Peer prediction markets to elicit unverifiable information

Aurélien Baillon*[1], Cem Peker[2], and Sophie van der Zee[3]

[1]Emlyon Business School & GATE UMR 5824
[2]School of Management, Polytechnic University of Milan
[3]Erasmus School of Economics, Erasmus University Rotterdam

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Abstract

We introduce an incentive mechanism to elicit answers to binary questions that cannot be verified for accuracy. Agents choose whether to receive a costly private signal, which leads them to endorse "yes" or "no" as an answer. Then, they either buy or sell an asset, whose value is determined by the endorsement rate of "yes" answers. We obtain a separating equilibrium, where agents want signals and trade the asset as a function of their signal. Two experimental studies test the theoretical results. The first shows that the mechanism motivates costly information acquisition. The second demonstrates feasibility in a natural setting.

*Corresponding author: baillon@em-lyon.com

1 Introduction

"Have you stood less than 6 feet apart from another person in a queue yesterday?" Health surveys often require respondents to recollect past experiences. This experience can be seen as a private signal that respondents acquire by exerting effort (recalling, to their mind, what they did a day earlier.) But how can we ensure that the respondents will, first, provide such effort and then, answer accurately if there is no way to compare their answer to some ground truth?

Starting with Crémer and McLean (1988), the mechanism design literature has explored ways to reveal private signals. Miller et al. (2005), and more broadly the peer-prediction literature (Witkowski and Parkes, 2012a, 2013; Liu and Chen, 2017a), have proposed solutions exploiting the informativeness of a respondent's answer in predicting their peers' answers. For instance, imagine that we have some prior expectations about the rate of yes answers to the 6-feet-apart question. A respondent answering yes increases our expectations about the proportion of *other* people answering yes. Formally, this increase is a simple application of Bayesian updating when respondents draw a private signal (yes/no), with unknown probability p of yes signals: a yes signal makes higher values of p more likely than initially believed.[1] Intuitively, the yes answer to the 6-feet-apart question can suggest that others also had difficulty complying with a social distancing guidelines.

In this paper, we propose and implement a novel solution to incentivize private signals acquisition and revelation: a peer-prediction market (PPM). In a PPM, yes respondents are rewarded with the formula "yes answer rate - prior expectations of yes answer rate". Those who answer no get the opposite reward. If there are fewer yes answers than expected, yes respondents get a negative reward while no respondents get a positive one. Equivalently, a PPM can be presented as yes (no) respondents buying (selling) a single asset, the value of which is eventually determined by the proportion of yes answers. The price is set to the prior

[1] We assume here that signals are conditionally independent, i.e. independent given the probability of success. The probability of success is assumed to be itself drawn from a non-degenerate distribution over $(0, 1)$.

expectations. In a situation in which the yes-answer rate is expected to follow a random walk, a repeated PPM can be implemented in which the price at period t is the value of the asset at $t-1$.

First, we show that signal acquisition and revelation is a Bayesian Nash equilibrium, providing a partial-implementation solution to the static problem. Our solution is minimal, in the sense that it does not ask respondents to provide more than their answer and it does not require the surveyor to share more than prior expectations with the respondents. We then extend our analysis to incorporate psychological costs, capturing the possible (mild) discomfort of reporting an answer and potential deception costs.

Second, we test PPM in an online experiment closely following the theoretical model: respondents may exert an effort (i.e., complete a real-effort task borrowed from the experimental economics literature) to obtain a signal and report the beliefs they derive from it; or they may simply answer randomly. We compare PPM with two benchmarks: flat fee (no incentives) and accuracy incentives (incentives when the signal generation process is observable). The latter is not applicable in surveys, where such process in unobservable but it provides a gauge for the effect of PPM. In our experiment, a flat fee decreases the effort rate by about 20 percentage points with respect to accuracy incentives. PPM allows us to recover half of this difference.

Third, we demonstrate feasibility in a natural setting. We implement the repeated PPM in the context of a health survey, involving questions of the 6-feet-apart type. The asset price is set to the previous week yes-rate. We hypothesize that people not exerting recollection efforts or feeling some slight discomfort for not complying with health guidelines are likely to deny having experienced such situation, and therefore that PPM will trigger higher rate of yes answers than a flat fee. We indeed obtain that more people admit experiencing situations in contradictions with health guidelines in the PPM treatment than in the flat fee treatment. This second study shows that PPM can be applied to socially relevant questions, where psychological costs of reporting non-compliance may be present.

Related literature - PPMs relates to the mechanism design literature starting with Myerson (1986) and (Crémer and McLean, 1988).[2] This strand of literature built signal revelation mechanism exploiting between-agent signal correlation. As in Myerson (1986), signal revelation in our paper is not the only equilibrium, which is known as partial implementation (see for instance Maskin (1999) for an example of full implementation that excludes undesirable equilibria).

PPMs offer a market-based solution to the problem of incentivizing effort in information elicitation without verification (Waggoner and Chen, 2013). Previous work introduced peer prediction mechanisms that consider the signal revelation problem only, and does not explicitly model costly signal acquisition. The original peer prediction method (Miller et al., 2005) can be adjusted for costly effort via re-scaling of payments. PPMs are more transparent than typical peer prediction methods (Miller et al., 2005; Witkowski and Parkes, 2012a, 2013; Liu and Chen, 2017a), which used scoring rules instead of simple trades. The present paper is also the first of this stream of literature to include both cost of efforts and psychological costs in the model.

The PPM method relaxes the typical common prior assumption made, for instance, by Miller et al. (2005), by requiring agents to share their prior *expectation*, instead of the full prior. Weakening beliefs assumptions is central in the literature on (partial or full) implementation (Bergemann and Morris, 2005, 2009a,b). A mechanism is more robust if it provides incentive compatibility for a larger set of beliefs (Ollár and Penta, 2017, 2019).

Follow-up work developed peer prediction mechanisms for effort elicitation in crowdsourcing problems with unverifiable tasks, such as peer grading, content classification etc. Witkowski et al. (2013) study output agreement mechanisms, in which agents receive positive payment if their reports agree with their peers'. Simple output agreement mechanisms do not achieve signal revelation when an agent believes to hold a minority signal, which may also affect effort decision. PPMs do not have this problem.

[2] In that, we differ from the (Bayesian) information design literature, where the payoff structure is fixed (Kamenica, 2017, 2019).

Methods to elicit private signals face the tradeoff between *minimality* (Witkowski and Parkes, 2012a), i.e. asking only one question as we do, and being *detailed-free*, i.e. not requiring specific knowledge from the center, to follow the desiderata of the Wilson doctrine (Wilson, 1987). Peer prediction methods choose minimality. By contrast Bayesian truth serum (Prelec, 2004) and its variants (Witkowski and Parkes, 2012b; Radanovic and Faltings, 2013, 2014) are detail-free. They do not require any knowledge of the prior. However, respondents are asked to provide some information about it on top of their answers. Cvitanić et al. (2019) proposes the most general form, even replacing the additional information about prior by another verifiable question. All these mechanisms are however not minimal and theorefore more demanding to respondents than PPMs.

Closest to PPMs, but also not minimal, are Bayesian markets (Baillon, 2017), which provide a market solution to binary elicitation problems in a similar Bayesian setup to ours, except that information is not costly. Moreover, unlike PPM, agents first report their answers, which determines whether they can buy or sell an asset defined as in PPMs. Then a price is determined randomly and the agents must decide whether to actually trade at this price. In equilibrium, agents report their private signal to be eligible for their desired trade. In the way they are set-up, PPMs aim to be closer to prediction markets than Bayesian markets are. The price is pre-specified and agents make only one buy-or-sell decision.

Settings with multiple, correlated questions allow for minimal and detail-free methods. Dasgupta and Ghosh (2013) use reports in multiple auxiliary questions to penalize agreement without effort in a binary question of interest. Shnayder et al. (2016) generalize Dasgupta and Ghosh (2013) to obtain correlated agreement mechanism for non-binary questions and Baillon and Xu (2021) simplifies the method using bets. Correlated agreement uses multiple questions and requires specific assumptions about correlations across questions or shared signal technology, which PPMs do not require. Peer truth serum for crowdsourcing is another peer agreement mechanism which uses agents' responses to multiple questions Radanovic et al. (2016). Liu and Chen (2017b) develop sequential peer prediction, in which agents submit answers sequentially and the mechanism learns the optimal reward for effort elicitation over time. Sequential peer prediction is minimal, but unlike PPM, requires a dynamic setup. In binary elicitation problems, PPM offers a simpler minimal alternative to other peer prediction mechanisms to incentivize signal acquisition and revelation, which also works in one-shot problems.

2 Theory

2.1 Agents and their information

A *center* (a researcher, a survey company) is interested in eliciting N *agents*' informed answers to a question Q, with possible answers $\{0, 1\}$. Agents can answer randomly at no cost but they may also decide to provide an effort (thinking, remembering, looking for information, etc.) to obtain their informed answer. Formally, agent $i \in \{1, \ldots, N\}$ can obtain a *signal* $s_i \in \{0, 1\}$ by providing *effort* $e_i = 1$ at a cost $c_i > 0$ (expressed in monetary terms). The cost of no effort ($e_i = 0$) is 0. There are two possible interpretations for s_i. It is either directly the informed answer to the question (agent i remembers what happened) or a signal that unequivocally influences the agent's opinion about the correct answer, i.e., signal 1 leads the agent to believe that answer 1 is correct and signal 0 induces the opposite belief. To keep notation minimal, we do not formally differentiate between signals and signal-induced beliefs. As usual in this literature (e.g., Prelec, 2004; Miller et al., 2005), we assume that the probability of getting signal 1 is the same for all agents (hence, it is independent of the effort cost) but is unknown. We model it as a random variable ω over $[0, 1]$. Denoting $s = (s_1, \ldots, s_N)$, a *state of nature* is thus a realization of ω and s, with the *state space* being $\Omega = [0, 1] \times \{0, 1\}^N$.The probability space is (Ω, Σ, P), with Σ the Borel $\sigma-$algebra of Ω and we assume that P is countably additive. The next assumption describes the full signal technology.

Assumption 1 (Signal technology)**.** *The signal technology is such that for all* $i, j \in \{1 \ldots, N\}$,

$i \neq j$, and $o \in [0,1]$:

1. *$P(s_i = 1|\omega = o) = o$;*

2. *$P(s_i = 1|s_j, \omega = o) = o$;*

3. *and $P(\omega)$ is continuous over $[0,1]$.*

Part 1 of Assumption 1 states that the signal technology is anonymous, part 2 that it satisfies *conditional independence*, and part 3 that no value of ω has a probability mass. The latter excludes degenerate cases in which all agents could get the same signal for sure or in which ω would be known.

Let P_i represent the belief of agent i about the signal technology, and P_0 that of the center. It is common to assume $P_i = P_0 = P$ in peer prediction mechanisms.[3]. We allow agents to have different opinions on how likely various values of ω are but the following assumption restrict their belief in two ways.

Assumption 2 (Unbiased prior expectations)**.** *For all $i \in \{0, \dots, N\}$, P_i satisfies properties 1-3 of Assumption 1 and $E_i(\omega) = E(\omega)$.*

Assumption 2 states that all agents and the center agree on the main properties of the signal technology and share the same prior expectation. It is a strong assumption, despite relaxing the often-used common prior assumption. Assumption 2 is plausible if (i) question Q is new and people have no reason to believe that answer 1 is more likely than answer 0, i.e., $E(\omega) = 0.5$; or (ii) signals of another group of agents have been publicly revealed (possibly with another mechanism); or (iii) the agents have no clue about ω but the center shares its prior expectation. In case (i), we do not need to assume uniform P_i over the possible values of ω; e.g., it can be bell-shaped for some agents. Case (ii) can correspond to situations in which question Q was asked in the past (to other agents) but the center and the (new)

[3]Or $P_i = P$ with no assumption on P_0 in the Bayesian truth-serum of (Prelec, 2004) or Bayesian markets of (Baillon, 2017)

agents do not know whether the signal distribution will be exactly the same. For instance, imagine that, a month ago, it was published that 73% of people reported they could always stay 6 feet away from others. There are many reasons why this proportion might change but before agents try to remember their own experience, 73% is a good average guess about what others will answer. Case (iii) may occur when the center has the means to study the signal technology; for instance, a review website where people report their (binary) experience with hotels or movies can study signal distribution and display prior average expectation. Let us denote $\bar{\omega} \equiv E(\omega)$, $\bar{\omega}_i^0 \equiv E_i(\omega|s_i = 0)$ and $\bar{\omega}_i^1 \equiv E_i(\omega|s_i = 1)$.

Lemma 1. *Under Assumptions 1 and 2, for all $i \in \{1, \ldots, N\}$, $0 < \bar{\omega}_i^0 < \bar{\omega} < \bar{\omega}_i^1 < 1$.*

Proof. First part 3 of Assumption 1 excludes $\bar{\omega} \in \{0, 1\}$.

Second, $P_i(s_i = 1) = \int_0^1 P_i(s_i = 1|\omega = o) \times P_i(\omega = o)do = \int_0^1 o \times P_i(\omega = o)do = E_i(\omega) = \bar{\omega}$. $\bar{\omega}_i^1 = \int_0^1 \frac{P_i(s_i=1|\omega=o)\times P_i(\omega=o)\times o}{P_i(s_i=1)}do = \int_0^1 \frac{o^2\times P_i(\omega=o)}{\bar{\omega}}do > \bar{\omega}$ because $\int_0^1 o^2 \times P_i(\omega = o) > \left(\int_0^1 o \times P_i(\omega = o)\right)^2 = \bar{\omega}^2$ by Jensen's inequality applied to the convex squared function and the inequality is strict because we degenerate cases were excluded by Part 3 of Assumption 1, which also excludes a posterior expectation of 1. The proof of $0 < \bar{\omega}_i^0 < \bar{\omega}$ is symmetric. $\square$

Lemma 1 shows that under our assumptions, all agents receiving signal 1 have higher expectations about ω than they had ex ante (and than the center) whereas agents with signal 0 decrease their expectations. Finally, we make the following assumption on agents' risk preferences:

Assumption 3 (Risk neutrality)**.** *Agents are risk neutral.*

Assumption 3 implies that agents maximize their expected payoffs. Section 2.2 introduces a market mechanism to exploit the difference in expectations established in Lemma 1. Assumption 3 suggests that agents' optimal strategy will not depend on a risk parameter.

2.2 The Market

The center implements a *peer-prediction market* for Q, in which an asset is traded whose value will be the proportion of agents reporting 1 as answer for Q multiplied by π, a scaling constant. If the currency is the dollar, $\pi = 10$ means that the asset is worth \$5 if 50% of the agents report 1.

Definition 1. *A peer-prediction market is defined by the following steps:*

1. *The center announces the asset price $\bar{\omega}\pi$.*
2. *Agents simultaneously choose a report $r_i \in \{0, 1\}$. Those who report 1 become buyers of the asset and those who report 0 become sellers.*
3. *The center computes the asset value $\bar{r}\pi = \frac{\pi}{N}\sum_{i=1}^{n} r_i$.*
4. *If $\bar{r} = 0$ or $\bar{r} = 1$, the market is stopped; no payment occurs.*
5. *Otherwise, buyers pay $\bar{\omega}\pi$ to the center in exchange of $\bar{r}\pi$ and sellers receive $\bar{\omega}\pi$ from the center in exchange of $\bar{r}\pi$.*

In a peer-prediction market, reporting a 1 answer ($r_i = 1$) is equivalent to betting that the proportion of 1 answers will be higher than $\bar{\omega}$, that is, buying the asset. Symmetrically, reporting a 0 answer is a bet on a proportion of 1 answers lower than $\bar{\omega}$. Step 5 specifies that all trades are made with the center, and not directly between agents. Direct trading would lead to complications such as the no-trade theorem (Milgrom and Stokey, 1982): knowing that someone wants to sell informs the buyer that someone received a 0 signal, and conversely. Ultimately, agents who report 1 get $(\bar{r} - \bar{\omega})\pi$ and those who report 0 get $(\bar{\omega} - \bar{r})\pi$. The center subsidies the market if need be. The agents subtract c_i from their earnings if they provided an effort.

2.3 Strategies and Equilibria

The agents' strategies in the peer-prediction market involve first deciding whether to exert an effort, and then what to report. We will consider mixed strategies only in reports, so agent i's strategy is given by (e_i, R_i, R_i^0, R_i^1) with R_i, R_i^0, and R_i^1 the probabilities of $r_i = 1$ if $e_i = 0$, if $e_i = 1$ and $s_i = 0$, and if $e_i = 1$ and $s_i = 1$ respectively. The strategy space is thus $\{0,1\} \times [0,1]^3$. The center is interested in situations in which agent i exerts an effort and reveals s_i, i.e., $e_i = 1$, $R_i^0 = 0$, and $R_i^1 = 1$. We need to make one final assumption, about what agents know about each others.

Assumption 4 (Common knowledge)**.** *The peer-prediction market functioning, the strategy space, the signal technology, the beliefs P_i, the costs c_i and agents' risk neutrality are common knowledge.*

Assumption 4 ensures that we have specified all the elements of a *Bayesian game*, as defined by (Osborne and Rubinstein, 1994, Definition 25.1). If beliefs and costs were not common knowledge, we would have to define higher-order beliefs, which would complicate the proofs. As we will see below the crucial part is not so much that agents know the exact beliefs of everyone, but rather that all agents know that Lemma 1 holds. Again for convenience, we let $N \to \infty$. It allows us to assimilate signal probability with signal proportion. It also allows us to neglect the impact of a single agent on the asset value.

