Beyond Value: on the Role of Symmetry in Demand for Information*

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Abstract

We study demand for symmetric and asymmetric information sources in the laboratory. While participants respond to incentives and instrumental considerations, they exhibit a systematic bias towards symmetric sources. These patterns persist among individuals with higher cognitive abilities and better task comprehension, and are not accounted for by their elicited subjective beliefs.

Keywords: information acquisition, symmetric information, laboratory experiment

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1 Introduction

Decision-making often requires balancing different types of errors, with greater weight typically placed on those perceived as more costly or prevalent. For instance, venture capital firms are typically more concerned with missing a high-growth start-up than with funding failures, as their success depends on a handful of exceptional investments. In executive hiring, organisations tend to prioritise avoiding a poor appointment over the risk of overlooking a strong candidate, due to the high costs associated with leadership failure. In mergers and acquisitions, firms often enter negotiations confident about the target's strengths and focus their due diligence on uncovering hidden risks that could threaten the success of the deal.[1]

When individuals acquire information to guide their decisions, the value of an information source often depends on how well it reduces the specific type of error they most wish to avoid (Neyman and Pearson, 1933). Consider a hiring manager who is initially uncertain about a candidate's suitability: in this case, she may benefit from an information source that provides a balanced view of both strengths and weaknesses. But if she is already highly confident in the candidate's fit, her primary concern becomes uncovering any red flags that might challenge her initial assessment. In other words, the optimality of an information source depends not only on its overall quality, but also on their relative strength in detecting different types of error.[2]

This paper examines whether individuals understand this principle and choose among information sources based on their instrumental value. Specifically, we study whether people recognise the value of asymmetric sources—those better at detecting certain errors than others—and explore how symmetry influences the demand for and use of information. According to classic models of information, the value of information lies in its ability to change our views and help us make better decisions. In particular, the value of a source depends on how it maps prior beliefs into posteriors, as decisions are ultimately based on posteriors. Symmetry, by contrast, is defined independently of the decision-maker's beliefs and does not necessarily correspond to informativeness. Therefore, sym-

[1] These are just a few examples. Conservative banks prioritise reducing loan defaults over maximising approval rates, since credit risk poses a greater threat than lost interest income. Quality control systems in manufacturing are designed to prevent defective products from reaching the market, even at the expense of occasionally rejecting non-defective items, as the reputational and legal risks outweigh the loss in efficiency. Doctors who encounter potential cancer patients are primarily concerned with avoiding the failure to detect cancer rather than the risk of misdiagnosis.

[2] Another well-known example of the value of asymmetric sources is Fox News in political decision-making (DellaVigna and Kaplan, 2007). Conservative voters generally expect strong support for Republican candidates, so a lukewarm endorsement—or even mild criticism—can act as a strong negative signal, as arguably occurred with John McCain in 2008.

metry should not guide the choice among different sources.

We present findings from a laboratory experiment where participants obtain a prize if they guess the state of the world correctly. Prior to making their prediction, they choose whether to receive information from a symmetric source or an asymmetric source. To eliminate potential confounds, such as reputation concerns or motivated beliefs, we adopt a minimalist approach and present information to the participants in an abstract setup with binary states and binary signals. In this context, we manipulate participants' prior beliefs and the precision of the symmetric source. We thus vary the instrumental value and the relative order of the two information sources, allowing us to identify systematic preferences for the symmetric source beyond its instrumental value.

The data broadly align with the comparative statics predicted by the payoff-maximising benchmark: participants are more likely to select an information source as its instrumental value increases. Yet the optimal strategy is followed in only 49.1% of cases, indicating substantial deviations from the rational benchmark. We identify two systematic departures. First, participants exhibit a consistent *bias toward the symmetric source*, choosing it more often than warranted by its instrumental value. Second, regardless of which source they select, participants tend to *overuse information*—frequently following the signal even when it would be optimal to rely on their prior beliefs. Together, these patterns suggest that participants assign more than instrumental value to information sources, finding symmetry particularly appealing.

To understand the mechanisms behind the observed bias for symmetric information, we examine and rule out two potential alternative explanations: noise and belief distortions. First, we provide evidence that the bias is not an artefact of noisy decision making. Second, although participants systematically overestimate the value of the symmetric source in their beliefs, we show that these distortions do not account for their observed choices. In fact, decisions based on reported beliefs deviate even further from payoff-maximising behaviour. Finally, we explore the possibility that participants rely on symmetry as a heuristic, either due to innate preferences or as a response to cognitive demands. We find that higher numeracy is associated with more optimal choices, but not with a weaker bias toward symmetry. In contrast, better task-specific comprehension is linked to a stronger symmetry bias. Yet even the most sophisticated participants display a substantial and persistent preference for symmetric sources.

Our findings have implications for a range of managerial settings where decision-makers gather information endogenously. One particularly relevant application concerns information processing within organisations. Recent advances in the theory of the firm highlight the central role of information acquisition and interpretation in shap-

ing decision rights and organisational structure (Holmström and Roberts, 1998; Bolton and Dewatripont, 1994).[3] A common assumption in this literature is that the nature of acquired information is either known or inferred through equilibrium strategies. Our paper provides a cautionary perspective on this structural assumption in organizational theory. If individuals have different biases for certain types of information—such as symmetric sources—regardless of their instrumental value, this assumption may fail. In such cases, the receiver of information may misinterpret its quality or relevance, leading to breakdowns in effective communication.

2 Literature Review

Empirical research on demand for information has revealed that people have motivations that go beyond information's instrumental value. For example, economic agents seek evidence that justify their own beliefs or decisions (see Jones and Sugden, 2001; Eliaz and Schotter, 2007, 2010; Charness and Dave, 2017); or information is also demanded *after* decisions have been made as a way to manage the moment in which uncertainty is revealed (see Von Gaudecker, Van Soest and Wengström, 2011; Falk and Zimmermann, 2014; Zimmermann, 2014; Nielsen, 2020). While the motivations driving non-instrumental value may vary, a common feature in these deviations from the standard benchmark is the existence of a specific uncertainty dimension of the underlying decision that is being reduced.[4] In contrast, symmetry is a property of the information source itself, which is independent of the actual need to mitigate uncertainty.

Our paper directly relates to papers that present information in purely statistical terms and study demand for *biased* information. Masatlioglu, Orhun and Raymond (2023) study choices between information sources that have no value. They document evidence that participants demand positively skewed information, seeking a particular reduction of uncertainty. Charness, Oprea and Yuksel (2021) study choices between asymmetric sources. They identify patterns of demand for information for confirmatory, anti-

[3] Aghion and Tirole (1997) examine the relationship between "formal authority," which stems from access to information, and "real authority," which arises from decision-making power. Harris and Raviv (2008) analyze the optimal composition of corporate boards, considering how insiders and outsiders differ in their information-processing capabilities. Dessein, Galeotti and Santos (2016) explore how endogenous information acquisition drives organizations to concentrate on core competencies, thereby influencing strategic decision-making.

[4] There are also some environments in deviations from the Bayesian framework goes on the opposite direction. For example, Guan, Oprea and Yuksel (2023) found that people prefer information structures that have the same value but with a lower *entropy informativeness*. There is also evidence that participants avoid information (Huck, Szech and Wenner, 2015; Golman et al., 2022).

confirmatory, and uncertainty reduction reasons, that depends closely on the particular type of information structure. In their experiment, participants' mistakes cannot result from calculation errors but reflect heuristics highlighting the above mentioned motives. Montanari and Nunnari (2019) use a similar setup and confirm similar patterns regarding confirmatory and uncertainty-reducing motives. They also find that participants use information suboptimally when it contradicts their prior belief and comes from the source biased against their priors.

Unlike these papers, we focus on choices between symmetric and asymmetric sources and vary the value of information by manipulating the prior. This allows us to compare situations when both sources have no value (as in Masatlioglu, Orhun and Raymond, 2023) and when only one has value (as in some cases in Montanari and Nunnari, 2019; Charness, Oprea and Yuksel, 2021). We find that participants rely too much on information, i.e, they use it too much. Symmetry emerges as a desirable characteristic, as participants choose the symmetric source even at an expected loss.

Ambuehl and Li (2018) also use a minimal framework to study how individuals respond to information. They derived an indirect ranking of information sources by eliciting a lottery equivalence to using each information source. They find intrinsic preferences for certainty revealing information but no difference between symmetric and asymmetric sources. In all of the treatments in Ambuehl and Li (2018), the prior was uniform and all information sources had instrumental value. In contrast, we vary the prior and the instrumental value to find that the comparison between valuable and non-valuable information sources plays a crucial role in identifying the effect of symmetry.

Finally, Aina, Amelio and Brütt (2023) examine how contingent thinking influences belief updating in a "ball-and-urns" experiment with uniform priors. The paper, like ours, compare symmetric and asymmetric information sources. They find that participants are more consistent across elicitation methods when the source is symmetric, and that they exhibit stronger underinference when it is asymmetric. We document a similar asymmetry in underinference in our setting (see Llorente-Saguer, Oliveros and Zultan, 2024, for more details), despite employing non-uniform priors. While their focus is on belief updating, ours is centered on understading demand for information.

3 Conceptual Framework

An agent must guess an unobserved state of nature, ω, which can be either blue or red, i.e., $\omega \in \{B, R\}$. The red state, R, materialises with probability ρ, and the blue one, B, with probability $1-\rho$. The agent obtains a payoff of 1 if her guess matches the state and

zero otherwise, i.e., $\pi(g|\omega) = \mathbb{1}_{g=\omega}$.

Before making a guess, the agent can collect information from one of two different sources of information: the symmetric source S, or the asymmetric source A. Each informational source $k \in \{S, A\}$ provides a binary signal $s \in \{b, r\}$ with distribution contingent on the state. The probability that source k produces signal b in state B is denoted by $p_k^b \equiv \Pr(b|B,k)$ and the probability that the same source produces the signal r in state R is analogously denoted by $p_k^r \equiv \Pr(r|R,k)$. It is useful to define the expected precision of source k for priors ρ

$$\mathbf{p}_k(\rho) = p_k^r \rho + p_k^b (1-\rho)$$

Note that given the expected precision, $\mathbf{p}_k(\rho)$, is also the expected payoff of an agent with prior ρ who always follows the signals provided by source k.

We assume that under the symmetric source (S), the probability that the signal is correct is constant across states $p_S \equiv p_S^b = p_S^r$ which implies that the expected precision is constant for all ρ: $p_S = \mathbf{p}_S(\rho)$. In contrast, under the asymmetric source (A), the likelihood of receiving the right signal varies across states. We refer to this source A as *asymmetric source*. In particular, we assume that

$$\tfrac{1}{2} \leq p_A^b < \mathbf{p}_S < p_A^r < 1. \tag{1}$$

That is, the probability of receiving the right signal from source A in state R is higher than from source S but it is lower in state B.

The optimal decision. In this section we characterise the optimal behaviour of a (Bayesian) payoff maximiser. Note first that the optimal decision given a posterior, is to choose the most likely colour. Without information agents guess the most likely colour given the prior: B when $\rho < \frac{1}{2}$ and R when $\rho > \frac{1}{2}$. We call these guesses the *default guess (given the prior)*. It follows that the expected payoff without information is equal to the expected payoff of playing the default guess:

$$\underline{\pi} = \max\{\rho, 1-\rho\}.$$

When the priors are extreme, signals from sources with moderate precision cannot induce the agent to deviate from the default guess (determined by the prior). Why is it optimal to discard information? When receiving a signal, the agent updates her belief in the direction of the signal. If the signal goes against the prior and the precision of the source is not strong enough, the new posterior still remains on the same side of $\frac{1}{2}$ as the

prior. Hence, for extreme priors and moderate precision sources, both potential posteriors are on the same side of $\frac{1}{2}$, and the optimal decision is the default guess for both signals yielding expected payoff $\underline{\pi}$.

