Looking into Crystal Balls: A Laboratory Experiment on Reputational Cheap Talk*

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Abstract

We experimentally study information transmission by experts motivated by their reputation for being well informed. In our game of *reputational cheap talk*, a *reporter* privately observes information about a state of the world and sends a message to an *evaluator*; the evaluator uses the message and the realized state of the world to assess the reporter's informativeness. We manipulate the key driver of misreporting incentives: the uncertainty about the phenomenon to forecast. We highlight three findings. First, misreporting information is pervasive, even when truthful information transmission can be an equilibrium strategy. Second, consistent with the theory, reporters are more likely to transmit information truthfully when there is more uncertainty on the state. Third, evaluators have difficulty learning reporters' strategies and, contrary to the theory, assessments react more strongly to message accuracy when reporters are more likely to misreport. In a simpler environment with computerized evaluators, reporters learn to best reply to evaluators' behavior and, when the state is highly uncertain and evaluators are credulous, to transmit information truthfully.

Keywords: Forecasting; Experts; Reputation; Cheap Talk; Laboratory Experiments

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1 Introduction

Do professional forecasters, analysts, and experts truthfully report their expectations when they make predictions? Experts' predictions of future trends play a key role in shaping decisions ranging from corporate investment to public policy. As a consequence, forecaster accuracy is actively monitored, and forecasters who attain outstanding reputation face remarkable career prospects.[1] The strength of these incentives might lead one to believe that reputation motives and market forces should ensure performance and truthfulness of forecasters. As reported by Keane and Runkle (1998), "since . . . analysts' livelihoods depend on the accuracy of their forecasts . . . we can safely argue that these numbers accurately measure the analysts' expectations."

Building on models of career concerns (Holmström, 1999) and herding (Scharfstein and Stein, 1990), this belief has been challenged by a theoretical literature positing that forecasters are economic agents who make strategic choices and may be reluctant to truthfully report information that might reflect negatively on their reputation for being well informed. This literature analyzes a game of *reputational cheap talk* between a *reporter* and an *evaluator*, with the following basic structure (Ottaviani and Sørensen, 2006a):

- The reporter privately observes a signal about a state of the world and sends a message to the evaluator.
- The informativeness of the reporter's signal is uncertain and initially unknown to both the reporter and the evaluator.
- The evaluator assesses the informativeness of the reporter's signal on the basis of the reporter's message and the realized state of the world.
- The objective of the reporter is to maximize the reputation for being well informed, according to the assessment made by the evaluator.

As explained below, the theory predicts that the reporter has a somewhat subtle incentive to misreport signals that indicate poor information. Variants of this game have been extensively used to model strategic incentives in the context of financial recommendations, news reporting, managerial decisions, and communication in organizations (Trueman, 1994; Graham, 1999; Ottaviani and Sørensen, 2001, 2006a,b; Prat, 2005; Gentzkow and Shapiro, 2006; Levy, 2007; Visser and Swank, 2007; Deb et al., 2018; Otto and Volpin, 2018). Moreover,

[1] For example, Alan Greenspan and Lawrence Meyer ran successful consulting firms offering forecasting services before becoming members of the Board of Governors of the Federal Reserve Bank. Financial analysts who are highly ranked in the "All-Star" ranking conducted by the Institutional Investor magazine receive larger bonuses and have better prestige than non-ranked analysts (Groysberg et al., 2011; Brown et al., 2015).

biases in expert reports due to reputational incentives have important implications for the literature on forecast aggregation (Lichtendahl et al., 2013).

Testing the predictions of the theory of reputational cheap talk has proven challenging for observational studies, which cannot easily measure, let alone manipulate, the information available to reporters and evaluators. This paper develops an experimental framework that overcomes these challenges and addresses the following open questions: Do models of reputational cheap talk accurately predict behavior and the ensuing informational biases? Do reporters misreport available information to appear competent? How does this depend on uncertainty about the phenomenon to forecast? Are evaluators able to interpret forecasts or are they naive? We answer these questions through an experiment designed to measure and exogenously manipulate the information structure, the degree of uncertainty about the variable to be forecasted, and the evaluators' expectations about the reporters' strategy.

A first challenge for the experimental design is to find a simple way to implement the information structure posited by the theory. We meet this challenge by developing a novel urn scheme with nested balls. As in the classic urn setting pioneered by Anderson and Holt (1997), the private signal observed by the reporter corresponds to the color of a ball drawn from an urn (either blue or orange). We innovate by introducing an inner core inside the outer shell of each ball; the color of the core—which is not visible to the reporter—represents the state of the world (either blue or orange). We then capture the informativeness of the signal about the state by constructing urns containing a different composition of nested balls. An informative urn contains balls whose shell and core have the same color. In an uninformative urn, instead, the color of the shell gives no indication of the color of the core.

A second challenge for the experimental design is to find a way to control for evaluators' beliefs about reporters' behavior, a key driver of misreporting incentives. Indeed, these beliefs are difficult to pin down for both the experimenter analyzing the data and for reporters engaged in the experimental task. This is due to the existence of multiple Bayes-Nash equilibria and to the high level of strategic sophistication required for equilibrium play. We meet this challenge by designing treatments where human reporters face computerized evaluators. We use these treatments to analyze how reporters learn best-reply behavior and how limited strategic sophistication may act to select one of several equilibria. These treatments also help us gain additional insight on how to design markets for professional forecasters and how to improve the transmission of information between experts and their clients.

In particular, to study reporters' strategic incentives, we employ six different treatments, manipulating two crucial dimensions of the game: the common prior belief about the state of the world, and evaluators' expectations about reporters' behavior. We consider two values of the prior about the state, a treatment with a *mildly unbalanced* prior and a treatment with a *strongly unbalanced* prior. We further vary evaluators' beliefs about reporters' behavior through three games: a game with *human* evaluators who have *free* beliefs about reporters' behavior (HF); a game with *computerized* evaluators that are *credulous* and believe that reporters always report truthfully (CC); and a game with *computerized* evaluators that are initially agnostic about reporters' behavior and whose beliefs evolve according to Bayesian *learning* based on interactions with reporters (CL)[2]

According to the theory, the prior belief about the state of the world and evaluators' beliefs about reporters' truthfulness jointly determine which of two competing forces driving reporting incentives prevails. To understand the intuition, suppose that the prior about the state of the world is unbalanced in favor of blue (as in our experiment) and that the evaluator believes that the reporter truthfully reports the observed shell. If the evaluator's assessment was formed just on the basis of the report but without observing the state of the world, the reporter would always want to report a signal corresponding to the most likely state (that is, blue), so as to improve the evaluator's assessment that the signal was informative (blue shells being more frequent in the informative urn). This first force pushes toward misreporting whenever the reporter's signal corresponds to the least likely state of the world (that is, an orange shell).

However, the evaluator's assessment is also based on the realized state of the world. Since a matching signal and state of the world are indicative of an informative urn, this second force creates an incentive for the reporter to truthfully report the observed signal. The second force prevails when the reporter, upon observing an orange shell, thinks that the core is more likely to be orange than blue. This is the case when the prior is mildly unbalanced and, thus, there exists an equilibrium in which the reporter truthfully reports the observed shell. If, instead, the prior is strongly unbalanced, truthful reporting cannot be an equilibrium because the reporter has an incentive to report a blue shell even when observing an orange shell.

Empirically, we find that reporters are prone to misreport information supporting the *ex-ante* unlikely state, even when truthful information transmission can be an equilibrium strategy. However, as predicted by the theory, reporters are more likely to report information truthfully when they are more uncertain about the state of the world. We also find that evaluators use the information they receive about signal informativeness (report and core) in a way which is compatible with Bayesian updating: assessments based on different report and

[2]Games CC and CL transform the reputational cheap talk game in a decision problem for reporters. For other experiments where a game is reduced to a decision problem with the use of computerized opponents, see Roth and Murnighan (1978), Fehr and Tyran (2001), Esponda and Vespa (2014), and Koch and Penczynski (2018).

core combinations are ranked in the order predicted by theory; assessments after messages which cannot be used to misreport do not depend on reporters' incentives; and assessments after messages which can be used to misreport can be rationalized by *some* belief on reporters' behavior.

At the same time, we find that evaluators' behavior is incompatible with learning how reporters' strategies change with the environment and using this knowledge to make correct inference on informativeness. In particular, we find that evaluators' assessments are more responsive to the accuracy of the report—that is, whether the report predicts or not the realized state of the world—in the treatment where reporters have stronger incentives to misreport (and do misreport more frequently). We show that this overreaction can be generated by a learning model where accuracy is erroneously taken to represent truthfulness and inaccuracy to represent misreporting.

Importantly, the observed behavior of evaluators dampens reporters' incentive to misreport, in comparison to the behavior of a Bayesian evaluator who learns the strategies of reporters in the experiment and uses this information correctly to make inference on reporters' informativeness. Nonetheless, this is not enough to lead reporters to transmit information truthfully because evaluators' overreaction to message accuracy only occurs in the treatment where misreporting is the unique Bayes-Nash equilibrium. Finally, we show that truthful transmission of information can prevail when reporters face computerized evaluators who use Bayes rule to form assessments and trust reporters to transmit information truthfully. In this case, with a mildly unbalanced prior, truthful reporting is in the reporters' best interest and reporters in the experiment do learn to report private information without distortion. On the other hand, reporters' behavior is unchanged when they face human evaluators or computerized evaluators whose beliefs about reporters' behavior are initially agnostic and evolve based on interactions with reporters. The conclusion discusses the implications of these results for the design of markets for professional forecasting.

While there is a large experimental literature on the statistical herding models of Banerjee (1992) and Bikhchandani et al. (1992),[3] this is the first paper experimentally testing the basic building block of the reputational herding model of Scharfstein and Stein (1990) with a single sender. Other recent experimental papers in this area (Fehrler and Hughes, 2018; Mattozzi and Nakaguma, 2019; Renes and Visser, 2021) focus on situations with multiple senders (that is, committees of experts). Contrary to our experiments, the main experimental treatment of these works is the information available to the evaluator before making his assessment and

[3]The investigation of informational cascades in the laboratory was pioneered by Anderson and Holt (1997) and further developed, among others, by Hung and Plott (2001), Kübler and Weizsäcker (2003), Çelen and Kariv (2004), Goeree et al. (2007), and Eyster et al. (2015). See Anderson and Holt (2008) for a review.

their main focus is on the strategic interaction among experts. The only study other than ours where experts send a message to evaluators about the information they possess is Blume et al. (2019). In both their setting and ours, experts' utility depends on evaluators' belief about their type. However, their experiment investigates different forces driving informational inefficiency than ours: in their setting, experts have private information about their type and the question posed to them ('are you the good type?' or 'are you the bad type?'), evaluators only observe experts' messages, and experts' incentives to report their type truthfully are driven by lying costs and evaluators' uncertainty about the question posed to experts.

Our work is also related to the experimental literature testing models of *partisan advice* (Cai and Wang, 2006; Kawagoe and Takizawa, 2009; Wang et al., 2010). There are three key differences between partisan and professional advice. First, while in our setting the sender cares about his reputation, in the canonical model of cheap talk à la Crawford and Sobel (1982), the sender cares about a decision made by the receiver. Second, our receiver has access to an additional source of information (the realized state) before taking the action (evaluation of the sender). Third, while the strategic tension toward misreporting is present in both models, it is driven by different forces: in models of partisan advice, the key driver of misreporting incentives is the presence of a conflict of interest between the sender and the receiver, and truth-telling equilibria exist when preferences are aligned. By contrast, in our setting, misreporting crucially depends on the features of the information structure and truth-telling equilibria exist when the ex-ante uncertainty about the state of the world is sufficiently large. In a comprehensive review, Blume et al. (2020) note that, "from its inception, the experimental literature on strategic information transmission with a single sender and a single receiver documents systematic over-communication, relative to the most informative equilibria." This is in sharp contrast with reporters' behavior in our game of reputational cheap talk.[4]

The experimental literature on *naive advice* also explores the determinants and consequences of advice transmitted from informed senders who internalize, at least partially, the receiver's well being (Schotter, 2003; Schotter and Sopher, 2007; Chaudhuri et al., 2009; Çelen et al., 2010). Given that the reporter's utility depends on the beliefs of the evaluator about the reporter's type, reputational cheap talk is a psychological game (Geanakoplos et al., 1989; Battigalli and Dufwenberg, 2009). In typical applications of psychological games, the effect of beliefs on utility is mediated by emotions, thus reducing the appeal of direct belief manipulation via computerized agents (our work) or payoff distributions (Khalmetski,

[4]An exception is Cabrales et al. (2020) who find under-communication when there is a market for cheap-talk information. As in their experiment, the incidence of misreporting in our setting could be due to subjects' social preferences and to the fact that, contrary to treatments with truth-telling equilibria in games of partisan advice, the sender's and the receiver's payoffs in our professional advice game do not coincide.

2016; Ederer and Stremitzer, 2017), in favor of the elicitation and communication of beliefs (Ellingsen et al., 2010) or their indirect manipulation (Dufwenberg and Gneezy, 2000; Charness and Dufwenberg, 2006).

The paper proceeds as follows: Section 2 introduces the model and explains the design of our main experimental treatments, with human reporters and human evaluators. Section 3 derives the testable hypotheses we take to the laboratory. Section 4 presents the experimental results. Section 5 discusses additional experimental treatments with computerized evaluators. Section 6 concludes.

2 Model and Experimental Design

We consider a Bayesian game of reputational cheap talk between a *reporter* and an *evaluator*. The reporter and the evaluator are uncertain about a state of the world (corresponding in the experiment to the color of the *core* of the ball), which can be either *blue* or *orange*, $c \in \{b, o\}$. The common prior belief is unbalanced toward state b, $\Pr(c = b) = q \geq 1/2$.[5] This belief is our main experimental manipulation and it is varied between a *mildly unbalanced* prior with $q = 6/10$ and a *strongly unbalanced* prior with $q = 8/10$.[6] The reporter privately observes a signal about the state (the color of the *Shell*), which can be either *Blue* or *Orange*, $S \in \{B, O\}$. There are two types of reporters (*urns* from which signals are drawn), $u \in \{I, U\}$: reporters with $u = I$ receive perfectly *informative* signals, meaning that core and shell color are equal for sure. Reporters with $u = U$ receive perfectly *uninformative* signals, meaning that, regardless of the color of the shell, the likelihood of the core being blue is the same (q). The reporter and the evaluator are uncertain about the signal's informativeness and, ex-ante, believe that both possibilities are equally likely, $\Pr(u = I) = \Pr(u = U) = 1/2$.

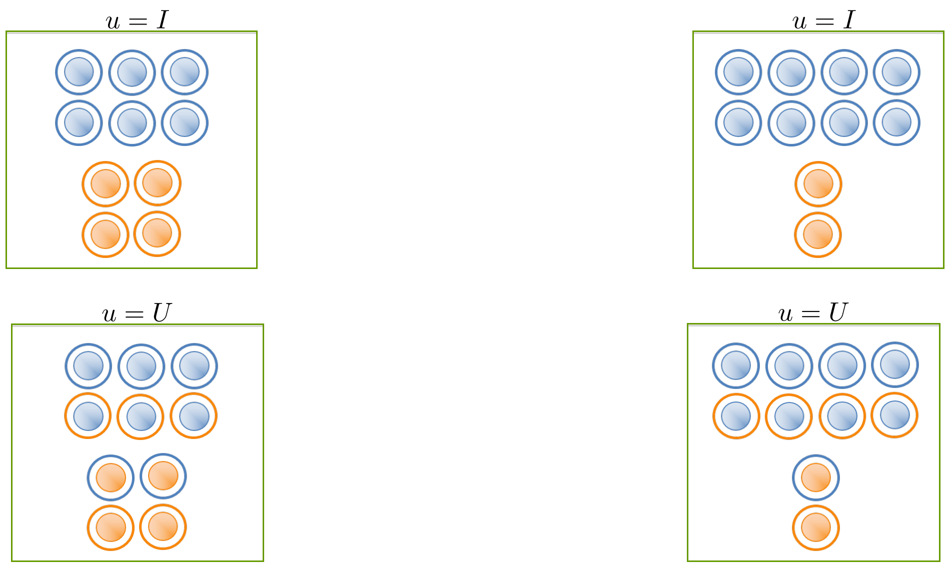
In the experiment, urns are composed of 10 balls, among which $10q$ have a blue core and the remainder an orange core. The two panels of Figure 1, which are given to subjects as part of the instructions, represent the urn composition in our two experimentral treatments. Consider the case with a *mildly unbalanced* prior of $q = 6/10$ (Figure 1a). In this case, the informative urn is composed of six balls with a blue shell and a matching blue core, and of four balls with an orange shell and a matching orange core. The uninformative urn also contains six balls with a blue core and four balls with an orange core. However, the uninformative urn always contains five balls with an orange shell and five balls with a blue shell. Among the five balls with an orange shell, only two have an orange core and, similarly, among the five balls with a blue shell, only three have a blue core. As the prior probability

[5]Since the model is perfectly symmetric with respect to c, this is without loss of generality.

