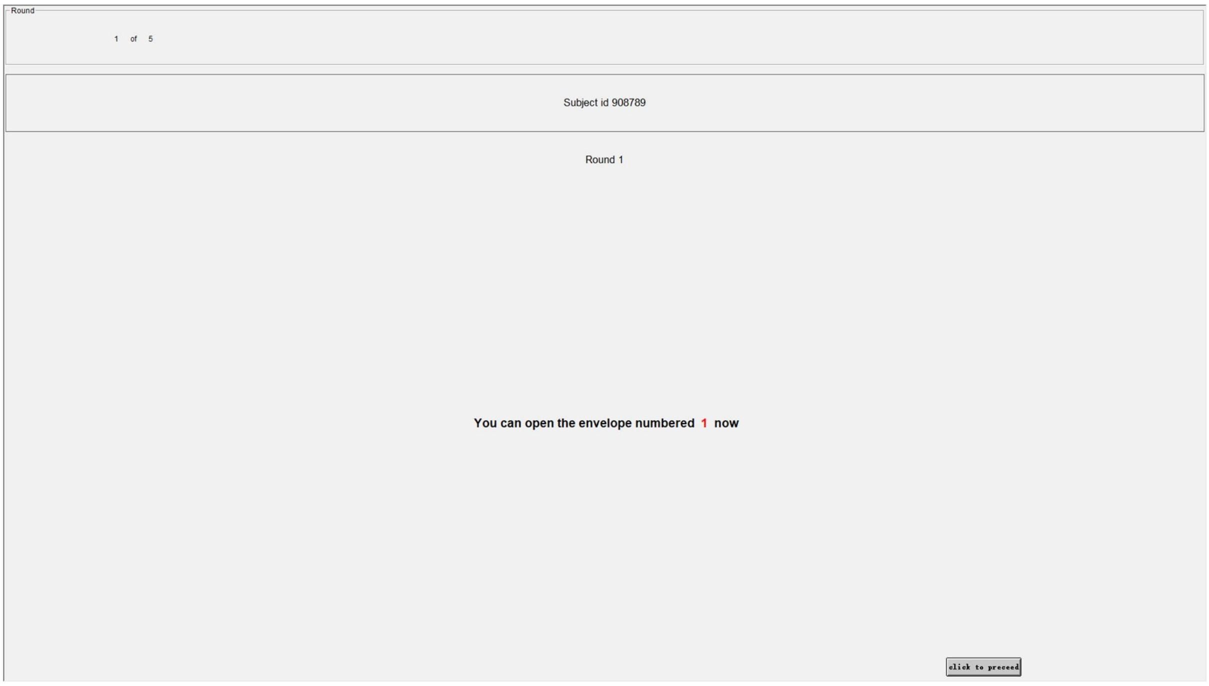


(Expert - No Info and Expert - Full Info Condition)

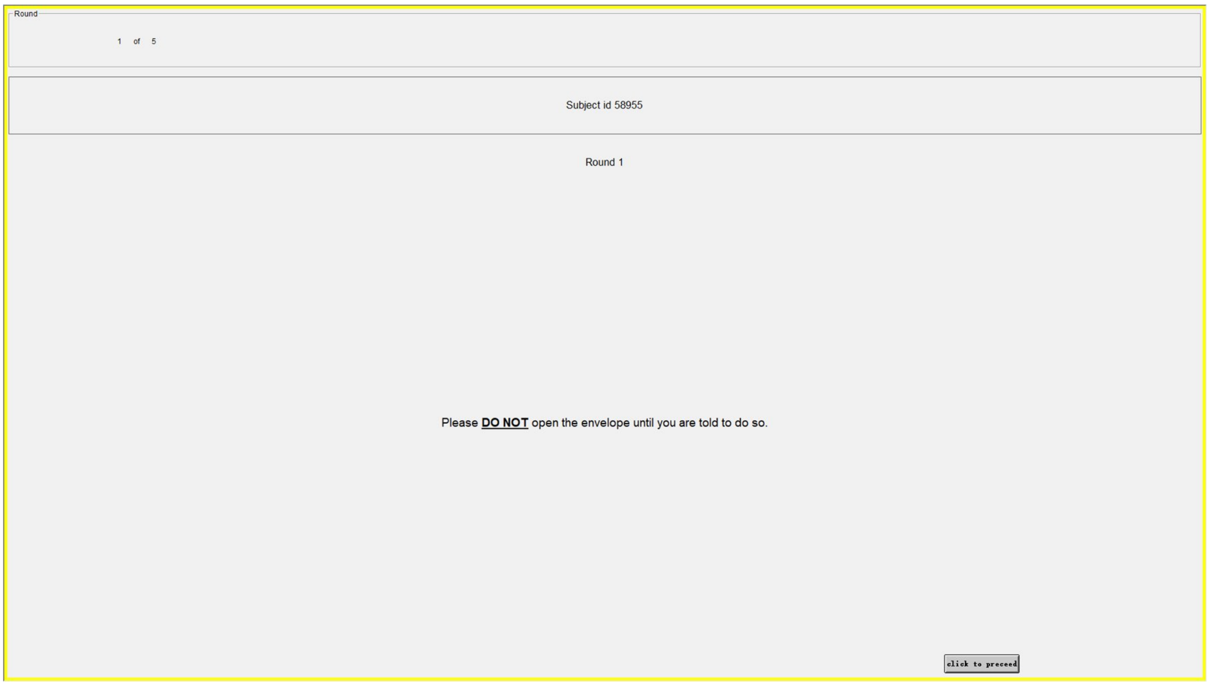


(Charity - No Info and Charity - Full Info Condition)