Proposition 1. *Under Assumptions 1 to 4 and with N infinite, if $c_i > \pi$ for all $i \in \{1, \ldots, N\}$, then Nash equilibria are characterized by $e_i = 0$ and $R_i \in \{0, \bar{\omega}, 1\}$. Expected payoffs are 0.*

Proof. Possible earnings $(\bar{r} - \bar{\omega})\pi$ and $(\bar{\omega} - \bar{r})\pi$ are both strictly lower than π, and therefore than c_i if $c_i > \pi$. There are no incentives to provide efforts; hence, $e_i = 0$. Consider agent i and assume all other agents $j \neq i$ have the same probability to report 1 ($R_j = R$ for some $R \in [0,1]$). Hence, with N infinite, the asset value $\bar{r}$ is R. Agent i hence expects to earn $[R_i \times (R - \bar{\omega}) + (1 - R_i) \times (\bar{\omega} - R)] \times \pi$. If $R \in (\bar{\omega}, 1]$, then $R_i = 1$ is optimal. If $R \in [0, \bar{\omega})$, then $R_i = 0$ is optimal. Finally, if $R = \bar{\omega}$, then any $R_i \in [0,1]$ is optimal. Nash equilibria require $R_i = R$ such that no one has incentives to deviate. Hence, we must have either $R_i = 1$ for all i, or $R_i = 0$ for all i, or $R_i = \bar{\omega}$ for all i. In all these cases, earnings are 0 (remember that if $\bar{r} = 0$ or 1, no payoffs occur as specified in step 4 of Definition 1. $\square$

Proposition 1 highlights three equilibria in which agents make no efforts. In two of these equilibria, they all report the same answer, either 0 or 1. In the third equilibrium, the probability to report 1 is equal to the prior probability. Study 1 will explore what agents do when they decide not to get a signal.

Proposition 2. *Under Assumptions 1 to 4 and with N infinite, if for all $i \in \{1, \dots, N\}$ $\frac{c_i}{\pi} < \bar{\omega} \times (\bar{\omega}_i^1 - \bar{\omega}) + (1 - \bar{\omega})(\bar{\omega} - \bar{\omega}_i^0)$, acquiring and revealing signals ($e_i = 1$, $R_i^0 = 0$, and $R_i^1 = 1$) is a Nash equilibrium, and it strictly dominates the no-effort equilibria.*

Proof. Let us consider agent i's view point and assume $e_j = 1$, $R_j^0 = 0$, and $R_j^1 = 1$ for all $j \neq i$. Without any signal, agent i's expected earnings are $[R_i(E_i(\omega) - \bar{\omega}) + (1 - R_i)(\bar{\omega} - E_i(\omega))] \times \pi = 0$ by Assumption 2.

With signal 1, agent i's expected earnings are $[R_i^1(\bar{\omega}_i^1 - \bar{\omega}) + (1 - R_i^1)(\bar{\omega} - \bar{\omega}_i^1)] \times \pi$. By Lemma 1, this is maximum for $R_i^1 = 1$, yielding $(\bar{\omega}_i^1 - \bar{\omega}) \times \pi > 0$.

With signal 0, agent i's expected earnings are $[R_i^0(\bar{\omega}_i^0 - \bar{\omega}) + (1 - R_i^0)(\bar{\omega} - \bar{\omega}_i^0)] \times \pi$. By Lemma 1 again, this is maximum for $R_i^0 = 0$, yielding $(\bar{\omega} - \bar{\omega}_i^0) \times \pi > 0$.

Before getting a signal, the expected gain is therefore,

$$\left[P_i(s_i = 1) \times \left(\bar{\omega}_i^1 - \bar{\omega}\right) + P_i(s_i = 0)\left(\bar{\omega} - \bar{\omega}_i^0\right)\right] \times \pi = \left[\bar{\omega} \times \left(\bar{\omega}_i^1 - \bar{\omega}\right) + (1 - \bar{\omega})\left(\bar{\omega} - \bar{\omega}_i^0\right)\right] \times \pi.$$

This is strictly positive by construction and strictly more than c_i by assumption. Hence, the net earnings (once the costs are subtracted) are strictly positive and providing an effort is worth it. As a consequence, $e_i = 1$, $R_i^0 = 0$, and $R_i^1 = 1$ is a Nash equilibrium.

Finally, let us consider the case in which all agents but i provide no efforts and report 1 with probability R. The expected earnings are

$$\begin{cases} [R_i^1 \times (R-\bar{\omega}) + (1-R_i^1) \times (\bar{\omega}-R)] \times \pi & \text{with signal 1} \\ [R_i^0 \times (R-\bar{\omega}) + (1-R_i^0) \times (\bar{\omega}-R)] \times \pi & \text{with signal 0} \\ [R_i \times (R-\bar{\omega}) + (1-R_i) \times (\bar{\omega}-R)] \times \pi & \text{with no signal.} \end{cases}$$

As in Proposition 1, the only equilibria must be of the form $R_i = R \in \{0, \omega, 1\}$, and by similar arguments $R_i^1 = R_i^0 = R \in \{0, \omega, 1\}$. The earnings are always 0 and the net earnings with effort are even strictly negative. Hence, $e_i = 0$, $R_i \in \{0, \omega, 1\}$ is also a Nash equilibrium (with $R_i^1 = R_i^0 = R_i$) but it is dominated by the equilibrium with signal acquisition and revelation ($e_i = 1$, $R_i^0 = 0$, and $R_i^1 = 1$). □

In Proposition 2, the effort cost is lower than the expected gain of signal acquisition and revelation for all agents, while it was too high in Proposition 1. Intermediary situations are addressed in the following propositions.

Proposition 3. *Under Assumptions 1 to 4 and with N infinite, if for $T \times 100\%$ of the agents $\frac{c_i}{\pi} > \bar{\omega} \times (T\bar{\omega} + (1-T)\bar{\omega}_i^1 - \bar{\omega}) + (1-\bar{\omega})\left(\bar{\omega} - T\bar{\omega} - (1-T)\bar{\omega}_i^0\right)$ and the inequality is reversed for the remaining agents, then there is a Nash equilibrium in which these $T \times 100\%$ will exert no efforts and report 1 with probability $\bar{\omega}$ and where the other agents acquire and reveal their signals.*

Proof. First, let us assume that all agents but i play the strategy described in the proposition. With signal 1, agent i expects the asset value to be $T\bar{\omega} + (1-T)\omega_i^1$, and with signal 0 $T\bar{\omega} + (1-T)\omega_i^0$. By Lemma 1, $T\bar{\omega} + (1-T)\omega_i^0 < \bar{\omega} < T\bar{\omega} + (1-T)\omega_i^1$, and with the same argument as in the proof of Proposition 2, it is best to reveal signals, $R_i^0 = 0$ and $R_i^1 = 1$. Ex ante, the expected benefit of exerting an effort is therefore $[\bar{\omega} \times (T\bar{\omega} + (1-T)\bar{\omega}_i^1 - \bar{\omega}) + (1-\bar{\omega})\left(\bar{\omega} - T\bar{\omega} - (1-T)\bar{\omega}_i^0\right)]\pi - c_i$.

If $\frac{c_i}{\pi} \le \bar{\omega} \times (T\bar{\omega} + (1-T)\bar{\omega}_i^1 - \bar{\omega}) + (1-\bar{\omega})\left(\bar{\omega} - T\bar{\omega} - (1-T)\bar{\omega}_i^0\right)$ then $e_i = 1$ is optimal.

If $\frac{c_i}{\pi} > \bar{\omega} \times (T\bar{\omega} + (1-T)\bar{\omega}_i^1 - \bar{\omega}) + (1-\bar{\omega})(\bar{\omega} - T\bar{\omega} - (1-T)\bar{\omega}_i^0)$, an effort leads to negative net earnings, whereas exerting no efforts gives $[R_i \times (T\bar{\omega} + (1-T)E_i(\omega) - \bar{\omega}) + (1-R_i)(\bar{\omega} - T\bar{\omega} - (1-T)E_i(\omega))]\,\pi = 0$ because of the common prior expectations assumption. Hence, $e_i = 0$ and $R_i = \bar{\omega}$ is a best response in this case. □

In the equilibrium of Proposition 3, the proportion T of agents not providing an effort have negative externalities on others by decreasing the extent to which the asset value can differ from the prior expectations. This reduces the value of providing an effort for everyone.

2.4 Psychological costs

So far, we have only considered effort costs. In this subsection, two additional costs are considered:

- *Asymmetric reporting cost:* Sometimes, one answer may be slightly stigmatizing, regardless of the truth, for instance admitting not compliance with guidelines. We model this as a cost $a_i \geq 0$ borne by agent i when reporting $r_i = 1$ per se, no matter whether the agent receives a signal and what this signal may be. We choose 1 arbitrarily, and without loss of generality. This cost can reflect a stigma associated with answer 1. As we will see in the theoretical results and later in the experimental applications, a_i should not be too high, thereby excluding major incentives to lie. However, a_i can arise from social desirability bias (Tourangeau and Yan, 2007), including descriptive (what behaviours are common) and injunctive norms (what behaviours are acceptable).

- *Deception cost:* The cost $d_i \geq 0$ of reporting $r_i = 0$ after receiving signal $s_i = 1$ or reporting $r_i = 1$ after receiving signal $s_i = 0$. This cost captures people's preference to tell the truth, as shown by Abeler et al. (2019) and also known in psychology as the Truth-Default Theory (Levine et al., 2010; Levine, 2014). People are averse towards lying about private information (Lundquist et al., 2009). Moreover lying tends to be more cognitively demanding, leading to increased reaction times (Suchotzki et al., 2017), and negatively affecting people's self-concept (Mazar et al., 2008). We assume that such costs can only occur when a signal has been received because cost for reporting an answer in spite of having no signal would be equivalent to decreasing the effort costs.

Assumption 5. *Agents bear asymmetric reporting costs* $a_i \geq 0$ *and deception costs* $d_i \geq 0$ *and these costs are common knowledge.*

Proposition 4. *Under Assumptions 1 to 5 and with* N *infinite, if for all* $i \in \{1, \ldots, N\}$ $\frac{c_i}{\pi} < \bar{\omega} \times \left(\bar{\omega}_i^1 - \bar{\omega} - \frac{a_i}{\pi}\right) + (1 - \bar{\omega})\left(\bar{\omega} - \bar{\omega}_i^0\right)$ *and* $\frac{a_i}{\pi} < \frac{d_i}{\pi} + 2\left(\bar{\omega}_i^1 - \bar{\omega}\right)$*, signal acquisition and revelation (*$e_i = 1$*,* $R_i^0 = 0$*, and* $R_i^1 = 1$*) is a Nash equilibrium, and it strictly dominates the no-effort equilibrium.*

Proof. Let us consider agent i's view point and assume $e_j = 1$, $R_j^0 = 0$, and $R_j^1 = 1$ for all $j \neq i$. Without any signal, agent i's expected earnings are

$$\left[R_i\left(E_i(\omega) - \bar{\omega} - \frac{a_i}{\pi}\right) + (1 - R_i)\left(\bar{\omega} - E_i(\omega)\right)\right] \times \pi \leq 0.$$

With signal 1, agent i's expected earnings are

$$\left[R_i^1\left(\bar{\omega}_i^1 - \bar{\omega} - \frac{a_i}{\pi}\right) + (1 - R_i^1)\left(\bar{\omega} - \bar{\omega}_i^1 - \frac{d_i}{\pi}\right)\right] \times \pi - c_i.$$

This is maximum for $R_i^1 = 1$, because $\frac{a_i}{\pi} < \frac{d_i}{\pi} + 2\left(\bar{\omega}_i^1 - \bar{\omega}\right)$. With signal 0, agent i's expected earnings are

$$\left[R_i^0\left(\bar{\omega}_i^0 - \bar{\omega} - \frac{a_i}{\pi} - \frac{d_i}{\pi}\right) + (1 - R_i^0)\left(\bar{\omega} - \bar{\omega}_i^0\right)\right] \times \pi - c_i.$$

This is maximum for $R_i^0 = 0$. Before getting a signal, the expected payoff is therefore, $\left[\bar{\omega} \times \left(\bar{\omega}_i^1 - \bar{\omega} - \frac{a_i}{\pi}\right) + (1 - \bar{\omega})\left(\bar{\omega} - \bar{\omega}_i^0\right)\right] \times \pi - c_i$. This is strictly positive by assumption. Hence, providing an effort is worth it. As a consequence, $e_i = 1$, $R_i^0 = 0$, and $R_i^1 = 1$ is a Nash equilibrium.

Finally, let us consider the case in which all agents but i provide no efforts and report 0 (as in Proposition 1). The best agent i can do is to provide no effort and report 0 as well, yielding expected earnings 0, which is dominated by signal acquisition and revelation. $\square$

Proposition 4 establishes two sufficient conditions for the existence of an equilibrium in which signals are acquired and revealed. The first one, as in Proposition 2, ensures that the expected payoffs with effort is higher than with no effort. The second one ensures that the cost of reporting the stigmatizing answer does not exceed the benefit of truthfully revealing one's signal. This benefit is twofold: the agent does not lie (so no deception costs d_i) and buys the asset instead of having to sell it. This leads to three remarks. First, costs of reporting a stigmatizing answers are moderated by the cost of lying. Second, if $\frac{a_i}{\pi} > \frac{d_i}{\pi} + 2\left(\bar{\omega}_i^1 - \bar{\omega}\right)$, the corresponding agent will anticipate to never report 1 anyhow and therefore, has no incentives to provide an effort. In other words, in our model, conscious lying has no reason to occur because agent will simply prefer not to get a signal and report the more acceptable answer. Third, a higher π is useful to both stimulate effort and reduce incentives to lie.

3 Experimental Evidence

Section 2 established the existence of an equilibrium where agents in a PPM seek costly information and make informed trades. Agents' incentives in trading are based on their peers' behavior, as value of the asset is determined by other agents' trades. Are such peer-based incentives effective in eliciting effort in practice? This section presents evidence from two experimental studies. Section 3.1 provides a brief overview of the two studies and the findings. Sections 3.2 and 3.3 provide detailed information on the two studies and present the results.

3.1 Overview

We run two experimental studies to test if PPM elicit effort in judgment formation. Study 1 aims to test PPM in a controlled setting. We recruit participants for an online experiment where they are presented with pairs of virtual boxes, containing yellow and blue balls of unknown proportions. In each pair, one of the boxes is the 'actual box' with equal probability. Participants are asked to pick a box within each pair. Before making a pick, participants could independently draw a single ball from the actual box by completing a real effort task, which involves counting the number of zeroes in a binary matrix. In this design the actual box is known to the experimenter, implying that the information is verifiable. Testing the PPM in a verifiable task allows us to implement incentives for ex-post accuracy as a benchmark. Study 1 consists of three experimental conditions in which participants complete the same task. The control condition offers fixed rewards (a flat participation fee) while the two treatments implement PPM incentives and incentives for ex-post accuracy. Results suggest that the PPM elicits significantly more effort than fixed rewards while the effort is highest under incentives for ex-post accuracy. As discussed before, ex-post accuracy is not observable in practical elicitation problems of unverifiable information. The results of Study 1 suggest that the PPM are effective when ex-post rewards are not feasible.

Study 2 explores the feasibility of PPM in a practical problem of elicitation of unverifiable information. In response to the Covid-19 pandemic in 2020, governments around the world issued guidelines for social distancing and other safe practices. Policy makers would like to know if such guidance is followed by the public. When asked to self-report if they were following a safe practice, people may not recall instances where they failed to do so. In addition, people may be reluctant to admit unsafe practices due to the social stigma associated with such anti-social behavior. We implement the PPM in an online survey aimed at the residents of the UK. Participants are asked 8 questions, each involving an unsafe practice according to the Covid-19 guidance issued by the UK government. We find that under the PPM incentives, participants are more likely to admit not following the guidance and they took longer to respond on average. Study 2 allows us to test the PPM in a setup where psychological costs as well as effort costs are relevant.

3.2 Study 1 - PPM in a simple prediction task

3.2.1 Design and procedures

Tasks. Participants complete 10 *prediction tasks*. Each prediction task displays a pair of boxes as shown in Figure 1 below. There are 10 such pairs and each pair appears in a single prediction task only. One of the boxes in each pair is set as the 'actual box' via a virtual coin flip prior to the experiment. Participants are informed that one of the boxes is the actual box, but they do not know which. In each task, participants are asked to pick one of the boxes, which may affect their rewards depending on the experimental condition.

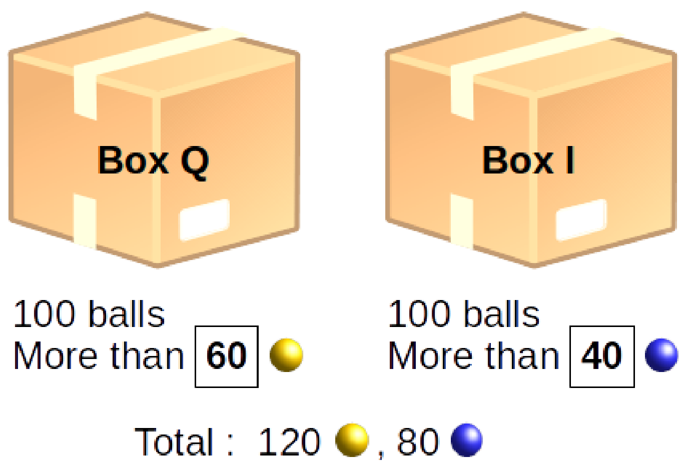

Figure 1: An example pair of boxes

In Figure 1, there are 120 yellow and 80 blue balls in total. Box Q contains more than 60 yellow balls while Box I contains more than 40 blue balls. The exact number of balls of each color are determined randomly according to the specifications. Hence, the number of yellow balls in Box Q is within $(60, 100]$. For example, if Box Q contains 80 yellow and 20 blue balls, Box Z contains 40 yellow and 60 blue balls. In the experiment, pairs of boxes are presented as shown in Figure 1. Thus, participants do not know the exact number of yellow and blue balls in a box. The boxes are constructed such that the left box (Box Q in Figure 1) always contains more than half of the total number of yellow balls. Table A1 in Appendix A provides the composition of all 10 pairs.

Before picking a box, each participant is offered a choice to observe a single draw from the actual box with replacement. Participants have to complete a *real effort task* to observe their draw. The effort task is counting the number of 0s in a matrix. Figure 2 shows one such matrix. There is a unique matrix for each effort task and there is a single effort task associated with each prediction task. The number of 0s in each matrix varies between 8 and 16.

$$\begin{array}{cccccc} 0 & 0 & 1 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 0 & 1 \end{array}$$

Figure 2: An example binary matrix

The sequence of events in each prediction task is as follows: First, participants are shown a pair of boxes and asked if they want to complete the effort task. Participants skipping the effort task are immediately asked to pick a box. Otherwise, they are presented the associated binary matrix and asked to report the number of 0s. They are required to report an accurate count to proceed and are allowed an unlimited number of retries to do so. Upon reporting the accurate count, the participants observes a personal random draw, which is either a blue or a yellow ball, and proceed to picking a box.