[6]A second manipulation, varying evaluators' beliefs about reporters' strategy is discussed in Section 5.

Figure 1: Information Structure of the Reputational Cheap Talk Game.

(a) $q = 6/10$ (b) $q = 8/10$



Notes: Panel (a), on the left, shows the informative (upper) and uninformative (lower) urns when the prior is mildly unbalanced—6 balls have a blue core. Panel (b), on the right, shows the two urns when the prior is strongly unbalanced—8 balls have a blue core.

of the blue state of the world increases to generate a *strongly unbalanced* prior, $q = 8/10$ (Figure 1b), the number of balls with a blue core increases to eight in both urns, but the number of balls with a blue shell only increases in the informative urn.

After observing the signal, the reporter sends a report to the evaluator, $R \in \{B, O\}$. In the theoretical analysis as well as in the experiment, we constrain the reporter to report $R = B$ after observing $S = B$ and we allow *misreporting* only after observing $S = O$.[7] The reporter in our game has two possible strategies:

- *Misreporting* (M): always report $R = B$, regardless of the signal.
- *Truth-telling* (T): report $R = B$ when $S = B$; report $R = O$ when $S = O$.

In the experiment, we use the strategy method to elicit reporters' strategies as a plan of action set out before they observe the shell of the drawn ball. After observing the report R and the state of the world c, the evaluator assesses the likelihood that the reporter was informed (i.e., that the signal was drawn from the informative urn): $\Pr(u = I|R, c) = p_{Rc}$.

[7] This restriction of the strategy set means that, differently from the standard cheap-talk game, in our simplified game the reporter can prove one of her reports. Allowing the reporter to misreport only after one signal simplifies the reporter's task in the experiment and reduces the number of pure-strategy equilibria of the game, thus facilitating analysis and interpretation of experimental results. Importantly, the essence of reputational cheap-talk models is maintained because in the equilibria of our game information may be lost due to reputational considerations.

The reporter benefits from being perceived as informed with a payoff proportional to this *assessment*. We assume the reporter to be risk neutral, with expected utility from either strategy proportional to the expected evaluator's assessment across states of the world (unknown at the time a report is made), $E[p_{Rc}]$. The evaluator's objective is to make an accurate assessment of the reporter's informativeness. In the experiment, the reporter's payoff equals €P, where $P \in [0, 1]$ represents the evaluator's assessment of the probability that the ball was drawn from the informative urn, and we compensate evaluators using a *binarized scoring rule* (Harrison et al., 2013; Hossain and Okui, 2013).[8]

All experimental sessions were conducted at the Bocconi Experimental Laboratory for the Social Sciences and, in total, they involved 94 participants. Subjects participated in only one session and maintained their role of reporter or evaluator throughout the whole session. An experimental session consists of 4 blocks of 16 periods, for a total of 64 periods. Each reporter is randomly re-matched with an evaluator at the beginning of each period. The value of q is fixed during a block but it changes from one block to the next, so that each value occurs in two non-consecutive blocks. This means that the treatment variation is within subject as both priors are implemented in each session. We use the term *first block* to indicate the block in which a given value of q is encountered for the first time, and *second block* to indicate the block in which this same q is encountered for the second time. To control for order effects, we ran two sessions where the initial block had $q = 6/10$ and two sessions where the initial block had $q = 8/10$. At the beginning of each session, instructions were read out loud with the help of a twenty-minutes long video. Written instructions and a link to the video are provided in Online Appendix G. Each session lasted around two and a half hours (including instructions and payments) and average earnings (including a €5 show-up fee) were €36.40 for reporters and €39.66 for evaluators. The experimental interface was programmed using zTree (Fischbacher, 2007).

3 Theoretical Analysis and Experimental Hypotheses

In this section we derive the Bayes-Nash equilibria of our reputational cheap talk game as a function of q, the prior probability that the state is b. We start by determining evaluators' optimal behavior in each information set and then study reporters' best-reply behavior.

[8]Given this incentive scheme, it is optimal for evaluators to truthfully report their personal assessment, even if they are risk averse or do not have expected utility preferences, provided they prefer a binary lottery that assigns a higher probability to the larger reward to one that assigns a lower probability to the same reward. An exact description of this scoring rule can be found in the instructions in Online Appendix G. To ease understanding of the rule, we provide participants in the role of evaluators with a calculator to help them compute the chance of winning the reward for any assessment (see Figure 9 in Online Appendix G).

For ease of presentation, we initially treat evaluators' beliefs about reporters' behavior—an endogenous variable—as a parameter on which players' behavior depends.

3.1 Evaluator's Assessments

In this game, it is optimal for the evaluator to assess the urn's informativeness using the Bayesian posterior belief given the information received and the belief that the reporter is truthful. We let p_{Rc} denote the evaluator's assessment for every report-state pair. If the signal was observable, the evaluator would always update the prior belief about signal quality based on whether or not the state of the world matched the signal. Specifically, a matching signal and state is twice as likely to occur if the signal is informative than if it is uninformative, and a mismatch between signal and state of the world is impossible if the signal is informative. This logic applies without qualifiers when the evaluator receives a report $R = O$, since reporters are not allowed to use this report falsely. Thus, in this case, the posterior from a match is $p_{Oo} = 2/3$, and from a mismatch is $p_{Ob} = 0$. Instead, when receiving a report $R = B$, the evaluator knows the reporter may have misreported. The observation of *report* and state of the world, thus, differs in its informational content from the observation of *signal* and state of the world. Specifically, given report B, state of the world c, and belief f, by Bayes' rule the evaluator's assessment that the reporter is informed is

$$p_{Bc} = \Pr(u = I | R = B, c, f) = \frac{\Pr(R = B | c, u = I, f)\,\frac{1}{2}}{\Pr(R = B | c, u = I, f)\,\frac{1}{2} + \Pr(R = B | c, u = U, f)\,\frac{1}{2}}. \quad (1)$$

The evaluator's assessment after a Blue report crucially depends on the belief that the reporter is truthful, f. A belief that the reporter may misreport, $f < 1$, dampens the evaluator's favorable inference about informativeness following a match between report and state, p_{Bb}, as well as the unfavorable inference following a mismatch, p_{Bo}. From (1), we have

$$p_{Bb} = \frac{1}{\frac{3}{2} + (1 - f)\frac{1}{2}} \text{ and } p_{Bo} = \frac{(1 - f)}{\frac{1}{2} + (1 - f)\frac{3}{2}}.$$

It is easy to see that, for $f \in [0, 1]$, $p_{Bb} \in [1/2, 2/3]$, strictly increasing in f, and $p_{Bo} \in [0, 1/2]$, strictly decreasing in f. Intuitively, an evaluator with low trust in the reporter's truthfulness—a low f—learns little from the received report and, hence, has a posterior that is close to the prior probability of an informative urn, $1/2$.

This analysis delivers two predictions we can use to test whether evaluators' assessments in the experiment are consistent with Bayesian updating (given some belief about reporters' behavior). First, assessments after reports that cannot be used to misreport information (that is, $R = O$) do not depend on reporters' incentives and, thus, are unaffected by the experimental treatment. Second, assessments are ranked in all experimental treatments: $p_{Oo} = 2/3 \geq p_{Bb} \geq p_{Bo} \geq p_{Ob} = 0$ for any $f \in [0,1]$, and this ranking is strict if $f \in (0,1)$.

3.2 Reporter's Incentives and Bayes-Nash Equilibria

The reporter's choice depends on the payoff expected from each available action after observing $S = O$. Reporting $R = O$ yields a payoff of either p_{Oo} or p_{Ob}, depending on the true state of the world. Analogously, reporting $R = B$ yields either p_{Bo} or p_{Bb}. Importantly, the probability the reporter assigns to each state of the world and, hence, each possible evaluator assessment, is the posterior probability of a blue core after observing $S = O$, which we denote q_O. Define the *gain* from misreporting after observing $S = O$, as

$$\Delta_{EU}(q,f) = \underbrace{\left[(1-q_O)\,p_{Bo} + q_O p_{Bb}\right]}_{=EU_M} - \underbrace{\left[(1-q_O)\,p_{Oo} + q_O p_{Ob}\right]}_{=EU_T}. \tag{2}$$

The reporter will prefer to misreport if $\Delta_{EU}(q,f)$ is positive, and to be truthful if it is negative. The gain from misreporting depends on f because the evaluator's assessment depends on the belief about the reporter's truthfulness, and it depends on q because the reporter's posterior probability that the state is $c = b$ is given by

$$q_O = \frac{\frac{1}{4}q}{\frac{1}{4}q + \frac{3}{4}(1-q)}.$$

The analysis of the reporter's best reply hints at the structure of the equilibria. If the common prior belief about the state of the world is such that the reporter's best reply to an evaluator with perfectly trusting beliefs is to report truthfully, then such behavior can be sustained in equilibrium. Otherwise, only misreporting can be sustained in equilibrium.

Proposition 1 (Bayes-Nash Equilibria) *When the prior belief about the state is mildly unbalanced, $q \in [1/2, 3/4]$, there are three Bayes-Nash equilibria: (i) an equilibrium in which the reporter reports truthfully, (ii) an equilibrium in which the reporter misreports, and (iii) a mixed-strategy equilibrium in which the reporter reports truthfully with probability:*

$$f^*(q) = \frac{8q-4}{4q-1} \tag{3}$$

and misreports with complementary probability, $1 - f^*$. When the prior belief is strongly unbalanced, $q \in [3/4, 1]$ there is only an equilibrium in which the reporter misreports.

3.3 Equilibrium Selection with Level-k Model

Proposition 1 shows that truth-telling can be sustained in equilibrium when $q = 6/10$, while this is not the case when $q = 8/10$. This suggests that reporters should be more likely to transmit information truthfully in the treatment with mildly unbalanced prior. Nonetheless, equilibria with both misreporting and truth-telling exist when $q = 6/10$. To strengthen our testable hypotheses, we show that a widely used behavioral model, the *level-k model* of limited strategic sophistication, delivers a unique prediction for both our treatments.[9] While our experiment is not designed to directly test this model, its predictions further highlight the importance of the uncertainty about the phenomenon to forecast (q) for reporters' strategic incentives in the reputational cheap-talk game.

The level-k model, which has been successfully used to explain behavior in a wide variety of experiments (Crawford et al., 2013; Georganas et al., 2015), departs from standard game theory by assuming that players are limited in their ability to anticipate the strategic behavior of opponents. In particular, players are distinguished by their level of thinking and higher level players are more sophisticated about the strategic behavior of others. Level 0 players are non-strategic and each higher type believes that other players are of the immediately lower type: $L1$ best replies to $L0$ behavior, $L2$ best replies to $L1$ behavior, and so on.

In complete information games, $L0$ players are usually assumed to randomize uniformly across all actions. In adapting the level-k model to cheap-talk games, researchers have specified the $L0$ sender (i.e., the reporter) as naively revealing actual information and the $L0$ receiver (i.e., the evaluator) as credulously believing the sender's message to be true (Crawford, 2003; Cai and Wang, 2006; Kawagoe and Takizawa, 2009; Ellingsen and Östling, 2010; Wang et al., 2010; Li et al., 2021).[10]

This leads to the following structure of strategic incentives. A Level 0 reporter does not think strategically and reports truthfully. For higher levels, an Lk reporter believes the evaluator is $L(k-1)$ and best replies. Thus, an Lk reporter prefers to misreport if and only if the gain from misreporting, $\Delta_{EU}(q, f_{k-1})$ in equation (2), is positive, where f_{k-1} is the belief about the reporter's strategy held by an $L(k-1)$ evaluator. An Lk evaluator believes the reporter is Lk and best replies. Thus, an Lk evaluator assesses the Lk reporter's informativeness using the Bayesian posterior belief given the report, the state of the world, and the belief that an Lk reporter is truthful. When $q \in (3/4, 1]$, $\Delta_{EU}(q, f_{k-1})$ is positive—

[9]Blume et al. (2022) also use a level-k model as equilibrium selection argument in a cheap-talk game.

[10]Under this assumption, credulous $L0$ evaluators are, in effect, best replying to truthful $L0$ reporters. Thus, assuming that $L1$ evaluators best reply to $L0$ reporters leads to identical predictions for $L1$ and $L0$ receivers. Similarly, $L1$ and $L2$ reporters would have identical behaviors and so on. To avoid this duplication, we follow the literature and reorganize the levels of thinking: an Lk evaluator believes the reporter is Lk and an Lk reporter believes the evaluator is $L(k-1)$.

and, thus, reporters prefer to misreport—for any $f_{k-1} \in [0,1]$. As a consequence, the best reply of all Lk reporters is to misreport and all Lk evaluators (with the exception of $L0$) believe reporters always misreport. When $q \in [1/2, 3/4)$, instead, an Lk reporter's best reply depends on the $L(k-1)$ evaluator's belief about the $L(k-1)$ reporter's strategy: $\Delta_{EU}(q, f_{k-1})$ is negative—and, thus, reporters prefer to report truthfully—if and only if f_{k-1} is sufficiently large. Level 0 evaluators believe Level 0 reporters never misreport — that is, $f_0 = 1$—and Level 1 reporters best reply by reporting truthfully. The same logic applies to higher levels of strategic sophistication.

Proposition 2 (Level-k Model Predictions) *When the prior belief about the state is mildly unbalanced,* $q \in [1/2, 3/4)$*, level-k reporters report truthfully and level-k evaluators believe reporters always report truthfully for any* $k \geq 0$*. When the prior belief is strongly unbalanced,* $q \in (3/4, 1]$*, level-k reporters misreport and level-k evaluators believe reporters always misreport for any* $k > 0$*.*

The assumed behavior of non-strategic players is an important element of any level-k thinking model. Thus, it is instructive to understand how the predictions from Proposition 2 depend on the exogenous distribution of actions of Level 0 reporters. As discussed above, when $q \in (3/4, 1]$, Level 1 reporters' best reply does not depend on Level 0 evaluators' beliefs and, thus, on Level 0 reporters' behavior. On the other hand, when $q = 6/10$, a Level 1 reporter's best reply depends on a Level 0 evaluator's beliefs. For example, when $q = 6/10$, $\Delta_{EU}(6/10, f_0)$ is negative if and only if $f_0 > 4/7$, that is, if and only if non-strategic reporters are sufficiently likely to reveal their actual information. This means that, with $q = 6/10$, the predictions of the level-k thinking model are sensitive to the posited behavior of non-strategic players. At the same time, the model predicts truth-telling for a wide range of assumptions on Level 0 reporters, including perfect truth-telling (the common assumption when applying level-k thinking to cheap talk games), imperfect truth-telling (up to a 3/7 chance of misreporting), and, as shown in Online Appendix F, uniform randomization over the available actions (the common assumption when applying level-k thinking to games of complete information).[11]

Propositions 1 and 2 deliver the following testable hypotheses:

Hypothesis 1 (Treatment Effect on Reporters' Behavior) *Reporters are more likely to misreport in the treatment with greater certainty about the state of the world* ($q = 8/10$)*.*

[11] In Online Appendix F, we consider an alternative level-k model with a mixture of $L0$ reporters and evaluators: a fraction of $L0$ reporters are uniformly randomizing and the remainder are truthful; also, a fraction of $L0$ evaluators are uniformly randomizing and the remainder are credulous. This alternative model delivers the same testable hypothesis as the basic model introduced in this Section.

Hypothesis 2 (Treatment Effect on Evaluators' Behavior) *Evaluators' assessments after reports that can be used to misreport information ($R = B$) are less sensitive to reports' accuracy in the treatment with greater certainty about the state of the world ($q = 8/10$).*

To understand the second hypothesis, remember that a blue report contains more information about the reporter's informativeness, and, thus, leads to a stronger updating of beliefs, when the evaluator expects the reporter to be less likely to misreport.

4 Experimental Results

Our experiment is explicitly designed to investigate the effect of q, the common belief about the state of the world, on the reporters' incentives to misreport. Thus, we can use observed reporters' and evaluators' behavior to test Hypothesis 1 and Hypothesis 2 from Section 3. Throughout Section 4, we focus on experienced subjects, that is, on decisions belonging to the second block for each treatment.[12] Whenever we state a result is significant, we refer to significance at the 1% level.

4.1 Reporters' Behavior

In the experiment, when reporters hold a strongly unbalanced prior ($q = 8/10$), the probability they choose the truthful plan of action is 37%. On the other hand, when reporters hold a weakly unbalanced prior ($q = 6/10$), they choose a truthful plan of action 49% of the time. This means that misreporting is the modal plan of action even in the treatment where truthful reporting can be an equilibrium strategy and represents the unique best reply to evaluators with limited strategic sophistication (as in the level-k model from Section 3.3). It should be noted that, given evaluators' behavior in the experiment, reporters' expected payoff (that is, their expected assessment) from misreporting is much larger than their expected payoff from truth-telling for $q = 8/10$ ($\Delta_{EU} = 10.41$), while for $q = 6/10$ truthful reporting is a best reply with near indifference ($\Delta_{EU} = -2.4$).