We say that an information source *has value (for prior ρ)* if the signals induce posteriors that lie on different sides of $\frac{1}{2}$. In the context of our experiment, we say that a source has value if an agent's unique optimal guess after signal r is R and after signal b is B. Given the previous discussion, when priors are not extreme, sources can have instrumental value. In fact, given assumption (1), both sources have value for some intermediate priors.

The following proposition summarises the discussion above and presents the priors under which each source induces a choice different than the default guess. It describes the optimal *use of information*:

Proposition 1. *Source S has value if and only if* $\max\{1-\rho,\rho\} < \mathbf{p}_S$. *Source A has value if and only if* $\max\{1-\rho,\rho\} < \mathbf{p}_A(\rho)$.

An immediate implication of Proposition 1 is that no information source is optimal for extreme priors, as neither source has value in such cases. Specifically, this occurs when $\max\{1-\rho,\rho\} \geq \max\{\mathbf{p}_A(\rho), \mathbf{p}_S\}$. For all remaining priors, one source is always the optimal choice. If one source has value while the other one does not, the source with value becomes the unique optimal choice. When both sources provide value, a payoff-maximising agent compares the payoffs provided by each source: $\pi(S) = \mathbf{p}_S$ for source S and $\pi(A) = \mathbf{p}_A(\rho)$ for source A. By assumption (1), both sources have value for some range of intermediate priors.

Since $\mathbf{p}_A(\rho)$ is increasing in ρ due to assumption (1), and $\mathbf{p}_S$ remains constant, source S is optimal for intermediate but low priors, provided its precision is sufficiently high.[5] Similarly, source A is optimal for intermediate but high priors, again contingent on its precision being sufficiently high which is true in our experiment for some treatments.[6] The following proposition precisely determines the cutoff values that render each source optimal and characterizes how this agent *chooses information sources* under the relevant parameters of our experiment:

Proposition 2. *A is the optimal choice if* $\frac{\rho}{1-\rho} \in \left(\max\left\{\frac{p_S-p_A^b}{p_A^r-p_S}, \frac{1-p_A^b}{p_A^r}\right\}, \frac{p_A^b}{1-p_A^r}\right)$ *and S is the optimal choice if* $\frac{\rho}{1-\rho} \in \left(\frac{1-p_S}{p_S}, \min\left\{\frac{p_S-p_A^b}{p_A^r-p_S}, \frac{p_S}{1-p_S}\right\}\right)$*; otherwise, following the priors (ignoring the signal) is optimal.*

[5] In our experiment, source S in the low precision treatment is never optimal.

[6] In our experiment, source A is always optimal for some priors.

To build intuition for Proposition 2, consider the conditions under which source A is chosen. First, observe that the inequality $\frac{\rho}{1-\rho} \in \left(\frac{1-p_A^b}{p_A^r}, \frac{p_A^b}{1-p_A^r}\right)$ corresponds to the requirement for source A to have positive value, as established in Proposition 1. That is, A must be a useful source. The additional condition $\frac{\rho}{1-\rho} \geq \frac{p_S - p_A^b}{p_A^r - p_S}$ ensures that the value of using A exceeds that of using source S. This can be more intuitively understood by rewriting it as:

$$(p_S - p_A^b)(1-\rho) \leq (p_A^r - p_S)\rho.$$

Here, the left-hand side represents the expected loss in precision from using A instead of S, driven by S's higher precision in state b—i.e., the opportunity cost of choosing A. The right-hand side reflects the expected gain in precision from using A instead of S, due to A's higher precision in state r—i.e., the marginal benefit of choosing A.

4 The Experiment

To test our theoretical predictions on choice of sources and use of information, we ran a controlled laboratory experiment. The experiment consisted of four parts: the main task, two belief elicitation tasks, and survey questions.[7]

First part. The main part of the experiment consisted of 40 rounds of the decision problem described in Section 3. In each round, participants had to guess the colour of a triangle (the state of the world), choosing between two possible options (e.g., blue or red). Before making their guess, they had to decide whether to receive information from a *symmetric source* or an *asymmetric source*, which were randomly labelled as Advisor 1 and Advisor 2. Each advisor was represented by two urns, one corresponding to each possible state of the world. The urns contained 20 balls of the two possible colours, with their composition reflecting the precision of the information source. For instance, for the asymmetric source, the urn corresponding to a blue triangle contained an equal mix of blue and red balls ($p_A^b = 0.5$), while the urn for a red triangle contained 19 red balls and 1 blue ball ($p_A^r = 0.95$).

After selecting an advisor, participants made two conditional guesses—one for each possible signal they could receive. Once these choices were made, a ball was drawn from the urn corresponding to the true triangle colour, and the participant's guess for the real-

[7] The experimental software and replication materials are available at `https://osf.io/wn3tm/?view_only=b81be1548ce14b44b58cbb264cf2d349`.

ized signal was implemented.[8] At the end of each round, participants received feedback on (i) the actual color of the triangle, (ii) the signal drawn from the urn, (iii) their choice for that signal, and (iv) their payoff, which was 100 if they guessed correctly and 0 otherwise.

The precisions of the asymmetric source were $p_A^b = 0.5$ and $p_A^r = 0.95$ across the experiment. We manipulated the prior $\rho \in \{0.1, 0.4, 0.55, 0.75\}$ within-subjects,. We intentionally refrained from the uniform prior of 0.5, for which the posterior given a symmetric information source simplifies to the source's precision. This makes symmetric sources easier to process than asymmetric ones and therefore confounds symmetry with complexity (cf. Enke, Graeber and Oprea, 2023; Enke and Shubatt, 2023; Oprea, 2024).[9]

The precision of the symmetric source $p_S \in \{0.6, 0.75\}$ varied between-subjects.[10] We refer to the treatments with $p_S = 0.6$ as the *low-precision* treatments and to the treatments with $p_S = 0.75$ as the *high-precision* treatments.

The 40 rounds were divided into four blocks, each consisting of ten identical rounds.[11] The primary variation across blocks was the prior probability, ρ. Additionally, each block featured a distinct pair of triangle colours—representing the two states of the world—and a specific assignment of advisors (S or A) to Advisor 1 and Advisor 2. The possible colour pairs were blue/red, yellow/brown, green/pink, and orange/purple. The assignment of priors and colour pairs to each block was fully randomized at the individual level (without replacement), while advisor labels were randomized independently in each

[8] See Brandts and Charness (2000, 2011) for a discussion on differences between the strategy method and direct-response method in sequential games. See also Aina, Amelio and Brütt (2023) for a discussion on these differences in belief elicitation.

[9] Aina, Amelio and Brütt (2023) show that, under a uniform prior, beliefs tend to align more closely with Bayesian posteriors when information is drawn from symmetric rather than asymmetric sources. For non-uniform priors, as in our experimental design, it is less clear whether computing posteriors should be substantially more complex in the asymmetric case. While symmetric sources require tracking one accuracy parameter compared to two parameters for asymmetric sources, the fundamental Bayesian updating (non-trivial) operations remain the same across both cases.

[10] In our setup, participants knew the reliability of each source. Liang (2024) explores how individuals learn from sources with unknown reliability, which adds another layer of complexity to the demand for information. Relatedly, Guan (2023) examines how participants choose among information bundles.

[11] We deliberately chose to repeat the exact same problem within each block and provide feedback after each round in order to allow participants to familiarize themselves with the relatively complex environment and refine their strategies over time. While this design choice could, in principle, influence the accuracy of belief elicitation in later parts through differential exposure to information sources, our analysis finds no systematic evidence of such bias.

block.[12]

Second and third parts. The implicit assumption in the predictions of section 3 is that participants are Bayesian expected-payoff maximisers. In these parts, we elicited participants' beliefs to establish whether mistakes in belief updating can explain deviations from the benchmark predictions. In part two of the experiment, we elicited the posteriors for every prior, source, and signal encountered in the first part. In part three of the experiment, we elicited the perceived likelihood of receiving each signal for every prior and information source from part one.[13] We elicited beliefs with the binarised scoring rule proposed by Hossain and Okui (2013), as implemented in Wilson and Vespa (2016). The order of priors, sources, and their respective colours was the same as in the first part of the experiment.

Fourth part. The fourth part consisted of a basic questionnaire, a 16-trial version of the raven test and a numeracy test.[14] This part was not incentivised.

4.1 Experimental Procedures

The experiment was conducted at the ESSEXLab in December 2019. We ran four sessions with $p_S = 0.6$ and four sessions with $p_S = 0.75$, with a total of 190 participants (93 and 97 respectively). Students interacted through computer terminals, and the experiment was programmed and conducted with the software z-Tree (Fischbacher, 2007).

All sessions followed the same procedure. At the beginning of each part, participants received detailed written instructions, which an instructor read aloud. Before starting each of the parts, participants were required to complete a comprehension questionnaire to ensure their understanding of the experimental design.[15] The questions were not incentivised, but participants could only proceed after answering each one correctly.

To determine payments at the end of the experiment, the computer randomly selected two rounds in each of the four blocks of part one, two rounds from part two and two rounds from part three. Participants earned the total earned in these rounds. Points

[12] We varied elements across blocks—such as colours and advisor labels—to minimize pattern recognition and reduce potential biases arising from participants' desire for consistency (see Cialdini, 1984 and Falk and Zimmermann, 2017) and induce participants to approach each block as a distinct decision-making scenario.

[13] The utility of following source k can be written as $u(k) = \Pr(R|r,k)\Pr(r|k) + \Pr(B|b,k)\Pr(b|k)$, where posteriors are multiplied by the likelihood of each signal.

[14] Due to a technical issue, we were unable to collect the Raven's test scores during the first session, resulting in the absence of scores for 20 participants.

[15] The number of comprehension questions in Parts 1, 2 and 3 were 12, 6, and 6, respectively.

were converted to pounds at the rate of 50 points = £1. In total, participants earned an average of £19.17, including a show-up fee of 5 pounds. Each experimental session lasted approximately two hours.