Link with the theory. The prediction task is a representation of the binary question Q, where the two boxes in any pair correspond to the possible answers. Let us assimilate reporting picking the left (right) box with $r_i = 1$ ($r_i = 0$). The effort task corresponds to the costly signal c_i in the theoretical framework. Participants are allowed to skip the effort task, in which case they make a pick without observing a draw. We can denote $s_i = 1$ the fact of drawing a yellow ball. In any given pair, the total number of yellow (and blue) balls are known and boxes are a priori equally likely to be the actual box, which induces a common prior expectation on the number of yellow balls in the actual box. For example, the common prior expectation of getting a yellow ball (i.e. getting signal 1) in Figure 1 is $\bar{\omega} = 0.6$. Participants drawing a yellow (blue) ball increase their probability of the left (right) box being the actual box. Hence, signals unequivocally influence belief and revealing signals coincides with $r_i = s_i$. The representations of v and p are explained in the rewards below.

Design & Rewards. We set up three experimental conditions which differ only in reward structure. In the *Flat* condition, participants receive a fixed reward of £3.25 for completing the experiment. In the *Accuracy* treatment, participants receive a basis reward of £3.25. In addition, they earn £0.20 per accurate pick and lose £0.20 per inaccurate pick, where the accurate pick in a pair is picking the actual box. Thus, a participant's total reward is within $[£1.25, £5.25]$. The *PPM* treatment implements our new incentive mechanism. Similar to the accuracy treatment the basis reward is £3.25. In addition, participants may earn a bonus from each pick which is determined by their peers' picks in the same pair and composition of the boxes. To illustrate, consider a participant who is asked to pick a box in the pair shown in Figure 1. Suppose, among all other participants, 82% picked Box Q and 18% picked Box I. Then, the participant earns $82 - 60 = 22$p when picking Box Q, loses $40 - 18 = 22$p if Box I. The value of the asset v for a given box is simply the percentage of people who pick that box. The number within the square below each box corresponds to the price p. We set $\pi = 1$, so the bonus per task is simply $v - p$. A negative total reward in the PPM condition is possible but extremely unlikely. Table B1 in Appendix B shows that the minimum realized reward was £2.05. Appendix B further describes how expected bonuses were kept comparable between the Accuracy and the PPM treatments.

Participants in the Flat condition have no direct financial incentives to complete the effort tasks as their reward does not depend on prediction accuracy. In contrast, rewards in the accuracy condition are determined by prediction accuracy. Thus, participants in the accuracy condition could be expected to complete effort tasks more frequently to maximize their accuracy. The PPM condition also provides incentives to complete effort tasks if, as predicted by the theory, participants consider their signal informative on others' picks. Consider a truthful equilibrium outcome for the example in Figure 1. If the actual box is Q, then more than 60% of others to draw a yellow ball and pick Q. The percentage of blue draws (and I picks) will be less than 40%. In that case, picking Box Q gives a positive expected payoff while picking Box I leads to a loss. The opposite is true when Box I is the actual box. Participants have an incentive to complete the effort task because their draw provides information on the actual box, which in turn suggests which box is more likely to be picked more often than the prior (60 and 40 for Boxes Q and I in Figure 1).

Note that the exact expected payoff of a participant depends on her beliefs on the composition of the boxes, which are not restricted by the experiment following the heterogeneity of posterior expectations in the theory. Suppose the participant have a uniform belief over all possible compositions of Boxes Q and I given that Box Q contains more than 60 yellow and Box I contains more than 40 blue. In that case, the participant expects 80 yellow in Box Q and 60 blue in Box I, implying that 80% (60%) are expected to pick Box Q (I) if the actual box is Box Q (I). Since the priors 60 and 40 respectively, the participants expect 20p from picking the actual box and -20p from a wrong pick. In the absence of a draw, Q and I are equally likely to be the actual box and the expected payoff is zero. If a participant completes the effort task and draws yellow, the expected payoff from picking Box Q is Pr(actual box is Q | yellow) 20 + Pr(actual box is I | yellow)(-20). Observe that, in this example, the expected payoff conditional on the draw is identical in the Accuracy and PPM conditions because win/loss per task in the Accuracy condition is also 20p. This need not hold for all participants and tasks. The expected payoff in the PPM condition depend on the participants beliefs on the composition of the boxes. So, the expected bonus from an accurate pick may differ from 20p. Table A2 in Appendix A.1 shows the range of anticipated bonus from an accurate pick in each prediction task. Consider uniform beliefs over the possible yellow/blue ratios, given participants' information on the pairs. Then, the expected bonus from a truthful pick ranges between 15p and 25p across the tasks, with an average of 20p. In order to make the PPM and Accuracy conditions payoff-equivalent, we set the bonus per pick in the Accuracy condition at 20p.

Participants. We recruit 210 participants from Prolific, an online platform for conducting surveys. We restrict our participant pool to U.S. citizens who are students at the time of the experiment. Table B1 in Appendix B provides further information on the participants.

Procedure. The experiment was published on Prolific in May 2020 and implemented via Qualtrics. Participants are randomly selected into one of the experimental conditions. They are first presented with instructions, which differ across the experimental conditions in rewards only. Then, the participants respond to a quiz question about the rewards in their experimental conditions. Depending on the answer, the experiment provides feedback with an example illustration of the rewards. The quiz marks the end of instructions and the beginning of the main body of the experiment. Participants complete the 10 prediction tasks. The order of the prediction tasks is randomized. Finally, participants complete a short survey on demographics. The survey also elicits subject's opinion on the clarity of the experimental instructions and their self-reported training in statistics. The latter could be relevant for subjects' ability to process their signal properly. Appendix A.1 provides the full text of the instructions, the quiz stage and the final survey. Figure B1 in Appendix B provides the frequency distribution of responses on the clarity of instructions. Figure B2 depicts the levels of training in statistics across the treatments.

3.2.2 Results

The primary question of interest is whether participants are more likely to seek costly information under the incentives provided by a PPM compared to fixed rewards. The effort task completion in control and PPM treatments allows us to test the effect of PPM incentives in eliciting effort. Furthermore in our prediction task, the ground truth (the actual box in any pair) is known to the experimenter. The accuracy treatment implements rewards for ex-post accuracy, which are not feasible in practice for elicitation without verification. We compare accuracy and PPM treatments to assess the effectiveness of PPM incentives relative to ex-post rewards.

We measure the frequency with which participants completed the effort tasks across the experimental conditions. Figure 3 depicts the percentage of instances per prediction task and experimental condition where participants completed the associated effort task.

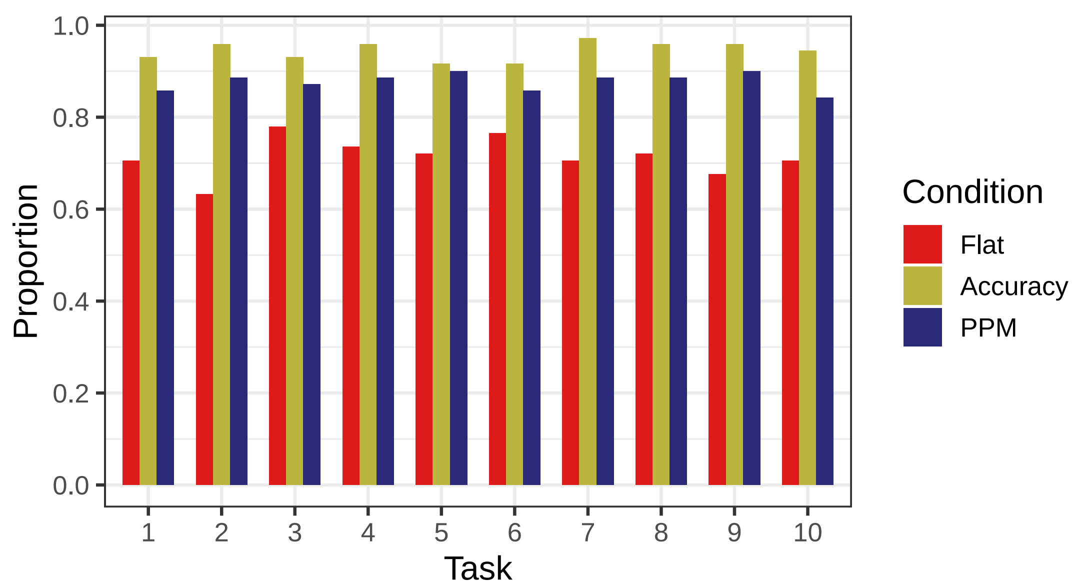

Figure 3: Proportion of times participants completed the effort task associated with the prediction task on the x-axis.

The effort level is substantial, even in the Flat condition. Effort task completion is higher in the PPM and accuracy treatments while the latter achieves the highest proportions. Figure 3 suggests that incentives provided by a PPM is effective in eliciting a higher proportion of informed judgments compared to a fixed reward. Incentives in the accuracy treatment are the most effective in eliciting effort. Figure 3 also indicates that the effort level in the PPM condition is similar across tasks. Section 3.2.1 discussed that the expected bonus from an accurate pick may differ according the composition of the boxes, which vary across tasks. Figure C1 in Appendix C shows that the effort rate does not differ significantly across the levels of expected bonuses provided in Table A2.

For a statistical analysis on effort task completion, we estimate logistic regressions where probability of effort task completion is the dependent variable. Table 1 below shows the average marginal effects. The pooled data includes 2100 decisions to complete the effort task or not. We include binary indicators for the experimental conditions as dependent variables. The coefficient of 'PPM' in Table 1 measures the average marginal effect of implementing PPM incentives (instead of a flat fee) on the likelihood of effort task completion. The coefficient of 'Accuracy' measures the same for rewarding participants for ex-post accuracy. Models (1) and (2) use the whole sample of participants. In (3) and (4), participants who gave an incorrect answer in the post-experimental quiz are excluded to construct a filtered sample. Specifications (2) and (4) also include various controls. The variables 'US citizen' and 'Female' are binary indicators for US residents and gender respectively while 'Age' is a numeric variable. In all models, standard errors are clustered at participant level.

In all specifications, the marginal effects for PPM and accuracy treatments are positively significant. Based on model (2), we see that a participant in the PPM treatment is 14 percentage points (ppt) more likely to complete the associated effort task in a given prediction task. Incentives provided by a PPM motivates agents to exert more effort compared to a fixed payment. For a comparison between Accuracy and PPM, Table C2 estimates the same logistic regression except that PPM is the baseline category. Incentives for ex-post accuracy is 7-9 ppt more likely to elicit effort compared to a PPM. We can infer that incentives for ex-post accuracy is the most effective in effort elicitation, followed by PPM and flat payments. In the absence of verifiability, PPM provides an alternative for incentivizing effort.

We now investigate if participants revealed their signals, which means picking the left (right) box when a yellow (blue) ball is drawn. Given the simplicity of the predictions task, participants do not have any external motives to make a hide their signals. However,

Dep. var.: P(effort task completed)				
	(whole sample)		*(filtered sample)*	
	(1)	(2)	(3)	(4)
PPM	0.16^{**}	0.14^{**}	0.16^{**}	0.14^{*}
	(0.05)	(0.06)	(0.06)	(0.06)
Accuracy	0.23^{***}	0.23^{***}	0.23^{***}	0.23^{***}
	(0.05)	(0.05)	(0.05)	(0.05)
Age		-0.00		-0.00
		(0.00)		(0.00)
Female		0.04		0.04
		(0.04)		(0.04)
US resident		-0.03		-0.02
		(0.07)		(0.07)
Num. obs.	2100	2070	2060	2030
Likl. Ratio.	148.93	175.79	146.39	173.35
LR test p-val	< 0.0001	< 0.0001	< 0.0001	< 0.0001
AIC	1649.70	1549.38	1638.88	1539.16

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

Table 1: Marginal effects, logistic regression (baseline category: Flat)

deviations from signal revelation may occur due to confusion or errors, or due to beliefs that others will deviate. Figure 4 shows participants' picks given their draw. The 3x3 grid depicts the three experimental conditions as well as the three possible situation after the effort task. Participants receive a yellow or blue draw if they complete the effort task. Alternatively, they do not receive a draw if they skip the effort task. The bars show the number of picks in each task. Since picking the left (right) box when the draw is yellow (blue) is the signal-revelation strategy, the number of left (right) picks are represented by yellow (blue) colored bars. The black dots show participants' prior expectation on the number of yellow balls in the actual box, given that left and right boxes are equally likely to be the actual box. Table A2 in Appendix A provides the prior expectations on the number of yellow balls in each task.

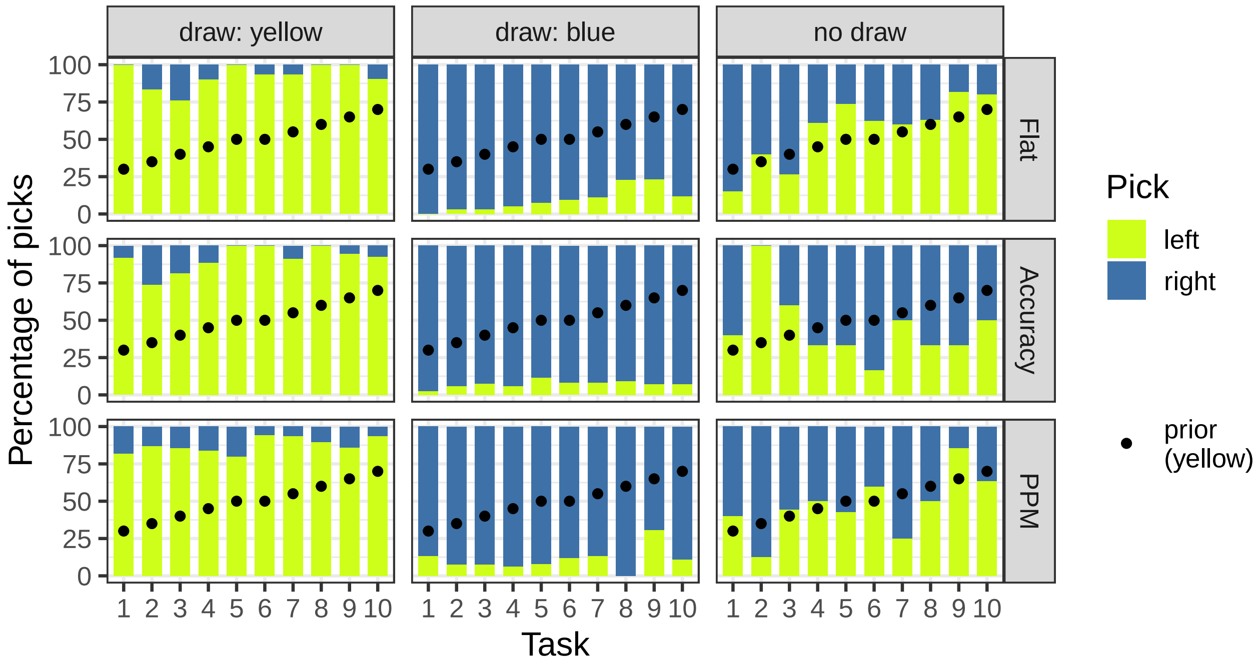

Figure 4: Participants' picks

Figure 4 strongly suggests that the participants mostly reveal their signals. Participants who observe a yellow (blue) draw typically pick the left (right) box. The distribution of picks in PPM and Accuracy are very similar, so we can argue that the PPM incentives reveals acquired signals as well as Accuracy incentives do. The same is true for the Flat condition.

The right-hand panel of Figure 4 illustrates the strategy participants use if they do not draw a ball. Interestingly, participants in the PPM treatment (and in the Flat treatment) appear to follow a mixed strategy (at the aggregate level), reporting left with a probability equal to the prior, as described in the equilibrium of Proposition 3. The proportion of left reports and the prior are correlated (Pearson: $\rho = 0,64$, $p = 0.048$) and not significantly different (t-test $t = -0.34$ $p = 0.739$) for PPM participants who do not draw a ball, whereas they are uncorrelated and significantly different for those who draw a yellow ball or a blue ball (see Table C1 in Appendix C).

3.3 Study 2 - Eliciting Covid-19 experiences using PPM

Study 2 implements PPM incentives in measuring if the residents of the UK followed safety guidance during the Covid-19 pandemic. For most of the safe practices in the guidance, it is not feasible to monitor all individual behavior. Self-reported behavior is practically unverifiable. In an unincentivized or a flat-fee survey, participants may not exert the mental effort to recall (signal acquisition) and report their behavior truthfully (signal revelation). Furthermore, reporting costs can be asymmetric. Unsafe behavior is typically stigmatized and likely to be under-reported (Tourangeau and Yan, 2007). We investigate if the PPM motivate participants to spend more time in answering questions and report their unsafe practices at a higher rate.