Page 5: Waiting Page

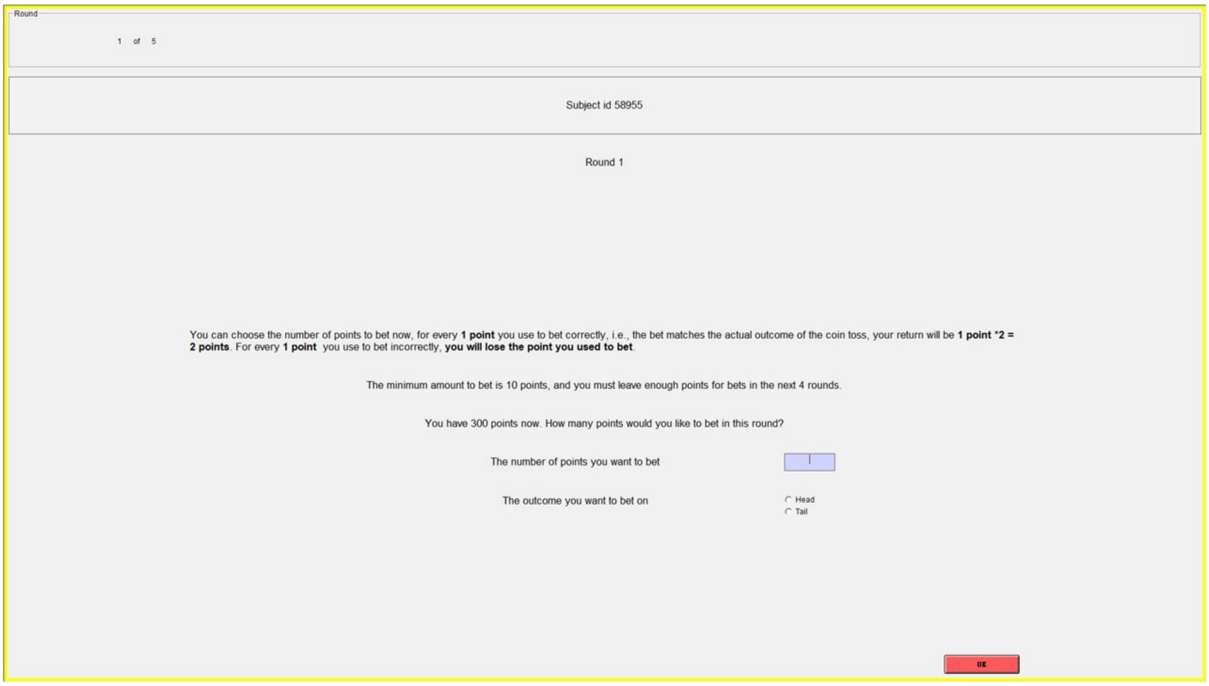


(If subject purchased/ donated in this round)

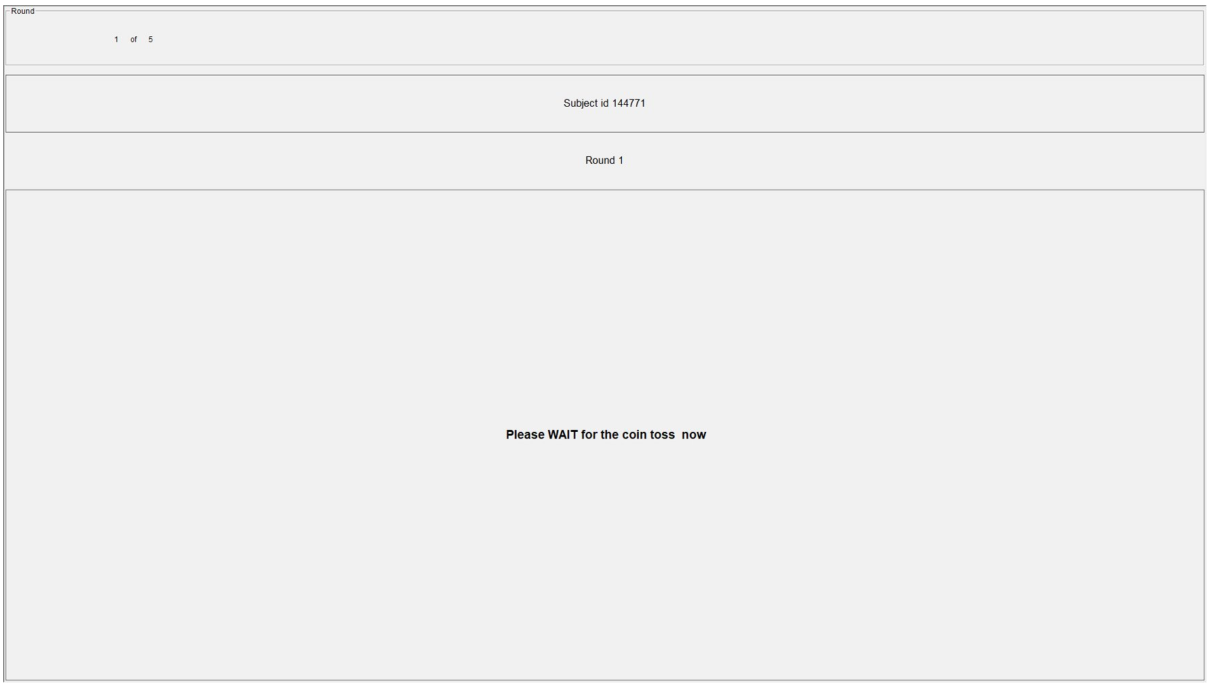


(If subject didn't purchase/ donate in this round)

