Updating Social Judgments after Cooperative Behavior: Investigation of Belief-Based Gender Discrimination

Martijn J. van Den Assem* Dennie van Dolder† Uyanga Turmunkh‡ Stefano Nasini§

November 2024

Abstract

This study investigates the dynamics of social judgment in a game show context, specifically focusing on how judges update their beliefs about contestants based on cooperative versus uncooperative behavior in a setting resembling the Prisoner's Dilemma. Using a laboratory experiment where participants (judges) evaluate contestants from the British TV show *Golden Balls*, we explore how judges revise their perceptions of contestants' competence, warmth, and moral character after observing their strategic choices in a cooperative game. We propose two complementary models for belief updating: an autoregressive model and a Bayesian model. In the autoregressive model, judges' beliefs evolve as beta distributions conditioned on contestants' observable features and behavior, while the Bayesian model treats contestants' decisions as signals of their underlying traits, leading to probabilistic belief updates. We analyze how contestants' gender influences belief updating, and whether judges' revisions align with Bayesian reasoning. Our results highlight the complex interplay between initial beliefs, observable traits, and game behavior in shaping social judgments. The study contributes to understanding belief dynamics in strategic decision-making contexts, with implications for both theoretical models of social cognition and practical applications in media and public opinion formation.

Key words: Belief updating, Structural econometrics, Social judgment

1 Introduction

Belief-based gender discrimination has been suggested as one of the potential explanations behind inferior labor market outcomes of women as compared to those of men. Across fields and ranks, men earn more than women employed in similar functions, and men climb the career ladder faster and further than women with similar levels of education and experience. Belief-based discrimination

*Vrije Universiteit Amsterdam

†University of Essex

‡IESEG School of Management, Lille Catholic University, Lille, France

§IESEG School of Management, Lille Catholic University, Lille, France

implies that there are systematic, gendered differences in employers' beliefs about men's and women's performance-relevant characteristics, such as their ability. In Economics, belief-based discrimination has sometimes been equated with statistical discrimination (Phelps, 1972), which states that in the absence of more relevant signals employers rely on group identity (e.g., gender) to form their beliefs about an employee's ability or productivity. From this perspective, differences in beliefs about men's vs. women's characteristics are due to differences in priors (reflecting differences in group averages), and, as the amount and weight of performance-relevant signals grows, updated beliefs (i.e., beliefs conditional on observed signals) should display minimal gender-based differences.

In Management and Psychology, however, belief-based discrimination has often been attributed to differential, gendered processing of signals. From this perspective, gender differences in employers' beliefs are not mere reflections of differences in priors built upon perceived (accurate or inaccurate) differences in group averages, but rather, they are driven by gendered differences in how performance-relevant signals are interpreted by employers. For example, an anecdotally prominent narrative implying such gender-difference in the processing of otherwise identical performance-relevant information is the "double-standards" narrative. According to this narrative, women (especially in leadership positions such as a high political office) are judged against a higher standard compared to men, so that, as a result, a female leader may be penalized more severely for an error for which a male leader would not be penalized nearly as much. Although numerous studies in Management and Psychology have proposed different possible narratives that can accommodate gender-dependent differences in signal processing, empirical evidence showing that identical signals are indeed interpreted differently depending on the evaluated person's gender are still scarce.

There are two important challenges that hamper an empirical investigation of this question. Firstly, in order to establish whether gender bias in beliefs is driven by differences in priors (i.e., stereotypes) or by a biased information processing, we need an empirical setting which allows separate measurements of observers' prior beliefs and their posterior (i.e., after having processed some signals) beliefs about a performance-relevant characteristic of targets. Moreover, to ensure external validity of observed (if any) gender differences, the target population should be sufficiently large and reflecting as much as possible the real-world richness in differences between individuals beyond their gender. Secondly, a statistical framework for belief updating is needed, which can separately assess the effects of gender on the initial beliefs versus its effect on how signals are processed. By relying on an experimental design and statistical model that meet these challenges, this study is able to investigate in the context of cooperative behavior whether identical signals are processed differently depending on the target's gender.

In the literature to date, several experimental studies investigate whether target person's gender plays a role in how observers for beliefs about the target's unobservable abilities based on a set of observable signals. For example, Moss-Racusin et al. (2012) conducted a laboratory experiment in which science faculty rated the application materials for laboratory manager position of a student applicant, who was randomly assigned either a male or female name. The authors found that faculty participants rated the male applicant as more competent and hireable than the (identical) female applicant. Other studies, all relying on a similar experimental paradigm which employs otherwise-identical-profiles as evaluation stimuli, also find that, men are perceived as more competent (in particular, in a quantitative field) than women with identical profiles.

However, findings of these studies do not clary whether the observed biases in raters' beliefs are driven by raters' biased priors about men's vs. women's competence or to what extent these biases were a result of the raters' biased processing of the identical signals provided in the experimental stimuli. Our study contributes to this literature by separately measuring raters' prior beliefs about targets' characteristics and their posterior beliefs, after having processed new information about the targets. To the best of our knowledge, the only other experimental study that looks at gender biases in beliefs by differentiating prior beliefs from posterior beliefs is Campos-Mercade and Mengel (2024). In their study, the authors find evidence of conservatism (i.e., giving a higher weight to prior belief than warranted under Bayesian belief updating), but no evidence that identical performance signals were weighted differently depending on the target's gender. Thus, they conclude that in their setting the observed biases in raters' beliefs about male and female abilities (to do logical tasks) were driven mainly by overly high weights given to the biased priors.

We study social judgments of people following their cooperative or uncooperative behavior, and we investigate whether cooperation (or defection) is judged differently depending on whether the person is male or female. This is the second contribution of our paper. In our laboratory experiment, participants (henceforth, judges) watch a series of two-contestant interactions from the British TV game show *Golden Balls*, and are asked to judge each contestant along three fundamental dimensions of social cognition: *competence*, *warmth*, and *moral character*. Judges observe contestants in two stages: first, by watching a series of short videos in which the contestants are introduced to the audience by the show's host, and second, by watching the contestants' behavior during the strategic interaction with a fellow contestant in the Prisoner's Dilemma. We study how judges update their beliefs about the contestants after observing their cooperative or uncooperative behavior in the game.

The complexity of this belief-updating process lies in the way judges form and modify their impressions. Judges start with an initial set of beliefs about the contestants' character traits based on the observable characteristics of the contestants during the introductory videos. Subsequently, judges update these initial beliefs after witnessing the contestants' behavior in the Prisoner's Dilemma game. To capture these belief dynamics, we model judges' initial and updated beliefs as probability distributions, assuming that the belief-updating process relies on observable features of both the contestants and their behavior in the game.

In each game interaction, two contestants decide simultaneously whether they wish to *split* a commonly held money prize with each other or *steal* it all from the other. If both contestants behave cooperatively by choosing to split, then each gets to go home with half of the money prize. If one defects by choosing to steal while the other chooses to split, then the defector ends up with all of the money prize while the cooperator goes home with nothing. If both choose to steal, then the show keeps the money and both contestants go home with nothing. Before making their split-or-steal decisions, the two contestants get a chance to communicate with each other briefly about what they intend to do. Our analysis focuses on how a set of key observables impact the way in which judges update their beliefs about the contestants. In particular, we look at the role of contestants' gender (i.e., whether male contestants are judged differently from female contestants, controlling for behavior). We are also interested in the dynamics of belief-updating. For example, whether judges update their beliefs in accordance with Bayesian updating.

