Contingent Belief Updating

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Abstract

We study the impact of contingent thinking on belief updating. Engaging in contingent thinking calls for both processing hypothetical information and contrasting multiple contingencies during the belief-updating process. Our experimental findings show that contingent thinking leads to significant deviations from Bayesian updating when signals are asymmetric in diagnosticity. We find that deviations are driven by the diminished perceived informativeness of all hypothetical signals; contrasting contingencies, however, can counteract this distortion for symmetric signals but not for asymmetric ones. These results establish contingent thinking as a distinct source of belief distortions with implications for contingent planning, information acquisition, and information design.

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JEL Classification: C91; D83; D91.

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1 Introduction

To determine the best course of action, it is often essential to consider future realizations of information and to anticipate how expectations could respond to these diverse contingencies. Think of writing a contingent contract, pricing a structured financial asset, or deciding to run a survey to collect new data. Yet, research in economics and psychology has focused on settings where individuals incorporate an already-realized piece of information into their belief system. Do we process the same information in the same manner in these circumstances? While, according to the Bayesian benchmark, belief updating should not depend on whether individuals engage with data contingently, this study shows that it does.

This paper experimentally studies whether and to what extent contingent thinking affects belief updating. Economics examines several situations that require the use of contingent thinking in belief updating. To formulate a strategy in sequential games, players often have to form beliefs contingently about the opponent's type or the state of nature. Also, decisions to acquire information, to experiment, or to design information structures call for an ex-ante assessment of the value of information for different contingencies. In line with these applications, we focus on the following working definition of contingent thinking: Ahead of the resolution of some uncertainty, individuals reason through the mutually exclusive potential realizations of such uncertainty (contingencies), assessing their reaction to each potential realization.

As an illustration, consider a doctor deciding whether to administer a test to a patient. The test produces an informative but noisy signal from which the doctor can learn about the patient's health. To make this decision, the doctor has to anticipate how they would learn given each result, thereby engaging in contingent thinking. To do so, the doctor has to reason through both scenarios of a positive and a negative test result and update their beliefs for each contingency without having observed either. This is what we refer to as *contingent belief updating*, that is, assessing updated beliefs for all the possible signal realizations that could materialize. We distinguish this from what we call *conditional belief updating*: One observes a new piece of information and then assesses the updated beliefs only for that realized and relevant signal. Are beliefs assessed contingently the same as beliefs assessed conditionally? If not, would contingent belief updating help you form more accurate beliefs, or would this only lead to more biased beliefs?

We conduct an online experiment to investigate the effect of contingent belief updating. The experiment implements three between-subject treatments in the commonly used "balls-and-urns" updating paradigm with binary state and signal. To investigate the underlying mechanisms, we employ two approaches. First, we identify two features of contingent belief updating that set it apart from conditional belief updating: (i) the hypothetical nature of the considered contingency (*hypothetical thinking*), and (ii) the consideration of all possible contingencies (*contrast reasoning*). Our treatments break down the effect of contingent thinking into these two components. The participants face contingent belief updating by employing the strategy method to elicit beliefs, while conditional belief updating can be induced by eliciting beliefs with the direct method. Both components of contingent thinking are present in the first, but absent in the second. Therefore, we introduce a third treatment that requires hypothetical thinking but not contrast reasoning by eliciting posteriors conditional on one (random) hypothetical contingency. Second, we examine how the characteristics of the information structure and individual traits interact with the effect of contingent thinking. Specifically, participants face ten different signal-generating processes with different characteristics that could affect their updating, such as how diagnostic signals are (signal strength) and whether the different signals are equally diagnostic for different states (symmetric vs. asymmetric signal-generating processes).

We find that, overall, contingent thinking leads to more distortion in belief updating: compared to the Bayesian benchmark, we report both more biased beliefs in terms of the absolute distance and more underinference if beliefs are elicited contingently compared to conditionally. Contingent belief updating increases the absolute bias by one-third. In the doctor's example, this finding would suggest under-testing by an uninformed doctor. Crucially, this aggregate treatment effect varies substantially with the symmetry of the signal-generating process. In fact, the biasing effect of contingent thinking is only present for asymmetric signal-generating processes.

Decomposing the effect of contingent thinking, we document a distinct pattern. Hypothetical thinking leads to an increase of more than 50% in absolute bias and pushes participants to systematically underinfer more. The effect of hypothetical thinking is independent of whether the signal-generating process is symmetric or not. We also find that hypothetical thinking worsens a wide range of accuracy and consistency measures: not only are beliefs further from being Bayesian, but there is also more noise in the reported beliefs and less consistency in how beliefs are updated across contingencies. The biasing effect of hypothetical thinking is more pronounced with stronger signals, and it also makes the task appear more challenging for participants.

Unlike the effect of hypothetical thinking, the effect of contrast reasoning varies with the symmetry of the signal-generating process. Our data show that contrast reasoning fully offsets the negative impact of hypothetical thinking when the signal-generating process is symmetric but has no effect when asymmetric. We explain this sharp result by showing that the effectiveness of contrast reasoning diminishes continuously as the signal structure becomes more asymmetric. We can trace back the resulting increase in the bias to a particular heuristic: some participants respond to asymmetric signals as if they were symmetric. Substituting the complex, asymmetric problem with a simpler, symmetric one becomes increasingly harmful the more asymmetric a signal-generating process is. As a consequence, contingent and conditional belief updating do not differ for symmetric signal-generating processes but do for asymmetric ones. In the example, the doctor's assessment of how their beliefs evolve to the test's potential outcomes is accurate only when the false positive and false negative rates coincide. Contrast reasoning also counteracts the distorting effects of hypothetical thinking on belief consistency.

The importance of studying the impact of contingent thinking on belief updating is emphasized by the fact that it is non-trivial, even for experts, to predict its directional effect. We asked a sample of academic experts in economics to predict how contingent belief updating affects belief distortions. We document significant heterogeneity in experts' predictions, with the majority expecting biases would be unaffected or reduced if individuals update their beliefs contingently compared to conditionally. Our findings directly oppose these predictions.

Our project speaks to several strands of literature. First, we contribute to the literature on biases in beliefs. Ample evidence shows that individuals tend to underinfer from information (Benjamin, 2019). Crucially, this literature predominantly studies belief updating after a signal has been realized. We take this as our benchmark to investigate whether established biases persist when reasoning through contingencies. Recent studies by Augenblick et al. (2025) and Ba et al. (2025) replicate this result, studying belief updating for several levels of signal diagnosticity, but also find overinference for weak signals. We purposefully exclude weak signals from our design to restrict our attention to underinference, allowing for a stronger identification of the effect. However, inspired by these studies, we employ several signal-generating processes that vary in signal strength to study how contingent belief updating is affected. Closely related to our work, Gonçalves et al. (2026) find that people underinfer from retractions due to their increased complexity, which also requires contingent thinking. In contrast, we offer a direct test of the role of contingent thinking in belief updating.

Second, there is a growing and recent body of literature in economics related to contingent thinking. These studies highlight the widespread challenges associated with contingent thinking (e.g., Li, 2017; Martínez-Marquina et al., 2019; Esponda and Vespa, 2014, 2024; Ngangoué and Weizsäcker, 2021).[1,2] Our approach complements the existing literature on contingent thinking, recently surveyed by Niederle and Vespa (2023), as it differs in three key aspects from these papers. First, our focus lies on belief updating — processing of new information to report revised beliefs — rather than choosing an action — evaluating and comparing the implications of each alternative to implement the preferred one. Second, in these papers, individuals are normatively expected to engage in contingent reasoning to optimally solve the task at hand. Instead, one can treat each contingency in isolation to report accurate beliefs. Third, our approach involves participants reporting multiple contingency-specific guesses, either in the case where one contingency is observed (ex-post) or in the case there is uncertainty on the relevant realized contingency (ex-ante). In contrast, previous works focus on ex-ante decision-making, where contingent thinking is instrumental in properly comparing the different contingency-specific consequences to choose the optimal action. Regardless of these differences, our paper and this literature document ways in which contingent thinking could impede payoff maximization, primarily rooted in the difficulty of considering hypothetical realizations, as discussed further in Section 5.

Our results have broad implications for situations that involve contingent thinking in belief updating, such as information acquisition, information design, and experimentation. First, our findings offer an explanation for the "compression effect" in information acquisition documented in Ambuehl and Li (2018), where individuals undervalue informative sources due to underinference in belief updating. We

[1] As in these papers, we assume contingencies to be known and foreseeable, ruling out concerns related to unawareness. While we believe this to be an interesting strand of literature (e.g., Schipper, 2024; Becker et al., 2025; Karni and Vierø, 2013, 2017), it is beyond the scope of this paper. Moreover, we focus on contingent thinking instead of *counterfactual thinking.* In the psychological literature, (e.g., Kahneman and Tversky, 1982; Epstude and Roese, 2008; Byrne, 2016), counterfactual thinking refers to mental simulations of past events. Hence, the distinction between the two concepts lies in the object of the simulation: an alternative version of a realized event (counterfactual) rather than a potential future event (contingency). Recent studies embrace a clear-cut distinction between the two (Pearl, 2009; Ferrante et al., 2012; Gerstenberg, 2022).

[2] Recent studies highlight mental imagery—"*representation resulting from perceptual processing not triggered by sensory input*"(Stanford Encyclopedia of Philosophy)—as a tool for improving economic outcomes (Dube et al., 2025; Ashraf et al., 2025; John and Orkin, 2022; Alan and Ertac, 2018).

provide a new perspective on this result: when individuals consider acquiring information, they also engage in contingent belief updating. This leads to underinference and can generate this compression effect. Second, our results also provide insights into the behavior observed by Zultan et al. (2025), where participants favor acquiring information from symmetric sources rather than asymmetric ones, even when suboptimal. We not only observe a higher degree of underinference when beliefs are elicited contingently, but this effect is particularly pronounced for asymmetric signal-generating processes, which can explain why participants underestimate the informational value from these sources.

Last, this paper also contributes to the literature on elicitation methods by investigating whether there is a systematic difference across beliefs elicited with the direct or strategy method. While most studies investigating biased beliefs employ the direct method to elicit beliefs, others adopt the strategy method (e.g., Esponda et al., 2024; Cipriani and Guarino, 2009; Toussaert, 2017; Charness et al., 2021b; Agranov et al., 2025). Most recently, Tsakas (2026) proposes that the strategy method using instrumental variables can identify beliefs even under state-dependent utility. Similarly, Kozakiewicz (2022) and Lilley and Wheaton (2024) use hypothetical signals to identify the effect of motivated reasoning on belief updating. While these approaches may solve certain problems of belief identification, our results suggest it may introduce a new one. If applied, one should account for the higher underinference that arises with an asymmetric probability structure. Yet, while the distinction between elicitation methods is well-documented for eliciting actions (e.g., Brosig et al., 2003; Casari and Cason, 2009; Aina et al., 2020; and Brandts and Charness, 2011 for a review), the literature on belief elicitation has focused on the impact of payment schemes, rule complexity, and correspondence with actions (e.g., Charness et al., 2021a; Schlag et al., 2015; Schotter and Trevino, 2014). To the best of our knowledge, our study is the first to demonstrate that the method of belief elicitation impacts the reported posterior beliefs.

The rest of the paper is organized as follows: Section 2 describes our experimental design and data collection, Section 3 briefly describes the experts' predictions, Section 4 presents the results, and Section 5 discusses our findings.

2 Experimental Design

Studying how contingent thinking affects belief updating and the underlying mechanisms requires (i) a setting that prompts contingent thinking in belief updating,

(ii) a treatment variation that disentangles the effects of hypothetical thinking and contrast reasoning, and (iii) a clean manipulation of the characteristics of the signal-generating process.

To study belief updating, we employ the classic balls-and-urns paradigm. The participants face two bags, A and B, which are equally likely to be selected, $\Pr(A) = \Pr(B) = 50\%$. Each bag has a total of either 80 or 60 balls, which are either blue or orange.[3] While the participants do not know which bag is selected, they know the distribution of the colored balls in the bags and the computer draws from the selected bag a ball whose color can be informative. The participant's task is to guess the probability of each bag being selected given the available information.[4]

Table 1: Treatments

		Contrast Reasoning	
		No	Yes
Hypothetical Thinking	No	Conditional	—
	Yes	One-Contingency	All-Contingency

2.1 Treatments

To manipulate whether participants engage in hypothetical thinking and contrast reasoning, the treatments change the method of belief elicitation. The treatments vary whether the signal for which beliefs are reported has been observed (signal realization observed *vs.* hypothetical) and how many contingencies are considered (one *vs.* both signal realizations), as shown in Table 1. The three between-subject treatments, as detailed below, are summarized in Figure 1 and the corresponding choice interface is shown in Figure 2 (see Online Appendix 3.2 for all interfaces).

1. Conditional: The beliefs are elicited conditional on the realized signal. The participant observes the color of the drawn ball and is then asked to assess beliefs only conditional on that relevant contingency. This corresponds to the classic balls-and-urns task and what we refer to as *conditional belief updating.* It also corresponds to eliciting beliefs with the direct method.

[3]We do not use bags with a total of 100 balls to avoid the heuristic answer (i.e., the probability of bag A after observing a blue ball is the number of blue balls in bag A) corresponds to the correct answer for the symmetric signal-generating processes.

[4]We employ a version of this task in which participants are in control of each step: first, by clicking on 'Select the bag,' a bag is selected through a virtual coin flip; then, by clicking on 'Draw the ball,' a ball is drawn from the selected bag. We use graphical animations for the coin flip and the ball draw to create a realistic setting online and to remind participants of the basic structure of the task in each round.

2. All-Contingency: The beliefs are elicited conditional on both possible signal realizations. Before observing the color of the drawn ball, the participant is asked to report beliefs conditional on both cases on the same screen, in a randomized order: (i) the computer draws an orange ball, and (ii) the computer draws a blue ball. Thus, participants consider the two hypothetical contingencies with the possibility of comparing their beliefs conditional on one signal realization to their beliefs conditional on the other signal realization. After the beliefs are reported, the participants learn the color of the drawn ball. We refer to this as *contingent belief updating*. This features both *hypothetical thinking* and *contrast reasoning*. This treatment corresponds to a belief elicitation that employs the strategy method (as introduced in Mitzkewitz and Nagel, 1993).

3. One-Contingency: The beliefs are elicited conditional on only one possible signal realization. When participants have not yet observed the signal realization, they are asked to consider one of the following hypothetical cases: (i) the computer draws an orange ball, or (ii) the computer draws a blue ball. Each case is chosen with equal probability in each round. As in *All-Contingency*, participants learn the color of the drawn ball after the belief elicitation. This treatment, therefore, requires engaging in *hypothetical thinking*, but not *contrast reasoning*.[5]

2.2 Signal-Generating Processes

The task is repeated for ten rounds. In each round, participants face a different signal-generating process (hereafter, SGP). Figure 3 summarizes and illustrates the 10 SGPs used in this experiment in terms of their characteristics and induced Bayesian posteriors for both signals. In what follows, we refer to each SGP with the respective "$\Pr(blue|A) - \Pr(blue|B)$" as in Figure 3a.

Each SGP specifies how diagnostic a ball of a specific color ball is for each bag. We measure the *signal strength of signal s for bag A* as

$$\lambda_s = \frac{\Pr(s|A)}{\Pr(s|B)}.$$

[5]Although other treatments could have been designed to disentangle the effect of hypothetical thinking and contrast reasoning, we found this version to be the cleanest for our purpose. For example, beliefs could have been elicited sequentially for each hypothetical signal realization. We discard this option as it might have triggered contrast reasoning over rounds. Alternatively, beliefs could have been elicited conditional on the observed signal realization for two identical but independent tasks on the same screen. This approach would trigger contrast reasoning whenever different signals were observed for the two independent tasks. We chose to avoid this treatment because participants may not easily understand the independence assumption.

