

# Learning with Misspecified Models: The Case of Overestimation

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## **Abstract**

I design a laboratory experiment that allow for the comparison of multiple theories of misspecified learning. I focus on a framework in which agents learn from a single signal that is informative about their type as well as a state. Within this setup I study three forces that can lead to the persistence misspecified beliefs in the long run: incorrect initial beliefs, learning traps and biased updating. I find that biased updating is the main driver of misspecified beliefs in the lab. In addition, I vary the degree of ego-relevance the parameters by introducing an additional treatment where subjects learn about someone else's type instead of their own. The data is consistent with biased updating in both cases but for potentially different reasons: when learning about themselves, subjects attribute successes to their own ability and failures to luck. Instead, when learning about others, they compensate for initial negative biases by over-attributing positive signals to their ability. This translates into similar observed choices but different dynamics in beliefs. My results help rationalize the prevalence of overestimation of parameters as well as the prevalence of stereotypes.

# 1 Introduction

A growing body of literature in economics explores how people develop incorrect beliefs about fundamentals. Most of this research centers on scenarios where agents passively observe the world, and incorrectly integrate the received information into their beliefs.<sup>1</sup> However, many real-world situations cast agents as active participants in the generation of information. In these cases, the information they observe is influenced by their actions and subsequent behavior is in turn determined by how they incorporate the information into their beliefs.

As an example, consider a student who needs to decide how much effort to put into studying for an exam. Their decision will depend on two factors: their belief about their intrinsic ability and their belief about how difficult the exam will be. The outcome they observe will be affected by how much they decide to study. Imagine that the student exerts a moderate amount of effort and gets a surprisingly good grade. Did they get a good grade because they are smarter than they thought? Or because the exam was easier than they had anticipated? Their future exam-preparation strategy will depend fundamentally on which line of reasoning they take. This feedback loop is referred to as an *endogenous information process* and is at the center of the forces I study.

To understand what main forces are at play, I compare a set of theories that model learning in settings with endogenous information and can rationalize the persistence of misspecified beliefs. I develop a unifying framework that nests multiple theories of learning and generates testable predictions for each of them. Then, I cast this framework in a laboratory experiment and test the predictions to identify which of the theories are consistent with the behavior I observe in the lab. The experiment features an agent who needs to learn two parameters: one that pertains to their own characteristics (an *ego-relevant* parameter), and an exogenously determined state. In the context of the student preparing for exams, the two parameters would be their intrinsic ability and the difficulty of the exam.

Misspecified beliefs about an ego-relevant parameter are often referred to as over-

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<sup>1</sup>See Benjamin [2019] for a review of the literature on errors of probabilistic thinking.

confidence (or underconfidence) and have been documented by behavioral scientists<sup>2</sup> and economists<sup>3</sup> in a variety of settings. [Oster et al. \[2013\]](#) find subjects who are at high risk of having Huntington’s disease overestimate their probability of being healthy, and they make retirement decisions as if they were healthy. [Hoffman and Burks \[2020\]](#) show workers overestimate the quality of their match to their current employment and are unlikely to look for other opportunities. [Camerer and Lovo \[1999\]](#) find entrepreneurs are overconfident about the quality of their enterprise, which leads to excessive entry and early exit from markets.

In all of these examples, holding an incorrect belief about a fundamental leads to sub-optimal choices with potentially high costs. In spite of the abundance of evidence, the scope of the existing research is limited in terms of the frameworks it considers. Most of the experimental evidence documenting the bias is collected in settings where subjects are passive learners.<sup>4</sup> They observe a noisy signal and report their beliefs over subsequent rounds.<sup>5</sup> Although these studies provide important insights, they are not flexible enough to incorporate the richer theories that have been proposed more recently. In particular, they do not allow the study of endogenous learning or for learning about multiple parameters at once.<sup>6</sup>

In my experiment, I move away from the standard framework of passive learning to analyze a richer set of learning mechanisms. In particular, the interaction between the two parameters together with an endogenous information process gives rise to three possible mechanisms that allow for the persistence of incorrect beliefs: the presence of learning traps, incorrect initial beliefs, and misattribution bias. The theories that I consider incorporate different combinations of these mechanisms.

When the setting features learning traps, even an agent who incorporates all information correctly may fall into learning traps, as outlined by [Hestermann and Yaouanq \[2021\]](#). These

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<sup>2</sup>[Kelley and Michela \[1980\]](#) provides a review of the psychology literature.

<sup>3</sup>See [Benjamin \[2019\]](#) and [Moore and Healy \[2008\]](#) for a review of the literature in economics.

<sup>4</sup>[Götte and Kozakiewicz \[2022\]](#) and [Ozyilmaz \[2022\]](#) are exceptions that study settings with endogenous information processes.

<sup>5</sup>[Bracha and Brown \[2012\]](#) and [Möbius et al. \[2022\]](#) are some examples.

<sup>6</sup>[Coutts et al. \[2020\]](#) studies an environment with an ego-relevant parameter and an exogenous state but does not incorporate the endogenous information process.

traps are characterized by a combination of an incorrect belief and an optimal action that produce information that confirms the incorrect belief. Once an agent falls into a trap, the belief will be stable and even with a correctly specified model of learning, they will not be able to abandon their misspecified beliefs. If the agent is dogmatic about their initial belief, [Heidhues et al. \[2018\]](#) show they will inevitably fall into a trap and thus will be able to rationalize and sustain their initial misspecification belief.<sup>7</sup>

[Ba \[2023\]](#) moves away from dogmatism and endows the agents with a mechanism through which they can abandon incorrect beliefs. This allows them to avoid falling into learning traps. To do so, agents perform Bayesian hypothesis tests that evaluate which of two possible parameters is more likely. By doing so, she characterizes the set of situations in which even agents who consider alternative paradigms may become trapped.<sup>8</sup> A more general model in this spirit is also illustrated by [Ortoleva \[2012\]](#), where the agent has a prior over priors and acts according to the most likely belief.

Lastly, misattribution bias is the more classical explanation and has been widely studied in behavioral science.<sup>9</sup> Agents who suffer from misattribution bias will attribute successes to their own ability—the ego-relevant parameter—and their failures to bad luck—the state. Under this model of learning, even an agent who initially has a correct initial belief may become overconfident if they observe a sequence of successes. In this case, the main driver of the bias is not an initial misspecification or the presence of learning traps; it is the updating procedure itself.<sup>10</sup>

These theories provide the main building blocks for a simplified framework that can be directly implemented in a laboratory experiment. In the experiment subjects make choices and receive feedback that depends on their own ability, an exogenous parameter and the choice they made. I track their choices as well as their beliefs about their own ability. The

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<sup>7</sup>[Götte and Kozakiewicz \[2022\]](#) study the case of agents with dogmatic initial beliefs in a laboratory experiment.

<sup>8</sup>A similar mechanism is proposed by [Schwartzstein and Sunderam \[2021\]](#) in a setting with persuasion.

<sup>9</sup>See [Kelley and Michela \[1980\]](#) for a review.

<sup>10</sup>A more general framework that can be used to model this bias has also been proposed by [Brunnermeier and Parker \[2005\]](#) and empirically studied by [Bracha and Brown \[2012\]](#).

goal is to identify which of the three forces—the presence of learning traps, misspecified initial beliefs, or misattribution bias—better explains the observed behavior. To determine the fit of the models, I compare the behavior predicted by each theory with the benchmark given by the fully-Bayesian updating procedure.

I also study whether the learning mechanism is inherently linked to the ego-relevance of the parameters or if it is a more general phenomenon. I vary the degree of ego-relevance by introducing a treatment in which subjects learn about the ability of another participant. In this treatment, the participants know only the gender and nationality of the other, and thus can induce stereotypes—a different type of misspecification. If correct learning about the parameters happens at higher rates in the stereotype treatment, this finding would suggest the bias is intrinsically linked to the ego-relevance of the parameter. By contrast, if similar biased behavior arises in both treatments, the main driver of these types of misspecified beliefs is more likely to be the updating procedure itself or the endogenous information process.

Although some agents do fall into learning traps, I find the behavior of most subjects is better explained by misattribution bias: good news are treated as signaling high ability, whereas bad news are attributed to a low state. I also find misattribution is no more prevalent in the ego-relevant than in the stereotype condition. This finding suggests the main driver of the misspecification is the updating procedure; however, the underlying mechanism by which the bias is generated may be different in both treatments. Whereas subjects in the ego-relevant condition prefer to hold themselves in high esteem, in the stereotype condition, updating seems to be driven by some sort of bias overcorrection—when subjects realize they underestimated the ability of another participant based on their gender and nationality, they compensate by overestimating their ability.

Finally, I estimate the structural parameters of the models to study model-heterogeneity in the sample. I find that even at an individual level, the behavior is better explained by an average model of misattribution bias for most subjects. A smaller group of subjects exists that can be better explained through dogmatic beliefs and hypothesis testing, and very few

of them behave in line with the fully Bayesian benchmark.

In what follows, I first discuss the theoretical framework and the predictions of each of the theories. Then, I introduce a unifying example and my hypotheses. In section 4, I describe the experimental design, and in section 5, I present the data and the results. Section 6 outlines the estimation of the parameters and the model fit analysis.

## 2 Theoretical Framework

The theories I consider make predictions in two distinct frameworks. I first detail each theory within their original framework and then develop a unifying example that allows me to compare the predictions of all of them. In framework 1, I consider a setting in which an agent observes a continuous output and infers the underlying parameters. In framework 2, the agent observes a binary outcome and infers the underlying probability of success, which is related to the parameters.

Although agents observe information and update their beliefs in both frameworks, the type of information available is very different in each of them. This means that the updating procedures are also different across frameworks. As a result, comparing the predictions of theories within a framework is easy, but comparing across frameworks is not straightforward. I will first describe each theory within its original framework and compare it to others in the same framework. In the following section I illustrate how it is possible to compare across frameworks within the unifying example.

### 2.1 Framework 1

An agent of type  $\theta \in \Theta$  faces an unknown exogenous state  $\omega$  drawn from density  $f$  over  $\Omega$ . The agent knows the distribution of  $\omega$  but not its realized value. His belief about the state  $\omega \in \Omega$  is  $p_0(\omega)$  and coincides with the true distribution,  $f$ . His belief about the type  $\theta \in \Theta$  is  $p_0(\theta)$ . Let the agent's true type be  $\theta^*$ , and the realized state be  $\omega^*$ .

An agent's belief about the type is *misspecified* if it assigns probability zero to their true type. Furthermore, the agent is *dogmatic* if he holds a degenerate belief that places probability one on being of type  $\hat{\theta}$ . An agent can be dogmatic and misspecified, in which case  $\hat{\theta} \neq \theta^*$  and  $p_0(\hat{\theta}) = 1$ .

The agent chooses an action  $a \in A$  and observes a noisy outcome  $h$ . The outcome is a function of the agent's type, the state, and the action. In particular,  $h = h(\theta^*, \omega^*, a) + \varepsilon$  with  $h(\cdot)$  increasing in both  $\theta^*$  and  $\omega^*$ , and such that conditional on a pair of parameters  $(\theta, \omega)$ , there is a unique optimal action. Additionally,  $\varepsilon \sim N(0, \sigma)$  is noise in the outcome.

After observing the outcome, the agent updates his beliefs about  $\theta$  and  $\omega$  using some algorithm and moves on to the next period. He repeats this process infinitely many times. I make the simplifying assumption that the agent is myopic and chooses the action that maximizes the payoff in each period. This assumption simplifies the analysis and plays a role in whether an agent who updates his beliefs using Bayes rule would learn the truth or not, however, for the main theory discussed in this section, the results hold even when relaxing this assumption as shown in [Heidhues et al. \[2018\]](#).

A key notion in this setting is that of a self-defeating equilibrium<sup>11</sup>. A *self-defeating equilibrium* is a belief and action pair,  $(p, a^*)$ , such that the agent's belief about his type is misspecified, and the outcome generated by the action is consistent with the misspecified belief. The agent's belief is said to be *stable* when this happens.

Given the choice that sustains the self-defeating equilibrium, they observe the *average output* given by

$$\bar{h}(a^*) = \frac{1}{T} \sum_t [h(\hat{\theta}, \hat{\omega}, a^*) + \varepsilon_t]$$

where  $\hat{\theta}$  and  $\hat{\omega}$  is the type-state pair on which the misspecified belief places all probability. That is, the agents belief is  $p(\hat{\theta}, \hat{\omega}) = 1$  and  $p(\theta, \omega) = 0$  for all other values of the parameter.

Within this framework, I consider two nested theories of belief updating: the first one

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<sup>11</sup>This notion is an adaptation of the Berk-Nash equilibrium in [Esponda and Pouzo \[2016\]](#) to this setting with only one agent

is a dogmatic modeler adapted from [Heidhues et al. \[2018\]](#). The second one is a switcher, as in [Ba \[2023\]](#). The dogmatic modeler can be seen as a switcher with an infinitely sticky initial belief so the two theories are nested. However, outside of the limiting case, they produce different predictions about the agent’s behavior. I discuss each of them separately in what follows.