To formalize this process, we use two complementary belief-updating models: an autoregressive belief updating model and the Bayesian belief updating model. In the autoregressive model, each judge's initial belief about a contestant is expressed as a beta distribution dependent on features like the contestants' age, gender, and educational level. The updated belief is then conditioned on both the initial belief and the contestant's final split-or-steal decision, as well as a series of observable characteristics of the game. Conversely, in the Bayesian model, the belief-updating process incorporates the contestant's final choice and the game-related characteristics as a signal that reveals information about the contestants' underlying character traits, allowing judges to update their beliefs in a probabilistic, inference-driven manner. This approach enables us to compare the sequential dependencies of the autoregressive model with the probabilistic inference mechanism in the Bayesian framework.

2 Belief-updating Models

2.1 Notation

Throughout this paper sets are denoted in calligraphic letters and vectors in boldface letters. Furthermore, we use capital letters when referring to random variables and the corresponding small letters for their realizations. We consider a collection $\mathcal{I}$ of contestants in the game show, each being judged in terms of a list D character dimensions and define the set $\mathcal{D} = \{1, \ldots, D\}$. We denote with w_i the i-th contestant binary choice on splitting and stealing.

The game has two stages. Firstly, the i-th contestant provides a collection of S binary signals $\sigma_{i,1}, \ldots, \sigma_{i,S}$ about its intention to split or steal. Secondly, he reveals his actual decision of splitting or stealing w_i.

We define $\boldsymbol{x}_j^{(J)}$ as the vector of the j-th judge features (e.g., judge j's gender), $\boldsymbol{x}_i^{(C)}$ as the vector of the i-th contestant features (e.g., contestant i's gender), and $\boldsymbol{x}_{g(i)}^{(G)}$ as the vector of the $g(i)$-th game features (e.g., the size of the money stake at play). Note that since each contestant $i \in \mathcal{I}$ appears in a single game, the indicator function $g(i) \in \mathcal{G}$ is used to refer to the game in which the i-th contestant appears.

We define the following signal aggregator function, which integrates the multiple signals into a single attitude:

$$\tilde{x}_i(\boldsymbol{\gamma}) = \begin{cases} 1 & \text{if } \Lambda\Big(\boldsymbol{\gamma}, \boldsymbol{\sigma}_i, \boldsymbol{x}_i^{(C)}, \boldsymbol{x}_{g(i)}^{(G)}\Big) \geq 0 \\ 0 & \text{otherwise,} \end{cases} \tag{1}$$

where Λ is a real valued function that combines these inputs—signals, contestant features, and contextual game characteristics—using parameters $\boldsymbol{\gamma}$ (which we aim to estimate), reflecting the relative importance or sensitivity assigned to different inputs.

The stepwise constant nature of the signal aggregation function reflects a key psychological insight: people often categorize information rather than treating it as a continuous spectrum. This tendency aligns with psychological theories of categorical thinking and decision heuristics, where individuals simplify complex inputs into discrete categories or thresholds to reduce cognitive load. From a psychological perspective, such a stepwise process may be driven by cognitive economy, where the brain simplifies decision-making by relying on salient boundaries or rules. For instance, in social judgment contexts, observers might not differentiate finely between similar signals but instead classify behaviors or traits into broad groups (e.g., "trustworthy" vs. "untrustworthy") based on intuitive thresholds. This discretization is consistent with research in social psychology showing that judgments often rely on prototypical examples or simplified heuristics rather than detailed, continuous evaluation.

Let random variable $Y^0_{j,i,d} \in [0,1]$ describe judge j's initial belief with respect to dimension d about contestant i, and let $y^0_{j,i,d}$ denote an observed realization of it through direct elicitation. The superscript 0 indicates the initial belief. Similarly, let random variable $Y^1_{j,i,d} \in [0,1]$ describe the corresponding belief of the same judge j with respect to the same dimension d about the same contestant i, which has, however, now been updated after the judge has watched the contestant's split-or-steal interaction in the game. We denote with $y^1_{j,i,d}$ an observed realization of $Y^1_{j,i,d}$ through direct elicitation. As dimensions are assumed to be independent, for ease of notation, we drop the d subscript from $Y^0_{j,i,d}$ and $Y^1_{j,i,d}$ (as well as from $y^0_{j,i,d}$ and $y^1_{j,i,d}$) whenever the context makes it clear that no confusion can arise.

2.2 Belief updating models

We now turn our attention to the modeling of belief updating after signals are revealed and aggregated into attitudes. This is a fundamental step of the construction of a statistical framework for the empirical estimation of belief updating about social judgment.

Autoregressive belief updating. Under the autoregressive belief updating, judges' beliefs are modeled as conditionally independent beta distributions. Specifically, we consider the marginal distribution of $Y^0_{j,i}$ and the conditional distribution of $Y^1_{j,i}$ (i.e., after observing a realization of the initial belief $y^0_{j,i}$), whose expectations depend on features $\boldsymbol{x}_j^{(J)}$, $\boldsymbol{x}_i^{(C)}$ and $\boldsymbol{x}_{g(i)}^{(G)}$:

$$Y^0_{j,i} \sim \text{Beta}(\alpha^0_{j,i}, \beta) \quad \text{and} \quad Y^1_{j,i} \mid (Y^0_{j,i} = y^0_{j,i}) \sim \text{Beta}(\alpha^1_{j,i,g(i)}, \beta^1), \tag{2}$$

where $\alpha^0_{j,i}$ and $\alpha^1_{j,i,g}$ capture the functional dependencies of beliefs on judge, contestant, and game features: $\alpha^0_{j,i} = \alpha^0(\boldsymbol{x}^{(J)}_j, \boldsymbol{x}^{(C)}_i, \boldsymbol{\theta}^0)$ and $\alpha^1_{j,i,g(i)} = \alpha^1(y^0_{j,i}, \tilde{x}_i(\boldsymbol{\gamma}), \boldsymbol{\theta}^1)$, with $\boldsymbol{\theta}^0$ and $\boldsymbol{\theta}^1$ indicating the model parameters to be empirically estimated from observed beliefs. By definition of beta distribution and using logit link function, we establish the following expectations:

$$\mathbb{E}[y^0_{j,i}] \quad = \frac{\alpha^0_{j,i}}{\alpha^0_{j,i} + \beta^0} = \frac{1}{1 + \exp\Big(-(\boldsymbol{\theta}^0)^\top \boldsymbol{x}^0_{i,j}\Big)} \tag{3}$$

$$\mathbb{E}[Y^1_{j,i} \mid Y^0_{j,i} = y^0_{j,i}] \quad = \frac{\alpha^1_{j,i,g(i)}}{\alpha^1_{j,i,g(i)} + \beta^1} = \frac{1}{1 + \exp\Big(-\theta^1_0 - \theta^1_y y^0_{j,i} - \theta^1_{\tilde{x}} \tilde{x}_{i,j}(\boldsymbol{\gamma})\Big)}, \tag{4}$$

where we used the vector notation $\boldsymbol{x}^0_{i,j} = (\boldsymbol{x}^{(J)}_j, \boldsymbol{x}^{(C)}_i)$, $\boldsymbol{\theta}^0 = (\boldsymbol{\theta}^{0,(J)}, \boldsymbol{\theta}^{0,(C)}, \beta^0)$, and $\boldsymbol{\theta}^1 = (\theta^1_0, \theta^1_y, \theta^1_{\tilde{x}}, \beta^1)$.