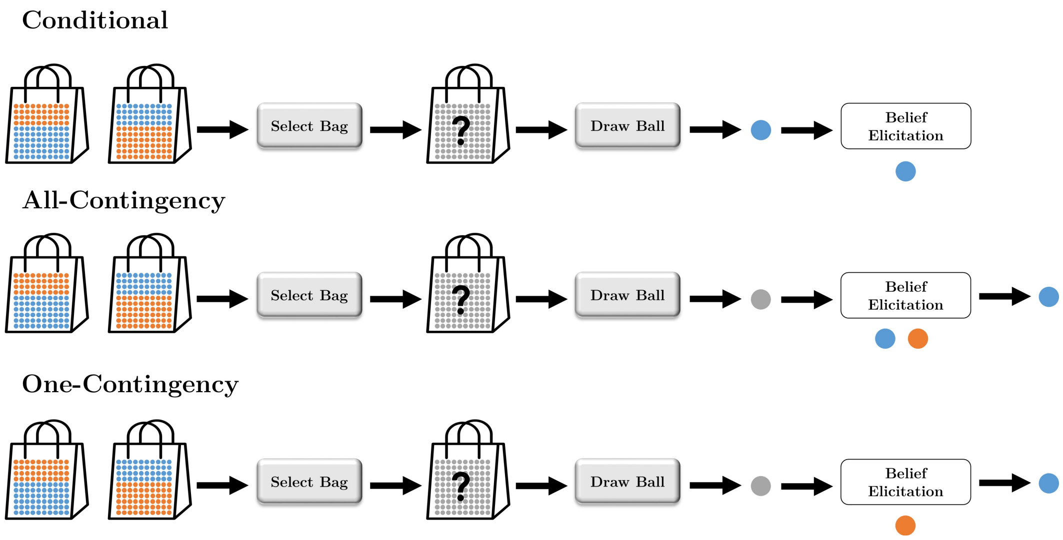


Figure 1: Task Timeline by Treatment

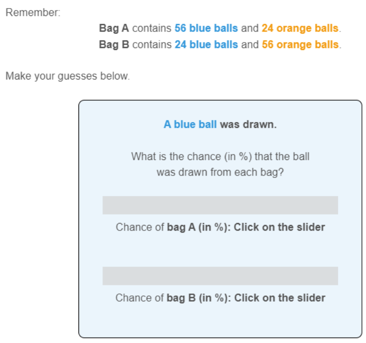
Notes. Treatments branch out after a ball is drawn from the selected bag. The treatments differ depending on whether the color of the drawn ball is revealed before or after the belief elicitation and whether the beliefs are elicited for one or two contingencies. In *Conditional*, participants observe an animated colored ball being drawn, while in the other two treatments, the drawn ball is uncolored with a question mark.

If $\lambda_s = 1$, the signal is not diagnostic for either bag; however, if $\lambda_s > 1$ ($\lambda_s < 1$), the signal is more diagnostic for bag A (B) and λ_s measures by how much.[6] To compare signals more easily across SGPs, we consider the signal strength of each signal in terms of the bag for which the signal is more diagnostic: $\bar{\lambda}_s = \lambda_s$ if $\lambda_s \geq 1$ and $\bar{\lambda}_s = \lambda_s^{-1}$ otherwise. Varying signal strength within-subject over rounds allows us to investigate the mechanism along this dimension and the robustness of the effect of contingent thinking on belief updating.

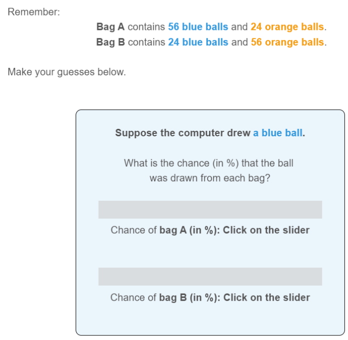
We include both symmetric and asymmetric SGPs. An SGP is *symmetric* if the probability of drawing a blue ball from bag A is the same as the probability of drawing an orange ball from bag B. Hence, for symmetric SGPs, the signal strengths of a blue ball and of an orange ball coincide, i.e., $\bar{\lambda}_{blue} = \bar{\lambda}_{orange}$. In such cases, examining only one bag provides all the necessary information to determine the signal strength and, thus, to guess the posterior correctly. This simple relationship between signal strengths might facilitate contrast reasoning, leading to a heterogeneous effect of contingent thinking for symmetric and asymmetric SGPs.

To explore this further, alongside the binary classification, we introduce a continuous measure that quantifies the degree of asymmetry in an SGP by comparing how diagnostic signals are against each other. This measure captures the extent to

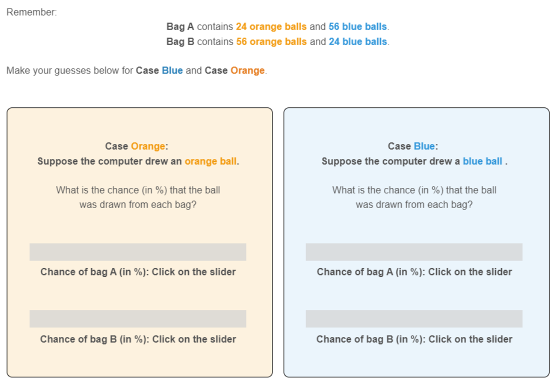
[6]Note that the Bayesian posterior for equal priors can be calculated as $\Pr(A|s) = \left(1 + \lambda_s^{-1}\right)^{-1}$.



(a) Treatment *Conditional*



(b) Treatment *One-Contingency*



(c) Treatment *All-Contingency*

Figure 2: Choice Interface by Treatment

Notes. The figure displays screenshots of choice interfaces for each treatment. Panel (a) presents the interface for *Conditional*, in the case where participants are asked to make a guess upon observing the drawing of a blue ball. Panel (b) presents the interface for *One-Contingency*, in the case where participants are asked to make a guess for the contingency in which the drawn ball was blue. Panel(c) presents the interface for *All-Contingency*.

which signals vary in their signal strength relative to their average signal strength:

$$\sigma\left(\bar{\lambda}_s, \bar{\lambda}_{s'}\right) = \frac{|\bar{\lambda}_s - \bar{\lambda}_{s'}|}{\bar{\lambda}_s + \bar{\lambda}_{s'}}.$$

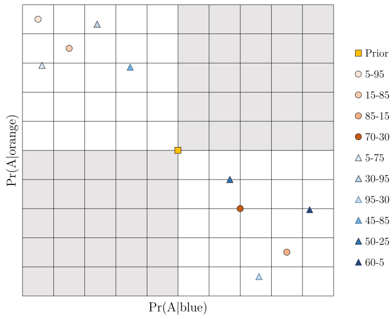
The ratio is zero for symmetric SGPs, but positive otherwise: the higher the ratio, the more asymmetric the signals are in their diagnosticity.[7,8]

[7] In perception studies (for a review in economics, see Woodford, 2020), the contrast between stimuli is quantified analogously to highlight the importance of relative rather than absolute differences in perceptual experience. In economics, salience theory (e.g., Bordalo et al., 2022) uses this functional form to measure the salience of certain attributes in decision-making.

[8] There is no canonical way to quantify the degree of asymmetry. We adopt this measure for its simplicity and intuitive relevance in our setting. As we preregistered a binary version of this measure, but not the continuous counterpart, Online Appendix 1.2 replicates related findings using a conceptually similar measure: the distance between the posteriors across signals.

Name	Pr(blue|A)	Pr(blue|B)	Symmetric	Mirrored	Total Balls
5-95	5%	95%	Yes	No	60
15-85	15%	85%	Yes	Yes	80
85-15	85%	15%	Yes	Yes	60
70-30	70%	30%	Yes	No	80
5-75	5%	75%	No	No	60
30-95	30%	95%	No	Yes	60
95-30	95%	30%	No	Yes	80
45-85	45%	85%	No	No	60
50-25	50%	35%	No	No	80
60-5	60%	5%	No	No	80

(a) Characteristics



(b) Bayesian Posteriors

Figure 3: Signal Generating Processes

Notes. Panel (a) summarizes the different characteristics of the SGP. Panel (b) illustrates the induced posteriors across signal realizations for the different SGPs. The name of the SGP refers to the corresponding "$\Pr(blue|A) - \Pr(blue|B)$".

Lastly, some SGPs are *mirrored*, meaning that participants are exposed to the same SGP twice, inverting the distributions of balls in the bags and changing the number of balls in the bag. Throughout the experiment, we vary whether the total number of balls in the bags is 80 or 60. The mirrored SGPs are presented once with bags with 80 balls and once with 60 balls. We mirrored one symmetric SGP (15-85 and 85-15) and one asymmetric SGP (30-95 and 95-30). The reason why we include mirrored SGPs is twofold. First, we use them to check the consistency of reported beliefs given the same signal across rounds. This is a measure of how stable the deviations from Bayesian updating are within-task (*within-consistency*). Second, this allows us to better compare *Conditional* and *One-Contingency* to *All-Contingency*. When beliefs are elicited contingently, participants report their conditional beliefs on both signal realizations, while they report their beliefs only conditional on one signal in *Conditional* and *One-Contingency*. This allows us to study whether posteriors across signal realizations are consistent with the Bayes rule between signal realizations (*between-consistency*).

For the last task, we also elicited cognitive uncertainty (Enke and Graeber, 2023). For comparability, the last choice displays the same SGP, 70-30, for all participants, while we randomize the order of the SGP for the remaining 9 choices. We pick 70-30 for this because this SGP is closest to the most widely used SGP (67-33) in this type of experiment (see meta-analysis by Benjamin, 2019).

2.3 Incentives

The belief elicitation was incentivized using the binarized scoring rule (Hossain and Okui, 2013): the closer the reported beliefs are to the realized state, the higher the probability of receiving the bonus of GBP 2.[9] One of the ten tasks is randomly selected for payment.

We design our incentives to (i) ensure incentive-compatibility for truthful reporting and (ii) keep the strength of the incentives comparable in all three between-subject treatments. To achieve the first, we ensure that each contingency occurs with non-trivial probabilities for all SGPs (50-50 for symmetric SGPs, and at most 70-30 for asymmetric SGPs). To keep the strength of incentives comparable to *Conditional*, the incentivization requires minimal adjustments in *One-Contingency* and *All-Contingency*. In *All-Contingency*, participants' beliefs are elicited for both contingencies, and the realized contingency determines which guess is relevant for the payment. Paying both belief elicitation tasks could have affected the participants' attention because of the difference in the magnitude of incentives across treatments, confounding our results. In *One-Contingency*, incentives are the same as in *Conditional* if the randomly-proposed contingency corresponds to the realized one; otherwise, the elicited guess is irrelevant for determining the bonus, and the participant receives a fixed payment of GBP 1.[10]

2.4 Logistics

The experiment was pre-registered on AsPredicted.[11] It was conducted on Prolific in March 2023, restricting the pool to participants located in the UK. The participants received a link to a Qualtrics survey that includes the instructions, choice tasks, cognitive uncertainty elicitation for the last choice, and a final survey — eliciting Cognitive Reflection Test (Frederick, 2005), Berlin numeracy task, demographics, and a short questionnaire. The average payment was 3.37 GBP, with an average duration of approximately 24 minutes. The participants earned GBP 2 for completing the study and could earn an additional bonus of GBP 2 depending on

[9]Danz et al. (2022) show that providing complex details on the elicitation procedure might confuse participants and distort their incentives. Therefore, instructions clarify that "to maximize the chance of winning the bonus, it is in your best interest always to give a guess that you think is the true chance." This is also checked in one of the control questions. If interested, participants could read further about the details of this elicitation rule.

[10]While some guesses being payoff-irrelevant could lead to lower attention, we chose this incentivization as consistency of incentives across treatments is our priority. We do not find any evidence that attention is affected, see Section 4.4.2. Furthermore, evidence in similar tasks has shown that the strength of incentives does not impact the belief accuracy (Enke et al., 2023a).

[11]The preregistration plan is available at `https://aspredicted.org/D2G_X81`.

their performance in the tasks.

Instructions were split into two blocks, each followed by a set of control questions. The first block was the same for all treatments: it welcomed the participants, provided general information on the experiment, and explained the balls-and-urns task in detail. The second block focuses on the treatment-specific choice procedure and payment, and thus it varies by treatment. See Online Appendix 3 for the instructions and control questions. Only participants who pass these questions are included in the analysis, as preregistered. A total of 525 participants completed the study, of which 86% passed the control questions about the experiment instructions (not statistically different between treatments: 88% in *Conditional*, 86% in *All-Contingency*, and 83% in *One-Contingency*). This leaves valid observations from 150 participants per treatment. In our final sample of 450 participants, 50% are female, 36% have low schooling ('High school' or lower educational level), and the median age is 37.

3 Expert Survey

To contextualize our findings, we elicit predictions from a sample of academic experts in economics that we considered knowledgeable about topics related to expectations or contingent thinking, before collecting the data. Answers to this expert survey were collected through the Social Science Prediction Platform. We report details of the data collection, survey, and results in Online Appendix 2.

Our survey focuses on the comparison of the treatments *All-Contingency* and *Conditional* and documents significant heterogeneity in experts' opinions on the effect of contingent belief updating. Of 38 responses, 37% expected more accurate beliefs when they are elicited contingently compared to when they are elicited conditionally, 61% did not expect any significant difference between the two elicitation methods, and only one expert expected the opposite. The majority of the experts also do not expect any heterogeneous effects based on the characteristics of the SGPs or individual traits. We take this expert survey as evidence that experts believe that beliefs are not less accurate when assessed contingently.

4 Results

In this section, we first introduce our two main outcomes of interest, *bias* and *underinference*, and we provide an overview of the main treatment effects. We continue with a discussion of potential mechanisms, considering the characteristics of both the SGPs and the participants as drivers of the treatment effects.

4.1 Main Outcomes

We investigate our treatment effects on two preregistered measures, both capturing distinct aspects related to deviations from Bayesian updating.

First, bias is defined as the absolute distance between the reported posterior and the Bayesian posterior for each task. We focus on absolute differences to determine whether individual guesses are systematically more accurate across treatments. In contrast, a directional measure assesses whether the average guess is more or less accurate, allowing individual biases to cancel out. Second, we consider how participants respond to the signal strength to capture directional deviations from Bayesian updating. We use the following model introduced by Grether (1980) that defines the posterior-odds ratio given equal priors as:

$$\frac{\Pr(A|s)}{\Pr(B|s)} = \left[\frac{\Pr(s|A)}{\Pr(s|B)}\right]^{\alpha} = \lambda_s^{\alpha}.$$

Deviations from $\alpha = 1$ capture participants' distortion in how their beliefs respond to the signal strength. While Bayes' rule prescribes $\alpha = 1$, *underinference* corresponds to $\alpha < 1$: the reported posteriors are as if the signal strength is perceived as less diagnostic for bag A and more diagnostic for bag B than it actually is. Conversely, *overinference* implies the opposite distortion, with $\alpha > 1$. Unlike bias, α is a directional measure of deviations from Bayesian updating defined across SGPs.[12] As our SGPs are chosen such that the signals would be classified as strong according to Augenblick et al. (2025), we expect underinference.