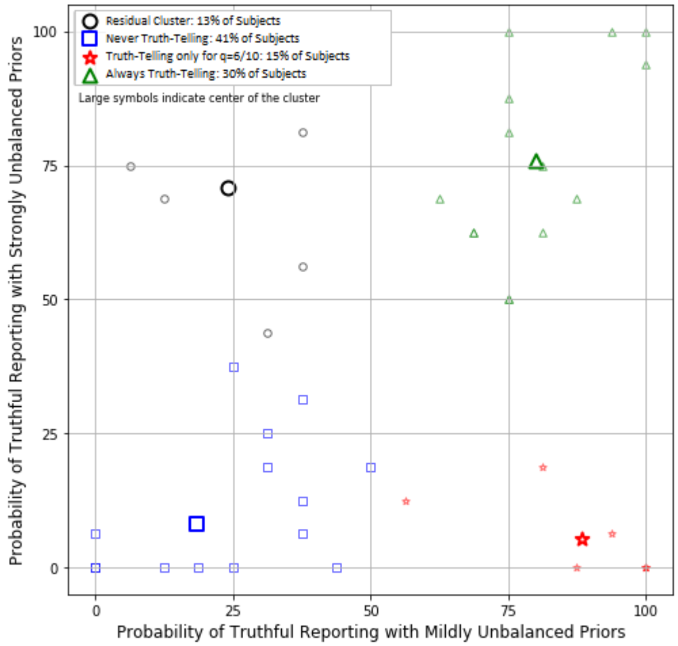
In spite of widespread misreporting in both treatments, the aggregate numbers suggest an effect of manipulating the prior belief about the state of the world which is in line with our theoretical predictions. To test whether this observed treatment effect is statistically significant, we use a random effects panel regression to account for the fact that each individual makes multiple decisions in a single session.[13] The coefficient of the treatment has the hypothesized sign and is significant at the 1% level.[14]

[12]We present results on the effect of experience in Online Appendix B.

[13]In these regressions, a unit of observation is a reporter in a period.

[14]This remains true if we include subject fixed effects.

Figure 2: Reporters' Strategies Grouped in Clusters.



Finding 1 (Reporters' Behavior) *Reporters misreport their information most of the time in both treatments. At the same time, reporters are more likely to misreport with greater certainty about the state ($q = 8/10$). This finding is in line with Hypothesis 1.*

Aggregate data might hide heterogeneity in individual behavior. To investigate this possibility, we use *k-means clustering* analysis of reporters' strategies.[15] We use a subject as one observation and we define each subject's strategy as a two-dimensional vector including the probability of truthful reporting when $q = 6/10$ and the probability of truthful reporting when $q = 8/10$. The results indicate that about 90% of subjects can be classified into three clusters, whose representative strategies are displayed in Figure 2.[16]

We highlight two results from this analysis of behavioral heterogeneity. First, the finding that reporters misreport their information most of the time in both treatments is not driven by outliers who always choose the same plan of action: 52% of reporters misreport most

[15] K-means clustering is a common unsupervised learning methodology used to group observations according to their similarity in a multidimensional space of observable characteristics (see MacQueen 1967, Hartigan 1975, Hastie et al. 2005, and Murphy 2012; for a recent use in experimental economics, see Fréchette et al. 2021). The procedure randomly selects k points in the space of observable characteristics to be the centers of k clusters; each observation is then associated with the closest center, and the location of centers is iterated to minimize the total within cluster variance. This procedure is repeated 10 times with 10 different random cluster centers; if the final clusters are different, the algorithm selects the best result.

[16] K-means clustering requires the choice of the number of clusters at the outset. As customary, we determined the number of clusters for evaluators and reporters with the elbow method. The figure also displays a "residual cluster" that gathers all the remaining, harder-to-categorize, subjects.

of the time with $q = 6/10$ (59% with $q = 8/10$) and 41% of reporters misreport most of the time in both treatments. Second, two clusters, accounting for 56% of subjects, exhibit behavior which is consistent with equilibrium predictions: subjects belonging to one cluster, which accounts for 41% of observations, misreport most of the time regardless of the belief on the state of the world; subjects belonging to a second cluster, which accounts for 15% of observations, misreport most of the time when they hold strongly unbalanced priors on the state and report truthfully most of the time when they hold mildly unbalanced priors. Another cluster, which includes 30% of subjects, displays truthful reporting regardless of the priors on the state, that is, including when priors are strongly unbalanced and the unique Bayes-Nash equilibrium prescribes misreporting. While inconsistent with equilibrium predictions, the behavior of these subjects can be accounted for by lying aversion (Gneezy et al., 2018) or preferences for truth-telling (Abeler et al., 2019) and contributes to explain the large incidence of truth-telling we observe in the aggregate data.

4.2 Evaluators' Behavior

According to the theory developed in Section 3, evaluators' assessments should be affected by three variables: the received report, the observed color of the core of the ball, and the belief about reporters' truthfulness, f. While we do not exogenously set any of these variables, we can exploit the variation in the realization of reports and states of the world, as well as the indirect effect of the common prior, q, on evaluators' beliefs, f, for our hypotheses tests. We, thus, use the behavior of evaluators in the experiment to check whether assessments are consistent with Bayesian inference, and to test for hypothesis HP2 from Section 3.

Figure 3, Table 1 and Table 2 show summary statistics for evaluators' assessments of the probability the urn is informative. Each boxplot (in the figure) and each row (in the tables) are for a different pair of observed report and observed core. Table 1 focuses on the treatment with mildly unbalanced prior ($q = 6/10$), while Table 2 focuses on the treatment with strongly unbalanced prior ($q = 8/10$).

We compare assessments following each report and core pair with Wilcoxon-Mann-Whitney tests. For both $q = 6/10$ and $q = 8/10$, evaluators are most confident that the signal is informative (that is, that the reporter is well informed) when they observe an orange report and an orange core, and least confident when they observe an orange report and a blue core. Observing a blue report and a blue core makes evaluators more confident than observing any inaccurate report and observing a blue report and an orange core makes them more confident than observing an orange report and a blue core but less confident than observing any accurate report. All differences are statistically significant at the 1% level. The only

Figure 3: Evaluators' Assessments by Observed Report-Core Pair and Treatment.

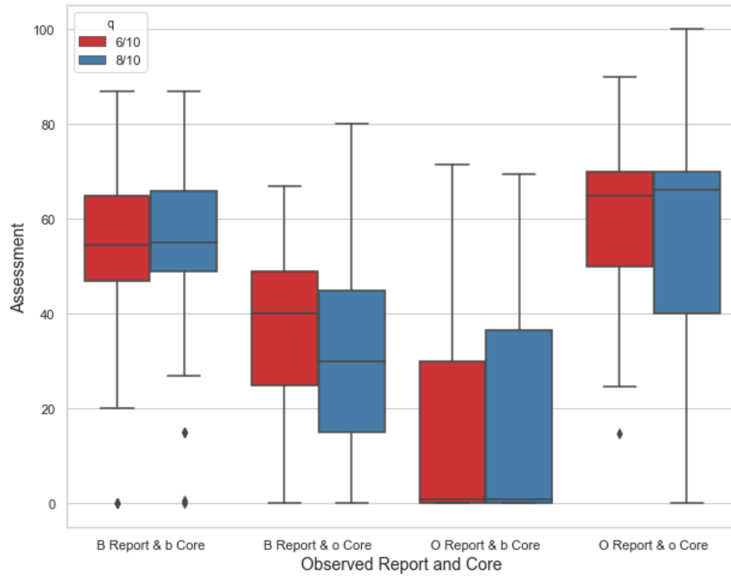


Table 1: Evaluators' Assessments by Observed Report-Core Pair, $q = 6/10$.

	N	Average	Median	Theory
Blue Report, Blue Core	383	54.4	54.5	[50, 66.7]
Blue Report, Orange Core	194	35.4	40.0	[0, 50]
Orange Report, Blue Core	54	15.2	0.8	0
Orange Report, Orange Core	105	58.6	65.0	66.7

exception is the difference between assessments following a blue report and a blue core and assessments following an orange report and an orange core with $q = 8/10$ (p-value = 0.092).[17] This provides evidence that, as predicted by the model, evaluators' assessments are ranked: $p_{Oo} \geq p_{Bb} \geq p_{Bo} \geq p_{Ob}$ (and, with one exception, this ranking is strict).

Table 3 shows estimates of the effect of holding strongly unbalanced ($q = 8/10$) rather than weakly unbalanced priors ($q = 6/10$) about the state of the world on evaluators' assessments of the probability the urn is informative. Each column focuses on a different report and core pair. From the perspective of evaluators who are trying to assess the informativeness of the urn, the only possible difference between the two treatments lies in the strategy adopted by reporters: both theoretically and empirically, reporters are less likely to report

[17] These tests employ as unit of observation an evaluator in a period. Results are unchanged if we use as unit of observation an evaluator (that is, if we use the average assessment given by an evaluator in each treatment and for each report-core pair rather than all assessments given by an evaluator). In this case, all differences are statistically significant at the 1% level with the exception of the difference between p_{Oo} and p_{Bb} which is statistically significant at the 5% level with $q = 6/10$ (p-value = 0.0471) and statistically indistinguishable from 0 with $q = 8/10$ (p-value = 0.3791).

Table 2: Evaluators' Assessments by Observed Report-Core Pair, $q = 8/10$.

	N	Average	Median	Theory
Blue Report, Blue Core	522	56.4	55.0	[50, 66.7]
Blue Report, Orange Core	117	30.2	30.0	[0, 50]
Orange Report, Blue Core	59	16.8	1.0	0
Orange Report, Orange Core	38	58.7	66.2	66.7

Table 3: Evaluators' Assessments as a Function of q.

	(1)	(2)	(3)	(4)
	Dependent Variable: Evaluator's Assessment			
$q = 8/10$	1.87**	-4.34**	1.52	-0.62
	(0.65)	(1.42)	(1.66)	(2.28)
Constant	54.99**	34.46**	15.53**	59.20**
	(1.69)	(1.89)	(3.13)	(2.40)
Report	Blue	Blue	Orange	Orange
Core	Blue	Orange	Blue	Orange
N	905	311	113	143

Notes: Random effects GLS regressions. Each subject is a panel and periods are times within a panel. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$.

their signal truthfully with $q = 8/10$ than with $q = 6/10$. A Bayesian evaluator who is aware of this differential behavior should give assessments that are further from the 50% prior (in the sense of rewarding to a larger extent a report matching the state and punishing to a larger extent a report mismatching the state) with $q = 6/10$ than with $q = 8/10$. At the same time, any difference in evaluators' beliefs about the strategy adopted by reporters with $q = 8/10$ and with $q = 6/10$ should not affect assessments following an orange report.

Columns (3) and (4) in Table 3 show that evaluators' assessments following an orange report are not significantly affected by the prior belief about the state of the world. On the other hand, assessments following an accurate blue report are significantly larger with $q = 8/10$ than with $q = 6/10$; and assessments following an inaccurate blue report are significantly lower with $q = 8/10$ than with $q = 6/10$. This suggests that evaluators are more sensitive to information with $q = 8/10$ than with $q = 6/10$.

This can be rationalized by a belief that reporters are more likely to report their signal truthfully with $q = 8/10$ than with $q = 6/10$. Indeed, this is confirmed by the structural estimation of evaluators' beliefs about reporters' strategies.[18] The median (average) esti-

[18]For each human evaluator, the estimated f is found as the minimizer of the sum of the squared distances from the Bayesian posteriors for all assessments this subject makes following a blue report in a given treatment. As for all results in this section, we focus on experienced evaluators (that is, on the second block

mated probability that reporters are truthful is 50% (43%) with $q = 6/10$ and 65% (51%) with $q = 8/10$. Evaluators' estimated beliefs are positively and significantly affected by the treatment according to a Tobit (p-value = 0.004) or linear (p-value = 0.037) regression with subjects fixed effects.

As discussed in Section 4.1 and Finding 1, this perception is not in line with reporters' actual behavior in the experiment. In fact, consider a Bayesian evaluator who best replies to reporters' observed behavior, that is, an evaluator who forms assessments using the empirical values of f. In the treatment with $q = 6/10$, this evaluator would estimate a 57% chance the signal is informative when observing a blue report and a blue core; and a 40% chance the signal is informative when observing a blue report and an orange core. In the treatment with $q = 8/10$, this evaluator would estimate a 55% chance the signal is informative when observing a blue report and a blue core; and a 44% chance the signal is informative when observing a blue report and an orange core. The observed assessments are close to the best replies with one exception: assessments following an inaccurate blue report with $q = 8/10$ are much more pessimistic than they should be (the average and median assessment being 30%).

Finding 2 (Evaluators' Behavior) *Evaluators' assessments are consistent with Bayesian updating given some belief about reporters' behavior. At the same time, assessments after reports that can be used to misreport information ($R = B$) are more responsive to report accuracy when there is greater certainty about the state ($q = 8/10$). This finding is not in line with Hypothesis 2 (or with Bayesian inference based on reporters' behavior in the experiment).*

This discrepancy cannot be simply attributed to confusion about the rules of the game or inability to do Bayesian updating. In addition to the aggregate evidence discussed above, in Online Appendix A, we show that this result is driven by a subset of subjects whose assessments are indistinguishable from those of a Bayesian learner when the inference does not depend on reporters' strategies. In Online Appendix D, we show that the behavior of evaluators in the experiment is also inconsistent with a learning model that posits they initially believe $f \sim U(0,1)$ and update beliefs according to Bayes' rule on the basis of their interaction with reporters but it is, instead, consistent with a learning model that posits they initially believe $f \sim U(0,1)$ and update beliefs considering report accuracy (inaccuracy) as a signal of truthful reporting (misreporting).[19]

of 16 periods) and, thus, each evaluator makes 16 assessments in each treatment.

[19] Another explanation for evaluators' differential behavior in the two treatments could be a higher willingness of evaluators to reward accuracy or punish inaccuracy at a cost when they detect more misreporting,

5 Computerized Evaluators

One puzzle from the experimental results presented in Section 4 is the incidence of misreporting, including in the treatment with a mildly unbalanced prior where truthful reporting can be an equilibrium strategy. The analysis of how reporters' behavior changes with experience in the game reported in Online Appendix B shows that reporters learn to misreport in the treatment with a unique Bayes-Nash equilibrium ($q = 8/10$) while no learning occurs in the treatment with multiple Bayes-Nash equilibria ($q = 6/10$). One possibility is that this is due to reporters' uncertainty over evaluators' beliefs or over evaluators' ability to best reply to held beliefs in a more complex strategic environment. To better understand reporters' learning in the game with human evaluators, this section presents results from two additional experimental treatments which we planned and ran at the outset.[20] The purpose of these treatments was to study reporters' learning to best reply in a 'sterile' environment where evaluators are computerized and programmed to form assessments using Bayes rule on the basis of either fixed or evolving beliefs on reporters' behavior. The game studied so far had *human* evaluators holding *free* beliefs and, thus, we label it HF for *Human Free*. Below, we describe two additional games, labeled CC (*Computerized Credulous*) and CL (*Computerized Learning*).

5.1 Computerized Credulous Evaluators

In game CC, evaluators' beliefs are fixed throughout the game. In particular, in each period of the game, evaluators assess the probability that the reporter is informed given the belief that reporters always report information truthfully. This means that computerized evaluators in game CC behave as $L0$ evaluators in the level-k model from Section 3.3. As shown by Proposition 2, when evaluators believe that reporters are truthful regardless of their actual behavior, reporters' unique best reply is to misreport when $q = 8/10$ and to report truthfully when $q = 6/10$. This observation provides us with an additional testable hypothesis.

Hypothesis 3 *In game CC, reporters learn to best reply to evaluators' fixed beliefs: they learn to misreport when* $q = 8/10$ *and to report truthfully when* $q = 6/10$.

We run two experimental sessions for game CC with a total of 47 subjects (all in the role of reporter) who did not participate in any other session.[21] Each session lasted about

perhaps because of reciprocal motives, as in Rabin (1993) and Dufwenberg and Kirchsteiger (2004). Our experiment is designed to test a model without social preferences and does not allow to test this mechanism.

[20] Online Appendix E descibes a fourth experimental game, CA (*Computerized Agnostic*).

[21] At the beginning of each session, instructions were read out loud with the help of a fourteen-minutes long video. Written instructions and a link to the video are provided in Online Appendix G.

Table 4: Reporters' Behavior in Games with Computerized Evaluators.