Bayesian belief updating. Hereafter we assume that judges' beliefs follow a Bayesian learning model, with initial beliefs following a beta distribution $Y^0_{j,i} \sim \text{Beta}(\alpha^0_{j,i}, \beta^0)$, as defined in (2). In the context of the Bayesian belief updating, this plays the role of a prior distribution of judges beliefs, so that $\alpha^0_{j,i}$ and $\beta^0_{j,i}$ are hyperparameters of the belief model.[1] Let $f_A(y; \alpha^0_{j,i}, \beta_0)$ denote the the probability density function of this prior distribution. As for $Y^1_{j,i}$, we consider a Bayesian update in which the actions of the contestants are regarded as a signal of its internal state y: $f_B(y \mid \tilde{x}_i(\boldsymbol{\gamma})) \propto L(\tilde{x}_i(\boldsymbol{\gamma}) \mid y) f^0_A(y; \alpha^0_{j,i}, \beta^0)$. In this context, we assume the signal to follow a Bernoulli distribution, so that

$$L(\tilde{x}_i(\boldsymbol{\gamma}) \mid y) = y^{\tilde{x}_i(\boldsymbol{\gamma})}(1-y)^{1-\tilde{x}_i(\boldsymbol{\gamma})}.$$

We have

$$\begin{aligned} f_B(y^1_{j,i} \mid \tilde{x}_i(\boldsymbol{\gamma}), \boldsymbol{\theta}^0, \beta^0)) \quad &= \frac{L(\tilde{x}_i(\boldsymbol{\gamma}) \mid y^1_{j,i}) \cdot f^0_A(y^1_{j,i}; \boldsymbol{\theta}^0, \beta^0)}{\displaystyle\int L(\tilde{x}_i(\boldsymbol{\gamma}) \mid y) \cdot f^0_A(y; \boldsymbol{\theta}^0, \beta^0)\ dy} \\ &= \frac{(y^1_{j,i})^{\tilde{x}_i(\boldsymbol{\gamma}) + \alpha^0_{j,i} - 1}(1 - y^1_{j,i})^{1-\tilde{x}_i(\boldsymbol{\gamma}) + \beta^0 - 1}}{\displaystyle\int (y)^{\tilde{x}_i(\boldsymbol{\gamma}) + \alpha^0_{j,i} - 1}(1-y)^{1-\tilde{x}_i(\boldsymbol{\gamma}) + \beta^0 - 1}\ dy}. \end{aligned}$$

Therefore, under the Bayesian belief updating, we have

$$Y^0_{j,i} \sim \text{Beta}(\alpha^0_{j,i}, \beta^0) \quad \text{and} \quad Y^1_{j,i} \sim \text{Beta}(\tilde{x}_i(\boldsymbol{\gamma}) + \alpha^0_{j,i}, 1 - \tilde{x}_i(\boldsymbol{\gamma}) + \beta^0). \tag{5}$$

It is important to note that while the Bayesian belief updating and the autoregressive belief updating agree on the initial belief distribution, the statistical dependency between $Y^0_{j,i}$ and $Y^1_{j,i}$ in (5) is established by an empirical Bayes characterization of the hyperparameters $\alpha^0_{j,i}$ and $\beta^0_{j,i}$, after a pointwise elicitation of $Y^0_{j,i}$:

$$y^0_{j,i} = \frac{\alpha^0_{j,i}}{\alpha^0_{j,i} + \beta^0}.$$

[1] In the context of Bayesian statistics, hyperparameters refer to the parameters that characterize a prior distribution.

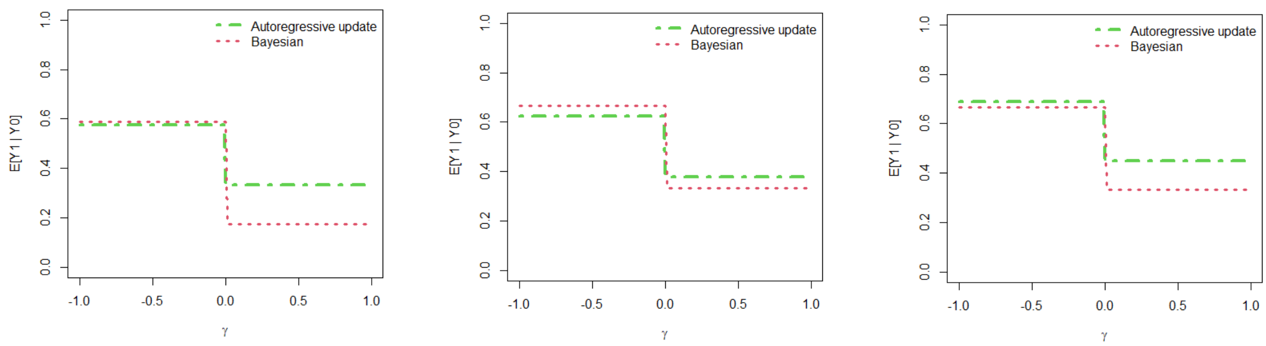
where the realization $y^0_{j,i}$ constitutes a pointwise elicitation of $Y^0_{j,i}$. We obtain

$$Y^0_{j,i} \sim \text{Beta}(\alpha^0_{j,i}, \beta^0) \quad \text{and} \quad Y^1_{j,i} \mid (Y^0_{j,i} = y^0_{j,i}) \sim \text{Beta}\left(\tilde{x}_i(\boldsymbol{\gamma}) + \frac{y^0_{j,i}\beta^0}{1 - y^0_{j,i}}, 1 - \tilde{x}_i(\boldsymbol{\gamma}) + \beta^0\right), \tag{6}$$

which implies

$$\mathbb{E}[Y^1_{j,i} \mid Y^0_{j,i} = y^0_{j,i}] = \frac{y^0_{j,i}\beta^0 + \tilde{x}_i(\boldsymbol{\gamma})(1 - y^0_{j,i})}{1 - y^0_{j,i} + \beta^0}. \tag{7}$$

Illustrative comparison. This subsection provides a more explicit comparison between the two forms of belief updating (autoregressive versus Bayesian belief updating). Figures 1 and 2 below compare the conditional expectation of the updated belief $Y^1_{j,i} \mid Y^0_{j,i} = y^0_{j,i}$ (as reported in (4) and (7), for the autoregressive and Bayesian belief updating models, respectively). In Figure 1, this expectation is depicted as a function of the signal effect γ (for three different fixed values of $y^0_{j,i}$), revealing the stepwise behavior of the expected belief with respect to γ. This stepwise behavior is consistent for both autoregressive and Bayesian belief updating, and has important implications on the idendifiability of the maximum likelihood estimation of γ, as discussed in Section 5.