Our experiment replicates the deviations from Bayesian updating reported in the literature for both measures. Comparing the available data in the online appendix of Benjamin (2019) to our results in *Conditional* for comparable SGPs (equal prior, symmetric SGPs, including SGPs 60-40, 67-33, and 83-17), we find that the average bias of 5.9 percentage points for the most similar SGP in *Conditional* (70-30) aligns closely with the average bias of 6.7 percentage points in comparable studies.

[12]In Online Appendix 1.1, we consider the alternative measure of underinference introduced in Ba et al. (2025) and show that our results are robust.

Moreover, in his meta-analysis, Benjamin (2019) estimates

$$\log \frac{\Pr(A|s)}{\Pr(B|s)} = \alpha \log \lambda_s + \beta$$

and finds strong evidence for underinference with $\hat{\alpha} = 0.86$ for incentivized similar tasks (equal prior, one observed signal, symmetric SGP). In line with this, the estimated coefficient in *Conditional* for symmetric SGPs is also exactly $\hat{\alpha} = 0.86$.

4.2 Treatment Effects

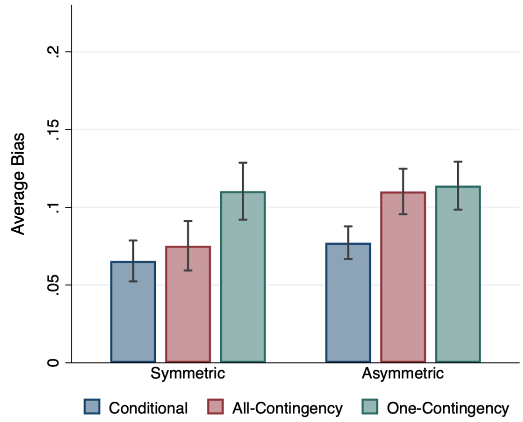
We begin examining our main treatment effects on the two outcomes of interest, presenting results both in aggregate and by SGP symmetry.

Bias in Contingent Belief Updating Figure 4a provides an overview of the average bias in posterior beliefs by treatment, distinguishing between symmetric and asymmetric SGPs as defined in Section 2.2. Column I of Table 2 displays the results for OLS regressions of the bias on indicators for the different treatments alone, Column II of Table 2 reports the difference-in-difference analysis of regressing the average bias on treatment indicators, a dummy indicator of whether the SGP is symmetric, and their interactions.[13]

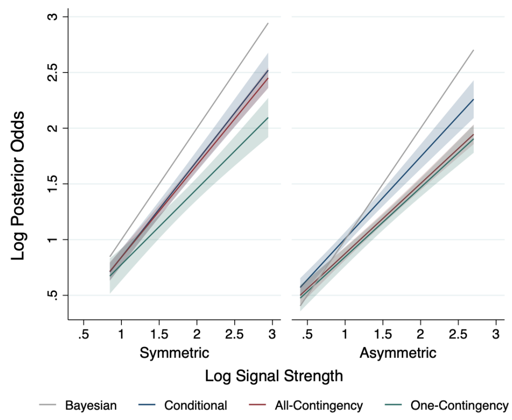
The treatment *All-Contingency* increases the bias compared to *Conditional*. The estimated bias amounts to 7.2 percentage points in *Conditional*. We estimate that the average bias increases in *All-Contingency* by 2.4 percentage points, so by one-third, compared to *Conditional* ($p = 0.006$; Column I in Table 2).

This aggregate result masks substantial heterogeneity in the treatment effect driven by the symmetry of the SGP. Overall, the average bias increases by 3.5 percentage points if signals are asymmetric ($p < 0.001$; Column II in Table 2), suggesting that asymmetric SGPs increase the difficulty of Bayesian inference. The impact of contingent thinking depends on the SGP symmetry We do not observe a significant increase in the average bias when beliefs are updated contingently compared to conditionally for symmetric SGPs ($p = 0.354$; Column II in Table 2), whereas for asymmetric SGPs, the average bias is significantly higher in *All-Contingency* than in *Conditional* ($p < 0.001$; Column II in Table 2).

[13] Analyses in Table 2 include SGP fixed effects. Table A1 reproduces the analyses with SGP $\times$ contingency fixed effects. Contingency here refers to the observed signal realization in *Conditional* and to the contingency relevant for the belief elicitation in *One-Contingency* and *All-Contingency*. This does not change our results.



(a) Bias by SGP Symmetry



(b) Underinference by SGP Symmetry

Figure 4: Treatment Effect by SGP Symmetry

Notes. Panel (a) shows the average bias defined as the absolute value of the difference between the reported posterior and the Bayesian benchmark by treatment split and the symmetry of the SGP. Panel (b) shows the estimated relationship between the log posterior-odds ratio and the log signal strength by treatment as an illustration of underinference split by the symmetry of the SGP. Error bars in Panel (a) and shaded areas in Panel (b) indicate 95% confidence intervals, clustered at the individual level.

Underinference in Contingent Belief Updating We find directionally similar results in terms of underinference. In Column I of Table 3, we report the results from regressing the log posterior-odds over the log signal strength interacted with treatment indicators.

Overall, there is strong evidence of underinference: the estimated coefficients $\hat{\alpha}$ are 0.76 in *Conditional* and 0.70 in *All-Contingency*, displaying significant deviations from the Bayesian benchmark of $\alpha = 1$ in both treatments ($p < 0.001$). While the slope is visibly less steep for *All-Contingency* than for *Conditional*, the estimated underinference in *All-Contingency* is not statistically different from the one in *Conditional* ($p = 0.243$; see the coefficient on 'Log Signal Strength $\times$ All-Contingency' in Column I of Table 3).

Interacting the variables to estimate the degree of underinference with indicators of the SGP symmetry in Column II of Table 3, we observe that the estimated underinference in *All-Contingency* is not statistically different from the one in *Conditional* for symmetric SGPs ($p = 0.538$; Column II of Table 3). However, there is an increase in underinference for asymmetric SGPs in *All-Contingency* compared to *Conditional* ($p = 0.072$; Column II of Table 3). Thus, there is a substantially stronger underinference due to contingent thinking if the SGP is asymmetric than if it is symmetric ($p = 0.023$; Column II of Table 3).

Table 2: Bias

	I	II	III	IV
All-Contingency	0.024**	0.010	0.017*	0.011
	(0.009)	(0.011)	(0.008)	(0.009)
One-Contingency	0.040***	0.045***	0.014	0.039***
	(0.009)	(0.011)	(0.010)	(0.010)
Asymmetric		0.026*		
		(0.010)		
All-Contingency × Asymmetric		0.023*		
		(0.009)		
One-Contingency × Asymmetric		-0.008		
		(0.010)		
Log Signal Strength			0.013*	
			(0.005)	
All-Contingency × Log Signal Strength			0.003	
			(0.006)	
One-Contingency × Log Signal Strength			0.015*	
			(0.007)	
Degree of Asymmetry				0.027*
				(0.012)
All-Contingency × Degree of Asymmetry				0.041**
				(0.015)
One-Contingency × Degree of Asymmetry				0.003
				(0.018)
Constant	0.062***	0.068***	0.019	0.064***
	(0.008)	(0.009)	(0.013)	(0.006)
N	6000	6000	6000	6000
adj. R^2	0.024	0.026	0.028	0.019
Clusters	450	450	450	450

Notes. OLS estimates. Individual-level clustered standard errors. SGP fixed effects in Columns I - III. The dependent variable is defined as the absolute value of the difference between the reported posterior and the Bayesian benchmark; * p<.05, ** p<.01, *** p<.001.

Finding 1. *Deviations from Bayesian updating are significantly larger if beliefs are updated contingently compared to conditionally if SGPs are asymmetric.*

Hypothetical Thinking vs. Contrast Reasoning Next, we look at how the effect of contingent thinking can be explained by its decomposition into hypothetical thinking and contrast reasoning. Recall that comparing *One-Contingency* to *Conditional* isolates the effect of hypothetical thinking without any opportunity for contrast reasoning, while comparing *All-Contingency* to *Conditional* captures both hypothetical thinking and contrast reasoning.

Comparing the bias in *One-Contingency* to *Conditional*, we find a significant increase of 4 percentage points ($p < 0.001$; Column I in Table 2), a relative increase of more than 50%. The average bias in *All-Contingency* falls between the bias in *Conditional* and in *One-Contingency*, although it is not statistically different from the latter ($p = 0.118$; see the difference of the coefficients on 'All-Contingency' and 'One-Contingency' in Column I in Table 2). Therefore, we can attribute the entire increase in the bias induced by contingent thinking to hypothetical thinking.

Turning to our second outcome measure, participants underinfer significantly more

Table 3: Underinference

	I	II	III
Log Signal Strength	0.768***	0.862***	0.874***
	(0.035)	(0.043)	(0.037)
All-Contingency	-0.034	0.034	-0.033
	(0.056)	(0.082)	(0.064)
One-Contingency	-0.012	0.118	0.005
	(0.071)	(0.116)	(0.082)
Log Signal Strength × All-Contingency	-0.058	-0.035	-0.007
	(0.046)	(0.057)	(0.050)
Log Signal Strength × One-Contingency	-0.129*	-0.184*	-0.137*
	(0.055)	(0.081)	(0.065)
Asymmetric		0.293***	
		(0.082)	
Log Signal Strength × Asymmetric		-0.127*	
		(0.056)	
All-Contingency × Asymmetric		-0.061	
		(0.101)	
One-Contingency × Asymmetric		-0.169	
		(0.143)	
Log Signal Strength × All-Contingency × Asymmetric		-0.071	
		(0.067)	
Log Signal Strength × One-Contingency × Asymmetric		0.071	
		(0.098)	
Degree of Asymmetry			0.849***
			(0.166)
Log Signal Strength × Degree of Asymmetry			-0.382***
			(0.103)
All-Contingency × Degree of Asymmetry			0.018
			(0.215)
One-Contingency × Degree of Asymmetry			-0.002
			(0.278)
Log Signal Strength × All-Contingency × Degree of Asymmetry			-0.151
			(0.128)
Log Signal Strength × One-Contingency × Degree of Asymmetry			0.016
			(0.171)
Constant	0.199***	-0.019	-0.044
	(0.044)	(0.066)	(0.051)
N	6000	6000	6000
adj. R^2	0.249	0.252	0.258
Clusters	450	450	450

Notes. OLS estimates. Individual-level clustered standard errors. The dependent variable is defined as the logarithm of the ratio of the reported posterior belief for each bag for a given signal. The interactions of each treatment indicator and Log Signal Strength give the estimated underinference parameter $\hat{\alpha}$ per treatment; * p<.05, ** p<.01, *** p<.001.

in *One-Contingency* ($\hat{\alpha} = 0.63$) than in *Conditional*, with $\hat{\alpha}$ decreasing by 12.9 percentage points ($p = 0.021$; see the coefficient on 'Log Signal Strength × One-Contingency' in Column I of Table 3). Hypothetical thinking thus pushes participants to systematically underinfer more. The level of underinference is not statistically different between *One-Contingency* and *All-Contingency*, providing support for the argument that contrast reasoning neither further increases nor decreases deviations from Bayesian updating.

Finding 2. *Hypothetical thinking is driving the biasing effect of contingent belief updating.*

Given that the deviations documented in Finding 1 are driven by asymmetric SGPs, we next analyze how SGP symmetry interacts with hypothetical thinking and contrast reasoning.

For symmetric SGPs, we observe countervailing effects. Hypothetical thinking increases bias by 4.5 percentage points when participants consider one hypothetical contingency instead of observing the realized signal ($p < 0.001$; Column II in Table 2). However, contrast reasoning compensates this effect: we estimate that the posterior beliefs are 3.5 percentage points more accurate in *All-Contingency* than in *One-Contingency* ($p = 0.005$; see the difference of the coefficients 'All-Contingency' and 'One-Contingency' in Column II in Table 2).

In contrast, our results for asymmetric SGPs show that the average bias is significantly higher in both *One-Contingency* and *All-Contingency* than in *Conditional*. For asymmetric SGPs, the average bias increases by 4.5 percentage points when participants consider one hypothetical contingency instead of observing the realized signal ($p < 0.001$; Column II in Table 2). For asymmetric SGPs, hypothetical thinking with or without contrast reasoning increases the bias by 3.3 and 3.7 percentage points, respectively (both $p < 0.001$; see the sum of the coefficients of the treatment indicators and their interactions with 'Asymmetric' in Column II in Table 2), so by more than 40%. The biases in these two treatments are indistinguishable for asymmetric SGPs ($p = 0.727$).

By breaking down the effect of contingent thinking into hypothetical thinking and contrast reasoning, we shed light on Finding 1. Since hypothetical thinking increases bias irrespective of whether SGPs are symmetric, the larger deviations from Bayesian updating in contingent belief updating depend on the effectiveness of contrast reasoning. While contrast reasoning successfully compensates for the distortions induced by hypothetical thinking in symmetric SGPs, it fails to mitigate these distortions in asymmetric SGPs.

We also report a similar pattern in terms of underinference, as illustrated in Figure 4b. While hypothetical thinking increases the degree of underinference also if the SGP is symmetric ($p = 0.024$; see the coefficient on 'Log Signal Strength $\times$ One-Contingency' in Column II of Table 3), hypothetical thinking in combination with contrast reasoning only does so marginally for asymmetric SGPs ($p = 0.084$; see the sum of the coefficients on 'Log Signal Strength $\times$ All-Contingency' and 'Log Signal Strength $\times$ All-Contingency $\times$ Asymmetric' in Column III of Table 3). Therefore, contrast reasoning reduces the degree of underinference if the SGP is symmetric but fails to do so if it is asymmetric.

Finding 3. *The impact of hypothetical thinking does not vary with the symmetry of the SGP. Contrast reasoning fully compensates this effect for symmetric SGPs, but not for asymmetric SGPs.*

Robustness of Main Effects Moreover, the treatment effects cannot be attributed to a small subset of participants. Figure A1 presents the estimated coefficients from quantile regressions across different quantiles of the absolute bias, separately for *All-Contingency* and *One-Contingency*. The figure shows that the treatment effects are widely dispersed; the effect is significantly different from zero, at the 5% level, for all values of bias above the 70th and the 30th percentile, for *All-Contingency* and *One-Contingency*, respectively.

Finally, Figure A2 shows the average bias by treatment for each SGP. The patterns described for symmetric vs. asymmetric SGPs are robust: The bias in *One-Contingency* is larger than that in *Conditional* for all SGPs and the bias in *All-Contingency* is larger than in *Conditional* only for asymmetric SGPs (with the exception of one SGP).[14]

4.3 Mechanisms

We now turn to the mechanisms underlying the effect of contingent thinking on belief updating. Any successful explanation must account for why asymmetry in signals limits the extent to which contrast reasoning offsets the impact of hypothetical thinking. We propose a mechanism that can explain this pattern, and subsequently rule out two alternatives. Our analysis of the mechanisms relies on two novel measures introduced below: the degree of asymmetry and relative underinference.

4.3.1 Treating Asymmetric Signals as Symmetric

Finding 3 shows a sharp result: contrast reasoning fully offsets the biasing effect of hypothetical thinking for symmetric SGPs, but has no impact for asymmetric SGPs. To further explore the relation between contrast reasoning and symmetry, we turn to a more nuanced measure: the degree of asymmetry. As formalized in Section 2, this quantifies the difference in signal strength between the two signals.

[14]See Figure A5 for an overview of the estimated degree of underinference by treatment and SGP. In all treatments, we observe underinference for most SGPs. For a more nuanced picture, Figure A6 provides an overview of the heterogeneity in the estimated degree of underinference by subject and treatment.