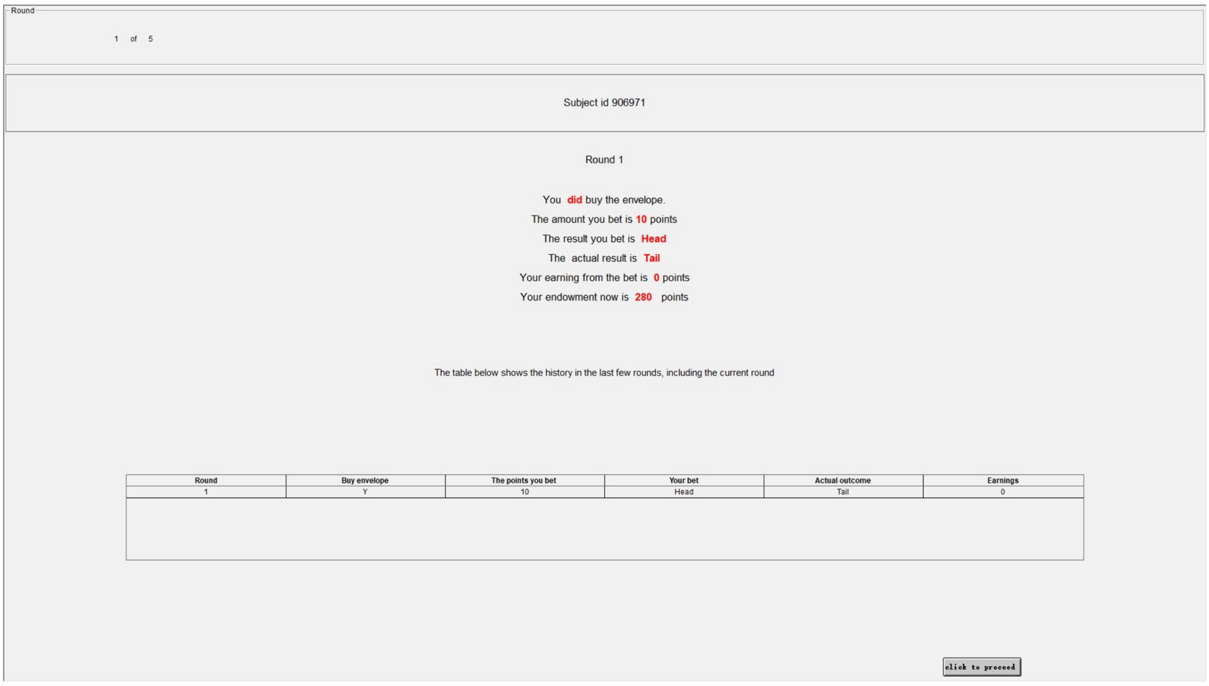
Page 6: Betting



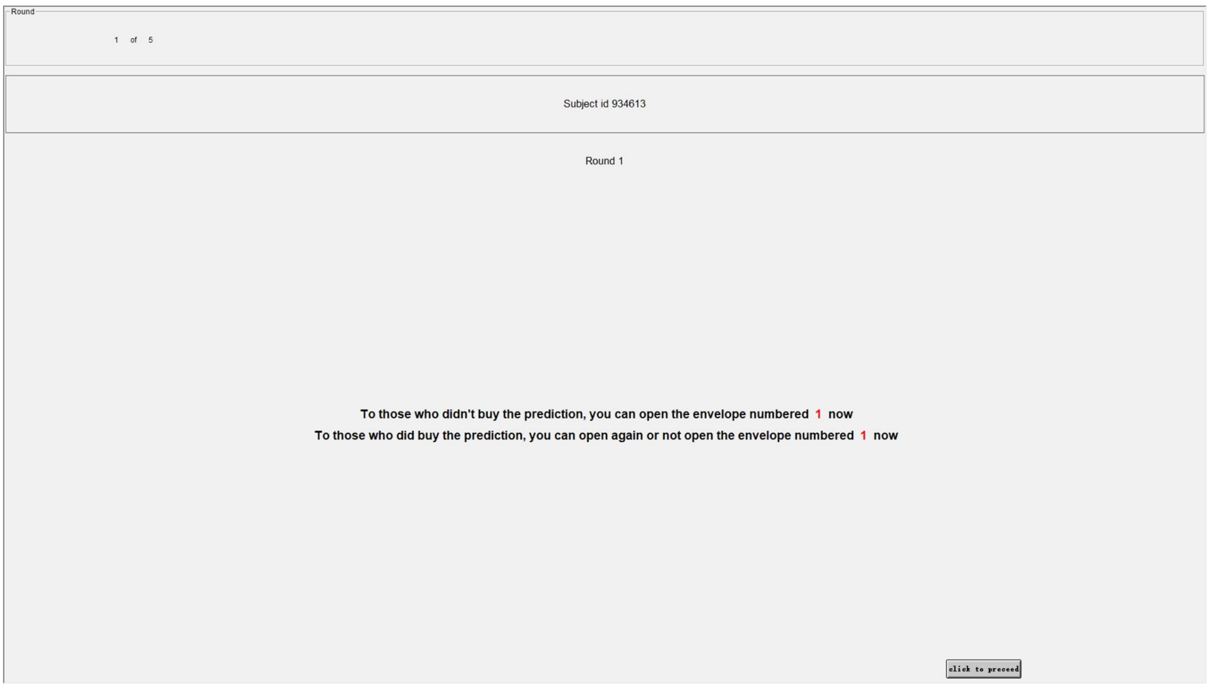
Page 7: Waiting Page



Page 8: Round Summary



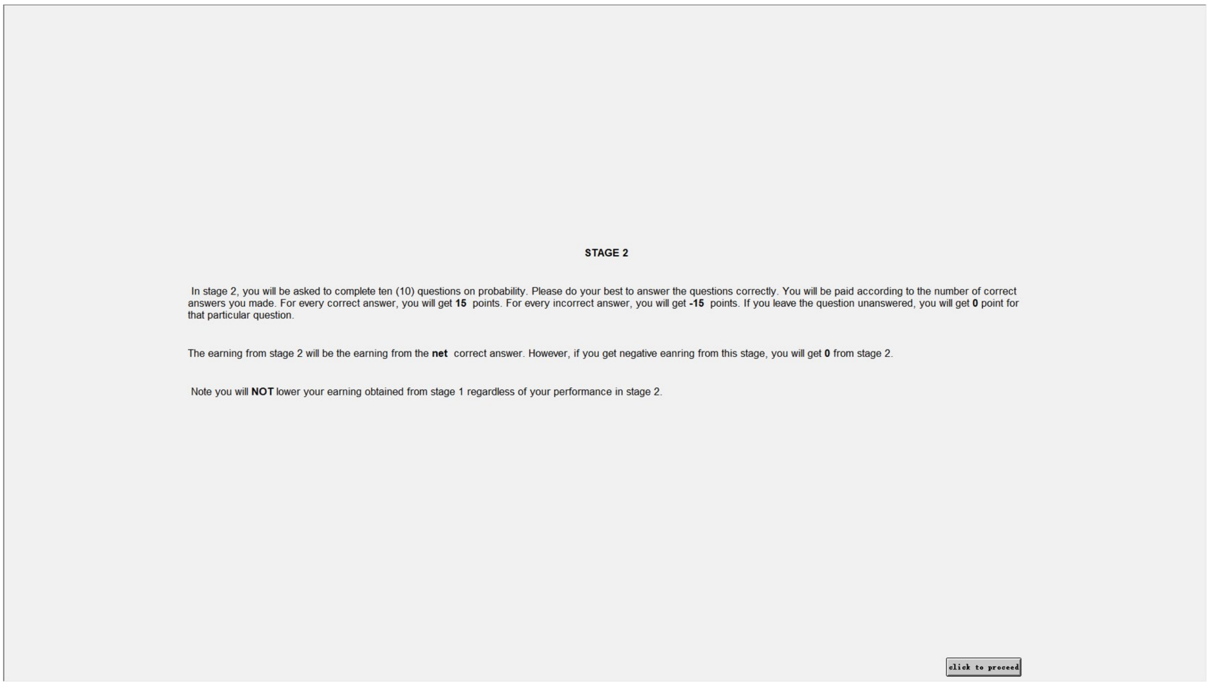
Page 9: Waiting Page



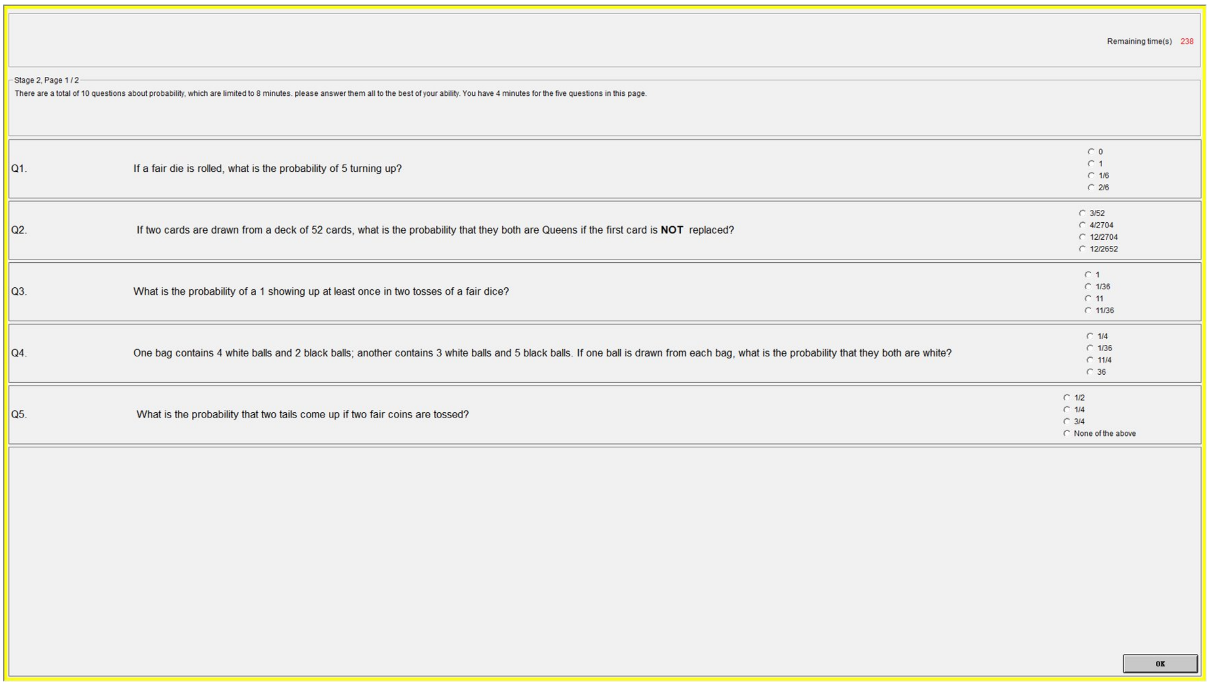
Repeat the same procedure until the end of the 5th round.