4.2 Testable implications

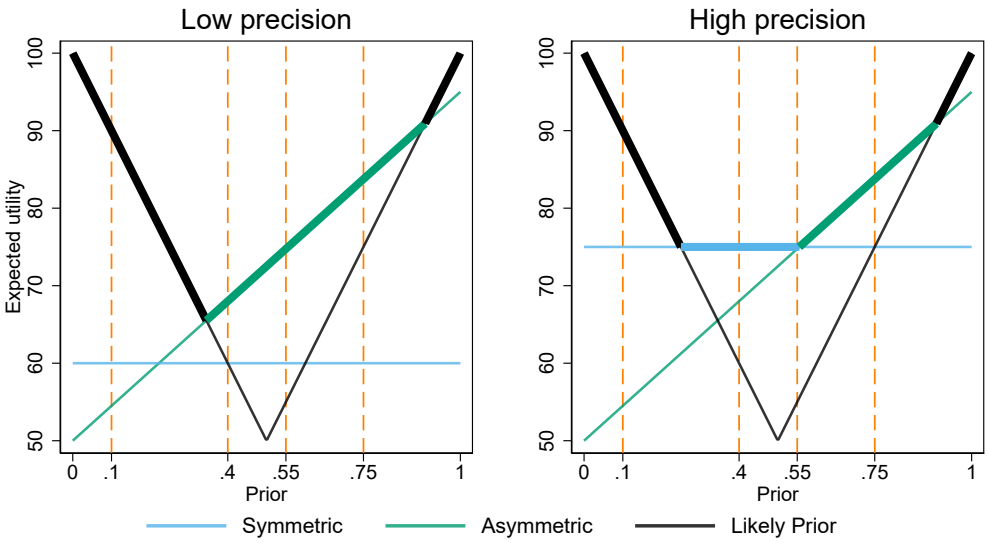

Figure 1: Expected payoff. The black line indicates the expected payoff of following the "Likely Prior", and the blue (green) one the expected payoff of following the symmetric (asymmetric) source. The vertical dashed lines mark the priors implemented in the experiment. Sources expected payoff above the "Likely Prior" denote positive information value, while the thicker lines indicate the optimal source choices.

Under the assumption that agents are payoff maximisers, Propositions 1 and 2 provide a series of testable implications regarding use of information and choice of source. Figure 1 depicts the expected payoff for different combination of strategies and source of information graphically, helping identify the optimal use of information and choice of source.

Prediction about use of Information. When the prior is $\rho = 0.1$, none of the sources of information in our experiment provides value. Similarly, with $\rho = 0.75$, the low-precision symmetric source has no value. In these cases, participants should ignore the

information and make the same prediction for both signal realizations. In cases where $\rho = 0.4$ with the low-precision symmetric source or $\rho = 0.75$ with the high-precision symmetric source, one of the signals leads to a posterior of 0.5, so participants are indifferent between following the information or not. Although these sources also lack value we cannot predict information usage for the signal realization that leaves them indifferent.[16] In all other situations, all information sources are valuable, and thus, information should be used.

Prediction about choice of source of information. In the cases where no information source has value ($\rho = 0.1$), we cannot predict which source will be selected. Furthermore, when $\rho = 0.55$, the high precision symmetric source and the asymmetric one provide the (approximately) same value and we cannot predict which source will be chosen between these two.[17] When $\rho = 0.4$, the high precision symmetric source provides higher value than the asymmetric one and, hence, the former should be chosen over the latter. In all other cases, the optimal choice is the asymmetric source.

Beyond these point predictions, we present two additional qualitative predictions regarding the choice of information when $\rho > 0.1$. First, we expect to observe a higher demand of source S when its precision is $p_S = 0.75$ compared to when its precision is $p_S = 0.6$. Second, as ρ increases, the demand for source A should also increase. In contrast, the demand for the symmetric source should decrease with ρ, regardless of whether its precision is high or low.

5 Experimental Results

5.1 Use of Information

Do participants appropriately use information when it is valuable and disregard it when it is not? Table 1 reports the percentage of instances in which participants followed the information provided by each source, broken down by source type and prior beliefs. Cases in which information should be used are highlighted in bold, while situations where following and ignoring the information are both optimal are marked in italics.[18]

[16] In these cases, the optimal guess for the the signal that reinforces the prior coincides with the prediction based solely on the prior. The indifference arises for the signal that contradicts the prior.

[17] When $\rho = 0.55$, the expected payoff from following the high-precision symmetric source is 75, while following the asymmetric source yields an expected payoff of 74.75. Given this minimal difference, we consider both choices as optimal in our analysis. Our results remain robust even if we treat only the symmetric source as optimal.

[18] All analyses reported here aggregate across the ten decision periods. Participants were generally consistent within blocks: in most blocks, participants chose the same strategy in at least 8 out of 10 repe-

Table 1: Frequency of following the information.

	Prior				
Source	0.1	0.4	0.55	0.75	Overall
Asymmetric	45.55	**72.17**	**67.03**	**56.99**	61.45
Symmetric High	45.07	**76.27**	**86.39**	*76.72*	69.60
Symmetric Low	26.12	*67.50*	**67.37**	57.10	50.71
Total	38.32	72.42	73.32	62.00	61.51

Notes: Percentage of following the information by source type and prior. Bold indicates positive value. Italics indicate that following the signal and following the prior provide the same chances of guessing correctly.

Although the observed frequency of use deviates substantially from the extreme theoretical benchmarks of 0% and 100% predicted by Proposition 1, participants exhibit a clear tendency to follow information more frequently when it should be used than when it should be ignored (69.47% vs. 40.90%, $z = 9.25, p < 0.001$).[19] This 28.57 percentage point difference is more pronounced under symmetric sources: it is 35.89 percentage points for the high-precision symmetric source and 31.79 for the low-precision symmetric source, compared to only 18.61 for the asymmetric source.[20]

We next look at how symmetry affects the use of information, depending on the source's value. When sources have *no* value, participants follow the signal at similar levels across sources (45.55%, 45.07%, and 35.58% under the asymmetric, high-precision symmetric, and low-precision symmetric sources, respectively; $\chi^2(2) = 3.69, p = .158$ for the joint test). By contrast, when information *should* be used, the differences are substan-

titions. Some variation within identical tasks is nonetheless common in experimental settings, as also documented in Agranov and Ortoleva, 2017 and Agranov, Healy and Nielsen, 2023. To test whether participants learn to make better choices across the experiment, we ran a logistic regression of whether the chosen strategy (combination of source choice and guesses conditional on signal) is optimal on the block and prior (as categorical variables), period (as continuous variable), and their interactions. There is some evidence of learning across blocks ($\chi^2(3) = 7.67, p = .053$ for the joint comparison of all blocks against the grand mean), resulting from slightly more optimal decisions in the last block (52.0% vs. 49.7% overall). There is also an overall slight improvement across periods within blocks ($\beta = .007, p < .001$). Nonetheless, our results, and in particular the tendency to choose symmetric sources, are robust to including only the last block or the last five periods within each block.

[19] We omit the situations where following the signal yields the same expected payoff as following the prior. The statistical tests reported in this section are based on a logistic regression for following information on the chosen information source interacted with whether that source has positive value, with robust standard errors clustered on individuals.

[20] The increase in information use is significantly smaller for the asymmetric source than for either the high-precision symmetric ($z = 2.58, p = .010$) or the low-precision symmetric source ($z = 1.94, p = .052$). The difference between the two symmetric sources is not statistically significant ($z = 0.63, p = .530$).

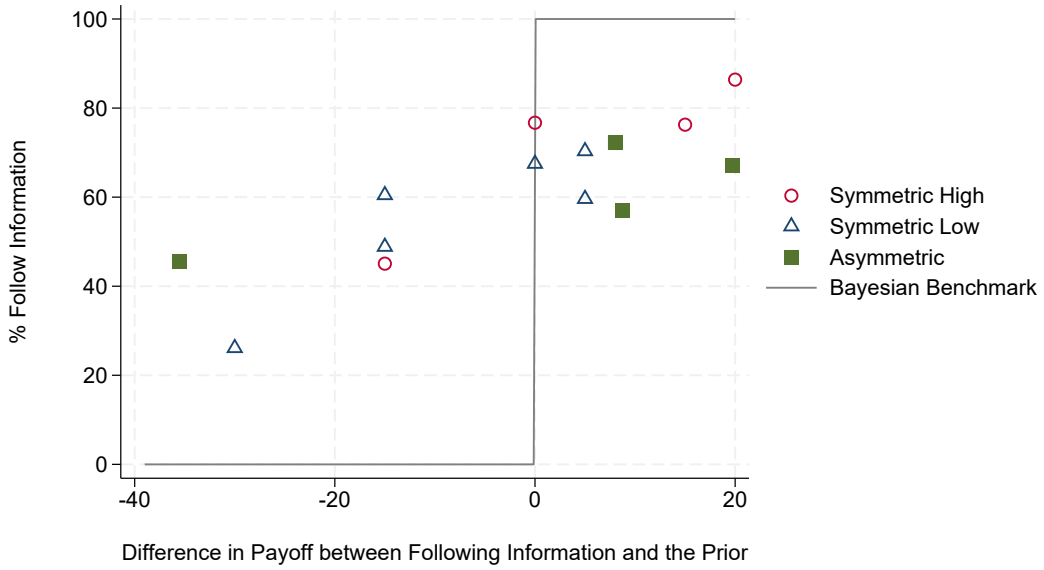

Figure 2: Relationship between interim expected payoff difference and use of information. The interim payoff difference is calculated as the difference in expected payoffs between following the signal and relying on the prior.

tial and significant ($\chi^2(2) = 22.26, p < .001$). Participants follow the signal more frequently under symmetric sources (77.94% when both sources are pooled) than under the asymmetric source (64.16%), and this difference is statistically significant ($\chi^2(1) = 11.07, p < .001$).[21]

It is important to note that the payoff difference between following the information and relying on the prior varies across situations. Does the extent to which participants follow information depend on the magnitude of this difference? Figure 2 plots the frequency of using information against the *interim payoff difference*—defined as the expected payoff difference between following the signal and ignoring it, calculated before the signal is realised. A positive interim payoff difference indicates that the source has value, whereas a negative difference suggests it does not. While theory predicts a sharp step function, the data reveal a smoother, monotonic relationship: the likelihood of following the signal increases gradually with the interim payoff difference. This pattern suggests

[21] Separately, the difference between the low-precision symmetric source (67.37%) and the asymmetric source (64.16%) is not statistically significant. However, both differ significantly from the high-precision symmetric source (80.96%) at the 5% level. Note that it is sufficient to compare the source precision and the prior to identify whether a symmetric source has value, whereas identifying whether an asymmetric source has value requires some calculation. This, however, does not explain why the effect of symmetry is only apparent conditional on positive value and for the high-precision symmetric source.

that the interim payoff difference influences the likelihood of participants choosing the optimal action in the information use stage beyond what value solely suggests.

Result 1. *Participants use information more when it has value, yet they sometimes follow it when it does not and ignore it when it does. In contrast to Proposition 1 where value is the sole determinant of use, the likelihood of selecting the optimal action increases with the interim payoff difference.*

5.2 Choice of Information Source

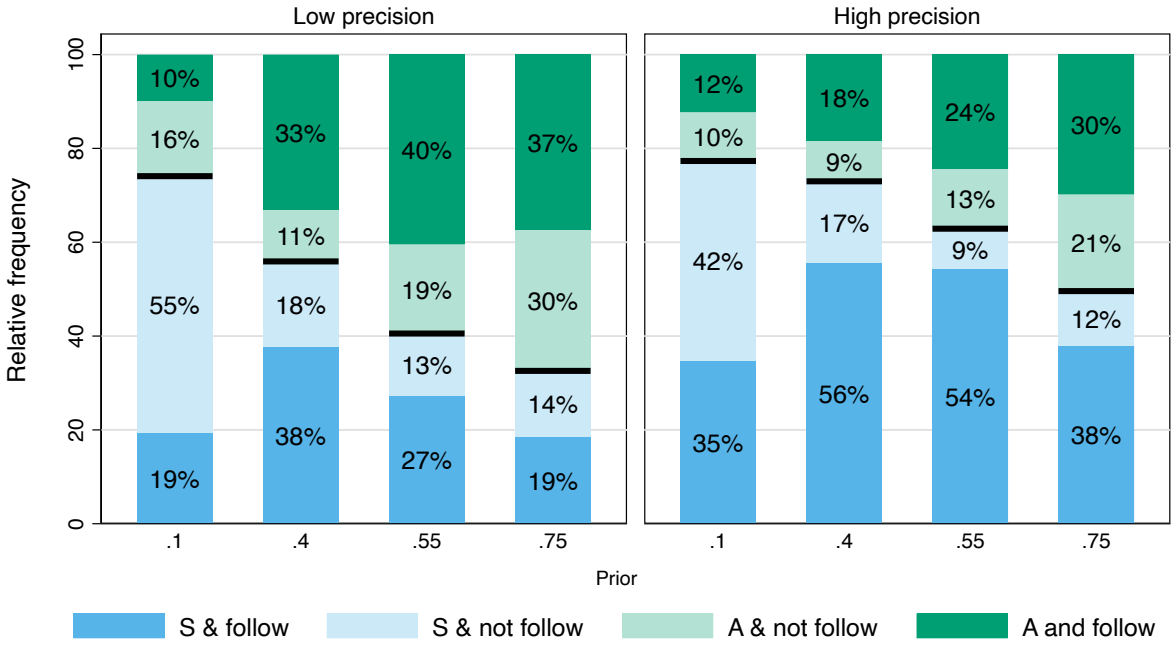

Figure 3: Source choice and decisions. The figure indicates whether participants chose the symmetric source (S) or the asymmetric one (A), and whether they followed the information of the chosen source or not.