### 2.1.1 The Dogmatic Modeler

Take the action space to be the same as the state space  $\Omega$  and let  $\Omega = A := [\underline{a}, \infty)$ .

A dogmatic agent is characterized by a learning model where he does not update his beliefs about  $\theta$  and instead, holds a degenerate belief that places all probability on  $\hat{\theta}$ , which is potentially misspecified. In this case, no matter how much evidence he gathers against being of type  $\hat{\theta}$ , he will not update the beliefs about his type. Any discrepancies between the observed outcomes and his believed type are incorporated using the Bayes rule to update his beliefs about  $\omega$ . [Heidhues et al. \[2018\]](#) show that, under certain assumptions on the per-period utility,<sup>12</sup> a dogmatic modeler will inevitably fall into a self-defeating equilibrium. The equilibrium will be such that the outcomes he observes reinforce his belief on  $\omega$  in such a way that as  $t \rightarrow \infty$  the agent will be sure that the state is some  $\omega'$  consistent with their believed type and the observed data. In other words, he will be in a self-defeating equilibrium with a stable belief that places probability one on the incorrect parameters  $(\hat{\theta}, \omega_\infty)$

The mechanism by which the dogmatic agent falls into the self-defeating equilibrium is the following: suppose the agent holds the dogmatic and misspecified belief that they are type  $\hat{\theta} > \theta^*$ . For any prior over  $\omega$ , the agent will be disappointed by the outcome. That is:

$$\frac{1}{T} \sum_t [h(\theta^*, \omega^*, a_t^*) + \varepsilon_t] < \mathbb{E}_{\approx} [h(\hat{\theta}, \omega, a_t^*)]$$

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<sup>12</sup>The assumptions are that  $u$  is twice continuously differentiable with: (i)  $u_{aa} < 0$  and  $u_a(\underline{a}, \theta, \omega) > 0 > u_a(\bar{a}, \theta, \omega)$ , (ii)  $u_\theta, u_\omega > 0$  and (iii)  $u_{a\theta} < 0$  and  $u_{a\omega} > 0$ . Where  $\underline{a}$  is the minimal action and  $\bar{a}$  is the maximal one. The direction of the derivatives is a normalization and the results would hold even when the signs are reversed.



where the right-hand-side of the inequality represents the average outcome that the agent expected given his beliefs about their type and the state. The left hand side is what they observed.

There are two possible sources for the disappointment: the first is that the realized state  $\omega^*$  is lower than what the agent expected,  $\mathbb{E}[\omega]$ ; the second source is that the agent is of type  $\theta^*$  and therefore, for all possible states, his gain will be lower than what he expected when the variance of the error term is low or  $T$  is large. That is, when  $\frac{1}{T} \sum_t \varepsilon_t$  is close to zero.

Because the agent is dogmatic, he will not update his beliefs about  $\theta$  and, as a consequence, will attribute the disappointment to the state being lower than expected. He will continue to update in this way until he converges to a belief about  $\omega$  that is stable. Such a belief will explain the observed utility perfectly and allow the agent to rationalize his dogmatic belief about  $\theta$ . Under the assumptions of [Heidhues et al. \[2018\]](#), there is a unique value of  $\omega$  at which the belief is stable, I will refer to such value as  $\omega_\infty$ . This mechanism is illustrated in Example 1.

**Example 1:** Set  $A = \Omega = [\underline{a}, \infty)$  and consider a student (she) with intrinsic ability  $\theta^* \geq 0$  who faces a grading procedure  $\omega^*$  that is unknown to her. The student knows that a higher  $\omega^*$  is more likely to yield a higher grade. In particular, she knows the grade is given by  $(\theta^* + a)\omega^*$ .

The student must choose an effort level  $a$ , which determines her grade. For whatever the chosen effort level, the student must pay a cost  $c(a) = \frac{1}{2}a^2$ . She repeats this process for infinitely many periods. Assume also that the student's prior is such that  $\mathbb{E}[\omega] = \omega^*$  and she is dogmatic about being of type  $\hat{\theta} > \theta^*$ .<sup>13</sup> Therefore, the student's payoff in period  $t$  is given by

$$u_t(a_t; \theta^*, \omega^*) = (\theta^* + a_t)\omega^* - \frac{1}{2}a_t^2 + \varepsilon_t \quad (1)$$

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<sup>13</sup>The example is illustrated for an overconfident student but the results are symmetric for a dogmatic student who initially places probability one on some  $\tilde{\theta} < \theta^*$ .

*Under this specification, the myopic optimal effort level is  $a_t^* = \omega^*$ . Because the student does not know  $\omega^*$ , she will choose  $a_t = \mathbb{E}_t(\omega)$  where the expectation is taken with respect to the student's belief at the beginning of period  $t$ . If she does not revise his effort choice for  $k$  periods, she will receive an average utility of  $(\theta^* + a_t^*)\omega^* - \frac{1}{2}a_t^{*2}$  but was expecting an average utility of  $(\hat{\theta} + a_t^*)\omega^* - \frac{1}{2}a_t^{*2}$ . In response, she will apply Bayes rule to update his beliefs about  $\omega$  to get the posterior belief with  $\mathbb{E}_{t+k}[\omega] = \frac{(\theta^* + \omega^*)\omega^*}{\hat{\theta} + \omega^*}$  which is lower than the initial belief. This will cause the student to choose a lower effort at  $t + k$ . As a result, she will again receive an average utility that is lower than what he expected which will cause her belief to drift further down. This process will continue until the average utility equals her expected utility under the dogmatic belief that assigns probability 1 to  $\hat{\theta}$ . At that point, the student will have reached a self-defeating equilibrium and she will continue to choose sub-optimal effort forever.*

Although the model of a dogmatic modeler rationalizes the prevalence of overconfident (underconfident) beliefs, the assumption that the agent has a degenerate belief and no mechanism through which he can update such belief is very restrictive. An alternative approach is proposed by Ba [2023]. She proposes an extension of the dogmatic agent who is able to switch from one dogmatic belief to another. By doing so, the agent can avoid the self-defeating equilibria and end up being dogmatic and correctly specified.

### 2.1.2 The Switcher

An agent is a *switcher* if they behave as a dogmatic, but are willing to entertain the possibility that they are of a different type. In particular, when they start off as a misspecified dogmatic, they are willing to switch to a different dogmatic belief if the data is convincing enough. Their prior is still degenerate and assigns probability one to a particular type, and zero to all other types. This means that a Bayesian update on  $\theta$  does not change their beliefs about the type. However, they are willing to entertain two such beliefs and have a mechanism by which they decide which belief to adopt at any period  $t$ .

In order to abandon their initial dogmatic belief, the agent needs to observe a sequence

of outcomes that are sufficiently unlikely to have happened if they were of the type they initially believed. In order to evaluate if the evidence is convincing enough, they keep track of the likelihood that each of the possible types generated the data. If the likelihood ratio is sufficiently large, the agent will switch to the alternative and behave as if they are dogmatic about the new type.

In particular, for an agent that starts with a dogmatic belief that they are of type  $\hat{\theta}$  but is willing to consider the alternative explanation that they are of type  $\tilde{\theta}$ , the agent will switch to the alternative if

$$\frac{p[h^t|\tilde{\theta}]}{p[h^t|\hat{\theta}]} > \alpha \geq 1$$

where  $h^t$  is the history of outcomes up to time  $t$  and  $\alpha$  is the switching threshold.<sup>14</sup> By keeping track of the likelihood ratio, the agent can perform a *Bayesian hypothesis test* and adopt the Dogmatic belief that best fits the data.<sup>15</sup>

By allowing the agent to keep track of the likelihoods and switching to an alternative type, the switcher can avoid the self-confirming equilibria. However, if the prior belief on  $\omega$  is sufficiently tight around a self-defeating equilibrium, the switcher might look identical to the dogmatic even in a case where  $\alpha$  is not too large. This happens because under the agent's prior, the likelihood ratio is unlikely to grow as fast as it is needed to escape the self-defeating equilibrium. In such situations, we say that the misspecified belief about  $\theta$  is *persistent*.

A more general model that can be considered here is that of [Ortoleva \[2012\]](#). In his model agents have a prior over priors and choose a single prior to act according to. If this prior over priors only considers degenerate beliefs, the model will essentially reduce to the setting described here. The main difference is that in order to determine if there is a paradigm shift,

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<sup>14</sup>Notice that if  $\alpha \rightarrow \infty$ , the behavior of the switcher will be indistinguishable from that of the Dogmatic modeler. In this sense, the switcher is a generalization of the dogmatic type.

<sup>15</sup>In a related problem [Schwartzstein and Sunderam \[2021\]](#) proposes a similar updating procedure which relies on the Bayesian hypothesis test. However, in their model there is a sender who optimally chooses to propose a model that fits the data

the agent does not compare the likelihoods of two models, he simply looks at the likelihood of the current model and decides to switch paradigms if the likelihood is below a certain threshold. In this model the agent thus considers all possible theories and has a more flexible rule for that allows for paradigm shifts.

## 2.2 Framework 2

As in framework 1, the agent is of some type  $\theta^* \in \Theta$  and the state is  $\omega$  is distributed according to  $F(\Omega)$ . In this case, the agent chooses an action  $a \in A$  and observes a binary outcome that is either a success or a failure. Denote the outcome by  $o \in \{s, f\}$ . The probability of observing a success is increasing in  $\theta$  and in  $\omega$ . Whenever the agent observes a success, he gets a payoff  $v > 0$  and whenever the outcome is a failure, the payoff is 0. In addition, the probability of success is such that for each state, there is a unique optimal action that maximizes the agent's expected payoff. Therefore, the probability of success can be seen as an order-preserving transformation of the utility from Framework 1.

I focus on two nested theories that have been widely studied within this framework: full Bayesian updating and self-serving attribution bias. I explain each of these classical models of belief updating in what follows.

### 2.2.1 The Bayesian

A Bayesian agent simultaneously updates their beliefs about  $\theta$  and  $\omega$  by using Bayes' rule. The posterior at period  $t + 1$  about  $\theta$  after observing outcome  $o$  is given by:

$$p_{t+1}(\theta, \omega | h^t) = \frac{p[o|\theta, \omega]p_t(\theta, \omega)}{\sum_{(\theta', \omega')} p[o|\theta', \omega']p_t(\theta', \omega')}$$

where  $p_t$  is the belief at the start of period  $t + 1$  and includes all the information gathered so far.

Bayesian agents choose the effort level that maximizes their expected flow payoff by

taking expectations over  $(\theta, \omega)$  using their beliefs at period  $t$ . Since agents are myopic, there will be instances in which the Bayesian will not learn even with infinite amounts of data. This happens because myopic agents do not internalize the trade-off between flow payoff and learning. This can result in too little experimentation to learn their true type. An approach in which agents intentionally introduce variation in their choices is given by [Hestermann and Yaouanq \[2021\]](#) and is discussed in the concluding remarks. Regardless, this approach is useful as a benchmark for the other theories discussed in this paper.

Notice that if a fully Bayesian agent has a dogmatic prior, they will never update their beliefs about the parameter that they are dogmatic about. This will imply that they are prone to the same types of errors as the dogmatic modeler in framework 1.

### 2.2.2 The Self-Serving Updater

A Self-Serving Bayesian is an agent who uses a biased version of Bayes rule to update his beliefs. He will update his beliefs about the state  $\omega$  and his type  $\theta$  simultaneously by over-attributing successes to a high value of  $\theta$  and under-estimating the role of higher  $\omega$ . Similarly, he will attribute failure to a low state to a greater degree than an unbiased agent would. For instance, if the student from the example attributed a high grade to being of high ability while attributing low grades to a harsh grading system. This sort of biased updating is referred to as *misattribution bias*.

To model the misattribution bias, I take the approach of [Benjamin \[2019\]](#), where the posterior odds are given by:

$$p_{t+1}(\theta, \omega | h^t) = \frac{p[h^t | \theta, \omega]^{c(\theta, \omega, o_t)} p_t(\theta, \omega)}{\sum_{(\theta', \omega')} p[h^t | \theta', \omega']^{c(\theta', \omega', o_t)} p_t(\theta', \omega')}$$

with  $c(\theta, \omega, o)$  decreasing in  $\theta$  and increasing in  $\omega$ .  $h_t$  is the history of signal realizations observed up to period  $t$ .

This formulation allows the bias to be introduced by distorting the perceived likelihood that the signal was generated by either high values of  $\theta$  when it is a success, or by low values

of  $\omega$  when it is a failure. The parameter  $c$  determines the degree of bias and imposes enough restrictions to ensure that the model is still falsifiable.

Define the distortion in the likelihood by  $\Delta_c p(h^t|\theta, \omega) = p(h^t|\theta, \omega)^{c(\theta, \omega, o_t)} - p(h^t|\theta, \omega)$ . Notice that because  $p(h^t|\theta, \omega) < 1$ , if  $c(\cdot) < 1$ , a smaller exponent  $c$  implies a larger distortion upward for a fixed  $h^t$ , and fixed parameters  $\theta$  and  $\omega$ . While a  $c(\cdot) > 1$  implies a distortion downward and it is larger when  $c(\cdot)$  is larger.