	(1)	(2)	(3)	(4)
	Dependent Variable: Pr[Reporter Chooses Truthful Plan of Action]			
Game CC	0.17**	−0.03		
	(0.07)	(0.07)		
Game CL			−0.02	−0.00
			(0.07)	(0.07)
Constant	0.49**	0.37**	0.49**	0.37**
	(0.05)	(0.05)	(0.05)	(0.05)
Game	HF & CC	HF & CC	HF & CL	HF & CL
q	6/10	8/10	6/10	8/10
N	1488	1488	1504	1504

Notes: Random effects GLS regressions. Each reporter is a panel and periods are times within a panel. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$.

one hour and forty minutes (including instructions and payments) and average earnings (including a €5 show-up fee) were €36.42. Columns 1 and 2 of Table 4 investigate how reporters' behavior in each treatment of this game with computerized evaluators compares with behavior in the corresponding treatment of the game with human evaluators. As in Section 4, we focus on experienced subjects.

Finding 3 (Reporters' Behavior with Credulous Evaluators) *With greater certainty about the state ($q = 8/10$), reporters behave identically when facing credulous computerized evaluators rather than human evaluators. With lower certainty about the state ($q = 6/10$), reporters behave differently when facing credulous computerized evaluators and, in this case, they report truthfully most of the time. This is in line with Hypothesis 3.*

5.2 Computerized Learning Evaluators

In game CL, computerized evaluators are initially agnostic about the distribution of reporters' strategies in the population—that is, in the first period of the game, they make their assessments given a belief that the proportion of truthful reporters is uniformly distributed, $f \sim U[0, 1]$—and they are programmed to update this belief according to Bayesian learning, based on the outcome of past individual interactions with reporters.[22]

[22] Online Appendix C describes in detail how the beliefs of CL evaluators evolve. The same appendix presents expressions for evaluators' posterior beliefs given any learning path and the implied expected assessments (taking expectations over the posterior distribution of reporters). This learning model also serves as benchmark to study learning by human evaluators (see Online Appendix D). We note that, in an alternative

When the prior is strongly unbalanced ($q > 3/4$) and evaluators use Bayes rule to form assessments (given some belief on reporters' behavior), misreporting is the best reply to *any* evaluator belief. For this reason, we expect reporters to misreport when the prior is strongly unbalanced ($q = 8/10$). Moreover, we expect reporters in this treatment of game CL will have an easier time than reporters in the same treatment of game HF to learn that misreporting is the optimal behavior: given that computerized evaluators are programmed to form their assessments optimally (conditional on the beliefs they hold), treatment CL removes reporters' uncertainty about whether evaluators best reply to held beliefs.

More interestingly, when the prior is mildly unbalanced ($q = 6/10$), truth-telling is reporters' best reply against the evaluators' Bayesian assessments at the beginning of their interaction. If, in the initial periods of the game, reporters are truthful, computerized evaluators learn to be more confident that reporters can be trusted and the incentive to report truthfully is reinforced. However, the initial expected payoff advantage from truth-telling is small and, if reporters' initial behavior is erratic or prone to misreporting, computerized evaluators' updating of f based on interactions with reporters may quickly change reporters' incentives in favor of misreporting.

Thus, we use this game to study how experience in the game affects convergence toward an equilibrium and to explore whether initial evaluators' beliefs that make truthful reporting a best reply lead to coordination on the truth-telling equilibrium. This discussion delivers an additional testable hypothesis.

Hypothesis 4 *In game CL, reporters learn to best reply to evaluators' evolving beliefs: when* $q = 8/10$*, reporters learn to misreport; when* $q = 6/10$*, reporters' best reply to evaluators' initial belief is to report truthfully; this initial incentive is reinforced if reporters are truthful, while it is eventually replaced by an incentive to misreport if they misreport.*

We run four experimental sessions for game CL with a total of 48 subjects (all in the role of reporter) who did not participate in any other session in this experiment.[23] Each

model where computerized evaluators assume all reporters are either truthful or misreporting and initially hold an agnostic belief (i.e., a 50% chance that all reporters are truthful), learning would quickly halt after signals indicating that the reporter in the current round was truthful (e.g., Orange report) or misreporting (e.g., Blue report, orange core, and informative urn). In this alternative model, the learning process would be ill defined (as evaluators could encounter zero probability events) and of little use in future interactions with human reporters (if different human reporters in the experiment use different strategies).

[23] At the beginning of each session, instructions were read out loud with the help of a seventeen-minutes long video. Written instructions and a link to the video are provided in Online Appendix G. Participants are told that computerized evaluators believe there is some fraction f of reporters that uses the truthful plan of action but, since they do not know the value of f, they form beliefs about it. Participants are further told that computerized evaluators update their belief about f based on their experience across all periods with the same prior, q. Instructions state that when a given q is encountered for the first time, computerized

session lasted about two hours (including instructions and payments), and average earnings (including a €5 show-up fee) were €36.95. Columns 3 and 4 of Table 4 investigate how reporters' behavior in each treatment of this game with computerized evaluators compares with behavior in the corresponding treatment of the game with human evaluators. As in Section 4, we focus on experienced subjects.

Finding 4 (Reporters' Behavior with Learning Evaluators) *With both values of q, reporters behave identically when facing human evaluators rather than computerized evaluators which are initially agnostic about reporters' behavior and update this belief with Bayesian learning on the basis of interaction with reporters.*

The fact that reporters' behavior in game HF and in game CL is indistinguishable can be explained by reporters facing similar incentives. With a strongly unbalanced prior, incentives are in fact equal, since reporters' best reply to any belief held by human or computerized evaluators is to misreport. With a mildly unbalanced prior, reporters' best reply depends on evaluators' beliefs. As discussed above, reporters' best reply to evaluators' initial belief is to report truthfully with a small initial gain from truth-telling. Unexperienced reporters do not choose either plan of action consistently: misreporting occurs 46% of the time in the first block of 16 rounds. Therefore, computerized evaluators have mixed experience with evaluators, encountering a truthful evaluator in a period and a misreporting evaluator in another. This slows down their learning, keeping their belief close to the initial level and incentives for truth-telling weak. This highlights that, with respect to game HF, game CL ensures evaluators' assessments are Bayesian given some beliefs on reporters' behavior but, at the same time, the process of forming (first and second order) beliefs about reporters' behavior is similarly complex in the two games, leading reporters' behavior to be indistinguishable.

6 Conclusion

This paper presents a laboratory experiment designed to test a widely applied model of reputational cheap talk where a reporter wants to convince an evaluator of being well informed.

evaluators think all values of f are equally likely (an example of this is provided), while across periods with the same value of q, "[e]ach computerized evaluator updates its belief about the fraction f on the basis of the experience accumulated in each of the previous individual interactions with reporters. This experience consists of: [(i)] The reports received by that specific computerized evaluator; [(ii)] The color of the cores observed by that specific computerized evaluator; [(iii)] Whether each ball was drawn from the informative or the uninformative urn." Finally, participants are told that experience is used to *infer* the plan of action used by reporters encountered in the past and *interpret* the report and *make an assessment* about the urn's truthfulness for the reporter they encounter next.

The theory suggests that, for truthful information transmission between reporters and evaluators to occur, we need (a) the reporter to be confident that his private information will coincide with the state (even when this information supports the ex-ante unlikely state); and (b) the reporter's reputation to react strongly to the ex-post accuracy of his message. The first condition is met when there is sufficient ex-ante uncertainty over the phenomenon to forecast. The second condition is met when the evaluator trusts the information received by the reporter to be in line with his private information.

The combined experimental evidence from our treatments with human and computerized evaluators shows that (a) reporters are indeed more willing to reveal their private information when there is more uncertainty on the state but also that (b) the second condition is difficult to meet: evaluators' trust in reporters is fragile and is sensitive to evaluators' initial beliefs and experience with reporters. Without trust in reporters' truthfulness, evaluators cannot learn about reporters' ability and—even in environments where truthful information transmission can be sustained in equilibrium and is most beneficial to evaluators (that is, with high uncertainty over the phenomenon to forecast)—the reputational mechanism is a blunt tool.

Our results have important implications for the use of expert advice as input of managerial decision-making and the design of markets for professional forecasting. Obtaining accurate estimates of uncertain variables is a crucial input to managerial decisions: for example, a producer obtains forecasts (from sales people, designers, product managers) about the demand for a new product before deciding whether to launch and what price to charge; once the product is developed and priced, a retailer is interested in predicting demand to determine what quantity to order (Fisher and Raman 1996). When should managers consult experts to obtain these forecasts? And how can organizations improve the quality of the information they receive from the experts they consult?

First, our experimental evidence suggests that firms should trust experts' advice when the phenomenon to forecast is more uncertain. On the other hand, when the firm already has accurate information and the relevant variables are less uncertain, expert advice is not only less valuable but also less trustworthy and, as such, it should be appropriately discounted. Second, as our results indicate, experts have a strong incentive to reveal their private information truthfully when their reputation is strongly affected by the ex-post accuracy of their statements. This is the case when clients trust the experts' advice and form their assessments using Bayes' rule. This is also the case when clients do not trust experts to transmit information truthfully but suffer from a judgment bias and, as in our experiment, overreact to the accuracy of the experts' message. This suggests that making experts' ex-post accuracy (rather than experts' advice) a salient element of the information available to clients might facilitate the emergence of this judgment bias, ameliorating forecasters' performance and the transmission of information. An example of such focus on accuracy is TipRanks (www.tipranks.com), a dataset of analysts, hedge fund managers, financial bloggers, and corporate insiders that uses Natural Language Processing algorithms to aggregate and analyze financial data online. Additionally, explicit incentives that do not depend on the clients' trust (e.g., monetary rewards or non-discretionary ratings in a formal recommendation system) can be associated to ex-post accuracy. When the phenomenon to forecast is sufficiently uncertain, linking outcomes to ex-post accuracy reduces the experts' incentives to misreport information supporting the ex-ante unlikely state.

Finally, our experiment suggests that current models of reputational cheap talk correctly capture reporters' behavior but might be missing important elements in the way evaluators process the available information or reward reporters for their advice. Much attention has been given to how evaluators *should* interpret reports issued by reporters prone to behavioral biases (Grushka-Cockayne et al., 2017; Tetlock, 2005), while less attention has been given to how evaluators *do* interpret received reports (Budescu and Yu, 2007; Çelen et al., 2010).

Future work should continue to investigate strategic information transmission between professional forecasters and decision-makers interested in their expertise, for example, by developing experimental treatments with computerized senders and by using alternative methods to elicit evaluators' beliefs about the reporters' informativeness (Danz et al., 2022). It would also be interesting to experimentally verify the strategic distortions resulting when forecasters compete, as in contest models recently advanced by Lichtendahl et al. (2013), Grushka-Cockayne et al. (2017), and Banerjee (2021).

Appendix

Proof of Proposition 1. Plugging p_{Bb}, p_{Bo}, and q_O in equation (2), we obtain

$$\Delta_{EU}(q,f) = \frac{\frac{3}{4}(1-q)}{\Pr(S=O)}\left[\frac{(1-f)}{\frac{1}{2}+(1-f)\frac{3}{2}} - \frac{2}{3}\right] + \frac{\frac{1}{4}q}{\Pr(S=O)}\left[\frac{1}{\frac{3}{2}+(1-f)\frac{1}{2}}\right].$$

Since $\Delta_{EU}(q,f)$ is the gain from misreporting *given* that the reporter sees an Orange shell (signal $S=O$), the expected gain from misreporting before receiving the signal, is

$$\Pr(S=O)\,\Delta_{EU}(q,f) = \frac{3}{4}(1-q)\left[\frac{(1-f)}{\frac{1}{2}+(1-f)\frac{3}{2}} - \frac{2}{3}\right] + \frac{1}{4}q\left[\frac{1}{\frac{3}{2}+(1-f)\frac{1}{2}}\right].$$

From the above, the reporter will prefer misreporting to truthful reporting *iff*

$$\Pr(S=O)\,\Delta_{EU}(q,f) > 0 \Rightarrow q > (4-f)\,/\,[4(2-f)]\,.$$

Consider a strongly unbalanced prior, $q \in (3/4, 1]$, and notice that the condition for the reporter to prefer misreporting is satisfied for all values of f: the right-hand side is strictly increasing in f, and equals 3/4 when $f = 1$. Therefore, there can only be equilibria where the reporter misreports. Since the condition is also satisfied when the evaluator believes the reporter misreports for sure ($f = 0$), misreporting and misreporting beliefs constitute a perfect Bayesian Nash equilibrium—the unique PBE when the prior is strongly unbalanced.

Now consider a mildly unbalanced prior, and suppose the evaluator holds beliefs $f^*(q) = \frac{8q-4}{4q-1}$. The following simplified expression for the reporter's expected gain from misreporting,

$$\Pr(S = O)\,\Delta_{EU}(q, f) = \frac{4q\,(2-f) + (f-4)}{2\,(4-f)\,(4-3f)},$$

has a positive denominator always. Replacing $f = \frac{8q-4}{4q-1}$, the numerator of the above expression equals 0 and, thus, the reporter is indifferent between misreporting and truth-telling. Hence, the evaluator's beliefs that the reporter picks a mixed strategy of truth-telling with probability $\frac{8q-4}{4q-1}$ can be sustained with reporter's best-replying behavior at those beliefs. This shows that the MSE exists. If the evaluator holds beliefs $f > \frac{8q-4}{4q-1}$, $\Delta_{EU} < 0$ and, thus, the reporter prefers to be truthful. The only belief $f > \frac{8q-4}{4q-1}$ that can thus be sustained by reporters' behavior, is $f = 1$, where the reporter is truthful and the evaluator believes this: an equilibrium with truth-telling exists. If the evaluator holds beliefs $f < \frac{8q-4}{4q-1}$, $\Delta_{EU} > 0$, meaning that the reporter prefers misreporting. Therefore, the only belief $f < \frac{8q-4}{4q-1}$ that can be sustained by the reporter's best-replying behavior is $f = 0$, where the reporter misreports and the evaluator believes so: an equilibrium with misreporting exists.

Proof of Proposition 2. By assumption, an $L0$ reporter reports truthfully for any $q \in [0, 1]$ and the belief of an $L0$ evaluator about the probability reporters are truthful is $f = 1$ for any $q \in [0, 1]$. From the proof of Proposition 1 above, we know that a reporter prefers misreporting to truthful reporting if and only if $q > (4-f)\,/\,[4(2-f)]$. As a consequence, an $L1$ reporter (who believes the evaluator is $L0$) best replies by misreporting if and only if $q > 3/4$. An $L1$ evaluator (who believes the reporter is $L1$) best replies by forming assessments with the belief $f = 0$ if $q > 3/4$ and $f = 1$ if $q < 3/4$. An $L2$ reporter (who believes the evaluator is $L1$) best replies by misreporting if and only if $q > 3/4$ (as an $L1$ reporter): for $q < 3/4$, $f = 1$ and the reporter's best reply is to misreport if and only if $q > 3/4$ (that is, for no value of q in this range); for $q > 3/4$, $f = 0$ and the reporter's best reply is to misreport if and only if $q > 1/2$ (that is, for all values of q in this range). An $L2$ evaluator (who believes the reporter is $L2$) best replies by forming assessments with the belief $f = 0$ if $q > 3/4$ and $f = 1$ if $q < 3/4$ (as an $L1$ evaluator). The same logic applies to all higher levels.

References

Abeler, Johannes, Daniele Nosenzo, and Collin Raymond, "Preferences for Truth-Telling," *Econometrica*, 2019, *87* (4), 1115–1153.

Anderson, Lisa and Charles Holt, "Information Cascades in the Laboratory," *American Economic Review*, 1997, *87* (5), 847–862.

_ and _ , "Information Cascade Experiments," in Charles Plott, ed., *Handbook of Experimental Economics Results*, Vol. 1 Elsevier 2008, pp. 335–343.

Banerjee, Abhijit V., "A Simple Model of Herd Behavior," *Quarterly Journal of Economics*, 1992, *107* (3), 797–817.

Banerjee, Sanjay, "Does Competition Improve Analysts' Forecast Informativeness?," *Management Science*, 2021, *67* (5), 3219–3238.

Battigalli, Pierpaolo and Martin Dufwenberg, "Dynamic Psychological Games," *Journal of Economic Theory*, 2009, *144* (1), 1–35.

Bikhchandani, Sushil, David Hirschleifer, and Ivo Welch, "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades," *Journal of Political Economy*, 1992, *100* (5), 992–1026.

Blume, Andreas, Ernest K. Lai, and Wooyoung Lim, "Eliciting Private Information with Noise: The Case of Randomized Response," *Games and Economic Behavior*, 2019, *113*, 356–380.

_ , _ , and _ , "Strategic Information Transmission: A Survey of Experiments and Theoretical Foundations," in Monica Capra, Rachel Croson, Mary Rigdon, and Tanya Rosenblat, eds., *Handbook of Experimental Game Theory*, Cheltenham, UK and Northampton, MA: Edward Elgar Publishing, 2020.