Figure 3 displays the proportion of times participants selected each source by treatment and prior, broken down choices by whether the signal was followed or ignored. In line with our findings on information use, the precise point predictions from Proposition 2 do not fully materialise, as participants frequently make suboptimal choices. Nevertheless, the main qualitative predictions of the conceptual framework section hold. First, participants select the symmetric source more often in the high-precision treatments than in the low-precision ones. While the low-precision symmetric source is chosen 50.78%

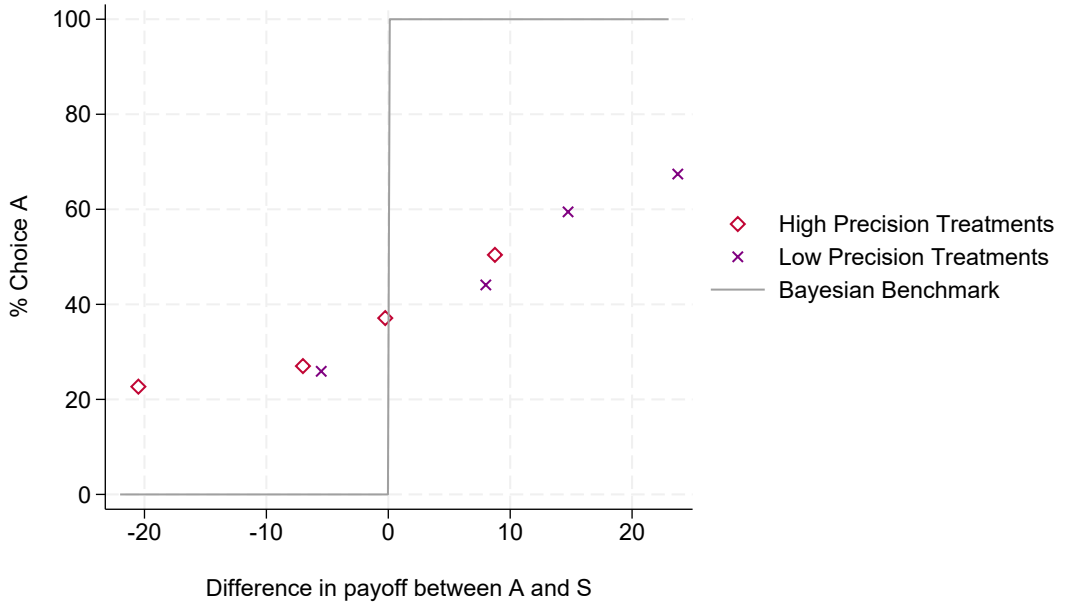

Figure 4: Relationship between expected payoff difference and choice of information source. Expected payoffs are computed under the assumption that participants always follow the signal, regardless of whether doing so is optimal.

of the time, the high-precision source is selected 65.70% of the time.[22] Second, the frequency of choosing the symmetric source decreases as the prior ρ increases, a pattern observed in both the high- and low-precision treatments. Overall, the symmetric sources were chosen 75.74%, 64.63%, 51.95% and 41.26% of the time for ρ equal to 0.1, 0.4, 0.55, and 0.75, respectively.[23]

Result 2. *Participants' source choices frequently deviate from the predictions of Proposition 2. However, consistent with the main qualitative predictions, the high-precision symmetric source is selected more often than the low-precision one, and the likelihood of choosing the symmetric source decreases as the prior increases. The likelihood of selecting the payoff maximising source increases with the payoff difference.*

There are two remarkable deviations from the theoretical predictions that merit attention. First, the symmetric source is chosen far more often than expected. When ex-

[22] A logistic regression with robust standard errors clustered on participants confirms that this difference is statistically significant for all $\rho > 0.1$ separately and jointly for all priors.

[23] Adjacent contrasts confirm that participants choose the symmetric source less as ρ increases($p < 0.001$ for all steps). At the individual level, 69 of the 190 (36.32%) participants are monotonic in the sense that they never choose the symmetric source more often for higher priors. Additional 59 participants for a total of 128 (67.37%) exhibit only one deviation from monotonicity. A permutation test reveals that these two numbers are significantly higher than expected by chance given the choice distribution for each treatment and prior ($p < .001$).

actly one source has value, the symmetric sources should be chosen 20.51% of the time, yet in the data, they are selected 50.51% of the time.[24]

Second, while the evaluation of information sources typically focuses on whether they provide value and, if so, compare the magnitude of that value, the data suggest that considering the *expected payoff* from following the information provided by a source offers a better fit with the observed behaviour. That is, beyond the difference in instrumental value, the difference in interim payoffs plays a role in decision-making. For instance, although no source provides value when $\rho = 0.1$, the source that delivers the highest expected payoff (source S in both treatments) is chosen most frequently and information is followed more with the high-precision symmetric source than with the low-precision one. Figure 4 shows that the frequency of selecting source A increases significantly with the size of the payoff difference associated with following the various information sources.

Result 3. *Expected payoff and symmetry appear to influence the selection and use of information sources beyond their instrumental value.*

5.3 An hedonic approach

To formally test and quantify the deviations from the model predictions, we fit a binary choice model under the assumption that participants have fixed preferences over information characteristics and the observed behaviour results from noisy implementation of these preferences. The probability of implementation error is assumed to be a decreasing value of the cost of error. We use maximum likelihood estimation using the logit regression

$$Prob(c) = \frac{e^{\gamma \cdot u(c)}}{\sum_{c' \in C} e^{\gamma \cdot u(c')}},$$

where γ is a precision parameter and c is an element of the set C, which comprises the eight possible combinations resulting from crossing the choice of source and guess for each possible signal it can generate. We estimate the behavioural patterns in the data by allowing $u(c)$ to include terms for choosing the symmetric source, for following the signal, and for following the symmetric source specifically. That is,

[24] When the symmetric source is superior, it is chosen 74.81% of the time. This frequency decreases to 62.89% when the two sources are (almost) indifferent and further to 44.71% when the asymmetric source has greater value. When neither source has value ($\rho = 0.1$), the symmetric source is chosen 75.74% of the time.

$$u(c) = \pi(c) + \delta \mathbb{1}_S + \lambda \mathbb{1}_F + \xi \mathbb{1}_{FS}, \tag{2}$$

where $\pi(c)$ is the expected payoff from following choice c. $\mathbb{1}_S$ is an indicator for the four strategies that choose the symmetric source, $\mathbb{1}_F$ is an indicator for the two strategies that follow the signal, and $\mathbb{1}_{FS}$ is an indicator for the strategy of following the symmetric signal.[25]

A payoff maximiser is characterised in equation (2) by $\delta = \lambda = \xi = 0$ and by $\pi(s_k)$ equal to the objective value. Column (1) in Table 2 presents the results of the restricted version and Column (2) the results of the unrestricted version of Equation (2), with the parameters scaled by a factor of 100. The results support the qualitative observations in Result 3: the AIC and BIC values indicate that the unrestricted model has a better fit than that of the baseline model.

Table 2: Regression estimation for choice and use of information.

	(1) Baseline	(2) Preferences	(3) Subjective beliefs
δ	–	8.217***	12.38***
		(4.59)	(5.52)
λ	–	13.44***	18.26***
		(5.39)	(5.65)
ξ	–	2.946	0.989
		(1.29)	(0.36)
γ	0.0608***	0.0535***	0.0461***
	(27.49)	(22.21)	(17.19)
N	7600	7600	7600
log lik.	$-11,894$	$-11,116$	$-11,490$
AIC	23,791	22,239	22,989
BIC	23,798	22,267	23,017

Notes: t-statistics in parentheses based on robust standard errors clustered on individuals. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The estimated parameters in (2) reveal two clear and economically significant patterns of deviation from optimal behaviour. First, participants exhibit a substantial bias toward selecting the symmetric source, even when it is not payoff-maximizing. This

[25] In this setting we want to assess preferences over characteristics; as such the concept of value is ill-defined as we are assuming that information is demand for other reasons beyond pure ability of changing actions.

preference for symmetry leads to a notable efficiency loss: on average, it reduces the probability of winning the prize by approximately 8.2 percentage points. Second, participants tend to follow the information they receive too frequently, even when the expected value of doing so is low. This tendency to over-rely on signals results in an even larger payoff cost, lowering the probability of winning by around 13.4 percentage points. Importantly, however, we do not find significant evidence that participants are more likely to follow a signal from the symmetric source than from the asymmetric one. This finding holds even when we condition on the precision of the symmetric source, suggesting that the overuse of signals is not itself mediated by the identity of the source.

Together, these patterns suggest that participants systematically depart from the optimal strategy in ways that have meaningful implications for performance, and they highlight inefficiency in both choice of source and use of information.

Result 4. *Participants follow signals too much and tend to choose the symmetric source inefficiently.*

5.4 Mechanisms

The previous section established econometrically a systematic bias in favour of the symmetric source. In this section, we explore potential mechanisms underlying this effect. First, we rule out the possibility that the observed bias is merely an artifact of noisy decision-making. Second, using the elicited beliefs, we also rule out belief formation as a mediator. Taken together, these findings establish the direct effect of symmetry on choices. This effect may reflect preferences for symmetric information. Alternatively, people may find the task too demanding or confusing and rely on symmetry as an heuristic, possibly because of humans' innate general preference for symmetry (Enquist and Arak, 1994; Bertamini, Rampone et al., 2020).[26] If the heuristic explanation holds, one would expect the symmetry bias to diminish among participants with higher cognitive abilities or better understanding of the task. In this case, participants with high cognitive abilities or better understanding of the task should not show a preference for symmetry. We find that cognitive ability is correlated with more payoff-maximising decisions, but not with bias for symmetry. In contrast, specific task comprehension is correlated with such a bias, suggesting that a heuristic response to symmetry does play a role in the observed choices. Nonetheless, even participants with better task comprehension exhibit a substantial bias for symmetry.

[26] We thank an anonymous referee for suggesting this link.