This continuous measure of asymmetry captures meaningful variation in our data, predicting when contrast reasoning is effective in reducing bias.[15] The coefficient of the interaction between the degree of asymmetry and *All-Contingency* is significantly positive ($p = 0.009$; Column IV of Table 2) and significantly larger than the coefficient of the interaction between the degree of asymmetry and *One-Contingency* ($p = 0.033$; Column IV of Table 2). Therefore, as the degree of asymmetry increases, the effectiveness of contrast reasoning in counteracting the biasing effect of hypothetical thinking diminishes.

A higher degree of asymmetry may limit the debiasing effect of contrast reasoning because individuals may wrongly interpret an asymmetric SGP as if it were symmetric. That is, they substitute the difficult, asymmetric updating problem with a simpler, symmetric one. This heuristic reduces complexity: For symmetric SGPs, the reported posteriors for the same bag across signals should sum up to one since $\Pr(A|b) = \Pr(B|o)$. While this property does not hold for asymmetric SGPs, applying this logic becomes increasingly distorting as the degree of asymmetry increases, leading to higher bias. This may explain why contrast reasoning proves ineffective in reducing bias for more asymmetric signals.

To detect the use of such a heuristic, we classify pairs of guesses in *All-Contingency* as 'Treated as Symmetric' if there is an absolute distance between the reported posteriors $\Pr(A|b)$ and $\Pr(B|o)$ of at most one percentage point.[16] Assuming that participants use this heuristic, we should observe (i) a substantial share of pairs of guesses classified as 'Treated as Symmetric,' and (ii) that the bias increases more with the degree of asymmetry for those pairs of guesses than for those that do not fall under this classification. Our data confirm both patterns. Among all pairs of guesses for asymmetric SGPs, 14.1% are classified as 'Treated as Symmetric.'[17]

As Figure 5 illustrates, the increase in bias in *All-Contingency* with the degree of asymmetry can be attributed to guesses classified as 'Treated as Symmetric.' The bias increases significantly more with the degree of asymmetry for guesses being classified as 'Treated as Symmetric' than for those that are not ($p < 0.001$; Column I in Table A2). Note that, while the share of guesses treating signals as symmetric decreases in the degree of asymmetry ($p < 0.001$), the magnitude of the mistake

[15] We restrict our analysis of the degree of asymmetry to bias. Analyzing its effect on underinference would be hard to interpret as both measures are defined in terms of signal strength.

[16] The results are similar if we use more or less strict classifications. We cannot perform this analysis in the other treatments, as it requires a pair of guesses within the same SGP and variation in the degree of asymmetry across multiple SGPs.

[17] The pairs of guesses for symmetric SGPs in *All-Contingency* classified 'Treated as Symmetric' is 75.3%. Figure A9 illustrates the scatter plot of these pairs of guesses by SGP symmetry.

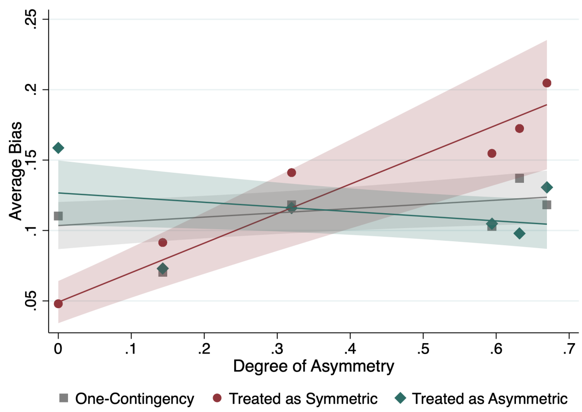


Figure 5: Treating an SGP as Symmetric and the Degree of Asymmetry

Notes. Average bias in *One-Contingency* and *All-Contingency* (split into "Treated as Symmetric" and "Treated as Asymmetric") by the degree of asymmetry for pairs of guesses from asymmetric SGPs. Shaded regions indicate 95% confidence intervals.

becomes more severe. In fact, we find that the entire increase in the bias with the degree of asymmetry is driven by the pairs of guesses classified as 'Treated as Symmetric' ($p = 0.057$ for the negative coefficient 'Degree of Asymmetry' in Column I in Table A2).

Additional evidence suggests that contrast reasoning promotes the use of the described heuristic. To isolate this channel, we compare *All-Contingency* to *One-Contingency*, thereby identifying the effect of contrast reasoning. In *One-Contingency*, bias increases with the degree of asymmetry, more so than in the pairs of guesses in *All-Contingency* that are not classified as 'Treated as Symmetric' ($p = 0.005$; Column II in Table A2). In contrast, for guesses classified as 'Treated as Symmetric,' the bias increases sharply with the degree of asymmetry, significantly more so than in *One-Contingency* (see also Figure 5); the difference in how bias varies with the degree of asymmetry across these groups is statistically significant ($p < 0.001$; Column III in Table A2). These findings support the interpretation that contrast reasoning increases the use of the symmetry heuristic, thereby amplifying bias for more asymmetric SGPs. [18]

Finding 4. *With contrast reasoning, the bias increases in the degree of asymmetry. This pattern is attributable to guesses that treat asymmetric SGPs as symmetric.*

[18] Guan et al. (2025) show that people tend to misjudge the value of information, attributing this to them behaving as if signals are equally likely ex-ante. In a binary-signal setting with uniform priors, this heuristic leads to the same perceived signal structure as treating an asymmetric SGP as symmetric, making their and our heuristics observationally equivalent.

4.3.2 Alternative Mechanisms

This section considers two alternative mechanisms that could explain an interaction between contrast reasoning and SGP asymmetry. Both mechanisms rely on participants misinterpreting the simultaneous presentation of signals in the *All-Contingency* treatment. First, participants might update beliefs "as if" both signals were realized simultaneously. Second, they might conflate the diagnosticities of the two signals. We examine and rule out these possibilities below.

Simultaneous Realizations Participants in *All-Contingency* might misinterpret the simultaneous elicitation when asked to report their beliefs for both contingencies on the same screen. Specifically, it may lead participants to update their beliefs "as if" both signals were realized rather than processing each hypothetical contingency in isolation.

Crucially, each SGP is such that each signal points to a different direction: one signal is more diagnostic for bag A ($\lambda_s > 1$), and one signal is more diagnostic for bag B ($\lambda_{s'} < 1$). Thus, if participants misinterpret the treatment *All-Contingency* in this manner, their beliefs should be reported as if they respond to a convex combination of the two signal strengths for bag A, λ_{blue} and λ_{orange}. Such aggregation would mechanically dampen the belief update and generate a clear prediction: a higher underinference in *All-Contingency* compared to *One-Contingency*, particularly for symmetric SGPs where the opposing signals should cancel each other. However, as reported in Section 4.2, we do not observe this pattern across treatments and across SGPs' symmetry, ruling out this mechanism.

Signal Strength Averaging The last explanation we consider for why contrast reasoning fails to reduce bias in asymmetric SGPs is that individuals mix the diagnosticity of the two signals. Unlike the previous mechanism, where participants mistakenly assume both signals realize, here they correctly consider one contingency at a time but perceive its signal strength as a convex combination of the two signal strengths, $\bar{\lambda}_{blue}$ and $\bar{\lambda}_{orange}$.

To test this prediction, we introduce a new measure: relative signal strength. For symmetric SGPs, signals have the same signal strength, but for asymmetric ones, it is possible to distinguish between a weaker and a stronger signal. Formally, signal s is stronger than signal s' if $\bar{\lambda}_s > \bar{\lambda}_{s'}$. That is, the stronger signal moves beliefs further away from the prior compared to the weaker signal.[19] If participants were averaging the diagnosticities in *All-Contingency*, we should observe an attenuation pattern relative to *One-Contingency*: There would be less underinference for the stronger signal and more underinference for the weaker signal.

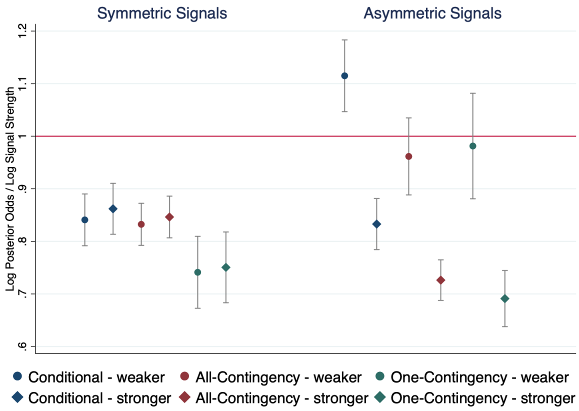


Figure 6: Underinference for Stronger and Weaker Signals

Notes. The ratio of log posterior-odds and the log signal strength by treatment, symmetry of the SGP, and stronger *vs.* weaker signal; for symmetric SGPs, signals are equally diagnostic, and we classify the blue ball as stronger arbitrarily. Error bars indicate 95% confidence intervals.

Figure 6 reports the average underinference level by weaker *vs.* stronger signal, treatment, and SGP symmetry. Since signals are equally diagnostic in symmetric SGPs, the underinference level should not vary by signal within the same treatment. Indeed, we observe no different reaction to the two signals. Turning to asymmetric SGPs, a clear pattern emerge across treatments: reported guesses exhibit a significantly higher degree of underinference for stronger signals compared to the weaker ones.[20]

Considering the underinference gap allows us to test this last mechanism. If beliefs reflect averaging signal strengths in *All-Contingency*, the distinction between stronger and weaker signals should blur, effectively shrinking the underinference gap compared to *One-Contingency*. However, as shown in Table A3, the underinference gap does not differ across treatments, ruling out the averaging signal strength as

[19] One can show that, for an asymmetric SGP, the stronger signal is the a priori less likely one, that is, $\bar{\lambda}_s > \bar{\lambda}_{s'}$ is equivalent to $\Pr(s) < \Pr(s')$. This allows us to offer another interpretation of these results based on the comparison between more likely or less likely signals. Note that the bias decreases in the probability of the signal ($p < 0.001$), but the probability of the signal does not interact with our treatment effect ($p = 0.293$ and $p = 0.338$).

[20] This result builds and extends on the key result in Augenblick et al. (2025) in terms of different levels of signal strength. Instead, we show that relative signal strength also drives the level of underinference by focusing on asymmetric SGPs in which signals may differ in strength within the same SGPs.

the driver of our results.

This analysis, however, reveals how relative signal strength matters for inference. Not only the underinference gap is stable across treatments, but we find evidence of this gap even at the individual level for *All-Contingency*: the average individual underinfers more in response to the stronger signal compared to the weaker one when reporting guesses on the same screen (Figure A7). Moreover, we observe significant differences in the level of underinference across treatments. These differences follow the same pattern as in Finding 3, both for symmetric and asymmetric signals. While underinference prevails for most treatments, for *Conditional*, weaker signals generate significant overinference for asymmetric SGPs.

4.4 Additional Measures

In the previous sections, we show how the SGPs' characteristics, specifically their symmetry and relative signal strength, influence our treatment effects, considering our two main outcomes. We will now consider measures of consistency and additional individual measures.

4.4.1 Consistency Measures

Our analysis of the mechanisms continues by looking at the treatment effects on additional outcomes related to consistency.

Table 4: Consistency

	Δ Posteriors	Bayes-Inconsistent
All-Contingency	0.011	0.026
	(0.016)	(0.024)
One-Contingency	0.066**	0.081*
	(0.022)	(0.035)
Constant	0.112***	0.068**
	(0.015)	(0.021)
N	904	896
adj. R^2	0.016	0.006
Clusters	379	375

Notes. OLS estimates. Individual-level clustered standard errors. Symmetry SGP fixed effects. The dependent variable in Column I is the absolute difference in the reported posteriors for the same signal for mirrored SGPs, and in Column II a dummy taking value one if the vector of posteriors for mirrored SGPs is Bayes-inconsistent; * p<.05, ** p<.01, *** p<.001.

Within-Consistency Exploiting the mirrored SGPs, we investigate the stability of the reported posteriors within a task, *within-consistency*. This measure allows us to evaluate whether the treatments have the important side effect of increasing the noise in how beliefs are updated.[21]

With this goal, our dependent variable ΔPosteriors is defined as the absolute difference between the posteriors for the probability of bag A given the same signal reported for two mirrored SGPs (see Appendix A.4.1 for details). While participants should report the same beliefs in both instances and this difference should be zero, our pooled data provides evidence of inconsistent beliefs for the same task: the average ΔPosteriors is 12 percentage points (statistically different from zero, with $p < 0.001$), with a median of 5 percentage points.[22]

Compared to *Conditional*, participants in *One-Contingency* are significantly more likely to be inconsistent ($p = 0.004$; Column I in Table 4). This is not the case in *All-Contingency* ($p = 0.477$; Column I in Table 4), where we observe a higher level of within-consistency than in *One-Contingency* ($p = 0.009$; see the difference of the coefficients of the treatment indicators in Column Δ Posteriors in Table 4). Therefore, hypothetical thinking leads to less within-consistent beliefs, while the presence of contrast reasoning counteracts this increase completely.

Between-Consistency So far, we have looked at measures of deviations from Bayesian updating given a signal realization. Next, we consider a way to categorize deviations from Bayesian updating by looking at the performance across contingencies: the consistency of the reported beliefs across signal realizations given the same SGP (*between-consistency*).

Bayes' rule prescribes that beliefs cannot be updated in the same direction for all signal realizations. Therefore, holding posteriors given both signal realizations either above or below the prior would be an extreme violation of Bayesian updating. For this analysis, we need for each participant the reported *vector of posterior beliefs*, that is, the elicited posteriors conditional on each contingency given an SGP. We construct those thanks to our mirrored SGPs; see Appendix A.4.2 for details. Following Aina (2025), we say that a vector of posteriors is *Bayes-inconsistent* if both posteriors are higher or lower than 50%. Bayes-inconsistency is an extreme deviation from Bayesian updating because not only are the posteriors different from the ones implied by the known SGP, but it is also impossible to find an SGP that

[21]This measure is conceptually related to cognitive uncertainty under the assumption that participants are well-calibrated in assessing their own performance, which is not the case for belief-updating tasks (Enke et al., 2023b). Also, since our measures of within-consistency and cognitive uncertainty are measured for different SGPs, they are not properly comparable.

[22]While on average beliefs are inconsistent within a task, a good portion of participants are perfectly consistent. Figure A8 shows the cumulative distribution of this measure by treatments. 30% are perfectly consistent in *All-Contingency*, 20% in *Conditional*, and 16% in *One-Contingency*.

would rationalize the reported vector of posteriors given the prior (Aina, 2025; Bohren and Hauser, 2024). Bayes-inconsistency is quite rare: 6% in *Conditional*, 8% in *All-Contingency*, and 14% in *One-Contingency* in our mirrored SGPs.

This analysis underlines the biasing effect of hypothetical thinking in the absence of contrast reasoning. In *One-Contingency*, there is an 8.1 percentage points increase in Bayes-inconsistent vectors of posteriors ($p = 0.021$; Column II in Table 4). This is, even if only marginally significantly so, a larger increase than the statistically insignificant increase in *All-Contingency* ($p = 0.096$; see the difference of the coefficients of the treatment indicators in Column II in Table 4). Thus, there is suggestive evidence that contrast reasoning decreases Bayes-inconsistencies, while hypothetical thinking does the opposite.[23]

Finding 5. *Hypothetical thinking leads to more inconsistent belief updating both within a task and across contingencies. Due to contrast reasoning, the consistency of belief updating does not differ between contingent and conditional belief updating.*

4.4.2 Individual Measures

Finally, we examine the role of individual measures both for heterogeneous treatment effects and additional measures.