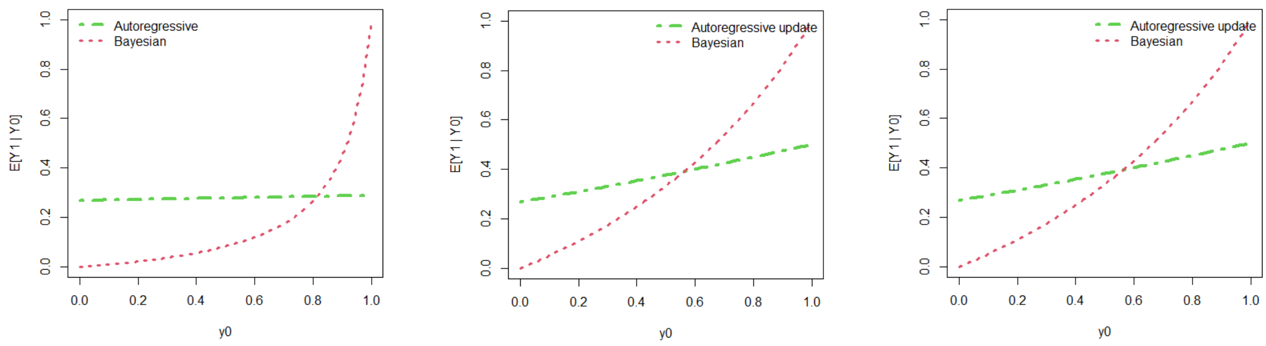
(a) $y^0_{j,i} = 0.3$. (b) $y^0_{j,i} = 0.5$. (c) $y^0_{j,i} = 0.8$.

Figure 1: Functional behavior of $\mathbb{E}[Y^1_{j,i} \mid Y^0_{j,i} = y^0_{j,i}]$ as a function of γ, fixing $\theta^1_y = 1.0$ and $\beta^0 = 1.0$.

In Figure 2, the conditional expectation $\mathbb{E}[Y^1_{j,i} \mid Y^0_{j,i} = y^0_{j,i}]$ is depicted as a function of the pointwise elicitation $y^0_{j,i}$, for different values of θ^1_y (in the autoregressive update) and β^0 (in the Bayesian update). Visibly, the value of $y^0_{j,i}$ has a sizable impact on $\mathbb{E}[Y^1_{j,i} \mid Y^0_{j,i} = y^0_{j,i}]$. However, this impact strongly depends on θ^1_y (in the case of the autoregressive updating) and on β^0 (in the case of the Bayesian updating), with the Bayesian update appearing more sensitive to $y^0_{j,i}$ than the autoregressive update.

3 Minimal Maximum Likelihood Estimation

This section details the construction of a specialized estimation approach which allows circumventing the non-identifiability of $\boldsymbol{\gamma}$ as a result of the piecewise constant behavior of the signal aggregation function (1), as illustrated in Figure 1.



(a) $\theta_y^1 = 0.1$ and $\beta^0 = 0.1$. (b) $\theta_y^1 = 0.5$ and $\beta^0 = 0.5$. (c) $\theta_y^1 = 1.0$ and $\beta^0 = 1.0$.

Figure 2: Functional behavior of $\mathbb{E}[Y_{j,i}^1 \mid Y_{j,i}^0 = y_{j,i}^0]$ as a function of $y_{j,i}^0$, fixing $\tilde{x}_i(\boldsymbol{\gamma}) = 1$.

To elucidate our estimation procedure, let us define the following density functions of judge j's initial and updated beliefs about contestant i with respect to a given dimension in the autoregressive belief update is:

$$f_A(y_{j,i}^0; \boldsymbol{\theta}^0) = \frac{(y_{j,i}^0)^{\alpha_{j,i}^0 - 1}(1 - y_{j,i}^0)^{\beta^0 - 1}}{B(\alpha_{j,i}^0, \beta^0)} \quad \text{and} \quad f_A(y_{j,i}^1 \mid y_{j,i}^0; \boldsymbol{\theta}^1, \boldsymbol{\gamma}) = \frac{(y_{j,i}^1)^{\alpha_{j,i,g(i)}^1 - 1}(1 - y_{j,i}^1)^{\beta^1 - 1}}{B(\alpha_{j,i,g(i)}^1, \beta^1)}, \quad (8)$$

where B is a beta function. Once a collection of observations of $y_{j,i}^0$, $y_{j,i}^1$, $\boldsymbol{x}_j^{(J)}$, $\boldsymbol{x}_i^{(C)}$ and $\boldsymbol{x}_{g(i)}^{(G)}$ are provided, a likelihood function is defined for each $\boldsymbol{\theta}^0$, $\boldsymbol{\theta}^1$ and $\boldsymbol{\gamma}$ as follows:

$$L(\boldsymbol{\theta}, \boldsymbol{\gamma}, Y, X) = \prod_{i \in \mathcal{I}} \prod_{j \in \mathcal{J}} f(y_{j,i}^1 \mid y_{j,i}^0; \boldsymbol{\theta}^1) \times f(y_{j,i}^0; \boldsymbol{\theta}^0),$$

where $f(y_{j,i}^1 \mid y_{j,i}^1; \boldsymbol{\theta}^1)$ and $f(y_{j,i}^0; \boldsymbol{\theta}^0)$ are as specified in (8).

While $L(\boldsymbol{\theta}, \boldsymbol{\gamma}, Y, X)$ is continuous in $\alpha_{j,i}^1$, we can observe that the latter is piecewise constant in γ, resulting in the possible non-identifiability of the maximum likelihood estimator. Specifically, for the case of the autoregressive updating, solving (4), for $\alpha_{j,i,g(i)}^1$, and using the signal aggregation function (1), we can express the scale parameter as a function of judge, contestant, and game features:

$$\alpha_{j,i,g(i)}^1 = \begin{cases} \dfrac{\beta^1}{\exp\left(-\theta_0^1 - \theta_y^1 y_{j,i}^0 - \theta_{\tilde{x}}^1\right)} & \text{if } \Lambda\left(\boldsymbol{\gamma}, \boldsymbol{\sigma}_i, \boldsymbol{x}_i^{(C)}, \boldsymbol{x}_{g(i)}^{(G)}\right) \geq 0 \\[2ex] \dfrac{\beta^1}{\exp\left(-\theta_0^1 - \theta_y^1 y_{j,i}^0\right)} & \text{otherwise,} \end{cases}$$

Similarly, for the case of the Bayesian updating, using the signal aggregation function (1), we can express the scale parameter as a function of judge, contestant, and game features:

$$\alpha_{j,i,g(i)}^1 = \begin{cases} 1 + \dfrac{y_{j,i}^0 \beta^0}{1 - y_{j,i}^0} & \text{if } \Lambda\left(\boldsymbol{\gamma}, \boldsymbol{\sigma}_i, \boldsymbol{x}_i^{(C)}, \boldsymbol{x}_{g(i)}^{(G)}\right) \geq 0 \\[2ex] \dfrac{y_{j,i}^0 \beta^0}{1 - y_{j,i}^0} & \text{otherwise,} \end{cases}$$

In both cases, $\alpha^1_{j,i,g(i)}$ is piecewise constant in $\boldsymbol{\gamma}$, which entail that the likelihood function can have constant values within a specified interval $[\gamma_s^-, \gamma_s^+]$, for some $s = 1, \ldots, S$.