### 3 A Unifying Example

In order to compare the predictions of the theories discussed above, I develop a unifying example where the forces behind each of the theories can be isolated. The example is modified from [Heidhues et al. \[2018\]](#) and is adapted to be implementable in the lab.

The agent can be of one of 3 types:  $\theta \in \{\theta_L, \theta_M, \theta_H\}$  with  $\theta_H > \theta_M > \theta_L$ . They face an unknown exogenous success rate  $\omega \in \{\omega_L, \omega_M, \omega_H\}$  with  $\omega_H > \omega_M > \omega_L$ . Each of the values of  $\omega$  is realized with equal probability. The agent knows the distribution of  $\omega$  but not its realized value.

Denote the true type by  $\theta^*$  and the true state by  $\omega^*$ . The agent holds some prior belief about  $\theta^{16}$  and chooses gamble  $e \in \{e_L, e_M, e_H\}$ . The agent observes whether the gamble is a success or a failure and gets a payoff of 1 if it is a success; they get 0 otherwise.

The probability of success is increasing in both  $\theta$  and  $\omega$  and is fully described in Table 1

	$\omega_H$	$\omega_M$	$\omega_L$		$\omega_H$	$\omega_M$	$\omega_L$		$\omega_H$	$\omega_M$	$\omega_L$
$e_H$	50	20	2	$e_H$	80	50	5	$e_H$	98	65	25
$e_M$	45	30	7	$e_M$	69	65	30	$e_M$	80	69	35
$e_L$	40	25	20	$e_L$	65	45	40	$e_L$	75	55	45
	$\theta_L$				$\theta_M$				$\theta_H$		

Table 1: Probability of success for each type  $\theta$ , gamble  $\omega$ , and effort level  $e$

For each type, the agent's flow payoff is maximized by choosing the gamble that matches

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<sup>16</sup>which is potentially misspecified as in the dogmatic and switcher cases discussed above

the state. For example, if the value of  $\omega$  is  $\omega_H$ , the agent's flow payoff is maximized by choosing  $e_H$  and if the state is  $\omega_L$  the flow payoff is maximized by choosing gamble  $e_L$ , regardless of the value of  $\theta$ . The agent myopically chooses gambles every period to maximize the flow payoff for  $T < \infty$  periods.

After observing the outcome of each gamble, the agent updates their beliefs using some procedure and moves on to the next period.

Notice that both  $\theta$  and  $\omega$  can be identified from the outcomes if enough variation in the effort choices exists. This can be seen by confirming that there are no two pairs of  $\theta$  and  $\omega$  such that produce the same the probability of success for all effort choices. Thus, by changing the effort choice, the agent can learn both their type and the state if they observe enough outcomes.

In this example, for an agent with a dogmatic belief about their type, a self-defeating equilibrium is one in which the agent chooses an effort level that, under the true  $\theta$ , yields a frequency of success that is consistent with the agent's misspecified belief. That is  $P[\text{sucess}|\theta^*, \omega^*, e^*] = P[\text{sucess}|\hat{\theta}, \hat{\omega}, e^*]$  where  $e^*$  is the agent's myopic optimal choice.

In the data-generating process described above, there are five such equilibria. For example, if the agent is of type  $\theta_M$  but mistakenly believes that he is of type  $\hat{\theta} = \theta_H$  and that  $\omega^* = \omega_M$ , when the effort chosen is  $e_L$ , the agent will observe a success with 45% chance. Because the agent dogmatically believes that their type is high, they will erroneously conclude that the rate is  $\omega_L$ . Under this belief, the optimal action is  $e_L$  which will continue to generate successes with a 45 probability, further reinforcing the incorrect belief. By doing so, the agent forgoes the payoff from gamble  $e_M$  which would yield a success with 65% chance.

By including self-defeating equilibria, the example captures the forces from each of the updating mechanisms discussed in the previous section and allows for the comparison of the main forces behind the theories. This is because the self-defeating equilibria in a discretized setting acptures the main forces from the dogmatic and Switcher models. Furthermore, the data generating process has been designed to satisfy the main assumptions of both frame-

works. For realizations of  $(\theta, \omega)$  for which there are self-confirming equilibria, the dogmatic agent will fall into the trap whereas the switcher will be able to escape it. Similarly, an agent with self-attribution bias will update their beliefs differently from an unbiased Bayesian, leading them to choose different gambles. I exploit such cases in order to test which model is a better fit for how subjects behave in a laboratory experiment. In what follows I explain the details of how this example was implemented in the lab and the predictions that each model makes.

## 4 Experimental Design

I recruited 86 undergraduate subjects from the CESS lab at NYU who participated in an in-person experiment. Sessions lasted approximately 45 minutes and subjects earned an average payment of \$22.6. The experiment was programmed using oTree [Chen et al., 2016].

The experiment consisted of 2 treatments: the *ego-relevant* condition and the *stereotype* condition. Subjects participated in only one of the treatments. All subjects within a session participated in the same treatment and the first 4 sessions were assigned the ego-relevant condition; the rest were assigned to the stereotype treatment. The tasks were identical across treatments. In the ego-relevant condition,  $\theta$  is the subject’s own performance in a quiz. In the stereotype condition, it is the performance of a randomly selected subject from another session.

The experiment had three parts. In Part 1 subjects had two minutes to answer as many multiple-choice questions as they could from a 20-question quiz. They did this for quizzes on 6 different topics. The topics were: Math, Verbal Reasoning, Pop-culture and Art, Science and Technology, US Geography, and Sports and Video Games.<sup>17</sup> In this part, they did not know how many questions were available and they were given no feedback.

After taking all 6 quizzes, they proceeded to part 2 where they were asked to guess their score on each of them. In the stereotype treatment, they were additionally asked to guess

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<sup>17</sup>This methodology is heavily based on Bordalo et al. [2019]



the score of a randomly drawn participant from a previous session. All they knew about the other participant was their gender identity and whether they were US nationals or not. For each guess, they had three score options: Low-Score (5 or fewer correct answers), Mid-Score (between 6 and 15 correct answers), High-Score (16 or more). Each of the score categories corresponded to  $\theta_L$ ,  $\theta_M$ , and  $\theta_H$  respectively. They were also asked to say how confident they felt about their choices. They had 4 possible answers: “it was a random guess,” “there is another equally likely score,” “I am pretty sure,” “I am completely sure.” I mapped these four answers to priors that place probabilities .33, .50, .75, and 1 to the chosen type. The remaining probability is split equally among the other two types. Questions in Part 2 were not incentivized, but subjects were told that providing an accurate answer would increase their chances of earning more money in the last part of the experiment.

The purpose of Part 2 is to classify subjects into overconfident, underconfident and correctly specified. If a subject guesses their score to be in a higher (lower) category than their true score, they are overconfident (underconfident); if they guess their score to be in the same category as their true score, they are correctly specified. This classification is done for each of the 6 topics separately.

Finally, in Part 3, subjects completed a belief updating task for each of the quizzes. Before starting the task they were reminded of their guess for the score. In the ego-relevant treatment, they were reminded of their guess about themselves and in the stereotype treatment they were reminded of their guess about the other participant. In the stereotype treatment, they were also reminded of the characteristics of the other participant.

For one topic at a time and in random order, they were presented with the three gambles from the unifying example and were asked to choose one of them. The probability of success was determined by their own score in the ego-relevant condition, and by the score of the other participant in the stereotype condition. Subjects had access to the three probability tables in the printout of the instructions at all times and the meaning of each cell was explained in detail.

In the interface, they had to choose which of the 3 tables they wanted to see before entering their choice in it. This was done as an alternative to a belief elicitation in each round. I take their choice of table to be indicative of their beliefs about the underlying type. I chose not to elicit the beliefs at each round to stay true to the forces in framework 1. The agent's task in Framework 1 is to learn the exogenous parameter and match it with their choice. By eliciting the beliefs about their type in each round and rewarding it for it, I add an incentive to additionally learn their type correctly. This can lead them to take actions that reveal their type when they wouldn't have done so in the case where there is no additional incentive.

Once they have entered their choice, they observe a sample of 10 outcomes from the gamble they chose. After observing the outcomes, they returned to the choice screen and entered a new choice. In the choice screen subjects had access to the entire history of gambles and outcomes for that task as well as a summary of the outcomes so far. Once they entered 11 gambles (and observed 110 outcomes), they moved on to the next topic and repeated the same procedure. They all did this for all 6 topics.

At the end of the experiment, one of the 6 topics was randomly selected to determine the payment. They earned \$0.20 for each correct answer in the quiz, and for each success in the task in Part 3 for the selected topic.

Randomness is controlled throughout the experiment and sessions by setting a seed at the beginning of the first session. The seed was drawn at random and remained fixed for all sessions.<sup>18</sup> By doing this I ensure that any two subjects who have the same type and face the same exogenous rate will observe the same outcomes. This feature allows me to identify differences across subjects in updating procedures since if they use the same updating procedure, they should be choosing the same gambles.

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<sup>18</sup>The seed that was drawn at the beginning of session 1 was 3452. The same seed was used for all sessions. It is used both for drawing  $\omega$  for each of the tasks in the experiment, as well as for drawing the outcomes from the gambles.

## 5 Predictions

In this section, I outline the behavior that is predicted by each of the theories discussed above. Some of the predictions are made relative to the Bayesian benchmark. In particular, the reaction to good and bad news is very informative of which model is most likely to be underlying the behavior. Denote the sample size by  $I$  and define *good news* to be a sample of signal realizations such that the number of successes in the sample is larger than the average number of successes observed so far. i.e. if

$$\sum_{i=1}^I \mathbb{I}\{o_{iT} = \text{success}\} \geq \frac{1}{T} \sum_{t=0}^T \sum_{i=1}^I \mathbb{I}\{o_{it} = \text{success}\}$$

where  $T$  is the current period and  $o_t = [o_{it}]_{i=1}^I$  is the sample observed at period  $t$ . Denote the set of good news at period  $t$  by  $\mathcal{G}_t$  and let  $s_t$  be the number of successes in  $o_t$ . *Bad news* are any other kind of samples of signal realizations.

Given the definition of good and bad news, the reaction of the agent to each kind of news is the change in their choice conditional on the signal realization. Therefore, what we are interested in are the coefficients of the following regression model

$$\Delta a = \beta_0 + \beta_1 \mathbb{I}\{o_t \in \mathcal{G}_t\} + \beta_2 (s_t - s_{t-1}) + \beta_3 \mathbb{I}\{o_t \in \mathcal{G}_t\} (s_t - s_{t-1}) + \varepsilon_t$$

where  $(s_t - s_{t-1})$  is the size of the surprise<sup>19</sup> and  $\Delta a = a_{t+1} - a_t$  is the change in action as a reaction after observing the latest sample.  $\beta_2$  is the reaction of the agent to bad news with surprise  $(s_t - s_{t-1})$ . And  $\beta_2 + \beta_3$  is the reaction to good news with surprise  $(s_t - s_{t-1})$ .  $\varepsilon_t \sim N(0, \sigma)$  is variation in the action choices that is not explained by the sample of signal realizations.

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<sup>19</sup>The surprise is the difference between the number of successes in the sample observed at time  $t$  and the average number of successes in previous samples.

## 5.1 Self-Attribution Bias

The key feature of Self-attribution bias is the asymmetric treatment of good news and bad news. In particular, the agent will over-attribute successes to a high type and under-attribute them to a low type. Similarly, they will over-attribute failures to a low state and under-attribute them to a high state. This implies that, after observing a failure, the agent will adjust their effort downwards by more than what an unbiased Bayesian would have done. In contrast, after observing a success, the agent will adjust their effort upwards by less than a Bayesian would have done and if the bias is large enough, it could be that the agent will not adjust their effort upwards at all, or even decrease their effort in response to a success.

This is in stark contrast with what a Dogmatic modeler would do. A dogmatic modeler always attributes any variation in the outcome to the state and never updates their beliefs about  $\theta$ . Therefore, they will always increase their effort choices after a surprising success and decrease it after a failure.

On the other hand, the biased behavior can be in line with the behavior of a switcher. In particular, if the agent starts with a misspecified belief on  $\hat{\theta}$ , and is willing to switch to a belief with  $\theta' > \hat{\theta}$ , whenever the paradigm shift happens, it will likely be in response to a surprising streak of successes. In this case, when they adjust their belief about  $\theta$ , they will also adjust their effort choice. Since they were initially underconfident, they had been choosing an effort that was too high relative to the true state, and therefore, the effort is likely to fall in response to a surprising streak of success.

Let  $\beta^A$  be the coefficients of the regression model when the agent updates with misattribution bias. Let  $\beta^B$  be the coefficients of the same regression model but when the agent is Bayesian.

**Prediction 1A:** *After observing a failure, the agent will adjust their effort downwards by more than a Bayesian would have done. After observing a success, the agent will adjust their effort upwards by less than a Bayesian would have done. If the bias is large enough, the agent might not adjust their effort upwards at all, or even decrease their effort in response*

to a success. That is  $\beta_2^A > \beta_2^B$  and  $\beta_2^A + \beta_3^A < \beta_2^B + \beta_3^B$

In addition to their behavior, there is an additional characteristic feature of misattribution bias that is not present in other models. This is the only model in which an agent could start off with a correct belief and become more overconfident. In the long-run.