Cognitive Reflection Test We study the moderating effect of a participant's cognitive reflection capacity, as measured by the Cognitive Reflection Task (CRT), on our treatments. The CRT measures an individual's tendency to override intuitive responses and engage in reflective and analytical thinking (Frederick, 2005); it appears to correlate with mental heuristics also related to belief updating (e.g., Oechssler et al., 2009; Hoppe and Kusterer, 2011; Augenblick et al., 2025).

We categorized participants who made one or no mistakes on the CRT as *high CRT* (56%), those who made two or more mistakes were categorized as *low CRT* (44%).[24]

In line with the existing literature, individuals classified as low CRT exhibit significantly higher biases, underlining that cognitive reflection captures a component

[23] In Table A5, we report analogous findings for a more nuanced measure of between-consistency: the squared distance between the reported and Bayesian vectors of posteriors.

[24] We modified the original version of the CRT, as reported in Online Appendix 3.3, to avoid confounds for participants who may have previously encountered the classic version. Out of the three questions, 26% of our participants made no mistakes, 30% made one mistake, 25% made two mistakes, and 19% made three mistakes. See Figure A4 for an illustration of this heterogeneity using the full scale (0-3) instead of the binary classification. The results are qualitatively comparable.

relevant to belief updating. If beliefs are elicited conditional on the observed signal, individuals with a high CRT are on average 4.3 percentage points closer to the Bayesian posterior ($p < 0.001$; Column V in Table A4) and display a lower levels of underinference ($p = 0.004$; Column VI in Table A4).

While a high CRT is associated with a lower bias and underinference in all three treatments, CRT seems to have no effect on hypothetical thinking ($p = 0.165$; Column V of Table A4) nor on contrast reasoning ($p = 0.282$; see the difference between 'All-Contingency × High CRT' and 'One-Contingency × High CRT' in Column V in Table A4). Column VI in Table A4 reports analogous results for underinference.

Cognitive Uncertainty Next, we examine whether our treatments impact cognitive uncertainty, which is measured for the last task in the experiment. Enke and Graeber (2023) define cognitive uncertainty as "[...] *people's subjective uncertainty over which decision maximizes their expected utility.*" Their findings indicate that, in a belief-updating setting, an increase in cognitive uncertainty is associated with a stronger bias. Consistently, pooling all treatments, we find that an increase in cognitive uncertainty increases the bias ($p = 0.001$): the more uncertain individuals tend to report more biased posteriors.

It is, therefore, relevant to assess to what extent cognitive uncertainty responds to hypothetical thinking and contrast reasoning in this setting, but we find no difference across treatments. The average cognitive uncertainty in *Conditional* is not significantly different from the one in *One-Contingency* ($p = 0.306$) or *All-Contingency* ($p = 0.657$). This suggests that cognitive uncertainty is unaffected by hypothetical thinking or reasoning. However, cognitive uncertainty was measured only for the 70-30 SGP, for which we observe no significant treatment effects.[25]

Measures of Engagement We consider two measures of engagement: response time and self-reported degree of challenge in completing the tasks.

Response Time. Response time is an important measure because it can provide insights into the cognitive processes that underlie decision-making (e.g., Woodford, 2014; Krajbich et al., 2015; Alós-Ferrer et al., 2021; Schotter and Trevino, 2021). We

[25]As discussed in Section 2.2, we elicit cognitive uncertainty for the SGP most similar to those used in the literature. Running the OLS regressions of the bias on indicators of the different treatment effects (as in Column I in Table 2) for each SGP, we find that 70-30 is the only SGP for which there is no treatment effect for either *All-Contingency* ($p = 0.728$) or *One-Contingency* ($p = 0.10$). For all other SGPs, at least one of the treatment effects is significant at the 5% level.

regard the response time as a proxy of the indirect costs associated with the belief elicitation method, given the comparable strength of incentives across treatments. Longer response times may indicate that individuals are exerting more effort in the belief elicitation task, thus willing to incur higher indirect costs. Pooled across treatments exhibit a lower bias when taking more time ($p = 0.033$), suggesting that taking more time to perform a task could be due to the fact that the participants are engaging in more deliberate and reflective thinking.

On average, the response time for each task is 27 seconds in *Conditional*, 46 in *All-Contingency*, and 31 in *One-Contingency*. We estimate that per elicitation task, the participants take more than 50% longer in *All-Contingency* than in *Conditional* ($p < 0.001$; Column I in Table A4). At the same time, the hypothetical nature of signals in *One-Contingency* appears not to decrease engagement with the task ($p = 0.110$; Column I in Table A4). This suggests that the longer response time is due to contrast reasoning, not hypothetical thinking.

Our treatment effects cannot be explained by the differences in time participants spent per elicitation task and treatment. Controlling for the response time, both *All-Contingency* and *One-Contingency* still significantly increase the bias compared to *Conditional*, by 2.7% and 4.1% respectively ($p = 0.002$ and $p < 0.001$; Column II in Table A4). Importantly, there is no interaction effect of the time spent per task and either treatment indicator ($p = 0.884$ and $p = 0.567$; Column III in Table A4). Therefore, we rule out the possibility that our findings are due to a particular treatment inducing some participants to spend less time on the task.[26]

Perception of Difficulty. The perceived level of challenge serves as a complementary measure to response time in assessing the difficulty in each treatment.[27] Unlike for response time, the self-reported challenge level is significantly higher ($p = 0.002$; Column 'IV' in Table A4) in *One-Contingency* compared to *Conditional*. Participants perceive a greater challenge when engaging in hypothetical thinking despite not disengaging with the task. Interestingly, contrast reasoning does not increase the perceived level of challenge despite the longer response time and the higher computational complexity. If anything, the reported level is lower in *All-Contingency* than in *One-Contingency*, but not significantly so ($p = 0.351$).

[26] A within-subject design would allow us to examine more general forms of individual-level heterogeneity in our treatment effects. However, we do not employ this approach due to the detected learning effects and the associated threat of spillover effects between treatments, where a demand for consistency may overshadow the perceived differences in the elicitation.

[27] In the final questionnaire, participants also answered an unincentivized question about how challenged they felt during the elicitation tasks on a 7-point scale.

5 Discussion

Our findings reveal a surprising effect of contingent thinking on how we process new information. While experts predict, if anything, a larger bias for conditional belief updating, our results indicate a different and more nuanced picture. Contingent belief updating can lead to less accurate beliefs than conditional belief updating. However, the effect is not uniform. We show how the effect varies depending on the characteristics of the signal-generating process. Our findings suggest that the effect is mediated by the complexity of the information structure (symmetry of the SGP) but not by one's ability to engage with it (performance in CRT).

To learn more about the mechanisms behind this finding, we break down the effect of contingent thinking into hypothetical thinking and contrast reasoning using a treatment that requires engaging only in the former. On the one hand, our findings show a harmful effect of hypothetical thinking that is systematic across a wide range of measures of deviations from Bayesian updating. Thus, the results cast doubt on our ability to properly process information that may only realize in a future scenario. This suggests that simulating a prospective scenario requires exerting mental effort. On the other hand, this data suggests that contrast reasoning can compensate to some extent for the negative consequences of hypothetical thinking. The range of this effect is broad: from fully compensating with symmetric SGPs, it continuously decreases in the degree of asymmetry of SGPs due to some individuals treating asymmetric SGPs as if they were symmetric.

Our findings speak to a range of economic settings in which agents acquire, design, and strategically use information. The results provide a mechanism for documented anomalies in information demand, specifically explaining the "compression effect" (Ambuehl and Li, 2018) and also clarifying why agents suboptimally favor symmetric over asymmetric sources (Zultan et al., 2025). They also have implications for information design. A behavioral agent acting as an information designer might choose information structures that are optimal only under this distorted belief-updating process. While the literature has focused on either Bayesian agents (e.g., Kamenica and Gentzkow, 2011) or only the receiver being biased (De Clippel and Zhang, 2022), our results suggest that belief distortion can also shape the designer's problem: Depending on the context, the designer might favor suboptimal symmetric information structures or asymmetric information structures that induce more extreme beliefs. In addition, experimentation also typically involves asymmetric signal structures, in which only one signal is fully conclusive. In such settings, agents may under-experiment (e.g., Meyer and Shi, 1995) because assessing the value of experimentation requires contingent reasoning about what additional exploration might reveal. More broadly, our results also open a promising avenue for future research regarding strategic interactions. This is because contingent belief updating is often required to formulate a strategy in sequential games with uncertainty about players' types or unknown payoff-relevant variables.

Finally, we want to address similarities and differences in our results with the emerging literature on failures of contingent thinking. In the recent survey, Niederle and Vespa (2023) argue that there are failures of contingent thinking *"when an agent does optimize in a presentation of the problem that helps her focus on all relevant contingencies (i.e., contingencies in which choices can result in different consequences), but does not optimize if the problem is presented without such aids (i.e., standard representation)."* At first glance, it would seem that we report the opposite effect, but this is not the case. There are important differences in our research questions, but similarities in the reported findings. As highlighted in the introduction, the main difference is not only the type of tasks — choosing an action *vs.* updating beliefs — but rather the overall problem structure and the type of suboptimal behavior under examination. In Martínez-Marquina et al. (2019) and Esponda and Vespa (2024), suboptimal behavior arises because participants should think contingently and fail to do so when making a choice ahead of the resolution of uncertainty, commonly implemented for all contingencies. Thus, individuals behave optimally when placed in the relevant contingency but struggle to determine the correct (common) action without knowing the realized contingency. Similarly, our paper also shows that participants' beliefs are less biased upon observing the relevant contingency. However, we do not compare this to a setting where individuals choose an ex-ante action implemented across contingencies. Instead, we study how people determine their contingency-specific behavior. We find that participants struggle when they have to update beliefs that may become relevant in a not-yet-observed contingency. So here, individuals are placed in a setting in which they have to think contingently, but doing so might bias how they would react if they were to observe the relevant contingency. Interestingly, a common aspect drives both suboptimal behaviors: biases related to thinking about hypothetical events.

Pitfalls of hypothetical thinking seem not to be limited to a specific type of task but rather to numerous instances of failures of contingent thinking (Esponda and Vespa, 2014; Ali et al., 2021; Farina and Leccese, 2024) and other relevant contexts (Paolacci and André, 2024; Gandhi et al., 2024). We show its relevance in a new setting, belief updating. Theoretical approaches have recently emerged to incorporate this bias in simulations of expected future utilities (Piermont and Zuazo-Garin, 2024; Piermont, 2024), to link associative memory to belief formation about novel risks (Bordalo et al., 2024), to explore cognitive frictions that could explain differences in ex-ante and ex-post posteriors (Samuelson and Steiner, 2024; Bohren and Hauser, 2024). Also, Cohen and Li (2025) consider an extensive-form solution concept where players neglect the information from hypothetical events, which Cohen (2024) builds on to model dynamic markets. These approaches can account for the biases introduced by hypothetical thinking. However, the effect of contrast reasoning is underexplored, both experimentally and theoretically. It would be valuable to develop formal models to incorporate both hypothetical thinking and contrast reasoning. As suggested by Bordalo et al. (2026), the framing of the inference problem can lead to observing different types of biased beliefs. A first key challenge in formalizing our findings is developing a compelling model that accounts for differences in belief updating based on the asymmetry of the signal-generating process. Only then, would it be possible to provide a comprehensive theoretical account of our treatment differences.

An open question is whether the presence of contrast reasoning could extend beyond merely neutralizing hypothetical thinking and thus lead to more accurate beliefs in other contexts. Two potential avenues could address this. One approach is to explore this question in settings where contingencies are more concrete and familiar to the participants. The stylized and abstract setting of this study allows us to have a well-grounded benchmark in the literature and easily vary conditions over rounds; however, it might have also amplified the difficulty of imaging hypothetical contingencies. Another potential avenue involves integrating contingent belief updating with nudging or training. For example, one could stress the importance of carefully imagining the proposed contingencies and encourage participants to contrast their answers across contingencies before proceeding. A novel paper by Ashraf et al. (2025) shows that the ability to imagine the forward-oriented scenario can be trained, and it is linked to improved economic outcomes. Enhancing such training to promote contrast reasoning may boost this effect further.

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A Appendix

A.1 Bias

Table A1: Bias with SGP×Contingency fixed effects

	I	II	III
All-Contingency	0.022*	0.010	0.026
	(0.009)	(0.011)	(0.013)
One-Contingency	0.038***	0.045***	0.054***
	(0.009)	(0.011)	(0.015)
Asymmetric		0.014	
		(0.012)	
All-Contingency × Asymmetric		0.020*	
		(0.009)	
One-Contingency × Asymmetric		-0.012	
		(0.010)	
High CRT			-0.043***
			(0.009)
All-Contingency × High CRT			-0.002
			(0.017)
One-Contingency × High CRT			-0.026
			(0.017)
Constant	0.057***	0.061***	0.080***
	(0.010)	(0.011)	(0.012)
N	6000	6000	6000
adj. R^2	0.027	0.028	0.056
Clusters	450	450	450

Notes. OLS estimates. Individual-level clustered standard errors. SGP×contingency fixed effects. Contingency refers to the realized signal in *Conditional* and to the relevant contingency in *One-Contingency* and *All-Contingency*. The dependent variable is defined as the absolute value of the difference between the reported posterior and the Bayesian benchmark; * p<.05, ** p<.01, *** p<.001.

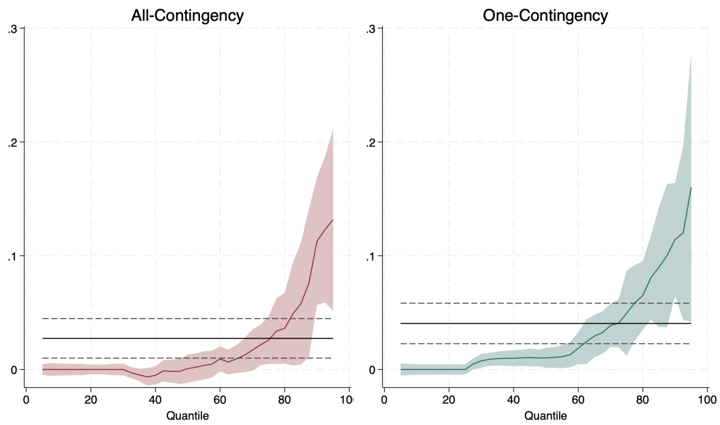


Figure A1: Bias: Quantile Regressions

Notes. Quantile regressions of the bias on treatment indicators, with *Conditional* as the baseline. Individual-level clustered standard errors. Shaded regions indicate 95% confidence intervals. Horizontal lines indicate the coefficient for the standard OLS model, with the dotted lines indicating the 95% confidence interval of the estimated coefficient.