5.4.1 Noisy choices

The stochastic element in human decision making can cause behavioural anomalies (Loomes, 2005; McGranaghan et al., 2024). A standard way of modelling noisy decisions is through adding noise to the expected utility, often referred to as the "expected utility plus white noise" model (Hey and Orme, 1994). In our experiment, the asymmetric source has a higher value in four of the eight environments while the symmetric source has higher value in only one. Note that the econometric analysis in Section 5.3 accounts for exactly such noise, with the precision term γ capturing decision noise independently of the estimated tendency to choose the symmetric source δ. Nevertheless, the model may not fully account for noise if the noise structure is misspecified. We, therefore, conducted the following additional tests. First, our experimental design intentionally included environments where the two sources provide equal expected utility. These environments reveal a systematic bias for symmetry, whereas noise models are unable to account for such systematic preferences.[27] Second, to further assess the role of noise, we simulated data based on a model of expected utility plus uniform noise, and re-estimated the model in Section 5.3 on the simulated data. The estimated δ parameter was significant at the 0.05 level in only 46 out of 1,000 simulations, with a mean value of 0.112—compared to 8.217 in the actual data. This confirms that the observed bias towards the symmetric source is not an artifact of noise. See the online appendix for the full details.

5.4.2 Subjective Beliefs

Symmetry may affect the way in which people form beliefs based on the provided information rather than directly affecting choices. Indeed, Table A4 in the Appendix shows that subjective beliefs systematically overestimate the value of the symmetric source while underestimating the value of the asymmetric source. However, this does not account for the observed bias toward symmetry. First, participants choose the payoff-maximising strategy in 49.1% of cases. When expected payoffs are computed using the self-reported beliefs, this figure drops to 42.1%, indicating that participants did not maximise expected utility given their subjective beliefs. More formally, we re-estimated the model from Section 5.3, calculating the expected payoff $\pi(c)$ using each participants' reported beliefs. The results, presented in Column (3) of Table 2, indicate that both δ and λ increase rather than decrease, while the model fit worsens compared to the baseline

[27] McGranaghan et al. (2024), for example, write that "[I]f $EU(A) - EU(B) = 0$, [...] then $Pr(A) = 1/2$".

specification.[28] This indicates that distortions in probability perceptions alone do not account for the bias for symmetry.[29]

5.4.3 Heuristic response to symmetry

It is possible that participants who find the task confusing rely on symmetry as a heuristic. This implies that the bias for symmetry should be stronger for confused participants, and disappear for participants who are able to comprehend the task. The Raven test and numeracy scores provide individual measures of cognitive abilities. Numeracy scores, but not performance in the Raven test, predict optimal choices. To determine whether this correlation is due to unsystematic mistakes or participants with lower cognitive abilities relying on symmetry as a choice heuristic, we re-estimated the model in Section 5.3 allowing the parameters to vary with the cognitive-ability measures. Higher numeracy scores were associated with lower decision noise, but not with a weaker bias towards symmetry. If anything, high-numeracy participants exhibited a slightly stronger bias. We further tested task-specific comprehension using individual performance on the comprehension questions.[30] Participants who made fewer than the median number of mistakes chose the optimal decision in 54.1% of cases, compared to only 41.3% among those who made more than the median number of mistakes. Estimating our model separately for these two groups of participants revealed that participants who made more mistakes in the control questions exhibited more noisy behaviour, a greater tendency to follow signals and a stronger bias toward the symmetric source. However, even among those who made fewer mistakes, the bias toward symmetry remained substantial and significant. See the appendix for the full details.

[28] When computing expected payoffs using subjective beliefs, we base the payoffs resulting from ignoring the signal on the prior. A more complex alternative is to compute the expected payoff based on the elicited beliefs for chosen source. This alternative specification does not alter the conclusions. The number of choices consistent with the payoff-maximizing strategies drop further, from 42.1 to 29.7%, and the estimate for δ increases from 12.38 to 16.72.

[29] In Llorente-Saguer, Oliveros and Zultan (2024), we show that the reported beliefs are informative. Specifically, the belief data identify two types of individuals based on their style of forming posteriors. Approximately half of the participants show base-rate neglect, meaning that they form their posteriors based on the characteristics of the information source and ignore the prior. The rest of the participants neglect the signal more than they do the prior. Only the former type overuses information (as reflected in the parameter λ, while both types tend to choose the symmetric source (as reflected in the parameter δ).

[30] Performance on comprehension questions can reflect different underlying factors, such as attention, task engagement, or cognitive ability. In our analysis, we remain agnostic about the precise source of variation and treat these measures simply as a proxy for participants' understanding of the experimental task.

6 Conclusion

In this paper, we examine how individuals choose between different information sources and how they use the information they acquire. Our results reveal systematic deviations from optimal decision-making. Participants disproportionately prefer symmetric information sources, even when asymmetric alternatives offer higher instrumental value. Moreover, they tend to use information even when the chosen source provides no value.

These findings have important implications for both economic theory and managerial practice, particularly in environments where agents can endogenously determine the type of information to acquire or provide. More broadly, our results highlight that features of information sources—such as symmetry—that should be normatively irrelevant under standard models of information acquisition can nonetheless significantly influence behaviour. Understanding how such non-instrumental attributes affect information demand and use is an important step toward developing more accurate models of decision-making under uncertainty.

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A Extended Discussion on Mechanisms

A.1 Noisy choices

In this section, we show that our findings are not an artifact of noisy decision-making. Specifically, we analyse the consequences of adding noise to payoffs, where the noise term is drawn from a symmetric distribution centred at zero (the so-called expected utility plus white noise (EU+N) model; Harless and Camerer, 1994; Hey and Orme, 1994). The econometric analysis in Section 5.3 explicitly accounts for noise, with the precision parameter γ capturing decision noise independently of the estimated tendency to choose the symmetric source, denoted by δ. Nevertheless, as the noise may be misspecified, we turn to two more direct tests of noise as a confounding factor.

Choice Probabilities Under Indifference. A central implication of the EU+N model is that when two strategies yield the same expected utility, they should be chosen with equal probability.[31] Our experimental design includes three environments in which the symmetric source has the same expected utility as either the asymmetric source or following the prior. The first three rows of Table A1 reports the probability of choosing the symmetric source versus the EU-equivalent alternative. Each row presents results from a logistic regression of a dummy variable for choosing the symmetric source, conditional on following a strategy that yields the same expected utility, with robust standard errors clustered on individuals.

The first row presents the High precision and $\rho = .55$ environment, where following both symmetric and asymmetric sources result in approximately the same payoff. The estimated probability of following the signal from the symmetric source conditional on following the signal is 69.1%, significantly higher than the (approximately) 50% predicted by the EU+N model. The next two rows present the two environments where the probability of guessing correctly is the same for choosing the symmetric source (either following it or guessing according to the prior) and choosing the asymmetric source and guessing according to the prior. Again, participants exhibit a systematic bias toward choosing the symmetric source.[32]

When ignoring the signal, the expected payoff is determined purely by the prior and the guess. Thus, according to the EU+N model, the predicted probability of choosing

[31] This prediction also holds for alternative noise models, such as trembles and random preferences (see Loomes, 2005).

[32] Considering the two strategies that involve choosing the symmetric source separately, the EU+N model predicts that the symmetric source is chosen with probability $\frac{2}{3}$ rather than $\frac{1}{2}$. Even so, the estimated probabilities are still higher than predicted, significantly so in the second environment.

Table A1: Choice of the symmetric source vs. an EU-equivalent alternative.

Symmetric precision	Prior	Included strategies	% choosing symmetric	95% CI
High	.55	S, A	69.1%	[61.5%–76.7%]
High	.75	S, S_r, A_r	71.0%	[62.5%–79.5%]
Low	.40	S, S_b, A_b	91.7%	[86.1%–97.3%]
All	All	S_r, S_b, A_r, A_b	58.1%	[54.0%–62.3%]

Notes: Estimates based on logistic regressions of chosen strategy on a constant with robust standard errors clustered on individuals. The regression in the last row includes fixed effects for prior by guess. The strategies are S(ymmetric) or A(symmetric). No subscript indicates following the signal. Subscripts *r* and *b* indicate ignoring the signal and guessing *r* and *b*, respectively.

the symmetric rather than the asymmetric source conditional on ignoring the signal, the prior, and the guess, should be .50. The last row in Table A1 presents the marginal probability for choosing the symmetric source based on a logistic regression with the prior, the guess, and their interaction, as independent variables with robust standard errors clustered on individuals and restricted to the rounds where the participant ignored the signal. The estimated probability of choosing the symmetric source is 58.1%, significantly higher than 50%.

Simulated Decision Noise. The results above establish a systematic tendency toward the symmetric source that cannot be explained purely by noise. However, it remains possible that noise contributes to this effect. To test this further, we estimated the model in Column (2) of Table 2 using 1,000 simulated data sets. Each dataset contains 760 observations, matching the experiment. For each observation, we assigned the chosen strategy based on the EU+N model, where expected utility was given by the probability of guessing correctly, with an added noise term drawn from a uniform distribution on $[-0.4, 0.4]$. The results indicate that the estimated δ parameter was significant at the .05 level in 46 out of the $1,000$ simulated data sets, with a mean value of 0.001 compared to 8.217 in the actual data. Thus, noise does not appear to bias the estimates upwards.[33]

[33] Noise does appear to bias the estimate for λ *downwards*, which cannot explain the significant *positive* estimate in the experiment. This effect does not exist for normally distributed noise.

A.2 Subjective beliefs

In this section we evaluate whether distortions in probability perceptions and belief updating can explain the bias towards the symmetric source.

Tables A2 and A3 report the average deviations of posterior beliefs and conditional probabilities of receiving a signal from the objective Bayesian benchmarks, normalized by the maximum possible deviation.[34] Interestingly, while deviations in posterior beliefs are generally larger for the asymmetric source, deviations in the conditional probabilities of receiving a signal tend to be more pronounced for the symmetric sources.

Table A2: Average deviation from Bayesian Posteriors across sources and priors, normalized by the maximum possible deviation.

	Prior			
Source	0.10	0.40	0.55	0.75
Asymmetric	35.85%	37.40%	32.15%	26.87%
Symmetric High	24.05%	18.85%	16.07%	22.74%
Symmetric Low	23.13%	17.03%	13.12%	21.85%

Table A3: Average deviation from objective probabilities of receiving each signal across sources and priors, normalized by the maximum possible deviation.

	Prior			
Source	0.10	0.40	0.55	0.75
Asymmetric	42.71%	22.73%	13.00%	10.80%
Symmetric High	58.18%	39.13%	22.75%	18.26%
Symmetric Low	50.44%	36.84%	24.78%	23.85%

A natural question is whether these deviations in subjective beliefs translate into differences in how participants perceive the value of the information sources. To investigate this, we calculate the subjective value of each source as the expected gain from following the signal compared to following the prior, where the expected payoffs are computed using the subjective probabilities elicited in Parts 2 and 3 of the experiment.

Table A4 provides evidence consistent with the idea that subjective valuations may help rationalize participants' choices. Notably, even when the objective value of the symmetric source is zero, subjective beliefs assign it a positive value in over half of the cases. Conversely, when the asymmetric source has positive objective value, subjective

[34] Similar qualitative patterns emerge when considering absolute deviations.

Table A4: Objective and subjective value of sources.