To circumvent this issue, we define a Minimal Maximum Likelihood Estimator (MMLE) as the solution of the following bilevel optimization problem:

$$\begin{cases} \max\limits_{\boldsymbol{\theta},\boldsymbol{\gamma}} & ||\boldsymbol{\gamma}||_1 \\ \text{s. to} & \max\limits_{\boldsymbol{\theta},\boldsymbol{\gamma}} \; L(\boldsymbol{\theta}, \boldsymbol{\gamma}, Y, X). \end{cases}$$

The MMLE can be interpreted as a psychologically realistic method for resolving ambiguities in judgment under uncertainty. Its design reflects a key psychological principle: when individuals face decision-making challenges with limited or non-identifiable information, they often gravitate toward minimally sufficient explanations or parsimonious models that explain observed data. Statistically, this estimation approach not only guarantees the uniqueness that the obtained $\boldsymbol{\gamma}$ effects, but also reduces the risk of overfitting to noise and facilitates the interpretability of the estimated coefficient (as the smallest effects compatible with the data). In Section 5, this estimation approach will be used to produce empirical results using experimental data.

4 Experiment & Data

Procedure. The experiment was conducted in November 2022 at the Essex Behavioral Science Lab, following an ethics review and an approval from the University of Essex. Participants ($n = 197$), recruited through the Lab's participant pool management system, included 115 women and 78 men (4 participants self-identified as "other"). The experimental questions were not incentivized. Each participant was paid £15 at the end of the experiment. On average, the experiment lasted 1 hour 15 minutes. Table 1 summarizes the experimental procedure. A detailed description of the experiment is given in Online appendix 1.

During the experiment, participants watched videos taken from the final round of the British TV game show "Golden Balls", which was originally aired in 2007–2009. In the final round of each "Golden Balls" episode, two contestants play a game called "split-or-steal", which is a cooperation game similar to the Prisoner's dilemma. The two contestants left in the final round of each episode have a common jackpot (typically a considerable sum, amounting to several thousand British pounds), and they must decide simultaneously whether they wish to *split* the jackpot with the other (i.e., cooperate) or *steal* the jackpot from the other (i.e., defect). If both contestants choose to split, then each receives half of the jackpot as a prize. If one contestant chooses to split, while the other chooses to steal, then the defector walks away with the entire jackpot, and the cooperator is left with nothing. If both contestants choose to steal, then the show keeps the jackpot and the two contestants walk away with nothing.

The experiment consisted of two main parts. In part 1, participants watched short introductory videos of the contestants who would later appear in the "split-or-steal" videos that the participants

Table 1: Summary of the Experimental Procedure.

General instructions read out to all participants	
Part 1 of experiment:	Instructions for part 1
	Example: video introducing a contestant
	Example (continued): participant's evaluation of the contestant in example video
	Contestant 1: video introducing Contestant 1
	Contestant 1 (continued): participant's evaluation of Contestant 1
	...
	Contestant 12: video introducing Contestant 12
	Contestant 12 (continued): participant's evaluation of Contestant 12
Part 2 of experiment:	Instructions for part 2
	Example: video of "split-or-steal" game between two contestants
	Comprehension quiz (about how the "split-or-steal" game is played)
	Game 1: video of "split-or-steal" game between Contestant 1 & Contestant 2
	Game 1 (continued): participant's evaluation of Contestant 1
	Game 1 (continued): participant's evaluation of Contestant 2
	...
	Game 6: video of "split-or-steal" game between Contestant 11 & Contestant 12
	Game 6 (continued): participant's evaluation of Contestant 11
	Game 6 (continued): participant's evaluation of Contestant 12
Survey of participants' background: gender, level of English fluency, age	

would watch in part 2 of the experiment. Following each introductory video, participants were asked to evaluate the contestant appearing in that video in terms of 12 different characteristics. In part 2, participants watched the "split-or-steal" games played by the contestants (who were introduced in part 1 videos). Here, participants were asked to evaluate again the same contestants in terms of the same 12 characteristics but after having watched their behavior in the "split-or-steal" games. The experiment concluded with a brief survey asking participants about their gender, level of English language fluency, and age.

In the experiment, each participant was assigned 6 episodes featuring 12 contestants (2 contestants per episode's "split-or-steal" game). The assignment of 6 episodes to each participant and the order in which participants watched the 6 "split-or-steal" games was randomly determined. However, two contestants of the same "split-or-steal" game were always presented one after the other, with the alphabetical ordering of their first names determining which appeared in the first place and which in the second.

Video stimuli. In total, 166 episodes of "Golden Balls" were used in the experiment (i.e., 166 different "split-or-steal" game videos). In selecting the episodes to be used in the experiment, our approach was to apply 3 main exclusion criteria: (1) we excluded "split-or-steal" games with jackpot sizes less than £500 (we wished to focus on games with large stakes); (2) we excluded episodes which were already available on YouTube (we wished to rule out the risk of participants being already familiar with the contestants and with their behavior in the "split-or-steal" game); and (3) we excluded several special episodes that featured returning contestants, and we also excluded few regular episodes if their contestants ended up returning to participate in a special episode and if this returning episode was made available on YouTube. After applying these exclusion criteria, we were left with 167 episodes (334 contestants). Furthermore, one episode's video quality was too poor (episode 4.29). Therefore, this episode had to be excluded. Thus, the final set of video stimuli consisted of 166 "split-or-steal" games (played by $166 \times 2 = 332$ contestants) and 332 short videos introducing these contestants.

Outcome variables. The main outcome variables are participants' evaluations of contestant characteristics. We examine participants' initial evaluations elicited in part 1 of the experiment, after participants had watched brief introductory videos of the contestants, as well as their updated evaluations, elicited in part 2 of the experiment, after participants had watched the contestants' behavior in the "split-or-steal" game.

Evaluations of contestants involved rating the contestants in terms of three character dimensions, each described by a set of four characteristics: competence (*capable*, *competent*, *intelligent*, *skillful*), sociability (*sociable*, *friendly*, *extroverted*, *warm*), and moral character (*moral*, *principled*, *trustworthy*, *honest*). The 12 characteristics comprising the three character dimensions appeared in a random order and in groups of 6 characteristics per page. For each characteristic, participants responded to the question "In your opinion, how much does the contestant possess the characteristic?" on a 9-point Likert scale, with verbal anchors "not at all", "moderately", and "extremely" appearing above the points 1, 5, and 9, respectively.

Predictor variables. The main predictor variables of interest in this study are contestants' cooperative behavior (i.e., their decisions in the "split-or-steal" games) and their gender. Furthermore, we consider the role that participants' gender may play in how participants evaluate the contestants.