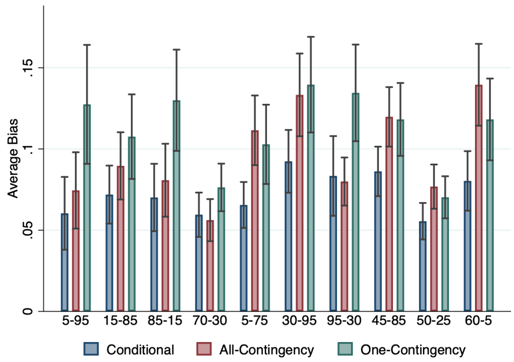
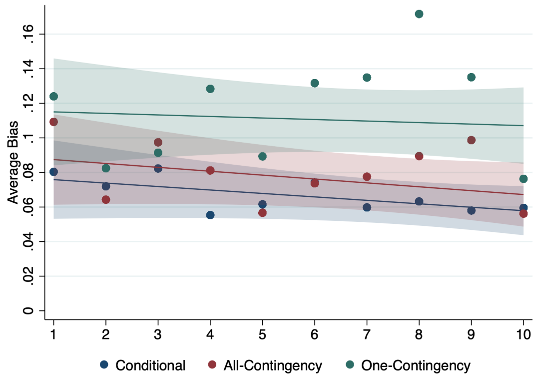
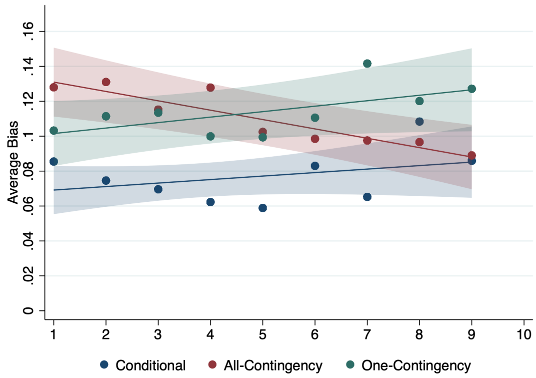


Figure A2: Treatment Effect in Bias by SGP

Notes. Each triplet of histograms represents the average bias by treatment and SGP. SGPs labels, reported on the x-axis, report the number of blue balls in the first and second bag, respectively (e.g., "5-75" indicated that for that SGP the first bag contained 5 blue balls and the second 75). Error bars indicate 95% confidence intervals.



(a) Trend for symmetric SGPs



(b) Trend for asymmetric SGPs

Figure A3: Trend in Average Bias by Round

Notes. Each point represents the average bias by treatment and round number. Lines indicate the linear predictions of the average bias by treatment, the shaded regions indicate 95% confidence intervals of these predictions. Panel (a) shows the average bias over rounds for symmetric SGPs. Panel (b) shows the average bias over rounds for asymmetric SGPs.

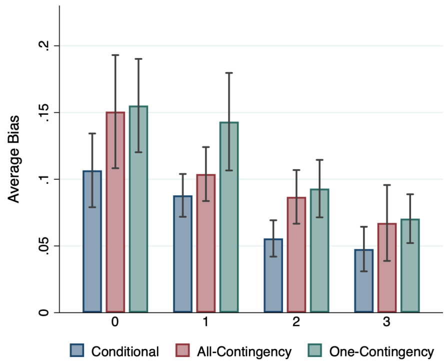


Figure A4: Treatment Effect in Bias by CRT scale

Notes. Each triplet of histograms represents the average bias by treatment and CRT level. Specifically, the latter is measured as the number of CRT questions correctly answered by participants, indicated on the x-axis label. Error bars indicate 95% confidence intervals.

Table A2: Bias and Treated as Symmetric

	I	II	III
Treated as Symmetric	-0.078***		
	(0.013)		
Degree of Asymmetry	-0.033	-0.033	0.210***
	(0.017)	(0.017)	(0.029)
Treated as Symmetric × Degree of Asymmetry	0.243***		
	(0.036)		
One-Contingency		-0.023	0.055***
		(0.014)	(0.011)
One-Contingency × Degree of Asymmetry		0.063**	-0.180***
		(0.022)	(0.032)
Constant	0.127***	0.127***	0.049***
	(0.012)	(0.012)	(0.008)
N	3000	3342	2658
adj. R^2	0.052	0.002	0.061
Clusters	150	295	290

Notes. OLS estimates. Individual-level clustered standard errors. The dependent variable is defined as the absolute value of the difference between the reported posterior and the normative (Bayesian) benchmark. The sample in Column I are all individuals in *All-Contingency*, in Column II all individuals in *All-Contingency* and observations in *All-Contingency* not classified as 'Treated as Symmetric', and in Column III all individuals in *All-Contingency* and observations in *All-Contingency* classified as 'Treated as Symmetric'; * p<.05, ** p<.01, *** p<.001.

A.2 Underinference

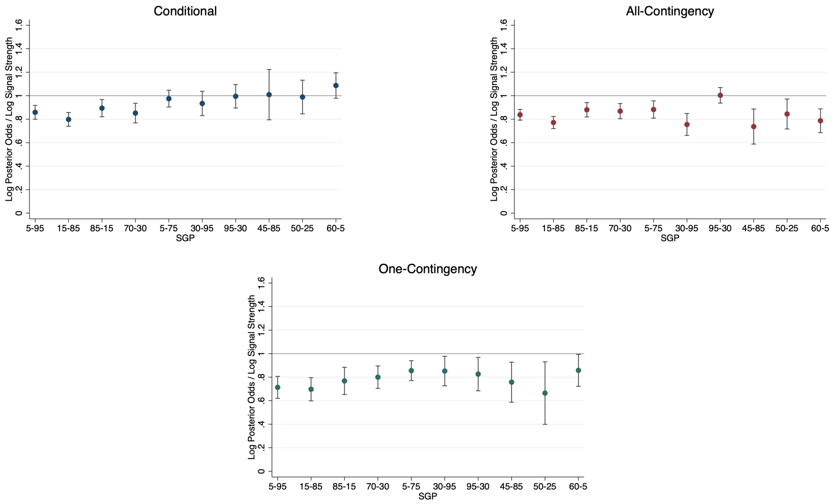


Figure A5: Underinference by SGP and Treatment

Notes. Each figure plots the estimated degree of underinference, measured as the average ratio of the reported log posterior-odds to the log signal strength for each SPG in a given treatment. The horizontal line at value one serves as the Bayesian benchmark: ratios below one indicate evidence of underinference, while ratios above one suggest evidence of overinference. Error bars indicate 95% confidence intervals.

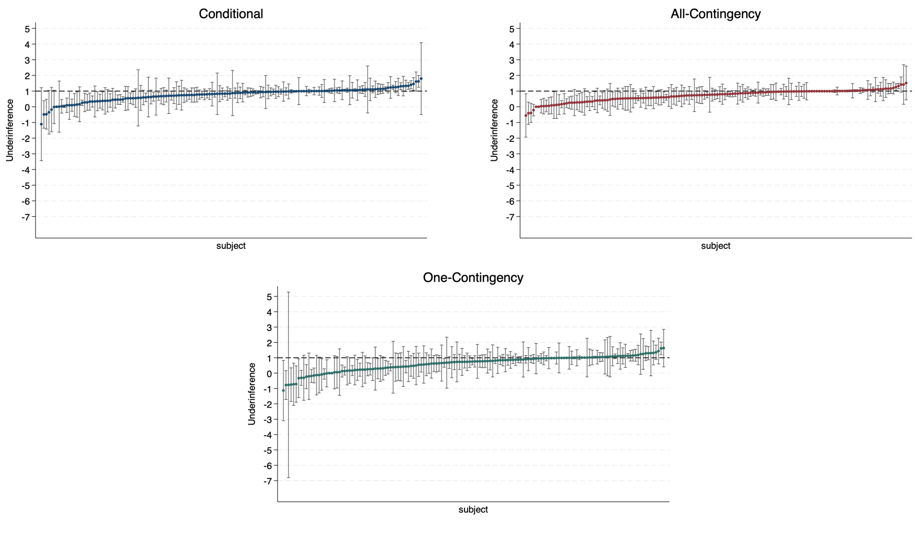
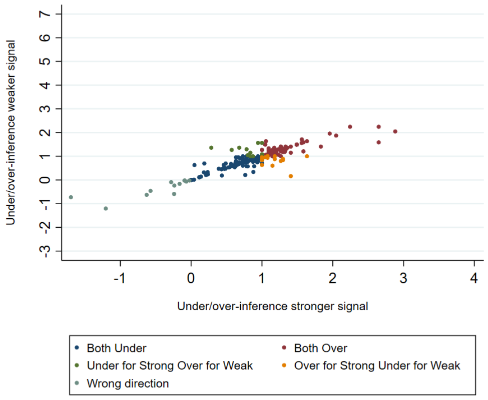


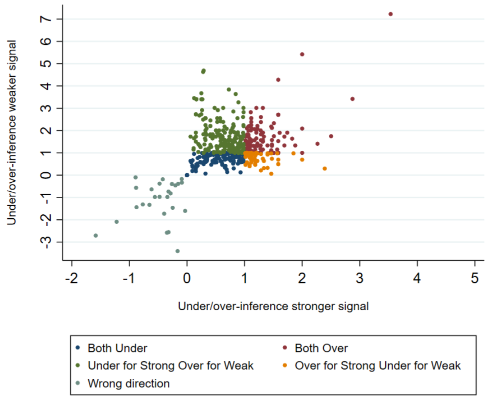
Figure A6: Underinference per Individual

Notes. Each figure plots the estimated degree of underinference, measured as the average ratio of the reported log posterior-odds to the log signal strength for each individual in a given treatment. The horizontal line at value one serves as the Bayesian benchmark: ratios below one indicate evidence of underinference, while ratios above one suggest evidence of overinference. Error bars indicate 95% confidence intervals.

A.2.1 Relative Signal Strength



(a) Symmetric SGPs



(b) Asymmetric SGPs

Figure A7: Relative Underinference Within Task: All-Contingency

Notes. Each point represents the estimated degree of underinference for the stronger (x-axis) and the weaker signal (y-axis), measured as the average ratio of the reported log posterior-odds to the log signal strength for each individual in a given task in *All-Contingency*; for symmetric SGPs, signals are equally diagnostic and we classified the blue ball as stronger arbitrarily.

Table A3: Relative Underinference

	I	II	III
Stronger Signal	-0.171***	0.021	-0.203***
	(0.033)	(0.035)	(0.055)
All-Contingency	-0.108*	-0.008	-0.075
	(0.048)	(0.043)	(0.086)
One-Contingency	-0.133*	-0.100	-0.103
	(0.054)	(0.051)	(0.096)
Stronger Signal × All-Contingency	0.036	-0.007	0.019
	(0.042)	(0.040)	(0.075)
Stonger Signal × One-Contingency	0.001	-0.012	-0.065
	(0.051)	(0.063)	(0.086)
Asymmetric		0.274***	
		(0.049)	
Stonger Signal × Asymmetric		-0.303***	
		(0.062)	
Stronger Signal × All-Contingency × Asymmetric		0.054	
		(0.079)	
Stronger Signal × One-Contingency × Asymmetric		0.003	
		(0.120)	
High CRT			0.108
			(0.067)
Stronger Signal × High CRT			0.063
			(0.067)
Stronger Signal × All-Contingency × High CRT			0.019
			(0.088)
Stronger Signal × One-Contingency × High CRT			0.104
			(0.102)
Constant	1.018***	0.841***	0.962***
	(0.033)	(0.031)	(0.057)
N	6000	6000	6000
adj. R^2	0.016	0.026	0.021
Clusters	450	450	450

Notes. OLS estimates. Individual-level clustered standard errors. The dependent variable is calculated as the ratio of the log posterior-odds and log signal strength for a given signal; * p<.05, ** p<.01, *** p<.001.

A.3 Individual Measures

Table A4: Individual Measures

	Time	Bias	Bias	Challenge	Bias	Log Odds
All-Contingency	18.719***	0.027**	0.028**	0.380*	0.028*	0.049
	(2.913)	(0.009)	(0.010)	(0.172)	(0.013)	(0.095)
One-Contingency	3.819	0.041***	0.038***	0.540**	0.055***	0.092
	(2.386)	(0.009)	(0.011)	(0.172)	(0.015)	(0.115)
Time		-0.000**	-0.000*			
		(0.000)	(0.000)			
All-Contingency × Time			-0.000			
			(0.000)			
One-Contingency × Time			0.000			
			(0.000)			
High CRT					-0.043***	-0.001
					(0.009)	(0.087)
All-Contingency × High CRT					-0.002	-0.137
					(0.017)	(0.116)
One-Contingency × High CRT					-0.024	-0.162
					(0.018)	(0.142)
Log Signal Strength						0.683***
						(0.049)
Log Signal Strength × All-Contingency						-0.070
						(0.073)
Log Signal Strength × One-Contingency						-0.214*
						(0.084)
Log Signal Strength × High CRT						0.165*
						(0.067)
Log Signal Strength × All-Contingency × High CRT						-0.001
						(0.093)
Log Signal Strength × One-Contingency × High CRT						0.120
						(0.108)
Constant	33.330***	0.069***	0.069***	4.407***	0.085***	0.199**
	(3.179)	(0.008)	(0.009)	(0.122)	(0.010)	(0.067)
N	6000	6000	6000	6000	6000	6000
adj. R^2	0.037	0.027	0.027	0.016	0.053	0.262
Clusters	450	450	450	450	450	450

Notes. OLS estimates. Individual-level clustered standard errors. SGP fixed effects. The dependent variable in Column I is the response time measured in seconds, in Column II, III and V the absolute bias, in Column IV the perceived degree of being challenged, and in Column VI the logarithm of the ratio of the elicited posterior belief for a given signal; * p<.05, ** p<.01, *** p<.001.

A.4 Additional Measures

A.4.1 Within-Consistency

To construct the within-consistency measure in our dataset, we proceed as follows.

First, for each pair of mirrored SGPs, all posteriors were reported in terms of one SGP (15-85 for symmetric and 30-95 for asymmetric). Second, we keep only the observation for which we can construct this measure. In *Conditional* and *One-Contingency*, the desired measure could only be constructed if the participant's posterior was elicited for the *same* signal for both mirrored SGPs (approximately in half of all cases, for each color of the ball). In *All-Contingency*, participants' beliefs are always elicited conditional on both signals for each SGP. Therefore, we keep 156 and 148 observations, respectively, in *Conditional* and in *One-Contingency*, and 600 in *All-Contingency*. Third, we calculate the difference between the posteriors conditional on the same signal. For any signal s and for any two mirrored SGPs M1 and M2, the dependant variable is defined as

$$\Delta\text{Posteriors} = |\Pr^{M1}(A|s) - \Pr^{M2}(A|s)|.$$

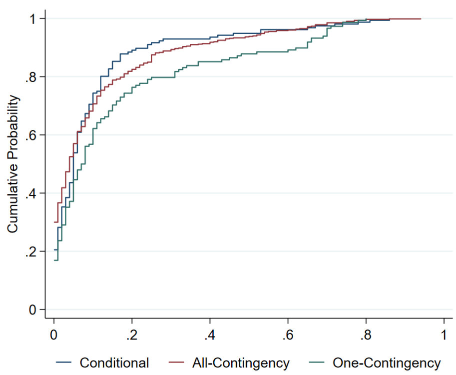


Figure A8: Cumulative Distribution of Δ Posteriors

A.4.2 Between-Consistency

To construct the between-consistency measure, we look at vectors of posteriors: $(\Pr(A|blue), \Pr(A|orange))$. Given the method of belief elicitation, these are available for all SGPs in *All-Contingency*. For *Conditional* and *One-Contingency*, we construct the vectors of posteriors exploiting the mirrored SGPs as follows.

First, for each pair of mirrored SGPs, all posteriors were reported in terms of one SGP (15-85 for symmetric and 30-95 for asymmetric). This part overlaps with the construction of Δ Posteriors. Then, we keep only the observations of the participants whose posteriors were elicited conditional on the *different* signal realizations for the mirrored SGPs (around half of the times, for each color of the ball). Therefore, we have 144 and 152 observations, respectively, in *Conditional* and in *One-Contingency*, and 600 in *All-Contingency*.