**Prediction 2A:** *After observing a streak of successes, the agent will update their belief about  $\theta$  upwards even when they started with a correct initial belief.*

## 5.2 Dogmatic Modeler

Since the domain of the problem is discrete and finite in the example, the predictions of the original theory of [Heidhues et al. \[2018\]](#) apply only to the combinations of parameters and initial beliefs for which there is a self-defeating equilibrium. In the unifying example, there are 5 such combinations. For each of them, the dogmatic model predicts that the agent will fall into the self-defeating equilibrium and will be able to sustain the dogmatic misspecified belief forever.

Table 2 describes the 5 self-defeating equilibria and the effort choices that sustain them. The first columns describe the combination of parameters and initial beliefs. The last column describes the effort choice that the agent will make in the long run. It is only for these combinations of parameter values and beliefs that the dogmatic model makes predictions within the Unifying example. Otherwise, the agent is not able to sustain the dogmatic belief and will be forced to use a different updating procedure to rationalize the signals that he observed.

**Prediction 1D:** *Whenever an agent is of a type  $\theta^*$  but mistakenly believes that they are of a type  $\hat{\theta}$ , and  $(\theta^*, \omega^*, \hat{\theta})$  are such that there is a self-defeating equilibrium, the agent will choose the effort level that sustains the misspecified belief forever.*

In term of the dogmatic's reaction to good and bad news, let  $\beta^D$  denote the coefficients of the regression model above when the actions are those predicted by the dogmatic model.

**Prediction 2D:** *Before falling into a trap, the dogmatic modeler reacts more to good*

and bad news than the Bayesian would. i.e.  $\beta_2^D > \beta_2$  and  $\beta_3^D > \beta_3$ .

**Prediction 3D:** *A dogmatic modeler never updates their belief about  $\theta$ .*

The model does not make predictions about what happens in cases where there is no stable belief. I assume that because there is no stable belief, the agent will eventually have to use some procedure to revise their belief about  $\theta$ . In such cases, I aim to determine which of the alternative explanations provided by the other theories is a better fit for the data.

True Type ( $\theta^*$ )	True State ( $\omega^*$ )	Believed Type ( $\hat{\theta}$ )	Believed state ( $\hat{\omega}$ )	Effort
$\theta_L$	$\omega_H$	$\theta_M$	$\omega_L$	$e_L$
$\theta_M$	$\omega_L$	$\theta_L$	$\omega_M$	$e_M$
$\theta_M$	$\omega_M$	$\theta_H$	$\omega_L$	$e_L$
$\theta_M$	$\omega_M$	$\theta_L$	$\omega_H$	$e_H$
$\theta_M$	$\omega_H$	$\theta_H$	$\omega_M$	$e_M$

Table 2: Stable beliefs and the effort choices that support them for the unifying example

Although the dogmatic model does not apply to all possible parametrizations and beliefs, whether subjects fall into the self-defeating equilibria or not is still informative of the updating procedure that they are using. Understanding if the presence of traps is a key feature preventing subjects from learning the optimal action is important for understanding the prevalence of overconfidence. Similarly, gaining insight into what happens when there are no traps is important for understanding the other reasons why overconfidence might arise and prevail.

### 5.3 Switcher

Since the switcher starts as the same dogmatic agent, the initial behavior of both types of agents is identical. However, because the switcher keeps track of the likelihood ratio, they will be able to escape the self-defeating equilibria if the evidence is convincing enough. Therefore there is positive probability that the switcher will adjust their initially misspecified belief about  $\theta$  and learn the true state.

**Prediction 1S:** *With positive probability, the switcher will escape the self-defeating*

*equilibria and learn the true state.*

Let  $\beta^S$  be the coefficients of the regression model when the actions are those taken by a switcher.

**Prediction 2S:** *When there is no change of paradigm, the switcher behaves as the dogmatic. When there is a change in paradigm, the reaction to good and bad news is attenuated or even in the opposite direction of what a Bayesian would have done. that is  $\beta_2^S < \beta_2^B$  and  $\beta_2^S + \beta_3^S < \beta_2^B + \beta_3^B$*

One caveat is that when the switcher and the dogmatic agent both start with a correctly specified belief, neither of them will fall into the self-defeating equilibria and thus will look identical even in the long run. This means that in order to distinguish between the two theories, I need to look at cases where the agent starts with a misspecified belief and the switcher changes paradigm. **Prediction 3S:** *Correctly specified switchers do not update their beliefs about  $\theta$*

The probability that the switcher will escape the self-defeating equilibria depends on the prior belief about  $\omega$ . If the prior is sufficiently tight around a self-defeating equilibrium, the likelihood ratio will not grow fast enough. In the unifying example, the prior is uniform over the states and therefore, the likelihood ratio is more likely to grow fast enough.

## 6 Stereotypes

So far I have focused only on the case of overconfidence about an ego-relevant parameter. However, each of the models can also be used to explain the prevalence of stereotypes. An agent can have a dogmatic belief about the ability of a particular group of people and either under or overestimate the associated parameter. Similarly, they can be willing to switch between two dogmatic beliefs about their ability as a switcher would. Finally, they can have a biased updating procedure in which they treat good news and bad news asymmetrically.

All the predictions discussed above apply to the case of Stereotypes as well. My analysis

of stereotypes will focus only on the degree to which ego-relevance of the type affects the updating procedure and not on the motivations behind the bias. I am particularly interested in whether the explanatory power of the models differs with the degree of ego-relevance of the type.

## 7 Results

### 7.1 Initial Beliefs and misspecifications

As mentioned in the predictions section, the dogmatic modeler and the switcher are only distinguishable when the agent starts with a misspecified belief. Figure 1 shows the distribution of misspecifications by treatment. The histogram considers the difference between the subject’s true score in the quiz and their guess about their score. If their guess is in a higher category than their true score, they are overconfident; if it is in a lower category, they are underconfident; and if it is in the same category, they are correctly specified. Overall, 43% of the guesses made in the questionnaire were misspecified. The rest of the guesses coincided with the true score.

Having widespread misspecifications is important for the analysis because it allows me to distinguish between the dogmatic modeler and the switcher. If there were no misspecifications, the two models would be indistinguishable.

### 7.2 Learning

In this section, I analyze the learning behavior of subjects in the experiment. There are two parameters that subjects can be learning about: the exogenous parameter  $\omega$  and the type  $\theta$ . Their belief about the exogenous parameter is tracked by their choice of effort, while their belief about the type is tracked by their choice of a matrix in which to enter their effort.



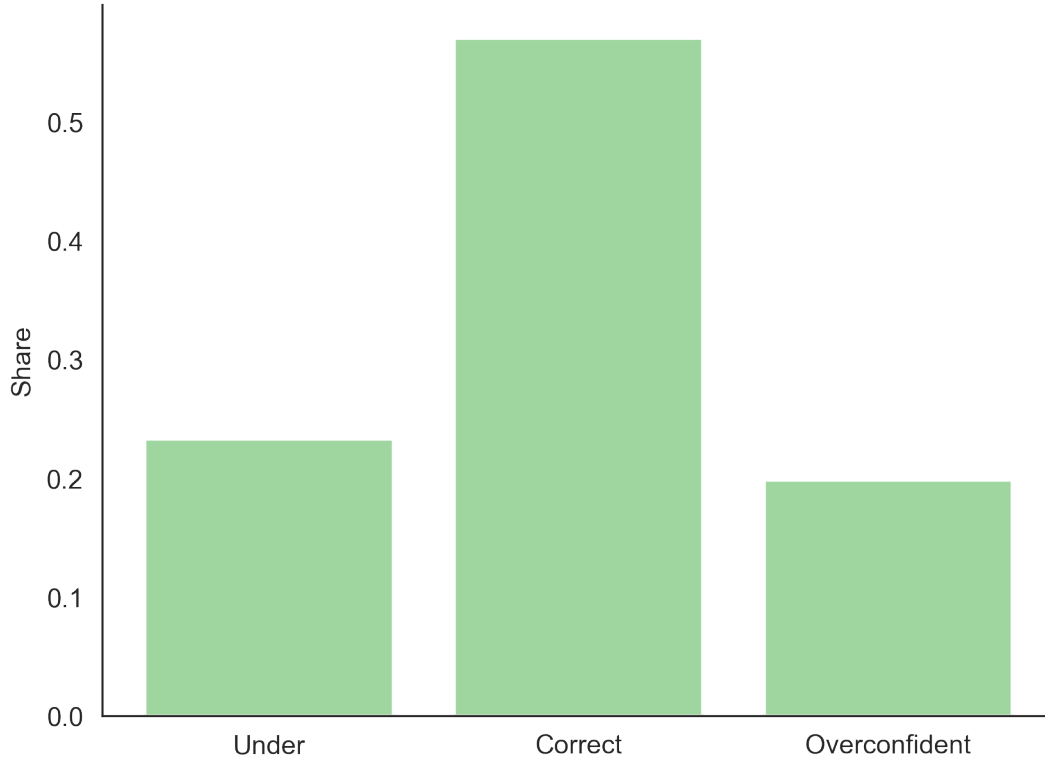


Figure 1: Initial specifications by treatment

### 7.2.1 Learning about the state

In order to analyze the learning about the state, I look at the share of optimal choices that are made at each round. I find that although subjects seem to be improving in their choices overall, the last choice coincided with the true state only in 52% of the choices in the last round of each task. This is statistically greater than the initial share of optimal choices ( $p < 0.01$ ). However, it is still far from complete learning. It is also important to note that learning is similar across treatments. The share of choices that were consistent with the true state for each round is reported in panel A of Figure 2.

A closer look at whether people learned or not reveals that there is a good amount of heterogeneity in the sample. Panel B of Figure 2 shows the share of optimal choices by round for subjects that chose an effort that matched the state in 3 out of the last 4 rounds. It also shows the share of optimal choices for subjects who chose an effort that matched the state in fewer than 3 out of the last 4 rounds. I label the former as learners and the latter as

non-learners, with learners making up 38% of the sample.

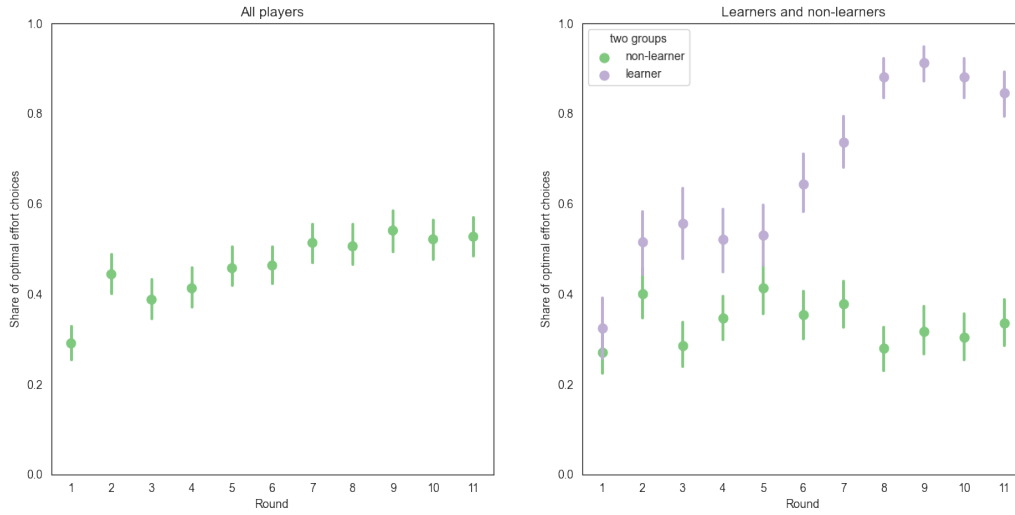


Figure 2: Share of optimal choices by round for subjects who learned (their effort in at least 3 out of the last 4 choices matched the state), and subjects who did not learn

In what follows I will try to disentangle the reasons for the lack of learning. I will argue that it is not due to the presence of traps, but rather due to biased updating. According to the theories, the main reason why subjects might not learn is that they have a misspecified initial belief about the type or they develop an misspecified belief.

### 7.2.2 Learning about the type

Since the elicitation of the belief about the type was not incentivized and not elicited in a standard way, I first need to confirm that subjects were not randomly choosing a matrix in which to enter their effort. The left panel of Figure 3 shows the share of subjects who chose a matrix consistent with their initial reported belief. In round 1, 69% of the subjects chose a matrix that was consistent with their initial belief. This indicates that subjects were not randomly choosing a matrix in which to enter their effort. From round 2 on, the share declines, but not as far as to indicate a random choice of matrices. This is consistent with the subjects moving away from their starting belief through some updating procedure.