Stage 2: Probability Test

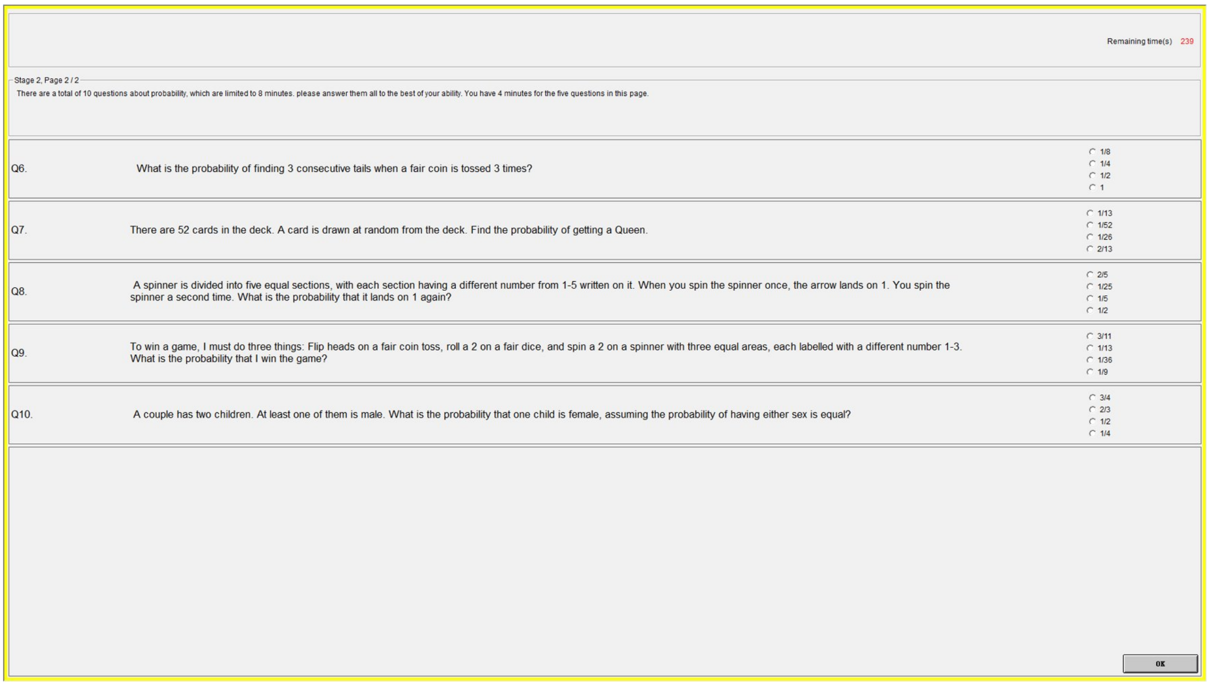
Page 1: Introduction



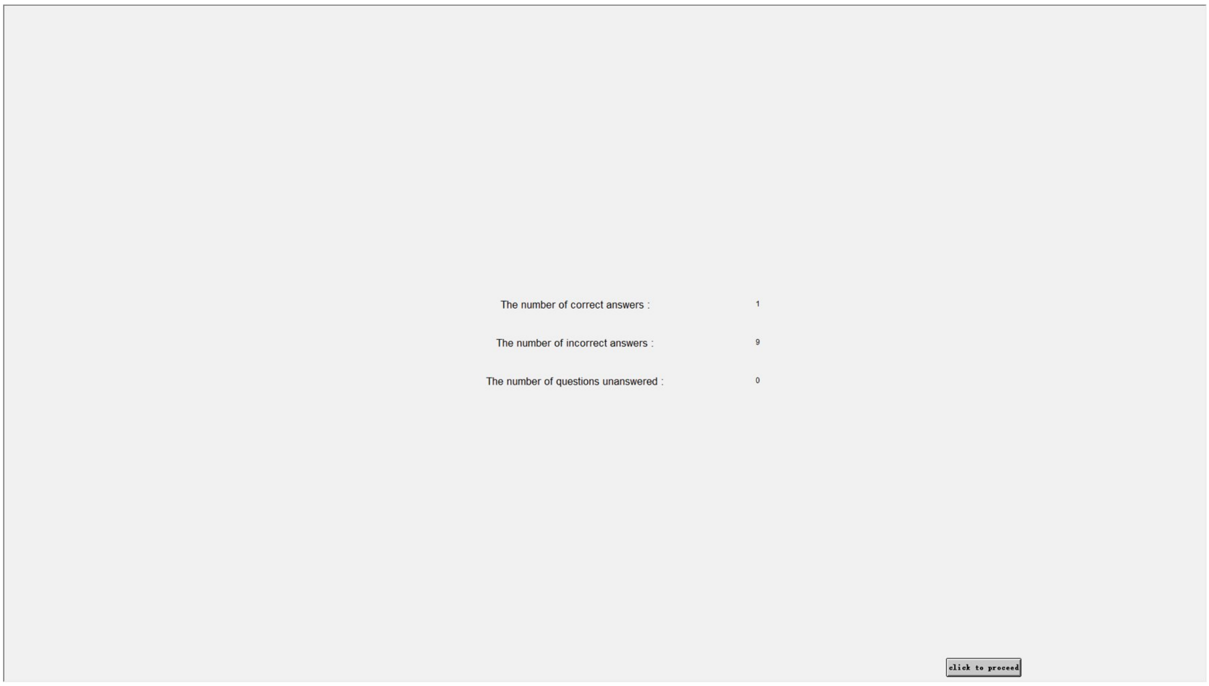
Page 2: Task Page 1



Page 3: Task Page 2

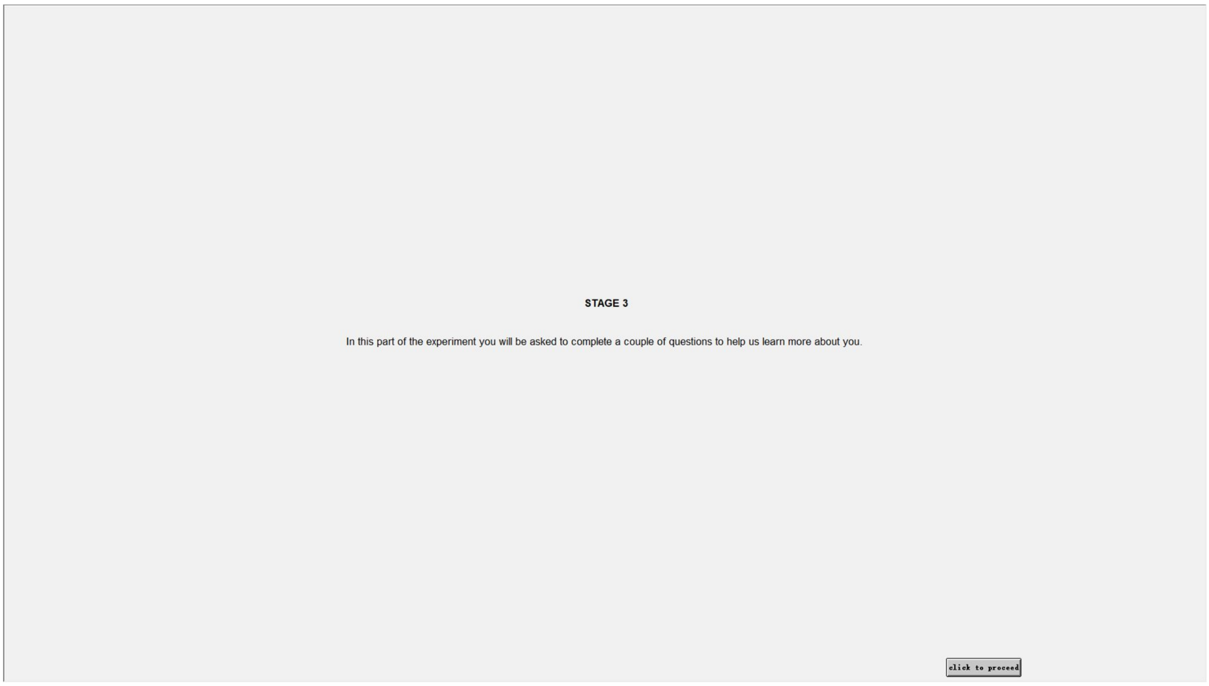


Page 4: Summary