_ , Ernest K Lai, and Wooyoung Lim, "Mediated talk: An experiment," 2022.

Brown, Lawrence D, Andrew C Call, Michael B Clement, and Nathan Y Sharp, "Inside the "Black Box" of Sell-Side Financial Analysts," *Journal of Accounting Research*, 2015, *53* (1), 1–47.

Budescu, David V. and Hsiu-Ting Yu, "Aggregation of Opinions Based on Correlated Cues and Advisors," *Journal of Behavioral Decision Making*, 2007, *20*, 153–177.

Cabrales, Antonio, Francesco Feri, Piero Gottardi, and Miguel A Meléndez-Jiménez, "Can There Be a Market for Cheap-Talk Information? An Experimental Investigation," *Games and Economic Behavior*, 2020, *121*, 368–381.

Cai, Hongbin and Joseph Tao-Yi Wang, "Overcommunication in Strategic Information Transmission Games," *Games and Economic Behavior*, 2006, *56* (1), 7–36.

Çelen, Boğaçhan and Shachar Kariv, "Distinguishing Informational Cascades from Herd Behavior in the Laboratory," *American Economic Review*, 2004, *94* (3), 484–498.

_ , _ , and Andrew Schotter, "An Experimental Test of Advice and Social Learning," *Management Science*, 2010, *56* (10), 1687–1701.

Charness, Gary and Martin Dufwenberg, "Promises and Partnership," *Econometrica*, 2006, *74* (6), 1579–1601.

Chaudhuri, Ananish, Andrew Schotter, and Barry Sopher, "Talking Ourselves to Efficiency: Coordination in Inter-Generational Minimum Effort Games with Private, Almost Common and Common Knowledge of Advice," *Economic Journal*, 2009, *119* (534), 91–122.

Crawford, Vincent P, "Lying for Strategic Advantage: Rational and Boundedly Rational Misrepresentation of Intentions," *American Economic Review*, 2003, *93* (1), 133–149.

_ and Joel Sobel, "Strategic Information Transmission," *Econometrica*, 1982, pp. 1431–1451.

_ , Miguel A Costa-Gomes, and Nagore Iriberri, "Structural Models of Nonequilibrium Strategic Thinking: Theory, Evidence, and Applications," *Journal of Economic Literature*, 2013, *51* (1), 5–62.

Danz, David, Lise Vesterlund, and Alistair J Wilson, "Belief Elicitation and Behavioral Incentive Compatibility," 2022.

Deb, Rahul, Mallesh M. Pai, and Maher Said, "Evaluating Strategic Forecasters," *American Economic Review*, 2018, *108* (10), 3057–3103.

Dufwenberg, Martin and Georg Kirchsteiger, "A Theory of Sequential Reciprocity," *Games and economic behavior*, 2004, *47* (2), 268–298.

_ and Uri Gneezy, "Measuring Beliefs in an Experimental Lost Wallet Game," *Games and Economic Behavior*, 2000, *30*, 163–182.

Ederer, Florian and Alexander Stremitzer, "Promises and Expectations," *Games and Economic Behavior*, 2017, *106*, 161–178.

Ellingsen, Tore and Robert Östling, "When Does Communication Improve Coordination?," *American Economic Review*, 2010, *100* (4), 1695–1724.

_ , Magnus Johannesson, Sigve Tjøtta, and Gaute Torsvik, "Testing Guilt Aversion," *Games and Economic Behavior*, 2010, *68*, 95–107.

Esponda, Ignacio and Emanuel Vespa, "Hypothetical Thinking and Information Extraction in the Laboratory," *American Economic Journal: Microeconomics*, 2014, *6* (4), 180–202.

Eyster, Erik, Matthew Rabin, and Georg Weizsäcker, "An Experiment on Social Mislearning," 2015. CEPR Discussion Paper 11020.

Fehr, Ernst and Jean-Robert Tyran, "Does Money Illusion Matter?," *American Economic Review*, 2001, *91* (5), 1239–1262.

Fehrler, Sebastian and Niall Hughes, "How Transparency Kills Information Aggregation: Theory and Experiments," *American Economic Journal: Microeconomics*, 2018, *10* (1), 181–209.

Fischbacher, Urs, "z-Tree: Zurich Toolbox for Ready-Made Economic Experiments," *Experimental Economics*, 2007, *10*, 171–178.

Fisher, Marshall and Ananth Raman, "Reducing the Cost of Demand Uncertainty through Accurate Response to Early Sales," *Operations research*, 1996, *44* (1), 87–99.

Fréchette, Guillaume, Alessandro Lizzeri, and Jacopo Perego, "Rules and Commitment in Communication: An Experimental Analysis," 2021.

Geanakoplos, John, David Pearce, and Ennio Stacchetti, "Psychological Games and Sequential Rationality," *Games and Economic Behavior*, 1989, *1* (1), 60–79.

Gentzkow, Matthew and Jesse M. Shapiro, "Media Bias and Reputation," *Journal of Political Economy*, 2006, *114* (2), 280–316.

Georganas, Sotiris, Paul J Healy, and Roberto A Weber, "On the Persistence of Strategic Sophistication," *Journal of Economic Theory*, 2015, *159*, 369–400.

Gneezy, Uri, Agne Kajackaite, and Joel Sobel, "Lying Aversion and the Size of the Lie," *American Economic Review*, 2018, *108* (2), 419–53.

Goeree, Jacob K, Thomas R Palfrey, Brian W Rogers, and Richard D McKelvey, "Self-Correcting Information Cascades," *Review of Economic Studies*, 2007, *74* (3), 733–762.

Graham, John R., "Herding Among Investment Newsletters: Theory and Evidence," *Journal of Finance*, 1999, *54* (1), 237–268.

Groysberg, Boris, Paul M Healy, and David A Maber, "What Drives Sell-Side Analyst Compensation at High-Status Investment Banks?," *Journal of Accounting Research*, 2011, *49* (4), 969–1000.

Grushka-Cockayne, Yael, Victor Richmond R. Jose, and Kenneth C. Lichtendahl, "Ensembles of Overfit and Overconfident Forecasts," *Management Science*, 2017, *63* (4), 1110–1130.

Harrison, Glenn W., Jimmy Martínez-Correa, and J. Todd Swarthout, "Inducing Risk Neutral Preferences with Binary Lotteries: A Reconsideration," *Journal of Economic Behavior and Organization*, 2013, *94*, 145–159.

Hartigan, John A, *Clustering Algorithms*, New York, NY: Wiley, 1975.

Hastie, Trevor, Robert Tibshirani, Jerome Friedman, and James Franklin, "The Elements of Statistical Learning: Data Mining, Inference and Prediction," *The Mathematical Intelligencer*, 2005, *27* (2), 83–85.

Holmström, Bengt, "Managerial Incentive Problems: A Dynamic Perspective," *Review of Economic Studies*, 1999, *66* (1), 169–182.

Hossain, Tanjim and Ryo Okui, "The Binarized Scoring Rule," *Review of Economic Studies*, 2013, *80* (3), 984–1001.

Hung, Angela A and Charles R Plott, "Information Cascades: Replication and an Extension to Majority Rule and Conformity-Rewarding Institutions," *American Economic Review*, 2001, *91* (5), 1508–1520.

Kawagoe, Toshiji and Hirokazu Takizawa, "Equilibrium Refinement vs. Level-k Analysis: An Experimental Study of Cheap-Talk Games with Private Information," *Games and Economic Behavior*, 2009, *66* (1), 238–255.

Keane, Michael P. and David Runkle, "Are Financial Analysts' Forecasts of Corporate Profits Rational?," *Journal of Political Economy*, 1998, *106* (4), 768–805.

Khalmetski, Kiryl, "Testing Guilt Aversion with an Exogenous Shift in Beliefs," *Games and Economic Behavior*, 2016, *97*, 110–119.

Koch, Christian and Stefan P Penczynski, "The Winner's Curse: Conditional Reasoning and Belief Formation," *Journal of Economic Theory*, 2018, *174*, 57–102.

Kübler, Dorothea and Georg Weizsäcker, "Information Cascades in the Labor Market," *Journal of Economics*, 2003, *80* (3), 211–229.

Levy, Gilat, "Decicion Making in Committees: Transparency, Reputation, and Voting Rules," *American Economic Review*, 2007, *97* (1), 150–168.

Li, Xiaolin, Özalp Özer, and Upender Subramanian, "Are We Strategically Naïve or Guided by Trust and Trustworthiness in Cheap-Talk Communication?," *Management Science*, 2021.

Lichtendahl, Kenneth C., Yael Grushka-Cockayne, and Phillip E. Pfeifer, "The Wisdom of Competitive Crowds," *Operations Research*, 2013, *61* (6), 1383–1398.

MacQueen, James, "Some Methods for Classification and Analysis of Multivariate Observations," *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability*, 1967, *1* (14), 281–297.

Mattozzi, Andrea and Marcos Y. Nakaguma, "Public Versus Secret Voting in Committees," 2019.

Murphy, Kevin P, *Machine Learning: A Probabilistic Perspective*, MIT Press, 2012.

Ottaviani, Marco and Peter Norman Sørensen, "Information Aggregation in Debate: Who Should Speak First?," *Journal of Public Economics*, 2001, *81* (3), 393–421.

_ **and** _ , "Reputational Cheap Talk," *RAND Journal of Economics*, 2006, *37* (1), 155–175.

_ **and** _ , "The Strategy of Professional Forecasting," *Journal of Financial Economics*, 2006, *81* (2), 441–466.

Otto, Clemens A. and Paolo F. Volpin, "Marking to Market and Inefficient Investment Decisions," *Management Science*, 2018, *64* (8), 3756–3771.

Prat, Andrea, "The Wrong Kind of Transparency," *American Economic Review*, 2005, *95* (3), 862–877.

Rabin, Matthew, "Incorporating Fairness into Game Theory and Economics," *American economic review*, 1993, pp. 1281–1302.

Renes, Sanders and Bauke Visser, "Strategic Expert Committees and the Markets that Assess Them: a Lab Experiment," 2021.

Roth, Alvin E and J Keith Murnighan, "Equilibrium Behavior and Repeated Play of the Prisoner's Dilemma," *Journal of Mathematical psychology*, 1978, *17* (2), 189–198.

Scharfstein, David S. and Jeremy C. Stein, "Herd Behavior and Investment," *American Economic Review*, 1990, *80* (3), 465–479.

Schotter, Andrew, "Decision Making with Naive Advice," *American Economic Review Papers & Proceedings*, 2003, *93* (2), 196–201.

_ **and Barry Sopher**, "Advice and Behavior in Intergenerational Ultimatum Games: An Experimental Approach," *Games and Economic Behavior*, 2007, *58* (2), 365–393.

Tetlock, Philip E., *Expert Political Opinion: How Good Is It? How Can We Know?*, Princeton University Press, 2005.

Trueman, Brett, "Analyst Forecasts and Herding Behavior," *Review of Financial Studies*, 1994, *7* (1), 97–124.

Visser, Bauke and Otto H. Swank, "On Committees of Experts," *Quarterly Journal of Economics*, 2007, *122* (1), 337–372.

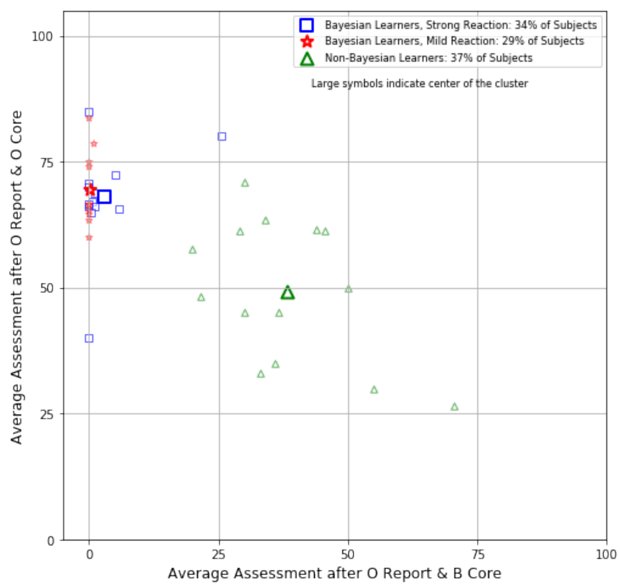
Wang, Joseph Tao-yi, Michael Spezio, and Colin F Camerer, "Pinocchio's Pupil: Using Eyetracking and Pupil Dilation to Understand Truth Telling and Deception in Sender-Receiver Games," *American Economic Review*, 2010, *100* (3), 984–1007.

Online Appendices

A Evaluators' Behavioral Heterogeneity

As for reporters, aggregate data might hide heterogeneity in evaluators' individual behavior. To investigate this possibility, we use k-means clustering analysis of evaluators' strategies. We define each subject's strategy as a six-dimensional vector including the average assessment when the report is orange and the core is blue (unconditional on the belief on the state of the world, as q does not matter for inference in this case), the average assessment when the report is orange and the core is orange (again, unconditional on q), the average assessment when the report is blue and the core is blue for each q, and the average assessment when the report is blue and the core is orange for each q.[24] The results indicate that subjects can be classified into three clusters, whose representative strategies are displayed in Figures 4 and 5 (for assessments following, respectively, an orange and a blue report).

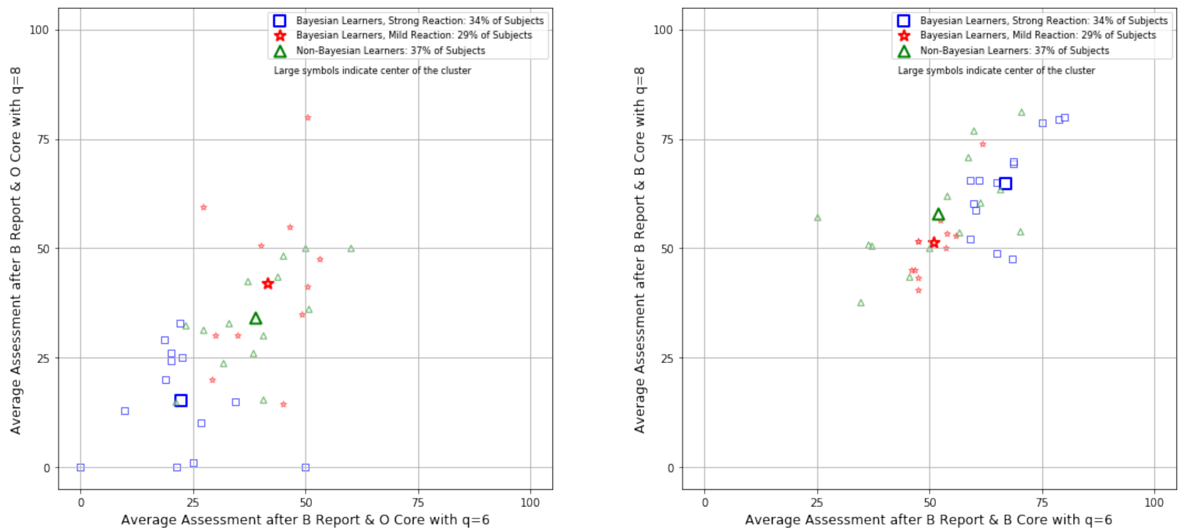
Figure 4: Evaluators' Strategies Grouped in Clusters, Orange Report.



The first two clusters, which encompass 63% of subjects, have one feature in common: assessments following an orange report — which is indicative of a truthful plan of action — are consistent with those of a Bayesian learner. The modal strategy in these two clusters is to assess a 0% chance the urn is informative following an inaccurate orange report and a 67% chance the urn is informative following an accurate orange report. We label these subjects as Bayesian learners. The third cluster is, instead, composed of subjects who fail to make these basic inferences: their average assessments following an orange core are dispersed and, in general, do not reward (punish) reporters sufficiently in case of an accurate (inaccurate)

[24]We exclude evaluators who do not make at least one assessment in each of these six instances (9/47).

Figure 5: Evaluators' Strategies Grouped in Clusters, Blue Report



(a) Inaccurate Blue Report

(b) Accurate Blue Report

report. We label these subjects as non-Bayesian learners. Interestingly, the two groups of Bayesian learners differ in the strategies following a blue report. While their assessments remain consistent with Bayesian inference (under some belief on reporters' strategy), subjects belonging to the first cluster do not update their prior much in either direction and their assessments do not depend on the prior beliefs on the state of the world: the typical assessments are around 51 after an accurate blue report and around 42 with an inaccurate blue report. On the other hand, subjects belonging to the second cluster respond strongly to the observed accuracy of a blue report, especially in the sense of punishing an inaccurate report: the modal assessments when the report is accurate are 52 with $q = 6/10$ and 58 with $q = 8/10$; when the same report is inaccurate, the typical response is to assess a 39% chance of an informative urn with $q = 6/10$ and only a 34% chance with $q = 8/10$. Inconsistent with best reply to the empirical rate of truth-telling, these subjects respond more strongly to the accuracy of a blue report in the treatment with $q = 8/10$ than in the treatment with $q = 6/10$ and are, thus, responsible for the pattern we documented in the previous section.