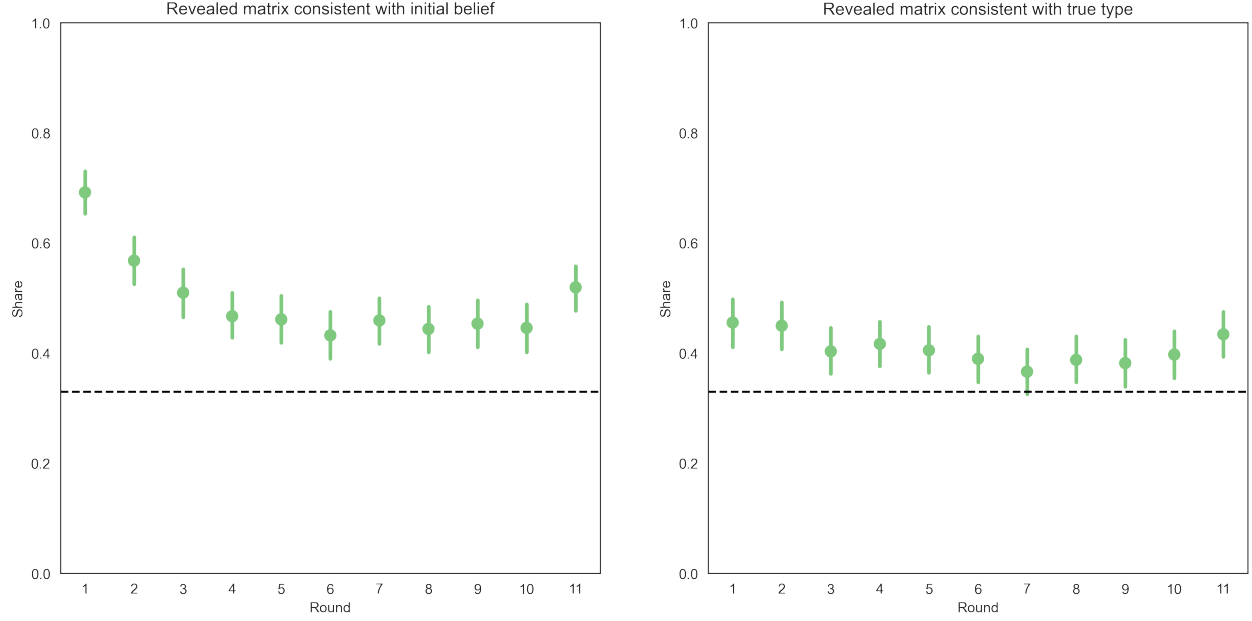


Figure 3: Matrix choices by round

On the right panel of Figure 3 I show the share of subjects who chose a matrix that is consistent with their true type. Unlike the left panel, there is no clear trend, which indicates that although they are moving away from their initial belief, they are not moving towards their true type, which means that overall, misspecification is not decreasing. A closer look at the data reveals a good amount of heterogeneity in the underlying behavior.

Figure 4 shows the transition matrix for subjects who started in each of the three possible starting specifications and the specifications that they ended up in at the end of the updating task. The two things to note are that the initial belief is the most likely end belief. This is consistent with some degree of stickiness of the misspecifications as the switcher and dogmatic models would predict. However, the data also presents a lot of subjects who started with a correct belief of the type and ended up overestimating it. This is consistent only with self-attribution bias. Lastly, subjects who initially overestimate the score, are the least likely to learn their true type.

The transition matrix points towards the presence of self-attribution bias in the data. However, it is still possible that there is heterogeneity in the updating procedure across

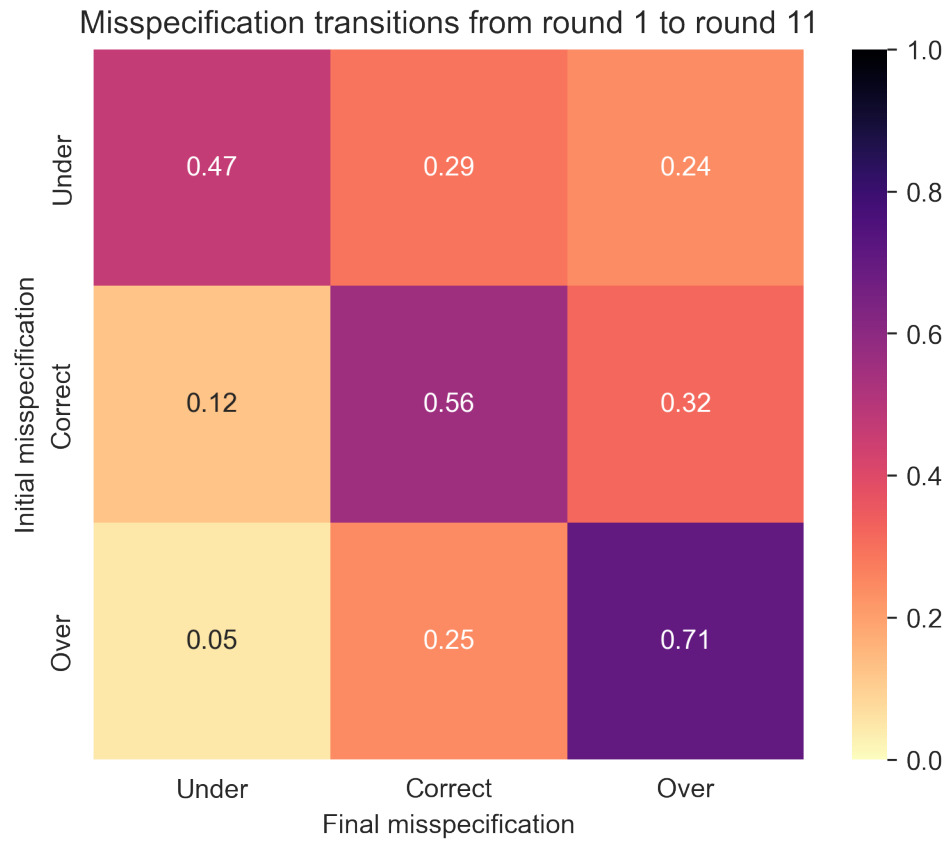


Figure 4: Transition matrix for subjects who started in each of the 3 possible starting specifications and the specification that they ended up in at the end of the updating task

subjects. In the next section I will look at the role of self-defeating equilibria in preventing learning.

### 7.3 Learning traps

As described in Framework 1, the presence of stable misspecified beliefs act as learning traps in this setting. If an agent falls into one of these traps, bayesian updating will lead them to choose the same effort forever. These self-defeating equilibria allow me to distinguish between the dogmatic modeler and the switcher. If the agent falls into a trap and stays there forever, they are more likely to be a dogmatic modeler. If they escape the trap, they are more likely to be a switcher or to be updating with some attribution bias.

Overall, it does not seem to be the presence of traps that is preventing learning. Panel A of Figure 5 shows that the share of subjects who learned in cases where there was a trap is larger than the share of subjects who learned in cases where there was no trap. This is true for both treatments. This indicates that even in the presence of traps, 43% of subjects learn. From the share that did not learn when there was a trap, 22% can be accounted for as being trapped.<sup>20</sup> While the rest of the subjects neither learned nor were trapped.

A closer look at the behavior of only the cases in which there were traps reveals that among those who did not learn, the choices that support stable beliefs were chosen much more often than among subjects who learned. Figure 5 shows the share of choices that were consistent with a stable belief for the learners and the non-learners. The difference is statistically significant ( $p < 0.01$ ). Thus, although the presence of self-defeating equilibria is not the main deterrent to learning, it does seem to be a factor in the behavior of those who do not learn.

So far I have accounted for 17% subjects as being trapped, and 38% having learned the state correctly. From the remaining 45%, 60% were prone to traps but did not fall into them, therefore they could not have been dogmatic modelers. Alternative explanations are

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<sup>20</sup>A subject is considered trapped when 3 out of their last 4 choices are consistent with a self-defeating equilibrium.

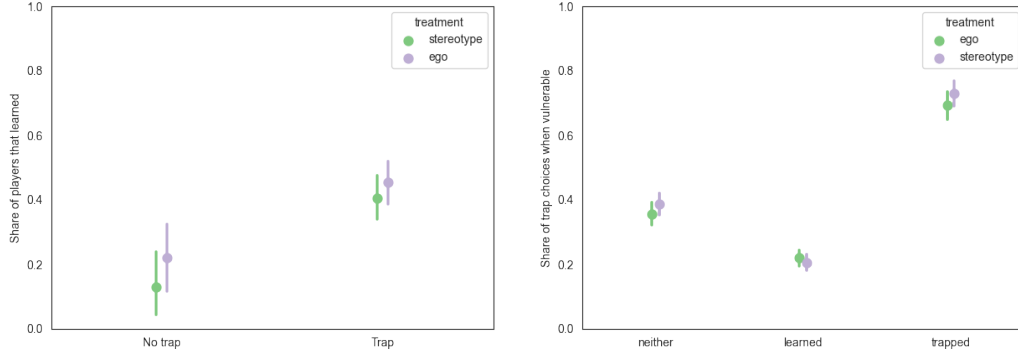


Figure 5: Panel A: Share of subjects who learned in cases where there was a trap and in cases where there was no trap. Panel B: Share of choices that were consistent with a stable belief for the learners, those who are in a trap and others

that they were switchers who considered an incorrect alternative model, or that they were updating with a bias so large that their effort choices were far from optimal. Behavior that is not consistent with either of these falls outside of the scope of the theories discussed here.

My results are consistent with the findings of [Götte and Kozakiewicz \[2022\]](#). In a laboratory experiment that stays true to Framework 1, they test the predictions of the dogmatic modeler. They find that the average pattern in behavior is in the direction of the dogmatic modeler, however, subjects do not fully act as dogmatics since their actions do not go as far as to fully support the self-defeating equilibrium. A lot of the differences between the observed behavior in their experiment and the model can be attributed to subjects avoiding the self-defeating equilibria and learning the true state. In contrast to their study, I can provide more insight into the reasons why subjects avoid the self-defeating equilibria.

## 7.4 Reactions to good and bad news

One of the key features of the self-attribution bias is that the agent will react differently to good news and bad news. In particular, they will overreact to bad news and underreact to good news. I define good news to be any sample of outcomes for which the realized number of successes is greater than the average number of successes so far. Similarly, I define bad

news to be any sample of outcomes for which the realized number of successes is smaller than the average number of successes so far. In addition, I calculate the difference between the realized number of successes and the average number of successes so far and call it the news differential but can be thought of as the “size’ ’ of the surprise. Figure 6 shows the correlation between change in effort and the news differential, separately for good and bad news.

The overall pattern is that bad news are associated with a decrease in effort, and a more negative news differential is associated with a larger decrease in effort. On the contrary, good news are associated with a small decrease in effort.<sup>21</sup> As mentioned in the predictions section, this is consistent with the self-attribution bias as well as with a change of paradigm. It is not consistent with the dogmatic modeler or the Bayesian. In addition, the fact that about a third of the subjects started with a correctly specified belief and ended up overconfident is consistent only with the self-attribution bias. This points towards the fact that misattribution bias is the most likely explanation for the aggregate behavior of the subjects in the experiment.

A regression analysis of this same data reveals that indeed, the slopes are different for good and bad news and that the difference is statistically significant.<sup>22</sup> The regression results are reported in Table 3. columns 2 and 3 of the table consider the model for each treatment separately. I find no significant differences in the parameters across treatment. This is consistent with the fact that the bias is not driven by the ego-relevance of  $\theta$ .<sup>23</sup>

More convincing evidence against the Switching model is the lack of inverse or attenuated correlation between the change in effort and the news differential. In particular, if the

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<sup>21</sup>This asymmetric treatment of good and bad news has also been recently documented by Coutts [2019] and @Barron2021

<sup>22</sup>I run a robustness check where I define good news to be a net-positive sample (half or more of the outcomes observed in the sample received in that round were successful) and bad news to be net-negative sample. I find the same pattern in this alternative regression model and the results are reported in the appendix.