	Objective value			
	Symmetric source		Asymmetric source	
	No value	Positive value	No value	Positive value
Subjective value				
No value	49.7%	25.8%	70.5%	59.5%
Positive value	50.3%	74.2%	29.5%	40.5%
N	473	287	190	570

Notes: Percentage of cases in which the subjective beliefs indicate no value or positive value conditional on whether the source has value based on the Bayesian posteriors. Subjective value is determined based on subjective beliefs elicited in Part 2 of the experiment.

beliefs often fail to reflect this, assigning it no value in approximately 60% of the cases. This asymmetry indicates a systematic tendency to overestimate the value of the symmetric source while underestimating the value of the asymmetric one.

Hence, the *belief* data reveals systematic deviations from Bayesian updating that could help explain departures from expected utility maximization in participants' *choices*. To further assess this explanation, we construct expected payoffs based on the elicited subjective beliefs and evaluate the frequency of payoff-maximizing strategies.[35]

Across the entire experiment, participants followed a payoff-maximizing strategy in 49.1% of rounds when payoffs are calculated using objective beliefs. This figure decreases to 42.1% when using subjective beliefs. Moreover, a substantial share (40.1%) of decisions cannot be rationalized by either objective or subjective beliefs, indicating that distortions in belief updating alone are insufficient to fully explain participants' choices.[36]

[35]There are eight possible strategies arising from the combination of two factors: the choice of information source (symmetric or asymmetric) and the color guess associated with each possible signal realization.

[36]Specifically, 31.3% of decisions are consistent with both objective and subjective beliefs, 10.8% only with subjective beliefs, and 17.8% only with objective beliefs.

A.3 Heuristic response to symmetry

In this section, we investigate whether the bias towards the symmetric source could result from confused participants relying on symmetry as a heuristic (Andreoni, 1995). To assess this, we examine how our results vary with participants' understanding of the task, using the number of mistakes made in the comprehension questions as a proxy. Additionally, we test the robustness of our findings by conditioning on cognitive abilities measured in the post-experimental questionnaire. While we observe some heterogeneous effects, our main results hold for the majority of participants.

Misunderstanding. To assess participants' understanding of the task, we examined the number of incorrect answers given to the comprehension questions before Part 1 of the experiment. After providing an incorrect answer, participants received feedback and could not proceed until answering all questions correctly. The total number of incorrect answers varied from zero (one participant) to 21 (also one participant), with a mean and median of 7 (see also Figure A1). This number significantly correlates with the choice of optimal strategies ($r(188) = -.369, p < .001$). Participants who made the median number of mistakes or less chose the optimal decision in 54.1% of cases, compared to only 41.3% among those who made more than the median number of mistakes.

Does this mean that the bias toward symmetry disappears among participants with better task comprehension? Table A5 presents our main model estimates alongside separate estimates for participants who made fewer or more than the median number of incorrect answers. The results indicate that those who who found the task difficult to understand were not only noisier (as reflected by a lower γ) but also exhibited a stronger tendency to choose the symmetric source (δ) and to follow signals (λ). However, even among participants who made fewer mistakes, the estimates for δ and λ remain substantial and statistically significant.

Figure A1 provides further insights by estimating δ conditional on the number of incorrect answers. Two key patterns emerge, reinforcing the results from Table A5. First, a higher number of mistakes is associated with a stronger bias toward the symmetric source. Second, the majority of participants (164 out of 190, or 86.3%) made between 3 and 12 incorrect answers, and across this range, all estimates of δ remain positive and close to the main model's estimate.

Cognitive abilities. In the postexperimental questionnaire, we tested cognitive abilities using the Raven matrices test and a numeracy test.[37] The regression in Table A6

[37] We did not collect Raven scores from 20 of the participants who participated in the first session due to a technical problem with presenting the matrices.

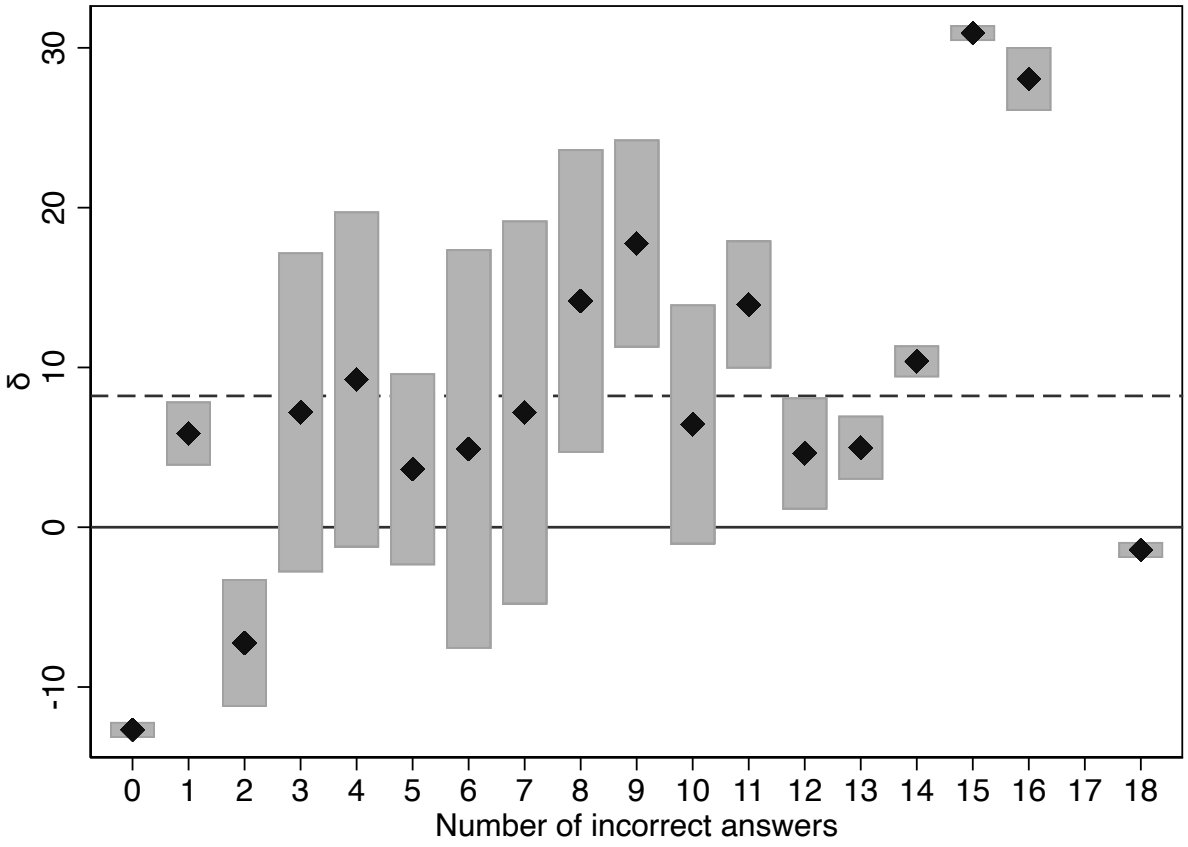


Figure A1: Misunderstanding and choosing the symmetric source.

Notes: Points mark the estimated δ conditional on number of incorrect answers to control questions. The bars represent the number of participants. The dashed line marks the estimate for δ in the main model. The figure excludes one outlier who gave 21 incorrect answers and chose the symmetric source in all but one round.

Table A5: Estimated effects of misunderstanding.

	None	Below median	Above median
δ	8.217***	6.119**	12.540***
	(4.59)	(3.17)	(3.47)
λ	13.442***	9.430***	20.999***
	(5.39)	(3.56)	(3.88)
ξ	2.946	1.214	6.120
	(1.29)	(0.46)	(1.40)
γ	0.054***	0.062***	0.043***
	(22.21)	(18.28)	(12.89)
N	7600	4600	3000

Notes: t-statistics in parentheses based on robust standard errors clustered on individuals. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

shows that numeracy, but not Raven, scores are associated with the share of optimal strategies at the individual level. Figure A2 shows the share of optimal strategies by numeracy score, with 95% confidence intervals based on a regressions of optimal strategies on dummies for numeracy scores.

This positive correlation may be because people with lower numeracy skills are less accurate, but also because they rely on heuristics that lead them towards the symmetric source or to follow signals when they should not. To identify the roots of this correlation, we estimated the parameters of the model presented in Section 5.3, allowing them to vary with the cognitive skills measures. Column (1) in Table A7 estimates the baseline model on the participants for whom we have numeracy and Raven scores. Column (2) allows the tendency to choose the symmetric source δ and the precision parameter γ and Column (3) allows all parameters to vary with numeracy. Column (4) estimates the model only for the 57 with the highest numeracy score of 5 out of 5. We see that high numeracy is significantly associated with lower noise (higher γ), but not with lower values of the choice parameters.[38] The estimates for δ and λ are, if at all, higher for high-numeracy participants, indicating that the tendencies to choose the symmetric source and to follow the signal can not be explained by low cognitive skills.

[38]The estimate for ξ varies significantly with numeracy, however the tendency to follow signals does not vary significantly with numeracy, either for the asymmetric source (λ) or for the symmetric source ($\lambda + \xi$).

Table A6: Cognitive ability and optimal strategies.

	Optimal straegies
Numeracy	0.0401**
	(3.30)
Raven	-0.0216
	(−1.23)
Intercept	0.378***
	(7.62)
N	170

Notes: OLS regression of proportion of optimal strategies on cognitive ability measures. t-statistics in parentheses.

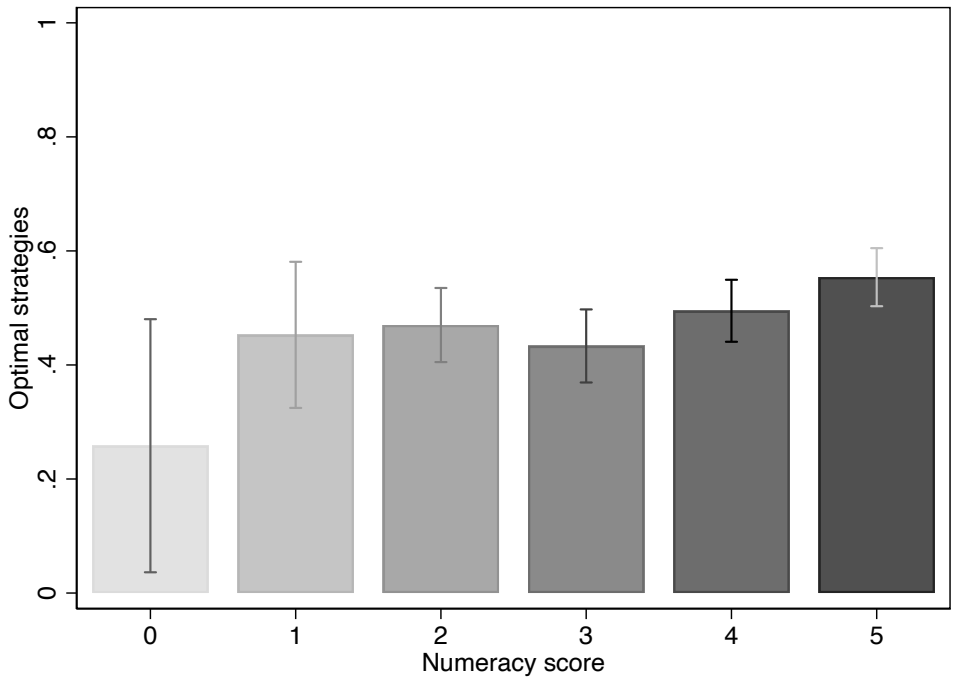


Figure A2: Optimal choices and numeracy.