Figures 3 and 4 show the distributions of the initial and final evaluations of the contestants given by participants.

Figure 3: Distributions of Initial Evaluations

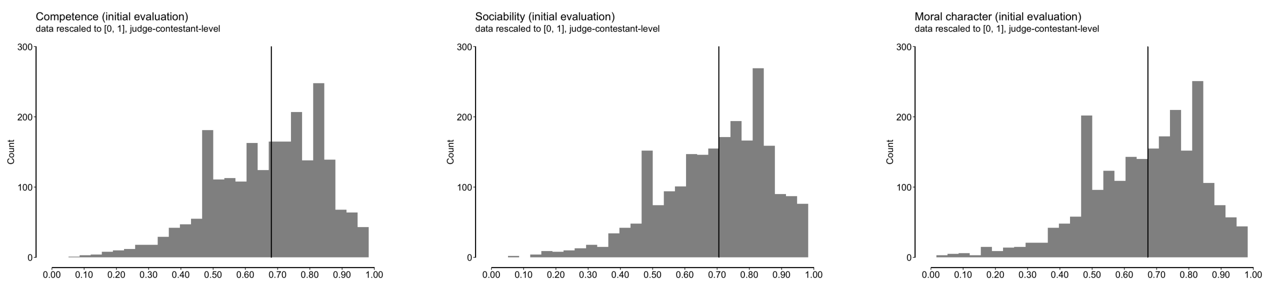
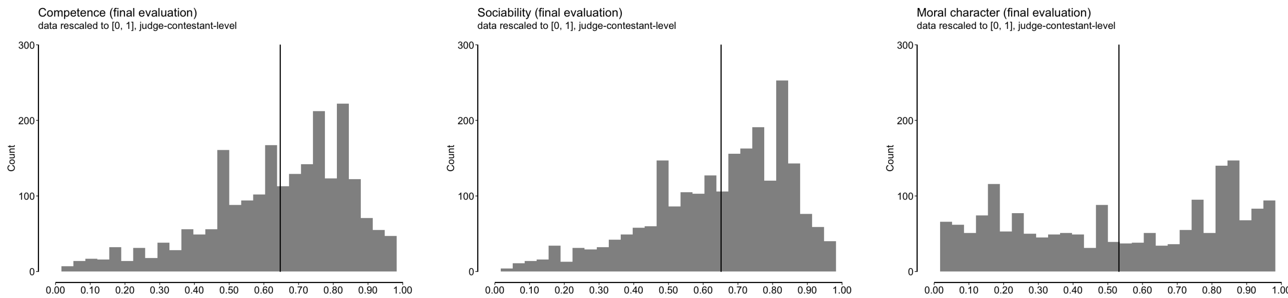


Figure 4: Distributions of Final Evaluations.



5 Estimation Results

In this section, we present the empirical estimation of the model parameters using the experimental data presented in Section 4, and applying the MMLE approach discussed in Section 5. Table 2 contains the results for the dimension *competence*. Table 3 contains the estimation results for the dimension *sociability*. Table 4 contains the estimation results for the dimension moral character. In all tables, we compare the estimates of a linear regression with parameter estimates of the two belief-updating models: the autoregressive belief-updating (ARU) model and the Bayesian belief-updating (BU) model.

Table 2 shows that participants' initial judgments of contestants' competence ($y0$) played a significant role in their final competence judgments. Furthermore, participants significantly updated their judgments in response to the contestants' observed cooperative behavior in the "split-or-steal" games.

	LR	LR Pr($>|t|$)	ARU	ARU Pr($>\chi^2$)	BU	BU Pr($>\chi^2$)
(Intercept)	0.39807	<1.0e-16	0.00073	0	–	<1.0e-16
y0	0.42668	<1.0e-16	0.36702	0	–	<1.0e-16
x_tilde	–	–	0.79557	0	–	<1.0e-16
beta_1	–	–	1.00000	0	1.80028	–
promise	−0.00552	0.649212	0.04721	0.17673	0.53138	0.128918
log_talkLength	0.01787	0.009289	0.00000	0.853051	0.53111	0.890218
steal	−0.33175	<1.0e-16	-0.27527	<1.0e-16	-0.7720	<1.0e-16
steal_gap	0.09912	<1.0e-16	0.01097	0.129587	0.01101	0.128581
male	0.00487	0.692677	0.05057	0.000290	0.41221	0.001201
edu_high	−0.00962	0.274398	0.07808	6.20e-05	0.51221	0.000112
age	0.00044	0.241666	0.00356	0.021759	0.00561	0.045819
log_stakeSize	−0.00216	0.658602	0.00258	0.350931	0.00813	0.398811
rater_male	−0.01424	0.079826	0.0347	0.000613	0.01678	0.001730
rater_nat_speak	−0.02413	0.003533	0.0000000	0.853051	0.00021	0.564486
promise.steal	−0.00449	0.788622	0.0038500	0.782946	0.02891	0.685515
steal.male	−0.03828	0.021036	-0.012070	<1.0e-16	-0.0452	<1.0e-16
steal.log_stakeSize	0.01698	0.007232	0.0000000	0.877354	0.00005	0.712558

Table 2: Parameter Estimates from Linear Regression and Beta-MLE Models for **COMPETENCE**

To summarize the main observations with regard to modeling:

	LR	LR Pr($>\|t\|$)	ARU	ARU Pr($>\chi^2$)	BU	BU Pr($>\chi^2$)
(Intercept)	0.3088	<1.0e-16	0.20355	<1.0e-16		
yy0	0.48452	<1.0e-16	0.28099	<1.0e-16		
x_tilde	0	<1.0e-16	0.85215	<1.0e-16		
beta_1	0	<1.0e-16	1	<1.0e-16		
promise	0.00251	0.814017	0.00000	1.00000		
log_talkLength	0.01813	0.002769	0.00000	1.00000		
steal	-0.21304	3.7e-05	-0.18891	<1.0e-16		
steal_gap	0.00366	0.612622	0.00000	1.00000		
male	-0.00119	0.913095	0.00000	1.00000		
edu_high	-0.00796	0.302181	0.00000	1.00000		
age	-0.00013	0.691696	0.00000	1.00000		
log_stakeSize	0.00289	0.503517	0.00000	1.00000		
rater_male	-0.00266	0.710608	0.00000	1.00000		
rater_nativeSpeaker	-0.01566	0.030086	0.00000	1.00000		
promise.steal	-0.01782	0.227034	0.00000	1.00000		
steal.male	-0.01065	0.46584	0.00000	1.00000		
steal.log_stakeSize	0.00187	0.736954	0.00000	1.00000		

Table 3: Parameter Estimates from Linear Regression and Beta-MLE Models for **SOCIABILITY**