3.3.1 Design and procedures

Tasks. Participants, all from the UK, are presented a survey consisting of 8 statements. Each statement describes a situation that was considered unsafe and inadvisable (if not prohibited) by the UK Covid-19 guidance at the time of this survey. All situations involve others' actions, thereby mitigating one's own responsibility and lowering the stigma (in the terms of our model, to keep cost a_i reasonably low). For each statement, participants pick 'true' or 'false' to self-report if they have been in the described situation. Table 2 provides the list of questions:

	Statement
1.	I have been in an elevator with another person in it at least once in the last 7 days
2.	I may have stood less than 2 metres away from the person in front in a queue at least once in the last 7 days
3.	I was seated less than 2 metres away from someone who is not part of my household in a restaurant/cafe/bar at least once in the last 7 days
4.	I have been in a social gathering with more than 6 people who are not part of my household at least once in the last 7 days
5.	I have been in a busy shop/market with no restrictions on number of customers at least once in the last 7 days
6.	I participated in an indoor activity with more than 6 people who are not part of my household at least once in the last 7 days
7.	I have been in a shop/market where one or more of the staff did not wear a mask at least once in the last 7 days
8.	I had an interaction with someone experiencing high body temperature, persistent cough or loss of taste/smell at least once in the last 7 days

Table 2: Covid-19 survey questions

We ran this survey for two weeks with a new sample of participants every week. The two iterations of the survey are referred to as week 1 and week 2 surveys respectively. As we will introduce below, week 1 and week 2 surveys include experimental conditions that implement the PPM. We also run a week 0 survey to elicit information necessary to initialize the PPM. The week 0 survey uses the same questions, but they are presented in a slightly different way to elicit more information on the number of instances participants engaged in the described behavior. For example, question 1 in Table 2 is presented as 'In the last 7 days, I have been in an elevator with another person in it ...' and the participant picks one of the following answers: 'once or more', 'twice or more', '3 times or more', '4 times or more', '5 times or more'. Based on the results of the week 0 survey, we decided to implement two versions of each survey in weeks 1 and 2. Both versions ask the questions in Table 2, but in the second version 'at least once' is replaced with 'at least twice' in each question. We provide more information on how week 0 survey is used in the design below.

Design. In week 0 survey, participants receive a flat fee only. In week 1 and 2 surveys, we manipulate incentives to create control and treatment conditions. As ground truth (guideline compliance) is not observable, an accuracy treatment as in study 1 is unfeasible. In the control, participants are rewarded with a flat fee for completing the survey while the treatment implements the PPM incentives. Figure 5 shows the experiment interface in the *PPM* condition.

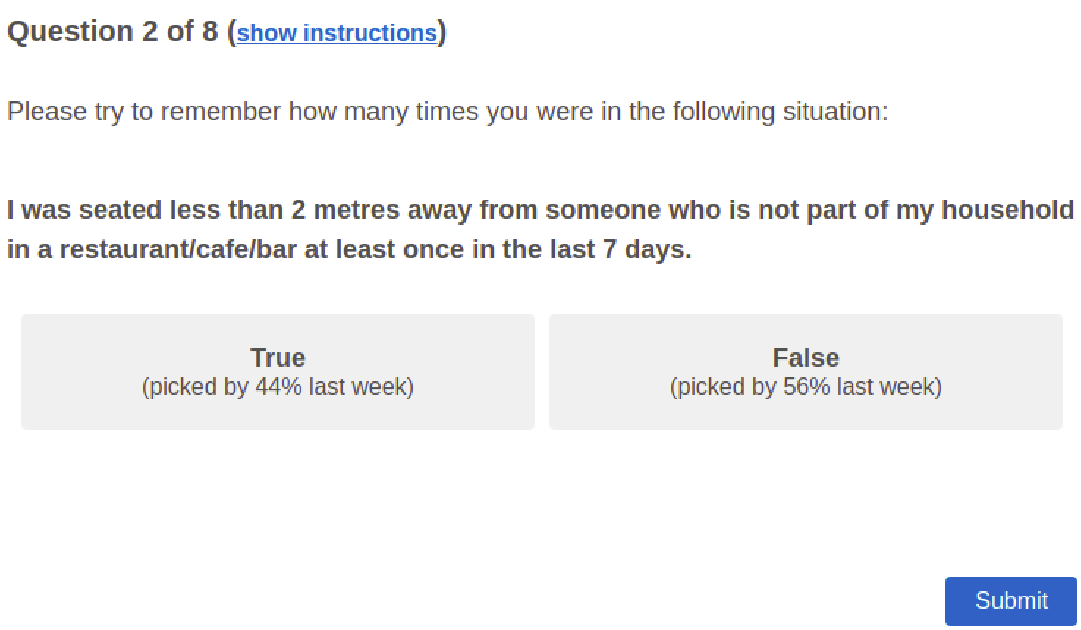

Figure 5: A screenshot from the treatment condition

The interface displays the statement and requires participants to pick 'true' or 'false'. The text below each alternative indicates the percentage of participants who endorsed that alternative in the previous week's survey. Recall that in our Bayesian setup, agents have a common prior expectation $\bar{\omega}$. To implement Assumption 2 in practice, we provide the participants with the latest realization of ω. The center sets $p = \bar{\omega}$, which leads to a separating equilibrium. Furthermore, participants' bonus depends on the endorsement rates. In Figure 5, the endorsement rate of 'true' in the last iteration is 44%. A participant who picks ‘true’ in this iteration wins a positive (negative) bonus from this question if the realized endorsement rate in this iteration exceeds (falls below) 44%. The same holds for ‘false’, except that the threshold is 56%. Thus, the PPM condition essentially implements a repeated PPM where last iteration’s realization determines the price for the current iteration. We provide more information on the rewards below. The PPM incentives are expected to incentivize mental effort and/or overcome the psychological costs of reporting one’s actual behavior. If PPM incentivizes signal acquisition, we may expect decision times–a proxy for mental effort–to be longer. If PPM incentivizes signal revelation in the presence of asymmetric costs $a_i > 0$, we may expect endorsement rates for ‘true’ to be higher.

The control surveys are similar to the treatment surveys except that participants are rewarded with a flat fee. We implement two different types of control surveys. In the *Flat* condition, the survey interface does not present any information on previous iterations’ endorsement rates. The Flat condition mimics how such questions would be implemented in a regular survey. The *Flat-PastRate* survey shows the same screen as the PPM condition by displaying previous week’s endorsement rates, as in Figure 5. The rewards are fixed in both Flat and Flat-PastRate surveys, thus the previous endorsement rates are irrelevant. Nevertheless, we included Flat-PastRate condition to check if merely presenting that information affects participants decision time and reports. First, processing additional information (previous endorsement rates) could, per se, increase decision times even if there is no additional effort to acquire signals. Secondly, it could influence endorsement rates by social proof (Cialdini, 1988) or conformity desire (Morgan and Laland, 2012).

Week 0 survey is used to determine the previous endorsement rates presented in the Flat-PastRate and PPM surveys of week 1. Furthermore, the week 0 survey motivates our choice to run two versions where the statements include ‘at least once’ and ‘at least twice’ respectively. Table B2 in Appendix B provides the percentage of participants who pick ‘true’ in each question in the week 0 survey. For ‘3 times or more’ and higher thresholds, the percentage of ‘true’ picks are close to 0. Then, participants in week 1 iteration of an ‘at least 3 times' version may report 'true' simply because the threshold is very low and a few 'true' picks could easily bring the week 1 endorsement rates above the threshold. To avoid such cases, we only run two versions with 'at least once' and 'at least twice' respectively. In each week $i \in \{1, 2\}$, we implement 6 surveys in a 3 (Flat, Flat-PastRate, PPM) $\times$ 2 ('at least once', 'at least twice') design.

Participants. As in Study 1, participants are recruited from Prolific but this time, we restrict our participant pool to students who currently reside in the UK. We chose the UK because it had uniform national social-distancing guidelines and sufficient Prolific participants at the time of the study. We restricted the study to students because we needed a homogeneous group such that Assumption 1 (signal technology) may plausibly hold. In total 692 participants completed our survey, 50 of which participated in week 0 survey while the remaining 642 participated in either week 1 or 2 (but not both). Participants in a given week $i \in \{1, 2\}$ are assigned randomly in one of the 6 conditions explained above. One participant is excluded for being in a non-student status at the time of data collection. All surveys are implemented via Qualtrics. Table B3 in Appendix B provides further information on the participants.

Rewards. The Flat and Flat-PastRate surveys pay a fixed reward of £1.75. In the PPM surveys, participants earn £0.75 for participation. In addition, they start with an endowment of £1, which represents the initial level of bonus. In each question, the bonus changes according to the difference between the endorsement rate in the current survey versus the endorsement rate in the previous iteration. To illustrate, suppose a participant picked 'true' in a question in week 2 survey and endorsement rate of 'true' was 50% in week 1. If the realized endorsement rate of 'true' in week 2 at the same question is 70%, the participant wins $70 - 50 = 20$p. In contrast, if the endorsement rate in week is 30%, the participant loses $50 - 30 = 20$p. The previous week's endorsement rate serves as the price p in a PPM while the current week's endorsement rate, unknown to the participant at the decision time, is analogous to realized value of the asset v. Similar to Study 1, we set $\pi = 1$ and the bonus is simply $v - p$. For each participant in the PPM condition, we sum the gains and losses over all question to determine the net bonus. As in Study 1, the total reward can be negative in the PPM condition. However, this is extremely unlikely and Table B3 in Appendix B shows that the minimum reward was £1.18.

Procedure. The experiment is conducted over three weeks and consists of week 0, 1 and 2 surveys that take place 7 days apart. The week 0 iteration is a single survey while in weeks 1 and 2, participants are randomly assigned to the different conditions. In each survey of each iteration, participants are first presented with instructions. Then they are asked to respond to the questions, which are presented in randomized order. Finally, participants complete a short survey on demographics and the clarity of the instructions. Appendix A.2 provides the full text of the instructions and the final survey. Figure B3 in Appendix B shows the distribution of self-reported clarity of instructions for week 1 and 2 surveys (pooled across "at least once" and "at least twice" versions).

Link with the theory. Let us assimilate endorsing "true" for a statement with $r_i = 1$. Remembering whether the situation described in the statement occurred corresponds to signal acquisition cost c_i in the theoretical framework. This cost may be purely cognitive (recollection effort) but also due to the discomfort to think about it. Clicking on an answer without thinking allows respondents to avoid the discomfort. The stigma to answer "true" corresponds to a_i and giving an answer whilst remembering the opposite corresponds to d_i. The previous-week endorsement rate of "true" mentioned beneath the choice corresponds to $\bar{\omega}$.

3.3.2 Results

Figure 6 shows the percentage of 'true' picks for each condition and version in the week 1 and week 2 surveys. Responses are pooled across questions and participants. Twelve observations have response time longer than 60 seconds, which suggests outliers as showed by Figure C3 in Appendix C. Table C4 provides the outliers. The "filtered" sample results in the statistical analyses below exclude the outlier responses.

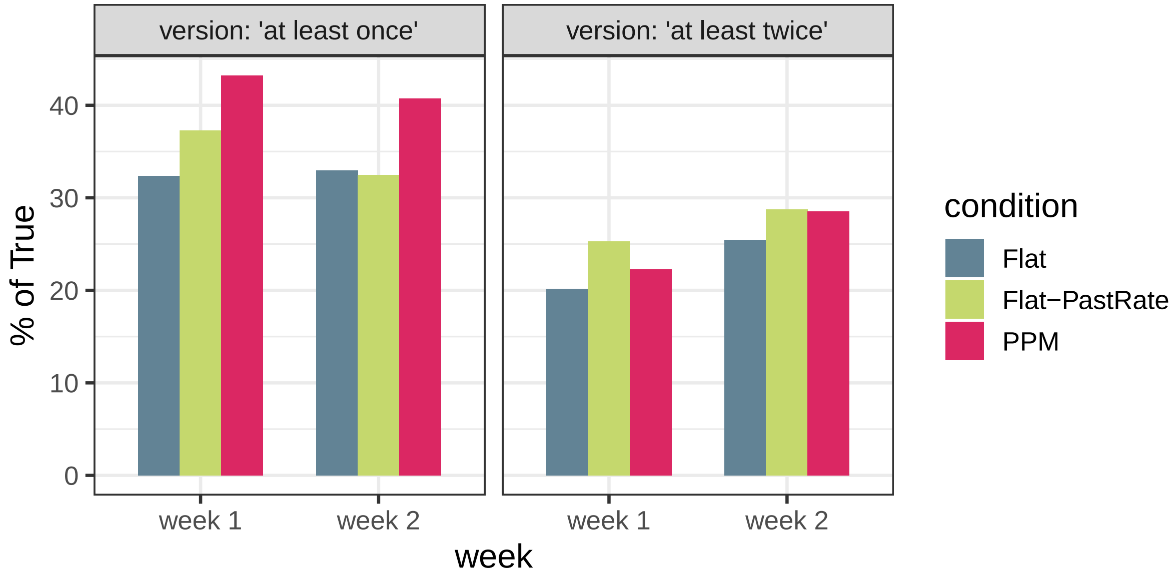

Figure 6: Percentage of ‘true’ picks in week 1 and 2 surveys.

In the ‘at least once’ surveys, the PPM survey elicits a higher percentage of ‘true’ responses compared to both controls. No such difference is observed in any iteration in the ‘at least twice’ version. Figure C2 in Appendix C shows a breakdown of percentage of ‘true’ across different questions. PPM elicits more ‘true’ in most questions in the ‘at least once’ version. Recall that week 1 surveys are initialized with the unincentivized week 0 survey (of a slightly different format) while week 2 surveys use data from week 1 survey of the corresponding condition. Since the prior has an effect on PPM, we will analyze the response data from weeks 1 and 2 separately.

Figure 7 depicts the response times for each version and week. We also categorize data according to the response type to see if response times differ.

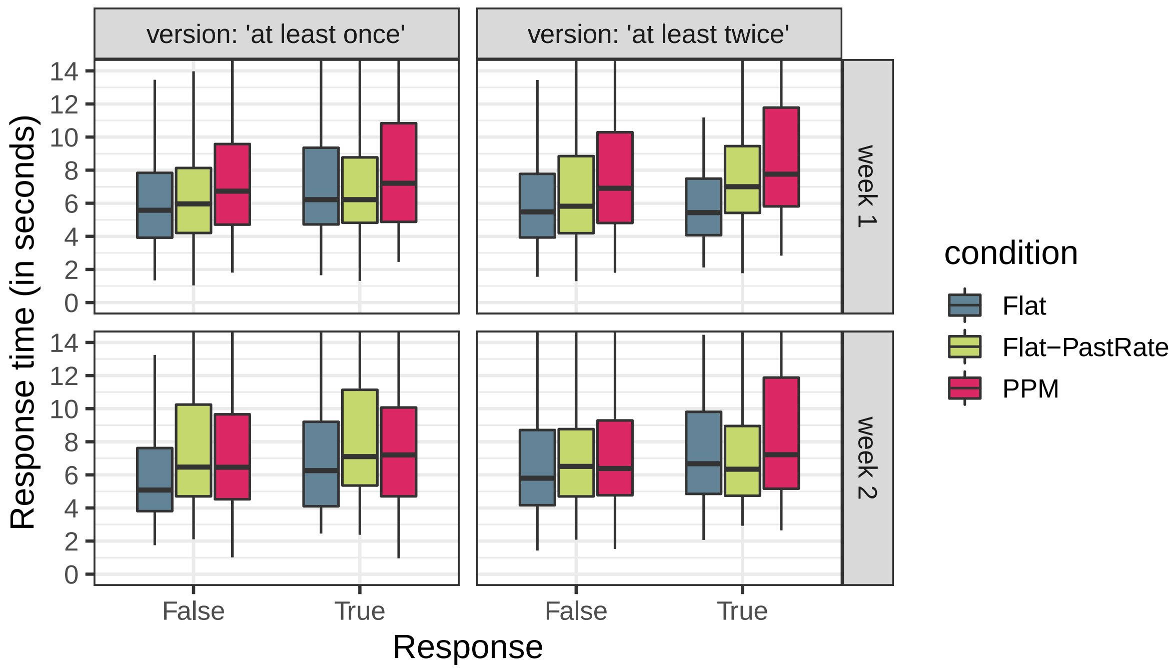

Figure 7: Response time of participants. The data points above 14 are included in calculations but not shown on the figure.

Figure 7 suggests that the median response time in the PPM condition is higher than the Flat surveys in all iterations. The same is true for the Flat-PastRate surveys in week 1. However, response times in the Flat-PastRate and PPM conditions are comparable in week 2 surveys. To test for significance, we estimate two classes of regression models. Firstly, we estimate a logistic regression for participants' likelihood of picking 'true' in any given question. Secondly, we estimate a linear regression model where response time is the dependent variable. In both models, Flat is the baseline category and binary indicators for Flat-PastRate and PPM are variables of interest. We also include various demographic controls representing the age, gender and citizenship of participants. We focus here on the 'at least once' versions of all iterations as Figure 6 suggested a possible difference for these versions only. Section C.2.2 in Appendix C performs the same analysis for 'at least twice' survey.

Table 3 presents the average marginal effects from the logistic regressions. Models (1,2) and (4,5) show the results with outliers excluded, while (3) and (6) include all responses.

Table C5 in Appendix C provides the corresponding parameter estimates. In all models, standard errors are clustered at the participant level.

	P(response = 'true'), marginal effects					
	|	*(week 1)*	|	|	*(week 2)*	|
	(filtered sample)		*(all)*	*(filtered sample)*		*(all)*
	(1)	(2)	(3)	(4)	(5)	(6)
Flat-PastRate	0.05	0.04	0.04	−0.00	−0.01	−0.00
	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
PPM	0.11***	0.09**	0.09**	0.08*	0.08*	0.08
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Response time		0.00	0.00		0.00	0.00
		(0.00)	(0.00)		(0.00)	(0.00)
Age		−0.00	−0.00		−0.00	−0.00
		(0.00)	(0.00)		(0.00)	(0.00)
Female?		0.02	0.02		−0.02	−0.02
		(0.03)	(0.03)		(0.03)	(0.03)
UK citizen?		−0.00	0.00		0.04	0.04
		(0.03)	(0.03)		(0.04)	(0.04)
Num. obs.	1259	1259	1264	1279	1279	1280
Likl. Ratio.	10.44	16.28	15.87	8.03	12.85	13.83
LR test p-val	0.0054	0.0123	0.0144	0.0180	0.0455	0.0316
AIC	1662.27	1664.43	1671.58	1660.66	1663.85	1664.94

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

Table 3: Logistic regression, average marginal effects

The average marginal effects in Table 3 show that the PPM survey elicits a higher frequency of 'true' picks. According to model (1), a participant in the PPM condition of week 1 survey is 9 ppt more likely to report 'true' for a given statement compared to a participant in the Flat condition. In contrast, Flat-PastRate condition has no effect. A similar result holds for the week 2 survey where the marginal effect of the PPM condition is estimated to be 8 ppt. Results support the equilibrium characterized in Proposition 4. PPMs motivate participants to declare unsafe practices at a higher rate, which suggest that such practices are under-reported in basic surveys. There are two possible mechanisms. PPM incentives may dominate potential reporting costs associated with the stigmatized response and/or they encourage participants to exert more mental effort. The next paragraph analyzes response time, as a proxy for mental effort.