Distance from Bayesian Vector of Posteriors We complement our between-consistency analysis by examining a more nuanced measure. We calculate the squared distance between the reported vector of posteriors and the Bayesian one:

$$\text{Distance} = \sqrt{\Big(\Pr(A|blue) - \hat{\Pr}(A|blue)\Big)^2 + \Big(\Pr(A|orange) - \hat{\Pr}(A|orange)\Big)^2}.$$

The results presented in Table A5 aligns with the findings of Section 4.4.1.

Table A5: Distance

	I	II
All-Contingency	0.022	0.009
	(0.019)	(0.014)
One-Contingency	0.067**	0.042*
	(0.025)	(0.021)
Constant	0.149***	0.116***
	(0.015)	(0.011)
N	896	817
adj. R^2	0.016	0.013
Clusters	375	360

Notes. OLS estimates. Individual-level clustered standard errors. SGP symmetry fixed effects. The dependent variable is defined as the squared distance between the reported posterior and the Bayesian benchmark. Column I includes all samples of vectors of posteriors, while Column II excludes vectors of posteriors that are not Bayes-consistent. * p<.05, ** p<.01, *** p<.001.

(a) Symmetric SGPs (b) Asymmetric SGPs

Figure A9: Vector of Posteriors: All-Contingency

Notes. Each circle represents the frequency of the corresponding vector of posterior beliefs in a given task across SGPs: the bigger the circle, the higher the frequency. Each black square corresponds to the Bayesian vector of posteriors associated with an SGP.

Online Appendix 1 Alternative Measures

Online Appendix 1.1 Overinference as in Ba et al. (2022)

Ba et al. (2025) introduce an alternative measure of underinference, which we use as a dependent variable as a robustness check. Their measure is defined in terms of overinference in the following manner. For a contingency-specific reported guess $\hat{\Pr}(A|s)$, the ratio used is defined as:

$$\frac{|\hat{\Pr}(A|s) - 0.5| - |\Pr(A|s) - 0.5|}{|\Pr(A|s) - 0.5|}$$

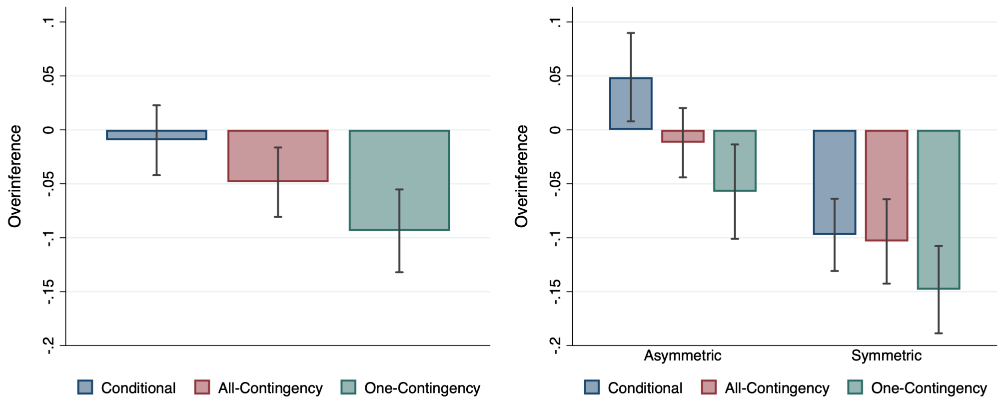
The higher the ratio, the higher the degree of observed overinference.

Table A1 replicates our main analysis using this ratio as a dependent variable.

Table A1: Overinference as defined in Ba et al. (2025)

	I	II	III
All-Contingency	-0.039	-0.006	-0.015
	(0.023)	(0.026)	(0.034)
One-Contingency	-0.084**	-0.051	-0.084
	(0.026)	(0.027)	(0.045)
Asymmetric		0.129***	
		(0.026)	
All-Contingency × Asymmetric		-0.055*	
		(0.026)	
One-Contingency × Asymmetric		-0.055	
		(0.028)	
High CRT			0.050
			(0.033)
All-Contingency × High CRT			-0.046
			(0.046)
One-Contingency × High CRT			-0.003
			(0.053)
Constant	-0.074***	-0.098***	-0.100***
	(0.018)	(0.019)	(0.027)
N	6000	6000	6000
adj. R^2	0.033	0.033	0.034
Clusters	450	450	450

Notes. OLS estimates. Individual-level clustered standard errors. The dependent variable is calculated as the difference of the absolute distances of (i) the elicited posterior and prior and, (ii) the Bayesian posterior and the prior, divided by the absolute difference of the Bayesian posterior and the prior; * p<.05, ** p<.01, *** p<.001.



(a) Overinference

(b) Overinference by Symmetry

Figure A1: Overinference (Ba et al., 2025) by Treatment and Symmetry

Notes. Panel (a) shows the average overinference, defined as as the difference of the absolute distances of (i) the elicited posterior and prior and, (ii) the Bayesian posterior and the prior, divided by the absolute difference of the Bayesian posterior and the prior, by treatment. Panel (b) shows this average overinference measure by treatment and symmetry of the SGP. Error bars indicate 95% confidence intervals, clustered at the individual level.

Online Appendix 1.2 Alternative Degree of Asymmetry

This section proposes an alternative measure of the degree of asymmetry and replicates the findings in the main text using this measure.

An alternative measure of degree of asymmetry for an SGP can be quantified by the absolute distance between the posterior across signals and bags:

$$|\Pr(A|s) - \Pr(B|s')|.$$

This difference is always zero for symmetric SGPs, and positive for asymmetric SGPs. The larger the difference in posteriors, the more asymmetric the SGP.

These two measures are conceptually similar, but not identical. The main difference is that this measure also captures the role of the prior, even if this is not relevant with equal prior. Another difference is that the measure used in the text better captures relative differences rather than absolute ones.

Table A2: Bias and Underinference with Alternative Measure of Asymmetry

	I	II
All-Contingency	0.010	0.012
	(0.010)	(0.068)
One-Contingency	0.041***	0.044
	(0.011)	(0.089)
Alternative Degree of Asymmetry	0.098*	2.756***
	(0.041)	(0.554)
All-Contingency × Alternative Degree of Asymmetry	0.154**	-0.336
	(0.055)	(0.715)
One-Contingency × Alternative Degree of Asymmetry	-0.006	-0.435
	(0.063)	(0.921)
Log Signal Strength		0.886***
		(0.038)
Log Signal Strength × All-Contingency		-0.023
		(0.052)
Log Signal Strength × One-Contingency		-0.152*
		(0.069)
Log Signal Strength × Alternative Degree of Asymmetry		-1.268***
		(0.354)
Log Signal Strength × All-Contingency × Alternative Degree of Asymmetry		-0.408
		(0.441)
Log Signal Strength × One-Contingency × Alternative Degree of Asymmetry		0.218
		(0.592)
Constant	0.064***	-0.067
	(0.006)	(0.054)
N	6000	6000
adj. R^2	0.020	0.256
Clusters	450	450

Notes. OLS estimates. Individual-level clustered standard errors. The dependent variable is defined as the absolute value of the difference between the reported posterior and the Bayesian benchmark in Column I and as the ratio of the log posterior-odds and log signal strength for a given signal in Column II; * p<.05, ** p<.01, *** p<.001.

Online Appendix 2 Expert Survey

Online Appendix 2.1 Survey Design & Data Collection

Our expert survey has three parts. First, we provide all relevant information on the experiment. The survey began with a short description of the goal of the study for which participants were asked to report predictions. After consenting to participate in our survey, we clarified that the experiment was already preregistered but not run yet; we informed the experts that the preregistration link was available at the end of the survey. Then, they read a detailed description of our experimental design. To keep the survey brief and focused on our main objective, we only describe two treatments: *Conditional* and *All-Contingency*. The survey participants could access further details on the design in linked documents, such as the instructions and control questions of these two treatments and information on the used SGPs. We also include information about the target sample, randomization, and incentives. Finally, we highlight as the key outcome of interest the bias as defined in Section 4.

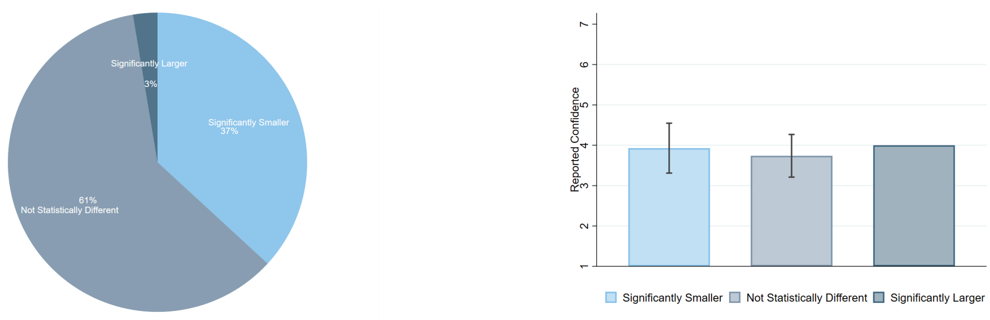
In the second part, we elicited the experts' predictions. This was followed by two sets of questions. First, we elicited the expected direction of the treatment effect: the participants reported whether they expected the bias in *Conditional* to be significantly smaller, higher, or not statistically significant than in *All-Contingency*. The participants also reported their confidence (1-7 scale) in their answers. Second, we elicited the participants' opinions on the heterogeneity of the treatment effect along two dimensions: CRT and the symmetry of SGPs. Also, for this set of questions, the participants reported their confidence in their previous answers (1-7 scale). Finally, the participants were asked how they classify their research (theoretical, experimental, and/or empirical). The pre-registration link was also available on the final screen.

The Qualtrics survey was distributed in February 2023 using the Social Science Prediction Platform (Study ID: sspp-2023-0007-v1) by invitation (the survey was not publicly accessible). We compiled a distribution list including researchers that we considered knowledgeable about topics related to expectations or contingent thinking for a total of 135 experts. We purposefully excluded colleagues who were aware of pilot results through conversations with us.

Online Appendix 2.2 Predictions

Sample In total, we gathered 38 responses (28% completion rate). Our final sample includes 17 faculty members, 6 postdocs, and 12 PhD students (with 3 participants not reporting their position). 89% described their research as experimental, 29% as theoretical, and 26% as empirical (these categories were not mutually exclusive). 83% include behavioral economics as one of their main fields; other fields include experimental economics, microeconomics theory, game theory, development economics, and political economics, among others.

Main Prediction Figure B1a illustrates how experts expect the bias in *Conditional* to change compared to *All-Contingency*. Compared to Conditional, 14 participants predicted a significantly smaller bias in *All-Contingency*, and only one predicted a significantly higher bias in *All-Contingency*. 23 experts predicted no significant difference between *Conditional* and *All-Contingency*. These percentages do not vary much depending on the research field. Also, there does not seem to be a difference in confidence in the expected direction of the treatment, as shown in Figure B1b.



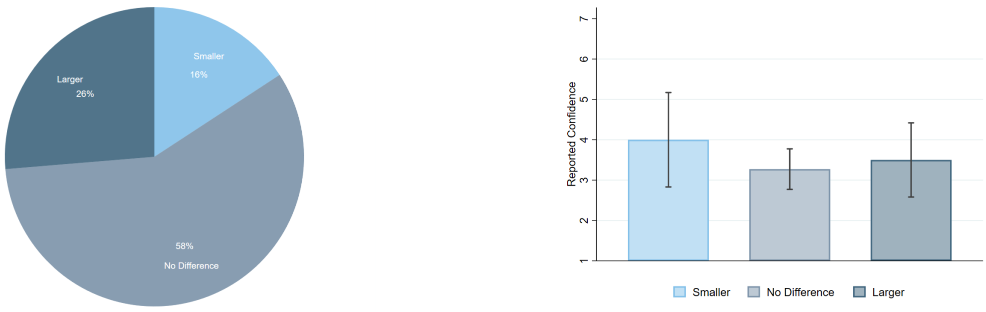
(a) Direction

(b) Confidence

Figure B1: Main Prediction

Notes. Panel (a) shows the shares of experts predicting a significantly higher, significantly lower, and no significantly different bias in *All-Contingency* compared to *Conditional*. Panel (b) shows for each possible prediction the confidence of the experts in their answers on a Likert scale (1-7).

Heterogeneous Effect of SGP Symmetry In Figure B2a, we report the expectations of the change in the bias for symmetric SGPs compared to the change for asymmetric SGPs. 58% predicted no significant difference in the change in the bias between asymmetric and symmetric SGPs. 26% expects a significantly higher change in the bias and 16% expects a significantly lower change in the bias for asymmetric SGPs compared to symmetric SGPs. The predictions do not seem different by the expected treatment effect (Figure B3).



(a) Direction (b) Confidence

Figure B2: Prediction about SGP Symmetry

Notes. Panel (a) shows the shares of experts predicting a significantly higher change in the bias, a significantly lower change in the bias, and no significantly different change in the bias for asymmetric compared to symmetric SGPs. Panel (b) shows for each possible prediction the confidence of the experts in their answers on a Likert scale (1-7).

Heterogeneous Effect of CRT Figure B4a summarizes how participants expect the change in bias for individuals who score low on the CRT to vary compared to individuals who score high on the CRT. 55% predicted no significant difference in the change in the bias between individuals who scored low and high on the CRT. 29% expect a significantly smaller change in the bias, and 16% expect a higher change in the bias for individuals with high CRT scores compared to individuals with low CRT scores. The predictions do not seem different from the expected treatment effect (Figure B5).

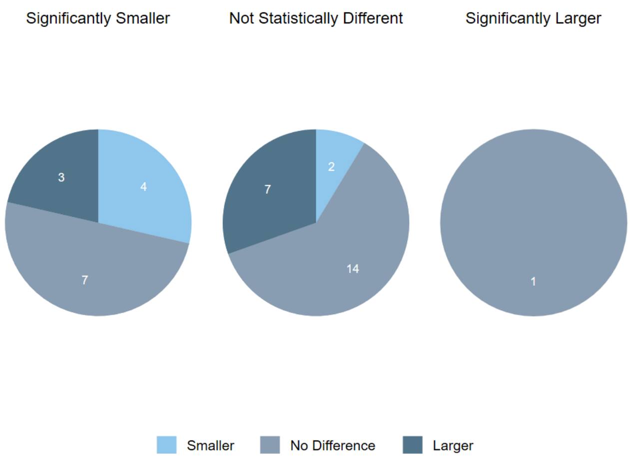
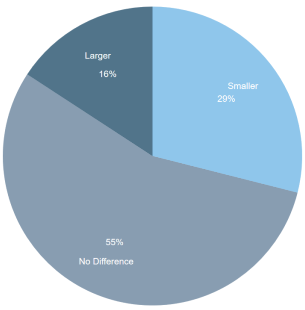
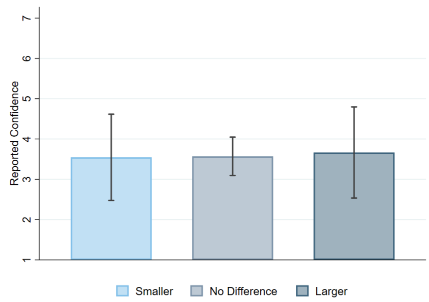


Figure B3: Prediction about SGP Symmetry, by Expected Treatment Effect

Notes. Shares of experts predicting a significantly higher change in the bias, a significantly lower change in the bias, and no significantly different change in the bias for asymmetric compared to symmetric SGPs by possible answers on the expected treatment effect.