	LR	LR Pr($>\|t\|$)	ARU	ARU Pr($>\chi^2$)	BU	BU Pr($>\chi^2$)
(Intercept)	0.39807	0	0.00073	<1.0e-16	–	–
yy0	0.42668	0	0.36702	<1.0e-16	–	–
x_tilde	0	0	0.79557	<1.0e-16	–	–
beta_1	0	0	1	<1.0e-16	1.3321	–
promise	-0.00552	0.649212	0.04721	0.176731	0.06681	0.096744
log_talkLength	0.01787	0.009289	0.00000	0.853051	0.00000	0.710225
steal	-0.33175	0	-0.27527	<1.0e-16	-0.5777	<1.0e-16
steal_gap	0.09912	0	0.01097	0.129587	0.02291	0.102881
male	0.00487	0.692677	0.05057	0.000290	0.08899	0.000546
edu_high	-0.00962	0.274398	0.07808	6.21e-05	0.07808	<1.0e-16
age	0.00044	0.241666	0.00356	0.021759	0.00489	0.085901
log_stakeSize	-0.00216	0.658602	0.00258	0.350931	0.00852	0.402851
rater_male	-0.01424	0.079826	0.034701	0.000613	0.04025	0.000258
rater_nativeSpeaker	-0.02413	0.003533	0.000000	0.853051	0.000000	0.976431
promise.steal	-0.00449	0.788622	0.003850	0.782946	0.005899	0.678946
steal.male	-0.03828	0.021036	-0.01207	<1.0e-16	-0.01863	<1.0e-16
steal.log_stakeSize	0.01698	0.007232	0.000000	0.877354	0.000000	0.785211

Table 4: Parameter Estimates from Linear Regression and Beta-MLE Models for **MORALITY**

- For both competence and sociabilitity, the models of initial judgments ($yy0$) produce similar results (tables with results not shown yet) with respect to gender: male contestants are believed to be more competent than female contestants, and female contestants are believed to be more sociable than male contestants.

- Differences emerge for models of posterior beliefs. The belief-updating model with non-linear signal aggregation is able to better identify the gender effects in updating. Moreover, the belief-updating model can be shown to fit the data better, both in sample (controlling for total number of regressors) and in particular out-of-sample.
- New research dimension to paper: Studying updating of social judgments. In particular, we can explore (I) Bayesian vs. non-Bayesian updating, and (II) linear aggregation of signals vs. non-linear aggregation of signals.
- New empirical effects detected under the belief-updating model: Male contestants who split are believed to be more competent than female contestants who split. Male contestants who steal, however, are believed to be less competent than female contestants who steal (though to a smaller extent). One storyline consistent with this result is that male actions are viewed more through the "competence"-lens, so that updating along this dimension is stronger for males than for females.
- For sociability, we would have then observed the reverse trend: female contestants' sociability being updated more strongly (positively for splitting, and negatively for stealing). But that's not what we observe. Male splitters are rated slightly better in terms of sociability compared to how women splitters are judged. Stealing is punished through negative updating of sociability judgments, but no gender effect is detected there.

6 Conclusions

References

Campos-Mercade, P., and F. Mengel. 2024. Non-Bayesian statistical discrimination. *Management Science* 70 (4): 2549–2567.

Moss-Racusin, C. A., J. F. Dovidio, V. L. Brescoll, M. J. Graham, and J. Handelsman. 2012. Science faculty's subtle gender biases favor male students. *Proceedings of the national academy of sciences* 109 (41): 16474–16479.

Phelps, E. S. 1972. The Statistical Theory of Racism and Sexism. *American Economic Review* 62 (4): 659–661.

Online Appendix 1: Experimental Procedure

The experiment began with the experimenters reading out to all participants a list of general instructions (Figure 5). In particular, participants were informed that during the experiment they would watch short videos and would be asked to evaluate the people appearing in those videos. No further information about the content of the videos was given at this stage. Next, after participants' informed consent forms have been collected, the experiment commenced. Participants were individually seated in partially isolated cubicles, wore noise-canceling headphones, and progressed through the computerized experiment at own speeds.

Figure 5: General instructions read out to all participants at the start of the experiment.

Thank you everyone for agreeing to participate. We would like to explain the general rules, so please listen carefully.

This study will last about 1 hour 15 minutes. At the end of the study, we will pay each of you 15 GBP for your participation.

We want to point out some important information:

1. **During this study, you will watch short videos and you will be asked to evaluate the people that appear in those videos.** What these videos are about, and how you evaluate the people in them — all this will become clear to you after you start the study.
2. **The quality of our data really depends on your careful and thoughtful participation. So please read all instructions, and give your evaluations carefully and thoughtfully.**
3. Some of the videos and photos may take a few seconds to load. Please give the computer some time if that happens. **Do not at any point during the study use the "back" button or the "refresh" button.** Pressing on back or refresh will interrupt the flow of the study, and will prevent you from completing and getting paid.
4. **If the loading is taking too long (longer than a minute), then please raise your hand**, and one of us will come and see.
5. Finally, **please refrain from using your mobile phones or opening other browsers or any other programs on the computer**.
6. If you have any questions or concerns at any point during the study, just raise your hand and one of us will come by.

We are now going to walk around and collect your consent forms. Then we will assign each of you an ID number. You can then put on your headphones and begin the study by entering the ID number that you've been given.

Participants watched videos taken from the British TV game show "Golden Balls", which was originally aired in 2007–2009. In total, 166 episodes of the game show were used in the experiment. The main video stimuli concerned the final round of each episode, where two contestants play a game called “split-or-steal”, which is a cooperation game similar to the Prisoner’s dilemma. The two contestants left in the final round of each episode have a common jackpot (typically a considerable sum, amounting to several thousand British pounds), and they must decide simultaneously whether they wish to *split* the jackpot with the other (i.e., cooperate) or *steal* the jackpot from the other (i.e., defect). If both contestants choose to split, then each receives half of the jackpot as a prize. If one contestant chooses to split, while the other chooses to steal, then the defector walks away with the entire jackpot, and the cooperator is left with nothing. If both contestants choose to steal, then the show keeps the jackpot and the two contestants walk away with nothing.

In the experiment, each participant was assigned 6 episodes featuring 12 contestants (2 contestants per episode’s “split-or-steal” game). The assignment of episodes to participants was randomized, subject to two constraints: (1) an episode was not assigned more than once to a participant; and (2) each episode was assigned to at least four different participants. The experiment consisted of two main parts. In part 1, participants watched 12 short videos introducing the 12 contestants (who would appear in the 6 “split-or-steal” videos that participants would later watch in part 2 of the experiment). Then, in part 2, participants watched the 6 “split-or-steal” games played by the 12 contestants (who were introduced in part 1 videos). The order in which participants viewed the 6 “split-or-steal” games was randomly determined. However, the order in which the 12 contestants’ introductory videos were presented in part 1 of the experiment matched the randomly determined order of the “split-or-steal” games in which the contestants appeared. Thus, for example, the two contestants playing the 1st “split-or-steal” game were introduced as contestant 1 and contestant 2, and the two contestants playing the 6th “split-or-steal” game were introduced as contestant 11 and contestant 12. Within an episode, the alphabetical ordering of the two contestants’ first names determined which appeared in the first place and which in the second place.