Table 4 presents the OLS estimates where the dependent variable is the response time in seconds. Similar to Table 3, standard errors are clustered at the participant level.

	OLS, Dep.Var.: Response time					
	(week 1)			*(week 2)*		
	(filtered sample)		*(all)*	*(filtered sample)*		*(all)*
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	6.38^{***}	6.97^{***}	7.60^{***}	6.82^{***}	7.92^{***}	8.04^{***}
	(0.27)	(1.09)	(1.19)	(0.46)	(1.00)	(1.03)
Flat-PastRate	0.87	0.78	0.54	1.60^{*}	1.58^{*}	1.59^{*}
	(0.57)	(0.58)	(0.60)	(0.66)	(0.64)	(0.64)
PPM	2.64^{***}	2.62^{***}	2.95^{***}	1.14	0.96	0.98
	(0.66)	(0.66)	(0.82)	(0.69)	(0.69)	(0.69)
Response (="True"?)	1.14^{*}	1.13^{*}	0.91	0.39	0.42	0.84
	(0.52)	(0.53)	(0.58)	(0.53)	(0.53)	(0.73)
Flat-PastRate × Response	−0.84	−0.85	−0.63	0.19	0.18	−0.23
	(0.74)	(0.74)	(0.77)	(0.87)	(0.87)	(1.01)
PPM × Response	−0.91	−0.91	−0.58	−0.07	−0.01	−0.43
	(0.81)	(0.80)	(0.99)	(0.83)	(0.81)	(0.97)
Age		−0.01	−0.02		0.00	−0.00
		(0.04)	(0.04)		(0.02)	(0.02)
Female?		0.26	0.01		0.42	0.30
		(0.50)	(0.57)		(0.51)	(0.53)
UK citizen?		−0.80	−0.76		-1.66^{*}	-1.63^{*}
		(0.52)	(0.54)		(0.64)	(0.65)
R^2	0.03	0.03	0.03	0.02	0.03	0.02
Adj. R^2	0.03	0.03	0.03	0.01	0.02	0.02
Num. obs.	1259	1259	1264	1279	1279	1280
RMSE	5.89	5.89	7.18	5.82	5.78	6.02

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

Table 4: Response time regressions.

The response time regressions show mixed results. In models (1)-(3), participants in the PPM survey spend significantly more time in their responses than the Flat survey. However, the week 2 results suggest otherwise. Models (4)-(6) do not indicate a strong difference in response times between the PPM and Flat surveys. The test of the two parameters (PPM vs Flat-PastRate) in (2) results in a significant difference (mean difference = 1.846, $t = 2.348$, $p = 0.019$) while the same test in (5) suggests no difference (mean difference = -0.6248, $t = -0.924$, $p = 0.356$). Thus, a difference in response times relative to the Flat survey could also be the result of the presentation of more information in both Flat-PastRate and PPM surveys. Week 1 results also suggest that response times are higher for those answering "True", which could indicate that respondents exerted more mental effort to remember their week. The effect does not vary with the treatments. Week 2 results show no effect for the response type.

To sum up, the PPM treatment increased the probability to report deviations from Covid guidelines, but this effect does not necessarily arise from additional mental effort as approximated by response time. We can exclude that the effect is an artefact of mentioning the answer rates of the previous week, creating some social norms, since treatment Flat-PastRate did not differ from treatment Flat. Hence, higher rates of admitting an unsafe practice indicate that the PPM incentives dominate potential reporting costs associated with the stigmatized response.

4 Discussion

4.1 Theoretical limitations

The signal technology assumption includes anonymity, i.e, that the probability to obtain signal 1 is the same for all agents. This assumption, even though common in the theoretical literature, limits possible applications. It can be easily implemented in artificial studies but for relevant topics, it requires implementing PPMs on homogeneous groups of respondents.

PPM, like similar mechanisms, assume risk neutrality. Risk aversion could decrease the perceived incentives provided by the mechanism. When participation is compulsory however, the no effort strategy is also risky. In the presence of high risk aversion, a degenerate equilibrium with no-one providing effort and everyone reporting the same answer would dominate equilibria with efforts. Loss aversion could also distort the results as some but it is unlikely to be substantial for the type of amounts used in surveys and in the presence of an initial endowment as in our studies. So far, the only mechanism to elicit unverifiable signals explicitly handling risk attitudes and even non-expected utility has been proposed by Baillon and Xu (2021). It requires, however, multiple questions with the exact same signal technology.

As illustrated by Propositions 1 to 3, there are several types of equilibria. To those should be added equilibria in which signal 1 agents report 0 and conversely. These latter equilibria did not occur in Study 1. Interestingly, at the aggregate level, participants seemed to play the strategies of Proposition 3, and those who did not draw a signal played a mixed strategy (at the aggregate level) where the randomization probability was equal to the prior.

We considered a very simple model, binary in all dimensions. Effort could be continuous, signal informativeness could be a function of effort, and answers could be non-binary. We leave these refinements for future research. Similarly, we limited our analysis to some types of psychological costs. Others would be possible but are unlikely to substantially change the results. For instance, symmetric reporting costs would not bring new insights but only require higher payoffs (by rescaling π).

The asymmetric reporting cost, a_i, is exogenous. However, setting up PPMs (or any incentive mechanism) may necessitate to break anonymity to process payment. The lack of anonymity may then increase a_i further. There are practical solutions to this problem. For instance, as we did in Study 2, one can erect a 'China wall' between the payment provider (Prolific, who knows identity but not people's answer) and the center (the researchers who know the answers but not the respondents' identities).

4.2 Empirical limitations

Study 1 borrowed tasks from the experimental literature, which allowed us to observe effort and signal acquisition. The main drawback is that those tasks were artificial, and may have been seen as quite unnatural. Furthermore, there was hardly any reason not to reveal the acquired signal. Study 2 was conducted to test whether PPM elicits signal acquisition and revelation in a more realistic context. Results of Study 2 give credence to the real-world validity of PPM but signal acquisition can only be proxied by decision time and ground truth is not observable.

Both studies were conducted online with participants from the Prolific platform. Participants from online platforms take part in experiments in an uncontrolled setting, for example, from home. This lack of experimental control has elicited concerns amongst researchers. However, experimental research has shown that this concerns is largely unfounded. Hauser and Schwarz (2016) demonstrated that participants from an online platform are more attentive than college students. Eyal et al. (2021) demonstrated that Prolific outperformed other participant platforms regarding data quality. To ensure high data quality in the current research, post-experimental quiz questions were included in Study 1, allowing to remove inattentive participants. In Study 2, the instructions in the PPM condition emphasize that the bonuses depend on others' responses.

We initially planned to run Study 2 over four weeks, but we had to stop earlier when the pandemics amplified in the UK (second wave), making our questions less applicable. Fortunately, data collected during weeks 0, 1, and 2 already provide valuable insights on the effectiveness of PPM in a real-world context with unverifiable ground truths.

In study 2, participants were asked about their violations of COVID guidelines. The discrepancy between the prevalence of self-reported lies (Debey et al., 2015) and lies told during experimental research (Feldman et al., 2002) demonstrates that people are reluctant to admit anti-social behavior. Since violations of COVID guidelines could negatively affect the health of both oneself and others, a violation of COVID guidelines can be seen as immoral behavior. However, the questions we use limited this effect. In most statements, non-compliance could have been due to behavior of others. Results of Study 2 demonstrate that participants in the PPM condition admitted more violations of COVID guidelines than in both control conditions. PPM may have helped overcome the discomfort of reporting non-compliance with health guidelines (a_i in the theory). However, PPM has no effect though when we replace 'at least once' by 'at least twice' in the statements. In the latter case, it is more difficult to minimize one's responsibility and the asymmetric cost is therefore likely to be higher.

5 Conclusion

When answers to questions are unverifiable, researchers and practitioners typically resort to simple surveys with fixed rewards, which do not provide incentives to acquire costly information and reveal it. Since Crémer and McLean (1988), the economic literature has proposed many mechanisms to elicit private signals but their practical use has been limited, due to their complexity. This paper introduces PPM, a simple market mechanism that incentivize agents to acquire and reveal private signals for binary questions. A first study demonstrates that it stimulates costly effort to acquire information and a second study shows that it can be implemented in practice to elicit more truthful answers to mildly stigmatizing questions.

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A Experimental materials

A.1 Study 1

Table A1 provides detailed information on the pairs of boxes in each prediction task. The exact composition of Yellow/Blue is unknown to subjects.

		Subjects' information		Exact Yellow/Blue	
Pair	Total Yellow/Blue	Left box	Right box	Left box	Right box
1.	60Y 140B	More than 30Y	More than 70B	40Y 60B	20Y 80B
2.	70Y 130B	More than 35Y	More than 65B	40Y 60B	30Y 70B
3.	80Y 120B	More than 40Y	More than 60B	48Y 52B	32Y 68B
4.	90Y 110B	More than 45Y	More than 55B	56Y 44B	34Y 66B
5.	100Y 100B	More than 50Y	More than 50B	62Y 38B	38Y 62B
6.	100Y 100B	More than 50Y	More than 50B	57Y 43B	43Y 57B
7.	110Y 90B	More than 55Y	More than 45B	69Y 31B	41Y 59B
8.	120Y 80B	More than 60Y	More than 40B	69Y 31B	51Y 49B
9.	130Y 70B	More than 65Y	More than 35B	78Y 22B	52Y 48B
10.	140Y 60B	More than 70Y	More than 30B	77Y 23B	63Y 37B

Table A1: The content of boxes and subjects' information in each pair

Table A2 shows the theoretical prior and posterior beliefs of a subject in each pair. Consider pair 1 where there are 60 yellow and 140 blue balls in total. The left (right) box includes more (less) than 30 yellow. Prior to observing the draw, each box is equally likely to be the actual box. Thus, the common prior expectation on yellow (blue) is 30 (70). If the draw is yellow, the left box will be considered more likely. Then, the posterior expectation on yellow will be within $(30, 60]$, while the posterior on blue is simply 100 minus the posterior on yellow. Note that the exact posterior expectation of a subject depends on the prior belief on the composition of the boxes, which is not restricted by the experiment, in accordance with the theoretical framework. Subjects with a yellow (blue) draw expect left (right) box to be more likely for the actual box. Under the equilibrium in Proposition 2, subjects with a yellow (blue) draw would pick the left (right) box. The last column in Table A2 gives the range of expected bonus in the PPM condition if the subject's pick (left if yellow draw, right if blue draw) corresponds to the actual box. Note that E[bonus | pick = actual] = 20p for all pairs in the Accuracy condition. This constant value is set to achieve a payoff equivalence between the PPM and Accuracy conditions. To illustrate, consider pair 1 and suppose a subject with a yellow draw has a uniform belief over all possible Yellow/Blue compositions in the left box. Then, the exact E[bonus | pick = actual] is 15p. Under the uniformity assumption, the expected bonus ranges from 15p to 25p across all pairs, with an average of 20p.

	Priors		Posterior on Yellow		Range of E[bonus | pick = actual]
Pair	Yellow	Blue	Yellow draw	Blue draw	Posterior (draw) - Prior (draw)
1.	30	70	(30,60]	[0,30)	(0p,30p]
2.	35	65	(35,70]	[0,35)	(0p,35p]
3.	40	60	(40,80]	[0,40)	(0p,40p]
4.	45	55	(45,90]	[0,45)	(0p,45p]
5.	50	50	(50,100]	[0,50)	(0p,50p]
6.	50	50	(50,100]	[0,50)	(0p,50p]
7.	55	45	(55,100]	[0,55)	(0p,45p]
8.	60	40	(60,100]	[0,60)	(0p,40p]
9.	65	35	(65,100]	[0,65)	(0p,35p]
10.	70	30	(70,100]	[0,70)	(0p,30p]

Table A2: Priors, posteriors and expected bonus conditional on an accurate pick.

Complete instructions for each experimental condition, the quiz question and the final survey on demographics are included below.

Instructions - PPM condition

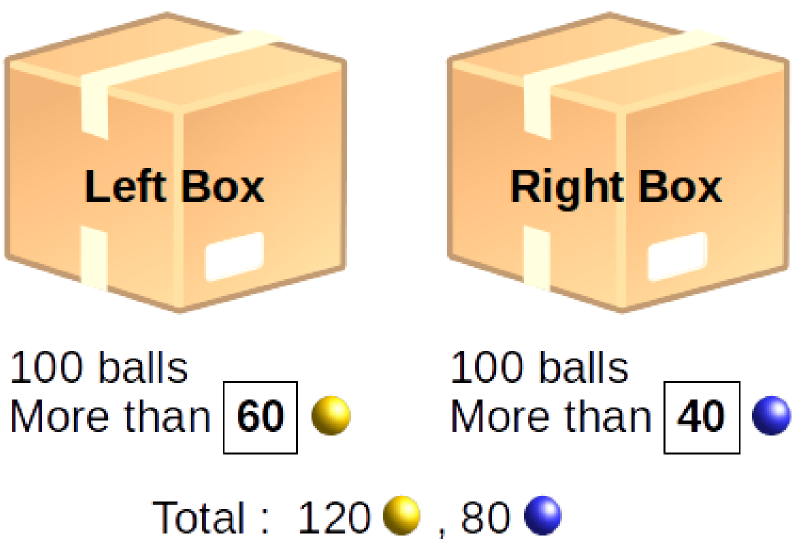
[918]Instructions

(page 1 out of 5)

In this experiment, you will answer 10 questions in total.

In each question, there are two new boxes, which contain yellow () and blue () balls in different proportions.

A picture like the one below will give you information on the boxes:



Numbers may change in each question. But, following is always true:

...Left box always contains more than half of all
...Right box always contains more than half of all
...Both boxes always contain 100 balls each.

In the example above, if left box contains 68 and 32 , right box contains 52 and 48

Instructions

(page 2 out of 5)

In each question, one of the boxes is the 'actual box'.

The actual box is predetermined by an unbiased coin flip. It is same for all participants, including you.

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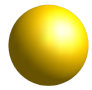
A ball will be drawn randomly from the actual box for you. Following is an example draw:



Note that...
...if you draw , Left box is more likely.
...if you draw , Right box is more likely.

The color of your draw helps you guess the actual box.

Instructions

(page 3 out of 5)

To see the color of your draw, you need to complete an **effort task**.

You will first see the following question:

Would you like to work on the effort task?

Yes | No

If you select 'Yes', you will be presented a table as below:

0	0	0	1	0	0
0	0	0	0	1	1
1	0	0	1	1	0
1	0	1	0	1	0

Your task is to count the number of 0s.

There is no time limit. You can try multiple times.

Once you submit the correct answer, you observe your draw.

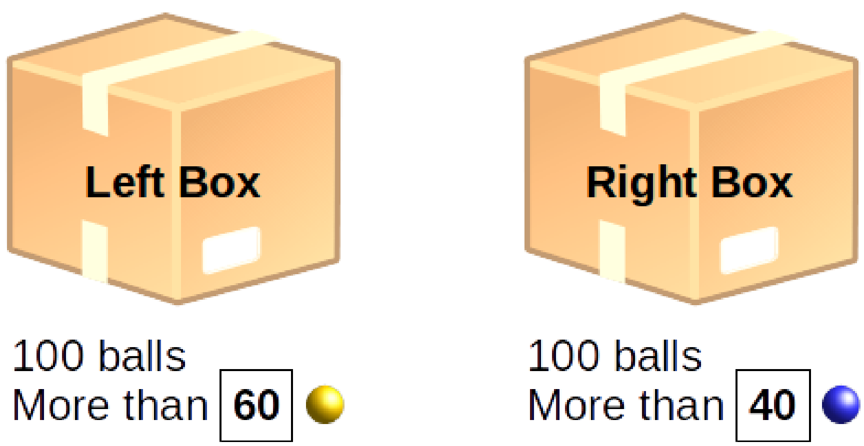
You may skip the effort task by selecting 'No'. Then, you will not see the color of your draw.

Instructions

(page 4 out of 5)

Finally, you will pick one of the boxes. The question will appear as below:

Which box do you pick?



You may click on...

Left box if you pick Left box

Right box if you pick Right box

Your pick will be submitted when you click Submit

Which box do you pick?

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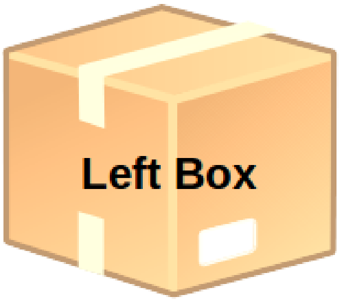
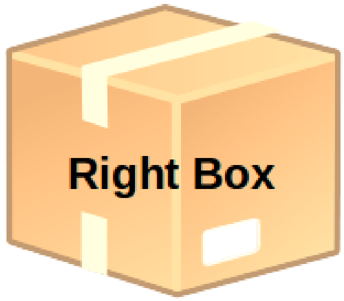




100 balls
More than $\boxed{60}$

100 balls
More than $\boxed{40}$

You may tap...

Left box if you pick Left box

Right box if you pick Right box

Your pick will be submitted when you tap Submit

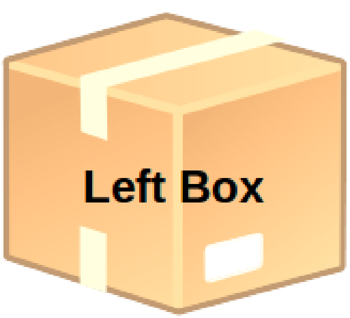
Instructions

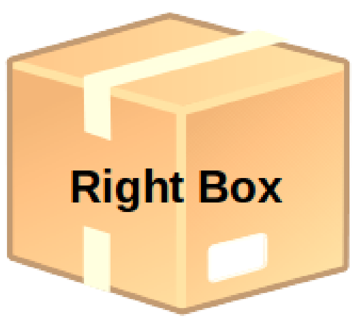
(page 5 out of 5)

You will earn £2 bonus, on top of £1.25, for completing the experiment.