<sup>23</sup>The ego-relevance of  $\theta$  is the motivation behind the self-attribution bias, however, the bias itself is due to an incorrect updating procedure in response to good and bad news. The presence of asymmetric updating in the stereotype condition can be due to self-censoring of the subjects. In particular, subjects who initially underestimated the performance of the other participant might have realized their mistake and by overestimating it after good news. This is consistent with the data presented here as well as with the data observed in the transition matrix for stereotypes which is reported in the Appendix

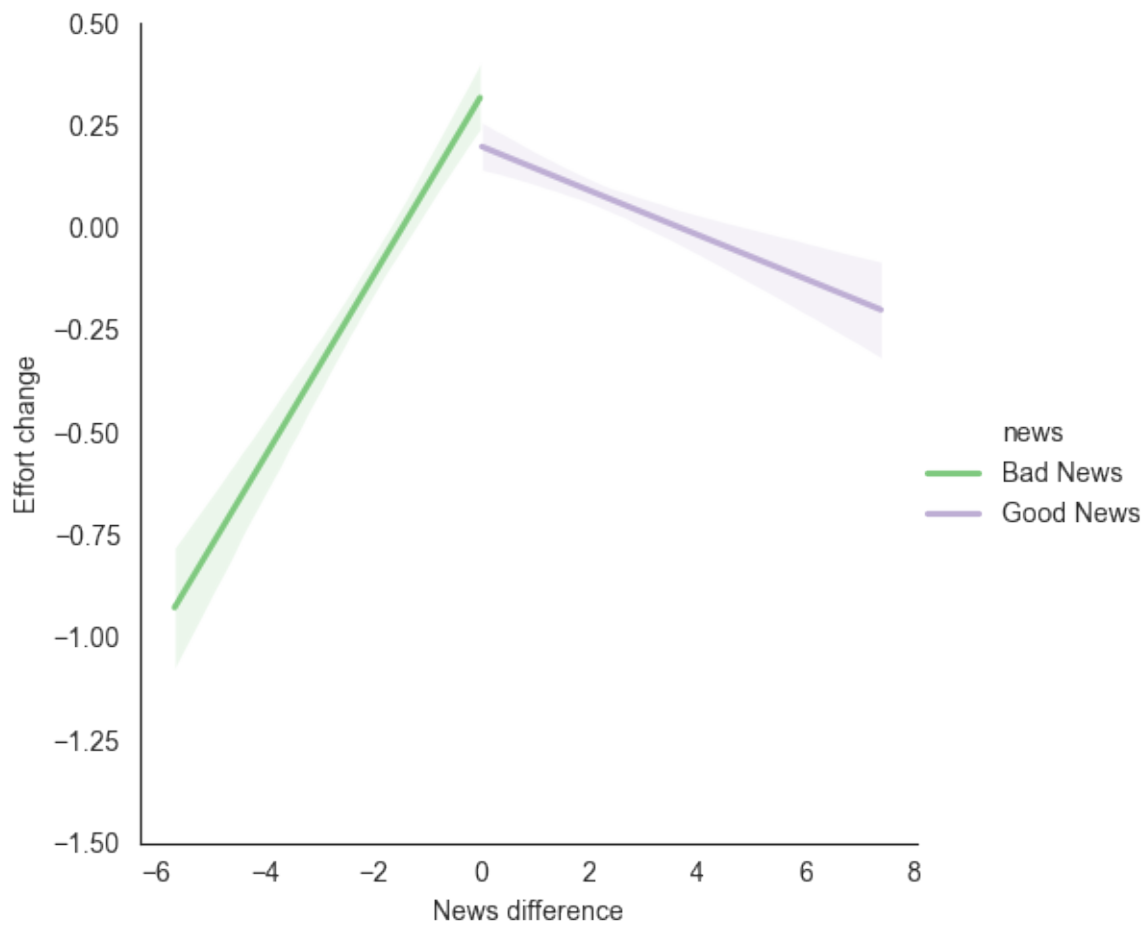


Figure 6: Change in effort by news differential



Table 3: Regression of effort change on news difference with robust standard errors

	<i>Dependent variable:</i>				
	Change in effort				
	All	Ego-relevant	Stereotype	Bayesian Simulation	Dogmatic Simulation
	(1)	(2)	(3)	(4)	(5)
Good news	−0.11** (0.05)	−0.16*** (0.05)	−0.04 (0.05)	0.09* (0.05)	−0.08 (0.05)
News difference	0.22*** (0.02)	0.22*** (0.02)	0.21*** (0.02)	0.06*** (0.02)	0.10*** (0.02)
News difference * Good news	−0.27*** (0.02)	−0.25*** (0.02)	−0.29*** (0.02)	−0.03 (0.02)	−0.06*** (0.02)
Constant	0.31*** (0.04)	0.31*** (0.04)	0.30*** (0.04)	−0.09** (0.04)	0.06 (0.04)
Observations	5,160	2,700	2,460	5,160	5,160
R <sup>2</sup>	0.04	0.04	0.04	0.05	0.06
Adjusted R <sup>2</sup>	0.04	0.04	0.04	0.05	0.06

*Note:*

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

switcher were the underlying model, I would expect overconfident subjects who start with an overestimation of  $\theta$  to increase their effort in response to surprising bad news. This would flatten the slope of the regression line for bad news relative to what a Bayesian would do. Table 3 shows that the slope for bad news for the simulation<sup>24</sup> of the Bayesian updates is much flatter than the slope in the data.

## 7.5 Stereotypes and the role of ego-relevance

Although the overall distribution is similar for both treatments, the misspecifications arise for different combinations of characteristics in each treatment. Figure 7 shows a heatmap of the specifications that arose in each treatment. In the stereotype treatment, subjects are most underconfident about the performance of other non-American females in Sports and Video Games. In contrast, they are most overconfident about the performance of American men in Verbal Reasoning. In the ego-relevant treatment, subjects are most underconfident about their own performance in pop culture and art, while most overconfident about their performance in Verbal Reasoning.

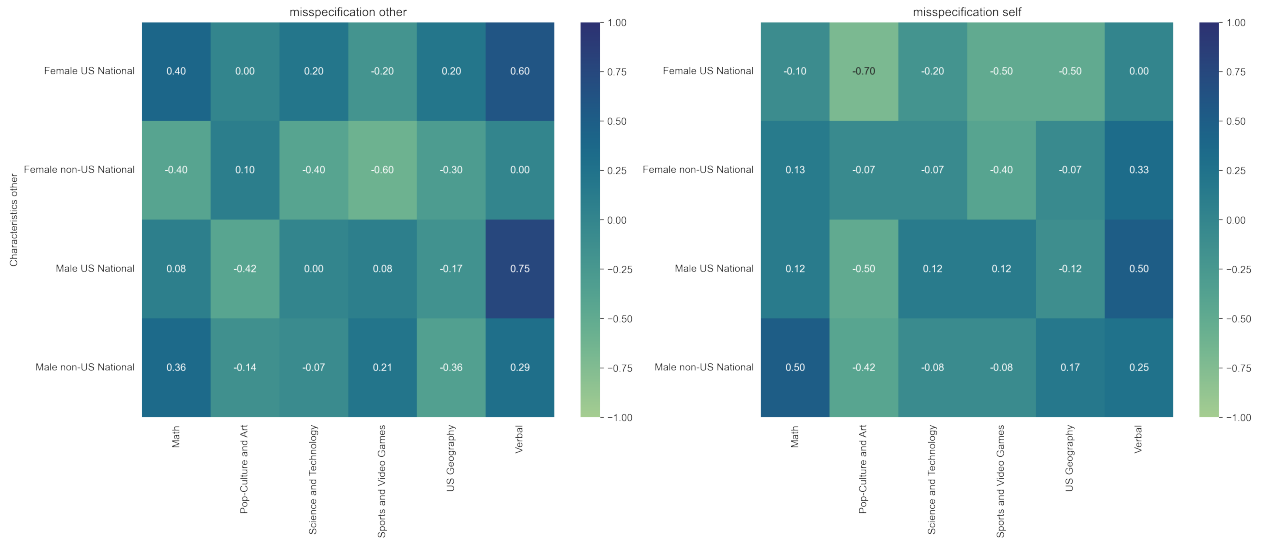


Figure 7: Initial misspecifications by treatment and characteristics. a -1 corresponds to all subjects being underconfident while 1 corresponds to all subjects being overconfidence. All subjects being correctly specified is assigned a value of zero.

<sup>24</sup>The details on how the data was simulated are explained in the Appendix

Throughout the experiment, there is little difference in the behavior of subjects across treatments. Two of the main differences are, first that subjects in the ego-relevant treatment are more likely to become overconfident when they start with a correct belief; and second, that subjects in the stereotype treatment are more likely to overreact to good news when they start by underestimating the performance of the other participant.

These two differences present as consistent with the self-attribution bias, however, the pattern in the stereotype treatment could also be due to self-censoring of the subjects. In particular, subjects who initially underestimated the performance of the other participant might have realized their mistake and over-compensated their mistake by overestimating it after good news. This is consistent with the data and offers a more intuitive explanation for why this pattern arises in the stereotype treatment. It is also consistent with the findings of [Bohren et al. \[2019\]](#), where they find that subjects initially underestimate the ability of women, however, after a sequence of good news for a woman, the attitude reverts and subjects evaluate that particular woman to be better than men.

Furthermore, I find no evidence of confirmation bias which is something that has been suggested in the literature of biased updating.<sup>25</sup> In particular, I find no evidence that subjects who overestimate the score of the other participant are more likely to over-attribute successes to a high type and under-attribute them to a low type. Symmetrically, I find no evidence that subjects who underestimate the score of the other participant are more likely to over-attribute failures to a low type and under-attribute them to a high type. This is consistent with what [Möbius et al. \[2022\]](#) find in their experiment in a less complex updating task.

## 8 Structural estimation

I have discussed two models that are consistent with the data: the self-attribution bias and the switcher. Although the data seems to point more convincingly towards the self-attribution bias, I cannot rule out the possibility that the switcher is the underlying model.

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<sup>25</sup>See [Benjamin \[2019\]](#) for a review of the literature in this and other biases.

In this section, I estimate the structural parameters of the two models and try to classify subjects into each of the models to assess how much of the data is explained by each of the two likely theories.

## 8.1 Estimation of the switching threshold

The switching threshold is the parameter that determines the likelihood ratio at which the switcher abandons the status quo paradigm and adopts the alternative. In order to estimate this parameter, I assume that all subjects are switchers and look at the rounds in which they chose to reveal a probability matrix that was different from the one they revealed in the previous round. I then calculate the likelihood ratio for the alternative paradigm to the status quo. I average across all such likelihood ratios and use the average as an estimate of the switching threshold.

In detail, Let  $b_t^\theta$  be the belief about  $\theta$  in period  $t$ .<sup>26</sup> And consider a subject for whom  $b_{\tau-1}^\theta \neq b_\tau^\theta$ , where  $b_t^\theta$ . That is, in period  $\tau - 1$  they chose to reveal a matrix that was different from the one they revealed in period  $\tau$ . The matrix revealed in period  $\tau - 1$  is the status quo paradigm and the matrix revealed in period  $\tau$  is the alternative paradigm. The likelihood ratio for the alternative paradigm to the status quo is

$$\ell = \frac{L(\theta|b_\tau^\theta)}{L(\theta|b_{\tau-1}^\theta)} = \frac{p_\tau(o_t|b_\tau^\theta)}{p_\tau(o_t|b_{\tau-1}^\theta)},$$

where  $p_\tau(o_t|b_\tau^\theta)$  is the probability of observing the signal  $o_t$  when the agent is of type  $b_\tau^\theta$ .

The estimate of the switching threshold,  $\alpha$ , is the average of the likelihood ratios across all subjects who switched in the experiment, which is given by

$$\hat{\alpha} = \frac{1}{N} \sum_{i=1}^N \ell_{i\tau},$$

where  $N$  is the number of switches observed in the experiment.

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<sup>26</sup>in the experimental data, I use the revealed matrix as a proxy for the belief. I take the matrix revealed in the previous period to be the status-quo and the matrix revealed in period  $t$  to be the alternative

Because the feedback that subjects receive is the equivalent of 10 signal realizations, the estimate of the parameter is an upper bound of the true parameter. A lower bound would be given by the average likelihood ratio in the round before the switch happens. I choose to estimate the upper bound to impose a harsher test on the theory.

Because the likelihood ratio is a function of the signal, it depends on the sequence of signals that subjects observe. This means that in some cases, the likelihood ratio increases by a large amount from one period to another. Although such cases are not common<sup>27</sup>, a few very large values can skew the average. To avoid a biased parameter, I restrict my sample to those observations for which the likelihood ratio is less than 5.<sup>28</sup> Under these assumptions, the estimate of the switching threshold is 1.09.

This means that the evidence supporting the alternative paradigm needs to be approximately 10% more compelling than the evidence supporting the status quo paradigm in order for the agent to switch. The estimation treatment by treatment is slightly larger for the Ego condition than for the Stereotype condition. However, the difference is not statistically significant (p-value=0.96).

I then use this estimate to simulate the behavior of the switcher to assess the fit of the model. Which is discussed in the next section.

## 8.2 Estimation of the self-attribution bias

I use the simulated method of moments to estimate the distortion parameters of the misattribution bias model. There is a total of 6 parameters in the model, however, I assume that the distortion is symmetric for good and bad news. Formally, I assume that  $c(\theta_H, \omega, \text{good news}) = c(\theta, \omega_L, \text{bad news})$ ,  $c(\theta_M, \omega, \text{good news}) = c(\theta, \omega_M, \text{bad news})$  and  $c(\theta_L, \omega, \text{good news}) = c(\theta, \omega_H, \text{bad news})$ .

To estimate them I use 4 moment conditions. The moments that I use are the regression coefficients from the reaction to good and bad news. That is: the slope and intercept of the

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<sup>27</sup>In the data, only 1.8 observations have a likelihood ratio that exceeds 5.

<sup>28</sup>The full distribution of likelihood ratios is reported in the appendix

relationship between the number of successes in the last signal sample and the change in effort as a consequence. The slope and intercept are different for good and bad news, which gives 4 moment conditions. To determine good news are samples for which there are more successes than failures. Bad news are outcome samples for which there are more failures than successes. The sample moments are reported in 4 and correspond to the following regression model:

$$\Delta effort_{it} = \beta_0 + \beta_1 signal_{it-1} + \beta_2 \mathbb{I}\{good\ news_{it-1}\} + \beta_3 I\{good\ news\} * signal_{it-1},$$

where  $i$  is an individual and task level index (each subject in each of the six tasks in the experiment represents a single observed path) and  $t$  is a round\_number index that ranges from 1 to 11. The variable  $signal_{it-1}$  is the number of successes observed in round  $t - 1$ , and the change in effort is  $\Delta effort_{it} = effort_{it} - effort_{it-1}$ . The coefficients  $\beta_0$  and  $\beta_1$  are the moments that rule the interaction between bad news and effort change, while  $\beta_0 + \beta_2$  and  $\beta_1 + \beta_3$  are the intercept and the slope for the relation between effort change and good news.