B The Effect of Experience

The game faced by our subjects is complicated and it might require some time to understand the underlying incentives. This is the reason why, in Section 4, we focused on experienced subjects, as customary in experimental economics. Here, we explore the possibility that behavior adapted to accumulated experience. Tables 5 and 6 show the estimates of random effects GLS regressions of, respectively, reporters' behavior and evaluators' assessments as a function of experience, separately for each of the two treatments.

Table 5: Reporters' Behavior as a Function of Experience.

	(1)	(2)
Dependent Variable:	Pr[Reporter Chooses	Truthful Plan of Action]
2^{nd} Block	-0.04	-0.07^{**}
	(0.02)	(0.02)
Constant	0.53^{**}	0.44^{**}
	(0.05)	(0.05)
q	6/10	8/10
N	1488	1481

Notes: Random effects GLS regressions. Each reporter is a panel and periods are times within a panel. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$.

Table 6: Evaluators' Assessments as a Function of Experience.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Dependent Variable: Evaluator's Assessment					
2^{nd} Block	0.04	4.86^{**}	-2.14	-0.62	-0.66	-3.13	-5.80^{*}	1.67
	(1.00)	(1.36)	(2.68)	(1.94)	(0.70)	(2.19)	(2.89)	(5.02)
Constant	54.84^{**}	29.71^{**}	19.38^{**}	59.83^{**}	57.37^{**}	34.35^{**}	22.21^{**}	53.12^{**}
	(1.54)	(1.88)	(3.11)	(2.37)	(1.75)	(2.41)	(3.44)	(4.52)
Report	Blue	Blue	Orange	Orange	Blue	Blue	Orange	Orange
Core	Blue	Orange	Blue	Orange	Blue	Orange	Blue	Orange
q	6/10	6/10	6/10	6/10	8/10	8/10	8/10	8/10
N	768	390	114	216	1058	230	115	78

Notes: Random effects GLS regression. Each subject is a panel and periods are times within a panel. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$.

Finding 5 (Experience Effects) *When there is greater certainty on the state and a unique Bayes-Nash equilibrium ($q = 8/10$), reporters learn to misreport with experience. When there is lower certainty on the state and multiple Bayes-Nash equilibria ($q = 6/10$), reporters' behavior does not change with experience. Evaluators' assessments are mostly unaffected by experience.*

C Learning Model for Computerized Evaluators

In treatment game CL, we program computerized evaluators to learn from their interactions with (human) reporters, thus changing the assessments given for each report-core pair as they gain experience. We again use this model in Appendix D to test if participants in our experiment in the role of evaluators perform Bayesian learning from their own experience starting from a uniform prior.

Underlying the model are the following assumptions:

1. There is a fixed proportion, f, of truth-telling reporters in the population. Alternatively, an evaluator faces a "representative" reporter who chooses truthful reporting with probability f. f is unknown to evaluators.

2. An evaluator wishing to learn f is initially agnostic and, thus, holds a uniform prior, $f \sim U[0,1]$.

3. To learn, an evaluator uses three pieces of information: the received report, the observed core, and information at the end of each experimental period, of the true informativeness of the urn. All values of this triple, (R, c, U) and their likelihoods conditional on f, are given in Table 7.

4. Evaluators are Bayesian learners.

Table 7: Bayesian Learning Model. Events and Likelihoods Used for Evaluators' Updating.

Event	Triples – (R, c, u)	Likelihood
Positive	(O, o, I) (O, o, U) (O, b, U)	$\frac{3-2q}{4} f$
Negative	(B, o, I)	$\frac{1-q}{2}(1-f)$
Muddy	(B, o, U) (B, b, U)	$\frac{1}{4}(2-f)$
Neutral	(B, b, I)	$\frac{q}{2}$

In this learning model, each experimental period is a trial allowing to collect information about the underlying distribution of truth-telling and misreporting. While the outcome of each trial is unique—the reporter was either truthful or misreporting in a period, the evaluator's signal about the outcome may be imperfect. Table 7 captures this characteristic: *positive* signals contain an Orange report, which can only be obtained from a truthful reporter; a *negative* signal, with differently-colored report and core coming from an informative urn, is impossible with truth-telling; and *muddy* or noisy signals—Blue report about a ball drawn from an uninformative urn—are possible, but differently probable, under both truth-telling and misreporting. In other words, the likelihood of a positive signal if $f = 0$ (sure misreporting), and the likelihood of a negative signal if $f = 1$ (sure truth-telling), are both zero. Instead, the likelihood of a muddy signal is positive for all values of f. Finally, the table also contains a *neutral* signal, which reveals no information about the trial's outcome, and it misses a triple, (O, b, I), that is impossible under our restriction on reporter strategies.

Since learning is about the probability distribution of a binary random variable (truth-telling or misreporting), and the signals used for learning reveal information on past realizations of this random variable (was the reporter truthful or misreporting last period?), our model is akin to a Bernoulli trial model. Since the Bernoulli model only considers perfect signals—our positive and negative signals, akin to heads or tails from a coin toss—ours is in fact a generalization of the Bernoulli model to allow for noisy or imperfect signals.

It is easy to see that a sample containing p positive signals, n negative signals, m muddy signals, and $neutral$ neutral signals, over a total of $p + n + m + neutral$ trials or periods, has a likelihood

$$\begin{aligned} l(p, n, m|f) &= \left[\frac{3-2q}{4}f\right]^p \times \left[\frac{1-q}{2}(1-f)\right]^n \times \left[\frac{1}{2}\left(1-\frac{1}{2}f\right)\right]^m \\ &= \left[\left(\frac{3-2q}{4}\right)^p \times \left(\frac{1-q}{2}\right)^n \times \left(\frac{1}{2}\right)^m\right] \times f^p \times (1-f)^n \times \left(1-\frac{1}{2}f\right)^m, \end{aligned}$$

where we have removed the neutral signals, as their likelihood is independent of f and will thus not affect posterior beliefs.

Recalling that by Bayesian updating, the posterior density of f equals

$$g(f; \cdot|p, n, m) = \frac{g(f; \cdot)\, l(p, n, m|f)}{\int_0^1 g(\varphi; \cdot)\, l(p, n, m|f)\, \mathrm{d}\varphi},$$

where $g(f; \cdot)$ is the prior belief over f, equal to 1 in our case, since we assume a uniform distribution over $[0, 1]$, and the "$\cdot$" absorbs all parameters relevant to the likelihood—in our case, the probability of a blue core, q, and the probability of an informative urn, $1/2$; and noticing that all terms of the likelihood that do not depend on f remain outside the integral in the denominator and, hence, cancel out with the same terms in the numerator, we obtain:

$$g(f; \cdot|p, n, m) = \frac{f^p (1-f)^n \left(1-\frac{1}{2}f\right)^m}{\int_0^1 \varphi^p (1-\varphi)^n \left(1-\frac{1}{2}\varphi\right)^m \mathrm{d}\varphi}. \tag{4}$$

Computerized evaluators' assessments conditional on their current beliefs and the observed report and core from the current interaction, are expectations over f of the assessments conditional on f.

Recall that these assessments conditional on f are given by

$$\begin{aligned} p_{Bb}(f) &= \frac{1}{\frac{3}{2}+(1-f)\frac{1}{2}} = \frac{1}{2}\left(1-\frac{1}{4}f\right)^{-1}, \text{ and} \\ p_{Bo}(f) &= \frac{(1-f)}{\frac{1}{2}+(1-f)\frac{3}{2}} = \frac{1}{2}(1-f)\left(1-\frac{3}{4}f\right)^{-1}. \end{aligned}$$

Computerized evaluators' assessments are thus found by integrating the above functions with respect to evaluators' posterior beliefs:

$$\begin{aligned} E\left[p_{Bb}(f)|p,n,m,\cdot\right] &= \frac{1}{2}\frac{\int_0^1 \varphi^p(1-\varphi)^n\left(1-\frac{1}{2}\varphi\right)^m\left(1-\frac{1}{4}\varphi\right)^{-1}\mathrm{d}\varphi}{\int_0^1 \varphi^p(1-\varphi)^n\left(1-\frac{1}{2}\varphi\right)^m\mathrm{d}\varphi}, \text{ and} \\ E\left(p_{Bo}(f)|p,n,m,\cdot\right] &= \frac{1}{2}\frac{\int_0^1 \varphi^p(1-\varphi)^{n+1}\left(1-\frac{1}{2}\varphi\right)^m\left(1-\frac{3}{4}\varphi\right)^{-1}\mathrm{d}\varphi}{\int_0^1 \varphi^p(1-\varphi)^n\left(1-\frac{1}{2}\varphi\right)^m\mathrm{d}\varphi}. \end{aligned}$$

D Learning of Human Evaluators

To shed light on the discrepancy between HP2 and Finding 2, here we ask whether evaluators update the beliefs they hold on reporters based on the information accumulated in their interactions. In particular, we investigate whether evaluators' assessments are consistent with the learning model that we explain in detail in Appendix C.

Using the results in Appendix C, we generate assessments given by hypothetical evaluators who update their beliefs on f as described above and have the same experience as human evaluators in the experiment. Table 8 reports estimates on the effect of holding strongly unbalanced rather than weakly unbalanced priors about the state of the world on these hypothetical evaluators' assessments. Assessments following an accurate blue report are significantly less generous and assessments following an inaccurate blue report are significantly less punitive with $q = 8/10$ than with $q = 6/10$. This is in line with hypothetical evaluators believing (correctly) that human reporters are more likely to misreport with $q = 8/10$ than with $q = 6/10$ but in disaccord with the observed treatment effect.

Table 8: Hypothetical Bayesian Evaluators' Assessments as a Function of q.

	(1)	(2)
Dependent	Variable:	Computer Assessment
$q = 8/10$	-1.34**	3.30**
	(0.13)	(0.57)
Constant	57.39**	37.21**
	(0.26)	(0.61)
Report	Blue	Blue
Core	Blue	Orange
N	905	311

Notes: Random effects GLS regressions. The unit of analysis is an hypothetical Bayesian evaluator in a period. Each hypothetical evaluator is a panel and periods are times within a panel. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$.

Another possibility is that evaluators have limited attention and do not use all the information available to them but focus on a salient piece of information, that is, whether reports were accurate or inaccurate. If this is the case, evaluators might naively infer reporters' strategies from report accuracy. In particular, we modify our learning model and assume that evaluators take any accurate report as a signal that the reporter he met this period was truthful for sure and any inaccurate report as a signal that the reporter he met this period misreported for sure. We generate assessments given by 'naive' or 'behavioral' hypothetical evaluators who update their beliefs on f as described above and have the same experience as human evaluators in game HF. Table 9 reports estimates on the effect of holding strongly unbalanced rather than weakly unbalanced priors about the state of the world on these hypothetical evaluators' assessments of the probability the urn is informative. As is the case

Table 9: Hypothetical Behavioral Evaluators' Assessments as a Function of q.

	(1)	(2)
Dependent	Variable:	Computer Assessment
$q = 8/10$	1.80**	-5.59**
	(0.09)	(0.54)
Constant	59.72**	32.72**
	(0.19)	(0.61)
Report	Blue	Blue
Core	Blue	Orange
N	905	311

Notes: Random effects GLS regressions. The unit of analysis ia an hypothetical behavioral evaluator in a period. Each hypothetical evaluator is a panel and periods are times within a panel. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$.

for human evaluators, assessments following an accurate blue report are significantly more generous and assessments following an inaccurate blue report are significantly more punitive with $q = 8/10$ than with $q = 6/10$. This is in line with hypothetical evaluators believing (incorrectly, and similarly to human evaluators) that human reporters are less likely to misreport with $q = 8/10$ than with $q = 6/10$.

Finding 6 (Evaluators' Learning) *The behavior of evaluators is inconsistent with a learning model that posits they initially believe $f \sim U(0,1)$ and update beliefs according to Bayes' rule but it is consistent with a learning model that posits they initially believe $f \sim U(0,1)$ and update beliefs considering report accuracy (inaccuracy) as a signal of truthful reporting (misreporting).*

E Additional Game with Computerized Evaluators

In addition to the experimental games reported in the paper (HF, CC and CL), we collected data for one additional experimental game where human reporters faced computerized evaluators with the purpose to calibrate initial reporters' incentives in game CL. In game CA (*Computerized Agnostic*), given a received report and an observed core, computerized evaluators assess the probability that the reporter is informed as if they believed the probability that reporters are truthful were uniformly distributed, $f \sim U[0, 1]$. This game is intermediate between CC and CL: like in CC, beliefs are fixed; like in CL, the starting belief is a uniform distribution over f. The objective of this experimental game was to understand reporters' incentives at the initial beliefs programmed for treatment CL. Since misreporting is the best reply to any evaluator beliefs when the prior is strongly unbalanced, reporters are expected to misreport when $q = 8/10$ also in game CA. Instead, when the prior on the state is mildly unbalanced, reporters' best reply is to truthfully report the observed signal. We ran 2 experimental sessions with game CA for a total of 47 subjects (all in the role of reporter). Instructions are available in Online Appendix G. Table 10 investigates how reporters' behavior in this game compares with behavior in the game with human evaluators. As in Sections 4 and 5, we focus on experienced subjects.

Table 10: Reporters' Behavior in Game with Agnostic Computerized Evaluators.

	(1)	(2)
Dependent Variable:	Pr[Reporter Chooses Truthful Plan of Action]	
Game CA	-0.04	-0.02
	(0.07)	(0.07)
Constant	0.49**	0.37**
	(0.05)	(0.05)
Game	HF & CA	HF & CA
q	6/10	8/10
N	1488	1488

Notes: Random effects GLS regressions. Each reporter is a panel and periods are times within a panel. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$.

Finding 7 (Reporters' Behavior with Agnostic Evaluators) *Reporters do not behave differently when facing human evaluators rather than computerized evaluators who are agnostic about reporters' behavior and have fixed beliefs.*

F Level-k Model Variation: Mixture of $L0$ Players

In applications of the level-k model to complete information games, naive behavior of $L0$ players is typically specified as uniformly randomizing across all actions. A natural question is whether such a specification would change the predictions of the level-k model in our reputational cheap talk game (a game of incomplete information). In this Section, following Li et al. (2021), we allow for a mixture of $L0$ reporters and evaluators, in which a fraction $\lambda \in [0,1]$ of $L0$ reporters are uniformly randomizing, and a fraction $(1-\lambda)$ are truthful; also, a fraction $\eta \in [0,1]$ of $L0$ evaluators are uniformly randomizing, and a fraction $(1-\eta)$ are credulous. This models encompasses both the level-k model we considered in Section 3.3 ($\lambda = 0$, $\eta = 0$) and the level-k model with uniformly randomizing players ($\lambda = 1$, $\eta = 1$) as special cases.

Proposition 3 (Level-k Model with Mixture of $L0$ Players) *When the prior belief about the state is mildly unbalanced, $q = 6/10$, level-k reporters report truthfully for any $k \geq 1$ and level-k evaluators believe reporters always report truthfully for any $k \geq 2$. When the prior belief about the state is strongly unbalanced, $q = 8/10$, level-k reporters misreport for any $k \geq 2$ and level-k evaluators believe reporters always misreport for any $k \geq 2$. In both treatments, level-1 evaluators believe the likelihood reporters report truthfully is $1 - \lambda/2$.*

Note that, according to Proposition 3, the observed frequency of misreporting with $q = 6/10$ should be $\gamma(\lambda/2)$, where γ is the incidence of $L0$ types in the population of reporters; and the frequency of misreporting with $q = 8/10$ should be $\gamma(\lambda/2) + (1-\gamma)$. This confirms HP1 as long as $\gamma < 1$ (that is, as long as the population of reporters include types other than the most naive ones). Also, Proposition 3 predicts that the expected assessments after blue reports, p_{Bb} and p_{Bo}, in the two treatments should be:

$$
\begin{aligned}
E\left[p_{Bb}(q=6/10)\right] &= \beta_0\left(\frac{1}{2}\right) + \beta_1\left(\frac{4}{6+\lambda}\right) + (1-\beta_0-\beta_1)\left(\frac{2}{3}\right) \\
E\left[p_{Bb}(q=8/10)\right] &= \beta_0\left(\frac{1}{2}\right) + \beta_1\left(\frac{4}{6+\lambda}\right) + (1-\beta_0-\beta_1)(0) \\
E\left[p_{Bo}(q=6/10)\right] &= \beta_0\left(\frac{1}{2}\right) + \beta_1\left(\frac{2\lambda}{2+3\lambda}\right) + (1-\beta_0-\beta_1)(0) \\
E\left[p_{Bo}(q=8/10)\right] &= \beta_0\left(\frac{1}{2}\right) + \beta_1\left(\frac{2\lambda}{2+3\lambda}\right) + (1-\beta_0-\beta_1)\left(\frac{1}{2}\right)
\end{aligned}
$$

where β_0 and β_1 are the incidence of, respectively, $L0$ types and $L1$ types in the population of evaluators. This confirms HP2 as long as $\beta_0 + \beta_1 < 1$ (that is, as long as the population of evaluators include types higher than $L1$).