Part 1 began with a general instruction page common for all participants (Figure 6a), which informed the participants that they would be watching 12 short videos taken from the TV game show “Golden Balls”, that each video would be showing a contestant who introduces themselves, and that following each video the participants would be asked to evaluate the contestant appearing in the video. Then participants watched an example introductory video of a contestant (Figure 6b). Two episodes were selected to be used for the example videos, one of which was randomly assigned to each participant. The introductory video of one of the two contestants featuring in the example episode assigned to a participant was then used as the example introductory video shown to this participant.

The example episodes were taken from the set of the excluded episodes so as not to reduce the number of the included episodes. Furthermore, the example episodes were selected such that (1) in order to show both the possibility of contestants choosing to steal and of choosing to split, each example episode featured one contestant choosing to split the jackpot while the other contestant choosing to steal; and (2) in order to avoid influencing participants’ expectations about contestant gender and contestant tendency to choose stealing or splitting, one example episode featured two male contestants

Figure 6: Part 1 instructions.

(a) General instructions for part 1.

In the first part of the study, you will watch 12 short videos. The videos are from the TV game show *Golden Balls*, which was aired in 2007-2009. Each video shows a contestant who introduces themselves.

Following each video, there will be two pages that ask you to evaluate the contestant on 12 different characteristics (six characteristics per page).

There are no right or wrong evaluations. We are interested in your **personal** opinion only.

Next

(b) Example video for part 1.

You will first be shown an example video. Following this video, you will be asked to evaluate the example contestant, so that you can become familiar with the evaluation process. If you want, you can always rewatch the video at the bottom of the evaluation screens.

Proceed to the next page to watch the example video. The video will play automatically.

Next

(with one contestant splitting and the other stealing), and the second example episode featured two female contestants (also, with one of the two splitting while the other stealing).

Following the example introductory video, participants were asked to evaluate the contestant appearing in the example video, in order for participants to become familiar with the questions asked in the experiment (Figure 7). The evaluation of a contestant involved rating the contestant in terms of 12 different characteristics (*capable*, *competent*, *intelligent*, *skillful*, *sociable*, *friendly*, *extroverted*, *warm*, *moral*, *principled*, *trustworthy*, and *honest*), appearing in a random order and in groups of 6 characteristics per page. Figure 7 shows the example evaluation page with the first 6 characteristics. The second, otherwise identical, page asked participants to evaluate the contestant on the remaining 6 characteristics.

After having watched the example contestant's introductory video and having given their evaluation of the example contestant, participants proceeded to completing part 1 of the experiment. Participants watched 12 videos introducing 12 different contestants (with the videos appearing in the above-explained order). Following each introductory video, participants evaluated the contestant appearing in that video in terms of the 12 characteristics (as illustrated in the example evaluation).

Part 2 of the experiment began with a general instruction page (Figure 8) common for all participants. It informed the participants that they would watch 6 videos, that each video would feature two of the previously introduced 12 contestants playing a game called "split-or-steal", and that, following each video, they would be asked to evaluate the two contestants once more. Furthermore, the instructions page explained how the "split-or-steal" game was played, how large the jackpot size on average was, and the fact that approximately half of the people choose to split and half choose to steal.

Participants then proceeded to watch the "split-or-steal" game taken from the example episode. In order to ensure that participants understood the game being played, the example video was followed by a comprehension quiz. When participants passed the comprehension quiz, they could proceed to completing part 2 of the experiment. Participants watched 6 "split-or-steal" game videos (appearing in the above-explained order) and, following each video, evaluated the two contestants appearing in that video. The evaluation pages in part 2 of the experiment were identical to the evaluation pages of part 1, except for the additional icon indicating a contestant's decision in the "split-or-steal" game now appearing at the bottom left corner of the contestant's photo. For example, Figure 9 shows an evaluation page for a contestant who chose to split the jackpot in the "split-or-steal" game, and Figure 10 shows an evaluation page for a contestant who chose to steal the jackpot.

Finally, the experiment thanked participants for giving their evaluations and concluded with few questions about the participants' background, including gender identification, self-assessed level of English language skills, and year of birth, as well as an optional, open-ended possibility of commenting on their opinion about the experiment.

Figure 7: Evaluation of the example contestant.

This is an example.

In your opinion, how much does this contestant possess each of the characteristics below? (Page 1/2)

	Not at all			Moderately			Extremely		
	1	2	3	4	5	6	7	8	9
Skillful	○	○	○	○	○	○	○	○	○
Friendly	○	○	○	○	○	○	○	○	○
Capable	○	○	○	○	○	○	○	○	○
Moral	○	○	○	○	○	○	○	○	○
Principled	○	○	○	○	○	○	○	○	○
Extroverted	○	○	○	○	○	○	○	○	○

Figure 8: Part 2 instructions.

Thank you for evaluating the 12 contestants. You will now proceed to the second part of the study.

In the second part, you will watch six videos. In each of these videos, two of the previous 12 contestants play a game that is called *Split or Steal*. After each video, you will be asked to evaluate the two contestants once more.

The game features a jackpot. The size of the jackpot varies across videos.

Each contestant receives two golden balls. One ball says *split* and the other ball says *steal* on the inside. The contestants have to simultaneously choose the ball they want to play. The jackpot is awarded as follows:

- If both choose *split*, they share the jackpot equally.
- If one chooses *split* and the other chooses *steal*, the contestant who steals takes the whole jackpot and the other gets nothing.
- If both choose *steal*, both get nothing.

Before the two contestants choose between *split* and *steal*, they briefly chat with each other. During this chat, they usually reassure each other that they intend to split, and try to learn the other's intentions. Occasionally, they refer to things that happened earlier in the show. Do not worry if you do not fully understand the meaning of those references.

Hundreds of people have played this game on TV. The average jackpot size was £13,000. Approximately half of the people choose *split* and half choose *steal*. On the next page, you will see an example video, followed by a comprehension quiz.

Make sure that you have read the above explanation carefully. If you are ready, you can proceed to the next page to watch the example video and then answer the comprehension questions. The video will play automatically.

Next

Figure 9: Evaluation page of a contestant who chose “split”.

In your opinion, how much does Contestant 2 (shown in the above picture) possess each of the characteristics below? (Page 2/2)

	Not at all				Moderately				Extremely
	1	2	3	4	5	6	7	8	9
Principled	○	○	○	○	○	○	○	○	○
Trustworthy	○	○	○	○	○	○	○	○	○
Capable	○	○	○	○	○	○	○	○	○
Sociable	○	○	○	○	○	○	○	○	○
Honest	○	○	○	○	○	○	○	○	○
Skillful	○	○	○	○	○	○	○	○	○

Next

Figure 10: Evaluation page of a contestant who chose “steal”.

In your opinion, how much does Contestant 10 (shown in the above picture) possess each of the characteristics below? (Page 1/2)

	Not at all				Moderately				Extremely
	1	2	3	4	5	6	7	8	9
Honest	○	○	○	○	○	○	○	○	○
Sociable	○	○	○	○	○	○	○	○	○
Warm	○	○	○	○	○	○	○	○	○
Capable	○	○	○	○	○	○	○	○	○
Trustworthy	○	○	○	○	○	○	○	○	○
Intelligent	○	○	○	○	○	○	○	○	○

Next