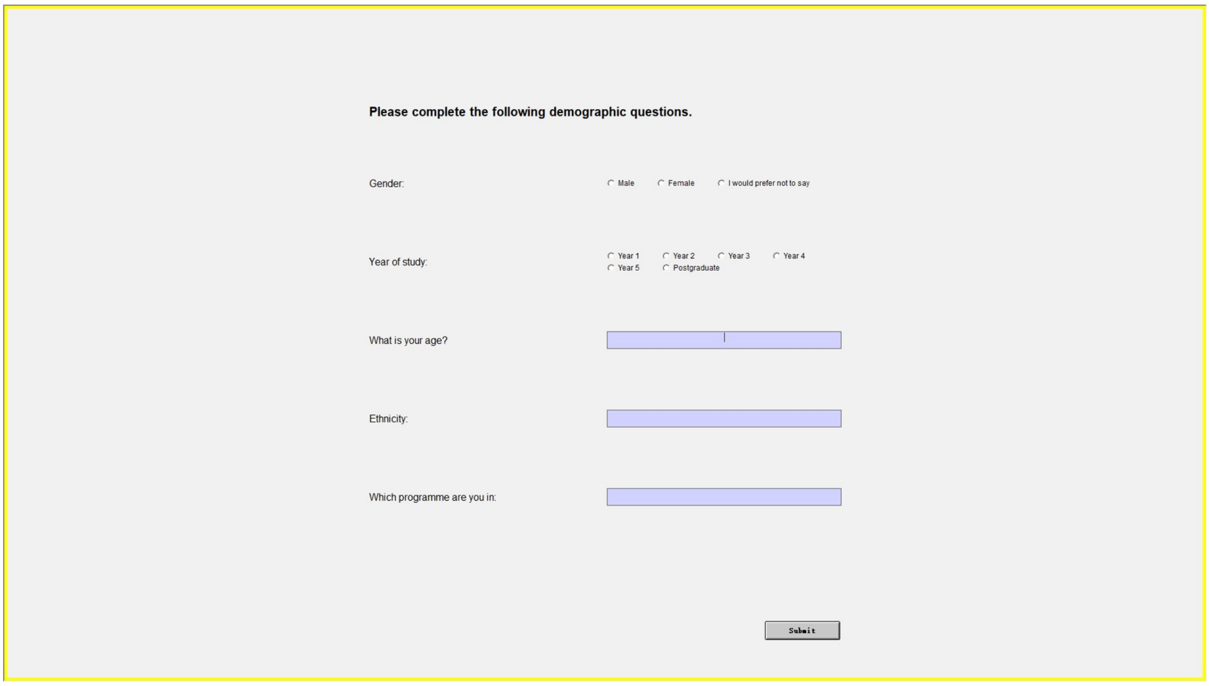


Stage 3: Post-questionnaire

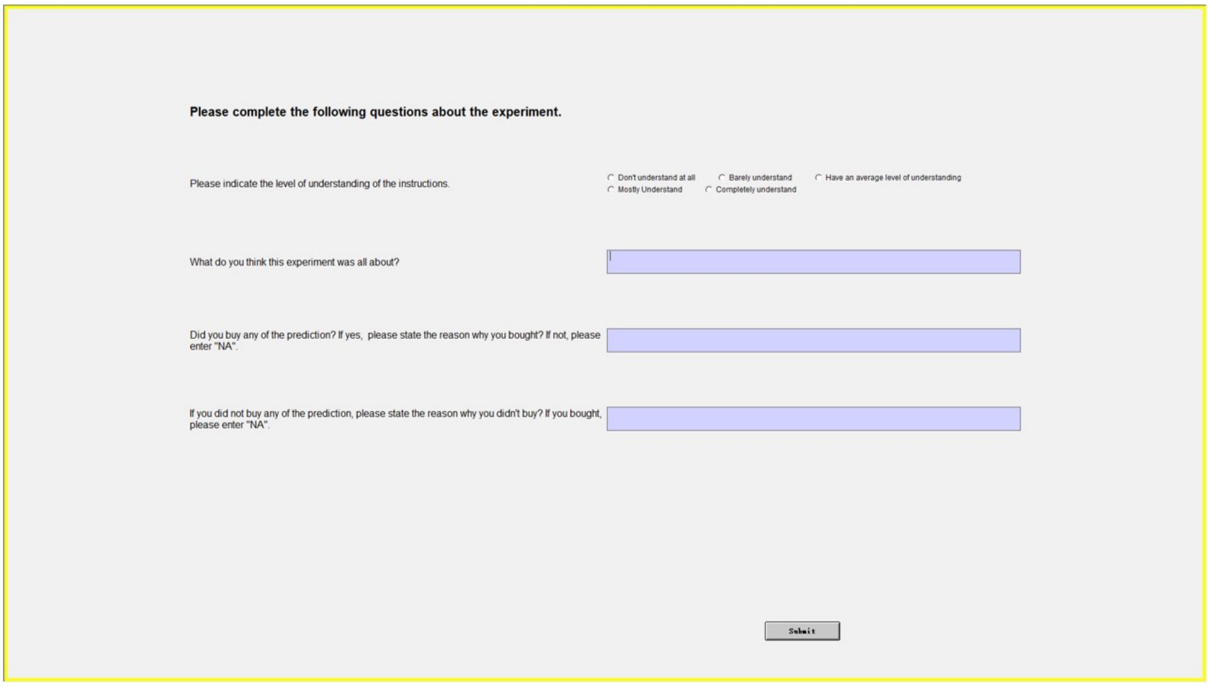
Page 1: Introduction



Page 2: Demographic Questions



Page 3: Purpose of the Study


Please complete the following questions about the experiment.