Proof. Assume that $L0$ reporters choose randomly whether to misreport or report truthfully ($f = 1/2$) with probability $\lambda \in [0,1]$, and, instead, report truthfully ($f = 1$) with probability $(1-\lambda)$. Moreover, assume that $L0$ evaluators choose randomly from all feasible assessments with probability $\eta \in [0,1]$, and, instead, are credulous (that is, $f=1$) and form assessments using Bayes' rule with probability $(1-\eta)$. In the remainder of the proof, we take the behavior of these two types for given and derive the best replies of higher types.

- $L1$ reporters, who best reply to $L0$ evaluators, misreport if and only if $q > 3/4$ regardless of η and λ. To see this, consider an $L1$ reporter's expected payoff from misreporting (M) and truth-telling (T) after observing $S=O$:

$$EU_M^{L1}(q,\eta) = \eta\frac{1}{2} + (1-\eta)(1-q_O)p_{Bo}^{L0} + (1-\eta)q_O p_{Bb}^{L0}$$
$$EU_T^{L1}(q,\eta) = \eta\frac{1}{2} + (1-\eta)(1-q_O)p_{Oo} + (1-\eta)q_O p_{Ob}$$

  The gain from misreporting after observing $S=O$ is

$$\Delta_{EU}^{L1}(q,\eta) = \eta\frac{1}{2} + (1-\eta)q_O\frac{2}{3} - \eta\frac{1}{2} - (1-\eta)(1-q_O)\frac{2}{3} = (1-\eta)\frac{2}{3}(2q_O-1)$$

  The reporter prefers to misreport if $\Delta_{EU}^{L1}(q,\eta)$ is positive, and to be truthful if it is negative. In this case, $\Delta_{EU}^{L1}(q,\eta) > 0$ if and only if $q_O > 1/2$ or, equivalently, $q > 3/4$.

- $L1$ evaluators, who best reply to $L0$ reporters, form assessments using Bayes rule with belief $f(\lambda) = (1-\lambda)1 + \lambda\frac{1}{2} = 1 - \frac{\lambda}{2}$ regardless of η. We have

$$p_{Bb}^{L1} = p_{Bb}\left(f = 1-\frac{\lambda}{2}\right) = \frac{1}{\frac{3}{2}+(1-f)\frac{1}{2}} = \frac{1}{\frac{3}{2}+\left(\frac{\lambda}{2}\right)\left(\frac{1}{2}\right)} = \frac{4}{6+\lambda}$$
$$p_{Bo}^{L1} = p_{Bo}\left(f = 1-\frac{\lambda}{2}\right) = \frac{(1-f)}{\frac{1}{2}+(1-f)\frac{3}{2}} = \frac{\frac{\lambda}{2}}{\frac{1}{2}+\left(\frac{\lambda}{2}\right)\left(\frac{3}{2}\right)} = \frac{2\lambda}{2+3\lambda}$$

- $L2$ reporters, who best reply to $L1$ evaluators, misreport if and only if $q > \overline{q}(\lambda) \in \left(\frac{35}{52}, \frac{3}{4}\right]$ regardess of η. To see this, consider an $L1$ reporter's expected payoff from misreporting (M) and truth-telling (T) after observing $S=O$:

$$EU_M^{L2}(q,\eta) = q_O p_{Bb}^{L1} + (1-q_O)p_{Bo}^{L1} = q_O\left(\frac{4}{6+\lambda}\right) + (1-q_O)\left(\frac{2\lambda}{2+3\lambda}\right)$$
$$EU_T^{L2}(q,\eta) = (1-q_O)\frac{2}{3}$$

  The gain from misreporting after observing $S=O$ is

$$\Delta_{EU}^{L2}(q,\eta,\lambda) = q_O\left(\frac{4}{6+\lambda} - \frac{2\lambda}{2+3\lambda} + \frac{2}{3}\right) - \frac{2}{3}$$

  The reporter prefers to misreport if $\Delta_{EU}^{L2}(q,\eta,\lambda)$ is positive, and to be truthful if it is negative. In this case, $\Delta_{EU}^{L2}(q,\eta,\lambda) > 0$ if and only if $q_0 > \frac{(\lambda+6)(3\lambda+2)}{2(28\lambda+3\lambda^2+12)}$ or, equivalently,

$q > \overline{q}(\lambda) = \frac{(3\lambda+2)(\lambda+6)}{4(8\lambda+\lambda^2+4)}$, which is strictly decreasing in λ, and equals 3/4 when $\lambda = 0$ and $35/52 \approx 0.67$ when $\lambda = 1$.

- $L2$ evaluators, who best reply to $L1$ reporters, form assessments using Bayes rule with belief $f = 0$ if $q > 3/4$ and $f = 1$ if $q < 3/4$ regardless of η and λ.

- $L3$ reporters, who best reply to $L2$ evaluators, misreport if and only if $q > 3/4$. As discussed in Section 3 and shown in the proof of Proposition 1, misreporting is reporters' best reply to evaluators who believe reporters misreport for sure ($f = 1$) regardless of q, and truth-telling is reporters' best reply to evaluators who believe reporters never misreport ($f = 0$) if and only if $q < 3/4$.

- $L3$ evaluators, who best reply to $L2$ reporters, form assessments using Bayes rule with belief $f = 0$ if $q > \overline{q}(\lambda)$ and $f = 1$ if $q < \overline{q}(\lambda)$ regardless of η.

- $L4$ reporters, who best reply to $L3$ evaluators, misreport if and only if $q > \overline{q}(\lambda)$ regardless of η. To see this, note that, when $q > \overline{q}(\lambda)$ and evaluators believe reporters misreport for sure ($f = 1$), misreporting is reporters' best reply regardless of q. On the other hand, when $q < \overline{q}(\lambda) < 3/4$ and evaluators believe reporters are truthful for sure ($f = 0$), truth-telling is reporters' best reply.

- $L4$ evaluators best reply to $L3$ reporters. Since $L3$ reporters behave in the same way as $L1$ reporters, the behavior of $L4$ evaluators is the same as $L2$ evaluators—that is, $f = 0$ if $q > 3/4$ and $f = 1$ if $q < 3/4$ regardless of η and λ—and this is true for all evaluators with $k \geq 4$ where k is even.

- $L5$ reporters best reply to $L4$ evaluators. Since $L4$ evaluators behave in the same way as $L2$ evaluators, the behavior of $L5$ reporters is the same as $L3$ reporters—that is, misreporting if and only if $q > 3/4$ regardless of λ and η — and this is true for all reporters with $k \geq 5$ where k is odd.

- $L5$ evaluators best reply to $L4$ reporters. Since $L4$ reporters behave in the same way as $L2$ reporters, the behavior of $L5$ evaluators is the same as $L3$ evaluators—that is, $f = 0$ if $q > \overline{q}(\lambda)$ and $f = 1$ if $q < \overline{q}(\lambda)$ regardless of η—and this is true for all evaluators with $k \geq 5$ where k is odd.

- $L6$ reporters best reply to $L5$ evaluators. Since $L5$ evaluators behave in the same way as $L3$ evaluators, the behavior of $L6$ reporters is the same as $L4$ reporters – that is, misreporting if and only if $q > \overline{q}(\lambda)$ regardless of η — and this is true for all reporters with $k \geq 6$ where k is even.

■

G Experimental Instructions

Experimental instructions were delivered in print and using a video of power point slides with explanations of the situation and decisions to be made. The videos for each game can be found at the following web addresses:

- For game HF, `https://youtu.be/lkryzADrpqM`
- For game CC, `https://youtu.be/IX6vg1Y_SpY`
- For game CL, `https://youtu.be/MASiP3fCv9E`
- For game CA, `https://youtu.be/9vY4daTwEvM`

Here we reproduce the words and some of the figures contained in the slides handed out to the subjects. Information outside boxes is relevant for all games; information inside boxes is relevant for a specific game or set of games only, as indicated in the title of the box. Some wording is slightly different between games CC, CL, and CA, on one side, and game HF on the other. These alternate wordings are indicated inside square brackets, with the wording used in game HF indicated in italics. We use square brackets and small caps to insert comments about the graphical interface of the delivered instructions.

An Experiment With Balls. Instructions

Welcome

- In this experiment your earnings will depend on your decisions, so that different participants may earn different amounts
- Your earnings will be paid in cash at the end of the session in a separate room to preserve the confidentiality of your scores
- Please be aware that your participation is voluntary and can be withdrawn at any time without giving any reasons, but in that case your earnings will be nil

Informed Consent Form

- Please read carefully the Information for Data Subjects and Consent Request document handed out along with these instructions. Please tick, date, and sign the Informed Consent Form at the end of that document
- The data will be collected in an anonymous way by associating a code with your identity
- The users of the data will associate the data with the code, but they will never be able to associate the data with your individual identities
- The anonymized data will be stored and analyzed by the Principal Investigator for the purpose of a research project on reporting and evaluating

- The anonymized data will be kept indefinitely by the Principal Investigator and will be made available to other researchers if and when the project leads to a publication in a scientific journal

Practicalities

- Please remember to turn off your cell phones
- Once the experiment starts, please do not talk or in any way communicate with other participants
- If you have any question or problem at any point, please raise your hand
- Participants intentionally violating rules may be asked to leave the experiment and may not be paid
- You can contact Marco Ottaviani (`marco.ottaviani@unibocconi.it`), the project's Principal Investigator, to ask for corrections, updates, or cancellation of your data at any time
- In case of ethical concerns related to the experiment, you can contact Bocconi's Ethical Committee (`comitatoeticoricerca@unibocconi.it`)

The Experiment

- This experiment consists of **four (4) blocks** of periods
- Each block consists of **sixteen (16) periods**

GAMES CC, CL, AND CA ONLY

- In each period you will play the role of reporter and you will interact with a **computerized evaluator**

GAME HF ONLY

- In each period you interact with another participant
- Half of you are assigned the role of reporter, the other half the role of evaluator
- You maintain the role assigned in the first period for the entire experiment

[SCREENSHOTS ARE SHOWN TO ILLUSTRATE THE INITIAL MESSAGE WHICH ASSIGNS THE ROLE OF REPORTER OR EVALUATOR TO EACH SUBJECT]

- In each period a reporter is randomly paired with an evaluator
- If you are a reporter, in each period you are equally likely to be paired with any of the evaluators, regardless of the evaluator you were paired with in the previous period

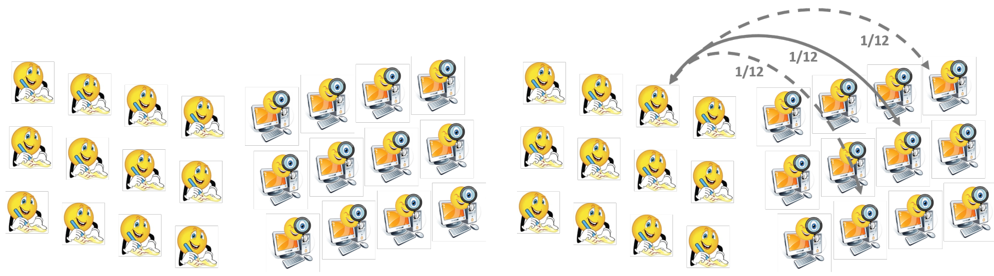


Figure 6: Game CL only: diagram to illustrate reporters' matching with computerized evaluators.

- You will never know the identity of the evaluators you are paired with
- If you are an evaluator, in each period the same mechanism randomly pairs you with a reporter, whose identity you will never know

Game CL only

[Accompanied by the diagram in figure 6.]

Reporters & Computerized Evaluators

The number of computerized evaluators is the same as the number of reporters, which in turn is equal to the number of experimental subjects in this room

Random Pairing

In each period you will be randomly paired with one of the computerized evaluators
Regardless of the computerized evaluator you were paired with in the previous period, in each period you are equally likely to be paired with any of the computerized evaluators

Balls

- In each period the software draws a **ball**
- Each ball is made of two parts: a crystal **inner core** and an opaque **outer shell**
- The inner core is either **blue** or **orange**; similarly, the outer shell that covers the core is either **blue** or **orange**
- Overall, there are four kinds of balls:
    1. Balls with blue core and blue shell
    2. Balls with blue core and orange shell
    3. Balls with orange core and blue shell
    4. Balls with orange core and orange shell

Urns

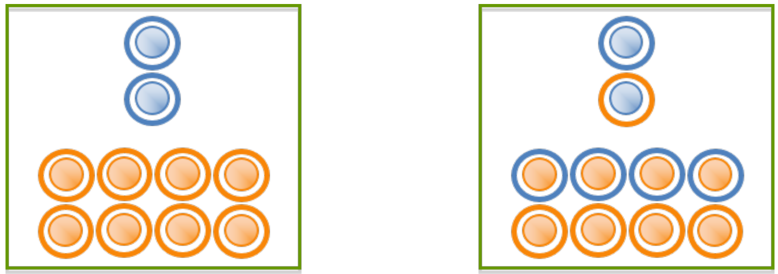


Figure 7: Informative (left) and uninformative (right) urn used as an example in the experimental instructions.

- The ball is drawn from one of **two urns** [FIGURE 7 IS SHOWN]
- The number of balls in each of the two urns is always equal to 10
- In each urn the number of balls with a **blue core** is equal to Q
- At the beginning of a block of periods you are told the number of balls with a blue core, Q, contained in each urn in every period of that block; the remaining 10 - Q balls in each urn have an orange core
- In the example above, in both urns Q=2 balls have a blue core, so that the remaining 10 - Q=8 balls have an orange core

<u>The Informative Urn</u>

In the informative urn, the core of each and every ball is covered by a shell of the same color EXAMPLE [THE LEFT PANEL OF FIGURE 7 IS SHOWN]: The informative urn contains:

- Two (Q=2) balls with a blue core and a blue shell
- Eight (10 - Q=8) balls with an orange core and an orange shell

<u>The Uninformative Urn</u>

In the uninformative urn, for half of the balls the core is covered by a shell of the same color, and for the remaining half of the balls the core is covered by a shell of the other color EXAMPLE [THE RIGHT PANEL OF FIGURE 7 IS SHOWN]

- Out of the two (Q=2) balls with blue core, one (2/2=1) is covered by an orange shell and one by a blue shell
- Out of the eight (10 - Q=8) balls with orange core, four (8/2=4) are covered by an orange shell and four by a blue shell

Notice that in the uninformative urn five (5) balls always have a blue shell and five (5) balls always have an orange shell

<u>Draw</u>

- At the beginning of each period, the computer will simulate the toss of a fair coin to determine from which of the two urns the ball is drawn
- If the coin lands Heads, the ball will be drawn from the informative urn
- If the coin lands Tails, the ball will be drawn from the uninformative urn
- When the ball is drawn, neither you (the reporter) nor the [computerized] evaluator know the outcome of the coin toss

Thus nobody knows from which of the two urns the ball is drawn

[Your Task] [*Task of the Reporter*]

[Your task as reporter] [*The task of the reporter*] is to make a report about the color of the shell

- The report has to be made through a plan to which [you] [*the reporter*] must commit before seeing the color of the shell

You [*The reporter*] must choose one of the following two plans:

(1) If I see a BLUE shell, I will report: "The shell is BLUE". If I see an ORANGE shell, I will report: "The shell is ORANGE".
(2) If I see a BLUE shell, I will report: "The shell is BLUE". If I see an ORANGE shell, I will report: "The shell is BLUE".

EXAMPLE: [Caricature of a reporter who thinks the following sentence.] If I see an ORANGE shell, I will report "The shell is BLUE".

[Screenshots are given to illustrate how this choice can be made using the computer interface of the experiment. See Figure 8.]