Table A7: Estimated effects of cognitive abilities.

	None	δ	All	High numeracy
δ	7.577***	13.257**	3.118	10.141***
	(4.11)	(2.58)	(0.54)	(3.41)
Numeracy$_\delta$		−1.721	0.871	
		(−1.43)	(0.66)	
Raven$_\delta$		0.541	0.742	
		(0.37)	(0.35)	
λ	13.057***	13.137***	−0.098	17.862***
	(5.02)	(5.20)	(−0.01)	(4.65)
Numeracy$_\lambda$			2.050	
			(0.93)	
Raven$_\lambda$			3.208	
			(1.19)	
ξ	3.604	3.275	18.408*	−4.164
	(1.56)	(1.42)	(2.36)	(−1.05)
Numeracy$_\xi$			−4.100*	
			(−2.30)	
Raven$_\xi$			0.265	
			(0.10)	
γ	0.054***	0.038***	0.045***	0.063***
	(21.10)	(5.47)	(5.02)	(12.34)
Numeracy$_\gamma$		0.005**	0.005*	
		(3.27)	(2.41)	
Raven$_\gamma$		−0.001	−0.004	
		(−0.39)	(−1.49)	
N	6,800	6,800	6,800	2,280

Notes: t-statistics in parentheses based on robust standard errors clustered on individuals. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B Experimental Instructions

Welcome and thank you for taking part in this experiment. Please remain quiet and switch off your mobile phone. It is important that you do not talk to other participants during the entire experiment. Please read these instructions very carefully; the better you understand the instructions the more money you will be able to earn. If you have further questions after reading the instructions, please give us a sign by raising your hand out of your cubicle. We will then approach you in order to answer your questions personally. Please do not ask aloud.

During the experiment all sums of money are listed in ECU (for Experimental Currency Unit). Your earnings during the experiment will be converted to pounds at the end and paid to you in cash. The exchange rate is 50 ECU = £1. The earnings will be added to a participation payment of £5.

In this experiment you will not interact with other participants. Your earnings will depend on your decisions and on chance, as will be explained in the following. The experiment is divided into three parts. Your final payoff will be the sum of your earnings in the three parts.

After the experiment, we will ask you to complete a short questionnaire, which we need for the statistical analysis of the experimental data. The data of the questionnaire, as well as all your decisions during the experiments will be anonymous.

Please, stay in your seat until all other subjects have finished the experiment. The lab administrator will let you know when to stand up.

INSTRUCTIONS PART I

This part consists of **four** blocks, and each block consists of **ten** rounds. The instructions are **identical** for each round. Your task in each round will be to **guess the colour of a triangle**. As explained below, you will know **how the computer chooses** the colour of the triangle. You will also be able to choose a computerised advisor to receive **advice** from regarding the colour of the triangle.

The Triangle Colour

The **colour of the triangle** will be **randomly** chosen at the **beginning of each round** to be one of two colours. For example, the triangle can be either blue or red . The **two possible colours** will change from block to block, and will be announced at the beginning of each block. In these instructions, we will use blue and red as in the example above.

The **probability** that the triangle is blue or red will also change from block to block and will be announced at the beginning of each block. For example, the triangle is blue with 40% probability, and red with 60% probability. This will be presented on the computer screen as:

The advisors

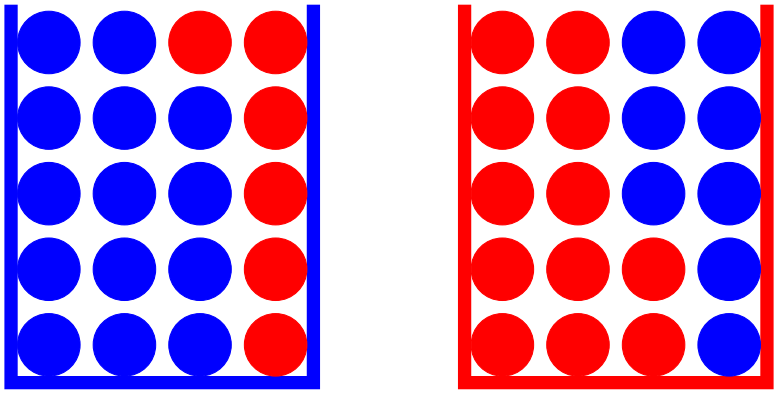
You will not know the colour of the triangle, and **your objective will be to guess the colour of the triangle**. For that, you will receive an advice from an advisor that will be simulated by the computer. You will be able to choose **one of two advisors**.

Each advisor **has two urns**, a **blue urn** and a **red urn** (corresponding to each of the colours). Each urn is filled with 20 balls, some of which are blue and the others are red. **There are always more blue balls in the blue urn than in the red urn** (and, therefore, more red balls in the red urn than in the blue urn).

Which advice an advisor gives you depends on a **random ball** drawn from the **urn that corresponds to the true colour of the triangle**. That is,

- if the colour of the triangle is blue , a ball will be drawn from the blue urn
- if the colour of the triangle is red , a ball will be drawn from the red urn.

For example, the blue urn may contain 14 blue balls and 6 red balls, and the red urn may contain 8 blue balls and 12 red balls, as in the figure below. As you can see, there are more blue balls in the blue urn than in the red urn.



Choosing advisors

In each round you will be asked to choose between **two advisors**. The computer will present you with the **two urns** of each of the **two advisors**. You should consider these urns carefully, and decide **which advisor you prefer to receive advice from**. The two advisors will be the same for all rounds within a block.

Guessing the colour of the triangle

After choosing the advisor, you will be asked to guess the **colour of the triangle**. Your choice can **depend on the advice** you receive, in the following way. The computer will ask you to guess the colour of the triangle **twice**. Once for the case that the advisor you chose gives you a blue advice, and again for the case that the advisor you chose gives you a red advice. After you have made the choice, and without observing the advice, the computer will determine the advice by randomly selecting a ball from the urn of the advisor you chose that corresponds to the colour of the triangle. That is, if the colour of the triangle is blue , the computer will choose a ball from the blue urn. If the colour of the triangle is red , the computer will choose a ball from the red urn. The colour of the **drawn ball** will determine the **advice you receive**, in the following way: if the ball drawn is blue, the computer will implement the guess that you chose after a blue advice, and if the colour of the drawn ball is red, the computer will implement the guess that you chose after a red advice. Your **payoff** will be determined by the **guess corresponding to the advice** and the colour of the triangle.

Summary of the round

1. The computer chooses the colour of a triangle according to a known rule (probability).
2. You choose one of two advisors.
3. You choose which colour to guess for each advice.
4. The computer determines the advice and follows your guess.

Your Payoff

Your payoff will depend on **whether you guessed the colour of the triangle correctly**. If your guess is correct, you will receive 100 ECU. Otherwise you will receive 0 ECU.

Information at the end of each Round

At the end of each round, you will receive the following information about the round: the **colour of the triangle**, which **advisor** you chose, what **advice** you received from the advisor, what was your **guess**, and your **payoff** for the round.

Final Earnings

At the end of the experiment, the computer will randomly select **two rounds** in each of the **four blocks**, which makes a total of **eight** rounds. You will receive the payoffs that you had earned in **each** of these selected rounds. Each of the 40 rounds has the **same chance** of being selected.

Control Questions

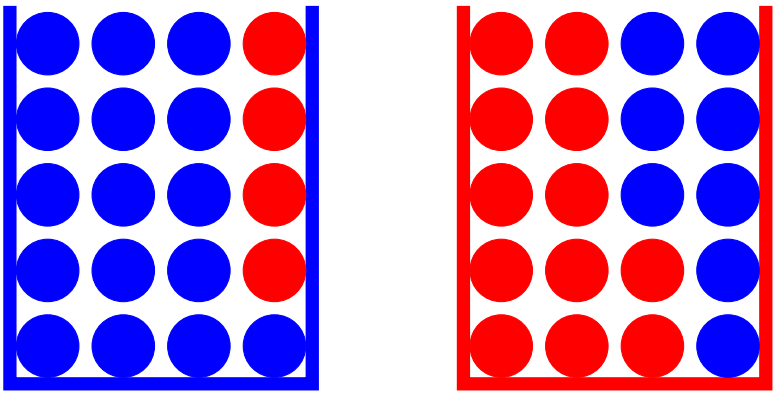
Before starting the experiment, you will have to answer some control questions in the computer terminal. Once you and all the other participants have answered all the control questions, Round 1 will begin.

Control Questions Part I

1. How many rounds will determine your earnings in this part?
   [Enter number]
2. Will you know the colour of the triangle before making your decision?
   Yes
✓ No
3. Will the triangle always have the same colour?
   Yes
✓ No
4. What is the probability that the triangle is of a certain colour?
   The probability will change from round to round.
✓ The probability will change from block to block.
   50%
   60%
5. In each round, you choose…
   Which advisor to receive advice from.
   Which advisor, and which urn of that advisor, to receive advice from.
✓ Which advisor to receive advice from, and which colour to guess for each possible advice.
   Which colour to guess for each of the two possible advisors.
6. The advice you receive depends on…
   Only on the colour of the triangle.
   Only on the advisor you chose.
✓ On the colour of the triangle and the advisor you chose.
   On the advisor you chose and one randomly selected urn of that advisor.
7. You are more likely to receive blue advice if…
   The probability of choosing the blue triangle is higher.
   There are more blue balls in the advisor's urn that corresponds to the blue triangle.
   There are more blue balls in the advisor's urn that corresponds to the red triangle.
✓ All of the above.
   None of the above.
8. If the advice from your advisor is [red/blue], the likelihood that the triangle is [red/blue] is always…
✓ Higher than if the advice was [blue/red].
   Lower than if the advice was [blue/red].

The same as if the advice was [blue/red].
Higher than the likelihood that the triangle is [blue/red].

9. Suppose that the two colours are blue and red, and that the advisor you chose has the following urns: [blue and red are randomly switched for half the participants]



Blue urn Red urn

If the selected triangle is Red, then the advice will be a random ball from an urn with…
16 blue balls and 4 red balls
✓ 8 blue balls and 12 red balls
10 blue balls and 10 red balls
None of the above.

10. Suppose that at the end of the period you learn that…
[This question is repeated three times. Each time, the triangle colour, guesses, and advice are determined randomly and independently, and the correct answer is set accordingly.]
    - The triangle was [red/blue]
    - You chose an advisor
    - Your guess was [red/blue] if your advisor's advice was Red
    - Your guess was [red/blue] if your advisor's advice was Blue
    - Your advisor's advice was [red/blue]

What is your payoff in this period?
0
✓ 100

INSTRUCTIONS PARTS II AND III

This part consists of **eight** rounds. The instructions will be the same in all rounds.

Recall that in **Part I** you had to select one of **two advisors** who would give you advice to guess one of **two possible colours** of the triangle.

[Part II] In **Part II**, your task will be **to estimate the chances of the triangle being of each colour** for each of the **two possible advices** you may receive from **a predetermined advisor**.

[Part III] In **Part III**, your task will be **to estimate the chances of receiving each of the two possible advices** from **a predetermined advisor**.

The Triangle Colour

In each round, the triangle will be of one of **two possible colours** (in these instructions we will stick to the example of blue or red). The **probability** that the triangle is of one or the other color will be presented on the computer screen using a coloured bar, exactly as in **Part I**. Here is again the example using the colours blue and red :

These probabilities will be different for each different pair of colours.