In order to find the parameters that correspond to the observed moments I rely on simulation. Rather than theoretically deriving the moments, I simulate what a large number of subjects would have done conditional on parameter values. I do this for a large number of parameter combinations that satisfy the restrictions on them. For each set of parameter values, I compute the simulated moments. These simulations are meant to approximate the population moments conditional on parameters. I then look for the set of parameters that minimize the weighted quadratic distance between the sample moments and the population moments. The weight I place on each of the moments is the inverse of the variance of the moment in the sample.

The model makes deterministic predictions about the choices subjects should make after each possible history of signals. However, in the data I observe significant variation. In order to account for variation in the simulation I introduce a noise parameter  $\varepsilon_{it} \sim U[0, 1]$  which introduces a tremble in the choice of subject  $i$  in period  $t$ . If  $\varepsilon_{it} < 0.1$  the subject chooses

an effort level at random. Otherwise they choose the optimal effort as predicted by the model. More details on the simulation can be found in the Appendix. While the estimated parameters are all interior solutions with  $\hat{c} = (0.4, 0.7, 1.5)$ .

Using the estimated parameters I proceed to simulate the deterministic choice paths for each of the models.

## 9 Model fit

I simulate each of the models for each possible combination of type and state  $(\theta, \omega)$ . I then compute the distance from the observed paths of each subject to each of the simulated paths that match the subjects type and state. I average across all paths for a single subject (each subject participated in 6 distinct effort tasks) and determine which model is a better explanation for that subject's behavior by finding the one that gives the minimal average distance between the observed behavior and the simulation.

In detail, let  $e_{ikt}$  be the effort chosen by subject  $i$  in task  $k$  at round  $t$ . And let  $\tilde{e}_t(\theta, \omega, j)$  be the simulated choices using model  $j$  for a subject of type  $\theta$  in state  $\omega$ . And let  $j$  be dogmatic, switcher, attribution or Bayesian. I solve the following problem to determine the best fitting model for each subject  $i$ .

$$\arg \min_j \sum_k \frac{1}{T} \sum_t [e_{ikt} - \tilde{e}_t(\theta, \omega, j)]^2$$

The histogram in Figure 8 shows the distribution of the best fitting models in the sample. The average fit of each model is reported in the Appendix.<sup>29</sup>

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<sup>29</sup>The best fitting models are robust to different distance functions. In particular, the share of subjects best explained by misattribution bias is the same when using norm 1.

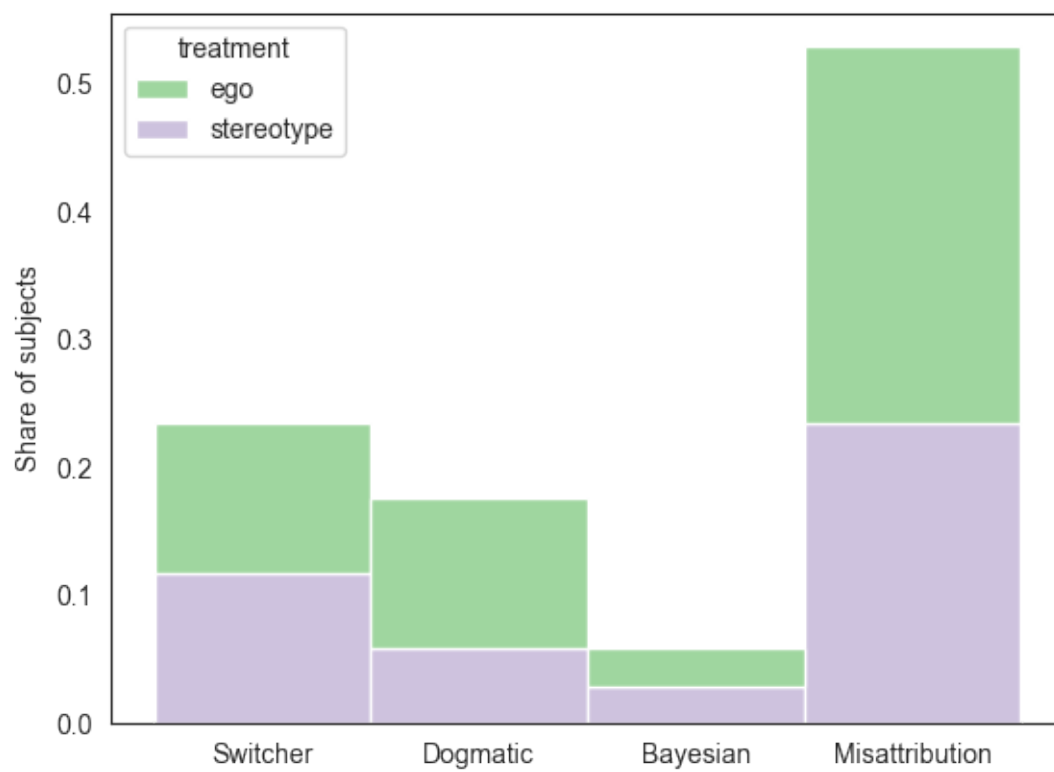


Figure 8: Distribution of the best fitting models at a subject level in each treatment



## 10 Conclusion

I designed a setting in which I can distinguish between the forces of dogmatism, paradigm shifts, and optimal expectations. Through a laboratory experiment, I collected data on behavior and infer beliefs from it. I find that the behavior of the subjects is consistent with the self-attribution bias. In particular, I find that subjects decrease their effort in response to bad news as well as to bad news, although the latter decrease is smaller. This is consistent with the self-attribution bias as well as with a change of paradigm. However, I also observe that about a third of the subjects started with a correctly specified belief and ended up overconfident. This is consistent only with the self-attribution bias. Therefore, I conclude that the model that best explains the data is that of optimal expectations.

I have small or no effects throughout on the ego-relevance of the type. Although the motivation behind the theories does not directly apply to the case of stereotypes, the lack of stark differences suggests that biases arise due to an incorrect updating procedure and not necessarily due to the self-serving motivation behind the bias. The lack of differences in the behavior of the subjects across treatments could also be due to self-censoring of the subjects. In particular, subjects might be initially reluctant to express their true belief about a particular group of people. In addition, as they learn and realize that their beliefs might be incorrect, they might overreact to signals to try to compensate for the initial bias. Such an updating procedure would be consistent with the self-attribution bias for the case of stereotypes. I remain agnostic about whether that is truly the case or whether the lack of differences is due to other factors.

A different bias that has been studied and suggested in the literature is the confirmation bias. In particular, it has been suggested that subjects who overestimate  $\theta$  in their prior, will over-attribute successes to a high type and under-attribute them to a low type. Symmetrically, subjects who initially underestimate  $\theta$  will over-attribute failures to a low type and under-attribute them to a high type. I do not find evidence of such a bias in the data. This is consistent with what Möbius et al. [2022] find in their experiment.

I further investigate possible heterogeneity in the underlying models being used by estimating the structural parameters of the models. I find that under the average parameters, most subjects are best explained by misattribution bias in both treatments. However, for the subjects for whom other models are a better explanation, those models have a better fit than the misattribution bias does for those better explained by it.

# A appendix

## A.1 Transition matrix by treatment

Figure 9 shows the transition matrix for each of the treatments separately. It shows that initial misspecifications are more sticky in the ego treatment and that subjects who underestimate the score of the other participant in the stereotype treatment are more likely to end up overestimating it than in the ego treatment. This may signal some sort of self-censoring or overreaction in the stereotype treatment.

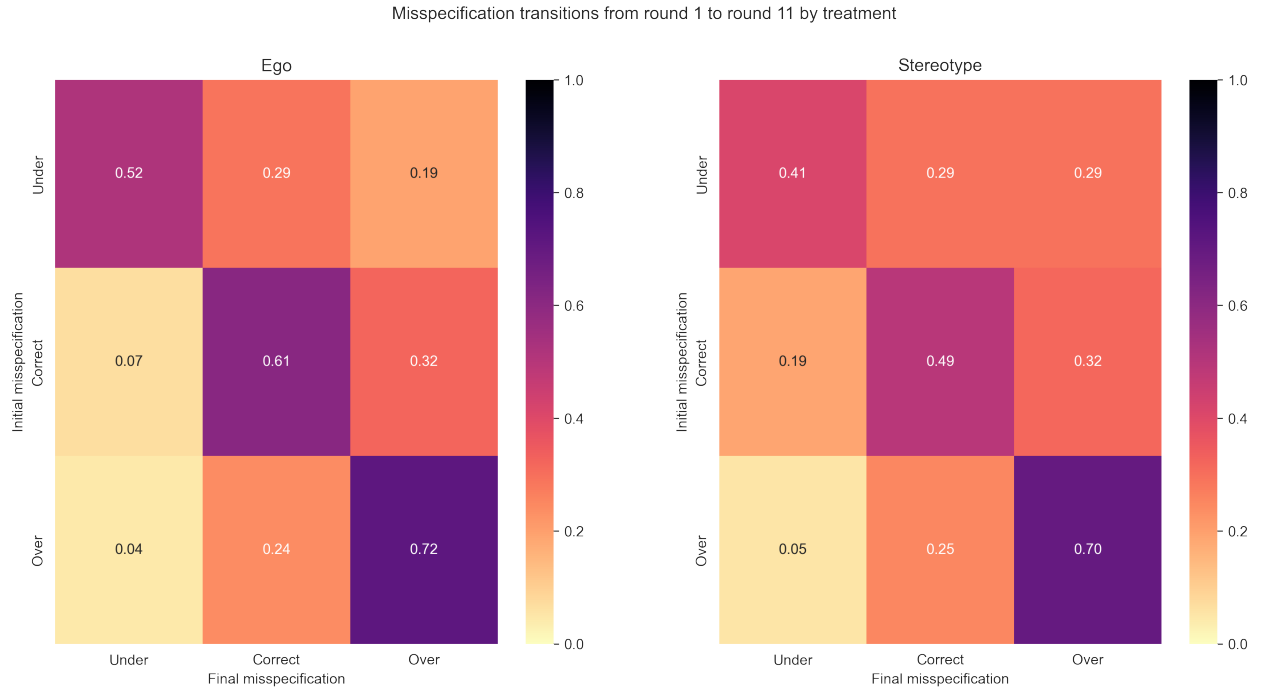


Figure 9: Transition matrix for subjects who started in each of the 3 possible starting specifications and the specification that they ended up in at the end of the updating task

## A.2 Full distribution of likelihood ratios

The likelihood ratios at rounds in which I observe a change in the belief about  $\theta$  presents a long right-tail. In particular, 1.8% of the observations have a likelihood ratio that exceeds 5 which would mean that the agent requires evidence that is 5 times more compelling in favor

of the alternative paradigm in order to switch. Figure 10 shows the distribution of likelihood ratios for all observations.

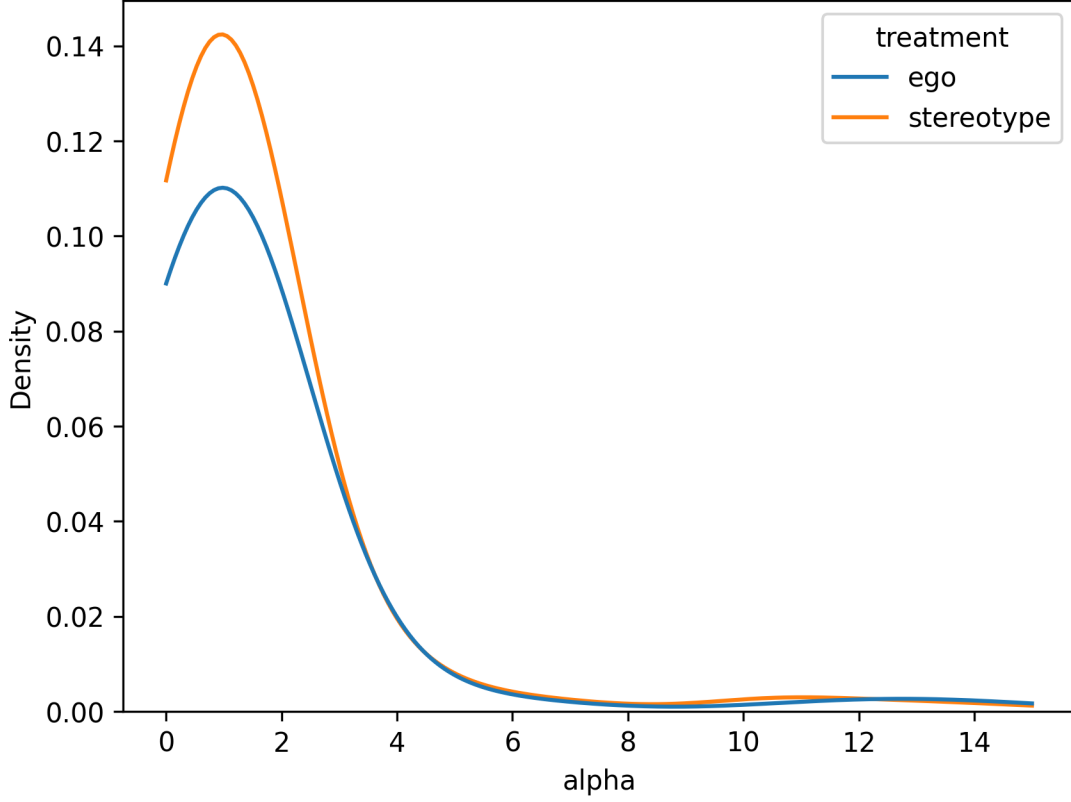


Figure 10: Distribution of likelihood ratios for all observed belief changes

### A.3 Simulated Method of Moments

I simulate the model on a grid with 3 parameters:  $c_1$ ,  $c_2$  and  $c_3$  such that  $c_1 < c_2 < c_3$ . All parameters on the grid take values between 0.1 and 2 with a distance of 0.1 between them. I simulate 1000 paths of choices of length 11 for each of the possible combinations of parameters. For each set of parameters I compute the moments by estimating the regression model described in section 8.2. Represent the simulated models for parameter vector  $c$  by  $\tilde{m}(c)$  and the sample moments by  $m$ . The estimates of the parameters are given by

$$\hat{c} = \arg \min_c (\tilde{m}(c) - m)^T W (\tilde{m}(c) - m)$$

It is also worth noting that since the randomness is fixed in the experimental data by setting a seed, I do the same in the simulation and use the same seed as in the experimental environment to account for the correlation in observed signals that exists in the sample.