In addition, you may earn bonus from each question.

Let's see how it works with the example boxes:





100 balls
More than $\boxed{60}$

100 balls
More than $\boxed{40}$

Total : 120 , 80

There will be at least 50 other participants in the experiment.

After the experiment, we calculate the percentage of participants other than you who
922 pick each box.

We compare those percentages to the numbers in .

Suppose 79% picked Left, 21% picked Right. Then,...
...you win 79 - 60 = 19p if you picked Left
...you lose 40 - 21 = 19p if you picked Right

So, **you win money if you pick the box that others will pick more often than indicated in** .

The color of your draw helps you guess others' draws, which may affect their picks.

The maximum total gain from your picks is +£2 and the maximum total loss is -£2.

So, your total reward at the end of the experiment is between £1.25 and £5.25.

Instructions - Flat condition

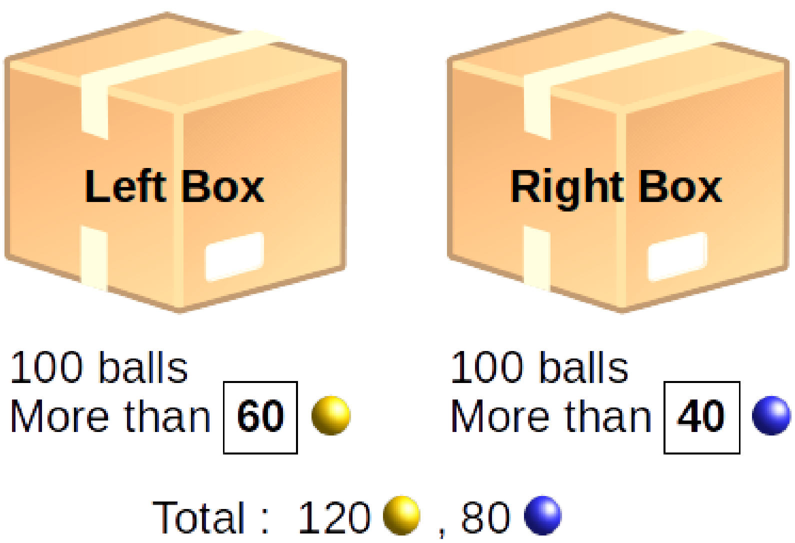
923 Instructions

(page 1 out of 5)

In this experiment, you will answer 10 questions in total.

In each question, there are two new boxes, which contain yellow () and blue () balls in different proportions.

A picture like the one below will give you information on the boxes:



Numbers may change in each question. But, following is always true:

...Left box always contains more than half of all
...Right box always contains more than half of all
...Both boxes always contain 100 balls each.

In the example above, if left box contains 68 and 32 , right box contains 52 and 48

Instructions

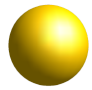
(page 2 out of 5)

In each question, one of the boxes is the 'actual box'

The actual box is predetermined by an unbiased coin flip. It is same for all participants, including you.

924

A ball will be drawn randomly from the actual box for you. Following is an example draw:



Note that...
...if you draw , Left box is more likely.
...if you draw , Right box is more likely.

The color of your draw helps you guess the actual box.

Instructions
(page 3 out of 5)

To see the color of your draw, you need to complete an **effort task**.

You will first see the following question:

Would you like to work on the effort task?

Yes	No

If you select 'Yes', you will be presented a table as below:

0	0	0	1	0	0
0	0	0	0	1	1
1	0	0	1	1	0
1	0	1	0	1	0

Your task is to count the number of 0s.

There is no time limit. You can try multiple times.

925 Once you submit the correct answer, you observe your draw.

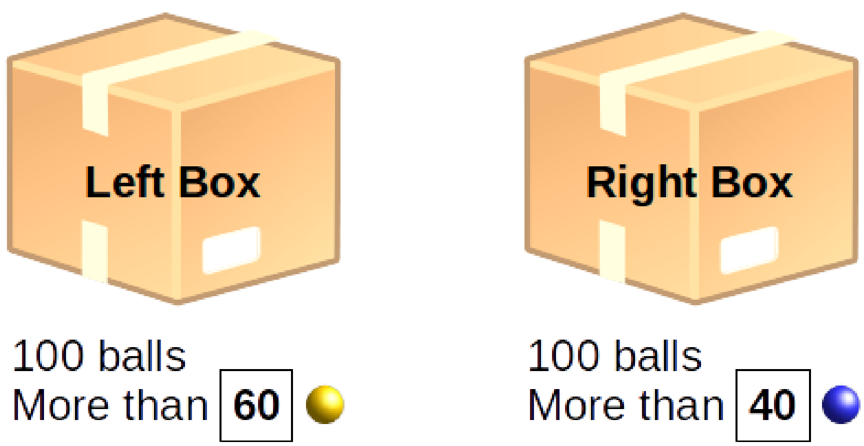
You may skip the effort task by selecting 'No'. Then, you will not see the color of your draw.

Instructions

(page 4 out of 5)

Finally, you will pick one of the boxes. The question will appear as below:

Which box do you pick?



You may click on...

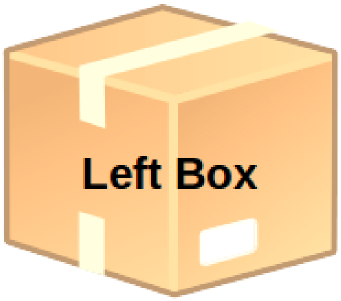
Left box if you pick Left box

Right box if you pick Right box

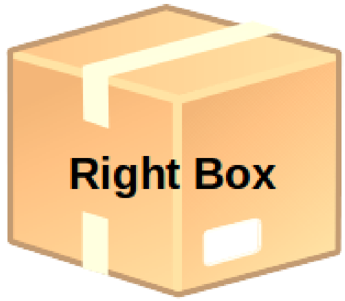
Your pick will be submitted when you click Submit

Which box do you pick?

926



100 balls
More than **60**



100 balls
More than **40**

You may tap...

Left box if you pick Left box

Right box if you pick Right box

Your pick will be submitted when you tap Submit

Instructions

(page 5 out of 5)

You will earn a fixed £2 bonus, on top of £1.25, for completing the experiment.

Your total reward will be £3.25.

Powered by Qualtrics

Instructions - Accuracy condition

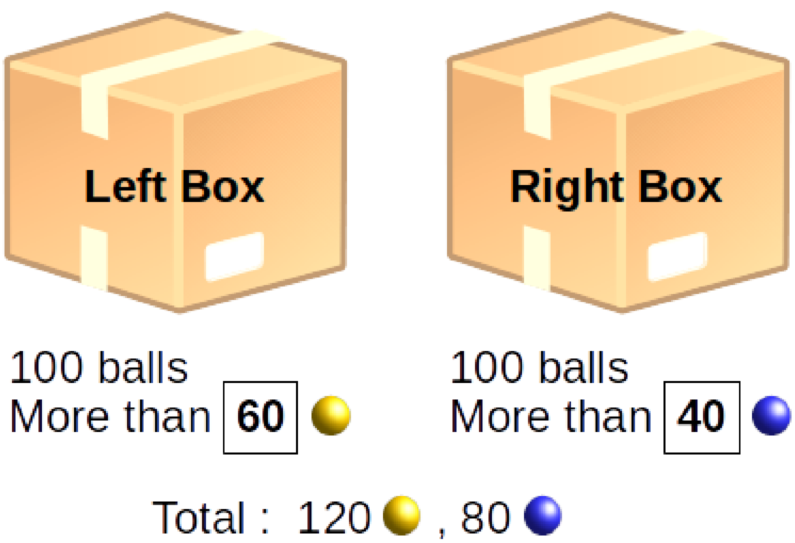
927 **Instructions**

(page 1 out of 5)

In this experiment, you will answer 10 questions in total.

In each question, there are two new boxes, which contain yellow ( ) and blue ( ) balls in different proportions.

A picture like the one below will give you information on the boxes:



Numbers may change in each question. But, following is always true:

...Left box always contains more than half of all
...Right box always contains more than half of all
...Both boxes always contain 100 balls each.

In the example above, if left box contains 68 and 32 , right box contains 52 and 48

Instructions

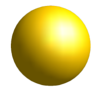
(page 2 out of 5)

In each question, one of the boxes is the 'actual box'

The actual box is predetermined by an unbiased coin flip. It is same for all participants, including you.

928

A ball will be drawn randomly from the actual box for you. Following is an example draw:



Note that...
...if you draw , Left box is more likely.
...if you draw , Right box is more likely.

The color of your draw helps you guess the actual box.

Instructions

(page 3 out of 5)

To see the color of your draw, you need to complete an **effort task**.

You will first see the following question:

Would you like to work on the effort task?

Yes	No

If you select 'Yes', you will be presented a table as below:

0	0	0	1	0	0
0	0	0	0	1	1
1	0	0	1	1	0
1	0	1	0	1	0

Your task is to count the number of 0s.

There is no time limit. You can try multiple times.

929 Once you submit the correct answer, you observe your draw.

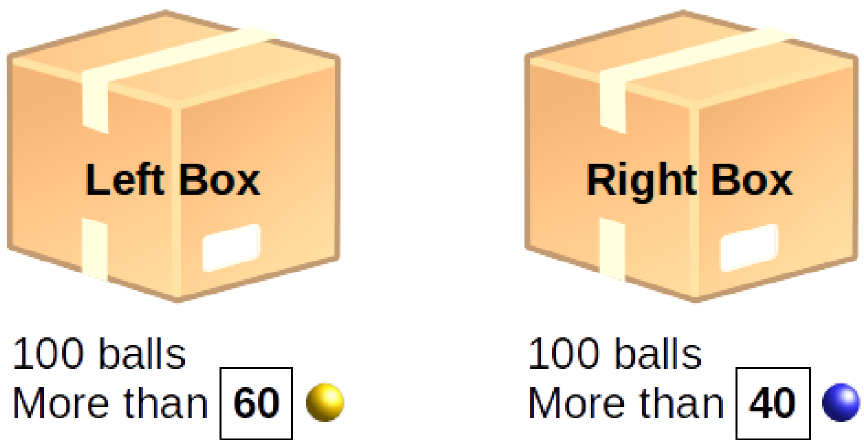
You may skip the effort task by selecting 'No'. Then, you will not see the color of your draw.

Instructions

(page 4 out of 5)

Finally, you will pick one of the boxes. The question will appear as below:

Which box do you pick?



You may click on...

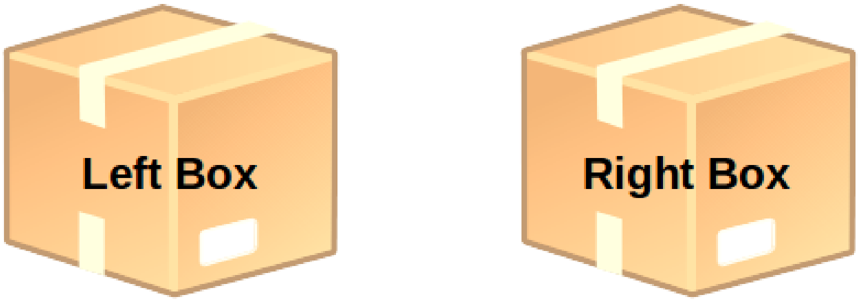
Left box if you pick Left box

Right box if you pick Right box

Your pick will be submitted when you click Submit

Which box do you pick?

930



100 balls
More than $\boxed{60}$

100 balls
More than $\boxed{40}$

You may tap...

Left box if you pick Left box

Right box if you pick Right box

Your pick will be submitted when you tap Submit

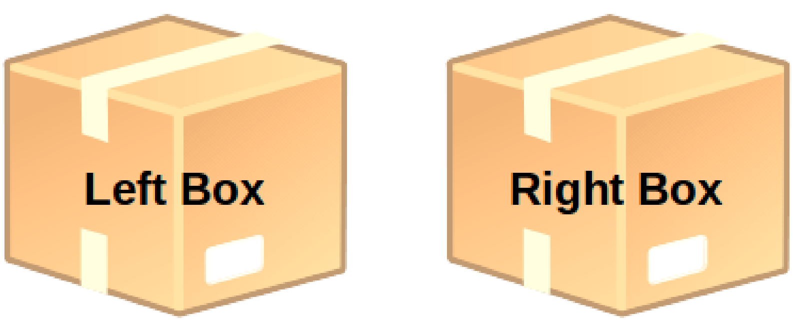
Instructions

(page 5 out of 5)

You earn £2 bonus, on top of £1.25, for completing the experiment.

In addition, you earn a bonus from each question if you guess the actual box accurately.

Let's see how it works with the example boxes:



100 balls
More than $\boxed{60}$

100 balls
More than $\boxed{40}$

Total : 120 , 80

Suppose Left is the actual box. Then,...
...you **win 20p** if you picked Left.
931 ...you **lose 20p** if you picked Right.

Suppose instead Right is the actual box. Then,...
...you **lose 20p** if you picked Left.
...you **win 20p** if you picked Right.

The maximum total gain from your picks is +£2 and the maximum total loss is -£2.

So, your total reward at the end of the experiment is between £1.25 and £5.25.

932 Quiz question is the same in all experimental conditions and provided below. The order of choices is randomized.

Quiz

Here's a small quiz on rewards!

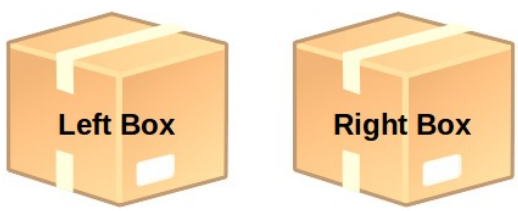
Which of the three statements is most accurate?

- My bonus is fixed, regardless of the box I pick.
- My bonus depends on the actual box and the box I pick.
- My bonus depends on the box I pick and what other participants pick.

Participants receive feedback according to their answer. In the PPM condition, the correct answer is “My bonus depends on the box I pick and what other participants.” If the correct answer is reported, the following is displayed:

TRUE! Your bonus depends on the box you picked and what other participants picked.

Here's an example. Suppose you have the following pair of boxes:



100 balls More than **55** (yellow) | 100 balls More than **45** (blue)

Total : 110 (yellow) , 90 (blue)

Suppose, of all other participants, 65% picked Right, 35% picked Left

Let's say your draw was (blue) and you picked Right.

Then, you win **65**-45 = 20p.

If you had picked Left instead, you would have lost 55-**35** = 20p.

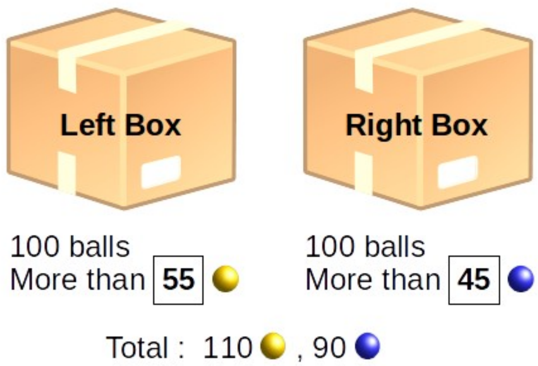
So, your reward depends on your pick AND other participants' picks.

The color of your draw helps you guess others' draws, which may affect their picks.

If a participant picks one of the wrong answers, the following is displayed:

FALSE! Your bonus depends on the box you picked and what other participants picked.

Here's an example. Suppose you have the following pair of boxes:



Suppose, of all other participants, 65% picked Right, 35% picked Left

Let's say your draw was and you picked Right.

Then, you win **65**-45 = 20p.

If you had picked Left instead, you would have lost 55-**35** = 20p.

So, your reward depends on your pick AND other participants' picks.

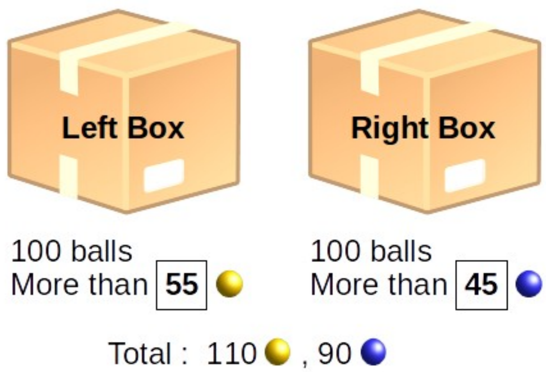
The color of your draw helps you guess others' draws, which may affect their picks.

In the Flat condition, the correct answer is “My bonus is fixed, regardless of the box I pick.” If the correct answer is reported, the following is displayed:

934

TRUE! Your bonus is fixed, regardless of the box you pick.

Here's an example. Suppose you have the following pair of boxes:



It does not matter if your pick is the actual box or not.

Other participants' picks are also irrelevant.

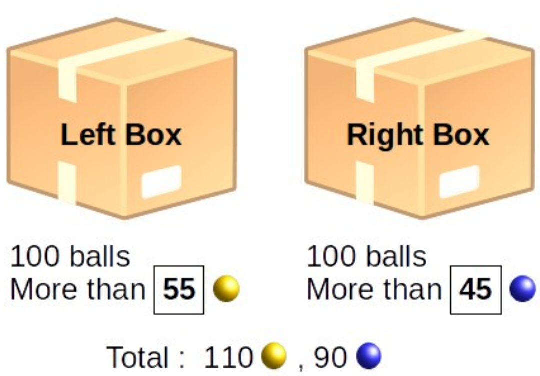
You will earn £2 bonus for completing the experiment. Your total reward will be £3.25.

There is no bonus for working on the effort tasks.

If a participant picks one of the wrong answers, the following is displayed:

FALSE! Your bonus is fixed, regardless of the box you pick.

Here's an example. Suppose you have the following pair of boxes:



It does not matter if your pick is the actual box or not.

Other participants' picks are also irrelevant.