The advisor

In **Part II**, there will be **only one advisor** in each round. As in **Part I** (**Parts I and II**), you will see the two urns of that advisor: in our example, a **blue urn** and a **red urn**. Each urn is filled with 20 balls, some of which are blue and the others are red. There are always more blue balls in the blue urn than in the red urn (and, therefore, more red balls in the red urn than in the blue urn).

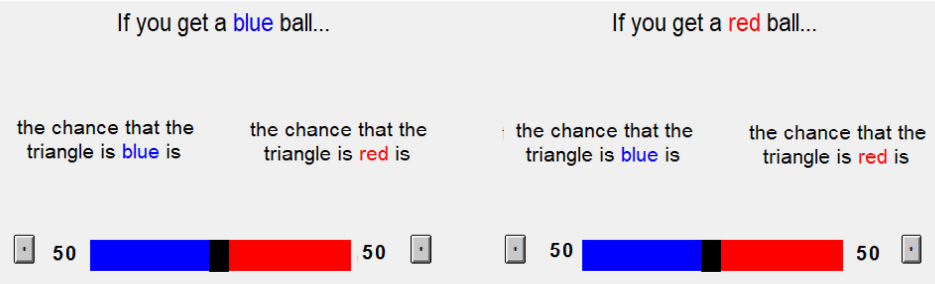
The advisor can give you one of two advices. Which advice an advisor gives you depends on a **random ball** drawn from the **urn that corresponds to the true colour of the triangle**. That is,

- if the colour of the triangle is blue , a ball will be drawn from the blue urn
- if the colour of the triangle is red , a ball will be drawn from the red urn.

Your decision (Only Part II)

For each possible advice that the advisor may give you (blue or red in the example), you must determine the **chance** (out of 100) that the **triangle is** blue and the **chance** that the **triangle is** red . For example, if you think that the triangle is **equally** likely to be blue or red , you should enter the number 50 for each colour. If you think that there is **80%** chance that the triangle is blue (and hence **20%** chance that the triangle is red) you should enter the number **80** for blue and **20** for red.

As you have to decide these chances for each of the advisors' advice, you will need to take your decision with two sliders that will look as follows:

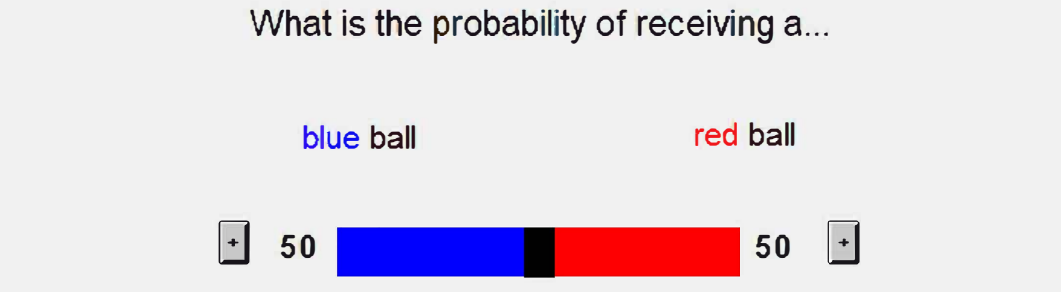


The slider on the left corresponds to the advice given by a blue ball and the slider on the right corresponds to the advice given by a red ball.

Your decision (Part III)

Your task is to estimate the **chance** of receiving each of the two possible advices (blue or red in the example). You can think about it this way: if the advisor gives you 100 advices, where the color of the triangle is chosen anew for each advice, how many times do you expect to receive a blue advice and how many times do you expect to receive a red advice?

For example, if you think that you are equally likely to receive a blue advice and a red advice, you should enter the number **50 for each colour**. If you think that there is **80%** chance of receiving a blue advice (and hence **20%** chance of receiving a red advice) you should enter the number **80** for blue and **20** for red.



You will need to take your decision with one slider that will look as follows:

[Both sections of the decision in Parts II and III continue as follows] **Both numbers on each slider change simultaneously** as the sum of the chances must be equal to 100. There are **two ways** in which you can change those numbers: by using the **slider** or by using the push **buttons** on the left and right of the slider.

- If you want to **increase** the chance of the triangle being blue (which will **decrease** the chance of the triangle being red) you can either **push the button on the left or move the slider to the right**.
- If you want to **increase** the chance of the triangle being red (which will **decrease** the chance of the triangle being blue) you can either **push the button on the right or move the slider to the left**.

In the beginning of each round, the slider will start at a chance of **50** for the triangle being of either colour. You will have to **click on the slider or push one of the buttons** at least once before you can submit your final decision. You will be able to practice with the sliders before starting this part.

Your Payoff

The computer will select the **colour of the triangle**, and then draw a random ball from the advisor's urn that corresponds to the **chosen colour of the triangle**.

[Part II] **Your payoff** will depend on the **colour of the triangle**, and your **guess about the chances** of each colour for the **corresponding advice** (that is, the drawn ball). You can **either** win a prize of **50 ECU**, or receive **0 ECU**. The procedure of determining your payoff, described below, is somewhat complex. It is designed to guarantee that **if your estimate of the chances is correct, you have the best chances of winning the prize if you enter the numbers according to what you truly believe**.

[Part III] Your payoff will depend on the **colour of the ball**, and your **guess**. You can **either** win a prize of 50 ECU, or receive 0 ECU. The procedure of determining your payoff, described below, is the same as the one used in **Part II**. To remind you, it is designed to

guarantee that **if your estimate of the chances is correct, you have the best chances of winning the prize if you enter the number according to what you truly believe**.

To determine whether you receive the prize of **50 ECU**, the computer will randomly choose **two numbers between 0 and 100** (including decimal numbers), with each possible number **equally likely** to be chosen. Draws are independent in the sense that the outcome of the first draw in no way affects the outcome of the second draw.

If the **colour of the [PII]: triangle / [PIII]: advice** is blue , you will receive the prize only if the number you have chosen for a blue is **higher** than at least one of the numbers that the computer chose.

If the **colour of the triangle** is red , you will receive the prize only if the number you have chosen for a red triangle is **higher** than at least one of the numbers that the computer chose.

You should consider the situation carefully and enter the chances **as you best estimate them**. This way, you have the **best chances of winning the prize**.

Summary of the task (Only Part III)

To sum, the procedure in **Part III** is similar to the procedure in **Part II**. In each round, you will see the two urns of a certain advisor. The difference is that, whereas in **Part II** you were asked to estimate the chances for each **colour of the triangle** based on the advice, in **Part III**, you will be asked to estimate the chances for each **advice**.

Information at the end of each Round

In this part, you will not receive any feedback at the end of the round.

Final Earnings

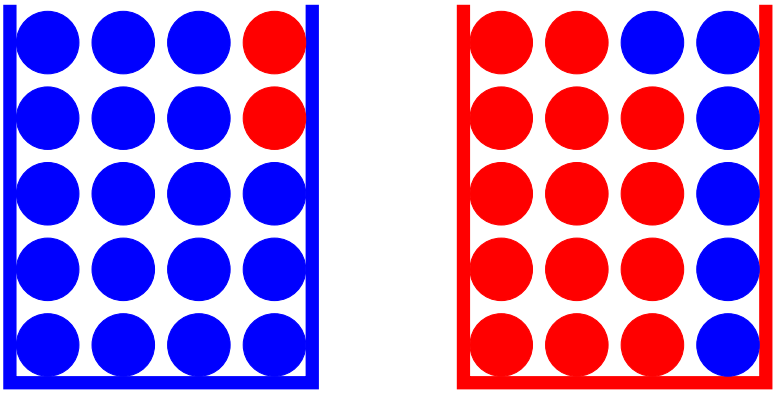
At the end of the experiment, the computer will randomly select two rounds of the eight rounds in this part. You will receive the payoffs that you had earned in each of these rounds. Each of the eight rounds has the same chance of being selected. You will only learn about the payoff for the selected rounds at the end of the experiment.

Control Questions

Before starting this part, you will have to answer some control questions in the computer terminal. Once you and all the other participants have answered all the control questions, Round 1 will begin.

Control Questions Part II

1. How many rounds will determine your earnings in this part? [Enter number]
2. Will you know the color of the triangle before making your decision?
   Yes
✓ No
3. What is the probability that the triangle is of a certain colour?
✓ The probability will change for different pairs of colors.
   50%
   60%
4. If the advice from your advisor is [red/blue], the likelihood that the triangle is [red/blue] is always…
✓ Higher than if the advice was [blue/red].
   Lower than if the advice was [blue/red].
   The same as if the advice was [blue/red].
   Higher than the likelihood that the triangle is [blue/red].
5. Suppose that the two colours are blue and red, and that the advisor you chose has the following urns: [blue and red are randomly switched for half the participants]



Blue urn Red urn

   If the selected triangle is Blue, then the advice will be a random ball from an urn with…
✓ 18 blue balls and 2 red balls
   6 blue balls and 14 red balls
   10 blue balls and 10 red balls
   None of the above.
6. Suppose that the two colours are blue and red. And suppose that your decision is that if you get a…

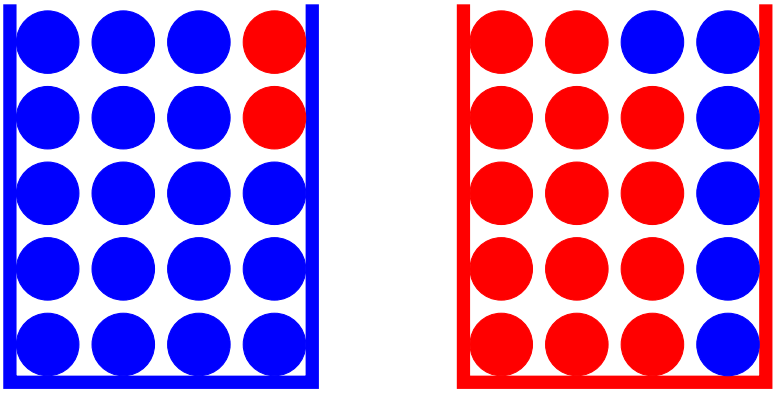
- blue ball, the chance that the triangle is blue is X
- blue ball, the chance that the triangle is blue is 100 – X
- red ball, the chance that the triangle is blue is Y
- red ball, the chance that the triangle is blue is 100 – Y

Select this decision using the sliders below.

[X and Y are random integer between 0 and 100. Participants respond on sliders as in the experiment.]

Control Questions Part III

1. How many rounds will determine your earnings in this part? [Enter number]
2. Will you know the color of the triangle before making your decision?
   Yes
✓ No
3. Will the triangle always have the same colour?
   Yes
✓ No
4. What is the probability that the triangle is of a certain colour?
✓ The probability will change for different pairs of colors.
   50%
   60%
5. Suppose that the two colours are blue and red, and that the advisor you chose has the following urns: [blue and red are randomly switched for half the participants]



Blue urn Red urn

If the selected triangle is Blue, then the advice will be a random ball from an urn with…

✓ 18 blue balls and 2 red balls

6 blue balls and 14 red balls
10 blue balls and 10 red balls
None of the above.

6. Suppose that the two colors are blue and red. And suppose that your decision is that…

   - The chance of a blue advice is X
   - the chance of a blue advice is 100 - X

   Select this decision using the sliders below.
   [X is a random integer between 0 and 100. Participants respond on sliders as in the experiment.]