Please indicate the level of understanding of the instructions.
Don't understand at all
Barely understand
Have an average level of understanding
Mostly Understand
Completely understand

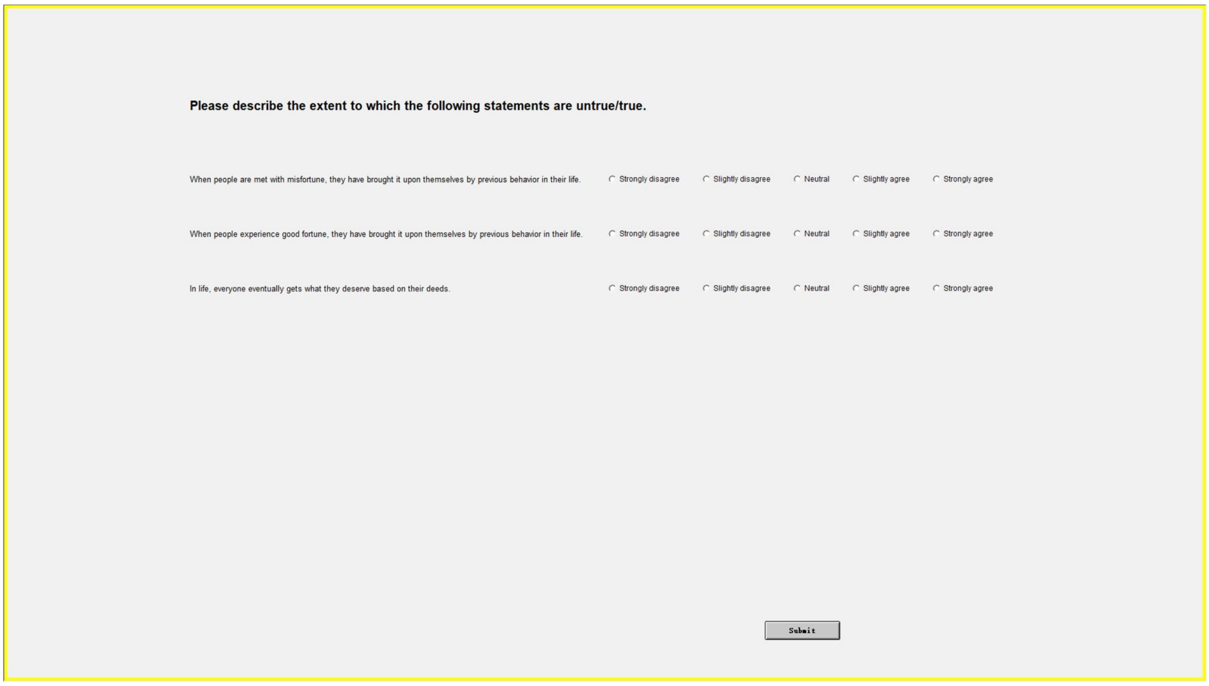
What do you think this experiment was all about?

Did you buy any of the prediction? If yes, please state the reason why you bought? If not, please enter "NA".

If you did not buy any of the prediction, please state the reason why you didn't buy? If you bought, please enter "NA".

Submit

Page 4: Belief in Karma


Please describe the extent to which the following statements are untrue/true.

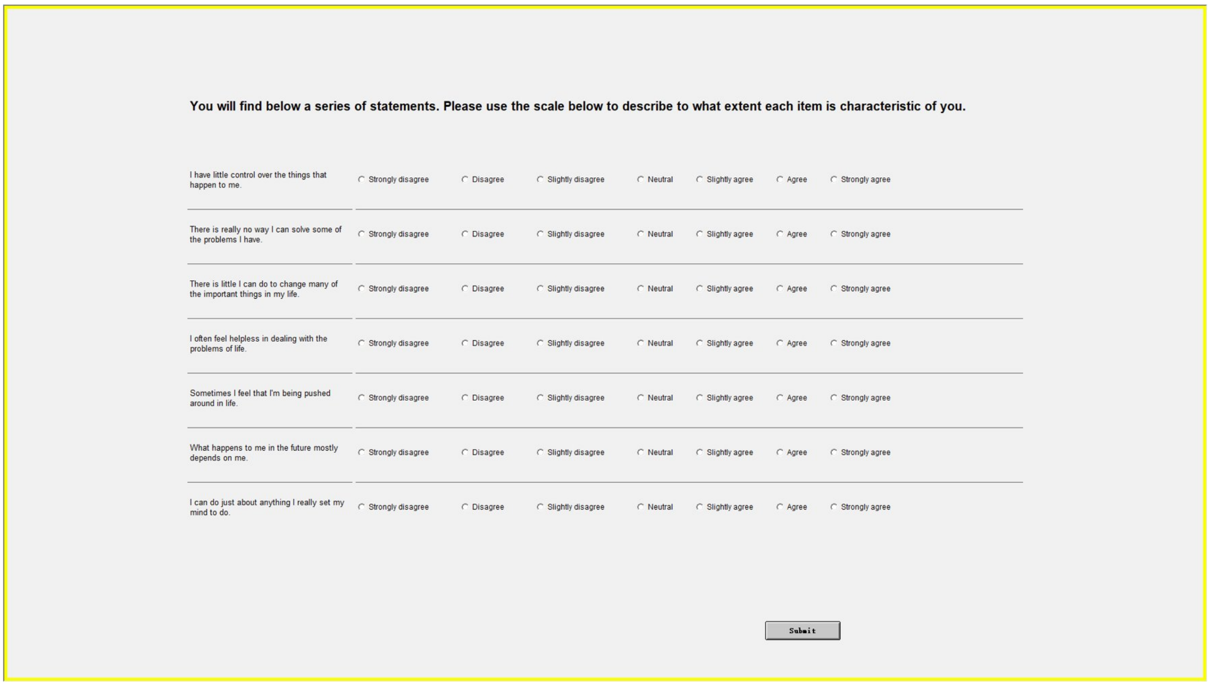
When people are met with misfortune, they have brought it upon themselves by previous behavior in their life.
Strongly disagree
Slightly disagree
Neutral
Slightly agree
Strongly agree

When people experience good fortune, they have brought it upon themselves by previous behavior in their life.
Strongly disagree
Slightly disagree
Neutral
Slightly agree
Strongly agree

In life, everyone eventually gets what they deserve based on their deeds.
Strongly disagree
Slightly disagree
Neutral
Slightly agree
Strongly agree