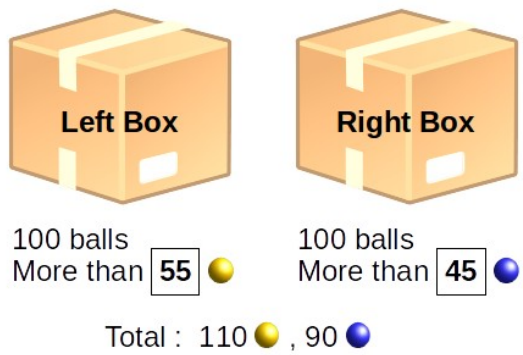
You will earn £2 bonus for completing the experiment. Your total reward will be £3.25.

There is no bonus for working on the effort tasks.

In the Accuracy condition, the correct answer is “My bonus depends on the actual box and the box I picked.” If the correct answer is reported, the following is displayed:

TRUE! Your bonus depends on the actual box and the box you picked.

Here's an example. Suppose you have the following pair of boxes:



Suppose Right box is the actual box.

Let's say your draw was and you picked Right.

Then, you win 20p because you guessed the actual box accurately.

If you had picked Left instead, you would have lost 20p.

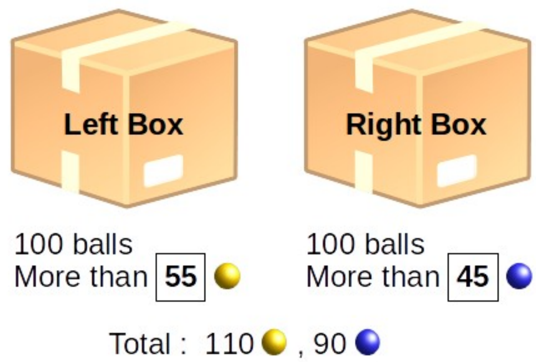
So, your reward depends on your accuracy only.

The color of your draw helps you make an accurate guess.

If a participant picks one of the wrong answers, the following is displayed:

FALSE! Your bonus depends on the actual box and the box you picked.

936 Here's an example. Suppose you have the following pair of boxes:



Suppose Right box is the actual box.

Let's say your draw was and you picked Right.

Then, you win 20p because you guessed the actual box accurately.

If you picked Left instead, you would have lost 20p.

So, your reward depends on your accuracy only.

The color of your draw helps you make an accurate guess.

Thank you for your answers!

937

To conclude, we would like you to answer some questions about your personal background and your experience in this experiment

How old are you?

What is your gender?

Male.

Female.

Other / Prefer not to disclose.

What is your education level?

Did you receive a training in statistics? If yes, on which level?

When did you receive this training?

How clear were the instructions in this experiment?

Very clear.	Mostly clear.	Understandable, but not very clear.	Mostly unclear.	Very unclear.

Which of the three statements is most accurate?

My bonus depends on the actual boxes and the boxes I picked.

My bonus depends on the boxes I picked and what other participants picked.

My bonus is fixed, regardless of the boxes I picked.

Do you have any other comments or suggestions?

Click Finish to complete the experiment. You will be redirected to Prolific.

Finish

A.2 Study 2

Complete instructions for each experimental condition and the final survey on demographics are included below.

Instructions - PPM condition

942 ## Instructions

(page 1 out of 5)

Welcome! In this survey, you will answer 8 questions on the COVID-19 pandemic.

The UK government issues COVID-19 guidance and passes regulations to control the pandemic.

This survey aims to collect data on people's behaviour to assess whether such guidelines are helpful.

In each question, we will ask you about your experience for certain situations related to the pandemic.

Instructions

(page 2 out of 5)

Here's an example on how questions will appear:

I may have stood less than 2 metres away from the person in front in a queue at least once in the last 7 days.

True **False**

You may pick True or False depending on whether you have been in the situation described in the question.

Your pick will be submitted when you click Submit

You may pick True or False depending on whether you have been in the situation described in the question.

Your pick will be submitted when you tap Submit

Instructions

(page 3 out of 5)

943 We ask the same questions every 7 days to a new group of at least 50 participants.

All participants are students who currently reside in the UK. The survey can be taken only once.

In all questions, you will see the percentage of people who picked each answer in the last survey, 7 days ago.

For example, if 65% of participants picked True and 35% picked False, the choices will appear as follows:

True (picked by 65% last week)	**False** (picked by 35% last week)

The following page will explain rewards.

Instructions

(page 3 out of 5)

We ask the same questions every 7 days to a new group of at least 50 participants.

All participants are students who currently reside in the UK. The survey can be taken only once.

In all questions, you will see the percentage of people who picked each answer in the last survey, 7 days ago.

For example, if 65% of participants picked True and 35% picked False, the choices will appear as follows:

True
(picked by 65% last week)

False
(picked by 35% last week)

The following page will explain rewards.

944 **Instructions**

(page 4 out of 5)

You will earn £0.75 for completing the survey.

In addition, you may earn bonus from each question.

Let's see how it works in the example question. Suppose you picked True, as shown below:

True (picked by 65% last week)	**False** (picked by 35% last week)

At the end of this survey, we calculate the percentage of participants other than you who picked each answer.

You start with £1 bonus. Your bonus increases if the answer you picked is more popular among others in this survey, compared to last week.

Suppose 80% of others picked True this week. Then, you win 80 - 65 = 15 pence from this question.

Suppose 55% of others picked True this week instead. Then, you lose 65 - 55 = 10 pence.

We sum your gains/losses over all questions. Your bonus is never negative and it can increase up to £2.

Your total reward is therefore between £0.75 and £2.75.

Instructions

(page 4 out of 5)

You will earn £0.75 for completing the survey.

In addition, you may earn bonus from each question.

945 Let's see how it works in the example question. Suppose you picked True, as shown below:

True
(picked by 65% last week)

False
(picked by 35% last week)

At the end of this survey, we calculate the percentage of participants other than you who picked each answer.

You start with £1 bonus. Your bonus increases if the answer you picked is more popular among others in this survey, compared to last week.

Suppose 80% of others picked True this week. Then, you win 80 - 65 = 15 pence from this question.

Suppose 55% of others picked True this week instead. Then, you lose 65 - 55 = 10 pence.

We sum your gains/losses over all questions. Your bonus is never negative and it can increase up to £2.

Your total reward is therefore between £0.75 and £2.75.

Instructions

(page 5 out of 5)

Note that your bonus depends on others' responses.

You earn a higher bonus if you picked answers that became more popular compared to the last survey, which covered the previous 7-day period.

Your own experience may help you guess how others respond.

In the example, say you recall staying too close in a queue at least once.

If keeping distance was more difficult in the last 7 days due to busier streets and shops,
946 it is likely that other people experience the same.

Then, you might expect a higher percentage of True picks among others. In that case, picking True increases your bonus.

Remembering your own experiences more accurately can improve your bonus.

Instructions - Flat condition

947 ## Instructions

(page 1 out of 4)

Welcome! In this survey, you will answer 8 questions on the COVID-19 pandemic.

The UK government issues COVID-19 guidance and passes regulations to control the pandemic.

This survey aims to collect data on people's behaviour to assess whether such guidelines are helpful.

In each question, we will ask you about your experience for certain situations related to the pandemic.

Instructions

(page 2 out of 4)

Here's an example on how questions will appear:

I may have stood less than 2 metres away from the person in front in a queue at least once in the last 7 days.

True	False
○	○

You may pick True or False depending on whether you have been in the situation described in the question.

Your pick will be submitted when you click Submit

You may pick True or False depending on whether you have been in the situation described in the question.

Your pick will be submitted when you tap Submit

Instructions

(page 3 out of 4)

948 We ask the same questions every 7 days to a new group of at least 50 participants.

All participants are students who currently reside in the UK. The survey can be taken only once.

The following page will explain rewards.

Instructions

(page 4 out of 4)

You will earn a fixed £1 bonus, on top of £0.75, for completing the survey.

Your total reward will be £1.75.

Instructions - Flat-PastRate condition

949 Instructions

(page 1 out of 4)

Welcome! In this survey, you will answer 8 questions on the COVID-19 pandemic.

The UK government issues COVID-19 guidance and passes regulations to control the pandemic.

This survey aims to collect data on people's behaviour to assess whether such guidelines are helpful.

In each question, we will ask you about your experience for certain situations related to the pandemic.

Instructions

(page 2 out of 4)

Here's an example on how questions will appear:

I may have stood less than 2 metres away from the person in front in a queue at least once in the last 7 days.

True	False
○	○

You may pick True or False depending on whether you have been in the situation described in the question.

Your pick will be submitted when you click Submit

You may pick True or False depending on whether you have been in the situation described in the question.

Your pick will be submitted when you tap Submit

Instructions

(page 3 out of 4)

950 We ask the same questions every 7 days to a new group of at least 50 participants.

All participants are students who currently reside in the UK. The survey can be taken only once.

In all questions, you will see the percentage of people who picked each answer in the last survey, 7 days ago.

For example, if 65% of participants picked True and 35% picked False, the choices will appear as follows:

True (picked by 65% last week)	**False** (picked by 35% last week)

The following page will explain rewards.

Instructions

(page 3 out of 4)

We ask the same questions every 7 days to a new group of at least 50 participants.

All participants are students who currently reside in the UK. The survey can be taken only once.

In all questions, you will see the percentage of people who picked each answer in the last survey, 7 days ago.

For example, if 65% of participants picked True and 35% picked False, the choices will appear as follows:

True
(picked by 65% last week)

False
(picked by 35% last week)

The following page will explain rewards.

951 **Instructions**

(page 4 out of 4)

You will earn a fixed £1 bonus, on top of £0.75, for completing the survey.

Your total reward will be £1.75.

Thank you for your answers!

952

To conclude, we would like you to answer some questions about your personal background and your experience in this experiment

How old are you?

What is your gender?

Male.

Female.

Other / Prefer not to disclose.

What is your education level?

How clear were the instructions in this survey?

Very clear.	Mostly clear.	Understandable, but not very clear.	Mostly unclear.	Very unclear.

Do you have any other comments or suggestions?

Click Finish to complete the survey

953

Finish

B Summary statistics

Table B1: Summary statistics, Study 1

	Experimental Condition		
	Flat	Accuracy	PPM
Number of participants	68	72	70
Female/Male	29/39	36/36	34/36
Average age	23.09	23.76	22.64
US resident	63	65	62
Average duration	8 min 59 sec	9 min 31 sec	9 min 8 sec
Min/Average/Max reward (£)	3.25/3.25/3.25	2.05/3.50/4.85	2.65/3.34/3.94
Correct answer in pre-experimental quiz	54	67	57
Correct answer in post-experimental quiz	68	72	66

Table B2: Study 2, Week 0 answers

	Percentage of 'true' picks				
Question	once or more	twice or more	3 times or more	4 times or more	5 times or more
1	18	12	6	4	4
2	76	50	20	6	2
3	58	22	8	4	2
4	16	8	0	0	0
5	70	34	14	4	2
6	24	10	8	4	2
7	54	24	8	2	2
8	12	4	2	2	2

Table B3: Summary statistics, Study 2

	Exp. Condition / version					
Week 1						
	Flat / 'once'	Flat-PastRate / 'once'	PPM / 'once'	Flat / 'twice'	Flat-PastRate / 'twice'	Treatment / 'twice'
Number of participants	53	53	52	54	54	53
Female/Male	36/17	36/17	33/19	36/18	25/29	33/20
Average age	24.85	23.53	22.73	23.11	23.57	25.17
UK/Non-UK citizen	42/11	36/17	40/12	44/10	45/9	37/16
Average duration	2 min 10 sec	2 min 38 sec	3 min 34 sec	2 min 14 sec	2 min 30 sec	3 min 38 sec
Min/Average/ Max reward (£)	1.75/1.75/ 1.75	1.75/1.75/ 1.75	1.49/2.03/ 2.39	1.75/1.75/ 1.75	1.75/1.75/ 1.75	1.43/1.81/ 2.23
Week 2						
Number of participants	54	52	54	54	54	54
Female/Male	31/23	31/21	39/15	37/17	39/15	38/16
Average age	24.39	25.65	24.98	25.13	24.25	25.09
UK/Non-UK citizen	46/8	44/8	43/11	43/11	46/8	48/6
Average duration	2 min 14 sec	2 min 52 sec	3 min 44 sec	2 min 45 sec	2 min 25 sec	4 min 12 sec
Min/Average/ Max reward (£)	1.75/1.75/ 1.75	1.75/1.75/ 1.75	1.47/1.66/ 1.88	1.75/1.75/ 1.75	1.75/1.75/ 1.75	1.18/1.73/ 2.16

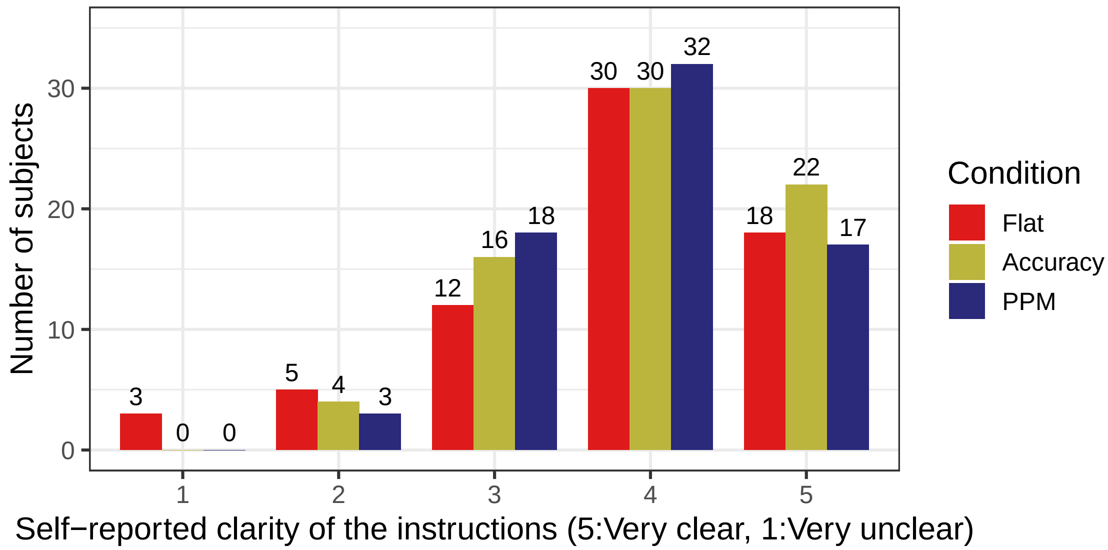


Figure B1: The distribution of subjects' responses to the question "How clear were the instructions in this experiment?" in Study 1, coded on a scale 1 to 5.

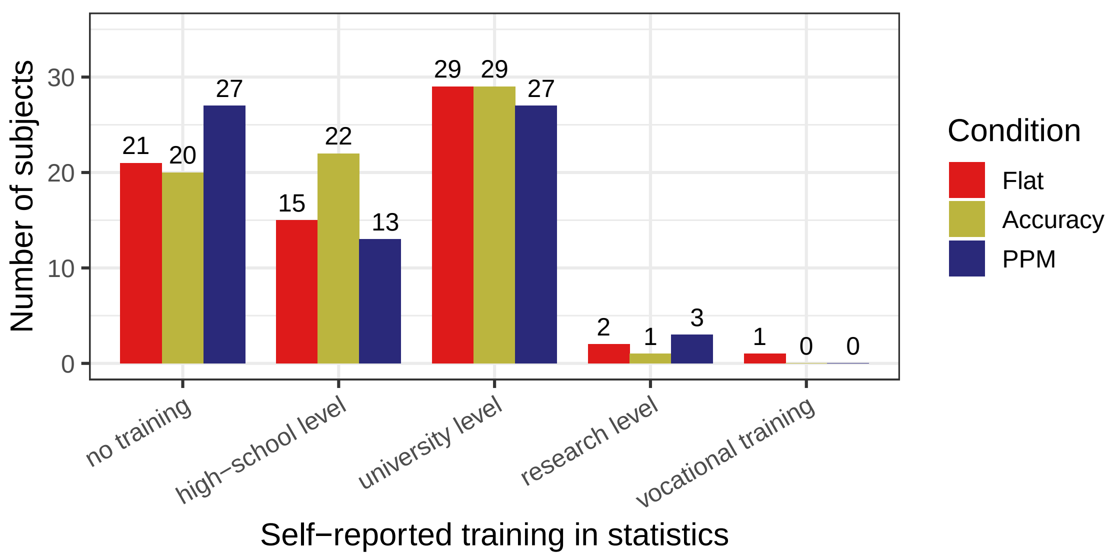


Figure B2: The distribution of subjects' responses to the question "Did you receive a training in statistics? If yes, on which level?" in Study 1.

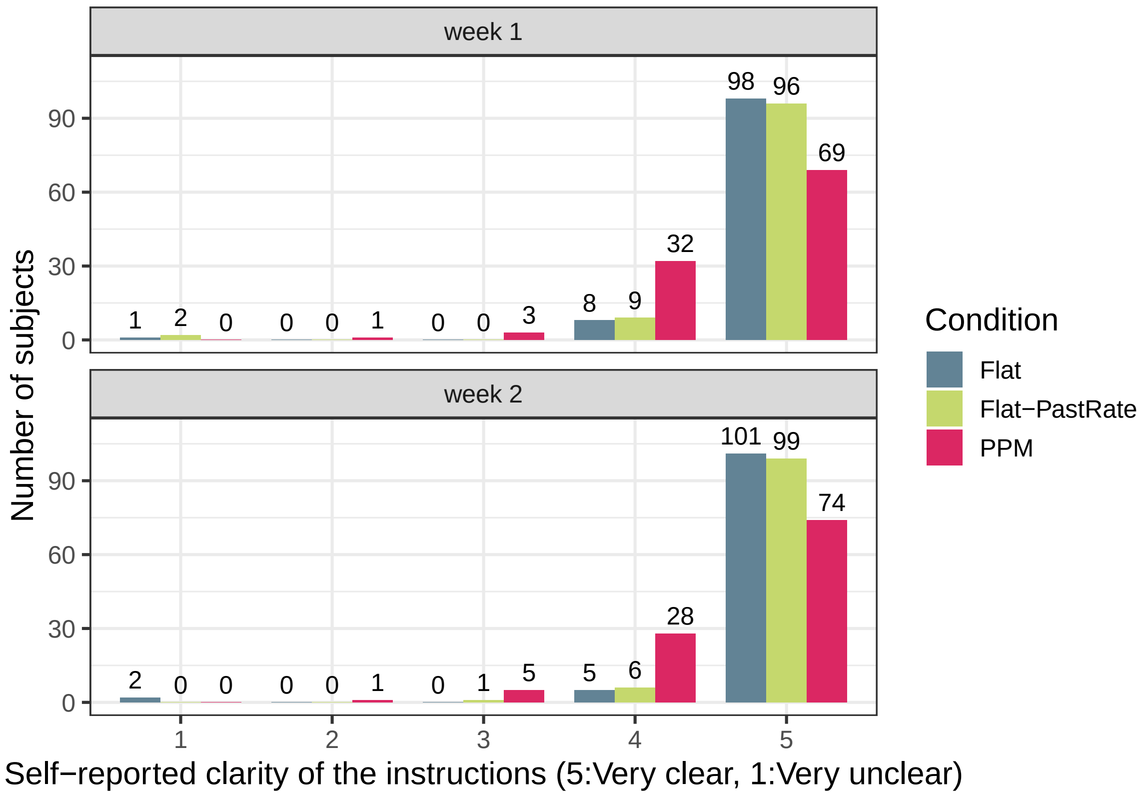


Figure B3: The distribution of subjects' responses to the question "How clear were the instructions in this experiment?" in Study 2, coded on a scale 1 to 5.