To determine the parameters  $\theta$  and  $\omega$  in the simulated individuals, I draw from the empirical distribution.

## A.4 Model simulation

In order to simulate the data for each of the models and assess their fit, I simulated the path that each type of agent would have taken given each possible realization of  $(\theta, \omega)$ . I fixed the seed of the random number generator to 3452<sup>30</sup> and fixed the signals that would be shown in each round after each choice by drawing them before simulating. This way, the signals that the simulation uses coincide exactly with the signals that a subject would have seen in the experiment. I then use each of the algorithms defined by the models to simulate the path that the agent would have taken given the signal and given an initial belief. For the dogmatic modeler and the switcher, I use each possible dogmatic belief. For the Bayesian and the self-attribution bias, I use a uniform belief on theta.

## A.5 Model fit

The average model fit for each of the simulated models is reported in Figure 11.

## A.6 Reaction to good and bad news (robustness check)

I use an alternate definition for good and bad news and check whether the results are robust to this. I define a signal to be a net positive if the number of successes is equal to or greater than the number of failures. I define a signal to be a net negative if the number of failures is greater than the number of successes. I now treat net positive signals as good news and net negative signals as bad news. I then rerun the regression analysis and find that the results

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<sup>30</sup>this is the seed that was drawn at random for the experiment

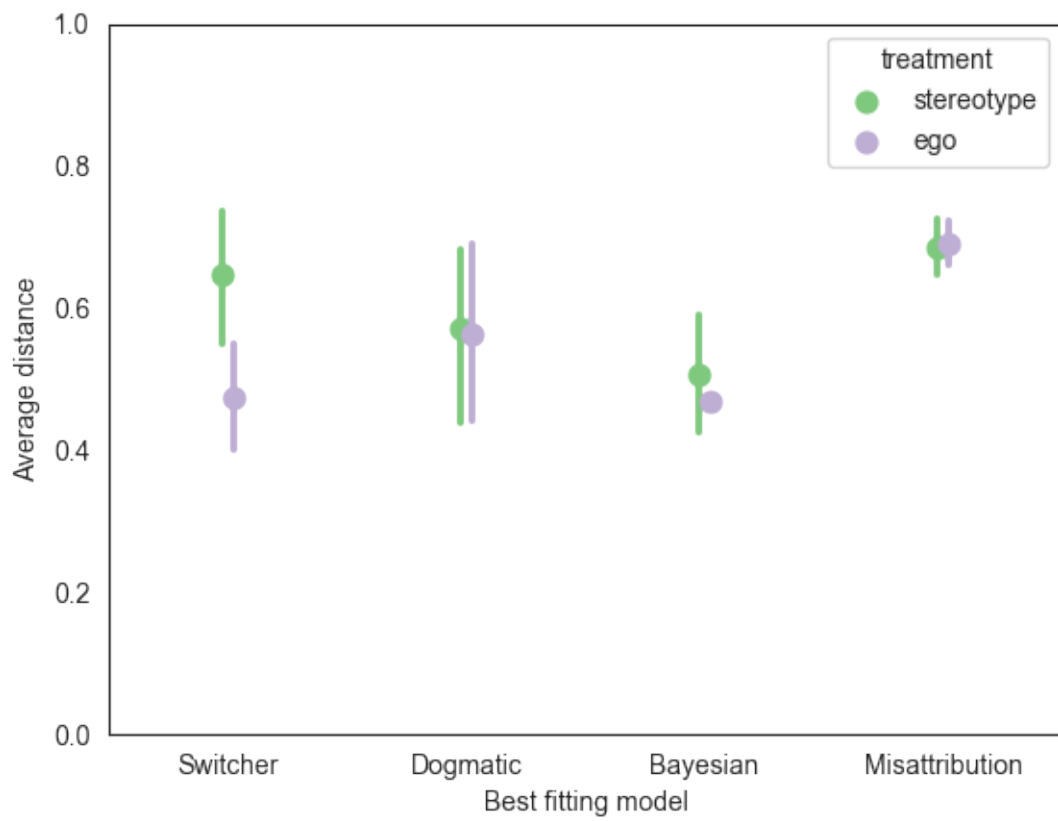


Figure 11: Average distance of subject behavior to the best fitting model

are robust to this alternative definition. In particular, net negative signals are associated with a stark decrease in effort for both treatments. Net positive signals are associated with a small decrease in effort for both treatments. The results are reported in Table 4.

Table 4: Regression of effort change on news difference with robust standard errors

	<i>Dependent variable:</i>		
	Change in effort		
	All	Ego-relevant	Stereotype
	(1)	(2)	(3)
Net-positive signal	1.01*** (0.05)	0.80*** (0.05)	1.22*** (0.05)
Signal value	0.21*** (0.02)	0.22*** (0.02)	0.20*** (0.02)
Signal value * Net-Positive signal	-0.28*** (0.02)	-0.26*** (0.02)	-0.31*** (0.02)
Constant	-0.48*** (0.04)	-0.48*** (0.04)	-0.49*** (0.04)
Observations	5,160	2,700	2,460
R <sup>2</sup>	0.05	0.05	0.05
Adjusted R <sup>2</sup>	0.05	0.04	0.05
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01			

## B Experimental Instructions

You are about to participate in an experiment on decision-making. What you earn depends partly on your decisions and partly on chance. Please turn off cell phones and similar devices now. Please do not talk or in any way try to communicate with other participants. We will start with a brief instruction period. If you have any questions during this period, raise your hand, and your question will be answered so everyone can hear.

### General Instructions

The experiment is separated into two parts. You will be given instructions for each part when it is reached.

**Part 1:**

In part 1, you will be asked to solve a series of quizzes. In each quiz, you will answer multiple choice questions on one of 6 topics: Math, Verbal Reasoning, US Geography, Science and Technology, Pop Culture, and Sports and Video Games.

The order of the topics will be determined randomly.

You will see only one question at a time. Select an answer and then click the “Next” button to move on to the following question.

If you leave a question unanswered, it will be marked as incorrect. You will not be able to go back to that question once you click the “Next” button.

You will have 2 minutes for each quiz. Once the time runs out, your answers will be submitted automatically.

At the end of the experiment, the computer will randomly select one topic (each chosen with equal probability), and you will be paid \$0.20 for each correct answer.

Your score on the quizzes will also affect how much you earn in part 2. The higher your score, the more likely you will be to make more money.

When you finish all six quizzes, there will be a short questionnaire that will not affect your payoff. Please answer all the questions as accurately as you can. You will have access to your answers from Part 1 when in Part 2, which can help you make better choices.

We will move on to Part 2 once everyone completes Part 1.

**Part 2 (Ego):**

The task in this part will be repeated once for each topic from Part 1. For each task, you will make 11 choices.

In this part, you will choose one of 3 gambles and see 10 outcomes for the one you choose. Each outcome will be either a success or a failure, and the probability with which each of them is a success is determined by 3 factors:



Your score on the quiz for the corresponding topic,

A randomly chosen success rate,

Your choice of a gamble.

Your score is either Low (if it is 5 or less), Mid (if it is between 6 and 15), or High (if it is 16 or more). You will not know your actual score, but you will be reminded of the guess you made in part 1.

The success rate will be chosen randomly by the computer, and it can be Rate A, B, or C. Each is drawn with an equal chance ( $1/3$  chance each), but you will not know which one was drawn. The rate is drawn once, at the beginning of the task, and stays fixed throughout.

To maximize the chance of success, you should choose the gamble that matches the underlying success rate: - Gamble A maximizes the probability of a success when the rate is A, - Gamble B maximizes the probability of success when the rate is B and - Gamble C maximizes the probability of success when the rate is C.

After 11 gamble choices, the task will change to the next topic. This means that the probability of success for this new task will be determined by the following: - The score you received on the quiz for the corresponding topic and - a new draw of the rate (A, B, or C)

At the end of the experiment, the computer will randomly pick one of the topics, and you will be paid \$0.20 for each success. (For each topic, there will be 110 outcomes: 10 outcomes for each of the 11 choices you made).

We will now go over the details of the probability of success. They are described by the tables in the back.

Three tables describe the probabilities. Each table corresponds to one of the score levels: Low, Mid, and High.

Each of the columns within the matrix corresponds to one of the success rates. You do not know which was drawn, but the gambles' outcomes can help you determine the rate.

You will choose a Row.

In order to enter your choice of a gamble, you will first need to choose which matrix you

want to see. If you choose a matrix that does not correspond to your score, the probabilities in the table will not match the probabilities with which the outcomes are successful.

The outcomes will be generated using: - your actual score (table), which you do not know for certain, - the gamble (row) that you chose, and - the rate (column), which you also don't know.

## **Part 2 (stereotype):**

The task in this part will be repeated once for each topic from Part 1. For each task, you will make 11 choices.

In this part, you will choose one of 3 gambles and see 10 outcomes for the one you choose. Each outcome will be either a success or a failure, and the probability with which each of them is a success is determined by 3 factors: - The score of another participant on the quiz for the corresponding topic, - A randomly chosen success rate, - Your choice of a gamble.

The other participant's score is either Low (if it is 5 or less), Mid (if it is between 6 and 15), or High (if it is 16 or more). You will not know the score but will be reminded of your guess in part 1.

The success rate will be chosen randomly by the computer, and it can be Rate A, B, or C. Each is drawn with an equal chance (1/3 chance each), but you will not know which one was drawn. The rate is drawn once, at the beginning of the task, and stays fixed throughout.

To maximize the chance of success, you should choose the gamble that matches the underlying success rate: - Gamble A maximizes the probability of a success when the rate is A, - Gamble B maximizes the probability of success when the rate is B and - Gamble C maximizes the probability of success when the rate is C.

After 11 gamble choices, the task will change to the next topic. This means that the probability of success for this new task will be determined by the following: - The score the other participant got on the quiz for the corresponding topic - A new draw of the rate(A, B, or C)

At the end of the experiment, the computer will randomly pick one of the topics, and you will be paid \$0.20 for each success. (For each topic, there will be 110 outcomes: 10 outcomes for each of the 11 choices you made).

We will now go over the details of the probability of success. They are described by the tables in the back.

Three tables describe the probabilities. Each table corresponds to one of the score levels: Low, Mid, and High.

Each of the columns within the matrix corresponds to one of the success rates. You do not know which one was drawn, but the gambles' outcomes can help you determine the rate.

You will choose a Row.

In order to enter your choice of a gamble, you will first need to choose which matrix you want to see. If you choose a matrix that does not correspond to the score, the probabilities in the table will not match the probabilities with which the outcomes are successful.

Once you enter a choice, the 10 outcomes will be generated using the following: - the actual score (matrix), which you do not know for certain, - the gamble (row) that you chose, and - the rate (column), which you also don't know.

*The full data generating process is printed on the rear side of the instructions and always available to the subjects throughout part 2. Each of the matrices is labeled with "if your/the other participant's score is..." depending on the treatment*

### **Screen walk-through script:**

This is the screen where you will enter your choices of gambles. First, you must choose the matrix that you want to see. Whatever matrix you choose to see does not change the probabilities with which the gambles are a success. Then, you must choose a gamble (which corresponds to a row). The computer will draw 10 outcomes for that gamble using the probability in the chosen row and the column corresponding to the rate for this task. On the right, you can choose to see either the total count of successes and failures for each gamble or the detailed history. That is the number of successes and failures for each of your choices.

The rate will be drawn again for the next task, corresponding to the next quiz topic. And you will repeat this process.

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