Submit

Page 5: Locus of Control - External

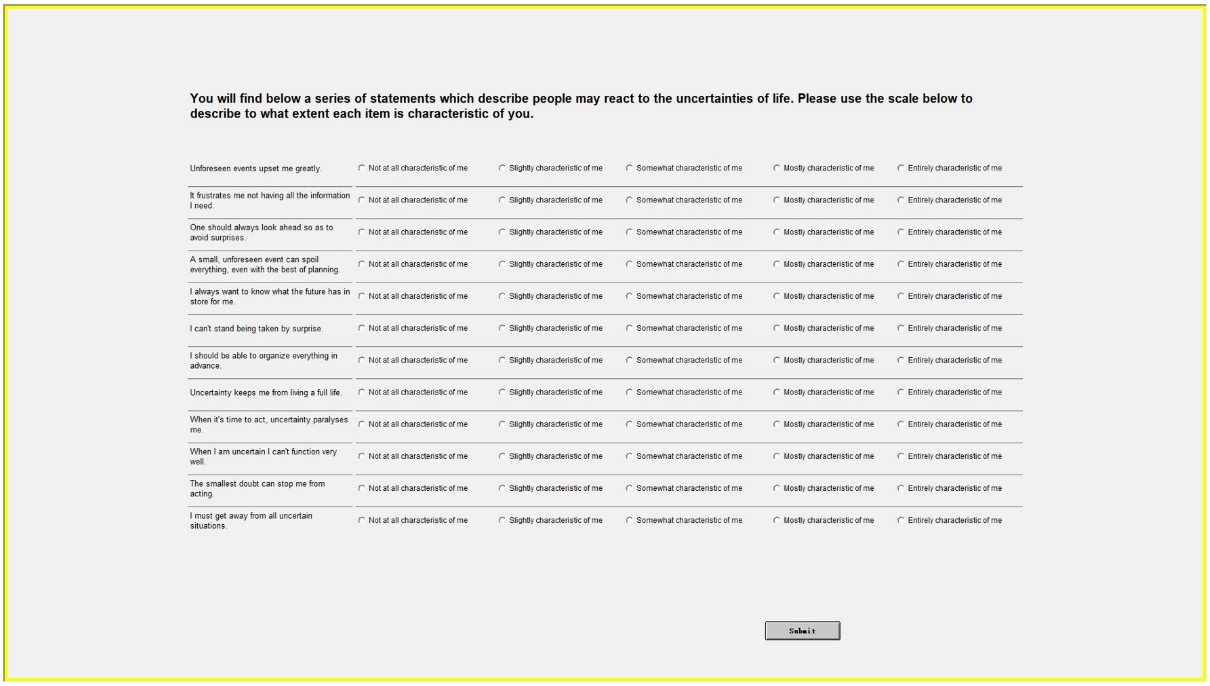


You will find below a series of statements. Please use the scale below to describe to what extent each item is characteristic of you.

I have little control over the things that happen to me.	Strongly disagree	Disagree	Slightly disagree	Neutral	Slightly agree	Agree	Strongly agree
There is really no way I can solve some of the problems I have.	Strongly disagree	Disagree	Slightly disagree	Neutral	Slightly agree	Agree	Strongly agree
There is little I can do to change many of the important things in my life.	Strongly disagree	Disagree	Slightly disagree	Neutral	Slightly agree	Agree	Strongly agree
I often feel helpless in dealing with the problems of life.	Strongly disagree	Disagree	Slightly disagree	Neutral	Slightly agree	Agree	Strongly agree
Sometimes I feel that I'm being pushed around in life.	Strongly disagree	Disagree	Slightly disagree	Neutral	Slightly agree	Agree	Strongly agree
What happens to me in the future mostly depends on me.	Strongly disagree	Disagree	Slightly disagree	Neutral	Slightly agree	Agree	Strongly agree
I can do just about anything I really set my mind to do.	Strongly disagree	Disagree	Slightly disagree	Neutral	Slightly agree	Agree	Strongly agree

Submit

Page 6: Tolerance of Uncertainty



You will find below a series of statements which describe people may react to the uncertainties of life. Please use the scale below to describe to what extent each item is characteristic of you.

Unforeseen events upset me greatly.	Not at all characteristic of me	Slightly characteristic of me	Somewhat characteristic of me	Mostly characteristic of me	Entirely characteristic of me
It frustrates me not having all the information I need.	Not at all characteristic of me	Slightly characteristic of me	Somewhat characteristic of me	Mostly characteristic of me	Entirely characteristic of me
One should always look ahead so as to avoid surprises.	Not at all characteristic of me	Slightly characteristic of me	Somewhat characteristic of me	Mostly characteristic of me	Entirely characteristic of me
A small, unforeseen event can spoil everything, even with the best of planning.	Not at all characteristic of me	Slightly characteristic of me	Somewhat characteristic of me	Mostly characteristic of me	Entirely characteristic of me
I always want to know what the future has in store for me.	Not at all characteristic of me	Slightly characteristic of me	Somewhat characteristic of me	Mostly characteristic of me	Entirely characteristic of me
I can't stand being taken by surprise.	Not at all characteristic of me	Slightly characteristic of me	Somewhat characteristic of me	Mostly characteristic of me	Entirely characteristic of me
I should be able to organize everything in advance.	Not at all characteristic of me	Slightly characteristic of me	Somewhat characteristic of me	Mostly characteristic of me	Entirely characteristic of me
Uncertainty keeps me from living a full life.	Not at all characteristic of me	Slightly characteristic of me	Somewhat characteristic of me	Mostly characteristic of me	Entirely characteristic of me
When it's time to act, uncertainty paralyses me.	Not at all characteristic of me	Slightly characteristic of me	Somewhat characteristic of me	Mostly characteristic of me	Entirely characteristic of me
When I am uncertain I can't function very well.	Not at all characteristic of me	Slightly characteristic of me	Somewhat characteristic of me	Mostly characteristic of me	Entirely characteristic of me
The smallest doubt can stop me from acting.	Not at all characteristic of me	Slightly characteristic of me	Somewhat characteristic of me	Mostly characteristic of me	Entirely characteristic of me
I must get away from all uncertain situations.	Not at all characteristic of me	Slightly characteristic of me	Somewhat characteristic of me	Mostly characteristic of me	Entirely characteristic of me

Submit

Page 7: Introduction of Risk Elicitation Question

In the next page, you will be asked to make a series of choices. How much you receive will depend partly on chance and partly on the choices you make. The decision problems are not designed to test you. What we want to know is what choices you would make in them. The only right answer is what you really would choose.

For each line in the table in the next page, please state whether you prefer option A or option B. Notice that there are a total of 10 lines in the table but just one line will be randomly selected for payment. You do not know which line will be paid when you make your choices. Hence you should pay attention to the choice you make in every line. After you have completed all your choices, the computer will randomly generate a number, which determines which line is going to be paid.

Your earnings for the selected line depend on which option you chose: If you chose option A in that line, you will receive $1. If you chose option B in that line, you will receive either $3 or $0. To determine your earnings in the case you chose option B there will be a second random draw. The computer will randomly determine if your payoffs 0 or $3, with the chances stated in Option B.

click to proceed

Page 8: Risk Elicitation Question

Line #	Option A	Option B	Please Choose A or B
1	**$1**	**$3** with 0% chance, **$0** with 100% chance	A / B
2	**$1**	**$3** with 10% chance, **$0** with 90% chance	A / B
3	**$1**	**$3** with 20% chance, **$0** with 80% chance	A / B
4	**$1**	**$3** with 30% chance, **$0** with 70% chance	A / B
5	**$1**	**$3** with 40% chance, **$0** with 60% chance	A / B
6	**$1**	**$3** with 50% chance, **$0** with 50% chance	A / B
7	**$1**	**$3** with 60% chance, **$0** with 40% chance	A / B
8	**$1**	**$3** with 70% chance, **$0** with 30% chance	A / B
9	**$1**	**$3** with 80% chance, **$0** with 20% chance	A / B
10	**$1**	**$3** with 90% chance, **$0** with 10% chance	A / B

OK

Online Appendix C
Instruction Sheets (Sample: Expert - No Info Condition)

REMARKS

Please be reminded that throughout this study:

1. You are not allowed to communicate with other participants at any point in the experiment. Any person caught violating this will be asked to leave the experiment without pay.