C Additional results

C.1 Study 1

(a) Correlation tests

Draw	Pearson's C.C.	Spearman's C.C.
yellow	r = 0.53, p = 0.118	ρ = 0.52, p = 0.121
blue	r = 0.28, p = 0.425	ρ = 0.21, p = 0.555
no draw	r = 0.64, p = 0.048	ρ = 0.68, p = 0.032

(b) Two-sided t-test and Wilcoxon test

Draw	T-test	Wilcoxon test
yellow	t = 8.56, p < 0.001	W = 100, p < 0.001
blue	t = -8.12, p < 0.001	W = 1, p < 0.001
no draw	t = -0.34, p = 0.739	W = 44, p = 0.676

Table C1: Proportion of left picks vs prior expectation on the number of yellow balls in the actual box.

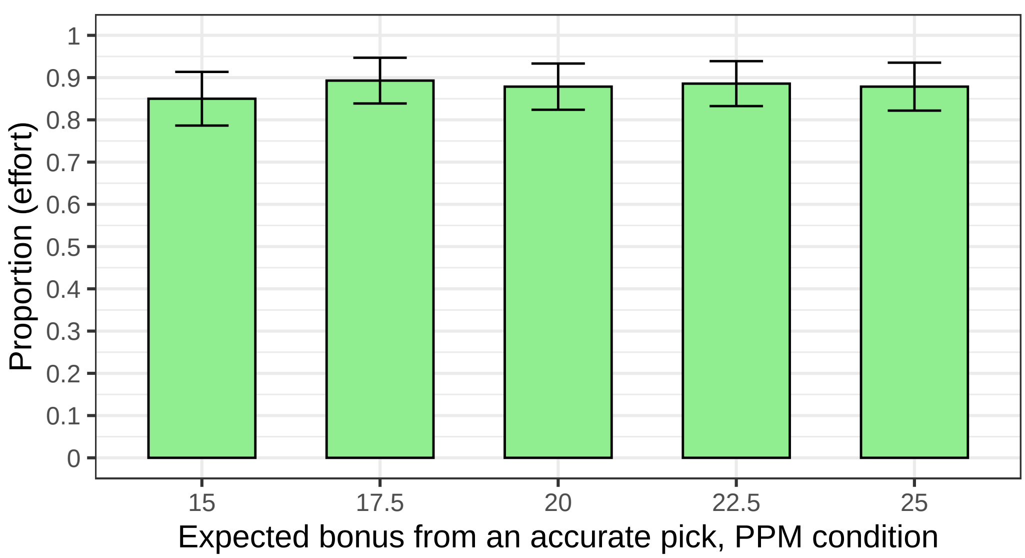


Figure C1: Effort levels in the PPM condition for different levels of the expected bonus from an accurate pick. Error bars show 95% bootstrap CI. See Table A2 for the derivation of expected bonuses.

Dep. var.: P(effort task completed)				
	(whole sample)		*(filtered sample)*	
	(1)	(2)	(3)	(4)
Flat	-0.16^{**}	-0.14^{**}	-0.16^{**}	-0.14^{*}
	(0.05)	(0.06)	(0.06)	(0.06)
Accuracy	0.07^{+}	0.08^{*}	0.07^{*}	0.09^{**}
	(0.04)	(0.03)	(0.04)	(0.04)
Age		-0.00		-0.00
		(0.00)		(0.00)
Female?		0.04		0.04
		(0.04)		(0.04)
US resident?		-0.03		-0.02
		(0.07)		(0.07)
Num. obs.	2100	2070	2060	2030
Likl. Ratio.	148.93	175.79	146.39	173.35
LR test p-val	< 0.0001	< 0.0001	< 0.0001	< 0.0001
AIC	1649.70	1549.38	1638.88	1539.16

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

Table C2: Marginal effects, logit regression (baseline category: PPM)

Dep. var.: P(effort task completed)				
	(whole sample)		*(filtered sample)*	
	(1)	(2)	(3)	(4)
(Intercept)	0.92^{***}	1.91^{*}	0.92^{***}	1.91^{*}
	(0.22)	(0.86)	(0.22)	(0.87)
PPM	1.05^{**}	0.96^{*}	0.98^{**}	0.89^{*}
	(0.36)	(0.37)	(0.36)	(0.37)
Accuracy	1.91^{***}	2.15^{***}	1.91^{***}	2.15^{***}
	(0.43)	(0.41)	(0.43)	(0.41)
Age		-0.04		-0.04
		(0.03)		(0.03)
Female?		0.37		0.33
		(0.33)		(0.33)
US_resident?		-0.24		-0.19
		(0.65)		(0.65)
Num. obs.	2100	2070	2060	2030
Likl. Ratio.	148.93	175.79	146.39	173.35
LR test p-val	< 0.0001	< 0.0001	< 0.0001	< 0.0001
AIC	1649.70	1549.38	1638.88	1539.16

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

Table C3: Logistic regression estimates (baseline: Flat)

957 ## C.2 Study 2

958 ### C.2.1 Additional figures and tables

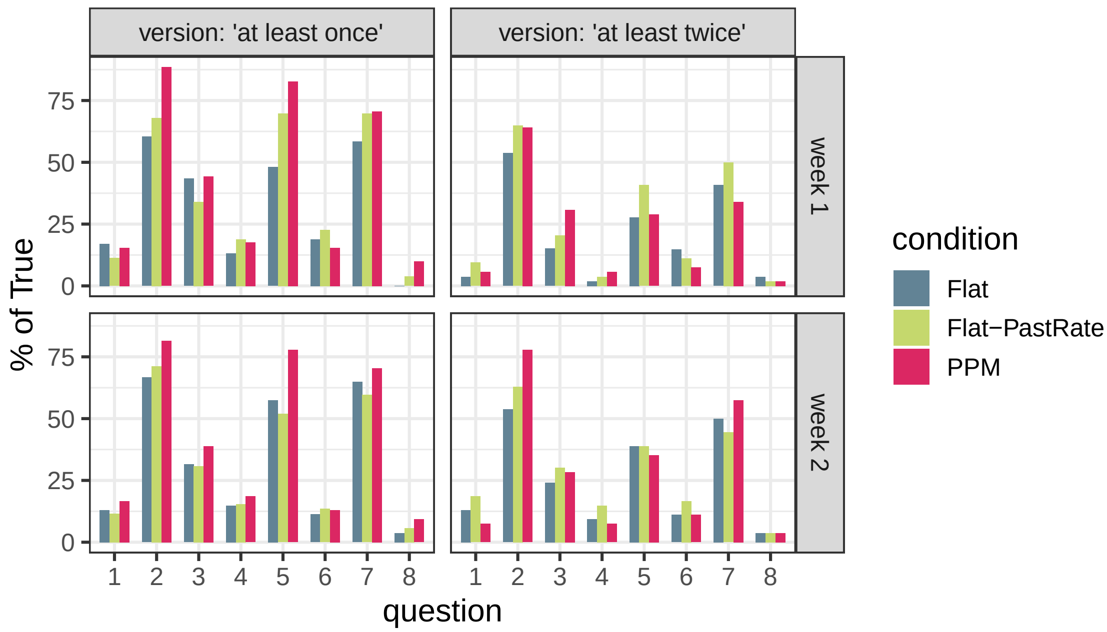


Figure C2: ...

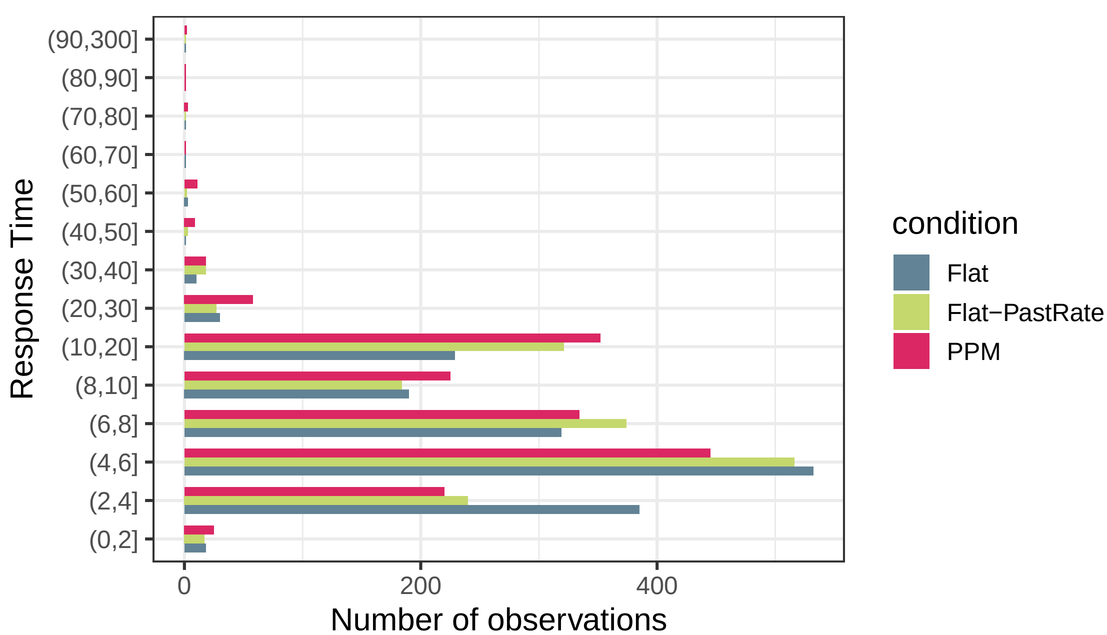


Figure C3: Response times

	week	version	cond.	resp. time	response		week	version	cond.	resp. time	response
1	1	“once”	Flat	71.074	“False”	10	2	“once”	Flat	67.074	“True”
2	1	“once”	PPM	78.342	“True”	11	2	“twice”	Flat-PR	73.208	“False”
3	1	“once”	PPM	80.594	“False”	12	2	“twice”	PPM	70.845	“True”
4	1	“once”	PPM	74.812	“False”						
5	1	“once”	PPM	65.680	“True”						
6	1	“twice”	Flat	287.396	“False”						
7	1	“twice”	Flat-PR	99.080	“True”						
8	1	“twice”	PPM	185.663	“False”						
9	1	“twice”	PPM	104.542	“True”						

Table C4: Study 2, outlier responses based on response time $>$ 60 seconds

	P(response = ‘true’), Logit estimates					
	(week 1)			*(week 2)*		
	(filtered sample)		*(all)*	*(filtered sample)*		*(all)*
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	-0.74^{***}	-0.42	-0.38	-0.71^{***}	-0.67^{*}	-0.69^{*}
	(0.10)	(0.34)	(0.33)	(0.11)	(0.30)	(0.30)
Flat-PastRate	0.22	0.18	0.19	-0.02	-0.03	-0.04
	(0.16)	(0.16)	(0.16)	(0.16)	(0.15)	(0.16)
PPM	0.46^{***}	0.39^{**}	0.41^{**}	0.34^{*}	0.35^{*}	0.34^{*}
	(0.13)	(0.13)	(0.13)	(0.16)	(0.16)	(0.16)
Response time		0.01	0.01		0.01	0.02
		(0.01)	(0.01)		(0.01)	(0.01)
Age		-0.02	$-0.02^{\cdot}$		-0.01	-0.01
		(0.01)	(0.01)		(0.01)	(0.01)
Female?		0.08	0.09		-0.10	-0.10
		(0.13)	(0.13)		(0.13)	(0.14)
UK citizen?		-0.00	-0.00		0.17	0.17
		(0.13)	(0.13)		(0.16)	(0.17)
Num. obs.	1259	1259	1264	1279	1279	1280
Likl. Ratio.	10.44	16.28	15.87	8.03	12.85	13.83
LR test p-val	0.0054	0.0123	0.0144	0.0180	0.0455	0.0316
AIC	1662.27	1664.43	1671.58	1660.66	1663.85	1664.94

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

Table C5: Logistic regression estimates

C.2.2 Analyses on the 'at least twice' survey data

	P(response = 'true'), Logit estimates					
	(week 1)			*(week 2)*		
	(filtered sample)		*(all)*	*(filtered sample)*		*(all)*
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	-1.37^{***}	-1.31^{***}	-1.27^{***}	-1.07^{***}	-0.68^{+}	-0.62^{+}
	(0.12)	(0.28)	(0.27)	(0.13)	(0.35)	(0.35)
Flat-PastRate	0.29^{+}	0.28^{+}	0.31^{+}	0.17	0.18	0.17
	(0.17)	(0.17)	(0.16)	(0.18)	(0.18)	(0.18)
PPM	0.13	0.20	0.23	0.16	0.15	0.15
	(0.18)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
Response time		0.01	0.00		0.03^{**}	0.03^{**}
		(0.01)	(0.00)		(0.01)	(0.01)
Age		-0.02^{*}	-0.02^{*}		-0.02^{*}	-0.02^{*}
		(0.01)	(0.01)		(0.01)	(0.01)
Female?		-0.01	0.01		-0.08	-0.08
		(0.14)	(0.14)		(0.15)	(0.15)
UK citizen?		0.47^{*}	0.47^{*}		-0.14	-0.14
		(0.18)	(0.18)		(0.20)	(0.20)
Num. obs.	1284	1276	1280	1294	1286	1288
Likl. Ratio.	3.24	17.33	17.48	1.49	17.27	17.89
LR test p-val	0.1983	0.0081	0.0077	0.4759	0.0083	0.0065
AIC	1374.64	1361.98	1368.80	1528.92	1514.03	1516.63

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

Table C6: Logistic regression estimates

	P(response = 'true'), marginal effects					
	(week 1)			*(week 2)*		
	(filtered sample)		*(all)*	*(filtered sample)*		*(all)*
	(1)	(2)	(3)	(4)	(5)	(6)
Flat-PastRate	0.05^{+}	0.05^{+}	0.05	0.03	0.03	0.03
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
PPM	0.02	0.03	0.04	0.03	0.03	0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Response time		0.00	0.00		0.01^{**}	0.01^{**}
		(0.00)	(0.00)		(0.00)	(0.00)
Age		-0.00	-0.00		-0.00	-0.00
		(0.00)	(0.00)		(0.00)	(0.00)
Female?		0.00	0.00		-0.02	-0.02
		(0.02)	(0.03)		(0.03)	(0.03)
UK citizen?		0.08^{*}	0.08^{*}		-0.03	-0.03
		(0.03)	(0.03)		(0.04)	(0.04)
Num. obs.	1284	1276	1280	1294	1286	1288
Likl. Ratio.	3.24	17.33	17.48	1.49	17.27	17.89
LR test p-val	0.1983	0.0081	0.0077	0.4759	0.0083	0.0065
AIC	1374.64	1361.98	1368.80	1528.92	1514.03	1516.63

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

Table C7: Logistic regression, average marginal effects

	OLS, Dep.Var.: Response time					
	|	*(week 1)*	|	|	*(week 2)*	|
	(filtered sample)		*(all)*	*(filtered sample)*		*(all)*
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	6.68***	8.98***	10.81***	7.39***	7.06***	6.63***
	(0.38)	(0.99)	(1.73)	(0.42)	(1.28)	(1.35)
Flat-PastRate	0.97	1.22*	0.17	0.34	0.42	0.64
	(0.60)	(0.56)	(1.07)	(0.56)	(0.57)	(0.59)
PPM	2.49***	2.54***	2.24$^{\cdot}$	0.58	0.66	0.65
	(0.71)	(0.71)	(1.17)	(0.57)	(0.56)	(0.56)
Response (="True"?)	0.40	0.54	−0.36	1.64*	1.57*	1.58*
	(0.63)	(0.63)	(1.06)	(0.73)	(0.76)	(0.75)
Flat-PastRate × Response	−0.19	−0.28	1.47	−1.78*	−1.61$^{\cdot}$	−1.81$^{\cdot}$
	(0.88)	(0.87)	(1.38)	(0.89)	(0.92)	(0.92)
PPM × Response	0.26	−0.04	1.37	0.37	0.46	0.95
	(0.94)	(0.94)	(1.96)	(1.10)	(1.11)	(1.18)
Age		−0.07*	−0.08$^{\cdot}$		0.06	0.07$^{\cdot}$
		(0.03)	(0.04)		(0.04)	(0.04)
Female		0.84	−0.20		−0.41	−0.51
		(0.55)	(0.96)		(0.51)	(0.53)
UK citizen?		−1.68*	−1.70$^{\cdot}$		−0.98	−0.84
		(0.72)	(0.99)		(0.78)	(0.78)
R^2	0.03	0.05	0.02	0.02	0.03	0.03
Adj. R^2	0.03	0.04	0.01	0.01	0.02	0.02
Num. obs.	1284	1276	1280	1294	1286	1288
RMSE	6.06	6.03	11.66	5.84	5.83	6.32

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

Table C8: Response time regressions.