(a) Direction



(b) Confidence

Figure B4: Prediction about CRT

Notes. Panel (a) shows the shares of experts predicting a significantly higher change in the bias, a significantly lower change in the bias, and no significantly different change in the bias for individuals with high compared to low CRT. Panel (b) shows for each possible prediction the confidence of the experts in their answers on a Likert scale (1-7).

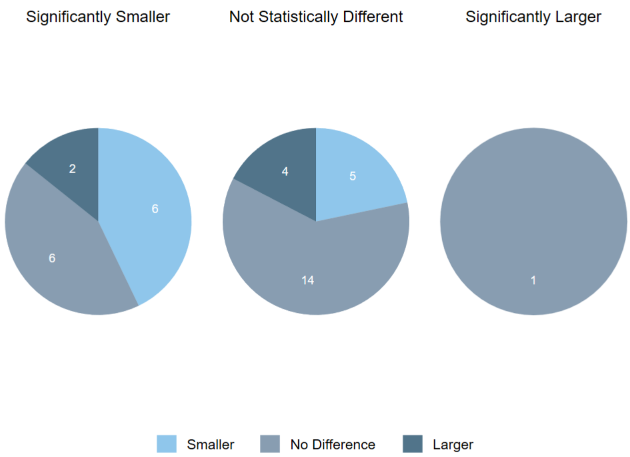


Figure B5: Prediction about CRT, by Expected Treatment Effect

Notes. Shares of experts predicting a significantly higher change in the bias, a significantly lower change in the bias, and no significantly different change in the bias for individuals with high compared to low CRT by possible answers on the expected treatment effect.

Online Appendix 3 Instructions & Interface

Online Appendix 3.1 Instructions

Online Appendix 3.1.1 General Instructions

WELCOME!

Thank you for participating in this study. You are guaranteed to receive GBP 2 for completing the study. If you follow the instructions carefully, you may earn an additional bonus of GBP 2, as explained later. Your earnings will depend on your decisions and chance.

Please read the instructions carefully. **There will be two checks of your understanding of these instructions, for which you have three attempts**. If you provide three incorrect answers in either set of these questions about the instructions, you will not be eligible for a bonus payment. You always have to complete the study to receive the guaranteed payment.

There will be two parts to the experiment. The first part is the main part of the experiment and will take up most of the time. The second part will be introduced after you have finished the first part. In total, this study should take around 30 minutes.

PART ONE

In the first part, you will be asked to make a series of choices that can impact your bonus payment. Most of these choices will be of a similar format: You have to guess the chance that a bag was selected based on the available information.

In each task, you are asked to consider two bags, bag A and bag B. In each bag, there are several balls. The total number of balls can be either 60 or 80. The balls are either orange or blue. The number of orange and blue balls in each bag varies across tasks. You will be informed about the number of orange and the number of blue balls in each bag.

The task proceeds as follows:

- You start by clicking 'Select the bag'.
- The computer randomly flips a **fair coin** to select bag A or bag B. It is **equally likely** that the computer selects bag A or bag B.
- You do not know whether bag A or bag B was selected.
- When you click 'Draw the ball', the computer draws either an orange ball or a or blue ball from the selected bag.
- The computer draws one ball from the selected bag.

Your task is to guess the chance (in %) that the computer chose bag A or bag B.

You will repeat this task ten times. For each task, the computer selects a new bag and then draws a new ball from the selected bag. **So you should think about which bag was selected in each task independently of all other tasks.**

Online Appendix 3.1.2 Control Questions 1

TESTING YOUR UNDERSTANDING OF THE INSTRUCTIONS

On the slider, please indicate the chance (in %) that a fair coin flip selects bag A.

Chance of **bag A (in %): Please click on the slider**

When you click 'Draw the ball', the computer draws a ball from the previously selected bag.

True

False

When you click 'Draw the ball', you know which bag was previously selected.

True

False

Online Appendix 3.1.3 Conditional Instructions

YOUR CHOICE

The computer draws either an orange ball or a blue ball. You observe the color of the ball. **You will be asked to guess the chance that the ball was drawn from bag A or bag B.**

You make your guess by selecting the chance between 0% and 100%. Higher numbers mean that you think it is more likely that this bag was selected. The guess for the chance that the ball was drawn from bag A and the chance that the ball was drawn from bag B will automatically sum up to 100%.

YOUR CHOICE: EXAMPLE

This is an example of the task. It is not relevant for your payment. Please familiarize yourself with the interface, then proceed with the instructions. **You can hover over the elements of the screen to see the explanations of each part of the screen.**

Remember:

Bag A contains **60 blue balls** and **40 orange balls**.
Bag B contains **40 blue balls** and **60 orange balls**.

Make your guesses below.

A blue ball was drawn.

What is the chance (in %) that the ball was drawn from each bag?

Chance of **bag A (in %): Click on the slider**

Chance of **bag B (in %): Click on the slider**

PAYMENT

For your bonus payment, one of the ten tasks will be randomly selected for payment. Your bonus payment will depend on your guesses in the selected task. Your guesses do not influence which task is selected for payment.

We have carefully chosen the payment rule such that you maximize the chance of winning a bonus of GBP 2 if you give your best guesses in all questions. To maximize the chance of winning the bonus, **it is in your best interest to always give a guess that you think is the true chance. The closer your guess is to the true chance, the higher is your probability of receiving the bonus.** If you are interested, further details on the payment are provided here.

▶ **Click here for further details**

Online Appendix 3.1.4 All-Contingency Instructions

YOUR CHOICE

The computer draws either an orange ball (case orange) or a blue ball (case blue). You do not observe the color of the ball when making your guesses.

For each of the two possible cases (orange and blue), **you will be asked to guess the chance that the ball was drawn from bag A or bag B.**

For each case, **you make your guess by selecting the chance between 0% and 100%.** Higher numbers mean that you think it is more likely that this bag was selected. The guesses for the chance that the ball was drawn from bag A and the chance that the ball was drawn from bag B will automatically sum up to 100%.

YOUR CHOICE: EXAMPLE

This is an example of the task. It is not relevant for your payment. Please familiarize yourself with the interface, then proceed with the instructions. **You can hover over the elements of the screen to see the explanations of each part of the screen.**

Remember:

Bag A contains **60 blue balls** and **40 orange balls**.
Bag B contains **40 blue balls** and **60 orange balls**.

Make your guesses below for **Case Blue** and **Case Orange**.

Case Orange:
Suppose the computer drew an **orange ball**

What is the chance (in %) that the ball was drawn from each bag?

Chance of **bag A (in %): Click on the slider**

Chance of **bag B (in %): Click on the slider**

Case Blue:
Suppose the computer drew a **blue ball**

What is the chance (in %) that the ball was drawn from each bag?

Chance of **bag A (in %): Click on the slider**

Chance of **bag B (in %): Click on the slider**

PAYMENT

For your bonus payment, one of the ten tasks will be randomly selected for payment. Your bonus payment will depend on your guesses in the selected task. Your guesses do not influence which task is selected for payment.

We have carefully chosen the payment rule such that you maximize the chance of winning a bonus of GBP 2 if you give your best guesses in all questions. To maximize the chance of winning the bonus, **it is in your best interest to always give a guess that you think is the true chance. The closer your guess is to the true chance, the higher is your probability of receiving the bonus.** If you are interested, further details on the payment are provided here.

▶ **Click here for further details**

You are asked about your guesses for case orange and case blue. Depending on the color of the ball drawn from the bag, only your guesses for that case will matter for your bonus payment. As you do not know the color of the ball when making your guess, it is therefore in **your best interest to give your best guesses for each case**.

As an example, imagine that the computer draws a blue ball. Then, only your guesses for case blue matter for your bonus payment.

Online Appendix 3.1.5 One-Contingency Instructions

YOUR CHOICE

The computer draws either an orange ball (case orange) or a blue ball (case blue). You do not observe the color of the ball when making your guesses.

You will be asked to guess the chance that the ball was drawn from bag A or bag B for one of the two possible cases (orange or blue). It is equally likely that you will be asked about each case. This does not depend on the actual color of the ball drawn by the computer.

You make your guess by selecting the chance between 0% and 100%. Higher numbers mean that you think it is more likely that this bag was selected. The guess for the chance that the ball was drawn from bag A and the chance that the ball was drawn from bag B will automatically sum up to 100%.

YOUR CHOICE: EXAMPLE

This is an example of the task. It is not relevant for your payment. Please familiarize yourself with the interface, then proceed with the instructions. **You can hover over the elements of the screen to see the explanations of each part of the screen.**

Remember:

Bag A contains **60 blue balls** and **40 orange balls**.
Bag B contains **40 blue balls** and **60 orange balls**.

Make your guesses below.

Suppose the computer drew a blue ball.

What is the chance (in %) that the ball was drawn from each bag?

Chance of **bag A (in %): Click on the slider**

Chance of **bag B (in %): Click on the slider**

PAYMENT

For your bonus payment, one of the ten tasks will be randomly selected for payment. Your bonus payment will depend on your guesses in the selected task. Your guesses do not influence which task is selected for payment.

We have carefully chosen the payment rule such that you maximize the chance of winning a bonus of GBP 2 if you give your best guesses in all questions. To maximize the chance of winning the bonus, **it is in your best interest to always give a guess that you think is the true chance. The closer your guess is to the true chance, the higher is your probability of receiving the bonus.** If you are interested, further details on the payment are provided here.

▶ **Click here for further details**

You are asked about your guess for one case, either case orange or case blue. If the color of the ball drawn from the bag matches the case you considered **your guess matters for your bonus.** Otherwise, you will receive a fixed payment of GBP 1. As you do not know the color of the ball when making your guess, it is therefore in **your best interest to give your best guess.**

As an example, imagine that you are asked about case orange. If an orange ball was drawn, your guess matters for the bonus payment. If a blue ball was drawn, you receive the fixed payment.

Online Appendix 3.1.6 Control Questions 2

TESTING YOUR UNDERSTANDING OF THE INSTRUCTIONS

The bonus payment will be implemented for one randomly selected task.

- True
- False

It is in your best interest to give your best guess of the chance that the ball was drawn from bag A or bag B.

- True
- False

We will ask you about the guess of the chance that the ball was drawn from bag A or bag B

- before you get to know the color of the ball.
- once you get to know the color of the ball.

Online Appendix 3.2 Task Interface

Online Appendix 3.2.1 Conditional

Part One: Task 1/10

Please click on the right arrow if you are ready to proceed to the next task.

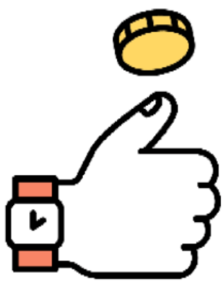
→

Bag A contains **9 orange balls** and **51 blue balls**.
Bag B contains **51 orange balls** and **9 blue balls**.

Next:
The computer randomly selects one bag by flipping a fair coin.

Select the bag

Flipping the coin to select the bag...



The coin was flipped and a bag was selected.

Next:
The computer will draw a ball from the bag that was previously selected.

Draw the ball

The computer draws a random ball from the bag that was previously selected...

Remember:

Bag A contains **9 orange balls** and **51 blue balls**.
Bag B contains **51 orange balls** and **9 blue balls**.

Make your guesses below.

A blue ball was drawn.

What is the chance (in %) that the ball was drawn from each bag?

Chance of **bag A (in %): Click on the slider**

Chance of **bag B (in %): Click on the slider**

Online Appendix 3.2.2 All-Contingency

Part One: Task 1/10

Please click on the right arrow if you are ready to proceed to the next task.

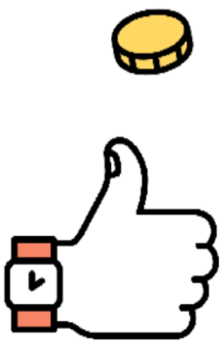
→

Bag A contains **42 orange balls** and **18 blue balls**.
Bag B contains **3 orange balls** and **57 blue balls**.

Next:
The computer randomly selects one bag by flipping a fair coin.

Select the bag

Flipping the coin to select the bag...

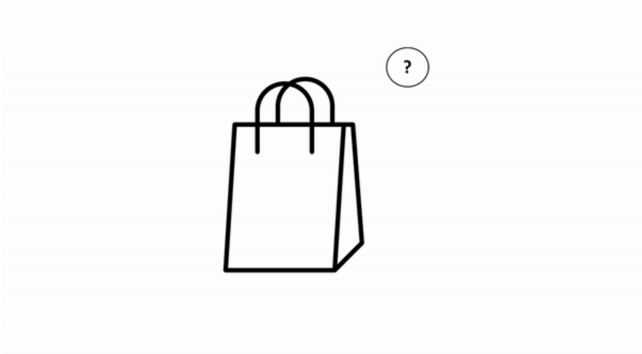


The coin was flipped and a bag was selected.

Next:
The computer will draw a ball from the bag that was previously selected.

Draw the ball

The computer draws a random ball from the bag that was previously selected...



Remember:

Bag A contains **42 orange balls** and **18 blue balls**.
Bag B contains **3 orange balls** and **57 blue balls**.

Make your guesses below for **Case Blue** and **Case Orange**.

Case Orange:
Suppose the computer drew an orange ball.

What is the chance (in %) that the ball was drawn from each bag?

Chance of bag A (in %): Click on the slider

Chance of bag B (in %): Click on the slider

Case Blue:
Suppose the computer drew a blue ball.

What is the chance (in %) that the ball was drawn from each bag?

Chance of bag A (in %): Click on the slider

Chance of bag B (in %): Click on the slider

An orange ball was drawn.

→

Online Appendix 3.2.3 One-Contingency

Part One: Task 1/10

Please click on the right arrow if you are ready to proceed to the next task.

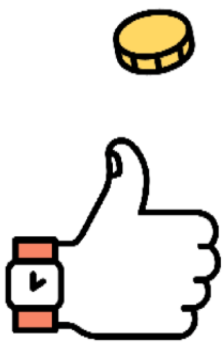
→

Bag A contains **68 orange balls** and **12 blue balls**.
Bag B contains **12 orange balls** and **68 blue balls**.

Next:
The computer randomly selects one bag by flipping a fair coin.

Select the bag

Flipping the coin to select the bag...

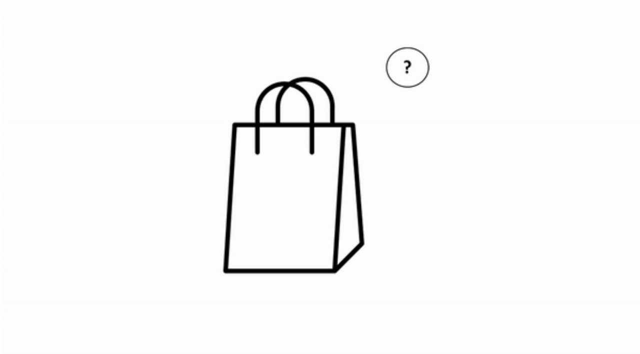


The coin was flipped and a bag was selected.

Next:
The computer will draw a ball from the bag that was previously selected.

Draw the ball

The computer draws a random ball from the bag that was previously selected...



Online Appendix 3.3 Modified Cognitive Reflection Test

We modified the original version of the Cognitive reflection test (Frederick, 2005) to avoid previous experiences or cheating, asking the following three questions.

1. Milk and a cookie cost GBP 3.20 in total. Milk costs GBP 2 more than the cookie. How much does the cookie cost?
2. If it takes 50 workers 50 minutes to pick 50 apples, how long would it take 1000 workers to pick 1000 apples?
3. A runner doubles the number of kilometers he runs every month. After one year, he runs a marathon, 42 km. After how many months did he run a half marathon, 21 km?