Implementation of Plan of Action

- After submitting the plan, [you] [*the reporter*] see the color of the shell of the ball that was actually drawn
- At this point, a report is automatically sent to the computerized evaluator according to [the plan you have previously chosen] [*the plan previously chosen by the reporter*]
- Recall that the report sent to the computerized evaluator is determined both by [your] [*the reporter's*] plan and by the color of the shell of the ball that was actually drawn
- Notice that the plan is made before [you] [*the reporter*] see the actual color of the shell

EXAMPLE: If I see an ORANGE shell, I will report "The shell is BLUE".
The following ball is drawn [Graphical display of a ball with an orange shell and an orange core. The shell is then isolated for the reporter to see. A

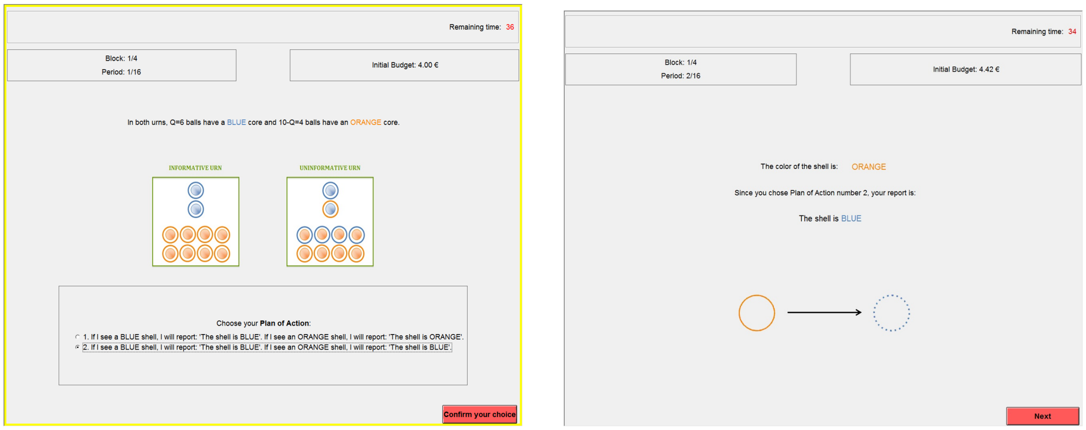


Figure 8: The reporter chooses plan of action (2) (left), a ball is drawn that has an Orange shell, so the reporter's report is Blue (right).

DASHED BLUE SHELL (INDICATING THE REPORT) IS THEN SENT TO THE EVALUATOR.]

[Your goal as reporter] [*The goal of the reporter*] is to be perceived as having seen a ball drawn from the informative urn

[SCREENSHOTS ARE GIVEN TO ILLUSTRATE HOW THE SHELL IS SHOWN TO THE REPORTER AND A REPORT IS AUTOMATICALLY SENT USING THE RULE GIVEN BY THE REPORTER'S CHOSEN PLAN OF ACTION. SEE FIGURE 8.]

Task of the [Computerized] Evaluator

The task of the [computerized] evaluator is to assess how likely it is that the ball was drawn from the informative urn

The [computerized] evaluator makes the assessment after receiving two pieces of information:

- The **report** sent by the reporter about the color of the shell
- The color of the **core** of the ball that has been drawn

GAME CC ONLY

- Throughout all the periods of this experiment, the computerized evaluator is programmed to believe that you always use plan (1)
  - Thus, in each period, the evaluator you face believes that the color of the shell you report is equal to the color of the shell you see

Game CA only

Throughout all the periods of this experiment, the computerized evaluator is programmed to interpret the report based on the belief that:

- A fraction f of the reporters uses plan (1) and a fraction $1 - f$ uses plan (2)
- All values of f between 0 and 1 are equally likely

This means, for example, that the computerized evaluator believes that the probability that a fraction $f = 2/10$ of reporters use plan (1) is the same as the probability that a fraction $f = 9/10$ of reporters use plan (1), and so on for all possible values of the fraction f

Game CL only

- In order to interpret the report and assess whether the ball was drawn from the informative urn, the computerized evaluator is programmed to believe that a fraction f of the reporters uses plan (1) and a fraction $1 - f$ uses plan (2)
- However, computerized evaluators do not know the value of f

Experience and Dynamics of Beliefs

Computerized evaluators accumulate experience across periods with the same value of Q, so that their belief about f evolves depending on their experience

- In each period, the **experience** of each computerized evaluator consists of the outcome of the interaction with the reporters with whom this computerized evaluator was paired in all previous periods with the same value of Q
- In the first period of a block of periods with a value of Q that has never been encountered before, all evaluators believe that any value of f between 0 and 1 is equally likely
- Thus, in the first period, the computerized evaluator believes, for example, that the probability that a fraction $f = 2/10$ of reporters use plan (1) is the same as the probability that a fraction $f = 9/10$ of reporters use plan (1), and so on for all possible values of the fraction f
- Each computerized evaluator updates its belief about the fraction f on the basis of the experience accumulated in each of the previous **individual** interactions with reporters. This experience consists of:
  - The **reports** received by that specific computerized evaluator
  - The color of the **cores** observed by that specific computerized evaluator

- Whether each ball was drawn from the informative or the uninformative urn

This experience allows the computerized evaluator to make an inference about the plan used by the reporters it encountered in all previous periods

- Note that the first time a block of periods with a certain Q starts, learning from experience starts anew
- The "memory" of the computerized evaluator is then reset to believe that all values of f between 0 and 1 are equally likely
- However, if a block starts a second time with the same Q as in an earlier block, the computerized evaluator carries over the experience from the earlier block with that same Q

Task of the [Computerized] Evaluator, continued

- The assessment of the [computerized] evaluator takes the following form:

"Given the core that I see and the reported shell, how likely is it that the ball was drawn from the informative urn? My assessment is P% =__%."

- The number P is between 0 and 100

The goal of the [computerized] evaluator is to make an accurate assessment
EXAMPLE: The following ball is drawn [Graphical display of a ball with an orange shell and an orange core. The core is separated from the shell. The core is directly given to the evaluator to see. The shell is given to the reporter who sends a dashed blue shell (report) to the evaluator. The graphic evaluator ponders:] Given the core that I see and the reported shell, how likely is it that the ball was drawn from the informative urn? My assessment is P% = __%.

Notice that the [computerized] evaluator sees [your] [*the reporter's*] report, but sees neither the reporter's plan nor the actual color of the shell

Game HF only

[Screenshots are given to illustrate the information the evaluator will have at the time when she/he will make her/his choice. See Figure 9.]

[Your Payoff] [*Payoff of the Reporter*]

- At the beginning of each block of periods [you] [*the reporter*] receive a budget of 4 euros

Figure 9: The evaluator is reminded that the report she/he will see is the choice of the reporter (up, left), and is given the opportunity to make a choice after receiving the report and observing the core of the drawn ball (up, right). The evaluator can make her/his choice using a slider (down, left), or by typing in a number (down, right).

- In each period [you] [*the reporter*] pay an operating fee of 25 euro cents and obtain a payoff equal to P euro cents
- P% represents the [computerized] evaluator's assessment of the probability that the ball was drawn from the informative urn

[A screenshot is shown to illustrate how feedback is given to the reporter about her choice, her payoff, and the truth about the core of the drawn ball and the urn informativeness. See Figure 10.]

Game HF only

<u>Payoff of the Evaluator</u>

The payoff structure of the evaluator is designed to give the evaluator an incentive to make and report an accurate assessment of the probability that the ball was drawn from the informative urn

- Depending on the evaluator's assessment, P%, the evaluator receives the following numbers of lottery tickets:
  - $N_I = \left[1 - (1 - P/100)^2\right] \times 10000$ tickets that are marked by I and numbered consecutively from 1 to N_I
  - $N_U = \left[1 - (P/100)^2\right] \times 10000$ tickets that are marked by U and numbered consecutively from 1 to N_U
- When the evaluator assesses P, the software displays the numbers N_I and N_U corresponding to every value of P in a friendly format
- The payoff of the evaluator depends on the outcome of the lottery as follows:
  - i. Selection of the letter:
    - ∗ If the ball was drawn from the informative urn, letter I is selected
    - ∗ If the ball was drawn from the uninformative urn, letter U is selected
  - ii. Selection of the number: The software extracts a random number between 1 and 10000 (in each period all numbers are equally likely to be extracted and extractions are independent across periods)
  - iii. If the evaluator owns the ticket with the selected letter and the selected number, the evaluator wins 75 euro cents; otherwise, the evaluator wins 0 euro cents

[Screenshots are given to show how the evaluator can make an assessment using either the keyboard or the slider in the experiment's computer interface. See Figure 9.]

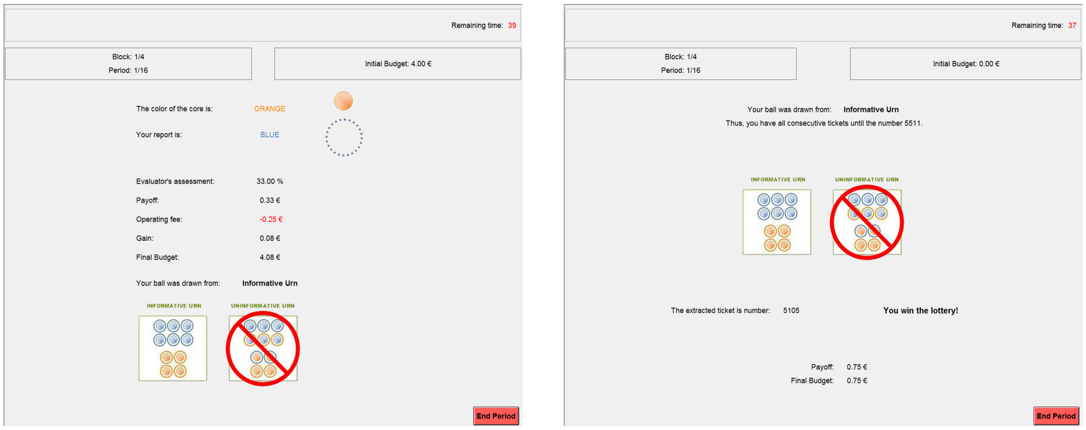


Figure 10: Feedback is given to the reporter(left) and to the evaluator (right) at the end of each period.

<u>Payoff of the Evaluator</u>

- Suppose that the ball was actually drawn from the informative urn
- Suppose that the software randomly extracts number 5105
- Given that the evaluator owns the winning ticket (number $I - 5105$), the evaluator wins 75 cents!
- Note that if the number extracted had been greater than 5511, the evaluator would have lost the lottery

[A SCREENSHOT IS GIVEN WITH THE EVALUATOR'S FEEDBACK ON PAYOFF. SEE FIGURE 10.]

<u>Evaluator Feedback</u>

Evaluator

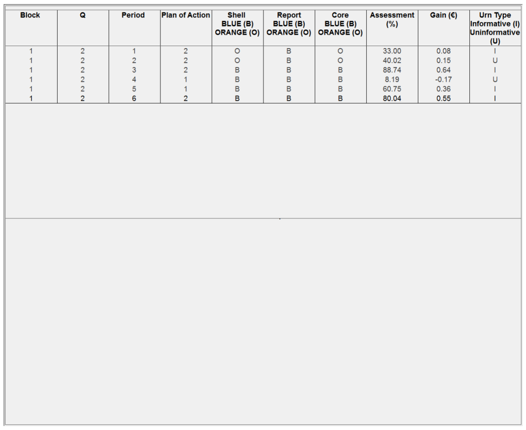
At the end of each period, the evaluator receives the following feedback about the outcome of that period:

- The urn (informative or uninformative) from which the ball was drawn
- The evaluator's own payoff

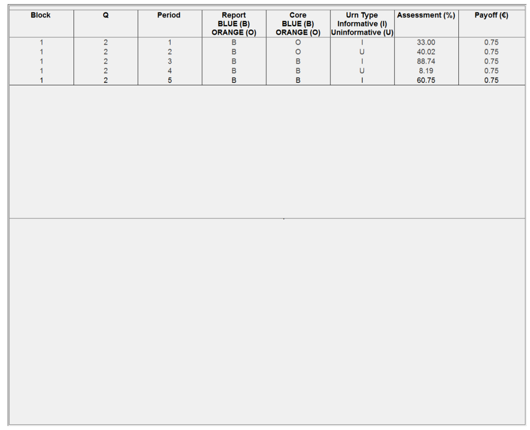
Recall that the evaluator sees neither the reporter's plan nor the color of the shell

[A SCREENSHOT IS GIVEN TO SHOW THE HISTORICAL FEEDBACK GIVEN TO EVALUATORS IN BETWEEN EXPERIMENTAL PERIODS. SEE FIGURE 11.]

<u>[Your] [*Reporter*] Feedback</u>



Block	Q	Period	Plan of Action	Shell BLUE (B) ORANGE (O)	Report BLUE (B) ORANGE (O)	Core BLUE (B) ORANGE (O)	Assessment (%)	Gain (€)	Urn Type Informative (I) Uninformative (U)
1	2	1	2	O	B	O	33.00	0.08	I
1	2	2	2	O	B	O	40.02	0.15	U
1	2	3	2	B	B	B	88.74	0.64	I
1	2	4	1	B	B	B	8.19	-0.17	U
1	2	5	1	B	B	B	60.75	0.36	I
1	2	6	2	B	B	B	80.04	0.55	I



Block	Q	Period	Report BLUE (B) ORANGE (O)	Core BLUE (B) ORANGE (O)	Urn Type Informative (I) Uninformative (U)	Assessment (%)	Payoff (€)
1	2	1	B	O	I	33.00	0.75
1	2	2	B	O	U	40.02	0.75
1	2	3	B	B	I	88.74	0.75
1	2	4	B	B	U	8.19	0.75
1	2	5	B	B	I	60.75	0.75

Figure 11: In between periods, the reporter (left) and the evaluator (right) are reminded of important outcome variables for all past periods.

At the end of each period, [you] [*the reporter*] receive the following feedback about the outcome of that period:

- The color of the core of the drawn ball
- [Your] [*The reporter's*] own payoff
- The urn (informative or uninformative) from which the ball was drawn

[A SCREENSHOT IS SHOWN ILLUSTRATING THE HISTORICAL FEEDBACK GIVEN TO THE REPORTER IN BETWEEN EXPERIMENTAL PERIODS. SEE FIGURE 11.]

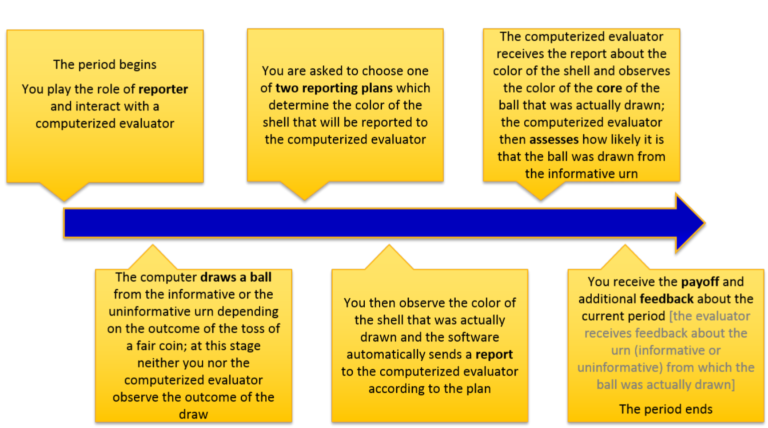
GAME CL ONLY

Evaluator Feedback

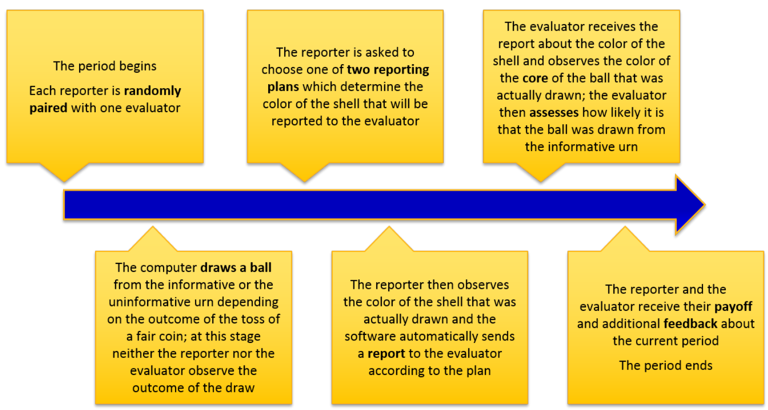
Computerized Evaluator
At the end of each period, the computerized evaluator receives feedback about the urn (informative or uninformative) from which the ball was actually drawn
Recall that the computerized evaluator sees neither your reporting plan nor the color of the shell

Transition Across Periods & Blocks

- At the end of each period the ball is returned to the urn from which it was drawn
- At the beginning of the following period a new coin flip is simulated and a new ball is drawn from the urn selected by the coin flip
- Urn selections and ball draws are therefore **independent** across periods
- You are allowed to take notes on scrap paper throughout the experiment



(a) Games CC, CL, and CA. Additional text for CL in gray.



(b) Game HF.

Figure 12: Graphical summary of the experiment used in the experimental instructions.

- At the end of each block of periods you will have time to take notes about your experience during that block
- You are advised to go over your notes whenever you happen to play again a block of periods with the same number (Q) of balls with a **blue core**

Summary

At the beginning of each of the four (4) blocks of periods you are told the value of Q, the number of balls with **blue core** out of the total ten (10) balls that are contained in each of the two urns

For each of the sixteen (16) periods within each block, the timing is as follows: [see Figure 12.]