2. You are **not allowed to open any of the envelopes in front of you unless instructed to do so by the experimenter.**

General Information

Welcome to all of you! **Please pay attention to the information provided here and make your decisions carefully. If at any time you have questions to ask, please raise your hand and we will attend to you in private.**

Your participation in this study is voluntary. You will receive 3 S$ show-up fee for participating in this study. You may decide to leave the study at any time. Unfortunately, if you withdraw before you complete the study, we can only pay you for the decisions that you have made up to the time of withdrawal, which could be substantially less than you will earn if you complete the entire study.

The amount of your earnings from this study depends on the decisions you make. At the end of this session, your earnings will be paid to you privately. It would be contained in an envelope (indicated with your unique user ID). You will need to sign a claim card given to you and exchange your claim card with your payment.

General Instructions

Each of you will be given **a unique user ID** and it **will be clearly stated on your computer screen**. Rest assured that your **anonymity will be preserved** throughout the study. You will **never be aware of** the personal identities of other participants **during or after** the study. Similarly, other participants will also **never be aware** of your personal identities **during or after** the study. You will only be identified by your user ID in our data collection. All information collected will **strictly be kept confidential** for the sole purpose of this study.

Specific Instructions

The total duration of this study is approximately **1 hour**. You will have to go through three stages.

The points you earn from the study will be converted to S$ equivalent at the end of this study at the exchange rate of (earnings will be rounded up to the nearest dollar): 50 points = S$1

STAGE 1

In stage 1, you will be asked to play a game of predicting the outcomes of coin tosses. The coin toss game will use a two-sided coin, i.e. head and tail (H-T). For a Singaporean coin, the **TAIL** is the **FLOWER** figure on the coin and the **HEAD** is the Singapore **COAT OF ARM** figure on the coin. The game, which will last for 5 (five) rounds, consists of tossing a coin in total **five (5) times**, one in every round. Participants will be asked **to make a bet on the outcome of each of the subsequent coin tosses**. Coins will be borrowed from participants and the tosses will be done by participants.

Below is the screenshot of the welcome page of the experiment.

[Screenshot 1]

At the beginning of Round 1, you will be given **300 endowment points** which you could use to place a bet on the outcome of each subsequent coin tosses. There is a minimum bet of **10 points per round.**

- For every **1 point** you use to bet correctly, i.e. the bet matches with the actual outcome of the coin toss, your return will be **1 point * 2 = 2 points**. So, if you have an endowment of 300 points and you used **X** points to make a bet, in a case where you have placed a correct bet, you will earn **2*X** points. In terms of endowment that can be used for the next round of betting: **300-X** points plus **2*X** points from the bet.

- For every **1 point** you use to bet incorrectly, **you will lose the point you used to bet**. So, if you have an endowment of **300** points and you used **X** points to make a bet, in a case where you have placed an incorrect bet, your endowment that can be used for the next round of betting will be **300 - X** points.

You are not allowed to go bankrupt before the final round of the coin toss, i.e. the 5th round.

Below is the screenshot.

[Screenshot 2]

Prediction

However, **before each round of the coin toss**, you will be given an option to buy a prediction containing in numbered envelopes about the coin toss that has not happened yet. The numbered envelope 1 will contain a prediction of either H (head) or T (tail) for round 1. The numbered envelope 2 will contain a prediction of either H (head) or T (tail) for round 2, and so on. **The predictions enclosed in the envelopes are entirely unknown, and the method by which the predictions are made remains undisclosed.** Below is the photo of the numbered envelopes, and the screenshot.

[A photo of the numbered envelopes]

[Screenshot 3]

If you choose **to buy** the prediction, which contains in the envelope we set out for you and which will cost a fix price of **10 points per prediction**, you will be given the opportunity to **open** and **view** the expert's prediction **before** placing the bet in that round (Screenshot 4). The prediction in the numbered envelope contains a prediction of either H (head) or T (tail) of that particular round.

If you decide **not to buy** the prediction we have provided for you, you will be asked not to open the envelope (Screenshot 5). Note that you will be given the opportunity to open the envelope **for free** and view the prediction **only after** the coin toss of that particular round had already taken place.

[Screenshot 4]

[Screenshot 5]

Betting

Once you have decided whether or not to buy the prediction, you will have to place your bet on the outcome of the coin toss that is about to be undertaken (Screenshot 6).

[Screenshot 6]

Once the betting is done, a coin toss will determine the outcome. We will borrow a coin from one of the subjects and invite a volunteer from the subjects to flip the coin in the laboratory. The flipping process will be projected on the screen, allowing all subjects to observe the outcome in real-time.

[Screenshot 7]

After that, a summary of result from the betting will be shown.

[Screenshot 8]

At this stage, those of you who decided not to buy the prediction can open the envelope numbered 1 to find out the prediction of the coin toss. Those of you who decided to buy the prediction can re-open again the envelope numbered 1 if you wish to do so. This is the end of Round 1 of the experiment.

After this, the procedures repeat again until all 5 (five) rounds of betting are completed. Below is the sample of the summary page at the end of Round 5.

End

STAGE 2 (Probability Test)

In stage 2, you will be asked to complete **ten (10) questions on probability**. Please do your best to answer the questions correctly. You will be compensated according to the number of correct answers you made. For every correct answer you will get **+15** points. For every incorrect answer you will get **-15** points. If you leave a question unanswered, you will get **0** point for that particular question. Here it is the screenshot.

[Screenshot 9]

You will be given 8 (eight) minutes to complete all questions. Once the time is out and you have not finished answering all questions, the questions left unanswered will be given 0 point.

After finishing all questions, a summary of your performance in the Stage 2 will be displayed (Screenshot 10).

[Screenshot 10]

End

STAGE 3 (Post-Questionnaire)

In this part of the experiment you will be asked to complete a couple of questions to help us learn more about you. Below is the screenshot of the questions.

[Screenshot 11]

You will be asked a few questions about your understanding of the experiment. Below is the screenshot of the questions.

[Screenshot 12]

You will find a series of statements and need to use the scale to describe to what extent each item you agree with. Below is the screenshot of the questions.

[Screenshot 13]

You will find a series of statements and need to use the scale to describe to what extent each item is characteristic of you. Below is the screenshot of the questions.

[Screenshot 14]

[Screenshot 15]

In the end, you will also be asked to make a series of choices. How much you receive will depend partly on chance and partly on the choices you make. The decision problems are not designed to test you. What we want to know is what choices you would make in them. The only right answer is what you really would choose.

For each line in the table in the next page, please state whether you prefer option A or option B. Notice that there are a total of 10 lines in the table but just one line will be randomly selected for payment. You do not know which line will be paid when you make your choices. Hence you should pay attention to the choice you make in every line. Below is the screenshot.

[Screenshot 16]

After you have completed all your choices, the computer will randomly generate a number, which determines which line is going to be paid.

Your earnings for the selected line depend on which option you chose: If you chose option A in that line, you will receive $1. If you chose option B in that line, you will receive either $3 or $0. To determine your earnings in the case you chose option B, there will be second random draw. The computer will randomly determine if your payoff is 0 or $3, with the chances stated in Option B.

End